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Research Paper

Parametrization of biowaste composting system for life cycle assessment

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A B S T R A C T

Composting is a widely used method for managing and valorizing biowaste. Life cycle assessment (LCA) is commonly applied to evaluate its environmental impacts. Current methods used to model life cycle inventories often oversimplify the complex physical, chemical, and biological processes involved. This study introduces the Parametrized Composting Tool for Environmental Assessment (PaCTEA), developed to better capture the influence of biowaste composition variability and operational parameters on composting environmental impacts. PaCTEA integrates a composting model that predicts direct emissions of CO_2, NH_3, CH_4, and N_2O, as well as the nutrient composition of the resulting compost. This detailed characterization enables a more accurate estimation of the potential substitution of fertilizers and peat. Even though the core of PaCTEA is a complex chemical engineering model, it is linked to a simple parametrization based on operational parameters. To demonstrate its functionality, simulations were performed to assess the influence of biowaste composition, aeration mode, and ambient temperature on the environmental performance of composting. The LCA results show clear differences between scenarios. Variations in biowaste composition reduced ecosystem quality and natural resource impacts by up to 29% and 52%, and increased human health benefits by nearly 9%. Passive aeration outperformed active aeration, improving ecosystem quality by up to 175% and human health benefits by 35%, while reducing natural resource impacts by 50%. Composting at 5°C increased ecosystem quality and resource impacts by up to 32% and 7%, and reduced human health benefits by about 5% compared to 25°C.

1. Introduction

Municipal organic waste management remains a major environmental and societal challenge in the transition toward circular economy. According to the World Bank, organic waste accounts for approximately 44–46% by mass of the total global production (Kaza et al., 2018). Among the various available treatment options, composting represents one possible pathway for biowaste management (Manea et al., 2024; Sánchez, 2025).

Composting is a bioprocess that consists of the degradation of organic matter under aerobic conditions by microorganisms into a humus-like substance called compost (Sánchez, 2025). Several factors are known to influence the process. Inadequate control of these parameters can increase environmental emissions and reduce compost quality. For instance, insufficient aeration has been shown to increase greenhouse gas emissions (CO_2, CH_4, N_2O), whereas higher aeration rates promote NH_3 volatilization (Han et al., 2018; Qin et al., 2025). Carbon-to-nitrogen ratio (C/N) is another key parameter, since it affects both compost maturity and gaseous emissions (Cai et al., 2024; Jiang et al., 2011; Tang et al., 2023). Altieri et al. (2024) emphasized that the composition of the initial mixture influences the yield of the final product and emissions generated during composting. Beyond the direct environmental impacts of the composting process, the compost produced can replace inorganic fertilizers and soil amendments. This substitution helps reduce reliance on synthetic inputs in agriculture, providing environmental benefit (Goldan et al., 2023; Lawrence and Melgar, 2023).

The environmental impacts of biowaste composting were evaluated through several LCA studies in different contexts (Abeliotis et al., 2016; Andersen et al., 2012; Blengini, 2008; Cadena et al., 2009; Chazirakis et al., 2023; Colón et al., 2010; Guillaume et al., 2023; Martínez-Blanco et al., 2010; Padeyanda et al., 2016; Saer et al., 2013; Tian et al., 2025). These LCA studies, as well as databases like ecoinvent, distinguish two generic technologies: industrial composting and home composting. Some studies rely on direct emissions data obtained from measurements carried out during experimental trials or collected from operational composting facilities. (Andersen et al., 2012; Blengini, 2008; Cadena et al., 2009; Colón et al., 2010; Martínez-Blanco et al., 2010; Tian et al., 2025). Thus, the completeness of the measurements depends on the means deployed, and only represents a particular context, i.e., a specific waste composition, technology, and period. Other studies use emission factors reported in the literature. This approach fails to account for the influence of actual waste composition and operation conditions on the environmental performance of the treatment process under study (Abeliotis et al., 2016; Guillaume et al., 2023).

The literature review conducted by Oviedo-Ocaña et al. (2023)

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examined 25 LCA studies on green waste and biowaste composting. Among these studies, the direct emissions most commonly considered were CH_4, N_2O, NH_3 and CO_2. According to Saer et al. (2013), there is a variability in the reported values of these emissions in the literature. Their study reveals that CH_4 emissions values ranged from 0.021 to 11.9 kg per ton of feedstock, N_2O emissions from 0.0003 to 0.252 kg per ton of feedstock, and NH_3 emissions from 0.025 to 1.3 kg per ton of feedstock. There is therefore an important variability in life cycle inventories of composting processes, likely reflecting the variability of operational parameters affecting its environmental performance.

Moreover, in LCA, composting is considered a multifunctional system because, in addition to providing a waste treatment service, it also produces compost. Through the system expansion method, compost provides environmental benefits by substituting products that perform equivalent functions. Some LCA studies consider that compost has only fertilizing functions by providing N, P and K nutrients to the plant (Banias et al., 2020; Weligama Thuppahige et al., 2022), while Sardarmehni et al. (2021) take into account its capacity to amend the soil. However, Oviedo-Ocaña et al. (2023) highlight the fact that compost characteristics are not sufficiently taken into account in the modeling of substitution, and standard substitution factors are used. These assumptions, however, can significantly influence LCA results (Viau et al., 2020).

To improve the representation of waste treatment processes, several modeling tools such as Easetech, Swolf, and Orware, have been developed to overcome these limitations. In these models, transfer coefficients are incorporated into the process representation, based on the assumption of a linear relationship between waste composition and resulting emissions (Clavreul et al., 2014; Dalemo et al., 1997; Levis et al., 2013). However, these transfer coefficients are empirically calculated and do not reflect complex physical and chemical processes that occur throughout the treatment. Thus, this approach is applicable for a narrow set of conditions close to those empirically observed, and it cannot capture the life-cycle impacts of specific operational parameters. Moreover, compositions of coproducts are not systematically considered in a rigorous manner in substitution modeling (Viau et al., 2020). However, for waste-valorizing processes such as composting, the characteristics of their coproducts determine their market uptake and their actual substitution of conventional products (Brinton, 2000).

Several studies aim to develop phenomenological models of the composting process. However, the objectives of these models vary. Some focus on specific physical processes, such as heat and mass transfer, (Bach et al., 1987; El Boudihi et al., 2022, 2022; Finger et al., 1976; Lai et al., 2025; Luangwilai et al., 2018; Van Lier et al., 1994) while others are developed to predict certain variables, like gas emissions. Even among the latter, the literature presents various biological process models, each targeting different types of emissions. For example, Sole-Mauri et al. (2007) developed a model predicting CO_2 and NH_3. On the other hand, Ge et al. (2016) focused on a model that simulates CH_4. The model developed by Didier (2013) predicts a wider range of emissions than the previous ones, ie CO_2, NH_3, N_2O and N_2, but does not account for CH_4. Although these cited studies are not exhaustive, our literature review revealed that no existing phenomenological model predicts all the emissions relevant for LCA. We find here an opportunity to integrate complex chemical engineering knowledge into LCA to better consider parameters that could affect environmental impacts of the process.

The objective of this study is to demonstrate the impacts of variability in biowaste composition and operational parameters within LCA through the PArametrized Composting Tool for Environmental Assessment (PaCTEA). By rigorously combining existing models, our tool estimates all relevant data for LCA in a specific territorial and technological context, particularly emissions during composting, compost composition, and its impact when used on land. Furthermore, by linking the complex chemical engineering model to a parametrization based on composting operational decisions (e.g., type of aeration, types of food waste), we will enhance the accessibility of the tool, making it more practical for LCA practitioners. A case study is performed to illustrate the functionalities of PaCTEA.

2. Methodology

2.1. Presentation of the Parametrized Composting Tool for Environmental Assessment (PaCTEA)

The structure of PaCTEA is illustrated in Fig. 1.

PaCTEA consists of three main components. The first is the core, which is composed of two parts: the active composting model, which predicts direct emissions, and the substitution model (blue boxes in Fig. 1). This core is linked to two levels of parameterization: the orange box corresponds to the parameterization for the LCA practitioner, while the gray box converts these parameters into input-data for model running. The green box represents the outputs of PaCTEA, which are the data used to perform the environmental assessment. The following sections describe each of these components in detail.

2.2. Development of the core of PaCTEA

2.2.1. Active composting model

The active composting model is one of the core components of PaCTEA, represented by the blue box in Fig. 1. It is developed primarily to predict the direct emissions of the process, based on a combination of models from the literature. The first selected model is that of Sole-Mauri et al. (2007), which simulates the production of CO_2 and NH_3. This model was chosen as a starting point because its input variables are the biochemical composition of the substrates, which, as we will see later, can be easily calculated in the case of biowaste. These variables are the concentrations of cellulose, carbohydrates, lipids, hemicellulose, lignin, and proteins. The microorganisms involved include bacteria, actinomycetes, and fungi, with distinctions made between mesophilic and thermophilic populations for each type. The complex molecules are first hydrolyzed by microorganisms to form soluble substrates. Carbohydrates, lipids, and proteins are hydrolyzed by bacteria, while actinomycetes and fungi are responsible for the hydrolysis of cellulose, hemicellulose, and lignin. The reaction rate is modeled in Contois-type, as follows:

$$v_{hydrolysis} = k_{h_{i,j}} \frac{[i]}{k_{hS}\cdot[j] + [i]}[j] \tag{1}$$

where $[i]$ (kg.kg^{-1} of total matter (TM)) is the quantity of insoluble substrate, $[j]$ (kg.kgTM^{-1}) is the quantity of microorganisms responsible for hydrolysis, $k_{h_{i,j}}$ (h^{-1}) is the hydrolysis constant of i by j, and k_{hS} (kg.kg^{-1}) is the saturation coefficient for contois kinetics. All hydrolysis reaction rates are detailed in Note S1 of Supporting Information (SI) and correspond to reactions 1 to 12.

Soluble substrates are then degraded to support microorganism growth in aerobic conditions. All bacteria grow on the hydrolyzed products of carbohydrates, cellulose, protein, and lipid. Soluble substrates from hemicellulose can be degraded by actinomycetes and fungi. The soluble lignin substrate can only be degraded by fungi. These aerobic degradation processes result in the release of CO_2. The degradation of soluble protein substrates leads to the production of ammonium. It is transferred from the liquid phase to the gaseous phase, and through aeration, NH_3 can volatilize into the environment. Microorganism growth is constrained by oxygen availability, substrate availability, and the temperature of the pile. The latter is predicted using a heat balance module, which considers the biological heat production and heat losses through conduction and convection. The limitations are reflected in the reaction rates, which are Monod kinetics, through specific limitation functions:

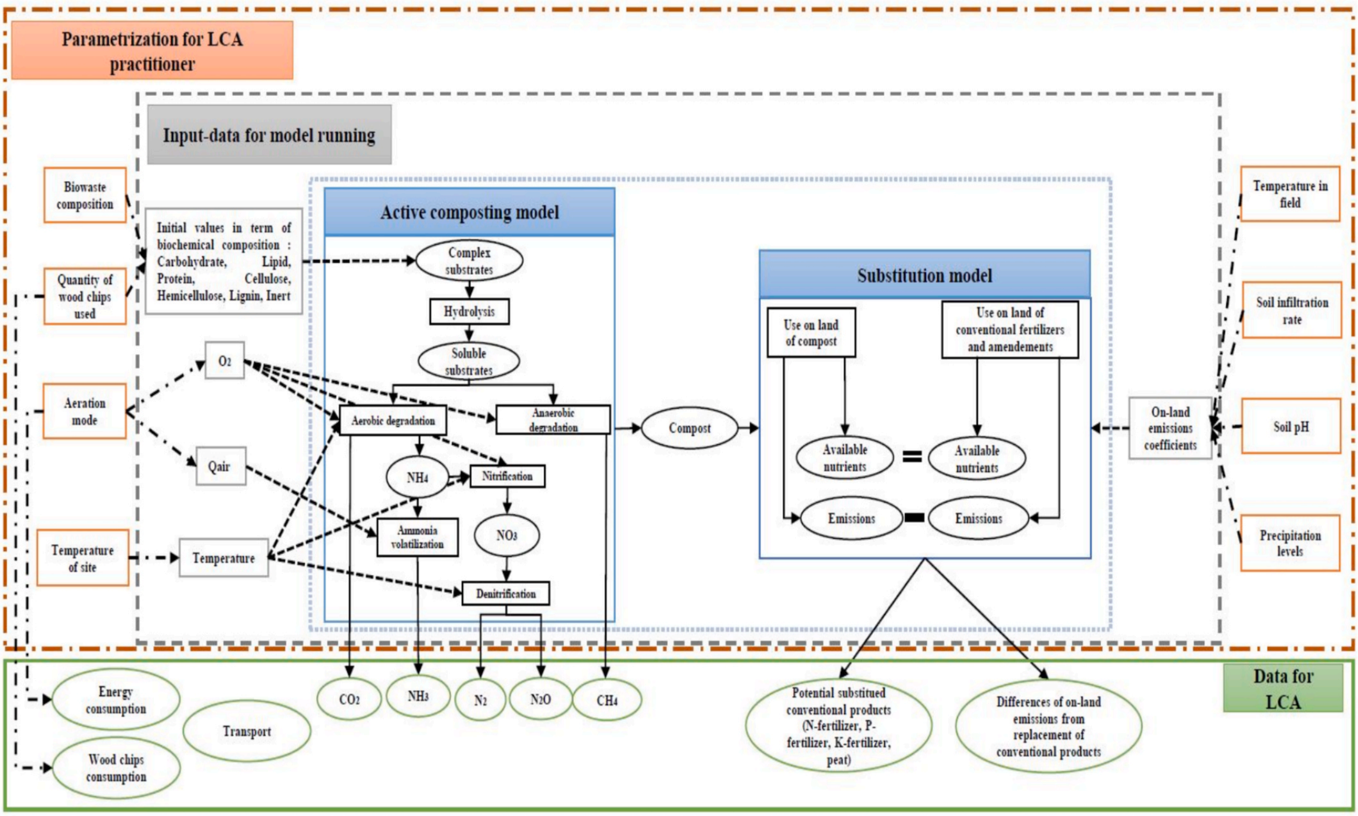

Fig. 1. General structure of PaCTEA.

$$v_{growth} = \mu_j \cdot \frac{[S_i]}{k_s + [S_i]} \cdot \frac{[S_{O_2}]}{k_{O_2} + [S_{O_2}]} \cdot f_T \cdot [j] \tag{2}$$

$$f_T = \frac{(T - Tmax)(T - Tmin)^2}{(Topt - Tmin)((Topt - Tmin)(T - Topt) - (Topt - Tmax)(Topt + Tmin - 2T))} \tag{3}$$

where μ_j (h^{-1}) is the specific growth rate of the microorganisms responsible for the degradation, $[S_i]$ (kg.l^{-1}) is the concentration of the soluble substrate in the liquid phase, k_s (kg.l^{-1}) is the substrate saturation constant, $[S_{O_2}]$ (kg.l^{-1}) is the concentration of dissolved oxygen in the pile, k_{O_2} (kg.l^{-1}) is the oxygen saturation constant, T (K) is the temperature of the pile, *Tmax* (K) is the maximum temperature for microorganisms' growth, *Tmin* (K) is the minimum temperature for microorganisms' growth, *Topt* (K) the optimum temperature for microorganisms growth. The reaction rates of microorganisms' growth on soluble substrates correspond to reactions 13 to 36 in Note S1 of SI.

For CH_4 production, the model from Ge et al. (2016) was used. Although composting is defined as the aerobic degradation of substrates, the absence of oxygen in certain areas of the matrix creates anaerobic digestion zones that produce methane. In their model, Ge et al. (2016) stated that the CH_4 production rate is correlated with the hydrolysis rate via a methane yield coefficient. The authors also consider a single substrate undergoing hydrolysis, and therefore a single methane yield coefficient. However, the previously selected model of Sole-Mauri et al. (2007) considers six insoluble substrates hydrolyzed into five soluble substrates. Thus, to combine the two models, we assume that hydrolysis products from aerobic microorganisms are also utilized by anaerobic microorganisms for CH_4 production. Each soluble substrate can contribute to CH_4 production, and we derived their respective methane yield coefficients from the literature. The total production of CH_4 is therefore the sum of CH_4 produced by each soluble substrate. To show the effect of oxygen on methane production, we add η, which is the sensitivity of methanogenesis to inhibition by oxygen that Arah and Stephen (1998) used in their model. The rate of methane production is described in the equation (4). The model by Ge et al. (2016) assumes that the methane produced can be oxidized to CO_2 in the aerobic layer. They modelled it using Michaelis-Menten kinetics, corrected by an Oxygen Uptake Rate (OUR) parameter. This parameter depends on particle size, which is challenging to determine in our context. Instead, we adopted the CH_4 oxidation model from Watson et al. (1997), which also uses Michaelis-Menten kinetics but is limited by the dissolved oxygen concentration (equation (5)). The net CH_4 quantity is thus the difference between the methane produced and the methane oxidized.

$$v_{methaneproduction} = Y_{CH_4,S_i} \cdot R_{S_i} \cdot \frac{1}{1 + \eta \cdot \frac{[S_{O_2}]}{M_{O_2}}} \tag{4}$$

where Y_{CH_4,S_i} (kg.kg^{-1}) is the methane yield coefficient of the soluble substrate S_i, R_{S_i}(kg.$kgTM^{-1}$.h^{-1}) is the sum of hydrolysis rates from which S_i is obtained, η (l.mol^{-1}) is the sensitivity of methanogenesis to inhibition by oxygen, M_{O_2} (kg.mol^{-1}) is the molar mass of O_2.

$$v_{methaneoxidation} = V_m \cdot \frac{[CH_{4_{gen}}]}{K_m + [CH_{4_{gen}}]} \cdot \frac{[S_{O_2}]}{K_{O_2,CH_4} + [S_{O_2}]} \tag{5}$$

where V_m (kg.kgTM^{-1}.h^{-1}) is the maximum rate of methane oxidation, K_m (kg.l^{-1}) is the Michaelis constant for methane oxidation, K_{O_2,CH_4} (kg.l^{-1}) is the Michaelis constant for oxygen, $[CH_{4_{gen}}]$ (kg.l^{-1}) is the concentration in the liquid phase of the methane produced, and $[S_{O_2}]$ (kg.l^{-1}) is the concentration of dissolved oxygen.

N_2O production occurs through the biological process of nitrification–denitrification, which also produces N_2. Nitrification consists of oxidizing NH_4^+ to NO_3^-. This reaction involves autotrophic microorganisms and occurs under aerobic conditions, as modeled in Lin et al. (2009). The reaction rate is limited by NH_4^+ and O_2 rate (equation (6)). Denitrification is the second step of the process. It implies the reduction of NO_3^- into N_2O and N_2. The denitrification part of Didier (2013) model is selected for this module. This assumes a parameter, noted *pmaxdenit*, which represents the maximum rate of denitrification from the NO_3^- stock. The denitrification reaction is limited by the NO_3^- stock and temperature (equation (8)).

$$v_{nitrification} = \mu_a \cdot \frac{[S_{NH_4^+}]}{K_n + [S_{NH_4^+}]} \cdot \frac{[S_{O_2}]}{K_{O_2,nit} + [S_{O_2}]} \tag{6}$$

$$K_n = 10^{(0.051T - 7.158)} \tag{7}$$

where μ_a (h^{-1}) is the specific growth of autotrophic microorganisms, $[S_{NH_4^+}]$ (kg.l^{-1}) is the concentration of NH_4^+ in the liquid phase, and K_n (kg.l^{-1}) is the half-saturation constant for ammonium oxidizer (equation (7)) (US EPA, 1975).

$$v_{denitrification} = pmaxdenit.[NO_3^-] \cdot \frac{[S_{NO_3^-}]}{k_{NO_3^-} + [S_{NO_3^-}]} \cdot flim_{Tdenit} \tag{8}$$

$$flim_{Tdenit} = \begin{cases} exp\left(\frac{(T-11)ln(89) - 9ln(2.1)}{10}\right), if\ T < 11^\circ C \\ exp\left(\frac{(T-20)ln(2.1)}{10}\right), if\ T \geq 11^\circ C \end{cases} \tag{9}$$

where *pmaxdenit* (h^{-1}) is the maximum rate of denitrification, $[NO_3^-]$ (kg.kgTM^{-1}) is the quantity of NO_3^-, $[S_{NO_3^-}]$ (kg.l^{-1}) is the concentration of NO_3^- in the liquid phase, $k_{NO_3^-}$ (kg.l^{-1}) is the half-saturation constant for denitrification.

Finally, the death and lysis of autotrophic and heterotrophic microorganisms lead to the production of insoluble protein substrates and inert matter (equation (10) and equation (11)). These correspond to reactions 37 to 43 and 46 in Note S1 of SI.

$$v_{death} = b_j.[j] \tag{10}$$

where b_j (h^{-1}) is the death rate constant and $[j]$ (kg.kgTM^{-1}) is the quantity of microorganisms.

$$v_{lysis} = k_{dec}.[X_{db}] \tag{11}$$

where k_{dec} (h^{-1}) is the decomposition constant of microorganisms and $[X_{db}]$ (kg.kgTM^{-1}) is the quantity of decayed microorganisms.

The model assumes spatial homogeneity of the composting matrix, i.e., perfect mixing conditions. As a consequence, no spatial gradients are represented.

Equations 1 to 48 in Note S1 of SI constitute the Ordinary Differential Equations (ODE) core of our model, and allow the calculation of carbon and nitrogen content of the compost. The different forms of mineral nitrogen (NO_3^- and NH_4^+) and organic nitrogen can be distinguished. These are necessary for the calculation of potential fertilizer substitution. For phosphorus and potassium, which are also nutrients for plants, we assume that there is no loss during the composting phase.

2.2.2. Substitution of conventional products

Based on the compost composition calculated by the active composting model, the substitution module calculates the quantity of avoided conventional products and the net emissions from use-on-land of compost.

2.2.2.1. Substitution of mineral fertilizer. For the fertilizing function of compost, each nutriment in the compost (N, P, and K) is considered individually, so that these can respectively substitute N-based, P-based, and K-based conventional fertilizers. Particularly for nitrogen fertilizing, there is a potential loss of nutriments to the environment during application of synthetic fertilizers and compost. To calculate mineral fertilizer equivalents, the work of Brockmann et al. (2018) is used, which states that the remaining nitrogen available for plant uptake is the portion that has not been lost to the environment. For compost, nitrogen forms that can be absorbed by plants include NO_3^-, NH_4^+, and a fraction of organic nitrogen that has been mineralized. For mineral fertilizers, all forms of nitrogen are directly absorbable by plants. To calculate NH_3 emissions from field, the model from Brentrup et al. (2000) is used. NH_3 volatilization comes from NH_4^+ pool. In the case of compost, volatilization is influenced by temperature, infiltration rate of the soil, and precipitation. For synthetic fertilizer, Brentrup et al. (2000) assumed that it depends on the soil pH. Nitrogen losses in the form of nitrous oxide N_2O and N_2 are quantified as 1.25% and 9% of the applied nitrogen, respectively, for both products, according to the same study. Additionally, nitrate N-NO_3 leaching accounts for 40% of applied nitrogen in compost and 30% in synthetic fertilizers, according to Intergovernmental Panel on Climate Change (IPCC) estimates (Arosemena Polo et al., 2024; Brentrup et al., 2000).

We assume that the use-on-land of compost doesn't result in any emission of P or K, which are then fully available to plants, in line with the assumptions of Hansen et al. (2006). In contrast, the application of one ton of P from a P-based fertilizer leads to 54 kg of PO_3^- runoff (Arosemena Polo et al., 2024).

2.2.2.2. Substitution of soil amendment. For its organic amendment function, we consider that compost substitutes peat, in alignment with the LCA conducted by Sardarmehni et al. (2021). Organic amendments improve soil properties to promote plant growth. Some studies have demonstrated a correlation between the carbon content in peat and compost and the improvement of soil properties, such as bulk density and water holding capacity (Khaleel et al., 1981; Moskal et al., 2001). Therefore, we assume that substitution rate is based on carbon content and set at 1:1. Moreover, the use of peat releases fossil carbon. It is assumed that peat contains 0.504 kg of carbon per kilogram of dry matter, and only 10% of this carbon remains stored in the soil after 100 years (Sardarmehni et al., 2021). The remainder is emitted into the environment as fossil CO_2.

2.2.3. Validation of the model core

The model is evaluated by comparing simulated direct emissions with emission factors reported in literature. Reference values originate from experimental studies or measurements from actual plants with similar feedstocks to those considered in the model. Such a comparison allows for assessing the consistency of the simulated results with empirically observed ranges, thereby supporting the reliability of the model.

2.3. Development of the parametrization levels of PaCTEA

PaCTEA includes two levels of parametrization. The first, represented by the gray box, consists of the input data required to run the model. When this level of information is available, the LCA practitioner can directly tailor the assessment to his specific context from this level. Otherwise, a second parametrization, depicted as the orange box, offers simplified operational decisions that rely on default input data.

The active composting model requires initial concentrations of insoluble substrates in the waste. These variables can be calculated by knowing the fractions present in the biowaste thanks to the database provided by Tonini et al. (2018). In addition to biowaste, composting also requires the incorporation of bulking materials to adjust the C/N ratio, with the type and quantity of these materials influencing the state variables. It also affects the pile's compaction, reflected in the free air space (FAS) parameter and its total volume. In this version of PaCTEA, the possible structuring material is wood chips. Default ratios for biowaste/wood chips are proposed, based on experiments of Adhikari et al. (2009).

Then, the oxygen concentration and the airflow are required, and both depend on the aeration. Oxygen is essential for aerobic degradation and nitrification, making it a limiting factor in equations, while insufficient oxygen supply promotes methane production. On the other hand, airflow has direct influence on ammonia volatilization. Three aeration methods are proposed in PaCTEA. The first is passive aeration, which involves placing pipes in the pile to facilitate air circulation. The convective air flow in the pile is taken from the work of Barrington et al. (2003), who measured it for this aeration type. Then, there is aeration through windrow turning. We assume that the aeration rate circulating in the pile is the same as for the first method. The last method is active aeration, where air is blown into the pile. For this, an aeration rate from Rasapoor et al. (2009) is used in the model.

The ambient temperature is also a key parameter in the thermal balance which predicts the temperature inside the pile. This latter affects different processes through limiting factors. PaCTEA proposes two temperatures, but it can be modified by the practitioner.

For the substitution part, the calculation of NH_3 emissions in the field requires correction factors that depend on regional parameters such as temperature, soil infiltration rate, soil pH, and precipitation levels. These correction factors are taken from Brentrup et al. (2000). The other on-field emissions are based on fixed coefficients.

2.4. PaCTEA: an open-source tool

PaCTEA is hosted on GITHUB to ensure transparency and to foster collaboration and open refinement/development of the tool by the broader community (https://github.com/nomenazo/PaCTEA.git). It includes an Excel file that calculates the initial variables of the active composting model. This model is implemented in MATLAB, using ODE15s to solve differential equations. The possible technological parameters are presented in the same code. The compost composition estimated by the active composting model is then passed to the Substitution model, coded in python. It calculates the quantities of conventional products avoided and the field emissions related to their replacement by compost, depending on the regional parameters involved.

Table 1
Biowaste composition in terms of food waste fractions.

Waste fraction	A (%weight)	B (%weight)
Fruit and vegetable waste	44.5	69.0
Pasta/rice/flour/cereals	0.4	12.4
Bread and bakery	3.8	2.8
Meat and fish	4.3	6.2
Dairy	2.0	1.4
Mixed meals	6.3	1.4
Beverage	27.5	0.0
Other foods	8.0	6.9

2.5. Case study

2.5.1. Presentation of the case study

In this study, simulations are performed to illustrate functionality of PaCTEA. We first evaluate the influence of the input composition, the aeration mode, and the ambient temperature on the outputs of PaCTEA. These are direct emissions of the composting process, the quantity of substituted conventional fertilizers and peat, and the net emissions from the replacement of these products by the compost. Two compositions from Zhang et al. (2013), labeled A and B, are compared (Table 1). For aeration mode, passive and active aerations are compared. Finally, the influence of variations in ambient temperature is assessed by running the model at 5°C and 25°C. For the last two parameters, composition B is used. The mass ratio between biowaste and wood chips is set at 8:1 for each case, which is a formula experimentally tested by Adhikari et al. (2009). As De Corato (2020) suggested for composting duration, we assess the impacts of the process after 90 days. The initial values for our simulations are described in Supporting information.

2.5.2. LCA modeling

2.5.2.1. LCA goal and scope. This LCA is specifically conducted to address the main objective of the present research, namely to assess the extent to which waste composition and operational parameters affect the environmental impacts of a composting system. The functional unit is defined as "Treatment of 1 kg of biowaste". Four scenarios are compared: scenario A uses waste composition A with an active aeration system, and the active composting is conducted at 25°C; scenario B uses waste composition B with an active aeration system at 25°C; scenario B_5°C uses waste composition B with an active aeration system at 5°C; scenario B_passive uses waste composition B with a passive aeration system at 25°C.

The system boundaries extend from the transport of biowaste to the facility, up to the use of compost in the fields, as presented in Fig. 2. The multifunctionality is addressed using the system expansion method. The geographical scope of the study is European countries.

2.5.2.2. Life cycle inventory. The system starts with the transportation of biowaste to the facility, assuming a distance of collection of 30 km. Then, biowaste goes through the pretreatment sorting. This process uses a combination of technologies, which are: drum-screen, shredder, piston press, as described by Alessi et al. (2020). It requires 9.98 kWh of electricity per ton of waste and can recover 77% of biowaste after sorting (Alessi et al., 2020; Beaufort and Lacout, 2016). The rejected biowaste is sent to incineration. After the pretreatment, the C/N of biowaste is adjusted by adding wood chips. A fixed biowaste-to-wood-chip mass ratio of 8:1 is applied in each simulation. The active composting is then carried out with an aeration system. The active aeration uses a compost fan which consumes 9 kWh of electricity per ton of waste (ECS STAFF, 2022), whereas the passive aeration requires no electricity. The direct emissions are calculated by the active composting module of PaCTEA. The produced compost is transported to agricultural land, and its use is included in the system. A distance of 20 km is assumed between the composting facility and the land of use. Through its fertilizing function, the compost generated by the system prevents both the production and the field application of synthetic fertilizers. Furthermore, through its soil amendment function, it avoids the production and land use of peat. The quantity of substituted products and the net on-land emissions are predicted by PaCTEA.

The resources and emissions related to the background processes as well as the avoided production of synthetic fertilizers and peat were obtained from ecoinvent database (version 3.9.1 cut-off). The reference region for these processes is Europe. The inventory data for the LCA and the matching with the background processes are detailed in Supporting information.

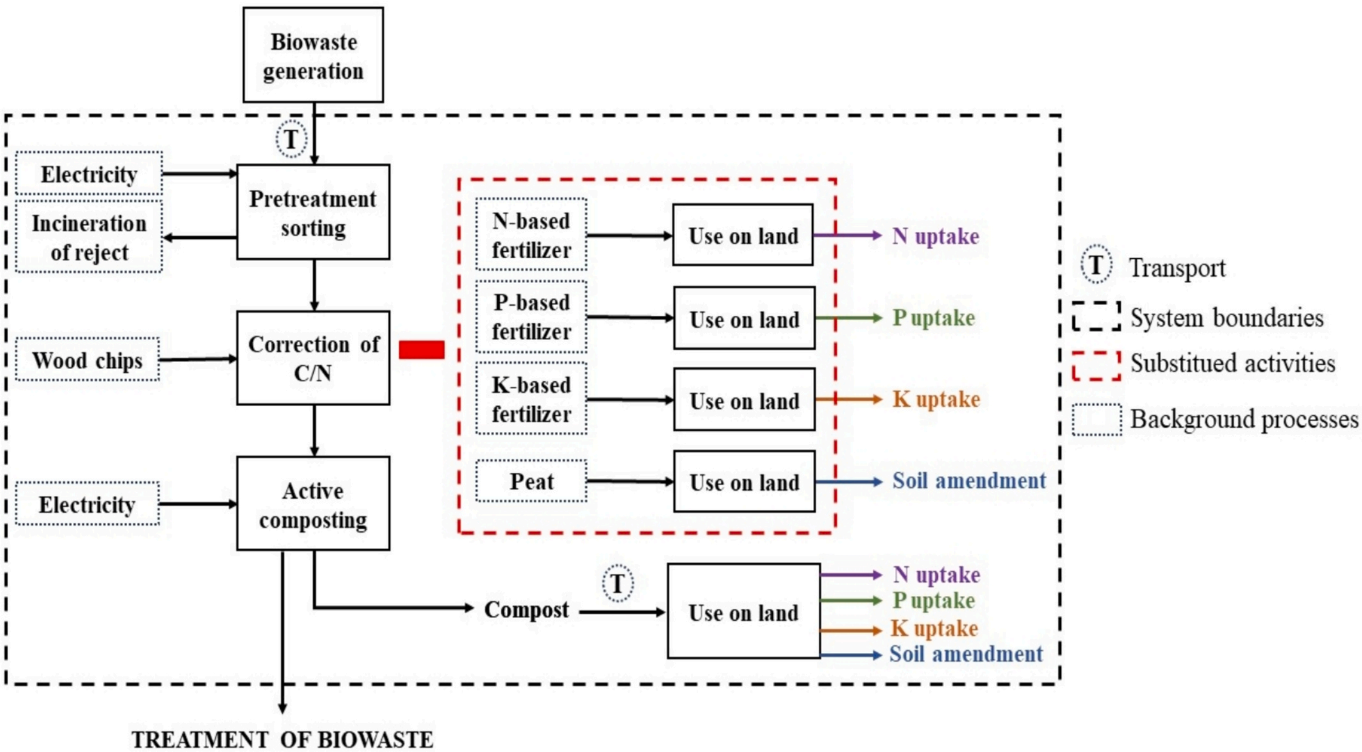

Fig. 2. System of biowaste management.

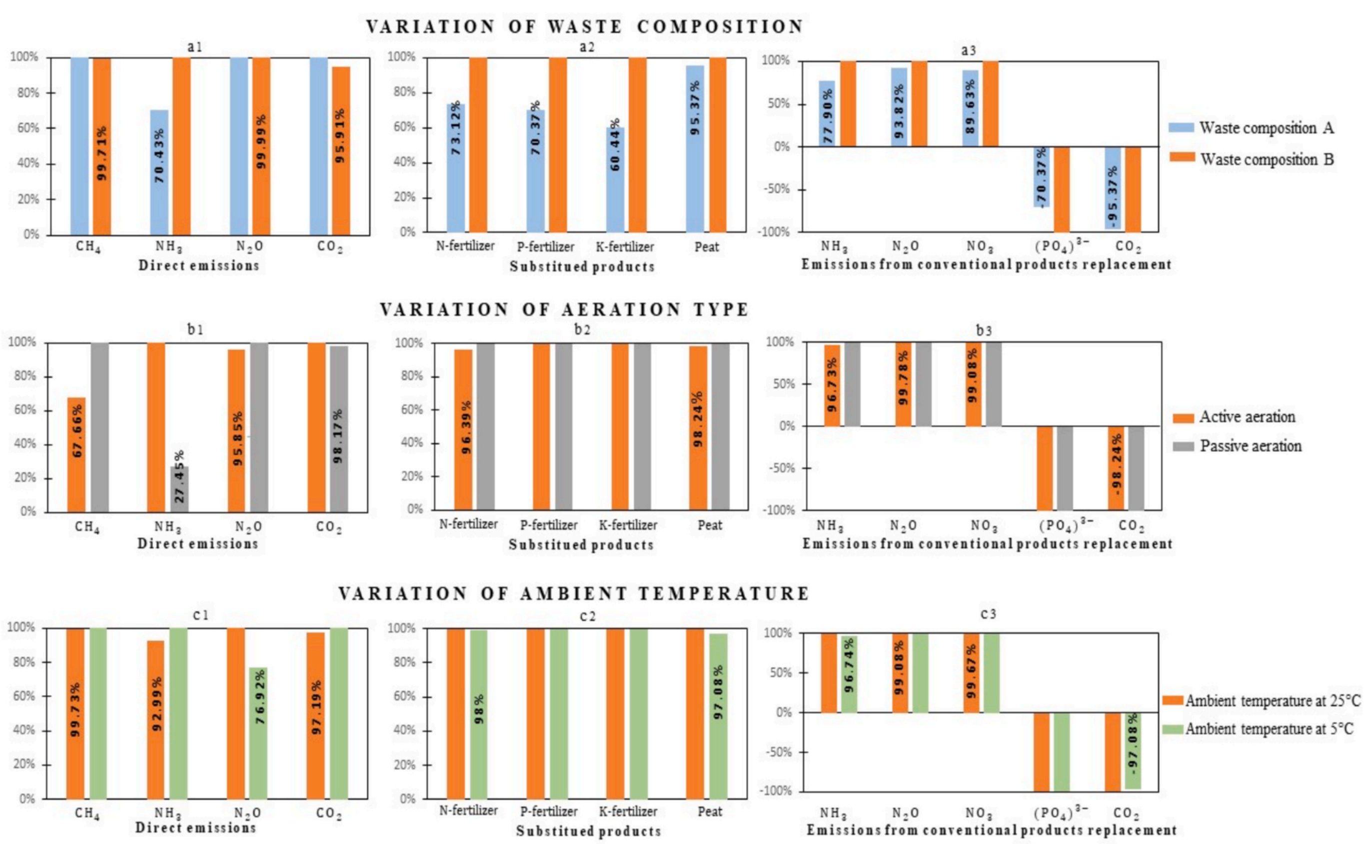

Fig. 3. Influence of variations in three parameters on direct emissions, quantity of substituted products, on-land emissions from conventional products replacement.

2.5.2.3. Life cycle impact assessment. For impact assessment, the *ReCiPe 2016 v1.03* method is used at both midpoint and endpoint levels.

3. Results and discussion

3.1. Influence of parameters variation on the outputs of PaCTEA

In terms of direct emissions, the effects of aeration are well marked (Fig. 3-b1). Lower aeration rates reduce NH_3 volatilization but create anaerobic zones that favor CH_4 production. Such effects of aeration intensity have been reported in experimental composting studies by (Jiang et al., 2015). Under passive aeration, the temperature within the pile is generally higher. This enhances nitrification–denitrification processes and consequently leads to increased N_2O emissions. Yuan et al. (2016) reported comparable results in their experiments.

NH_3 emissions increased at 5°C (Fig. 3-c1). At lower temperatures, NH_3 solubility in the aqueous phase decreases, resulting in a larger driving force for NH_3 mass transfer that enhances volatilization. In contrast, N_2O emissions were reduced at 5°C. This can be attributed to the lower temperature within the compost pile, which limits the denitrification reaction rate, as this microbial process is temperature-dependent and more active at higher temperatures. The effect of temperature on CH_4 emissions was less marked than for other gases. However, emissions at 25°C were slightly lower than those observed at 5°C.

The variation of biowaste composition mainly affected NH_3 emission, reducing it by 29.57% from B to A scenarios (Fig. 3-a1). Ammonia emissions start with protein degradation. Initially, biowaste A contains less protein than biowaste B. Looking more closely at the composition of different waste fractions in the database from Tonini et al. (2018), it is evident that meat and fish are the most nitrogen-rich fractions, followed by certain vegetable categories. The differences in biowaste composition explains why composting of B material emits more NH_3.

In all cases, CO_2 production is relatively insensitive to parameter variations. It is important to note that CO_2 emissions are considered biogenic — leading to no net addition of carbon in the atmosphere — and therefore estimated to have no net effect on global warming.

The differences in quantity of substituted fertilizer are more pronounced when varying waste composition (Fig. 3-a2), as B contains higher N, P, K contents than A. When aeration and ambient temperature variation were tested, no significant difference was observed in terms of nitrogen fertilizer substitution, even though direct composting emissions were more considerable (Fig. 3-b2 and Fig. 3-c2). This could be due to the ammonium pool being maintained despite ammonia volatilization, as ammonification from proteins released by the lysis of dead microorganisms continuously replenishes it. For the same parameters, the amounts of substituted P and K fertilizers remained unchanged, as these elements are not lost during composting due to these parameters.

Variations in biowaste composition, as well as changes in aeration and temperature parameters, did not significantly influence the quantity of substituted peat, with differences across scenarios ranging from 1.76% to 4.63% (Fig. 3-a2 and Fig. 3-b2 and Fig. 3-c2). Although notable differences in CH_4 emissions were observed with changes in aeration mode, these did not have a substantial impact on the residual carbon content in the compost. This can be attributed to the fact that carbon emitted as CH_4 represents a negligible fraction compared to the total carbon content of the biowaste.

Differences of on-field emissions from the replacement of nitrogen fertilizers are positive (in terms of numerical values) for all scenarios, meaning that compost results in higher emissions than the equivalent synthetic fertilizer. As observed for substituted fertilizers quantity, variations in waste composition led to the most pronounced effects on field emissions. Regarding the replacement of peat, higher CO_2 emissions from composting corresponded to lower substitution. Indeed, carbon losses via CO_2 are more significant than those from CH_4 emissions (Fig. 3-a3 and Fig. 3-b3 and Fig. 3-c3).

Table 2
Direct emissions from the model and other sources.

	Model results	Value ranges*
CO_2 ($kg.kgTM^{-1}$)	0.2949–0.3133	0.147–0.252
CH_4 ($kg.kgTM^{-1}$)	0.147E-3–0.217E-3	0.115E-3–13.030E-3
N_2O ($kg.kgTM^{-1}$)	0.05E-3–0.068E-3	0.00–0.788E-3
NH_3 ($kg.kgTM^{-1}$)	0.055E-3–0.217E-3	0.025E-3–0.972E-3

* Reviewed articles: Amlinger et al., 2008; Andersen et al., 2011; Colón et al., 2010; Martínez-Blanco et al., 2010; Matlach et al., 2025.

3.2. Validity of the model outputs

The direct emissions predicted by the active composting model were compared with reported values in the literature, as presented in Table 2. Five studies were selected that report values from experimental setups or measurements from real industrial composting facilities. The composted feedstock consisted of food waste, mixed with bulking agents in some cases. Composting durations were highly variable across studies, ranging from 3 weeks to one year (Amlinger et al., 2008; Andersen et al., 2011; Colón et al., 2010; Martínez-Blanco et al., 2010; Matlach et al., 2025).

For CH_4, N_2O, and NH_3, our model outputs fall within the range of transfer coefficient values reported in the selected studies. For CO_2, the model predicts higher values. However, this emitted carbon is biogenic, so its impact is accounted for at zero in LCA.

3.3. Results of LCA

Fig. 4 presents the midpoint impacts result for 18 categories. Across all impact categories, the four scenarios show concordant outcomes, uniformly indicating either environmental burdens or benefits, except for Water use and Freshwater eutrophication, where only scenario B_passive demonstrates environmental benefits. This is because it is the only scenario that does not consume energy for compost aeration. In 14 impact categories, scenario A exhibits the highest negative impact or the lowest environmental benefit, highlighting the significant influence of biowaste composition across the entire value chain.

Fig. 5 and Fig. 6 illustrate environmental impacts at the endpoint level, in terms of process and midpoint impact category contributions respectively. In the first representation, wood chips consumption, biowaste transport, and incineration of the sorting reject contribute to the same impacts in all scenarios, for the three areas of protection. The differences in total impacts between scenarios are therefore mainly driven by direct emissions, avoided impacts from the production and use of conventional products, and electricity consumption.

Comparison between scenarios A and B shows that waste composition influences environmental impacts. For all three impact categories, A remains less favorable than B. Compost derived from B allows for greater replacement of synthetic fertilizers and peat, as well as higher fossil CO_2 avoidance associated with peat use. In terms of ecosystem quality, A and B have respective impacts of 6.09×10^{-11} and 4.31×10^{-11} $species.year.kg^{-1}$ of biowaste, corresponding to a 29.2% lower impact for B. Regarding human health, impacts amount to -7.88×10^{-8} and -8.56×10^{-8} $DALYs.kg^{-1}$ for A and B, representing an 8.63% increase in net environmental benefit for B compared to A. In the natural resources category, A shows an impact of 1.15×10^{-3} $USD2013.kg^{-1}$, whereas B reaches 5.58×10^{-4} $USD2013.kg^{-1}$, corresponding to a 51.7% reduction in impact for B.

Results also show that composting at 25°C performs better than at 5°C across all three impact categories, represented by scenarios B and B_5, respectively. Compost produced at 25°C (scenario B) has higher quality, allowing for greater substitution of synthetic fertilizers and peat, and consequently higher fossil CO_2 avoidance. Scenario B_5 yields impact values of 5.69×10^{-11} $species.year.kg^{-1}$, -8.09×10^{-8} $DALYs.kg^{-1}$ and 5.95×10^{-4} $USD2013.kg^{-1}$. This corresponds to increases of

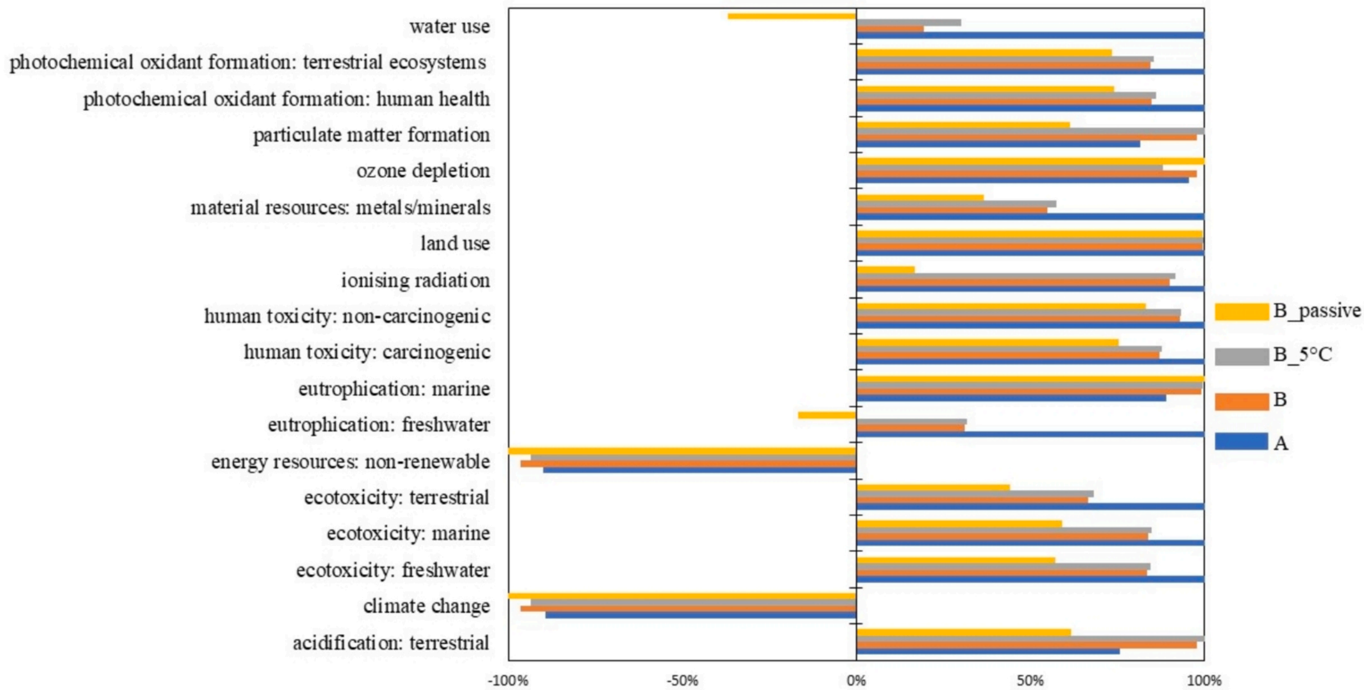

Fig. 4. Midpoint impact results.

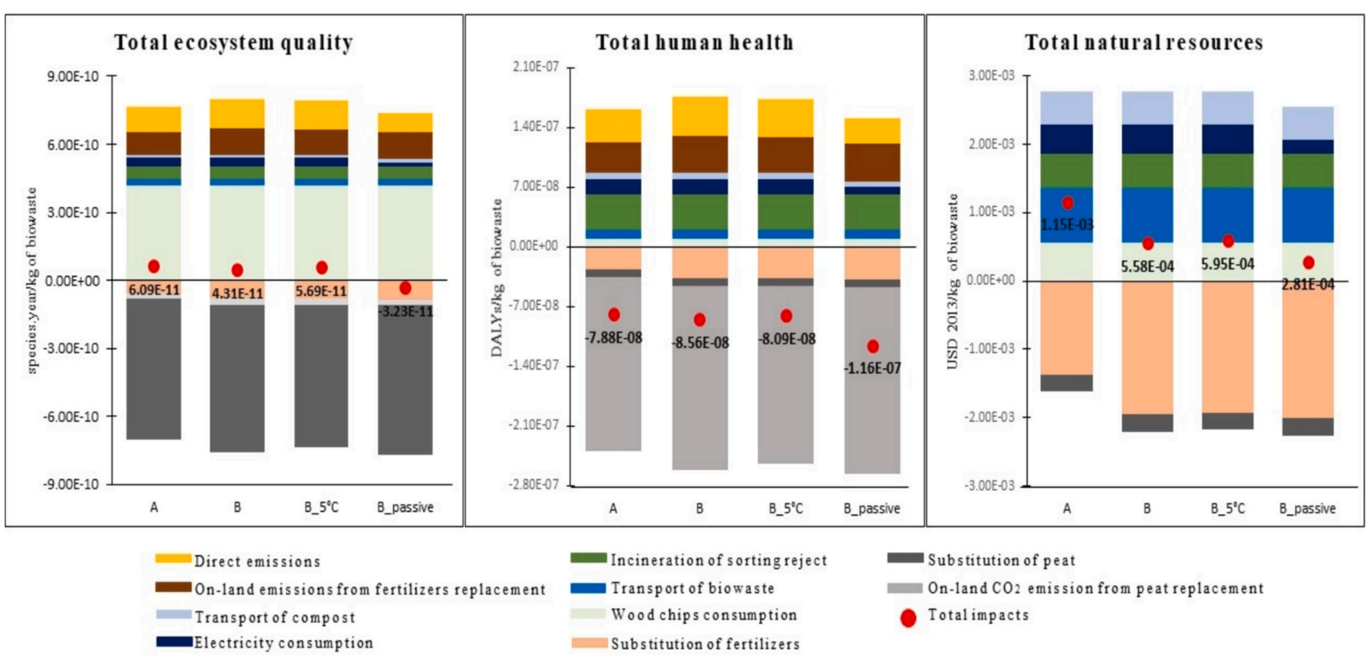

Fig. 5. Contribution of process to areas of protection.

31.8% and 6.65% in ecosystem quality and natural resource impacts, and a 5.45% reduction in net environmental benefit for human health compared with B.

Comparison between scenarios B and B_passive highlights that the aeration mode has a significant influence on all three impact categories. The B_passive scenario results in lower direct emissions and produces higher-quality compost, which enables greater substitution of synthetic fertilizers and peat, and leads to higher fossil CO_2 avoidance. Furthermore, passive aeration consumes less electricity than active aeration. For ecosystem quality, B_passive yields a net environmental benefit of -3.23×10^{-11} species.year.kg^{-1}, representing a 175% improvement compared with B. Regarding human health and natural resources, B_passive has impacts of -1.16×10^{-7} DALYs.kg^{-1} and 2.81×10^{-4} USD2013.kg^{-1} corresponding to relative improvements of 35.2% and 49.7% compared to B.

A closer look at Fig. 6 reveals that climate change is the main contributor to the improvement in total ecosystem quality and total human health. More specifically, it results from the substitution of peat by the compost, and from the avoided CO_2 fossil emission linked to the compost use.

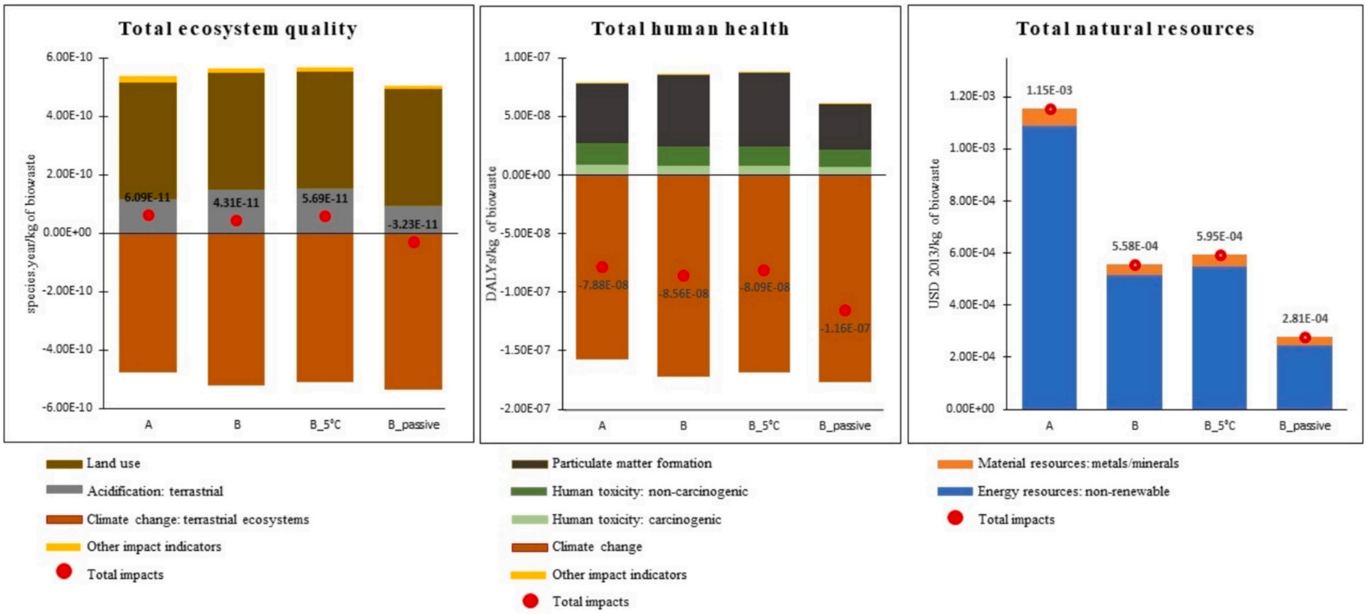

Fig. 6. Contribution of midpoint impact categories to areas of protection.

Despite the environmental benefits from substituting conventional products, the total natural resources still have a net negative environmental impact, mainly driven by the use of non-renewable energy resources.

3.4. Sensitivity analysis

Sensitivity analyses were conducted on the 36 parameters used in the active composting model, for all scenarios previously evaluated. First, we tested sensitivity of all composting direct emissions, the quantities of nitrogen fertilizers and peat substituted, and net field emissions from compost use (NH_3, N_2O, NO_3, CO_2). Then, the influence of parameters on endpoint impact categories was assessed. Details of the sensitivity analyses are reported in supplementary information.

3.4.1. Sensitivity of model outputs

Each parameter was varied by −10%, −5%, +5%, and +10%. A variable is considered sensitive to a parameter when its relative change is greater than that of the parameter in absolute terms.

Across the four scenarios, six parameters consistently influenced at least one variable: the specific growth rates of mesophilic and thermophilic bacteria (μ_{MB} and μ_{TB}), the specific growth rate of autotroph microorganisms (μ_A), the death constants for thermophilic bacteria and autotroph microorganisms (b_{MB} and b_A), and the sensitivity of methanogenesis to inhibition by oxygen (η). In addition, the mesophilic hydrolysis constant of carbohydrates (k_{h1C}) affected NH_3 emissions during composting in the sensitivity analysis for scenario B_5, and the maximum rate of methane oxidation (Vm) influenced CH_4 emissions in scenarios A, B, and B_5. The parameters that affected the greatest number of variables were the same across all four scenarios: μ_{MB}, μ_{TB}, and b_{MB}. The variables sensitive to these parameters included direct CO_2 and NH_3 emissions, substitution rates for nitrogen fertilizer and peat, and net field emissions of NH_3, N_2O, NO_3, and CO_2. The most pronounced change occurred in nitrogen fertilizer substitution in scenario A, which decreased by 19% when μ_{TB} was lowered by 5%. When these three key parameters were varied with the minimum and maximum values reported in the literature, variables varied between −34.03% to 68.13% across all scenarios.

3.4.2. Sensitivity of LCA results

Only three parameters—μ_{MB}, μ_{TB}, and b_{MB}—had an influence across all three impact categories. The largest observed change was a 17.78% decrease in the natural resources category when μ_{TB} was reduced by 5% in scenario A. This is due to the effect of this parameter on the quantity of nitrogen fertilizer substituted. However, the conclusion from comparing the scenarios remained unchanged despite parameter variations.

3.5. Discussion and limitations of the study

3.5.1. Comparison of PaCTEA to existing tools

As previously mentioned in the introduction, current models rely on empirical transfer coefficients to estimate emissions. This approach tends to oversimplify the complex physicochemical and biological mechanisms occurring during the composting process. PaCTEA was developed to overcome these limitations by introducing a phenomenological modeling approach. For instance, tools such as ORWARE and EASETECH include different composting technologies, but their main differences lie in energy consumption and emission control, rather than in the internal process mechanisms (Boldrin et al., 2011; Eriksson et al., 2002). In our study, it was highlighted that two key operational parameters significantly influence both direct emissions and the quality of the final compost: the aeration mode and the ambient temperature during the process.

Another major strength of PaCTEA lies in its ability to handle a high level of detail regarding the composition of input materials. Each fraction of biowaste can be characterized by its specific composition. In contrast, most existing LCA tools treat biowaste as a single homogeneous stream, which limits their capacity to represent real-world variability (Boldrin et al., 2011; Eriksson et al., 2002). Our results showed that differences in biowaste composition can substantially influence the environmental impacts of composting. Therefore, PaCTEA provides a means to adapt LCA to territory-specific conditions, enhancing the representativeness and robustness of environmental assessments.

3.5.2. Limitations

Some limitations must be acknowledged in this first version of PaCTEA. As revealed by the sensitivity analysis, the model outputs are particularly sensitive to three kinetic parameters (μ_{MB}, μ_{TB} and b_{TB}). Although the resulting values fall within the range reported in the literature, these parameters should be experimentally calibrated in order to enhance the robustness and reliability of the model.

In addition, several operational parameters remain simplified. The range of bulking agent types could be expanded to offer users greater flexibility and to better adapt the LCA study to specific local contexts, as the current version only includes wood chips, with two possible mixing ratios. Nevertheless, PaCTEA allows users to readily integrate alternative bulking materials when specific data on their composition and the free air space they provide are available. Furthermore, the available aeration configurations have been simplified and do not yet cover all existing operational practices. In particular, the aeration effect of pile turning is assumed to be equivalent to that of passive aeration. Future experimental studies could help improve PaCTEA's heat balance module by explicitly accounting for heat losses associated with turning operations. Finally, the representation of compost maturity and process duration remains challenging, particularly when attempting to link compost quality to regulatory standards.

4. Conclusion

By integrating complex chemical engineering knowledge into LCA, PaCTEA is capable of capturing the impact of variations in input composition and operational parameters throughout the entire value chain. Indeed, the active composting model not only predicts direct emissions during the process but also the composition of the compost. This knowledge of the compost's nutrient content has been essential for a more accurate determination of the fertilizers and soil amendments potentially substituted, as well as the field emissions resulting from the replacement of these conventional products.

PaCTEA is designed from the ground-up for integration with LCA, and the results highlight that the environmental performance of composting systems is significantly influenced by changes in biowaste composition and operational parameters.

This work has various implications for stakeholders. For the LCA community, it suggests the need to evolve the way waste management systems are evaluated, and to reflect the specificity of local feedstocks and operation conditions. This would better guide local decision-makers in adapting these systems according to territorial specificities. This study also highlights the environmental implications of operational practices of waste treatment system managers. They should be aware that these environmental impacts extend beyond the composting facility to the end use of co-products. Our study reminds LCA practitioners of the importance of data quality in obtaining reliable results. Although our tool offers a user-friendly parameterization, LCA experts are still expected to invest effort in understanding the system under study in order to select parameters that accurately reflect their specific context.

Finally, we hope that PaCTEA can serve as an open-source platform to consolidate future improvements in the modeling of composting processes by the LCA community, particularly with efforts toward greater calibration. Its parametrized approach opens the possibility of a collective refinement over time of a common, core tool, with analyses adaptable to a variety of specific contexts in a harmonized and comparable manner. We see great potential in extending this approach to other complex processes, showcasing the potential of further integration of chemical engineering modeling in system-wide LCA representations.

CRediT authorship contribution statement

Nomena Ravoahangy: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Guillaume Majeau-Bettez:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Olivier Schoefs:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.wasman.2026.115337.

Data availability

I have shared the link to my code and data in the manuscript

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