Machine learning-driven precision strategies to mitigate nitrogen and carbon losses from organic waste composting

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Abstract

Organic waste mismanagement threatens the attainment of multiple Sustainable Development Goals by degrading soils, increasing air and water pollution and reliance on synthetic fertilizers. Composting offers a circular solution to recycle nutrients and restore soil health, but nitrogen (N) and carbon (C) losses during the process undermine its agricultural and climate benefits. Using machine learning to analyze 848 global composting experiments, this study identified 19 key management parameters driving emissions of ammonia (NH_3), nitrous oxide (N_2O), methane (CH_4), and carbon dioxide (CO_2). We estimated annual global losses at 747 kt NH_3-N, 81 kt N_2O-N, and 592 kt CH_4-C from composting, these non-CO_2 emissions were equivalent to approximately 61 Mt CO_2eq per year. By optimizing strategies—such as adjusting aeration, additives, and C/N ratios—the composting chain could transition from a net emitter (40.1 Mt CO_2eq) to a C sink (-15.1 Mt CO_2eq), while conserving nutrients for crops. These innovations directly advance sustainable agriculture through waste-to-resource systems that boost food security and climate resilience.

Main

Currently, approximately 108 Tg of nitrogen (N) is fixed annually through the Haber-Bosch process to produce fertilizer for food production [1]. This process is energy-intensive as it converts N_2 from the atmosphere using hydrogen (H_2) into ammonia (NH_3) under high temperature and pressure [2]. The global NH_3 synthesis accounts for 3-5% of global natural gas consumption [2], corresponding to 0.46 Gt carbon dioxide equivalent (CO_2eq) annually, creating significant challenges for sustainable food production systems [3]. However, only a fraction of this fixed N ultimately supports food consumption: significant losses occur via livestock manure, sewage sludge, and food waste, collectively representing 5.8 Tg of recoverable N alongside phosphorus and potassium, essential nutrients for crop production [4]. Despite their potential to substitute synthetic fertilizers, these organic wastes are underutilized in agriculture, missing opportunities to reduce reliance on synthetic fertilizers, mitigate greenhouse gas (GHG) emissions, and advance closed-loop nutrient cycling. Closing this recycling gap directly contributes to multiple sustainable development goals (SDGs), including SDG 2 (Zero Hunger) through improved soil health, SDG 3 (Good Health and Well-being) through reduced air and water pollution, SDG 12 (Responsible Consumption and Production) by advancing a circular economy, and SDG 13 (Climate Action) through the reduction of GHG emissions from waste and agriculture.

Organic waste recycling faces systemic barriers, including high moisture content (limiting cost-effective transport), contamination by heavy metals or pathogens, and residual antibiotics or antibiotic resistance genes, all of which threaten soil and crop health if untreated wastes are applied directly to fields [5-7]. Composting emerges as a promising solution for dealing with fresh solid organic wastes to mitigate these risks [6]. When properly carried out according to crop requirements, compost application has the potential to enhance global cereal production by 4% (96 Tg) and contribute to soil C restoration for climate change mitigation and food security [4]. Additionally, compost improves soil health by enhancing its structure, increasing moisture retention, and providing essential nutrients, further promoting a more sustainable and productive agricultural system [5].

Nevertheless, composting can lead to significant environmental issues. During the traditional composting process, approximately 30% of N and 40% of carbon (C) can be lost in the form of NH_3, nitrous oxide (N_2O), methane (CH_4), and carbon dioxide (CO_2) [8,9]. This not only reduces the amount of N and C that can be returned to agricultural fields, but also contributes to N deposition and GHG emissions, both of which have already exceeded the safe operating limits for the Earth's ecosystem [10,11]. Previous studies have attempted to quantify NH_3 and GHG emissions from composting using linear regression mathematical modeling and meta-analysis [12,13]. However, accurately predicting N and C emissions during composting remains a challenge. The complexity arises from the fact that the production and emission of N and C gases are intricate processes in themselves, each varying independently and sometimes interacting with one another. For example, conditions that are conducive to reducing NH_3 emissions might inadvertently lead to an increase in N_2O emissions [14]. Moreover, the wide variety of composting materials, different composting methods, diverse aeration techniques, the various types and amounts of additives are all found to have certain effects on N and C losses [8,9,13]. These factors collectively impede a precise understanding of the N and C emissions that occur during the composting process.

Given the projected increases in food production, the generation of livestock manure, sewage sludge and food waste will continue to increase in the future [15,16]. Consequently, composting organic waste will likely be an essential practice for sustainable agriculture [5,13]. However, traditional empirical models often fail to capture inherent complexity of composting and struggle to provide accurate, generalized predictions for diverse composting scenarios [12]. Emerging machine learning (ML) methods provide a powerful means to uncover complex relationships. While previous studies have begun applying ML to predict GHG emissions from composting [17-19], such efforts are often constrained by scarce datasets and restricted input variables, which can compromise model generalizability and lead to predictions that deviate from underlying biochemical mechanisms. Moreover, the simultaneous prediction of multiple gases remains underdeveloped, yet this is crucial for understanding trade-offs and designing synergistic mitigation strategies. To address this challenge, we utilized a knowledge-guided machine learning (KGML) framework by synergistically combining data-driven algorithms with established principles of composting biochemistry [17,20]. The framework employed advanced ML algorithms (e.g., Categorical Boosting, eXtreme Gradient Boosting) to autonomously decipher the non-linear relationships between 19 composting parameters and multiple gas emission outcomes based on the global composting observatory experimental dataset, while ensuring that these relationships remained grounded in chemically and biologically plausible mechanisms. This capability enables the model to identify the underlying drivers of emissions and potential trade-offs, thereby providing actionable insights for process optimization.

Here, we utilized 848 global observations to develop ML models that predict multiple pathways of N and C losses based on 19 management parameters, including waste characteristics, composting practices, and the type and amount of additives. We identified key drivers of multi-gas emissions during composting and constructed the model. This model was then combined with multi-objective genetic algorithms (NSGA-II) and life cycle assessment (LCA) to optimize composting management practices for different wastes, aiming to minimize the net environmental burdens of N losses and GHG emissions at the global level. This research innovation directly supports multiple SDGs (zero hunger, good health and well-being, responsible consumption and production, climate action) by establishing closed-loop C and N recovery pathways.

Results and Discussion

N and C emissions under different composting managements

We collected 848 observations of N and C losses in various types of composting processes. These observations were sourced from 171 studies that were carried out globally within the time span of 1993 to 2023 (Fig. 1). The observed mean losses of NH_3-N relative to the original N content were on average ranged from 12.05% to 16.79% covering the poultry manure, cattle manure, pig manure, sewage and food waste for different type of organic wastes (Fig. 1). These values fall within the broad range reported in prior studies (9-27% of initial N) [8,21]. While the losses of N_2O-N accounted for a relatively small proportion of total N, ranging from 0.47% to 1.75% for different type of composting materials (Fig. 1), which is consistent with the general understanding that N_2O emissions, while climate-critical, represent a minor N pathway compared to NH_3 volatilization under aerobic conditions [13,21]. The losses of CH_4-C to total originated C content were also low, ranged from 0.18% to 1.48%, which similar to the ratio for N_2O-N losses. These align with literature values, as most reported composting trials typically well-aerated that suppress CH_4 production [9,21]. In contrast, the mineralization losses as CO_2-C were substantially larger than the other three types of losses, accounting for 14.85% to 56.90% of total C in the composted material (Fig. 1). which is expected as it represents the primary pathway for organic C decomposition [9]. However, an assessment based solely on mass loss is misleading for climate impact. When converted to CO_2eq using the 100 year global warming potentials (GWP-100), the mean emissions of N_2O and CH_4 reached 41-157 kg and 25-195 kg CO_2eq per ton of dry composted material, respectively, which together contributed over 90% of the total CO_2eq emissions (Fig. S5). This analysis revealed that the non-CO_2 gases (N_2O and CH_4) dominate the total GHG footprint, underscoring the critical need to target their mitigation.

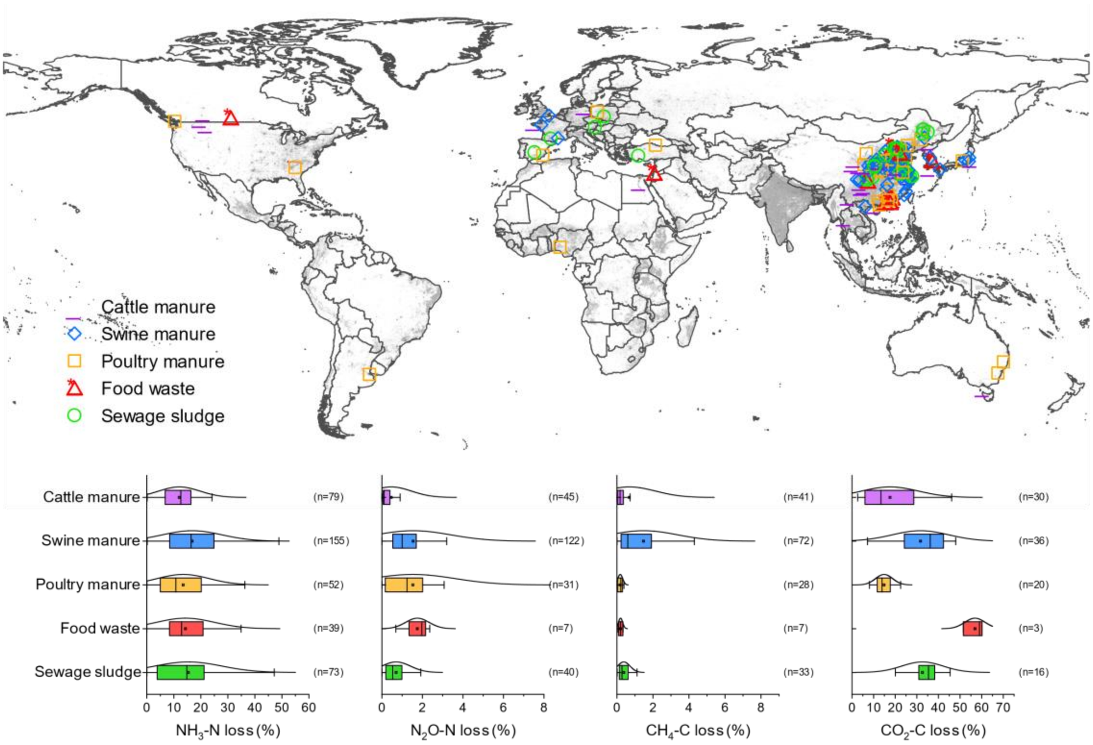

Fig. 1. Geographical distribution of the sample sites of the global dataset and the gas loss (% of initial TN or TC) from different organic waste composting. The markers on

the map indicate the location of the experimental sites for the composting of different raw materials. The black square represents the mean value, black solid lines in the boxplot represent the median quartiles, box boundaries indicate upper and lower quartiles. The whiskers indicate that values extend to 1.5 orders of the box length. The values in parentheses represent the numbers of experimental observations.

N and C losses during composting exhibit considerable variation across different organic waste types (Fig. 1), which is partly attributable to differences in the characteristics of the waste materials. For example, cattle manure typically has a high C/N ratio and lignocellulose content [13], resulting in slower decomposition and lower CO_2 (17.61%) and NH_3 (12.05%) losses during composting compared to other organic wastes (Fig. S3). Conversely, swine and poultry manures lose more NH_3-N (13.47-16.79%) due to their high initial content of easily mineralizable N [21]. Food waste composting often exhibits higher N_2O-N (1.75%) losses, primarily driven by its high moisture content and poor porosity [13]. Meanwhile, sewage sludge typically shows moderate C (32.59% CO_2-C, 0.38% CH_4-C) and N (15.38% NH_3-N, 0.70% N_2O-N) losses, influenced by its diverse sources and various pre-treatment processes [6,22]. These results are consistent with previous studies, confirming that the initial biochemical composition of the waste material serves as a fundamental driver of both C and N transformation and loss pathways [8,13]. However, the variations in N and C losses within each group of composting materials are larger than the differences between different types of materials (Fig. 1), indicating that the N and C losses are more closely related to the differences in management practices (Fig. 2). For example, the highest NH_3-N loss was observed with the combination of swine manure - windrow - forced aeration only - no additive (SM-WD-FA-NO) treatment, accounting for 37.35% of total initial N, primarily due to the open, forced aeration composting system and the higher initial content of easily mineralizable N [13]. In contrast, adding different additives during the composting can greatly reduce the NH_3-N losses to 0.70-1.39%, such as in the swine manure - reactor - forced aeration + turning - mixture of additives (SM-RE-FT-MI), and swine manure-reactor- forced aeration only - physical additive (SM-RE-FA-PH) treatments (Fig. 2). This reduction is primarily due to adsorption and/or fixation of ammonium N by additives [21].

The complexity of the production mechanism results in a wide range of N_2O-N loss during composting, with losses highest at 5.83% observed in the poultry manure – reactor - forced aeration + turning - none additive (PM-RE-FT-NO) treatment (Fig. 2). Additives and aeration offer greater potential for controlling N_2O-N losses during composting. The turning only (TU) and forced aeration only (FA) practices typically result in lower N_2O-N losses compared to the forced aeration + turning (FT) treatment. This is because the combined aeration and turning create a dynamically fluctuating redox environment, creating ideal conditions for the co-occurrence and coupling of nitrification (aerobic) and denitrification (anaerobic), which is a key driver of N_2O emissions [14,23]. Similar to the control of NH_3-N losses, additives can effectively reduce N_2O-N losses by approximately 12.2% to 75.2% (Fig. 2). However, it is important to note that the types of additives effective in reducing NH_3 volatilization (e.g., acidifying agents) often differ from those that suppress N_2O (e.g., nitrification inhibitors), since NH_3 emission is primarily governed by physico-chemical conditions whereas N_2O production is driven by microbial N transformation processes [9,21,23]. Such mechanistic divergence explains why conventional single-approach strategies often fail to achieve concurrent reductions of both gases [14,21,22], highlighting the need for a tailored, integrated strategy to target these distinct emission pathways simultaneously.

As a microbe-dominated aerobic degradation process, CO_2 emissions are unavoidable during composting [24]. CO_2-C loss can account for 5.73% of initial C content in the composted material, and up to 40.65% under different composting combinations (Fig. 2). The passive aeration (PA) generally results in lower CO_2 emissions compared to actively aerated composting (Fig. 2). However, this may prolong the composting duration and result in incomplete maturation [6]. A certain amount of CO_2 emissions is crucial, as it indicates the microbial degradation of toxic substances, which is essential for producing crop-beneficial compost [6]. Simultaneously, minimizing unnecessary CO_2 emissions while ensuring compost maturation is beneficial as this improves the C sequestration potential of the compost product [24]. CH_4 is mainly produced by methanogens in local anaerobic environments within the compost pile, ranging from 0.05% to 4.37% of initial C content under different management practices (Fig. 2). Hence, oxygen supply is a critical regulatory factor. Sufficient diffusion of oxygen into the matrix suppresses the activity of anaerobic methanogens while concurrently stimulating aerobic methanotrophs, which oxidize CH_4 to CO_2, establishing an internal biological sink within the system [25].

Key factors determining gas emissions during the composting process

The key factors affecting the emissions of different N and C losses during composting varied (Fig. 2). Turning frequency (TF) emerged as the dominant factor affecting the losses both of N and C. Regular turning optimizes oxygen diffusion and enhances material homogeneity, which facilitates organic matter mineralization while inhibiting CH_4 generation [8,9]. However, this practice may simultaneously promote NH_3 volatilization from the compost stack into the environment and drive the spatial redistribution of NO_x^-, transferring surface-derived NO_x^- from aerobic zones to internal anaerobic regions. This redistribution facilitates incomplete nitrification-denitrification processes, ultimately increasing N_2O emission dynamics [9,23]. Waste type (WT) also play a crucial role (Fig. 2), primarily due to the specific physicochemical properties and indigenous microbial communities that influence C and N transformation and lead to differences in gas emissions during composting [9,13].

Apart from these factors, additive application and aeration parameters emerged as critical drivers of NH_3 loss, including additive type (AT), additive amount (AA), aeration duration (AD), and aeration rate (AR) (Fig. 2). Specifically, additives effectively stabilize ammonium N through chemical immobilization or physical adsorption, thereby mitigating NH_3 emissions [21]. Conversely, longer AD and higher

AR typically result in higher NH_3 volatilization, as aeration enhances the mineralization of organic N, indirectly boosting NH_3 volatilization by increasing ammonium N content [9]. AR and initial total N (ITN) were identified as the most important factors (p<0.01) affecting N_2O emissions, except for TF and WT (Fig. S8). Higher aeration generally inhibiting N_2O reductase activity and enhancing nitrification, thus contributing to N_2O emissions [13,23]. Concurrently, substrate N enrichment (elevated NH_4^+–N and NO_3^-–N concentrations) promotes dual nitrification-denitrification pathways, resulting in an increase in N_2O emissions [14,26].

Composting duration (CD) and AD significantly affect CO_2 emissions (Fig. 2, Fig. S7c, S8c), as prolonged aerobic conditions inevitably lead to excessive mineralization of organic C [9]. Furthermore, pH critically regulates CH_4 emissions, as acidic (<6.0) or alkaline (>8.5) conditions suppress CH_4 production by disrupting methanogen metabolic activity [25]. Overall, our results highlight the complexity and heterogeneity of gas emission factors (EFs) associated with different composting management practices. Therefore, the development of comprehensive composting models that integrate multiple management variables is essential to accurately understand and mitigate gas emissions.

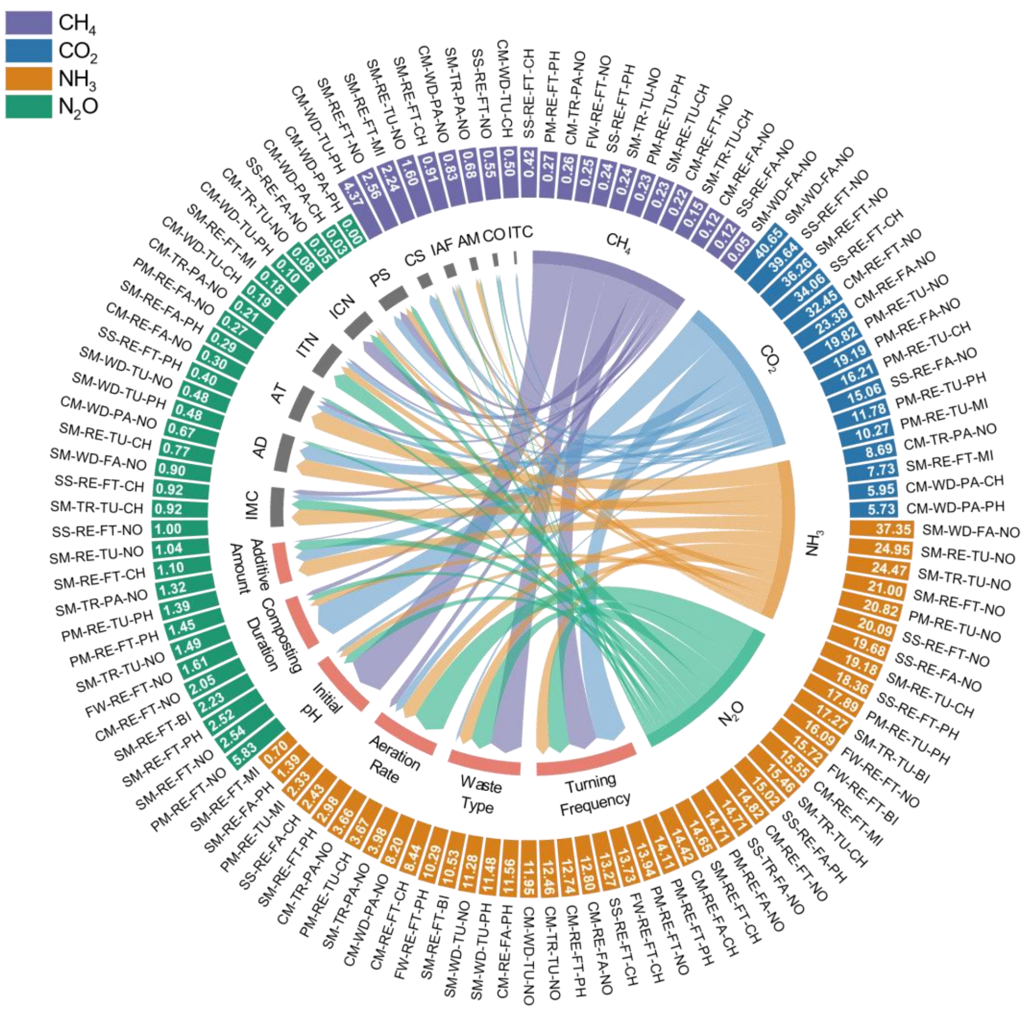

Fig. 2 EFs conditioned on management practices and importance analysis. The outer circle shows the gas emission under different management combinations (waste type, composting system, aeration method, additive type). The numbers on the bars represent the average gas losses (% of initial TN or TC) during composting and are ordered from highest to lowest. Each bar must contain experimental observations ≥3. The inner circle describes the permutation importance of the features for each gas. The widths of the link lines indicate the importance of each driver for different gases.

Note: SM, swine manure; PM, poultry manure; CM, cattle manure; SS, sewage sludge; FW, food waste; RE, reactor; TR, trough; WD, windrow; FT, forced aeration + turning; FA, forced aeration only; TU, turning only; PA, passive aeration; PH, physical additive; CH, chemical additive; BI, *biological additive; MI, mixture of the above additives (two or more); NO, none additive; WT, waste type; BA, bulking agent type; IMC, initial moisture content; ITC, initial total carbon; ITN, initial total nitrogen; ICN, initial C/N; IPH, initial pH; IBD, initial bulk density; CS, composting systems; AM, aeration method; TF, turning frequency; AR, aeration rate; IAF, intermittent aeration frequency; AD, aeration duration; CD, composting duration; CO, covered; PS, pile size; AT, additive type; AA, additive amount.*

Machine learning enabled prediction of N and C losses from composting

We employed 8 ML algorithms to predict the EFs for each of the four gases based on 19 management parameters (Fig. 3). For NH_3 prediction, Categorical Boosting (CAT) demonstrated the best stability and accuracy (R^2 = 0.63 ±0.07, MSE = 37.6 ±11.0). In contrast, eXtreme Gradient Boosting (XGB) exhibited excellent performance for N_2O, CO_2 and CH_4, with R^2 achieved 0.71 ± 0.07, 0.84 ± 0.03, 0.77 ± 0.05, respectively. While prior ML studies have reported higher predictive accuracy (often $R^2 > 0.9$) for composting GHG emissions, it is important to note that these models and ours were developed under different research scopes and data conditions [17-19]. Previous models have made valuable contributions, frequently by focusing on specific waste types or controlled composting scenarios with more homogeneous datasets and a curated set of input variables (Table S8). Such an approach appropriately prioritizes high accuracy within defined systems. In contrast, our model was deliberately developed on an extensive, globally representative dataset encompassing a wide array of waste types and conditions, aimed to build a generalized model capable of handling the high variability inherent in real-world composting practices. To this end, we integrated a substantially larger and more diverse dataset and incorporated a wider array of 19 operational and material parameters to capture system complexity. This design choice enhances the model's robustness and generalizability across diverse and unseen scenarios, while potentially lowering the absolute R^2 compared to models optimized for narrower conditions. The performance achieved under these more challenging and heterogeneous data conditions reflects a model that is calibrated for broad applicability, providing a reliable tool for large-scale emission assessment and strategy exploration across varied composting contexts.

By using the ML enabled prediction model, we provided more accurate EFs for NH_3, N_2O, CO_2 and CH_4 from composting of organic materials (Fig. 3). The IPCC (2019) guidelines provide default EFs for four different composting management systems (in-vessel, static pile, intensive windrow, passive windrow), reporting combined NH_3 and NO_x losses as 45–65% of initial N at Tier 1 [27]. Considering NO_x-N emissions from composting are typically less than 1% of the initial N [28], this default range effectively represents NH_3 emissions. Our ML model shows that EF of NH_3 is ranging from 13 to 23% of initial N, with minor variation observed across different composting methods and materials. This prediction aligns with current meta-analysis and literature review (Fig. 3), indicating that IPCC default value may overestimate NH_3 emission from composting.

The EF of N_2O emissions predicted by this model ranged from 0.5 to 2.3% of the initial N. Notably, the N_2O EF for cattle manure was consistent with the default IPCC Tier 1 recommendation, while the EFs for other waste materials were approximately twice the default IPCC Tier 1 recommendation (Fig. 3). This discrepancy was also observed in other studies, suggesting that the IPCC underestimated N_2O emissions from composting [8,13]. Additionally, our model shows that the EF of N_2O varies across different waste types, which suggests that more refined, composting material-specific EF should be considered for more accurate emission assessments in the future. According to the IPCC Tier 2 methodology (taking into account manure characteristics and management systems), CH_4 emissions range from 0.1 to 1.7% of initial C, which is similar to the results of this study (Fig. 3). The IPCC does not provide EFs for CO_2 emissions, as this process is considered part of natural C cycling. Our model provides CO_2 EF, ranging from 10 to 30% of initial C, which may provide useful information to estimate C sequestration potential of composting.

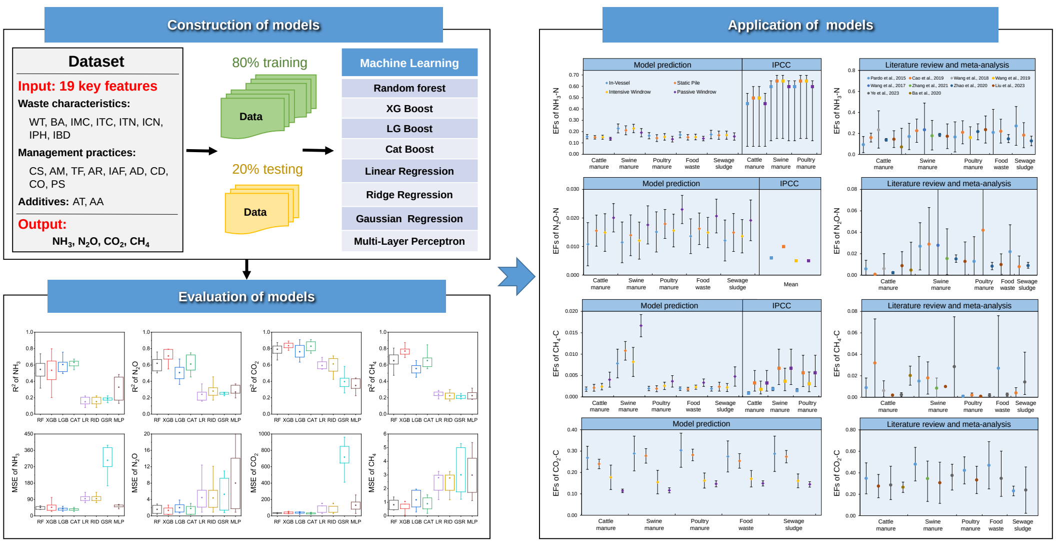

Fig. 3 The framework for the construction, evaluation and application of the composting simulation model. A larger R^2 and smaller MSE indicate higher accuracy

in model predictions. The center point indicates the mean and the box boundaries indicate the upper and lower quartiles.

Note: *WT, waste type; BA, bulking agent type; IMC, initial moisture content; ITC, initial total carbon; ITN, initial total nitrogen; ICN, initial C/N; IPH, initial pH; IBD, initial bulk density; CS, composting systems; AM, aeration method; TF, turning frequency; AR, aeration rate; IAF, intermittent aeration frequency; AD, aeration duration; CD, composting duration; CO, covered; PS, pile size; AT, additive type; AA, additive amount. RF, Random Forest; XGB, eXtreme Gradient Boosting; LGB, Light Gradient Boosting Machine; CAT, Categorical Boosting; LR, Linear Regression; RID, Ridge Regression; GSR, Gaussian Process Regression; MLP, Multi-Layer Perceptron.*

N and C losses from composting at the global level

Composting is widely used as an effective technology for recovering organic resources from waste, particularly for the manure treatment in China, the United States of America (USA) and Brazil (Fig. S17-19). In Europe, manure is rarely composted, but a high proportion of food waste and sludge is used for composting (Fig. S18). By using the updated EFs, we estimated that 747 ± 38 kt of NH_3-N, 81 ± 4 kt of N_2O-N, and 592 ± 36 kt of CH_4-C were emitted annually from the composting of organic wastes in 2020 (Fig. 5). These emissions accounted for 6.4% of NH_3 emissions, 23.8% of direct N_2O emissions, and 5.5% of CH_4 emissions from global manure management [29,30], highlighting that composting is an important contributor and will increase with the development of agricultural intensification and the increased rate of municipal organic waste collection. Major of the NH_3, N_2O and CO_2 emissions were attributed to cattle and poultry manure composting due to their large quantities resources used for composting (Fig. S18). Additionally, swine manure contributed more to CH_4 emissions (24%) because of its high CH_4 EF.

The predicted values are different with those of IPCC, especially for NH_3 and N_2O emissions, when considering the more accurate EFs of specific composting materials (Fig. S21). Specifically, global NH_3 volatilization from manure composting systems was projected to be 73% lower (equal to 1723 kt NH_3-N) than IPCC-derived estimates, while N_2O emission was simulated to be 171% higher (equal to 42 kt N_2O-N yr^{-1}). This discrepancy highlights the critical importance of waste-specific parameterization. In addition, large variations in N_2O emissions were also observed at the country level, especially in the United States, Canada, and Brazil. This is mainly due to these countries having a large proportion of swine and poultry manure, which have much higher N_2O EF than the default value of IPCC (Table. S4).

Machine learning guided strategies for lower reactive N losses and net C footprint

In total, we generated 100 thousand optimal composting management combinations (20 thousand combinations for each composting material) to explore the best strategies for reducing N and C losses from organic waste composting, which was guided by the ML model and NSGA-II (Fig. 4, Fig. S11). These solutions were generated under the dual constraints that C and N emissions must be lower than those from conventional composting, and the germination index (GI) must exceed 80% to ensure compost quality. The resulting solutions form a Pareto front, which reveals the inherent trade-offs between minimizing different loss pathways. For instance, simply focusing on maximizing the reduction of a single gas will not result in the lowest net C footprint due to both the trade-offs between gases and the indirect emissions associated with certain management practices themselves (Fig. S12-14, S22). Therefore, our model allows stakeholders to identify bespoke strategies tailored to specific priorities. Here, we presented and analyzed two fundamental and intuitive scenarios, i) minimizing reactive N (Nr) losses, as the combination of NH_3-N and N_2O-N losses, and ii) minimizing net C footprint, which accounts for the direct GHG emissions (N_2O, CH_4) and indirect emissions from composting operations (energy consumption, additive consumption, etc.), avoided emissions through substituting synthetic N fertilizer and the long-term soil C sequestration via properly recycle compost to crop production (Fig. 6, Fig. S20). Our results provide comprehensive strategies for each type of N and C losses from composting.

In general, minimizing NH_3 volatilization is prioritized to reduce N losses during composting, as NH_3 is the primary form of N loss. Our results suggest that the optimized Nr reduction strategy integrates three key interventions: i) maintaining initial C/N ratios between 28-33 by supplementing with lignocellulosic biomass (e.g., green waste, sawdust) to enhance NH_4^+ immobilization via microbial assimilation; ii) incorporating 6-10% acidic additives (e.g., gypsum, inorganic acids, Ca-superphosphate) to serve as a pH buffer, shifting the NH_3/NH_4^+ equilibrium; and iii) implementing low-frequency turning combined with low aeration rate (0.1-0.3 $L \cdot kg^{-1} \cdot min^{-1}$) to minimize NH_3 release from compost pile (Fig. 4). In contrast, the low-C emission management strategies focus on reducing N_2O and CH_4 emissions while utilizing interventions with a lower C footprint. The key strategies primarily include: i) applying additives with a lower C footprint (e.g., clay, mature compost); and ii) adopting an intermittent aeration to ensure emission control without increasing energy consumption (Fig. 4).

In the scenario optimized for the lowest Nr (NH_3-N and N_2O-N combined) losses, our results suggest that global composting of organic waste could be reduced by 694 kt of NH_3-N and 57 kt of N_2O-N, representing a decrease of approximately 70–93% compared to the current situation (Fig. 5a-b). These avoided N losses would accumulate in the commercial compost, which equal to 0.7% of global N fertilizer use, implying a reduction in economic inputs for fertilizer production and associated environmental impacts [3]. The lowest Nr losses solution would be accompanied by 6% reduction of CH_4-C emissions, but 12% increase of CO_2-C emissions compared to the current situation (Fig. 5c-d), reflecting the trade-off between C and N gas emission reductions.

Tailored composting management combinations for reactive N and GHG mitigation, respectively

GHGs mitigation   Nr mitigation

Material Characteristics					Management							Additives		Gas emissions (%)				Net C footprint ($CO_2eq\ t^{-1}$)
Waste Type	Bulking Agent	Initial C/N	Initial Moisture (%)	Initial pH	System	Aeration Method	Aeration Rate (L/min)	IAF (h/h)	Aeration Duration (days)	Turning Frequency (day/time)	Duration (days)	Type	Amount (%DM)	NH_3-N	N_2O-N	CH_4-C	CO_2-C	
Cattle manure	Green Waste	30	56	7.7	Reactor	Intermittent	0.03	1	30	-	58	Gypsum	4	5.00	0.04	0.09	16.58	-61
		33	58	6.6	Reactor	Continuous	0.10	-	40	-	40	Inorganic acid	10	1.03	0.10	0.18	18.54	128
Swine manure	Green Waste	20	53	6.4	Windrow	Intermittent	0.85	3	36	2	67	Clay	4	7.03	0.28	0.01	14.07	-31
		28	60	6.3	Reactor	Intermittent	0.16	2	41	5	41	Inorganic acid	9	0.70	0.99	2.71	24.05	550
Poultry manure	Sawdust	34	57	6.7	Reactor	Intermittent	0.71	3	25	-	29	Gypsum	5	10.77	0.08	0.09	13.85	-71
		30	70	5.5	Reactor	Continuous	0.32	-	45	-	49	Ca-superphosphate	6	1.10	0.63	0.05	12.25	14
Food waste	Green Waste	31	56	7.9	Reactor	Continuous	0.12	-	19	-	57	Clay	6	7.60	0.15	0.05	16.93	-53
		30	50	6.6	Reactor	Continuous	0.11	-	37	-	53	Gypsum	9	1.55	0.48	0.05	19.01	-31
Sewage sludge	Green Waste	32	69	7.8	Reactor	Intermittent	0.11	1	26	-	44	Mature compost	4	6.00	0.12	0.09	14.82	-56
		33	55	6.4	Reactor	Intermittent	0.13	1	40	-	55	Ca-Mg-P fertilizer	10	1.09	0.96	0.13	11.73	144

Fig. 4 Tailored composting management strategies for optimal GHG and reactive N mitigation, respectively.

Note: *The blue background indicates the optimal strategy for reducing reactive N emissions, while the white background represents the optimal strategy for reducing GHG emissions; IAF, intermittent aeration frequency;*

In contrast, the lowest C footprint scenario achieved only a 49% reduction in NH_3-N losses, which was significantly smaller than the reduction achieved under the lowest Nr losses solution (Fig. 5a). However, N_2O-N losses and CH_4-C losses would be reduced by 93% and 86% compared to current situation, respectively (Fig. 5b-c). The increase in CO_2-C losses under the lowest C footprint solution was relatively smaller than that of the lowest Nr losses solution (Fig. 5d). These reductions could be achieved through the integration of low-C-footprint additives (e.g., clay, gypsum) and optimized aeration, which together facilitate synergistic reductions in NH_3, N_2O and CH_4 emissions during composting (Fig. 4).

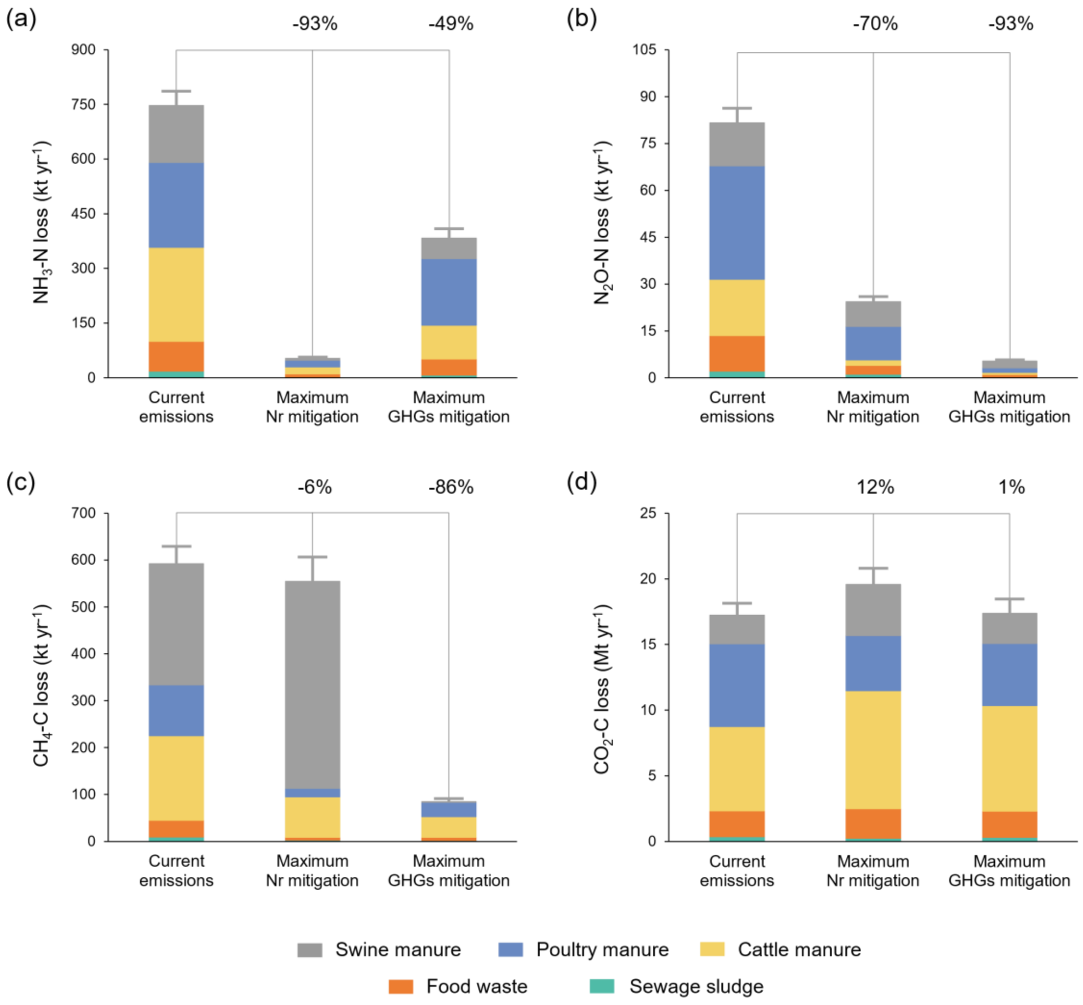

Fig. 5 Changes in C and N gas emissions from global organic waste composting with

the adoption of optimized management strategies. NH_3-N (a), N_2O-N (b), CH_4-C (c) and CO_2-C (d) emissions from composting under current practices, Nr mitigation strategies, and GHGs mitigation strategies.

When considering the net C footprint from a life cycle perspective, with system boundaries encompassing: i) upstream processes, including organic waste collection and transport; ii) the composting process, encompassing direct GHG and NH_3 emissions and indirect emissions from energy and additive consumption; and iii) downstream impacts, accounting for avoided emissions from synthetic fertilizer substitution and long-term soil C sequestration following compost application (Fig. S20). The net GHG emissions were estimated at 40.1 Mt CO_2eq from composting of all organic materials in 2020 (Fig. 6a), which were primarily attributed to the direct N_2O emissions (38.2 Mt CO_2eq) and CH_4 emissions (19.8 Mt CO_2eq), then followed by indirect N_2O emission via NH_3 emission (3.5 Mt CO_2eq) and the energy use in composting (1.0 Mt CO_2eq) in 2020. These emissions could be offset by around 15.4 Mt CO_2eq through the replacement of synthetic N fertilizer and 7.6 Mt of through the C storage in the soil, considering the overall C input rate and the 20 years long-term decomposition process [31].

Under the optimal Nr control scenario, the net GHG emissions would be reduced to 36.9 Mt CO_2eq compared to the status (Fig. 6b). Specifically, this reduction involves lowering indirect N_2O emissions to 0.3 Mt CO_2eq, direct N_2O to 11.4 Mt CO_2eq, and CH_4 to 18.4 Mt CO_2eq. However, achieving the lowest Nr emissions necessitates inputs of gypsum, inorganic acids and organic acids materials, which in turn increases the GHG emissions of the resource inputs from 0.6 to 29.8 Mt CO_2eq. This solution yields a further reduction of 2.7 Mt CO_2eq through more N conserved in the final commercial composting fertilizer. In comparison, under the solution for the lowest net C footprint, net GHG emissions amount to -15.1 Mt CO_2eq, transforming the system from a C source into a C sink (Fig. 6c). This is attributing to the great reduction in both direct and indirect N_2O emission during the composting process, which together will reduce emissions by 37.4 Mt CO_2eq. Additionally, CH_4 emissions are reduced by 17.0 Mt CO_2eq. while the low-C management strategy does not significantly increase the C footprint of resources and energy.

Overall, the C footprint of solid organic waste, from collection to compost production, indicates that composting can be a C source when it is poorly managed. However, with optimal management, composting has the potential to shift from a net emitter to a C sink, potentially reducing global net C emissions by 55.2 Mt CO_2eq (Fig. 6). Similarly, China, Brazil, and the United States are expected to be the top three C sinks for composting, collectively accounting for 65% of total emission reductions (Fig. 6d-f, Fig. S25). Meanwhile, reducing gas emissions during composting helps mitigate the risk of terrestrial ecosystem acidification, (equivalent to 1077.2 kt of SO_2 emissions per year), which is crucial for biodiversity conservation (Fig. S26). Therefore, we advocate for best practices in composting that minimize harmful emissions, promote cleaner recycling of organic waste and support policies that encourage sustainable waste management.

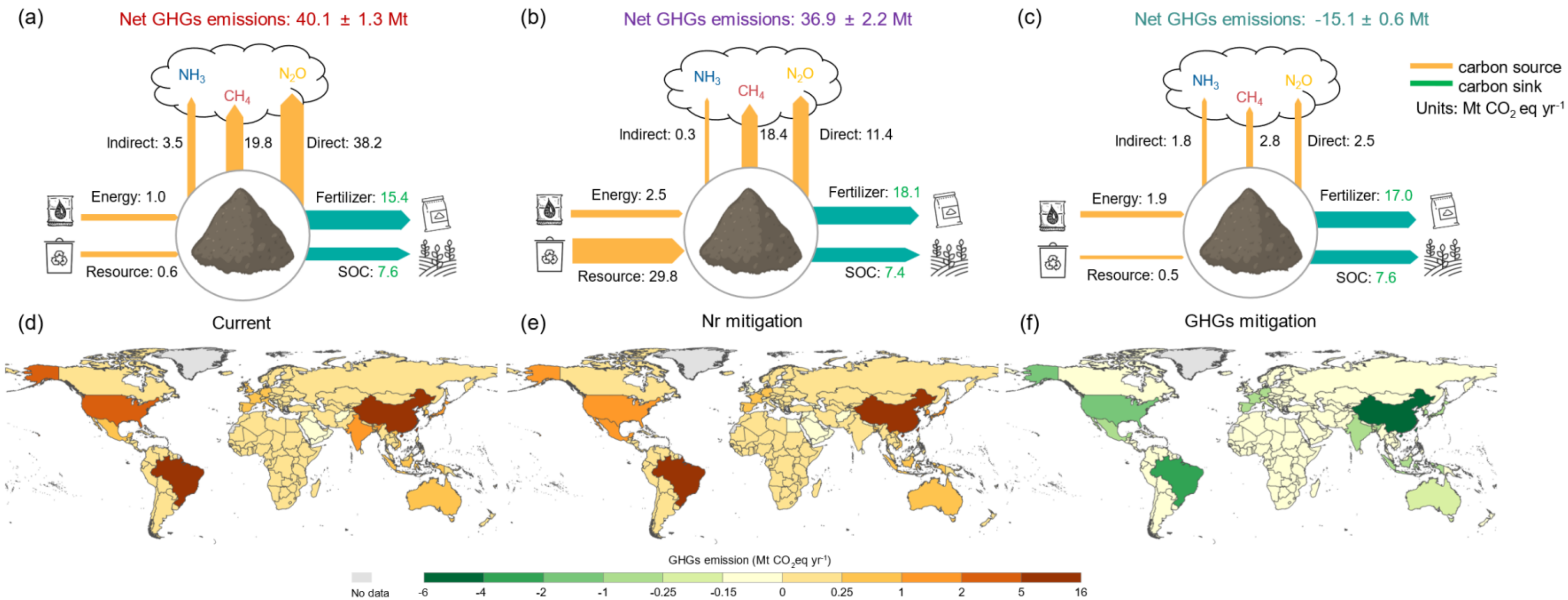

Fig. 6 Global GHGs emissions from whole organic waste composting chain by adopting integrated management strategies. (a, d): current, (b, e): Nr mitigation scenarios, (c, f): GHGs mitigation scenarios.

Note: *Energy: The fuel and electricity used for waste collection, transport, and composting operations (aeration, turning). Resource: The C emissions from all material inputs to the composting process, including composting facility and additives. Fertilizer substitution benefit: Avoided emissions from synthetic N fertilizer production due to compost use. SOC benefit: C sequestered in soil through compost application.*

Future implications

Our study indicated that waste composting has substantial C sink potential when managed effectively. Although the proportion of waste currently being composted is relatively low, the recycling of nutrient resources is actively promoted worldwide, with the proportion of composting steadily increasing each year [32]. For example, Ireland has set a target to composting 70% of organic waste by 2030 [33]. Our model can be a scientific tool for advancing waste composting management and emission reduction strategies, and assist farmers and compost producers in creating more optimized and scientifically grounded composting. However, it is important to note that the optimization strategies were designed based on industrial-scale to better guide production practices. While trained on multi-scale data (from lab-scale to industrial-scale), the model can capture fundamental relationships that are largely scale-invariant, providing robust guidance on key management principles (e.g., optimal C/N ratio). Nevertheless, the actual efficacy of these strategies in controlling gaseous emissions may vary across composting scales due to differences in physical conditions and operational implementation (Fig.S24). Future work should focus on integrating engineering principles to create a scale-explicit prediction framework. Additionally, with the availability of high-resolution input data to track dynamic changes in the composting process, there is an opportunity to explore time-series modeling of gas emissions. This remains a crucial area for future research and is essential for the precise control of gases during the composting process.

The ML based model would be able to provide the precise strategies for reducing different type of N and C losses. Though this study focusing on the all Nr losses and net C footprint, a differentiated strategy could be formulated when facing different needs. For example, CH_4 emissions is expected to be reduced at least by 30% between 2020 and 2030 to rapidly mitigate the global warming risks [34]. This is equal to a reduction of 18 Mt of CO_2eq per year in solid waste management [16]. This study showed that the composting system could offer a reduction close to the required mitigation rate if designed to minimize CH_4 emission (Fig. S14, S20). Similarly, there are a lot of regions facing with too much NH_3 emission related biodiversity risks and air pollution risks, and the lowest NH_3 emission mitigation solution in composting could also reduce NH_3-N emission by 92% (Fig. S12, S20), which also help to the alleviation the negative effects of NH_3 at the regional level. Furthermore, beyond pursuing minimizing either GHG emissions or Nr loss alone, compromise solutions can also be designed to address multiple objectives simultaneously, such as maximizing N conservation while ensuring the system acts as a net C sink (net GHG emissions < 0), or minimizing the net C footprint while ensuring Nr reduction exceeds 80% (Fig. S15-16, S23). Such trade-off solutions highlight the model's utility in supporting context-specific decision-making and can be used to guide the achievement of sustainable ecosystem at the country and local level.

This study used a data-driven approach to address the non-linear effects and complex interactions between C and N losses with waste properties and management strategies, which was previously impossible with process- and experience-based approaches. However, further improvements are needed to address model uncertainties in the future: i) constructing a more complete and higher-quality dataset by collecting more in situ observations and incorporating more key factors, such as climate and season, to improve the data source itself, and ii) integrating data-driven ML and biophysical-based model to develop hybrid models, while their configuration and parameters can be optimized through an ensemble learning approach [20,35].

Methods

Data collection

For this study, a comprehensive literature review was conducted using academic databases, such as Web of Science, Google Scholar, and the China National Knowledge Infrastructure. The search covered the period from 1993 to 2023 to ensure that comprehensive composting research was included at the outset of the project. The keywords used in the search included: composting, ammonia or NH_3, nitrous oxide or N_2O, greenhouse gases or GHGs, methane or CH_4, carbon dioxide or CO_2, nitrogen loss or N loss, and C loss or carbon loss.

To be included in this database, studies had to meet the following criteria: i) the composting process must be complete; ii) laboratory-scale incubation experiments are not included; and iii) the study must include emission factors for at least one of NH_3, N_2O, CO_2 and CH_4. As a result, 171 papers with 848 observations were eventually included in the analyses. All relevant primary trials and meta-analyses were included in the dataset (Supplementary References 1). To accurately and comprehensively establish the relationship between gas emission characteristics and management parameters, the dataset consisted of 19 key features, including waste characteristics (waste type (WT), bulking agent type (BA), initial moisture content (IMC), initial total carbon (ITC), initial total nitrogen (ITN), initial C/N (ICN), initial pH (IPH) and initial bulk density (IBD)), management practices (composting systems (CS), aeration method (AM), turning frequency (TF), aeration rate (AR), intermittent aeration frequency (IAF), aeration duration (AD), composting duration (CD), covered (CO), pile size (PS)) and additives use (additive type (AT) and amount (AA)) (Table S1, Fig. S1). In addition, the germination index (GI) of compost products was also included in the database and used as a predictor, considering that compost may be intended for use as organic fertilizers [36] .

Data pre-processing

A series of data preprocessing steps was performed to make the dataset more suitable for modelling. First, categorical features (WT, BT, CS, AT, etc.) were digitized using sequence coding. Secondly, a local outlier factor (LOF) analysis was used to assess the local relative density of each sample point and identify outliers for exclusion [37,38]. Then, we calculated the Pearson correlation matrix to identify and address potential multicollinearity. And the absolute value of Pearson's correlation coefficient was between 0.1 and 0.4 (Fig. S2), indicating that no significant overlap existed between variables [17]. Finally, we processed the missing values of the input features for different prediction objectives, where input features with more than 25% missing values were eliminated, whereas input features with a small number of missing values were filled using K-nearest neighbors (KNN) estimation [39,40].

Knowledge-guided ML model development and evaluation

First, the selection of 19 input variables was guided by prior knowledge of composting biochemistry to ensure mechanistic relevance. To ensure the biological and chemical plausibility of model predictions, we imposed physicochemical bounds on key input variables. These constraints, derived from established composting literature, prevented the model from extrapolating into unrealistic parameter spaces. For instance, the pH of composting materials was bounded within a realistic range (e.g., 5.0 to 9.5), as values below 5.0 would strongly inhibit most microbial activity and are not sustained in typical composting systems [6]. The original dataset was randomly partitioned 8:2 into training and test sets. Within the training set, we performed K-fold cross-validation (K=10) for model training. Eight different models were used for target prediction, including Random Forest (RF), eXtreme Gradient Boosting (XGB), Light Gradient Boosting Machine (LGB), and Categorical Boosting (CAT), Linear Regression (LR), Ridge Regression (RID), Gaussian Process Regression (GSR), and Multi-Layer Perceptron (MLP). To enhance predictive performance, Bayesian optimization was employed for hyperparameter tuning, effectively exploring the hyperparameter space to identify optimal model parameter combinations [41]. The root mean square error (RMSE) and coefficient of determination (R^2) values generated on the test set were used as metrics to compare the predictive performance of the models [41,42]. To reduce random errors and enhance generalization, we trained 10 random splits of the dataset, and used the average performance as the final criterion for model selection. Finally, the best model selected for each prediction target was finally trained on the entire dataset to ensure the development of a robust final model. All model training processes were performed using Python 3.8.

Feature importance and interaction analysis

Feature importance analysis plays a critical role in improving the model interpretability [43,44]. In our study, we used multiple metrics to assess the feature importance based on our optimal ML model, including MSE increase, node purity increase, P-value, and Shapley additive explanations (SHAP) value, which helps mitigate the limitations of relying on a single metric [45]. Features with higher SHAP values, larger MSEs, and greater node purity values generally contributed more significantly to the model outputs

[44,45].

Prediction of gas EFs from various wastes under different composting management systems

To establish baseline EFs, we used our optimal ML model to predict C and N gas EFs for different waste types under the four composting systems defined by the IPCC (2019 Refinement, Chapter 10, Table 10.21) (Table S2). These predictions represent a baseline scenario, assuming no advanced control measures (e.g., additives, aeration optimization). We then performed a systematic comparison of these ML-predicted EFs with the corresponding default EFs from the IPCC guidelines (Tier 1 for NH_3 and N_2O, Tier 2 for CH_4). To quantify prediction uncertainty, for each EF we conducted 500 Monte Carlo simulations by randomly sampling key input features (e.g., Initial total N (ITN), C/N ratio) within their observed ranges in the database, and reported the mean and standard deviation.

Co-optimization of multiple gas emission reductions

Based on the optimal machine learning model, we performed multi-objective optimization using the Non-dominated Sorting Genetic Algorithm II (NSGA-II), an efficient genetic algorithm that excels at classifying and maintaining elite solutions and is designed to search for the Pareto-optimal frontier, which represents the optimal trade-off between competing objectives [46]. Since the compost product must be plant-friendly to serve as organic fertilizer, the GI of the compost must exceed 80% [36]. To further guide practical production, the composting scale (PS) was set at industrial scale (>10 m^3). Management practices (BA, ICN, IPH, IMC, CS, AM, TF, AR, IAF, CD, CO, AT, AA) were then used as adjustable parameters to optimize the objective function, with the aim of minimizing emissions of multiple gases during composting and achieving a final GI>80%. Initially, the parameter boundaries for management practices were defined based on the database values. The Pareto solution set was then obtained by comparing the objective function values through 100 thousand iterative runs of NSGA-II.

Considering that changes in management practices have an indirect environmental footprint, a life cycle assessment (LCA) methodology was used to estimate the net environmental footprint of the different management practices based on obtaining the Pareto solution set. The system boundary encompasses three key stages: i) upstream (collection and transport of waste); ii) the composting process itself (direct and operational emissions); and iii) downstream (agronomic benefits from compost use, including fertilizer substitution and soil C sequestration) (Fig.S20). The LCA in this study is based on the ReCiPe impact assessment technique extracted from the Eco-invent database, which converts a list of full life-cycle inventory results into a limited number of indicator scores, including midpoint indicators and a normalized total environmental impact indicator [47,48]. We evaluated the potential environmental impacts of various composting management practices using the treatment of 1 ton of waste (dry weight basis) as the functional unit (FU). The environmental footprints of various composting management practices are shown in the Table S6. CO_2 emissions from the composting process were considered to have no net climate impact. However, the reduced CO_2 could eventually form stable soil organic C (accounting for about 8%), thereby acting as a C sink [4,31]. In addition, the reduced N loss can replace N fertilizer thus reducing the environmental footprint of N fertilizer production. The preparation and transport of materials were also considered in this study as we assumed that these factors were the same for all composting processes. The formulas for the assessment of the C footprint of the different composting management practices are as follows:

$$C_{Total} = C_{tech} + C_{gas} - C_{Fertilizer} - C_{SOC} \quad (1)$$

where C_{Total} is the total C footprint (kg CO_2eq·ton dry matter^{-1}); C_{tech} is the total C footprint of the different composting technologies (kg CO_2eq ·ton dry matter^{-1}), including the preparation and transport of materials, composting systems, aeration systems, additives, etc. (Fig. S20, Table S6); C_{gas} is the C footprint of gaseous emissions from the composting process (kg CO_2eq ·ton dry matter^{-1}), including NH_3, N_2O and CH_4. The conversion factor for NH_3-N to N_2O-N is 0.01, while the coefficients for converting N_2O and CH_4 into CO_2 equivalents are 298 and 25, respectively; $C_{Fertilizer}$ is the C footprint of replacing N fertilizers (kg CO_2eq ·ton dry matter^{-1}); and E_{soc} is the environmental footprint of C sequestration (accounting for about 8%) in soils (kg CO_2eq ·ton dry matter^{-1}).

The mitigation potential for each GHG was calculated as the difference between emissions under current (baseline) practices and those under optimized management scenarios.

Global mitigation potential assessment

We conducted a comprehensive assessment of the global potential for reducing emissions of reactive N and GHG emissions through model-optimized composting management practices (Fig. S10). Specifically, three type of manure (cattle, poultry and swine), sewage sludge and food waste were included in the global analysis as the main composting feedstocks. In the first step, we estimated the annual global production of the five target organic wastes. The generation of animal manure was sourced from the FAO database [30], while data for food waste and sewage sludge were drawn from established literature [16,49,50,51]. The total potential C and N quantities from each waste stream were then calculated by their respective C-N content and ratios (Fig. S4). In the second step, we quantified the fraction of produced waste that is actually composted. Country- or region-specific composting fraction (i.e., the proportion of collected waste used for composting) for each waste type were compiled from the literature[13,16,50,51]. The amounts of C and N used for composting were subsequently calculated by multiplying the total quantities by these composting fractions. All detailed data sources are provided in Supplementary Table S7 and Supplementary Data 1. In the third step, we calculated the total global gas emissions from the composting process based on the proportion of all current waste composting management systems and the gas emission factors of the different wastes (Table S4). Finally, the global emission reductions of different gases were simultaneously calculated based on the gas EFs of the optimized composting management practices. All map-related operations were performed using ArcGIS 10.6 software.

Uncertainties

For global predictions, uncertainty was associated with both the accuracy of machine learning model predictions and the quality of data collected from global and regional statistics, since most of these studies were carried out in China, Europe and Japan (Fig. 1). For example, the datasets for N_2O, CH_4 and CO_2 had fewer missing values, leading to more favorable prediction outcomes, when compared to NH_3 emissions. In addition, some other key factors influencing gas emissions during composting (e.g., climate, season) were not included due to insufficient data reports, which could affect the predictive performance of the model [8]. To address uncertainty in model predictions, we conducted 200 random runs for each EF using bootstrap and stratified sampling methods, then analyzed the model outputs by calculating the means, standard deviations, and confidence intervals [45]. The relative uncertainty of the data from global and regional statistics, surveys, and other sources (expressed as the coefficient of variation, CV) was estimated based on published literature and the authors' expert judgment [16,51]. Furthermore, we performed a Monte Carlo simulation with 1000 runs to characterize the total uncertainty in global C and N gas emissions from composting, based on variations in global input data and EFs following uniform and normal distributions, respectively.

Code and data availability

All codes developed for the machine learning model and to generate results are available from the corresponding author upon request.

Declaration of interests

The authors declare no competing interests.

Author contributions

Conceptualization, L.Z. and X.W.; formal analysis, L.Z., J.Y., J.L., and X.W.; investigation, L.Z., J.Y., J.L. and Y.R.; methodology, L.Z., J.Y., and J.L.; visualization, L.Z., J.Y., J.L.; writing – original draft, L.Z., X.W.; writing – review and editing, L.Z., L.Z., J.Y., J.L., and X.W.; supervision, X.W., H.Z., Z.B., and L.M.; funding acquisition, X.W., H.Z., and L.M.

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References

1. FAOSTAT (FAO, 2024); https://www.fao.org/faostat/en/#data.
2. Mingolla, S. & Rosa, L. Low-carbon ammonia production is essential for resilient and sustainable agriculture. Nat. Food 6, 610-621 (2025).
3. Zhang, X. et al. Nitrogen management during decarbonization. Nat. Rev. Earth Environ. 5, 717-731 (2024).
4. Zhao, S. et al. A precision compost strategy aligning composts and application methods with target crops and growth environments can increase global food production. Nat. Food 3, 741-752 (2022).
5. Chia, W. Y. et al. Sustainable utilization of biowaste compost for renewable energy and soil amendments. Environ. Pollut. 267, 115662 (2020).
6. Bernal, M. P. et al. Current approaches and future trends in compost quality criteria for agronomic, environmental, and human health benefits. Adv. Agron. 144, 143-233 (2017).
7. Zhao, K. et al. Optimizing the management of aerobic composting for antibiotic resistance genes elimination: A review of future strategy for livestock manure resource utilization. J. Environ. Manage. 370, 122766 (2024).
8. Pardo, G., Moral, R., Aguilera, E. & del Prado, A. Gaseous emissions from management of solid waste: a systematic review. Glob. Change Biol. 21, 1313-1327 (2014).

9. Liu, Y. et al. A global meta-analysis of greenhouse gas emissions and carbon and nitrogen losses during livestock manure composting: Influencing factors and mitigation strategies. Sci. Total Environ. 885, 163900 (2023).
10. Springmann, M. et al. Options for keeping the food system within environmental limits. Nature 562, 519-525 (2018).
11. Schulte-Uebbing, L. F., Beusen, A. H. W., Bouwman, A. F., & de Vries, W. From planetary to regional boundaries for agricultural nitrogen pollution. Nature 610, 507-512 (2022).
12. Walling, E., Trémier, A. & Vaneeckhaute, C. A review of mathematical models for composting. Waste Manag. 113, 379-394 (2020).
13. Zhao, S. et al. Towards the circular nitrogen economy – A global meta-analysis of composting technologies reveals much potential for mitigating nitrogen losses. Sci. Total Environ. 704, 135401 (2020).
14. Cao, Y. et al. Ammonium enrichment in livestock manure driven by ammonia-abatement practices can reduce nitrous oxide emissions. One Earth 7, 687-696 (2024).
15. Awasthi, M. K. et al. in Biosynthetic Technology and Environmental Challenges (eds Varjani, S. J. et al.) 271-305 (Springer Singapore, 2018); https://link.springer.com/chapter/10.1007/978-981-10-7434-9_16
16. Hoy, Z. X., Woon, K. S., Chin, W. C., Van Fan, Y. & Yoo, S. J. Curbing global solid waste emissions toward net-zero warming futures. Science 382, 797-800 (2023).
17. Wang, B., Zhang, P., Qi, X., Li, G. & Zhang, J.. Predicting ammonia emissions and global warming potential in composting by machine learning. Bioresource Technology 411, 131335 (2024).

18. Huang, N., Ma, S., Zhao, Z. & Zhou, C. Predicting greenhouse gases emissions from decentralized composting by applying explainable machine learning method. Bioresource Technology 442, 133726 (2026).
19. He, J. et al. Multi-model machine learning framework for prediction of greenhouse gas emissions during composting of organic solid waste. Bioresource Technology 443, 133901 (2026).
20. Liu, L. et al. Knowledge-guided machine learning can improve carbon cycle quantification in agroecosystems. Nat. Commun. 15, 357 (2024).
21. Cao, Y. et al. Mitigation of ammonia, nitrous oxide and methane emissions during solid waste composting with different additives: A meta-analysis. J. Clean. Prod. 235, 626-635 (2019).
22. Mira-Urios, M. Á. et al. Composting of olive mill wastewater sludge using a combination of multiple strategies: assessment of improvement in biodegradability, GHG emissions, and characteristics of the end product. Agronomy 15, 808 (2025).
23. Xu, Z. et al. Microbial sources and sinks of nitrous oxide during organic waste composting. Environ. Sci. Technol. 58, 7367-7379 (2024).
24. Wei, Z. et al. Microhabitat drive microbial anabolism to promote carbon sequestration during composting. Bioresour. Technol. 346, 126577 (2022).
25. Ge, J., Huang, G., Li, J. & Han, L. Particle-scale visualization of the evolution of methanogens and methanotrophs and its correlation with CH4 emissions during manure aerobic composting. Waste Manag. 78, 135-143 (2018).
26. García-Rández, A. et al. Monitoring of greenhouse gas emissions and compost quality during olive mill waste co-composting at industrial scale: The effect of N and C sources. Waste Manag. 193, 33-43 (2025).

27. Refinement to the 2006 IPCC guidelines for national greenhouse gas inventories. (The Intergovernmental Panel on Climate Change, 2019); https://www.ipcc.ch/report/2019-refinement-to-the-2006-ipcc-guidelines-for-national-greenhouse-gas-inventories/
28. Lee, S. -R. & Kim, G. Assessing ammonia (NH3) emissions, precursor gas (SO2, NOx) concentrations, and source contributions to atmospheric PM2.5 from a commercial manure composting facility. Appl. Sci. 14, 11467 (2024).
29. Uwizeye, A. et al. Nitrogen emissions along global livestock supply chains. Nat. Food 1, 437-446 (2020).
30. FAOSTAT (FAO, 2020); https://www.fao.org/faostat/en/#data
31. Li, B. et al. Responses of soil organic carbon stock to animal manure application: A new global synthesis integrating the impacts of agricultural managements and environmental conditions. Glob. Change Biol. 27, 5356-5367 (2021).
32. Cao, X. et al. Municipal solid waste compost: Global trends and biogeochemical cycling. Soil Environ. Health 1, 100038 (2023).
33. Waste Generation & Treatment in Ireland in 2018 (Environmental Protection Agency, 2018); https://www.epa.ie/publications/monitoring--assessment/waste/national-waste-statistics/Waste-Statistics-2018-Infographic.pdf
34. Global Methane Tracker 2022 (International Energy Agency, 2022); https://www.iea.org/reports/global-methane-tracker-2022
35. Hamrani, A., Akbarzadeh, A. & Madramootoo, C. A. Machine learning for predicting greenhouse gas emissions from agricultural soils. Sci. Total Environ. 741, 140338 (2020).

36. Ji, Z., Zhang, L., Liu, Y., Li, X. & Li, Z. Evaluation of composting parameters, technologies and maturity indexes for aerobic manure composting: A meta-analysis. Sci. Total Environ. 886, 163929 (2023).
37. Samariya, D. & Thakkar, A. A comprehensive survey of anomaly detection algorithms. Ann. Data Sci. 10, 829-850 (2023).
38. Phiwhorm, K., Saikaew, C., Leung, C. K., Polpinit, P. & Saikaew, K. R. Adaptive multiple imputations of missing values using the class center. J. Big Data 9, 52 (2022).
39. Emmanuel, T. et al. A survey on missing data in machine learning. J. Big Data 8, 140 (2021).
40. Kumar, K. & Pande, B. P. Air pollution prediction with machine learning: a case study of Indian cities. Int. J. Environ. Sci. Technol. 20, 5333-5348 (2022).
41. Fu, W. et al. Machine learning-driven prediction of phosphorus removal performance of metal-modified biochar and optimization of preparation processes considering water quality management objectives. Bioresour. Technol. 403, 130861 (2024).
42. Martini, G. et al. Machine learning can guide food security efforts when primary data are not available. Nat. Food 3, 716-728 (2022).
43. Bai, B. et al. Prediction models for bioavailability of Cu and Zn during composting: Insights into machine learning. J. Hazard. Mater. 471, 134392 (2024).
44. Shi, S. et al. Improving prediction of N2O emissions during composting using model-agnostic meta-learning. Sci. Total Environ. 922, 171357 (2024).
45. Deng, P. et al. Development potential of nanoenabled agriculture projected using machine learning. Proc. Natl Acad. Sci. USA 120, e2301885120 (2023).

46. Xiao, L. et al. Spatiotemporal co-optimization of agricultural management practices towards climate-smart crop production. Nat. Food 5, 59-71 (2024).

47. Huijbregts, M. A. J. et al. ReCiPe2016: a harmonised life cycle impact assessment method at midpoint and endpoint level. Int. J. Life Cycle Assess. 22, 138-147 (2017).

48. Liu, Z., Wang, X., Li, S., Bai, Z. & Ma, L. Advanced composting technologies promotes environmental benefits and eco-efficiency: A life cycle assessment. Bioresour. Technol. 346, 126576 (2022).

49. Silpa, K.et al. What a waste 2.0: a global snapshot of solid waste management to 2050 (World Bank Group, 2018); http://documents.worldbank.org/curated/en/697271544470229584

50. Powell, J. T., Chertow, M. R. & Esty, D. C. Where is global waste management heading? An analysis of solid waste sector commitments from nationally-determined contributions. Waste Manag. 80, 137-143 (2018).

51. Gómez-Sanabria, A., Kiesewetter, G., Klimont, Z., Schoepp, W. & Haberl, H. Potential for future reductions of global GHG and air pollutants from circular waste management systems. Nat. Commun. 13, 106 (2022).