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Reusable Perforated Plastic-Ball Bulking Agent for Decentralized Food Waste Composting: Maturity Validation, Nutrient Retention and Machine Learning-Based Process Interpretation

Amit Shivputra Dharnaik

dharnaikamit@gmail.com

MIT Art Design and Technology University https://orcid.org/0000-0003-3398-3202

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Abstract

High-moisture food waste composting is often limited by compaction, poor oxygen transfer, unstable degradation and nutrient loss. This study evaluated reusable perforated plastic balls as a synthetic bulking agent and inert aeration-support medium for improving in-vessel aerobic composting of food waste. Four SBA dosages, namely 0%, 2%, 4% and 8%, were tested for 30 days using food waste amended with biochar, neem powder, lime and jaggery. Composting performance was assessed using temperature, pH, total organic carbon, total Kjeldahl nitrogen, phosphorus, potassium, C/N ratio, compost quality indices, nutrient retention, kinetic modelling and machine-learning-based maturity interpretation. SBA8 showed the best overall response, with a peak temperature of 58°C, 11 thermophilic days, near-attainment of the optimum C/N maturity range by Day 18 and mature C/N status by Day 24. Phosphorus and potassium retention were highest in SBA8, reaching 45.65% and 22.96%, respectively. Random Forest identified nitrogen transformation, pH and moisture as major maturity-related variables, while LSTM reproduced treatment-wise C/N trends. Reusable perforated plastic-ball SBA improved aeration-controlled food waste composting by accelerating maturity development, conserving nutrients and supporting data-based process interpretation for decentralized solid waste management.

Introduction

Food waste generation has become a serious environmental and management concern, particularly in rapidly urbanizing regions [1, 2]. More than 1.3 billion tonnes of food waste are discarded globally each year and uncontrolled disposal leads to landfill emissions, odour nuisance and nutrient loss [3, 4]. Aerobic composting has been widely accepted as an economical and sustainable method for converting organic waste into value-added compost through controlled microbial oxidation [5, 6]. The efficiency of composting depends strongly on carbon, nitrogen, moisture condition and oxygen availability. Aeration is one of the most important factors in aerobic composting. When oxygen supply is inadequate, degradation of organic matter slows and the final product remains unstable [7, 8].

Conventional bulking materials such as sawdust, rice husk and wood chips are commonly used to improve porosity and airflow in the composting process. However, these materials often degrade during the process and gradually lose their structural role, which reduces air passage and affects process efficiency [9, 10, 11]. Recent studies have also examined the use of biochar, lime, neem powder and sugar-rich supplements to improve microbial growth, odour control and nutrient conservation [12]. Biochar provides a porous surface for microbial colonization and lime helps maintain a favourable pH range [13]. Neem suppresses unwanted microbial growth and improves biological stability [14]. Even with these advantages, natural bulking materials still show limited mechanical stability. Oxygen transfer in in-vessel systems is also affected by their irregular shape and progressive degradation [1, 11, 15, 16].

Synthetic bulking agents offer a different approach. These materials do not degrade during composting and can preserve void spaces for a longer period. This helps maintain airflow within dense food waste mixtures. Research on the use of synthetic bulking agents in composting remains limited [17, 18]. Another limitation in the available literature is the continued dependence on empirical models and first-order kinetic approaches. These models do not adequately capture the non-linear and time-dependent interactions among temperature, moisture, nutrient transformation and microbial activity. Data-driven methods are therefore needed to identify dominant controlling variables and predict compost maturity with better reliability [19, 20, 21].

The present study was undertaken to evaluate the efficiency of synthetic bulking agent in an in-vessel aerobic composting reactor treating food waste amended with biochar (8%), neem powder (5%), lime (5%) and jaggery (10%). Four experimental runs were conducted at SBA levels of 0%, 2%, 4% and 8%, while keeping the remaining additive composition constant. Along with experimental evaluation, the study integrated machine learning for interpretation of multivariate process behaviour and prediction of compost quality [22]. Special emphasis was given to the C/N ratio as the primary maturity index. Machine learning has increasingly been used in composting studies for outcome prediction, process optimization and management of interacting variables such as temperature, moisture and substrate composition [19, 23, 24]. These tools can represent non-linear interactions in biological treatment systems more effectively than conventional empirical approaches [25, 26].

This work combines controlled composting experimentation with machine learning-based interpretation. Random Forest regression was used to identify the relative influence of physicochemical variables such as temperature, pH, moisture, TOC, TKN, phosphorus and potassium. LSTM modelling was also used to forecast temporal changes in C/N ratio. The study was designed to provide process-level understanding as well as predictive capability. It also examined how SBA concentration influences degradation kinetics and nutrient stabilization during food waste composting.

Earlier studies have evaluated natural, synthetic and recyclable bulking agents for improving composting performance. However, limited attention has been given to linking reusable synthetic bulking agent performance with compost maturity validation, nutrient-retention behaviour, kinetic stabilization and data-driven process interpretation in food waste composting. Therefore, the present study does not claim novelty only in the use of a synthetic bulking agent. Instead, it evaluates how reusable SBA dosage influences aeration-controlled composting performance, final compost quality, nutrient conservation and maturity prediction. This integrated approach is relevant to decentralized food waste treatment, resource recovery and environmental management.

The novelty of this study lies in integrating reusable perforated plastic-ball SBA-assisted food waste composting with early maturity achievement, multi-indicator compost quality validation, nutrient-retention assessment, apparent first-order kinetic modelling and machine-learning-based process interpretation. The reusable SBA acts as a persistent void-forming medium within a dense, high-moisture food waste matrix and helps maintain aeration during composting. A key technical contribution of the study is that the higher SBA dosage enabled early stabilization, with SBA8 reaching approximately the optimum C/N maturity threshold by Day 18 and further stabilizing within the mature C/N range by Day 24, whereas the control treatment remained insufficiently stabilized even at the end of the composting period. The study evaluates how SBA dosage affects thermophilic development, carbon mineralization, nitrogen conservation, phosphorus and potassium retention and final compost quality. The work provides an environmental engineering framework for improving decentralized food waste composting and supporting circular nutrient management.

The objective of this study was to evaluate the performance of reusable perforated plastic balls as a synthetic bulking agent and inert aeration-support medium for in-vessel aerobic composting of high-moisture food waste. Four SBA dosages, namely 0%, 2%, 4% and 8%, were tested under controlled reactor conditions to examine their effect on aeration-assisted compost stabilization. The study assessed thermal behaviour, pH stabilization, organic carbon reduction, nitrogen enrichment, phosphorus and potassium retention, C/N maturity development and final compost quality. Particular attention was given to the time required to reach the optimum C/N maturity threshold, because early stabilization is important for improving reactor turnover and operational efficiency in

decentralized solid waste treatment systems. In addition, apparent first-order kinetic modelling and machine-learning approaches were used to interpret maturity development, identify dominant process variables and support data-based process monitoring. The broader aim was to support decentralized food waste management through improved compost stabilization, nutrient conservation and reusable aeration-support media.

Materials and Methods

Reactor Design and Configuration

The composting trials were conducted in an in-vessel aerobic composting reactor designed and fabricated in the Environmental Engineering Laboratory at MIT-ADT University, Pune. The reactor was developed to maintain controlled temperature, aeration and moisture conditions, by ensuring aerobic composting operation. The main composting chamber measured 55 cm × 55 cm × 80 cm and had an approximate capacity of 100 kg. It was fabricated from mild-steel perforated sheets and fitted with sixteen perforated MS pipes. These perforated MS pipes were arranged horizontally in a 4 × 4 matrix to ensure uniform air distribution through the composting mass. The reactor had two auxiliary side compartments, each of size 55 cm × 25 cm × 80 cm. The side compartments were provided with electric heaters and fans. The heaters maintained the thermophilic range of 45–60°C during the initial phase for rapid microbial activation. Air supplied by the fans maintained oxygen availability throughout the process. The aeration rate was fixed at 0.45 L min^{-1} and operated in a cyclic mode of 0.5 h on and 1 h off through a regulated manifold system. A perforated base was incorporated for leachate collection and recirculation to maintain suitable moisture conditions without manual turning. The reactor design helped reduce odour and supported pathogen destruction through sustained elevated temperature. The schematic and photographic views of the developed in-vessel aerobic composting reactor are shown in Fig. 1a and Fig. 1b, respectively.

Feedstock Composition and Additives

The food waste used in the experiments was collected from the MIT ADT University, Pune campus canteen. The collected material consisted mainly of cooked rice, vegetable residues and fruit waste. The collected waste was shredded to an average particle size below 20 mm. Neem powder (5%), lime (5%), jaggery (10%) and biochar (8%) were added to each batch on a wet weight basis. Neem powder was used as a natural antimicrobial additive and contributed to nitrogen stability. Lime was used to maintain pH suitable for microbial growth during composting. Jaggery was used as a readily available carbon source during the initial stage of composting. Biochar was used to improve porosity, aeration and nutrient retention in the composting process.

The only variable among the treatments was synthetic bulking agent (SBA), which consisted of perforated plastic balls of approximately 25 mm diameter used as inert aeration media. Four treatment sets were prepared, namely SBA0 (0%), SBA2 (2%), SBA4 (4%) and SBA8 (8%). These levels represented increasing proportions of SBA in the composting mixture. The aim was to examine the effect of structural aeration enhancement on thermal behaviour, nutrient conservation and compost stabilization.

Analytical Measurements

Process parameters were measured at two-day intervals during the composting period. Temperature was recorded using digital thermocouples placed at three different depths in the composting mass and the mean value was used for analysis. The pH was measured in a 1:10 (w/v) aqueous extract following IS 2720 (Part 26, 1987). Moisture content was determined by the gravimetric method according to IS 9235 (1979). Total organic carbon (TOC) was determined by the Walkley–Black titration method. Total Kjeldahl nitrogen (TKN) was measured using the Kjeldahl digestion–distillation procedure as per IS 10158 (1982). Phosphorus (P) and potassium (K) were analysed by spectrophotometry and flame photometry, respectively, after acid digestion. The C/N ratio was calculated as the ratio of TOC to TKN. All laboratory analyses were performed in duplicate and the mean values of measured observations were used for statistical analysis. The measured observations were used for treatment-wise comparison, while the processed dataset used for machine learning analysis is described in the Data Pre-Processing and Feature Engineering section.

Data Pre-Processing and Feature Engineering

The compiled dataset contained day, treatment, temperature, pH, moisture, TOC, TKN, P, K and derived C/N ratio. Process parameters were experimentally measured at two-day intervals during the 30-day composting period. For machine learning analysis, the measured time-series data were converted into uniform day-wise records from Day 0 to Day 30 using linear time-series preprocessing.

To capture process dynamics, first-order differences were calculated for major parameters, including ΔTemperature, ΔMoisture and ΔpH. Additional interaction variables such as TKN/TOC, K/P and Temperature × Moisture were generated to represent nutrient and process interactions within the composting system. Extreme observations were screened using the z-score method within ± 3σ. Numerical variables were standardized to zero mean and unit variance before model development.

The final engineered dataset consisted of 124 observations generated from four treatment conditions, namely SBA0, SBA2, SBA4 and SBA8. Each treatment contributed 31 day-wise records from Day 0 to Day 30. This processed day-wise dataset was used only for machine learning model development, while the original laboratory measurements were retained as the basis for treatment-wise interpretation and discussion.

For Random Forest regression, the full engineered dataset of 124 observations was divided into 80% training data and 20% testing data. For LSTM modelling, treatment-wise time-series data were converted into supervised learning sequences using a five-day sliding window, which generated 104 input-output sequences for temporal prediction of C/N ratio.

Machine Learning Modelling

Random Forest Regression

A Random Forest Regressor (RFR) was developed in scikit-learn v1.5 to model the non-linear relationship between input variables and compost maturity represented by C/N ratio. The dataset was divided into 80% training data and 20% testing data. Hyperparameters, including number of trees = 500, maximum depth = 6 and minimum split = 4, were selected using five-fold cross-validation. Model performance was evaluated using coefficient of determination (R^2) and Root Mean Square Error (RMSE). To reduce the possibility of direct

mathematical leakage, model performance was also checked by excluding ratio-derived variables. The same predictor ranking trend was observed, with TKN and pH remaining the dominant explanatory variables. Feature importance analysis identified TKN and pH as the dominant predictors of compost maturity. After excluding ratio-derived variables, TKN retained the highest importance, followed by pH, moisture, days and TOC. This confirms that nitrogen transformation and pH regulation were the main drivers of C/N reduction.

LSTM Time-Series Forecasting

Temporal prediction of C/N ratio was carried out using a Long Short-Term Memory (LSTM) neural network implemented in TensorFlow 2.17. Input variables included temperature, pH, moisture, TOC, TKN, P and K arranged in five-day sliding windows. Since each treatment contained 31 time-point observations, the five-day look-back window generated 26 supervised sequences per treatment and 104 sequences in total for LSTM training and validation. The model architecture consisted of one LSTM layer with 32 neurons and ReLU activation followed by a dense output layer. Training was performed using the Adam optimizer with mean-squared-error loss. Early stopping with patience = 20 epochs was applied and the generated sequences were divided into 80% training data and 20% validation data. Model adequacy was assessed through comparison of measured and predicted C/N values. The LSTM model was used mainly to examine treatment-wise temporal trends in C/N ratio rather than to develop a generalized large-scale prediction model. The model reproduced the decline in C/N ratio satisfactorily, especially under the SBA8 condition. The main machine learning models, their input variables, modelling settings and predictive performance are summarized in Table 1.

Table 1
Summary of machine learning models, input features, modelling settings and predictive performance.

Model	Purpose	Target variable	Input features	Modelling settings	Performance
Random Forest Regressor	Identify dominant predictors and estimate compost maturity	C/N ratio	Days, treatment, temperature, pH, moisture, TOC, TKN, P, K, derived and interaction features	124 observations, 80:20 train-test split, 500 trees, maximum depth = 6, minimum split = 4, five-fold cross-validation	R^2 = 0.98, RMSE = 1.66
LSTM	Forecast temporal variation in compost maturity	C/N ratio	Temperature, pH, moisture, TOC, TKN, P, K in five-day sliding windows	104 supervised sequences, five-day sliding window, one LSTM layer, 32 neurons, ReLU activation, dense output layer, Adam optimizer, early stopping, 80:20 train-validation split	Good agreement with measured C/N trajectories

Statistical Validation, Visualization and Workflow Integration

All statistical analysis was carried out in Python 3.12 using pandas, numpy and matplotlib. Correlation matrices and heatmaps were used to examine the relationships among measured, derived and interaction variables. Principal Component Analysis (PCA) was used to reduce multicollinearity and identify major sources of process

variation. The first two principal components accounted for nearly 76% of the total variance and were dominated by temperature and nitrogen-linked variables.

The processed time-series records were arranged into uniform day-wise inputs, engineered into dynamic and interaction features, standardized and evaluated using correlation analysis and PCA. Random Forest regression was used to identify dominant maturity predictors, whereas LSTM modelling was applied to forecast treatment-wise C/N trajectories using five-day sliding windows. Nutrient dynamics are presented in Fig. 4. The merged multivariate analysis and treatment comparison are presented in Fig. 5, comprising the correlation heatmap, PCA score plot and comparative treatment performance. The merged machine learning interpretation is presented in Fig. 6, comprising Random Forest actual versus predicted response, feature importance and LSTM-predicted versus measured C/N trajectories.

Compost Maturity and Quality Validation

Compost maturity and final product quality were evaluated using a multi-indicator approach. In addition to the final C/N ratio, Fertility Index (FI), Clean Index (CI) and compost quality class were used to validate the maturity and agricultural suitability of the final compost. The FI was calculated using selected fertility parameters, namely total organic carbon, total Kjeldahl nitrogen, total phosphorus, total potassium and C/N ratio. Each parameter was assigned a score based on its measured value and multiplied by the corresponding weighting factor. The final FI value was used to assess the fertilizing potential of the compost.

The CI was calculated using heavy metal score values and their respective weighting factors. A higher CI value indicates lower heavy metal risk and better suitability for agricultural use. Compost quality class was assigned by combining FI and CI values. Compost with FI greater than 3.5 and CI greater than 4 was classified as Class A compost, indicating high manurial value and low heavy metal content. Compost with FI between 3.1 and 3.5 and CI greater than 4 was classified as Class B compost, indicating very good quality compost with medium fertilizing potential and low heavy metal content. This multi-indicator approach allowed compost maturity to be assessed through stabilization, fertility value and safety-related quality indices rather than C/N ratio alone.

Nutrient Retention and Loss-Balance Assessment

A nutrient retention and loss-balance assessment was carried out to examine the influence of synthetic bulking agent dosage on carbon stabilization and nutrient conservation. Since complete dry mass, leachate mass and gaseous emission data were not available, the analysis was treated as a concentration-based nutrient loss-balance rather than a full mass balance. The assessment was based on changes in TOC, TKN, phosphorus loss and potassium loss during the 30-day composting period.

TOC reduction was calculated using the difference between initial and final TOC values. TKN enrichment was calculated from the relative increase in TKN concentration between the initial and final compost samples. Phosphorus and potassium retention were calculated from the measured percentage nutrient loss values using Eq. (1):

$$\text{Nutrient retention } (\%) = 100 - \text{nutrient loss } (\%)$$

1

The calculated retention values enabled comparison of nutrient conservation among SBA treatments during organic matter degradation and nitrogen enrichment. The resulting values were used to interpret the role of SBA in nutrient conservation and final compost quality.

Kinetic Modelling of TOC Degradation and C/N Stabilization

Kinetic modelling was carried out to quantify the rate of organic carbon degradation and compost maturity development under different SBA dosages. The time-series values of TOC and C/N ratio were fitted using an apparent first-order kinetic model. The first-order form was selected because the reduction in biodegradable organic carbon and C/N ratio during composting generally follows a declining trend with time as readily degradable substrates are progressively consumed.

The kinetic relationship was expressed using Eq. (2):

$$lnC_t/C_o = -kt$$

2

where (C_0) is the initial value of TOC or C/N ratio, (C_t) is the value at composting time (t), (k) is the apparent rate constant and (t) is the composting duration in days. The rate constant was estimated from the slope of the linear regression between ($\ln(C_t/C_0)$) and composting time. The coefficient of determination (R^2) was used to evaluate the goodness of fit. Separate rate constants were calculated for TOC degradation and C/N stabilization for SBA0, SBA2, SBA4 and SBA8 treatments.

Machine Learning Validation Strategy

A multi-level validation strategy was adopted to improve the reliability of machine learning-based compost maturity prediction. Since C/N ratio was used as the target variable and was derived from TOC and TKN, particular attention was given to reducing the possibility of direct mathematical leakage. Four validation strategies were therefore considered.

First, a baseline Random Forest model was developed using the full engineered feature set and an 80:20 train-test split. This model was used to assess the overall predictive capacity of the measured and engineered composting variables. Second, a leakage-free model was developed by excluding ratio-derived variables and direct mathematical predictors that could artificially improve C/N prediction. This model was used to verify whether the predictor ranking remained physically meaningful after removing features closely related to the target variable.

Third, leave-one-treatment-out validation was used to examine whether the model could predict compost maturity under an unseen SBA dosage. In this approach, the model was trained on three SBA treatments and tested on the remaining treatment. This procedure was repeated until each treatment was used once as the test set. Fourth, time-series split validation was applied to avoid random mixing of early and later composting stages. In this validation, earlier time points were used for training and later time points were used for testing.

Model performance was assessed using coefficient of determination (R^2), root mean square error (RMSE) and mean absolute error (MAE). Feature importance analysis was used to identify the dominant predictors of

compost maturity. This validation strategy assessed whether machine learning predictions were consistent with composting process behaviour and not limited to statistical fitting of the processed day-wise dataset.

Results and Discussion

Thermal and pH Evolution during Composting

Temperature served as a direct indicator of microbial activity and composting progress. All treatments showed a sharp rise in temperature during the first three days and entered the thermophilic range of 50–60°C, followed by a gradual decline towards ambient level by Day 30 (Fig. 2a). The SBA8 treatment recorded the highest peak temperature of 58°C and maintained thermophilic conditions for a longer duration than the control SBA0. This indicates better heat retention and stronger aerobic oxidation at a higher percentage of synthetic bulking agent (SBA). This may be due to improved air flow and lower compaction, which supported continued breakdown of degradable organic matter. An extended thermophilic phase in the reactor helped in sanitization and faster stabilization of compost.

The pH profile changed from acidic to near-neutral condition during composting, as shown in Fig. 2b. The initial pH was in the range of 4.6–4.8 and this may be due to the formation of low molecular weight organic acids during the early stage of decomposition. As the process progressed, pH increased and reached 6.9–7.4 by around Day 20. Lime helped buffer this change. Improved air movement under SBA4 and SBA8 also supported carbon dioxide release and reduced acid accumulation over a longer period. A pH range close to neutral during composting indicates better microbial balance and improved stabilization of nitrogenous compounds. These observations indicate that suitable thermal conditions and pH under higher SBA levels created a more favourable internal environment for aerobic composting.

Organic Matter Mineralization and Nitrogen Retention

TOC decreased continuously in all treatments and this indicates progressive mineralization of the biodegradable organic fraction. The maximum reduction was observed in SBA8, where TOC decreased from 52.8% to nearly 38%, as shown in Fig. 3a. This corresponds to about 28% reduction in organic carbon and indicates active oxidation of degradable substrates during the thermophilic stage and early curing period. The declining trend remained close to logarithmic and this suggests rapid consumption of readily available carbon during the initial stage of composting.

TKN increased with the progress of composting and the increase was more pronounced at higher SBA levels, as presented in Fig. 3b. In the SBA8 treatment, TKN increased from 0.99% to 1.89%. This rise indicates concentration of nitrogen in the stabilized compost mass and suggests better nitrogen conservation under improved aeration conditions. Lower leachate loss and improved ammonium retention in the presence of biochar may also have contributed to this response.

The C/N ratio declined steadily throughout the process and this confirms the advancement of compost maturity (Fig. 3c). The SBA8 treatment showed a decrease in C/N ratio from 53.33 on Day 0 to 20.13 on Day 18, 17.53 on Day 24 and 16.27 on Day 26. SBA8 approached the optimum C/N maturity range by Day 18 and reached the mature range by Day 24. In comparison, SBA0 remained insufficiently stabilized even by Day 26, with a C/N ratio of 35.60. This indicates that higher SBA dosage accelerated compost maturity and reduced the stabilization

period in dense food waste composting. The faster reduction in C/N ratio under SBA4 and SBA8 indicates stronger microbial turnover and more effective carbon oxidation under improved aeration. Similar behaviour has been reported in composting systems using structurally stable bulking agents that maintain void spaces and oxygen transfer [27]. The treatment-wise phosphorus and potassium profiles are presented in Fig. 4a and Fig. 4b. The final physicochemical characteristics and key performance indicators under different SBA treatments are summarized in Table 2.

Table 2
Final physicochemical characteristics of compost under different SBA treatments.

Treatment	Max. temp. (°C)	Therm. days	Final pH	Final TOC (%)	Final TKN (%)	Final C/N	Final P (%)	Final K (%)
SBA0	40	0	5.4	41.50	1.21	34.30	0.29	0.15
SBA2	52	6	7.8	35.20	1.99	17.69	0.33	0.17
SBA4	58	9	6.9	38.21	1.98	14.25	0.38	0.29
SBA8	58	11	7.3	37.75	1.89	14.68	0.55	0.48

Compost Maturity and Quality Validation

The maturity and quality of the final compost were evaluated using C/N ratio, Fertility Index, Clean Index and compost quality class, as summarized in Table 3. This additional validation was included because C/N ratio alone cannot fully describe compost quality, nutrient value and agricultural safety. The results show that the addition of synthetic bulking agent improved both compost maturity and final product quality.

The control treatment, SBA0, showed a final C/N ratio of 34.30, indicating incomplete stabilization. Although its Clean Index was 5.0, its Fertility Index was 3.3 and it was therefore classified as Class B compost. This indicates that the control compost had low heavy metal risk but only medium fertilizing potential. In comparison, the SBA-amended treatments showed clear improvement in maturity and quality. SBA2, SBA4 and SBA8 showed final C/N ratios below 20 and were classified as Class A compost based on their FI and CI values, as shown in Table 3.

The FI increased from 3.3 in SBA0 to 3.9 in SBA2, 4.1 in SBA4 and 4.4 in SBA8, while the CI remained 5.0 in all treatments. The highest FI value observed in SBA8 indicates that the use of 8% synthetic bulking agent improved the fertility value of the final compost. This improvement can be linked to better aeration, longer thermophilic activity, improved organic matter degradation and better nitrogen conservation during composting. The constant CI value of 5.0 across all treatments also shows that the use of synthetic bulking agent did not increase heavy metal risk.

The combined maturity assessment presented in Table 3 confirms that reusable synthetic bulking agent improved compost stabilization beyond simple C/N reduction. The SBA treatments, particularly SBA4 and SBA8, produced compost that satisfied maturity-related C/N requirements and achieved Class A quality status. This strengthens the engineering significance of SBA-assisted composting by showing that the treatment improved both process performance and final compost usability.

Table 3
Compost maturity and quality validation of SBA-assisted composting treatments

Treatment	Final C/N	Fertility Index (FI)	Clean Index (CI)	Compost class	Interpretation
SBA0	34.30	3.3	5.0	Class B	Very good quality but incomplete maturity due to high C/N
SBA2	17.69	3.9	5.0	Class A	Mature compost with high fertility and low heavy metal risk
SBA4	14.25	4.1	5.0	Class A	Mature compost with improved stabilization and fertility
SBA8	14.68	4.4	5.0	Class A	Best maturity-quality response with highest FI and low heavy metal risk

Nutrient Retention and Loss-Balance Assessment

The nutrient retention and loss-balance assessment was carried out to examine whether the improved compost maturity under SBA treatments was also associated with better nutrient conservation. The calculated TOC reduction, TKN enrichment, phosphorus retention and potassium retention values are summarized in Table 4. This assessment provides a stronger interpretation of composting performance because it links organic matter degradation with nutrient conservation.

The TOC reduction was lowest in SBA0 at 21.40%, indicating slower organic matter degradation in the absence of synthetic bulking agent. In comparison, SBA2, SBA4 and SBA8 showed higher TOC reduction values of 30.02%, 27.63% and 28.50%, respectively. This shows that the addition of SBA improved the internal physical condition of the composting matrix and supported more effective carbon mineralization. The higher TOC reduction under SBA-amended treatments can be attributed to improved aeration, reduced compaction and better microbial oxidation of degradable organic matter.

TKN enrichment also improved considerably under SBA-amended treatments. The control treatment showed only 22.22% enrichment, whereas SBA2, SBA4 and SBA8 showed 109.47%, 100.00% and 90.91% enrichment, respectively. This indicates that nitrogen concentration in the stabilized compost increased more strongly when synthetic bulking agent was added. The increase in TKN may be related to concentration of nitrogen in the residual compost mass, improved nitrogen conservation and reduced anaerobic loss pathways under better aerated conditions.

The phosphorus retention pattern further shows the benefit of higher SBA dosage. Phosphorus retention increased from 24.44% in SBA0 to 45.65% in SBA8. The lower phosphorus loss in SBA8 suggests that improved structural stability and reduced excessive leaching helped retain phosphorus within the compost matrix. SBA4 also improved phosphorus retention compared with SBA0 and SBA2, but SBA8 showed the strongest nutrient-conservation response.

Potassium retention remained lower than phosphorus retention in all treatments, which is expected because potassium is highly soluble and more prone to leaching during composting. However, SBA8 still showed the highest potassium retention of 22.96%, compared with only 7.69% in SBA0. This indicates that although

potassium loss could not be fully prevented, the use of higher SBA dosage reduced nutrient depletion compared with the control.

Overall, Table 4 shows that SBA8 provided the best combined response in terms of maturity, nutrient retention and stabilization. The treatment did not produce the maximum TOC reduction or TKN enrichment alone, but it achieved the most favourable balance between organic matter degradation and nutrient conservation. This balance is important from an environmental engineering perspective because composting should not only reduce organic load but also preserve the nutrient value of the final product.

Table 4
Nutrient retention and loss-balance assessment under different SBA treatments

Treatment	TOC reduction (%)	TKN enrichment (%)	P loss (%)	P retention (%)	K loss (%)	K retention (%)	Interpretation
SBA0	21.40	22.22	75.56	24.44	92.31	7.69	Weakest stabilization and highest nutrient loss
SBA2	30.02	109.47	75.00	25.00	91.19	8.81	Strong carbon reduction and nitrogen enrichment but poor K retention
SBA4	27.63	100.00	68.75	31.25	85.63	14.37	Balanced stabilization with moderate nutrient retention
SBA8	28.50	90.91	54.35	45.65	77.04	22.96	Best nutrient retention with strong stabilization

Kinetic Modelling of TOC Degradation and C/N Stabilization

The apparent first-order kinetic model was used to compare the rate of organic carbon degradation and maturity development under different SBA dosages. The apparent first-order kinetic constants calculated using Eq. (2) are presented in Table 5. The model provided an acceptable fit for both TOC degradation and C/N stabilization, indicating that the observed decline in organic carbon and maturity index followed a time-dependent degradation pattern.

Table 5
Apparent first-order kinetic constants for TOC degradation and C/N stabilization.

Treatment	TOC reduction (%)	kTOC (day^{-1})	R^2 for TOC model	C/N reduction (%)	kC/N (day^{-1})	R^2 for C/N model	Day of optimum C/N attainment	Interpretation
SBA0	21.40	0.0084	0.925	33.25	0.0159	0.941	Not achieved by Day 30	Slowest stabilization
SBA2	30.02	0.0126	0.869	64.04	0.0404	0.980	Day 24	Faster degradation and maturity development
SBA4	27.63	0.0115	0.845	69.25	0.0445	0.989	Day 24	Highest C/N stabilization rate
SBA8	28.50	0.0120	0.875	69.49	0.0440	0.970	Day 18	Strong and sustained stabilization

The TOC degradation constant was lowest in SBA0 at 0.0084 day^{-1}, confirming slower mineralization in the absence of synthetic bulking agent. The SBA-amended treatments showed higher TOC degradation constants, with values of 0.0126 day^{-1} for SBA2, 0.0115 day^{-1} for SBA4 and 0.0120 day^{-1} for SBA8. This indicates that the addition of synthetic bulking agent increased the rate of organic carbon degradation. The improvement can be attributed to better internal aeration, reduced compaction and improved oxygen availability within the food waste matrix.

The C/N stabilization constant showed an even clearer treatment-wise difference. SBA0 showed the lowest kC/N value of 0.0159 day^{-1}, whereas SBA2, SBA4 and SBA8 showed much higher values of 0.0404, 0.0445 and 0.0440 day^{-1}, respectively. This confirms that SBA-amended treatments achieved faster maturity development than the control. SBA4 showed the highest C/N stabilization rate, while SBA8 showed a very close rate with stronger nutrient retention and compost-quality performance.

The kinetic results support the earlier maturity and nutrient-retention findings. Although SBA2 showed the highest TOC reduction, SBA4 and SBA8 showed stronger C/N stabilization. This suggests that maturity development was controlled not only by carbon loss but also by nitrogen conservation and improved biological stabilization. The higher kinetic constants under SBA4 and SBA8 indicate that reusable synthetic bulking agent accelerated the transition from active degradation to mature compost formation.

The kinetic results also support the early maturity behaviour observed under SBA8. The higher C/N stabilization constants under SBA4 and SBA8 indicate faster maturity development compared with SBA0. Since SBA8 reached approximately the optimum C/N maturity threshold by Day 18, the treatment shows potential for shortening the active composting period in decentralized food waste treatment systems. This is technically important because reduced stabilization time can improve reactor turnover, operational efficiency and treatment capacity.

Correlation Network of Physicochemical Variables

Correlation analysis was performed to examine the relationship among major physicochemical variables during SBA-assisted composting. The correlation heatmap presented in Fig. 5a shows that compost maturity was strongly influenced by nitrogen transformation, carbon mineralization, pH adjustment and moisture variation. The C/N ratio showed a negative association with TKN and composting day, indicating that nitrogen enrichment and process duration contributed to maturity development. A positive association between TOC and C/N ratio was also observed, showing that higher residual organic carbon was linked with delayed stabilization.

Temperature showed a meaningful relationship with organic matter degradation and maturity progression. Higher temperature during the active composting phase was associated with improved degradation of organic matter and faster reduction in C/N ratio. This confirms that sustained thermophilic activity supported microbial oxidation and compost stabilization. The correlation pattern also indicates that pH and moisture acted as regulating variables. Near-neutral pH supported microbial activity, while moisture variation influenced oxygen diffusion and degradation efficiency.

The correlation network therefore supports the treatment-wise findings observed in SBA4 and SBA8. The improved maturity under higher SBA dosages was not controlled by a single parameter but by the combined effect of better aeration, stronger thermal activity, nitrogen conservation and organic carbon reduction. These relationships confirm that synthetic bulking agent improved the internal composting environment and supported faster stabilization of food waste.

Principal Component Analysis (PCA) of Process Variability

Principal Component Analysis was used to examine multivariate variation among treatments and process stages. The first two principal components together explained nearly 76% of the total variance, as shown in Fig. 5b. PC1 contributed 58% and was mainly governed by temperature, TKN and C/N ratio, which indicates that this component represented the thermal and nitrogen-linked stabilization pathway. PC2 explained about 18% of the variance and was influenced largely by pH and moisture. This suggests that the second component reflected environmental regulation within the composting matrix.

The distribution of samples in the PCA space indicates the influence of SBA dosage on composting behaviour. The SBA8 treatment showed higher temperature and lower C/N ratio and SBA0 showed higher TOC and moisture content. This result indicates that increasing SBA percentage helped achieve faster stabilization and stronger degradation during composting. The PCA pattern therefore supports the treatment-wise differences observed in the measured physicochemical parameters.

Random Forest Regression: Variable Importance and Model Accuracy

Random Forest regression was used to quantify the contribution of measured and engineered variables to compost maturity prediction. The model showed high predictive performance with $R^2 = 0.98$ and RMSE = 1.66. The agreement between observed and predicted values is presented in Fig. 6a, the feature-importance ranking is shown in Fig. 6b, and the treatment-wise LSTM-predicted versus measured C/N trajectories are presented in Fig. 6c.

TKN emerged as the most influential parameter in the Random Forest model. After excluding ratio-derived variables, TKN retained the highest importance, followed by pH, moisture, days and TOC. These results indicate that nitrogen transformation remained the main driver of C/N ratio reduction during composting. The model also suggests that pH and moisture affected maturity indirectly through their influence on microbial activity and nitrogen conservation. The Random Forest framework provided a dependable basis for identifying the major controlling variables in reactor-scale composting.

LSTM Forecasting of C/N Dynamics

The LSTM model was trained to capture the temporal behaviour of compost maturity using five-day sliding windows of normalized physicochemical inputs. The agreement between measured and predicted C/N ratio trajectories is presented in Fig. 6c. The model followed the treatment-wise trend satisfactorily and reproduced the progressive decline in C/N ratio across SBA0, SBA2, SBA4 and SBA8. The sharp early reduction and earlier stabilization observed under SBA8 were also reflected in the predicted profiles.

The results indicate that the LSTM model captured lag-dependent microbial and physicochemical interactions that are not easily represented by simple kinetic equations. Temporal forecasting of C/N ratio can support monitoring of maturity progression. It may also help future process control strategies in in-vessel composting systems.

Machine Learning Validation and Process Interpretation

The machine learning results were interpreted using a multi-level validation approach, as summarized in Table 6. The validation framework included baseline random split modelling, leakage-free modelling, leave-one-treatment-out validation, time-series split validation and LSTM-based temporal forecasting. This validation strategy linked machine learning predictions with composting process behaviour and reduced dependence on statistical fitting of the engineered dataset.

The leakage-free validation provided a more conservative assessment of model reliability. After excluding ratio-derived variables and direct mathematical predictors, the model retained a physically meaningful predictor ranking. TKN and pH remained among the dominant predictors, followed by moisture, composting day and TOC. This indicates that the model was not only responding to direct mathematical relationships but was also capturing the composting process behaviour associated with nitrogen transformation, pH regulation and moisture-controlled microbial activity.

Leave-one-treatment-out validation was included to test whether the model could predict compost maturity under an unseen SBA dosage. This validation is important because random train-test splitting can distribute data from the same treatment into both training and testing sets, which may overestimate model performance. In contrast, treatment-wise validation provides a stricter test of model generalization across SBA levels.

Time-series split validation was also considered because composting is a time-dependent biological process. Random splitting may mix early, active and mature-stage observations across training and testing sets. The use of time-series validation therefore helps verify whether the model can predict later-stage maturity development from earlier composting behaviour.

The combined validation framework strengthens the role of machine learning in this study. Random Forest was used primarily to identify dominant maturity drivers, whereas LSTM was used to examine temporal C/N trajectories. The results indicate that nitrogen transformation, pH adjustment and moisture regulation were the main process-linked variables governing maturity development. Therefore, the machine learning component should be interpreted as a process-understanding and decision-support tool rather than only as a numerical prediction exercise.

Table 6
Machine learning validation strategy for compost maturity prediction

Model / validation approach	Training strategy	Testing strategy	Main purpose	Performance indicators
Baseline Random Forest	80% random training data	20% random testing data	General predictive performance	R^2, RMSE, MAE
Leakage-free Random Forest	Excludes ratio-derived and direct mathematical predictors	20% testing data	Checks target leakage risk	R^2, RMSE, MAE, feature importance
Leave-one-treatment-out model	Three SBA treatments used for training	Remaining SBA treatment used for testing	Tests prediction for unseen SBA dosage	R^2, RMSE, MAE
Time-series split model	Early composting days used for training	Later composting days used for testing	Checks temporal generalization	R^2, RMSE, MAE
LSTM model	Five-day sliding-window sequences	Validation sequences	Forecasts temporal C/N trend	RMSE, MAE, trend agreement

Comparative Efficiency of Synthetic Bulking Agent Treatments

The overall treatment-wise comparison is presented in Fig. 5c. The SBA8 treatment showed the longest thermophilic duration, faster pH stabilization, improved nitrogen conservation and a lower final C/N ratio. SBA4 also performed well and remained close to SBA8 for several indicators, while SBA2 showed intermediate behaviour. The control treatment SBA0 remained weaker across the major performance measures and could not sustain thermophilic conditions effectively.

These observations confirm that synthetic bulking agent improved structural porosity and helped maintain oxygen transfer within the dense food waste reactor. The use of reusable synthetic bulking agent as aeration media also indicates practical value in reducing dependence on degradable bulking materials. In combination with biochar, jaggery, lime and neem powder, synthetic bulking agent (SBA) improved the physical condition of the composting bed. It also supported better biological stabilization within a shorter period.

Integration of Machine Learning with Process Engineering

The present work shows that machine learning can be integrated with compost reactor studies in a meaningful manner. Random Forest identified the major maturity control variables, while LSTM captured their temporal interaction through the composting cycle. This combined approach helped connect measured reactor behaviour

with predictive interpretation. Aeration control, moisture correction and maturity monitoring can benefit from such modelling support.

The study also indicates that relatively small but well-structured temporal datasets can yield useful process information when coupled with suitable data-driven tools. This is important for reactor-based organic waste management systems, where direct process control is often limited by time lag and complex variable interaction.

From an environmental management perspective, the use of reusable SBA is relevant for decentralized food waste treatment systems where high-moisture organic waste is generated continuously. Institutional campuses, hostels, canteens, hotels, residential complexes and local markets often require compact composting systems that are easy to operate and maintain. Reusable SBA can help maintain internal porosity without repeated consumption of degradable bulking materials. This can improve process consistency, reduce material replacement demand and support circular management of organic waste and plant nutrients.

Practical, Environmental and Economic Implications

The findings of this study have practical relevance for decentralized and reactor-based food waste composting systems. High-moisture food waste is often difficult to compost because of compaction, poor oxygen movement and unstable degradation. The experimental results showed that the addition of reusable synthetic bulking agent improved the composting environment by maintaining better aeration and supporting longer thermophilic activity. Among the tested treatments, SBA8 recorded a peak temperature of 58°C and maintained thermophilic conditions for 11 days, whereas the control treatment did not sustain effective thermophilic activity. This indicates that SBA can function as a stable structural aeration-support medium in dense food waste mixtures. Unlike degradable natural bulking materials such as sawdust, rice husk and wood chips, the synthetic bulking agent does not lose its physical structure during the process and can potentially be recovered and reused in subsequent composting cycles. This improves the practical value of the system for institutional campuses, residential complexes, hotels, markets and decentralized municipal food waste treatment facilities.

From an environmental perspective, SBA-assisted composting supports resource conservation by converting food waste into mature compost instead of allowing disposal in landfills. The results showed that SBA-amended treatments achieved better compost maturity than the control. The final C/N ratio decreased to 17.69, 14.25 and 14.68 in SBA2, SBA4 and SBA8, respectively, while the control treatment remained at 34.30. The compost maturity assessment further showed that SBA2, SBA4 and SBA8 achieved Class A compost quality, whereas SBA0 remained Class B. SBA8 also showed the highest Fertility Index of 4.4 and Clean Index of 5.0, indicating high fertilizing potential and low heavy metal risk. These results demonstrate that SBA-assisted composting improves not only process stabilization but also the usability of the final compost for soil application.

The nutrient conservation results further support the environmental value of reusable SBA. Phosphorus retention increased from 24.44% in SBA0 to 45.65% in SBA8, while potassium retention increased from 7.69% in SBA0 to 22.96% in SBA8. This shows that higher SBA dosage helped conserve nutrient value within the final compost. Such nutrient retention is important for circular nutrient management because composting should not only reduce waste quantity but also recover plant nutrients for agricultural or landscaping use. The kinetic results also showed faster stabilization under SBA-amended treatments. The C/N stabilization constant

increased from 0.0159 day⁻¹ in SBA0 to 0.0404, 0.0445 and 0.0440 day⁻¹ in SBA2, SBA4 and SBA8, respectively. This indicates that SBA addition accelerated maturity development and reduced the time required for compost stabilization.

The reusable nature of the synthetic bulking agent also has economic relevance. Conventional bulking materials are consumed or degraded during composting and therefore require repeated replacement. In contrast, inert synthetic bulking media may reduce recurring bulking-agent demand if recovered after composting. The improved thermophilic duration, Class A compost quality, higher phosphorus and potassium retention and faster C/N stabilization observed under SBA-amended treatments suggest potential operational advantages for decentralized composting systems. Although a detailed cost-benefit analysis was beyond the scope of this study, the results indicate that SBA reuse may reduce material replacement needs and improve process consistency. Future work should quantify SBA recovery efficiency, number of reuse cycles, cost per composting batch, avoided bulking-material cost, greenhouse gas reduction and life-cycle performance under pilot-scale operating conditions.

Conclusion

This study evaluated reusable perforated plastic balls as a synthetic bulking agent and inert aeration-support medium for in-vessel aerobic composting of high-moisture food waste amended with biochar, neem powder, lime and jaggery. The results showed that SBA addition improved the internal composting environment by reducing compaction, supporting oxygen movement and extending thermophilic activity. Among the tested treatments, SBA8 showed the best overall response, with a peak temperature of 58°C, 11 thermophilic days and final C/N ratio of 14.68. SBA8 approached the optimum C/N maturity range by Day 18 and reached mature C/N status by Day 24, whereas the control treatment, SBA0, remained comparatively unstable, with a final C/N ratio of 34.30.

The maturity validation confirmed that compost quality improved with SBA addition. SBA2, SBA4 and SBA8 achieved Class A compost status based on Fertility Index and Clean Index values, whereas SBA0 remained Class B due to incomplete stabilization. SBA8 showed the highest Fertility Index of 4.4 and Clean Index of 5.0, indicating high fertilizing potential and low heavy metal risk. This confirms that SBA-assisted composting improved not only C/N reduction but also final compost quality and agricultural suitability.

The nutrient retention and loss-balance assessment showed that SBA8 provided the best balance between organic matter degradation and nutrient conservation. Phosphorus retention increased from 24.44% in SBA0 to 45.65% in SBA8, while potassium retention increased from 7.69% to 22.96%. These results indicate that improved structural aeration helped conserve nutrient value in the final compost. Kinetic modelling also confirmed faster stabilization under SBA-amended treatments. The apparent C/N stabilization constant increased from 0.0159 day⁻¹ in SBA0 to 0.0404, 0.0445 and 0.0440 day⁻¹ in SBA2, SBA4 and SBA8, respectively.

Machine learning analysis supported the experimental interpretation. Random Forest regression identified nitrogen transformation, pH regulation and moisture condition as dominant maturity-related variables, while LSTM modelling reproduced treatment-wise C/N trajectories. The machine-learning-based and treatment-wise validation approach strengthened the role of machine learning as a process-supporting tool for maturity prediction within the tested experimental range.

Overall, the study demonstrates that reusable perforated plastic-ball SBA can improve aeration-controlled food waste composting by accelerating stabilization, improving compost maturity, conserving nutrients and supporting data-driven maturity prediction. From a resource conservation perspective, SBA can potentially reduce repeated dependence on degradable bulking materials and support decentralized circular food waste management.

However, the present study was conducted at laboratory reactor scale and did not include full mass-balance analysis, greenhouse gas monitoring, SBA recovery efficiency, reuse-cycle testing or detailed economic assessment. Future work should include pilot-scale validation, SBA recovery and reuse assessment, greenhouse gas monitoring, cost-benefit analysis and life-cycle assessment to confirm the environmental and economic viability of reusable SBA-assisted composting.

These findings support the use of reusable aeration-support media as an eco-innovation for decentralized food waste composting, particularly where resource recovery, compost quality and practical environmental management are important.

Declarations

Competing interests

The author declares that there are no relevant financial or non-financial competing interests related to this manuscript.

Ethics approval

Not applicable. This study did not involve human participants, human data, animals or animal-derived experimental subjects.

Consent to participate

Not applicable.

Consent for publication

Not applicable.

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Author contribution

Amit Dharnaik contributed to conceptualization, methodology, investigation, data curation, formal analysis, writing of the original draft, and review and editing of the manuscript.

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Availability of data and materials

The processed dataset, nutrient retention calculations, kinetic fitting details and machine learning input structure are available from the corresponding author on reasonable request.

Code availability

The code used for kinetic modelling and machine-learning analysis is available from the corresponding author on reasonable request.

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Figures

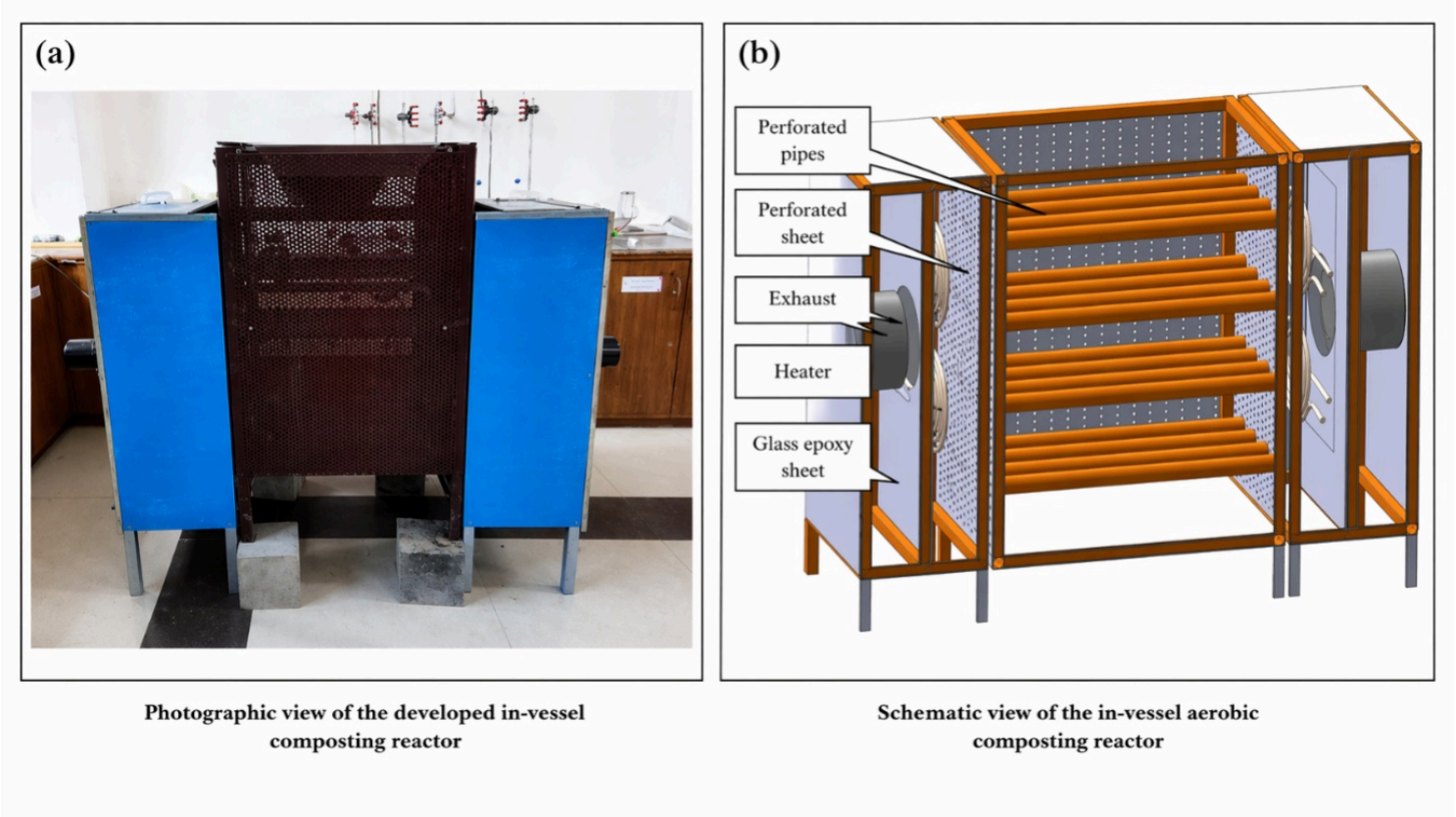


Figure 1

(a) Photographic view and (b) Schematic view of the in-vessel aerobic composting reactor

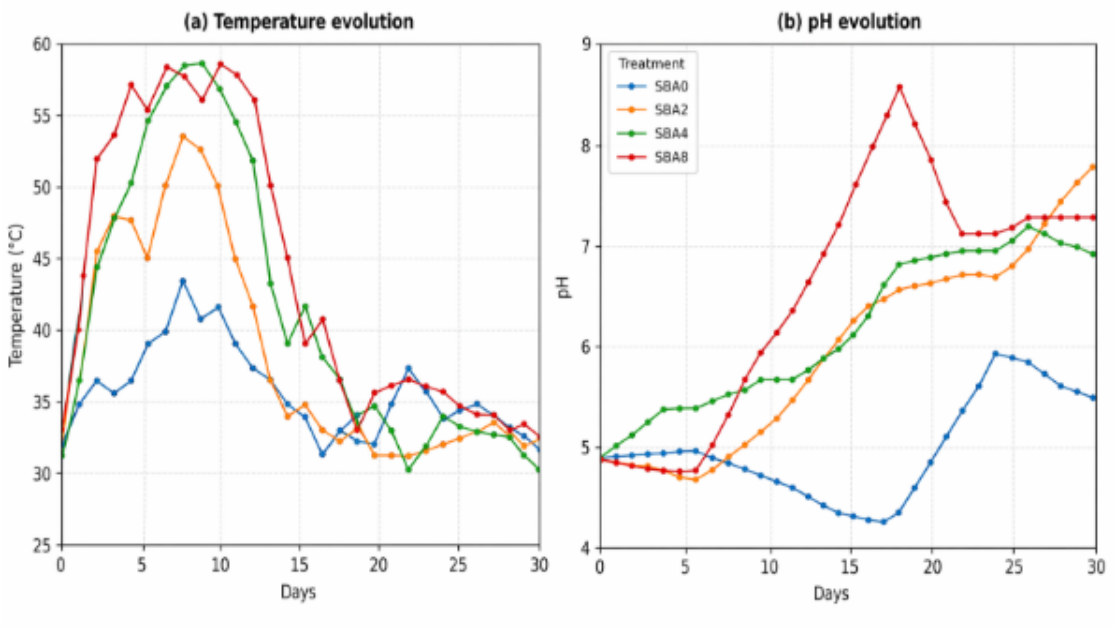


Figure 2

Evolution of key process parameters: (a) temperature and (b) pH

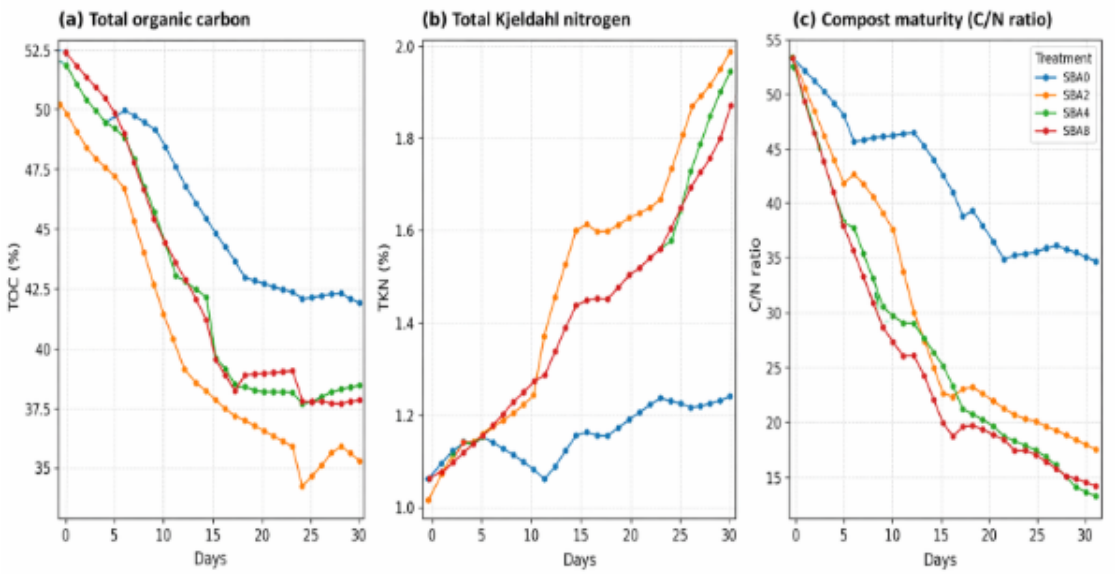


Figure 3

Organic matter degradation (a) total organic carbon (TOC) (b) total Kjeldahl nitrogen (TKN) and (c) C/N ratio

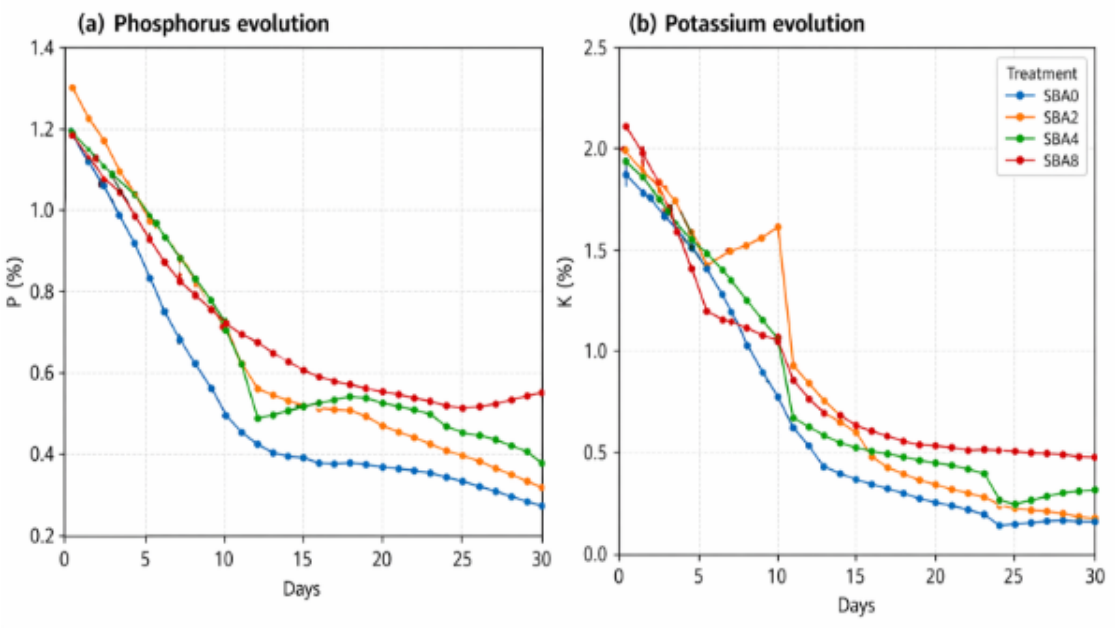


Figure 4

Nutrient dynamics during composting: (a) phosphorus and (b) potassium

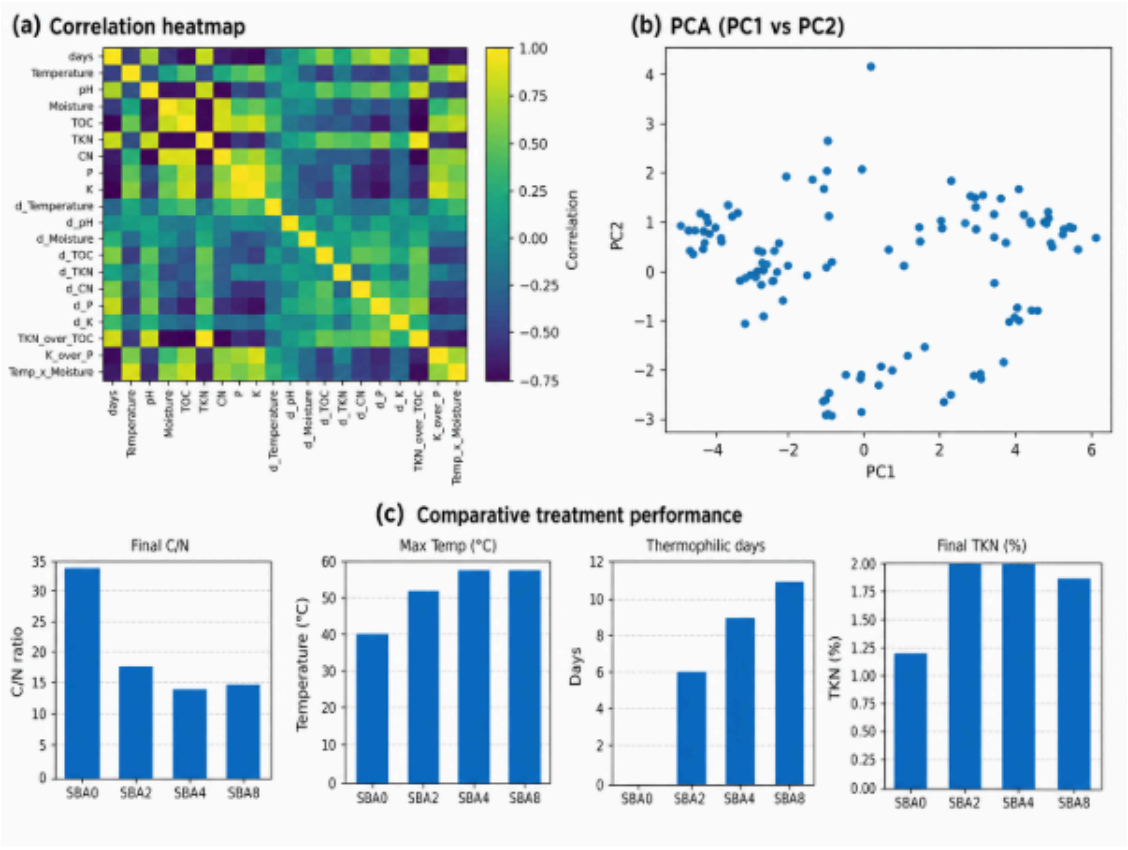


Figure 5

Multivariate analysis and treatment comparison: (a) correlation heatmap, (b) PCA score plot and (c) comparative performance of SBA0, SBA2, SBA4 and SBA8 treatments

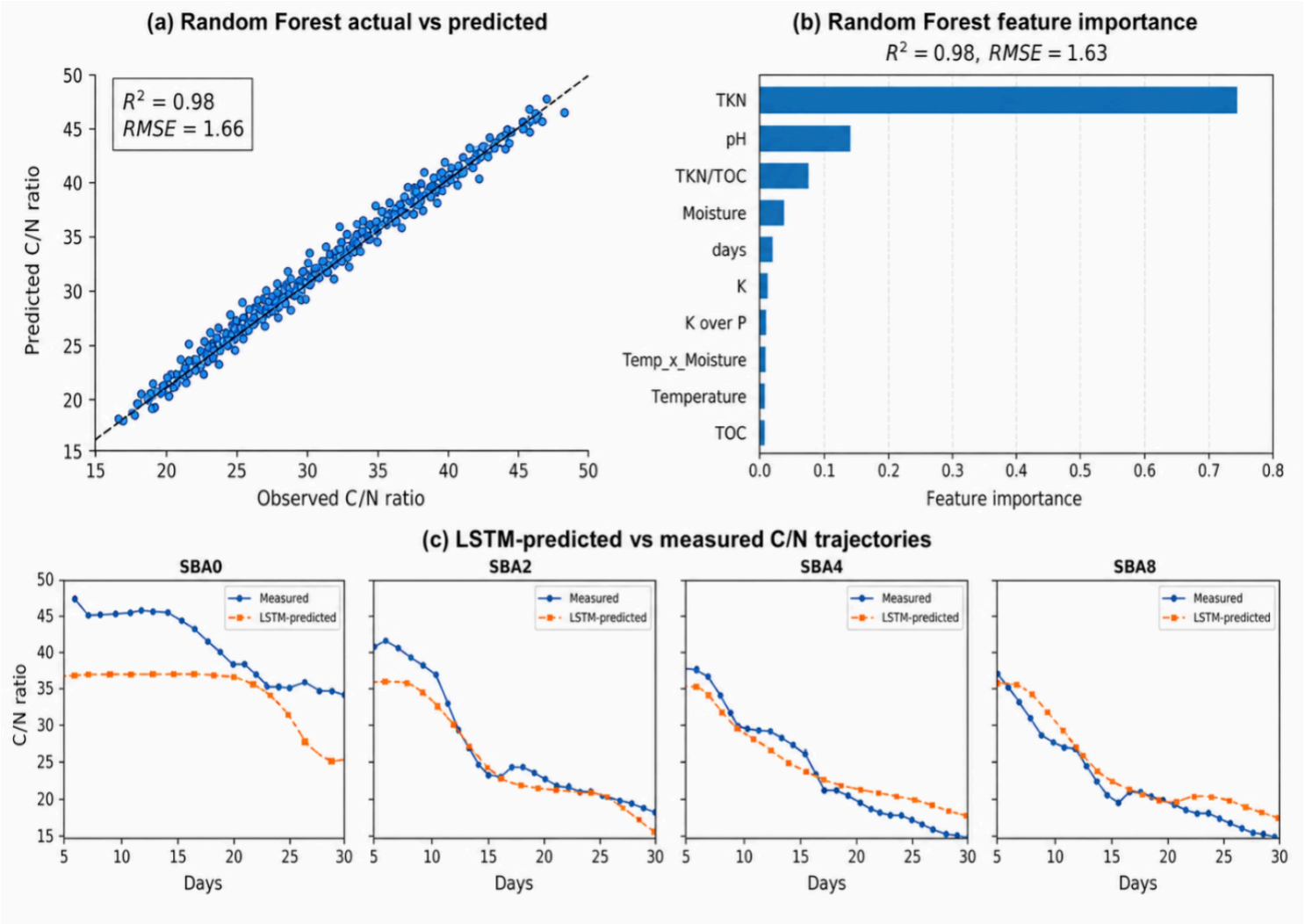


Figure 6

Machine learning model performance and interpretation: (a) Random Forest actual versus predicted C/N ratio, (b) Random Forest feature importance and (c) LSTM-predicted versus measured C/N ratio trajectories