

Influence of microbial consortia on the mitigation of greenhouse gas emissions during the automated composting of organic waste

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Abstract

Greenhouse gases (GHG) released during organic waste treatment have not been systematically evaluated. This research assessed GHG emissions during accelerated composting using an automated composter. Three 30-day composting processes were conducted using 23 kg organic waste mixed with corn stover in Process1 and Process2, and chicken manure in Process3, maintaining a C:N ratio of 30:1. Organic waste consisting of fruits, vegetables, and peels was collected from a market, shredded to 1–5 cm, and prepared for composting. The automated composter consisted of two identical chambers with two treatments: Reactor1, microbial consortia inoculated, and Reactor2, left uninoculated and used as a control. Both reactors were equipped with electrochemical sensors to measure CO₂, CH₄, and O₂ concentrations, and with actuators to control temperature and humidity. A biopreparation of beneficial microorganisms derived from Altamisa plant, immobilized on wheat bran, was applied weekly (250 g Reactor1) to enhance microbial activity and organic matter degradation. While the differences between Process were marginally significant, the treatment effect was highly significant. Microbial inoculation promoted more stable composting dynamics, reduced CO₂ emissions, and altered humidity and oxygen availability. The coupling between oxygen consumption and methane production and oxidation, promoting greater stability and predictability throughout the composting process in the reactor with microbial consortia inoculated. Despite the lack of biological replicates and direct microbial measurements, consistent results across statistical approaches and the large dataset support the reliability of these findings.

Introduction

The rapid increase in organic waste generation associated with population growth, urbanization, and changes in consumption patterns has intensified the need for waste management strategies that minimize environmental impacts while recovering valuable resources (Wu et al. 2014; Sánchez et al. 2015a). Composting has emerged as one of the most widely adopted treatments for organic waste, to stabilize organic matter, reduce waste volume, and produce soil amendments with agronomic value (Sánchez et al. 2015a). However, despite its environmental benefits, composting can contribute to greenhouse gas (GHG) emissions, particularly carbon dioxide (CO₂) and methane (CH₄), whose magnitude and temporal dynamics depend strongly on process conditions and microbial activity (Sánchez et al. 2015b; Pérez et al. 2023).

The composting process is characterized by distinct phases (mesophilic, thermophilic, and maturation), during which temperature, moisture, oxygen availability, and microbial community structure interact to regulate organic matter degradation and gas production (Lim et al. 2016). In addition, aerobic decomposition primarily generates CO₂, whereas localized anaerobic microenvironments can promote CH₄ formation, even under ostensibly well-aerated conditions (Pérez et al. 2023). Consequently, the balance between aeration, moisture, and microbial metabolism plays a critical role in determining both composting efficiency and GHG emissions (Sánchez et al. 2015b; Adebayo and Obiekezie 2018).

Microbial inoculation has been proposed as a strategy to enhance composting performance by accelerating organic matter degradation, stabilizing temperature profiles, and potentially reducing undesirable emissions (Barrena et al. 2014; Adebayo and Obiekezie 2018). Several studies have reported that inoculated composting systems exhibit higher temperatures, faster stabilization, and altered gas emission patterns compared to uninoculated systems (Barrena et al. 2006; Nair and Okamitsu 2010; Wang et al. 2011; Patidar 2013). However, the specific effects of microbial inoculation on CO₂ and CH₄ dynamics remain inconsistent across studies, partly due to differences in substrate composition, nitrogen sources, aeration regimes, and reactor design (Amlinger et al. 2008; Colón et al. 2012). Moreover, most previous research has relied on low-frequency measurements, limiting the ability to capture short-term fluctuations and temporal coupling between environmental variables and gas emissions (He et al. 2001; Boldrin et al. 2009; Sánchez-Monedero et al. 2010). Automated composting systems equipped with continuous monitoring sensors offer a valuable opportunity to address this limitation (Fakharulrazi et al. 2020). High-resolution temporal data allow for a more detailed characterization of the interactions among temperature, relative humidity, oxygen availability, and GHG emissions, as well as the specific role of microbial inoculation under controlled operational conditions (Ahmadi et al. 2020; Nenciu et al. 2022; Fouguira et al. 2026). Understanding these interactions is key to minimize GHG emissions, particularly by assessing how microbial inoculation affects CO₂ and CH₄ dynamics under automated conditions and across different substrates (Lin et al. 2022). In particular, the relative contribution of temperature, moisture, and oxygen availability in regulating CH₄ emissions remains insufficiently resolved (Lin et al. 2022; Rathnayake 2023), considering that methane is substantially higher global warming potential compared to CO₂ (Sánchez et al. 2015a, b).

This study evaluated the temporal dynamics of temperature, relative humidity, oxygen availability (O₂), carbon dioxide (CO₂), and methane (CH₄) in an automated composting system across three composting Processes, each consisting of an inoculated chamber (Reactor1) and an uninoculated chamber (Reactor2). Using high-frequency sensor data collected throughout the composting period, we aimed to quantify differences between Processes and Reactors, assess temporal emission patterns, and identify key environmental drivers of CO₂ and CH₄ variability. This study provides new insights into the mechanisms governing GHG dynamics in automated composting systems and contributes to the development of more efficient organic waste treatment strategies. We hypothesized that microbial inoculation would enhance metabolic efficiency, reduce CO₂ emissions, and stabilize the composting process, while also modulating the transitions between composting phases and altering the physical conditions of the substrate (Zhao et al. 2017; Li et al. 2026). We expected that inoculated reactors would show lower and less erratic CO₂ emissions (Li et al. 2022; Wang et al. 2024), a stronger coupling between O₂ consumption and CH₄ oxidation compared to uninoculated reactors (Avila-Núñez et al. 2026). We also expected a diminished sensitivity to past-oxygen fluctuations and a distinct phase-transition dynamics in inoculated than uninoculated reactors (Zhang et al. 2025; Zhao et al. 2026), and that inoculation affected humidity and oxygen availability by modifying substrate structure (Padhan et al. 2022).

Materials and methods

An automated composting system was used to evaluate the temporal dynamics of temperature, relative humidity, oxygen (O₂), carbon dioxide (CO₂), and methane (CH₄). The automated composter comprised two independent chambers (Reactor1 and Reactor2), allowing for the execution of comparative treatments. The same amount of organic waste was placed in both chambers. The biopreparation containing beneficial microorganisms was included in Reactor1, while it was not included in Reactor2 (Table 1).

Three composting Processes were conducted using organic waste collected on three occasions from the “27 de Febrero” farmers market in Andean city Cuenca, Ecuador. In the first Processes (Process1) and second Processes (Process2) the organic waste was mixed with corn stover, while in the third Process (Process3) organic waste was mixed with dry chicken manure (Table 1). In each Process, the composter rotated automatically four times a day to ensure adequate aeration. Additionally, continuous monitoring of humidity and temperature was performed.

Immobilized beneficial microorganisms (IBMs) were applied using a stratified incorporation technique, with 250 g of inoculum added per week until a cumulative dose of 1000 g was achieved. Bioaugmentation was sustained through weekly inoculations over the entire operational cycle. In contrast, the second compartment received no microbial additives and served as a negative control for assessing degradation performance.

Organic waste preparation

Three composting processes, each lasting 30 days, were conducted using an automated composter. In the first and second processes, organic market waste (OMW) was mixed with corn stover, while the third process used a mixture of OMW and low-moisture chicken manure. Each chamber was loaded with 23 kg of waste mixture to initiate composting. Each collection yielded 23 kg of organic waste, respectively, which included fruits, vegetables, peels, and other organic waste generated by the market’s vendors and customers. To ensure proper sorting, handling, and transportation, the waste was placed in designated containers. The waste was then shredded to a size range of 1 to 5 cm to create optimal conditions for degradation. The organic fraction, composed primarily of fruit and vegetable waste, was reduced to a particle size of 3–5 cm to ensure substrate homogeneity. Following biomass quantification, the carbon-to-nitrogen (C/N) ratio was adjusted to 30:1 by adding 0.218 kg of bovine manure per kilogram of organic waste, thereby optimizing nutrient availability for microbial activity. Nitrogen was sourced from vegetable waste collected at the market, while carbon was obtained from corn stover for Process1 and Process2, and from chicken manure for Process3. The mixture was then evenly distributed into both reactors (Reactor1 and Reactor2) of the automated composter.

The microbial consortium employed was isolated from the Altamisa plant (*Artemisia vulgaris*) and comprised a diverse assemblage of bacteria and yeasts with complementary functional roles in composting, in accordance with the methodology outlined by Alvarez (2018). Key bacterial genera

included *Bacillus* (*B. subtilis* and *B. megaterium*) and *Streptomyces* spp., which are well known for secreting extracellular enzymes involved in the degradation of complex carbohydrates and proteins and for maintaining metabolic activity during the thermophilic phase. The consortium also exhibited a high abundance of yeasts and lactic acid bacteria, notably *Pichia* spp. and *Lactobacillus* spp., which play a crucial role in the early stages of composting by fermenting soluble sugars from fruit and vegetable waste, thereby promoting pH adjustment and nutrient solubilization. Mineralization of organic matter was further enhanced by microorganisms such as *Thiobacillus* spp. and *Arthrobacter* spp., while the presence of *Serratia* spp. and *Flavobacterium* spp. was associated with potential biological control activity and siderophore production, conferring suppressive properties against phytopathogens. In addition, yeasts such as *Saccharomyces* spp. and *Schizosaccharomyces* spp. contributed to process stability through the production of secondary metabolites that favor humification. Overall, the high microbial diversity of the consortium ensured sustained functional performance under fluctuating moisture and oxygen conditions within the automated composter (Appendix 1). Subsequently, the microorganisms in the biopreparation were immobilized on an inert substrate, specifically wheat bran, to maintain their activity and facilitate rapid colonization of the organic matter. A total of 250 grams of the wheat bran-immobilized microorganisms were applied to the corresponding chamber once a week throughout each experimental period.

Automated composter

The automated composter used in this study is a rectangular prism (180 × 82 × 121.5 cm) containing a central cylindrical container (78 cm diameter, 122.5 cm length) divided into two chambers, each with a 0.231 m³ capacity. An electronically controlled motor rotated the chambers four times daily to ensure proper oxygenation, while an electrical resistance system with nickel-chromium heating elements maintained stable temperatures. Six heating elements per chamber, arranged evenly and enclosed within a double-walled stainless steel structure, provided uniform heat distribution via conduction and convection, with insulation minimizing heat loss. The temperature profile closely mirrored natural composting, remaining at 60°C during the first two weeks and gradually decreasing to 25°C by weeks three and four. Sensors continuously monitored temperature, methane, carbon dioxide, and oxygen concentrations throughout the process. After decomposition and drying, the final compost was extracted, allowing comparison between traditional and accelerated methods regarding duration, gas emissions, odor reduction, and pest minimization. Real-time monitoring was enabled by electronic sensors, including DHT22 sensors for ambient temperature and relative humidity (two-second sampling interval, factory-calibrated), type K thermocouples with MAX6675 modules for biomass temperature (0.25°C resolution), and electrochemical gas sensors. The MG-811 module detected CO₂ (analog output decreasing with concentration, requiring 48-hour pre-calibration), the SEN0465 oxygen sensor provided high stability with temperature compensation, and the MQ-4 methane sensor utilized semiconductor conductivity changes for quantification, also requiring calibration. Sensors for ambient temperature, humidity, and gases were installed in an upper enclosed section, protected from moisture and leachate by a metal mesh while allowing gas exchange. In contrast, thermocouples were placed at the bottom of

each chamber in direct contact with the compost to accurately measure thermal dynamics. This design enabled reliable characterization of the gaseous microenvironment while capturing the thermal evolution of the composting process under controlled conditions.

Statistical tests

Data from three independent composting processes (Process1, Process2, Process3) and two reactors per process (Reactor1, Reactor2) were combined into a unified dataset for analysis. The three-level factor Process was considered (likely representing experimental phases). Reactor1 was inoculated with a microbial consortium and Reactor2 was the non-inoculated control. Each process was monitored over approximately one month, with high-frequency measurements of compost temperature (°C), reactor ambient temperature (°C), relative humidity (%), oxygen availability (O₂ %vol), and CO₂ & CH₄ concentrations (ppm). The distribution of each environmental variable was evaluated across the six experimental groups (three processes × two reactors). Measurements were taken every ~ 15 seconds, generating a high-resolution time series. A total of 331105 measurements per reactor (overall N = 662,210) were recorded for the following variables. Normality was tested using the Kolmogorov–Smirnov test, which indicated that none of the variables were normally distributed (all $p < 0.001$). However, despite moderate deviations from normality in the original variables (common in high-frequency environmental data), the large sample size ($N > 600,000$) ensures the asymptotic robustness of the linear mixed model, GAMM and DSEM. Residual diagnostics (QQ-plots, ACF) did not reveal any severe violations, and non-parametric Random Forest together with a Bayesian autoregressive model (brms) confirmed the direction and significance of the treatment effect. Therefore, no variable transformation was deemed necessary for the validity of the conclusions..

To account for pseudoreplication and temporal dependence, a chronological index (time) was created and observations were grouped into blocks (batch) of 100 consecutive measurements, resulting in 6,623 blocks. The primary analysis consisted of a linear mixed model (LMM) with fixed effects: Process, treatment (Reactor), standardized time (time_sc), compost temperature (TemC) and relative humidity (Hrel); random effects included intercept and time slope per batch. The model was fitted using restricted maximum likelihood (REML) and degrees of freedom were approximated with the Satterthwaite method. Random Forest analysis (200 trees) was performed to assess variable importance in reactor classification. Change point analysis (PELT) was performed on the CO₂ series of the inoculated reactor. ARIMA models (auto.arima) was performed on the last 5,000 records to characterise temporal structure and predictability. Generalised additive mixed model (GAMM) with AR(1) correlation (bam) to model non-linear trends and control residual autocorrelation. Dynamic structural equation modelling (DSEM) with first-order cross-lags to explore temporal causal relationships among the four variables, estimated as a multigroup model (Reactor1 vs Reactor2). Bayesian autoregressive model (brms) with AR(1) structure per reactor, fitted on a subsampled dataset (every 100th observation) to verify robustness of effects. Model residuals were diagnosed graphically (ACF, PACF, Q-Q, residuals vs fitted). R v. 4.4.0 (R Development Core Team 2026) was used for all statistical analyses, using the packages lme4, lmerTest,

emmeans, randomForest, changepoint, qqgraph, forecast, mgcv, lavaan, brms and ggplot2. Model residuals were diagnosed graphically (ACF, PACF, Q-Q, residuals vs fitted).

Results

Both reactors showed similar mean compost temperatures (Reactor1: $49.0 \pm 16.3^\circ\text{C}$; Reactor2: $48.2 \pm 16.8^\circ\text{C}$). Relative humidity was constant throughout the experiment at 60.9% for Reactor1 and 58.7% for Reactor2. Mean CO_2 concentration was lower in Reactor1 (401 ± 11.6 ppm) than in Reactor2 (405 ± 20.3 ppm), with nearly double the variability in the control. CH_4 was similar (1.31 ± 0.45 ppm in Reactor1; 1.33 ± 0.36 ppm in Reactor2), while O_2 was slightly lower in Reactor1 ($18.6 \pm 0.3\%$) than in Reactor2 ($19.9 \pm 0.02\%$). The smoothed temporal evolution showed that both reactors started at similar values, but Reactor2 reached higher concentrations towards the end of the experiment. Showing significant differences (t-test: $p < 2.2\text{e-}16$), with Reactor2 exhibiting a higher median and greater variability (Fig. 1).

The differences between Process were marginally significant ($p = 0.0545$). The treatment effect was highly significant. The control reactor (Reactor2) emitted on average 7.68 ppm more CO_2 than the inoculated reactor (estimate = 7.68, SE = 0.543, $p < 0.0001$). Standardised time had a negative effect (-2.44 ppm per unit, $p = 1.82\text{e-}5$), temperature a small negative effect (-0.024 ppm/ $^\circ\text{C}$, $p = 4.70\text{e-}5$), and relative humidity also had a negative effect (-0.108 ppm/%, $p < 2.2\text{e-}16$, Table 1). Marginal means (averaged over Process) gave a difference Reactor1 – Reactor2 = -7.68 ppm (95% CI: -8.74 to -6.61), confirming that the inoculated reactor emitted significantly less CO_2 . The most important variables in descending order were Relative humidity, O_2 , CH_4 , Temperature and CO_2 , with relative humidity and oxygen being the best discriminators (OOB error of 0.03%; Reactor1 330,976 out observations correct; and Reactor2 331,024 out correct of 331,105). Multiple structural change points in the CO_2 series of the inoculated reactor was detected. Transitions occurred at approximately 50,000, 150,000 and 250,000 time steps, corresponding to classical composting phases (thermophilic, cooling and maturation, Fig. 1). Correlation networks showed distinct patterns between reactors. In Reactor1 a negative correlation between CH_4 and O_2 ($r \approx -0.2$) and a positive CO_2 -temperature relationship were observed. In Reactor2 correlations were weaker and more scattered, especially between CH_4 and the other variables (Appendix 2).

On the last 5000 records, the inoculated reactor (Reactor1) followed an ARIMA(0,1,1) with moving average coefficient ($\text{ma1} = -0.959$; SE = 0.0046) and root-mean-square error (RMSE = 8.55). The control reactor (Reactor2) required a more complex ARIMA(1,1,2; with coefficients $\text{ar1} = -0.764$, $\text{ma1} = -0.146$, $\text{ma2} = -0.731$ and RMSE = 14.00). The Ljung-Box test indicated white-noise residuals for Reactor1 ($p = 0.634$) while for Reactor2 was marginal ($p = 0.060$). Thus, the inoculated reactor's series is more predictable and less complex. The GAMM explained 23.1% of the deviance ($R^2\text{-adj} = 0.231$). Parametric effects showed that treatment was not statistically significant (estimate = 4.44, SE = 10.99, $p = 0.686$). Temperature and relative humidity were significant ($p = 0.0004$ and 0.0337 , respectively). Smooth terms indicated a strong global non-linear temporal trend ($s(\text{time})$, edf ≈ 69.6 , $p < 2\text{e-}16$) and significant differences in the shape of the trend between reactors ($s(\text{time})\text{:Reactor1}$ $p = 0.0224$; $s(\text{time})\text{:Reactor2}$ p

= 0.0331). Residuals showed negligible autocorrelation after AR(1) correction, and predictions captured the overall trend.

The multigroup DSEM (CFI = 1.000, RMSEA = 0.000) revealed substantial differences in the temporal causal network (Appendix 3). CO₂ autoregression was lower in Reactor1 (0.537) than in Reactor2 (0.599), indicating lower inertia and faster response in the inoculated reactor. The effect of past CH₄ on CO₂ was negative and significant in both, but stronger in Reactor1 (-1.52 vs -1.31, $p < 0.001$). The effect of past O₂ on CO₂ was not significant in Reactor1 (small estimate, $p = 0.001$) while in Reactor2 it was negative and larger (-0.248, $p < 0.001$). The effect of past CH₄ on O₂ was negative in both, but stronger in Reactor1 (-0.066 vs -0.031). Residual variance of CO₂ was much lower in Reactor1 (95.0) than in Reactor2 (252.5), confirming higher predictability. The Bayesian autoregressive model (Appendix 4) was fitted on 6624 subsampled observations (AR(1) coefficient = 0.53; 95% CI: 0.51–0.55) and a positive and significant treatment effect. The control reactor emitted 4.36 ppm more CO₂ than the inoculated reactor (95% CI: 2.96–5.79). Central temperature was not significant (95% CI includes zero), while relative humidity showed a negative effect (-0.19, 95% CI: -0.23 to -0.14). The residual standard deviation was 13.85.

Discussion

This research assessed and compared temperature, relative humidity, and the release of O₂, CO₂, and CH₄ in an automated composter across three different composting processes (Process1, Process2, Process3), each involving two chambers: Reactor1, inoculated with microbial consortia, and Reactor2, which remained uninoculated. Our outcomes confirm the existence of well-differentiated phases in the composting process, the transitions between phases occur differently in each reactor. The results consistently indicate that microbial inoculation reduces CO₂ emissions, with significant temporal trend that differs between treatments in mean level by non-linear interactions. The inoculated reactor exhibits a simpler and less erratic temporal dynamic, indicating that the process becomes more stable and predictable with inoculation, and suggesting that inoculation fosters a microbial community in which oxygen consumption is more intimately linked to methane production and oxidation. In addition, our results reflect that the inoculum profoundly affects humidity conditions and oxygen availability, possibly through changes in substrate physical structure. Finally, at least of the lack of biological replicates and the absence of direct measurements of enzymatic activity or microbial diversity, the robustness of findings across multiple statistical approaches and the extremely large sample size confer high reliability to the conclusions.

We found significant differences between the inoculated and uninoculated chambers (Reactor1 & Reactor2) in terms of O₂, CO₂, and CH₄ concentrations. The significant decline of CO₂ in reactor inoculated with microorganisms, suggesting that the introduced microbial consortium promotes more efficient metabolic pathways that reduce wasteful respiration or favour carbon assimilation into biomass (Li et al. 2026), thereby lowering mineralisation to CO₂ (Barla et al. 2024). Therefore, the evidence supports that the addition of microorganisms decreases CO₂ production (Zhao et al. 2017). This could

be due to a higher abundance of aerobic methanotrophs that oxidise CH_4 using O_2 , thereby reducing net emissions of both CH_4 and CO_2 (López et al. 2013). However, greenhouse gas (GHG) emissions varied significantly across the different composting stages. This pattern may be attributed to compost oxidation resulting from the turning schedule, which, as reported in previous studies, helps minimize CH_4 emissions (He et al. 2000; Sánchez-Monedero et al. 2010; Sánchez et al. 2015a). Considering that CO_2 emissions in composting process occur due to microbial degradation of organic matter, which is the primary source of biogenic CO_2 emissions, and the aerobic oxidation of CH_4 by methanotrophic bacteria (Sánchez et al. 2015b). In fact, the observed simplification and reduced variability in the temporal dynamics of the inoculated reactor suggest that microbial inoculation plays a key role in stabilizing system behavior (Xi et al. 2005). This increased stability may be attributed to the establishment of a more structured and functionally efficient microbial community (Li et al. 2022; Wang et al. 2024), capable of maintaining consistent metabolic activity over time (Fernandez et al. 2000; Briones and Raskin 2003). In fact, these findings are in line with previous studies indicating that targeted inoculation can improve process control, reduce variability, and promote more predictable outcomes in biological treatment systems, enhancing overall system efficiency and reliability (Xi et al. 2012; Zhang and Sun 2019).

The disappearance of the past-oxygen effect on CO_2 emissions in Reactor 1, together with the strengthened negative relationship between CH_4 and O_2 , indicates a shift in the underlying metabolic regulation driven by inoculation (Avila-Núñez et al. 2026). Specifically, the non-significant influence of prior oxygen conditions on CO_2 suggests that carbon mineralization becomes less dependent on legacy aeration states and more governed by current, stabilized microbial activity (Wichuk and McCartney 2010; Zhang et al. 2025). At the same time, the stronger inverse CH_4 – O_2 relationship points to a tighter coupling between oxygen availability and methane dynamics, likely reflecting enhanced coordination between methanogenic and methanotrophic populations (Awasthi et al. 2016). This implies that the inoculated community may facilitate more efficient methane production–oxidation turnover, where oxygen is rapidly consumed in methane oxidation processes, reducing methane accumulation and improving overall gas regulation (Awasthi et al. 2016). Therefore, our outcomes suggests a relationship between oxygen availability and organic matter decomposition, which is generally associated with compost quality (Wang et al. 2013; Zhao et al. 2026). Considering that adequate oxygenation is essential to support the efficient decomposition of organic matter by microorganisms, accelerating the composting process, and yielding a high-quality final product (Zhao et al. 2026). This behavior appears to be influenced by microbial processes, where oxygen may favor some microorganisms while inhibiting methane-oxidizing bacteria (Sánchez et al. 2015a; He et al. 2019; Günther et al. 2020).

In addition, the results suggest that the inoculum exerts a substantial influence on moisture dynamics and oxygen availability, likely mediated by modifications to the physical structure of the substrate (Padhan et al. 2022). The introduction of a structured and metabolically active microbial consortium may enhance the breakdown and redistribution of organic matter, leading to changes in porosity, water retention capacity, and aeration pathways (Tiquia and Tam 2002). These structural adjustments can improve oxygen diffusion while simultaneously regulating moisture content, reducing the occurrence of anaerobic microsites or excessive water accumulation (Agnew and Leonard 2003). As a result, the

system may achieve a more balanced microenvironment that supports aerobic processes and limits inhibitory conditions (Haug 1993). This interpretation is consistent with previous studies indicating that inoculation can indirectly optimize physicochemical properties of the substrate, thereby enhancing mass transfer processes and contributing to more efficient and stable reactor performance (Acevedo et al. 2005; Cao et al. 2024). Although, during decomposition, moisture loss through evaporation is typically lower than the water released by microbial activity, maintaining an optimal moisture range of 40–60% promotes the growth of composting microorganisms, resulting in stable, low-moisture compost that is free from pathogens (Epstein 1997; Soares et al. 2013). Nevertheless, the optimal moisture content for effective composting may vary depending on particle size and condition, as well as on the methods used during the compost process (Padhan et al. 2022). In fact, the proportion of microorganisms involved in composting primarily depends on the composition of the initial material, the pretreatment applied, the temperature-to-moisture ratio, and the aeration conditions maintained throughout the composting process (Nozhevnikova et al. 2019).

Finally, although the study is limited by the absence of biological replicates and the lack of direct measurements of enzymatic activity or microbial diversity, the consistency of the results across multiple statistical approaches and the exceptionally large sample size provide strong support for the reliability of the conclusions. The convergence of evidence obtained through different analytical frameworks reduces the likelihood that the observed patterns are methodological artifacts, while the high temporal resolution and data volume enhance statistical power and the detection of stable relationships. Nevertheless, these findings should be interpreted with caution, as the underlying biological mechanisms remain inferred rather than directly validated. Future studies incorporating replicated experimental designs and molecular or enzymatic analyses would be valuable to confirm the functional basis of the observed dynamics and to further strengthen the generalizability of the results (Li et al. 2026; Zhao et al. 2026).

Conclusion

This study showed that the composting process is governed by strong temporal dynamics in which microbial activity and physicochemical conditions interact to regulate organic matter degradation and greenhouse gas emissions. Substantial differences in temperature, relative humidity, oxygen availability, and CO₂ and CH₄ concentrations across processes and chambers highlight that composting performance cannot be attributed to a single factor, but rather emerges from the combined effects of substrate characteristics, microbial consortia, and operational control.

Microbial inoculation exerted a marked influence on the composting environment, particularly by increasing ambient temperature and modifying gas emission patterns. The positive association between CO₂ and CH₄ further indicates that microbial metabolism and environmental conditions are tightly coupled in shaping greenhouse gas dynamics. While CO₂ emissions were more variable and less predictable, their biogenic origin renders them climate-neutral in the context of composting, in contrast to CH₄, whose substantially higher global warming potential underscores the importance of methane mitigation. Most reactors exhibited higher CH₄ emissions during the initial stages of composting,

followed by a consistent decline, suggesting the establishment of methane-oxidizing activity as oxygen availability increased. Temperature emerged as a key driver of methane production, whereas relative humidity and oxygen played a central role in limiting CH₄ release, especially at high moisture levels.

From a process perspective, these findings emphasize that effective management of temperature, moisture, and aeration is critical for minimizing methane emissions while maintaining efficient compost stabilization. Automated composting systems equipped with real-time monitoring and control mechanisms appear particularly well suited to regulate these parameters. Such control not only improves process efficiency but also contributes to lowering the climate impact of organic waste treatment. In parallel, the development of advanced sensor technologies, data-driven control systems, and artificial intelligence-based prediction tools offer promising opportunities to manage greenhouse gas emissions in real time. Extending these analyses through life cycle assessments and across different composting scales would support the integration of automated composting into broader strategies for sustainable waste management and climate change mitigation.

In conclusion, evaluating different microbial consortia, assessing the role of feedstock composition and carbon-to-nitrogen ratios, and exploring optimized aeration and turning strategies could further enhance methane mitigation. A strategic integration of biological innovation and technological regulation represents a viable pathway toward more efficient, low-impact composting systems and improved valorization of organic waste.

Declarations

Author Contribution

VS & MA-V: Writing – original draft, visualization, data curation conceptualization. AC-S & J-CC-T– data curation conceptualization, review & editing. VS & MA-V: Supervision – review & editing. The article's submission was reviewed and approved by all authors.

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Data Availability

To access the data, please contact the corresponding author.

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54. Tabla 1. Coeficientes del modelo lineal mixto (LMM) con efectos fijos de Proceso (Proc), tratamiento (Reac), tiempo, temperatura central y humedad relativa. Se muestran las estimaciones, errores estándar, grados de libertad, valores t y p-valores. El efecto del tratamiento (ReacReac2 = + 7.68, $p < 0.0001$) indica que el reactor control emite más CO₂ que el inoculado. El factor Proceso fue marginalmente significativo ($p = 0.0545$).

Tables

Tabla 1. Coeficientes del modelo lineal mixto (LMM) con efectos fijos de Proceso (Proc), tratamiento (Reac), tiempo, temperatura central y humedad relativa. Se muestran las estimaciones, errores estándar, grados de libertad, valores t y p-valores. El efecto del tratamiento (ReacReac2 = +7.68, $p < 0.0001$) indica que el reactor control emite más CO₂ que el inoculado. El factor Proceso fue marginalmente significativo ($p = 0.0545$).

Predictor variable	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	401.7032	1.5903	3904.109	252.6012	<0.001
Process2	1.1013	1.1674	1743.196	0.9434	0.3456
Process3	3.7055	1.7932	4245.9	2.0664	0.0389
Reactor2	7.6769	0.5428	9072.911	14.1439	<0.001
Standardised time	-2.4385	0.5687	7594.595	-4.2882	<0.001
Temperature	-0.0244	0.006	94174.195	-4.0702	<0.001
Relative humidity	-0.1083	0.0127	15287.766	-8.5128	<0.001

Figures

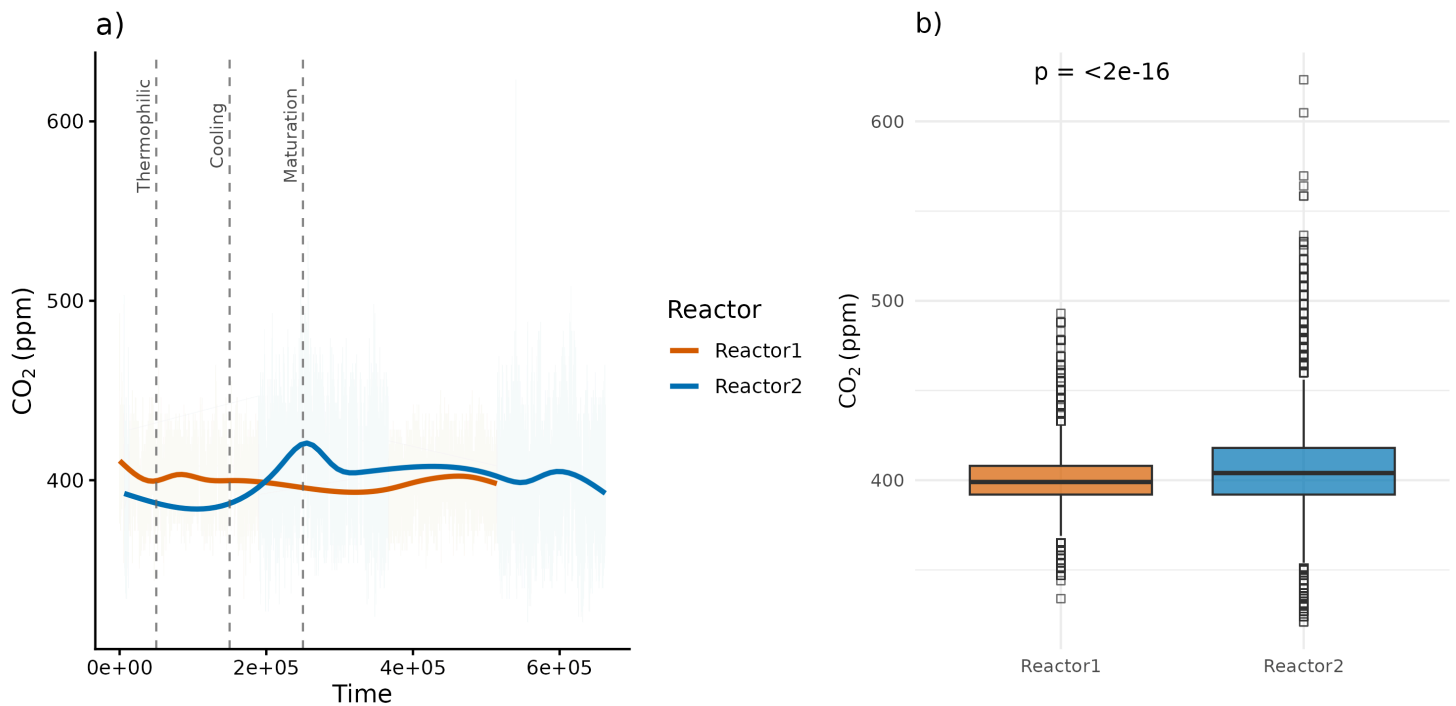


Figure 1

Panel a) shows CO₂ concentration over time (thin semi-transparent lines = raw data; thick smooth curves = GAM fit) for two reactors: orange = With microorganisms (Reactor1) and blue = Without microorganisms (Reactor2). Vertical dashed lines at 50k, 150k, and 250k time steps mark transitions between classical composting phases (start, thermophilic, cooling/maturation). Panel b) presents boxplots comparing the overall CO₂ distribution between the two reactors, with a t-test p-value displayed above; outliers are hidden for clarity.

Supplementary Files

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