Review

A Review of Composting Process Models of Organic Solid Waste with a Focus on the Fates of C, N, P, and K

Zheng Yang 1,*, Furqan Muhayodin 1, Oliver Christopher Larsen 1, Hong Miao 2, Bing Xue 1 and Vera Susanne Rotter 1,*

1 Chair of Circular Economy and Recycling Technology, Technische Universität Berlin, Straße des 17. Juni 135, 10623 Berlin, Germany; furqan.muhayodin@campus.tu-berlin.de (F.M.); oliver.larsen@tu-berlin.de (O.C.L.); bing.xue@tu-berlin.de (B.X.)
2 College of Mechanical Engineering, Yangzhou University, Yangzhou 225127, China; mh0514#163.com
* Correspondence: zheng.yang@campus.tu-berlin.de (Z.Y.); vera.rotter@tu-berlin.de (V.S.R.)

Abstract: To foster a circular economy in line with compost quality assessment, a deep understanding of the fates of nutrients and carbon in the composting process is essential to achieve the co-benefits of value-added and environmentally friendly objectives. This paper is a review aiming to fill in the knowledge gap about the composting process. Firstly, a systematic screening search and a descriptive analysis were conducted on composting models involving the fates of Carbon (C), Nitrogen (N), Phosphorus (P) and Potassium (K) over the past decade, followed by the development of a checklist to define the gap between the existing models and target models. A review of 22 models in total led to the results that the mainstream models involved the fates of C and N, while only a few models involved P and K as target variables. Most of the models described the laboratory-scale composting process. Mechanism-derived models were relatively complex; however, the application of the fractionation of substrates could contribute to reducing the complexity. Alternatively, data-driven models can help us obtain more accurate predictions and involve the fates of more nutrients, depending on the data volume. Finally, the perspective of developing composting models for the fates of C, N, P, and K was proposed.

Keywords: composting; organic solid waste; models; nutrients; modeling scale; checklist

1. Introduction

Organic solid waste (OSW), the solid waste containing organic matters (i.e., food waste, livestock manure, green waste), has been a critical issue for sustainable development due to its continuous increase in amount and non-recycled treatment [1–3]. Till today, most OSW is still disposed of in unsustainable and conventional ways, such as landfilling and incineration [4], which result in the emission of greenhouse gases and leachate containing heavy metals [5], toxic gases such as sulfur dioxide, dust, heavy metal fumes, and incombustible hydrocarbons, and losses of valuable nutrients [4]. Therefore, the effective management strategies of OSW, including composting, are attached with more importance by relevant stakeholders and policy makers, with the aim of overcoming the challenge of environmental protection, promoting the circular economy and, hence, achieving sustainable development [6–8].

Compared with landfilling and incineration, composting is now one of the most popular technologies to recycle nutrients from organic waste [9], which can significantly shorten the processing cycle and more efficiently recover the nutrients from organic waste [4,10,11]. In China, about 76% of the poultry and livestock manure collected by intensive farming was processed through composting in 2015 [12], which can promote the organic fertilizer production industry and increase the circulation of regional nutrients [13]. Even
though fruitful results have been achieved in the research on composing, there remains a large challenge when microorganisms convert complex substrates into ultimately useful products in the composting process, in which some by-products, such as Ammonia (NH₃), Carbon dioxide (CO₂), Methane (CH₄), Nitrous oxide (N₂O), etc., are produced to burden the atmosphere [14,15]. The accumulation of P in surface soil can lead to the transfer of Phosphorus (P) to groundwater, which becomes an environmental concern during the compost application [16]. During the composting process, the Carbon (C) loss to the atmosphere ranges from 30% to 63% [17], and the Nitrogen (N) loss ranges from 19% to 42% mainly because of the vigorous NH₃ volatilizations, while the Phosphorus (P) loss is less than 2% mostly due to the runoff [18,19]. These data may be different due to the origin of various raw materials. The loss and dissipation of nutrients may not only lead to potential environmental risks, but also reduce the agronomic quality of the composted product [20]. Instead, applying more remaining C from composted fertilizer to the soil can reduce greenhouse gas emissions and sustainably mitigate climate change through storage or sequestration strategies [21]. It will also contribute to the efficiency of other fertilizers by altering soil properties, so as to bring environmental and agronomic co-benefits [22]. Therefore, for composting technology, it is significant to minimize both C and nutrient losses for the production of stable products with high quality.

Generally, the motivation of modeling is to develop mathematical tools to integrate the knowledge with the phenomena, determine the direction of experimental design, evaluate experimental results, test hypotheses, reveal relationships between variables, predict the system development, and design the process and management strategies [23]. Since 1976, mathematical models of composting technology have appeared in the literature [24]. In recent years, many models have been developed to contribute to predicting the distribution of temperature, humidity, solids, oxygen content, and carbon dioxide during the composting process [25–31]. However, from an environmental and agronomic point of view, the focus should be placed on regional C and nutrients for a better understanding of composting technology and assessment of the effectiveness of this sustainable solution [32]. Moreover, the methodology for regional assessments, such as life cycle assessment and material flow analysis, requires the accuracy of the model and a certain number of target variables to be simulated when it is used to simulate and evaluate composting technologies on a regional scale with high accuracy [33]. According to the research of Lauwers et al., the models can be grouped as mechanism-derived models that are established based on the biochemical reaction to reveal more mechanisms and data-driven models focusing more on the experimental data than the process of intermediate reaction [34]. According to the research results from the database of the Web of Science Core Collection, the number of papers on the composting process has shown an increase from 74 in 2011 to 114 in 2020. Initially, the focus of relevant research was mechanism-derived models [24], while in recent years, data-driven models based on various algorithms have gained more popularity [35].

Previous articles on the review of composting models usually focused on composting kinetics to discuss the process parameters, such as temperature, water content, pH, and carbon-to-nitrogen ratio (C/N). For instance, Mason reviewed and extensively analyzed composting models proposed in published papers before the end of 2003 [24]. He systematically described the establishment and improvement of the models on heat balance and mass balance during the composting process. Walling et al. conducted a comprehensive review on composting models published in the last 40 years to determine the trend of the composting models in terms of the goal and method, focusing on the research development of composting kinetics, heat balance, and mass (mainly water and oxygen) balance [35]. In recent years, more importance has been given to the simulation of the fates of C, N, P and Potassium (K) in the composting model. However, due to the complexity of the composting process, only a few papers have been published about the systematic review of the modeling of the fates of C and nutrients in the composting process. So, a further study with the application of models is necessary to delve into the fates of C, N, P and K
during the composting process. Therefore, the following two research questions are to be addressed with the aim of attaining a deeper understanding and new knowledge based on available studies through the systematic review:

1. What are the key features of existing composting models that involve the fates of C, N, P, and K? (RQ1);
2. How could the gaps between the existing model and the target model be well defined and presented? (RQ2).

The following parts of this paper are structured as follows: Section 2 presents the applied methods to show the process of a systematic review with a descriptive analysis; Section 3 includes the results; Section 4 proposes the guiding perspective of composting models involving the fates of C, N, P, and K, as well as the discussion on the implications of the study, and includes the explanation of how the fate of C, N, P and K in composting can be effectively described through modeling.

2. Methods
2.1. Literature Screening

A systematic screening search of relevant literature was conducted based on the core collection in the database of Web of Science (https://www.webofknowledge.com), which is considered to cover papers of high quality and in sufficient quantity for a systematic review [36]. The time scope is defined as in the past ten years, from January 2011 to June 2020. The following search rule is used in the advanced search: “(TS = compost) AND (TS = model) AND ((TS = carbon) OR (TS = nitrogen) OR (TS = phosphorus) OR (TS = potassium))”, where TS is defined as Topics.

A total of 722 related articles were collected, followed by a precise refining process based on the following three criteria, including: (1) the substrates for composting were OSW; (2) the target variables of modeling objectives involved at least one of C, N, P, and K; (3) the research modeled the process of composting technology. Specifically, the process of study selection and data extraction consists of three steps of results retrieval [37,38], as shown in Figure 1. First, search for articles based on a prioritized search strategy. Then, filter out irrelevant or unsuitable articles according to their titles and abstracts. Third, read the filtered articles in full text. Finally, a total of 22 models were selected for further studies, which are mainly from peer-reviewed journals or conferences such as Bioresource Technology, Environmental Technology, and Waste Management.
2.2. Data Extraction

In order to further characterize the models, we developed code lists of target variables related to modeling objects, modeling approach types (mechanism-derived model types and data-driven model types), and applied environmental types as indicators to conduct data extraction as shown in S1, S2, S3, and S4. From these code lists, we then developed tables shown in S5 to describe and summarize the selected models.

2.3. Checklist for Model Assessment

A checklist approach was used to define the gap between the reviewed models and the target models. In this study, a checklist was designed according to the target models and the developing process of models. Given the fact that there is no consensus on the
best method of evaluating composting models, a brand-new checklist was finally developed and applied here to evaluate the models and help define the gaps of target models, while this method has been applied in other subject areas, such as ecology and medicine [39,40]. The most common questions in the checklists are whether the model clearly describes the objectives of modeling, whether the approach to modeling is reasonable, and whether the sensitivity and accuracy of the model are evaluated [39–41]. Developing a model follows six steps: analyze the problem, formulate a model, solve the model, verify and interpret the model’s solution, report by the model, and maintain the model [42]. Furthermore, the emphases in the previous research on composting models, such as the composting substrates [43] and the model’s reflection on the mechanism [44], have been combined in developing the checklist to determine three major categories: the start points of the model, the process of modeling, and the internal assessment of models. In addition, to be more in line with our review scope, the target variables of modeling were set on whether the fates of C, N, P and K are all involved as an indicator at the start point of the model. Moreover, since the nutrients’ transformation mechanism plays an essential role in studying the balance of elements [44], we set the 7th item to explore the part of the data-driven model of revealing the mechanism in order to better identify the main factors influencing the composting process. The weight of each category is 5-point. As the modeling process of the mechanism-derived models is different from that of the data-driven models, in the second category, different questions were applied to evaluate the two types of models. If we assume the score for the most optimal model is 15, the gap between the model in the checklist and the most optimal one is reflected by 15 subtracting the score for the model. The specific checklist for the composting model is shown in Table 1.

Table 1. The checklist for composting models

| Category               | Items                                                                 | References |
|------------------------|-----------------------------------------------------------------------|------------|
| Start points of models | Were the target variables of modeling clearly described? (1 point)     | [39,40]    |
|                        | Do the research objectives fit our review scope (C, N, P, and K)? (3 points) |            |
|                        | (1 point will be calculated for only one of C, N, P, and K involved in modeling; 2 points will be calculated for 2 or 3 of C, N, P, and K involved in modeling; 3 points will be calculated for all of C, N, P, and K involved in modeling. If partially involved in each related element only, such as CO₂ or C/N, 0.5 points will be calculated.) |            |
|                        | Were the substrates of the study clearly described? (1 point)          | [43,45]    |
| Mechanism-derived models | Does the selection equation in the model clearly list the reference basis? (1 point) | [39,41,42] |
| Data-driven models     | Does the study identify the sources of the data and describe how the data were collected clearly? (1 point) | [39,41,42] |
| Process of modeling    | Were the assumptions about the model clearly described? (1 point)      | [39,40,42] |
|                        | Was the modeling approach used clearly described?                      |            |
|                        | (1 point)                                                             |            |
|                        | Was the basis for the selection of relevant parameters clearly described? (1 point) | [24,40]    |
|                        | Was the basis for the selection of variables clearly described? (1 point) |            |
How about the complexity of the models? (1 point, 0.5 points, or 0 will be calculated for Not complicated, Complicated, and Very complicated, respectively)

How well does the model reflect the composting process? (1 point, 0.5 points, or 0 will be calculated for Well reflect, Partly reflect, and Not reflect, respectively)

Was the platform/software clearly described to solve/simulate the model? (1 point) [42]

Was the sensitivity analysis conducted? (1 point) [40, 46]

Were experiments conducted to compare the models? (1 point) [39]

Was the accuracy evaluation method of the models clearly described? (1 point) [34, 42]

How about the accuracy of the models? (2 points, 1 point, or 0 will be calculated for Very accurate, Relatively accurate, and Not accurate or not mentioned, respectively) [42]

3. Results

3.1. Overview of Reviewed Models

The substrates, modeling approaches, and target variables of objectives for 22 referred models are shown in Figure 2. The 22 models were divided into two main categories based on the modeling approaches: 10 mechanism-derived models and 12 data-driven models. In particular, semi-empirical models fell in between [44], which are established based on mechanism-derived models but modified with experimental data. Since these three semi-empirical models were developed from a process perspective, they were also summarized in the mechanism-derived model in this section. The composting substrates of these models were mainly related to two categories including municipal solid waste (MSW) and agricultural waste. The target variables involved in the simulation, however, were mostly C and N, and to a lesser extent, P and K.
3.2. Composting Substrates and Target Variables

The specific substrates of these models involved MSW and agricultural waste, as shown in Figure 3a. MSW mainly includes sludge (n = 5) and food waste or food processing waste (n = 3). In comparison, other types of municipal waste have been studied, including cardboard, boxwood leaves, and sawdust (n = 3). In these models, most of the simulation of agricultural waste concentrated on livestock manure and crop residues, such as pig manure, chicken manure, and cattle manure mixed with straws of rice, wheat, and corn (n = 8). In addition, other types of agricultural wastes include vegetable wastes and fruit leaves (n = 3).

To address the challenges posed by the complexity of the substrates for compost modeling, fractionation of the substrates was applied to separate the organic matter into multiple components. Simply put, the substrates are divided into three categories, namely, soluble, insoluble, and inert substrates [44, 47–50]. Furthermore, a more detailed fractionation method was applied, in which the organic matters were divided into five compartments: the easily degradable and soluble; slowly degradable and soluble; hemicelluloses, cellulose, and lignin fractions [51, 52]. With this method of fractionation, the degradation process of the organic matters can be described according to different degradation kinetics, thereby improving the accuracy of the model, and at the same time, providing a solution to the modeling of complex substrate composting.

Since the review scope of this paper was the fates of carbon and nutrients, only the target variables related to C, N, P, and K in modeling were included. There were two parts in each element: the remaining and the lost. It can be seen from Figure 3b that most models involved the simulation of C and N. Models involving carbon mainly included organic carbon (OC) (n = 3) and microbial carbon (MC) (n = 1). There was also research on the remaining of total carbon (TC) (n = 4). The simulation of carbon loss mainly involved CO2 (n = 9) and CH4 (n = 2). In terms of nitrogen, Bonifacio et al., St Martin et al. and Vasiliadou et al. developed models for organic nitrogen (ON) (n = 3) [33, 49, 53]. As for total nitrogen (TN) loss, Li et al. and Faverial et al. modeled this part as a whole variable (n = 2) [15, 54];
others focused on the emissions of N2O (n = 3) and NH3 (n = 3). There were some models related to the C/N that are considered to play a key role in the composting process, and these models also involve the mass balance of C and N (n= 3). Vasiliadou et al., Faverial et al., and Huang et al. have developed models for the mass balance of total phosphorus (TP) (n = 3) [15,49,55]. The research by Faverial et al. and Huang et al. also involved the model of total potassium (TK) (n = 2) [15,55].

In addition, mechanism-derived models mainly simulated the relevant mass balance of C and N, and, to a lesser extent, the mass balance of P. In contrast, the data-driven models could cover a broader range of simulated objects and even involved K. However, there were no mechanism-derived models that included K in the selected research.

3.3. Modeling Approaches

3.3.1. Mechanism-Derived Models

The mechanism-derived models are generally based on mass balance, energy balance, and kinetics [56]. Composting kinetics describes methods of controlling the rate of waste degradation through environmental factors, such as temperature, oxygen utilization, and moisture. So far, various kinetics models for biomass degradation through composting have been developed based on the physical and biochemical characteristics of composting materials [57]. A summary of 10 mechanism-derived models and modeling objectives is shown in Table 2.

![Figure 3. The specific situation regarding the (a) substrates and (b) the target variables of modeling objectives.](image)

Notes: The abbreviations are defined as follows: OC (organic carbon); MC (microbial carbon); TC (total carbon); ON (organic nitrogen); C/N (carbon-to-nitrogen ratio); MN (microbial nitrogen); OP (organic potassium); TP (total phosphorus); TK (total potassium).
Table 2. Summary of 10 mechanism-derived models and modeling objectives.

| No. | References                  | Mechanism-Derived Model Type Involved                                                                 | Related Modeling Objectives                                                                 |
|-----|-----------------------------|--------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------|
| 1   | Zhang et al. 2012 [51]      | Monod kinetics model, First-order kinetics model, Mass balance model                                   | CO₂ corresponding to mineralization (% of initial total organic carbon)                    |
| 2   | Oudart et al. 2012 [47]     |                                                                                                      | CO₂ emission rate                                                                          |
| 3   | Lashermes et al. 2013 [52]  |                                                                                                      | OC and CO₂ corresponding to mineralization (% of initial total OC)                          |
| 4   | Villaseñor et al. 2012 [50] | First-order kinetics model                                                                            | C degradation (% of DM)                                                                     |
| 5   | Vasiliadou et al. 2015 [49] | Monod kinetics model, First-order kinetics model, Mass balance model                                  | Insoluble organic matter mass, insoluble N and P mass, and CO₂ emission volume             |
| 6   | Petric and Mustafić 2015    | Monod kinetic model, Mass balance model, Heat (energy) balance model                                  | CO₂ mass                                                                                   |
| 7   | Ge et al. 2016 [48]         | First-order kinetics model, Michaelis–Menten kinetics model, Energy balance model, Mass balance model | CH₄ emission rate                                                                           |
| 8   | Kabbashi 2011 [58]          | Semi-empirical model, Multi-stage model                                                                | The remaining of TC and TN (% of DM)                                                       |
| 9   | Oudart et al. 2015 [44]     | Semi-empirical model                                                                                  | Production yield of CO₂, N₂O and NH₃                                                        |
| 10  | Bonifacio et al. 2017 [33,59]| Process-based model                                                                                   | OC, MC, ON, MN, NH₄⁺, NO₃⁻ (% of DM), and emission rates of CO₂, N₂O and NH₃               |

OC (organic carbon); TC (total carbon); TN (total nitrogen); MC (microbial carbon); ON (organic nitrogen); MN (microbial nitrogen); DM (dry matter).

The common kinetics model is the first-order kinetics model (n = 6) related to the degradation of volatile solids or the utilization of oxygen. Hence, it has a close connection with the fate of C. The first-order kinetics model is based on temperature, oxygen, moisture, biodegradable volatile solids (BVS), and free space as parameters that affect the rate of degradation [60,61].

Another widely used kinetics model is the Monod kinetics model (n = 5), which was developed from the mechanical or deductive point of view by integrating the basic principles of physics, chemistry, and microbiology involved in the composting process [56,62,63].

The derivation of each kinetics model focuses on their mathematical formulas, which allows them to explain certain processes in composting. In the first-order kinetics model, the substrate concentration is used as the primary force determining the reaction rate, while the Monod kinetics model involves microbial activity, which makes the model more realistic.

Semi-empirical models are based on the mechanism with test data to modify and determine their model parameters. This approach is different from other mechanism-derived models, which requires a comprehensive understanding of the process. Unlike data-driven models that rely on large amounts of data, it is developed based on internal processes or stages. Oudart et al. simulated the interaction of nitrogen and carbon during
animal manure composting based on the main processes governing carbon and nitrogen transformations [44]. Then, models were analyzed and simulated according to the experimental data. Bonifacio et al. developed a process-based model for simulating cattle manure compost windrows [33,64]. In their research, the fate of C and N through processes affected by compost windrows was established. Combined with a large amount of empirical data, the parameters were determined to study the mass balance of C and N.

In order to describe more variables, more equations and parameters are required, leading to the complexity of models. In mechanistically derived models, the studies by Bonifacio et al. and Oudart et al. involved more related modeling objectives [33,44]. The former included 10 equations and 52 parameters, while the latter included more, with 26 equations and nearly 90 parameters. In addition to using mathematical models to simulate microbial growth, nitrification, denitrification and other biochemical process reactions, some physical processes were also described. For example, Bonifacio et al. incorporated the leaching and runoff of $\text{NO}_3^-$, as well as ammonia volatilization, into the model [33]. Oudart et al. also considered ammonia volatilization [44].

3.3.2. Data-Driven Models

Data-driven models are usually accompanied by experimental and empirical data collection to ensure the effective prediction of fundamental parameters [34], thereby establishing a reliable relationship between the model and the prediction of essential parameters or variables. A summary of 12 data-driven models and simulation objects is shown in Table 3.

Table 3. The summary of 12 data-driven models and simulation objects.

| No. | References          | Modeling Type                              | Input Variables                                      | Target Variables Related to Modeling Objects |
|-----|---------------------|--------------------------------------------|------------------------------------------------------|---------------------------------------------|
| 1   | Sun et al. 2011 [65]| Genetic algorithm aided by the stepwise cluster analysis method | $\text{NH}_4^+ - \text{N}$ concentration, moisture content, ash content, mean temperature, and mesophilic bacteria biomass | C/N                                        |
| 2   | Huang et al. 2011 [55] | Linear regression analysis               | pH, EC, and DM content                               | The remaining TN, TP, and TK (% of DM)       |
| 3   | Bayram et al. 2011 [66] | ANN model MLR model                        | Food and yard percentage, ash and scoria percentage, moisture content, fixed carbon content, the total proportion of organic matter, high, calorific value, and pH | C/N                                        |
| 4   | Hosseinzadeh et al. 2020 [67] | pH, EC, C/N, $\text{NH}_4^+$/NO$_3^-$, water-soluble carbon, dehydrogenase enzyme, and total phosphorus | The remaining TN and TP (% of DM)                    |
| 5   | Boniecki et al. 2012 [59] | ANN model                                | Time, temperature, pH, EC, DM concentration, C/N, $\text{NH}_4^+ - \text{N}$ concentration | NH$_3$ emissions (% of air released from bioreactor chamber) |
| 6   | Díaz et al. 2012 [68] | An adaptive network-based fuzzy inference system | Aeration rate, moisture content, particle size, and time | CO$_2$ emission rate |
| 7   | St Martin et al. 2014 [53] | Critical exponential function            | Composting formula, time and composting formula interacting through time | TOC and TKN (% of DM) |
| No. | Authors and Year | Model Type                          | Equation/Variables                                                                 | Notes                                                                 |
|-----|------------------|-------------------------------------|-----------------------------------------------------------------------------------|----------------------------------------------------------------------|
| 8   | Faverial et al. 2016 [15] | Bayesian network model              | Total C, N, lignin, P and K contents, pH, and loss of mass                        | The remaining, and loss of, TN, TP, and TK (% of DM)                  |
| 9   | Mancebo and Hettiarchi 2015 [69] | Regression model                    | Air-filled porosity, moisture content, and dissolved OC content                  | CH₄ emission rate                                                     |
| 10  | Li et al. 2017 [54]            | Regression model                    | Moisture content, adding time, sucrose concentration                             | The loss TN ration                                                   |
| 11  | Varma et al. 2017 [70]         | RBF neural network model            | Moisture content, pH, EC, TOC, TKN, soluble biochemical oxygen demand, NH₄⁺ – N concentration, available phosphorous, C/N, total phosphorous, oxygen uptake rate, Na, K, Ca | CO₂ emission rate                                                   |
| 12  | Chen et al. 2019 [71]          | Backpropagation neural network model| Moisture content, C/N, aeration rate, and superphosphate content                | Proportion of N₂O on TN                                              |

ANN (artificial neural network); BP (backpropagation); RBF (radial basis functional); MLR (multiple linear regression); EC (electrical conductivity); DM (dry matter); C/N (carbon-to-nitrogen ratio); TN (total nitrogen); TP (total phosphorus); TK (total potassium); TOC (total organic carbon); TKN (total Kjeldahl nitrogen).

Artificial neural network (ANN) is most widely used in data-driven models (n=6), which is designed to simulate the biological nervous system’s response to real-world tasks [72]. In the reviewed articles, different types of neural networks have been studied, including multilayer perceptron (MLP) [59,67], backpropagation (BP) [71], and radial basis functional (RBF) [70]. BP is a systematic approach to training MLP. Bayram et al. (2011) used the MLP trained with the BP algorithm to develop models for simulating C/N of MSW composting [66].

Linear regression analysis of data is a monitoring technique used to model target values based on independent predictors [72]. The composting process can be modeled based on one variable (single regression) model or multiple variables (multiple linear regression (MLR)) model. St Martin et al. used different function models to simulate different parameters of the composting process, leading to the recognition that the composting temperature and OC are best described by the critical exponential function and the rectangular hyperbolic function, respectively [53]. ON, C/N, and pH are best described by double Fourier functions, while electrical conductivity (EC) is best described via Fourier functions. Huang et al. discussed the efficiency and feasibility of nutrient elements in chicken manure during composting with physical and chemical properties, such as pH, EC and DM [55]. It can be concluded that DM is a better predictor constructed as a single linear regression of nutrients, while DM and pH are more notable for MLR. Since MLR also involves multiple variables, it is usually compared with the ANN model in articles (n = 3). However, in terms of accuracy, the ANN model performed better in all three articles. Other models, such as Bayesian network models [15] and Genetic algorithms [65], are all used in data-driven models.

The selection of input is an important step in developing the data-driven model. As can be seen in Table 3, pH is the most commonly used input variable (n = 7), which has a
great influence on the decay, odor emission, nutrient conversion, and loss rate in the composting process [15,59]. Others, such as moisture content (n = 6), EC (n = 5), C/N (n = 4), and temperature (n = 3), are also commonly used as input variables.

3.4. Application Scales

Overall, as can be seen from Table 4, most of the mathematical models are still in the scope of the laboratory (n = 18). Bonifacio et al. and Oudart et al. developed semi-empirical models for the farm scale since the simulation and data collection were based on a farm over several years [33,44,64]. Huang et al. modeled based on data from composting plants in the perspective of a factory [55]. In addition, Vasiliadou et al. conducted a modeling study in the scale of the olive plant from the industrial plant scale [49]. According to the modeling approaches, both mechanism-derived and data-driven models could be studied at different scales. The research on the lab scale is more concerned with the composting reaction process itself through describing the target variables in detail. In contrast, research from the industrial plant scale and farm scale tends to account for more indicators.

Table 4. The numbers of reviewed models according to applied scales.

| Applied Scales          | Number of Reviewed Models |
|-------------------------|---------------------------|
|                         | Mechanism-Derived Models | Data-Driven Models |
| Lab scale               | 7                         | 11                |
| Industrial plant scale  | 1                         | 1                 |
| Farm scale              | 2                         | 0                 |

3.5. Sensitivity Analysis and Validation

Sensitivity analysis and model validation are the main approaches to evaluating models [42]. Since the mechanism-derived models have more parameters, sensitivity analysis on the model is often conducted to assess the uncertainty of model parameters (n = 6). It was noted in these studies that the maximum growth rate coefficient [49,51,56] and mortality constant have a more considerable influence on the composting process parameters [51,52]. For the data-driven model, in addition to the conventional sensitivity analysis (n = 7), there is the adopting analysis of variance (ANOVA), which can also be used to achieve the purpose of sensitivity analysis (n = 3) in terms of selected input variables. For instance, the ANOVA of St Martin et al. indicated that composting formula, time and composting formula interacting through time had a significant impact on the variables such as temperature, total organic carbon (TOC), total Kjeldahl nitrogen (TKN), C/N, pH, and EC [53]. Li et al. showed that the effect of addition ratio and addition time on nitrogen loss was statically significant at the 95% confidential level through ANOVA [54].

After obtaining a model, to verify the accuracy of the model, the determination coefficient (R²) (n = 12) and root-mean-square error (RMSE) (n = 6) are the most commonly used methods to evaluate the quality of the fitting accuracy under the assumption that the parameters of the model are normally distributed. The calculation formulas are as follows [47]:

\[
RMSE = \frac{100}{E} \sqrt{\frac{\sum_{i=1}^{n} (S_i - E_i)^2}{n}} \tag{1}
\]

\[
R^2 = \frac{\sum_{i=1}^{n} (S_i - E_i)^2}{\sum_{i=1}^{n} (E_i - E)^2} \tag{2}
\]

where \(E, S_i, E_i\) and \(n\) are referred to as the averages of experimental values, simulated values, experimental values, and the number of samples, respectively.

Others, such as Nash–Sutcliffe efficiency (NSE), a normalized statistic used to determine the relative size of the residual variance compared to the variation of the measured
data, is also used to evaluate a model’s quality [51,52,70]. St Martin et al. adopted a parallel curve analysis to carry out variance accumulation analysis of the effect of compost type and time on physical and chemical parameter models [53].

3.6. Gaps with the Target Models Reflected by the Checklist

With the checklist, the scores of gaps ranged from 1.3 to 7.7, which can be seen in Figure 4. The model’s scores were only obtained in the checklist that we created to show the gaps between the target models. The checklist could efficiently describe the fates of C, N, P, and K during composting. It was not aimed to completely distinguish the advantages and disadvantages of models, but largely focused on checking whether these models fit the scope and subject of the review, and how well they fitted the procedures modeled. It can be seen from Figure 4 that the research of Faverial et al. was more in line with the scope of the review, while the overall modeling was also in line with the specification, having an excellent performance in accuracy [15]. The paper of Chen et al., a conference paper with limited space, also attracted our attention, in which their scores were affected as some modeling procedures may not be described in details [71]. The starting points of the model involve the target variables of modeling objectives; however, there are many models that do not fully include C, N, P, and K. When the starting points of the model are excluded from checklist results, there are more models that also perform very well.

![Figure 4](image)

Figure 4. Results of the checklist for defining gaps.

4. Discussion

The purpose of developing models for the fates of C, N, P, and K is to improve process operations and, more importantly, deepen our understanding of the process, so as to improve the utilization of nutrients and reduce greenhouse gas emissions to achieve co-benefits for building the regional circular economy [73]. Therefore, the mechanics and the accuracy of the models are significant for the realization of the above purpose. Mechanism-derived models are ideal models for revealing mechanisms; however, a lot of effort is required due to the complexity of the models. Moreover, the composting process is a
biochemical reaction process that involves physical phenomena, such as volatilization and leaching [74], which are often ignored by most of the mechanism-derived models, resulting in compromised accuracy. With the study of microbial communities, more and more composition information about a data-rich microbial community will be gained to significantly improve the performance of the model. For example, further knowledge of microbial growth coefficients and mortality coefficients, etc., contributed a lot to the description of microbial activity in the composting process [34]. Additionally, in order to be able to simulate more nutrients, such as P and K, a focus on this part of the research would advance the development of mechanism-derived models of composting that involve more fates of nutrients. As Oudart et al. mentioned, black-box models such as data-driven models, due to the ignorance of complex reaction processes, often cause difficulty in explaining the differences between the results of simulation and observation [44]. The selection of input variables, sensitivity and uncertainty analysis is precisely the part that can react to the mechanism of the composting process. So, for data-driven models, this study will advance their role in revealing mechanisms. The issue of data reliability, however, has always been one of the top priorities for data-driven models. The application of advanced monitoring technology in the composting process will provide the model with certain intermediate process parameters, thereby reducing the possible errors.

At present, most of the models are at lab scale, which tend to focus on the fate of the C and nutrients in the process during composting. For the models on industrial plant or farm scales, more factors will be incorporated, such as N run off and leaching on the surface [33], as the data come from a wider perspective. In order to describe the modeling of composting in agricultural production activities on a regional scale, more indicators should be included, such as greenhouse gas emissions, nutrient losses, and proxies for ecosystem service that result from material exchanges among stakeholders [75].

Meanwhile, the development of open science will also promote the progress of the model. It is worth mentioning that among the 22 selected models, the model of Bonifacio et al. is based on the Integrated Farm System Model (IFSM) [33], which is a public integrated farm research tool for many physical and biological processes [76]. In addition, huge amounts of empirical data are included to provide support for the development of the model. In addition, it can be found that the researchers working on these models gradually began to pay attention to the significance of open science for scientific progress. For instance, Faverial et al. obtained the highest score in the checklist and their paper can be openly accessed [15]. Another treatment technology, anaerobic digestion (AD), a unified and open model of Anaerobic Digestion Model No. 1 (ADM1) was proposed as early as in 2002, which undoubtedly has played a positive role in the development of the AD models. Furthermore, some databases such as PHYLLIS 2 database are gradually being established, which provide a large amount of reliable, high-quality, and shared biomass processing data as strong support for the development of data-driven models.

Regarding this research, some limitations are also worth our attention: First, the research on latest models involving the fates of C, N, P, and K was conducted in the time scope of past decade, and only English-written papers from Web of Science were selected, which means less involved models were selected. Second, as we focused more on C and nutrients balance, the overview of composting modeling in our research is not as comprehensive as that in some other review papers regarding modeling of the composting process [35]. In fact, as was mentioned by Mason and Walling et al., heat balance, moisture content balance, and oxygen content balance have an essential impact on composting. Furthermore, there is inevitable subjectivity when the checklist is used to assess models [24,35]. These models and scientific articles are peer-reviewed and have a high level of creativity. However, data extraction through listing codes and the checklist evaluation method we applied are based on our review scope and more in line with the modeling procedure. Therefore, a degree of subjectivity may occur in our research of the checklist, mainly due to the professional background of the reviewers. More reviewers or multiple rounds of reviews would help to reduce the subjectivity. More importantly, our study
intends to provide guidance for future model development in the field of modeling on the fates of C, N, P, and K during composting process.

5. Conclusion

In this study, a systematic review was performed on the composting models involving C, N, P, and K. After reviewing the existing literature, 22 composting models were selected with the process of study selection. The application of a code-listing data extraction method could provide a framework for a better summary and cross-model comparisons. In addition, the characteristics and features of these 22 models were presented after data extraction. A checklist for composting models was created to define the gap between existing models and target models. The aim was to find the best fitting model for the composting of various types of substrates. According to the modeling approaches, 22 models were divided into two categories: the mechanism-derived models and the data-driven models. The results of the checklist showed that the score of the mechanism-driven models was slightly higher than that of the data-driven models. The main reason is that the description of the selection basis of variables is ignored in some data-driven models, resulting in a deficiency in highlighting the mechanism of the composting process.

The mechanism-derived model does not involve the simulation of the mass balance of K. Through the sensitivity analysis in these studies, it is found that maximum growth rate coefficients and mortality constants are the main factors for the kinetics parameters. Although the mechanism-derived model is complicated, adopting the method of substrates fractionation has reduced the complexity and improved the accuracy. At the same time, proposing a model framework such as ADM1 is also an approach to reducing the complexity of the model. With the development of artificial intelligence algorithms, data-driven models can cover more target variables involving more nutrients. However, how to reveal the mechanism of the composting process based on the selection of input variables and the establishment of a reliable database still needs some further research.

From the perspective of the model supporting the circular economy assessment at a regional scale, the focus should be on more indicators and high accuracy of models. On a larger scale, more indicators will be included in the modeling to allow for a more comprehensive assessment of circularity. At the same time, it is a scale-up process that requires a high level of accuracy for small scale models in order to ensure the accuracy of the regional model. These set requirements for the future development of composting models.

Abbreviations

| Abbreviation | Description                      |
|--------------|----------------------------------|
| AD           | Anaerobic digestion              |
| ADM1         | Anaerobic Digestion Model No. 1  |
| ANN          | Artificial neural network        |
| ANOVA        | Adopting analysis of variance    |
| BP           | Backpropagation                  |
| BVS          | Biodegradable volatile solids    |
| C            | Carbon                           |
| CH\(_4\)     | Methane                          |
| CO\(_2\)     | Carbon dioxide                   |
| C/N          | Carbon-to-nitrogen ratio         |
| DM           | Dry matter                       |
| EC           | Electrical conductivity          |
| IFSM         | Integrated Farm System Model     |
| K            | Potassium                        |
| MC           | Microbial carbon                 |
| MLP          | Multilayer perceptron            |
| MLR          | Multiple linear regression       |
Processes 2021, 9, 473

| Abbreviation | Description |
|--------------|-------------|
| MN | Microbial nitrogen |
| MSW | Municipal solid waste |
| N | Nitrogen |
| NH₃ | Ammonia |
| N₂O | Nitrous oxide |
| NSE | Nash–Sutcliffe efficiency |
| OC | Organic carbon |
| ON | Organic nitrogen |
| P | Phosphorus |
| R² | Determination coefficient |
| RBF | Radial basis functional |
| RMSE | Root-mean-square error |
| TC | Total carbon |
| TK | Total potassium |
| TKN | Total Kjeldahl nitrogen |
| TN | Total nitrogen |
| TOC | Total organic carbon |
| TP | Total phosphorus |
| VOC | Volatile organic compounds |

**Supplementary Materials:** The following are available online at www.mdpi.com/2227-9717/9/3/473/s1, Table S1: Code list of target variables related to modeling objects, Table S2: Code list of mechanism-derived model types, Table S3: Code list of data-driven model types, Table S4: Code list of applied scale types, Table S5: Summary of 22 models.

**Author Contributions:** Conceptualization and supervision, V.S.R.; methodology, Z.Y.; formal analysis, Z.Y., F.M., H.M., O.C.L., and B.X.; data curation, Z.Y.; writing—original draft preparation, Z.Y.; writing—review and editing, Z.Y., V.S.R., and B.X.

**Funding:** This study was supported by the China Scholarship Council Scholarship (No.201908320362) and the project “URA” (No. 01LE1804A1) funded by German Federal Ministry of Education and Research and German Aerospace Center.

**Acknowledgments:** The authors would also like to thank Jiawei Hu for his contribution to the checklist scoring work and Bo Sun of the Institute of Soil Science, Chinese Academy of Sciences, for reviewing and suggesting the checklist results. We acknowledge support by the German Research Foundation and the Open Access Publication Fund of Technische Universität Berlin.

**Conflicts of Interest:** The authors declare no conflict of interest.

**References**

1. Yalcinkaya, S. A spatial modeling approach for siting, sizing and economic assessment of centralized biogas plants in organic waste management. *J. Clean. Produc.* 2020, 255, 120040, doi:10.1016/j.jclepro.2020.120040.

2. Dhanya, B.S.; Mishra, A.; Chandel, A.K.; Verma, M.L. Development of sustainable approaches for converting the organic waste to bioenergy. *Sci. Total Environ.* 2020, 723, 138109, doi:10.1016/j.scitotenv.2020.138109.

3. Guo, H.-N.; Wu, S.-B.; Tian, Y.-J.; Zhang, J.; Liu, H.-T. Application of machine learning methods for the prediction of organic solid waste treatment and recycling processes: A review. *Bioresour. Technol.* 2021, 319, 124114, doi:10.1016/j.biortech.2020.124114.

4. Chen, T.; Zhang, S.; Yuan, Z. Adoption of solid organic waste composting products: A critical review. *J. Clean. Prod.* 2020, 272, 122712, doi:10.1016/j.jclepro.2020.122712.

5. Mor, S.; Ravendra, K.; Dahiya, R.P.; Chandra, A. Leachate characterization and assessment of groundwater pollution near municipal solid waste landfill site. *Environ. Monit. Assess.* 2006, 118, 435–456, doi:10.1007/s10661-006-1505-7.

6. Onwosi, C.O.; Igboke, V.C.; Odimba, J.N.; Eke, I.E.; Nwankwoala, M.O.; Iroh, I.N.; Ezeogu, L.I. Composting technology in waste stabilization: On the methods, challenges and future prospects. *J. Environ. Manag.* 2017, 190, 140–157, doi:10.1016/j.jenvman.2016.12.051.

7. Mayer, F.; Bhandari, R.; Gäth, S. Critical review on life cycle assessment of conventional and innovative waste-to-energy technologies. *Sci. Total Environ.* 2019, 672, 708–721, doi:10.1016/j.scitotenv.2019.03.449.
8. Wainaina, S.; Awasthi, M.K.; Sarsaiya, S.; Chen, H.; Singh, E.; Kumar, A.; Ravindran, B.; Awasthi, S.K.; Liu, T.; Duan, Y.; et al. Resource recovery and circular economy from organic solid waste using aerobic and anaerobic digestion technologies. Bioreour. Technol. 2020, 301, 122778, doi:10.1016/j.biortech.2020.122778.

9. Aguelmous, A.; El Fels, L.; Souabi, S.; Zamama, M.; Hafidi, M. The fate of total petroleum hydrocarbons during oily sludge composting: A critical review. Rev. Environ. Sci. Biotechnol. 2019, 18, 473–493, doi:10.1007/s11157-019-09509-w.

10. Kulkarni, M.B.; Ghaneagaonkar, P.M. Biogas generation from floral waste using different techniques. Glob. J. Environ. Sci. Manag. 2019, 5, 17–30, doi:10.22034/gjesm.2019.01.02.

11. Fernandez-Bayo, J.D.; Yazdani, R.; Simmons, C.W.; VanderGheynst, J.S. Comparison of thermophilic anaerobic and aerobic treatment processes for stabilization of green and food wastes and production of soil amendments. Waste Manag. 2018, 77, 555–564, doi:10.1016/j.wasman.2018.05.006.

12. Liu, Z.; Wang, X.; Wang, F.; Bai, Z.; Chadwick, D.; Misselbrook, T.; Ma, L. The progress of composting technologies from static heap to intelligent reactor: Benefits and limitations. J. Clean. Prod. 2020, 122328, doi:10.1016/j.jclepro.2020.122328.

13. Cerda, A.; Artola, A.; Font, X.; Barrena, R.; Gea, T.; Sánchez, A. Composting of food wastes: Status and challenges. Bioreour. Technol. 2018, 248, 57–67, doi:10.1016/j.biortech.2017.06.133.

14. Li, H.; Chen, Z.; Fu, D.; Wang, Y.; Zheng, Y.; Li, Q. Improved ADM1 for modelling C, N, P fates in anaerobic digestion process of pig manure and optimization approaches to biogas production. Renew. Energy 2020, 146, 2330–2336, doi:10.1016/j.renene.2019.08.086.

15. Faveria, J.; Cornet, D.; Paul, J.; Sierra, J. Multivariate Analysis of the Determinants of the End-Product Quality of Manure-Based Composts and Vermicomposts Using Bayesian Network Modelling. PLoS ONE 2016, 11, e0157884, doi:10.1371/journal.pone.0157884.

16. Galvez-Sola, L.; Morales, J.; Mayoral, A.M.; Marhuenda-Egea, F.C.; Martinez-Sabater, E.; Perez-Murcia, M.D.; Bustamante, M.A.; Paredes, C.; Moral, R. Estimation of phosphorus content and dynamics during composting: Use of near infrared spectroscopy. Chemosphere 2010, 78, 13–21, doi:10.1016/j.chemosphere.2009.09.059.

17. Tiquia, S.M.; Richard, T.L.; Honeyman, M.S. Carbon, nutrient, and mass loss during composting. Nutr. Cycl. Agroecosyst. 2002, 62, 15–24, doi:10.1023/A:1020337922816.

18. Eghball, B.; Power, J.F.; Gilley, J.E.; Doran, J.W. Nutrient, Carbon, and Mass Loss during Composting of Beef Cattle Feedlot Manure. J. Environ. Qual. 1997, 26, 189–193, doi:10.2134/eq1997.00472425002600010027x.

19. Zhao, S.; Schmidt, S.; Qin, W.; Li, J.; Li, G.; Zhang, W. Towards the circular nitrogen economy—A global meta-analysis of composting technologies reveals much potential for mitigating nitrogen losses. Sci. Total Environ. 2020, 704, 135401, doi:10.1016/j.scitotenv.2019.135401.

20. Qu, J.; Zhang, L.; Zhang, X.; Gao, L.; Tian, Y. Biochar combined with gypsum reduces both nitrogen and carbon losses during agricultural waste composting and enhances overall compost quality by regulating microbial activities and functions. Bioreour. Technol. 2020, 314, 123781, doi:10.1016/j.biortech.2020.123781.

21. Abdel-Shafy, H.L.; Mansour, M.S.M. Solid waste issue: Sources, composition, disposal, recycling, and valorization. Egypt. J. Pet. 2018, 27, 1275–1290, doi:10.1016/j.ejpe.2018.07.003.

22. Oladele, S.O.; Adetunj; A.T. Agro-residue biochar and N fertilizer addition mitigates CO2-C emission and stabilized soil organic carbon pools in a rain-fed agricultural cropland. Int. Soil Water Conserv. Res. 2020, doi:10.1016/j.iswcr.2020.09.002.

23. Petric, I.; Selimbasic, V. Development and validation of mathematical model for aerobic composting process. Chem. Eng. J. 2008, 139, 304–317, doi:10.1016/j.cej.2007.08.017.

24. Mason, J.G. Mathematical modelling of the composting process: A review. Waste Manag. 2006, 26, 3–21, doi:10.1016/j.wasman.2005.01.021.

25. Wang, Y.; Niu, W.; Ai, P. Assessing thermal conductivity of composting reactor with attention on varying thermal resistance between compost and the inner surface. Waste Manag. 2016, 58, 144–151, doi:10.1016/j.wasman.2016.09.018.

26. Wang, Y.; Ai, P.; Cao, H.; Liu, Z. Prediction of moisture variation during composting process: A comparison of mathematical models. Bioreour. Technol. 2015, 193, 200–205, doi:10.1016/j.biortech.2015.06.100.

27. Ma, S.; Sun, X.; Fang, C.; He, X.; Han, L.; Huang, G. Exploring the mechanisms of decreased methane during pig manure and wheat straw aerobic composting covered with a semi-permeable membrane. Waste Manag. 2018, 78, 393–400, doi:10.1016/j.wasman.2018.06.005.

28. He, X.; Han, L.; Ge, J.; Huang, G. Modelling for reactor-style aerobic composting based on coupling theory of mass-heat-momentum transport and Contois equation. Bioreour. Technol. 2018, 253, 165–174, doi:10.1016/j.biortech.2018.01.040.

29. Zambra, C.E.; Moraga, N.O.; Escudery, M. Heat and mass transfer in unsaturated porous media: Moisture effects in compost piles self-heating. Int. J. Heat Mass Transf. 2011, 54, 2801–2810, doi:10.1016/j.ijheatmasstransfer.2011.01.031.

30. Zambra, C.E.; Rosales, C.; Moraga, N.O.; Ragazzi, M. Self-heating in a bio reactor: Coupling of heat and mass transfer with turbulent convection. Int. J. Heat Mass Transf. 2011, 54, 5077–5086, doi:10.1016/j.ijheatmasstransfer.2011.07.025.

31. Alavi, N.; Sarmadi, K.; Goudarzi, G.; Babaei, A.A.; Bakshhoodeh, R.; Paydary, P. Attenuation of tetracyclines during chicken manure and bagasse co-composting: Degradation, kinetics, and artificial neural network modeling. J. Environ. Manag. 2019, 231, 1203–1210, doi:10.1016/j.jenvman.2018.11.003.

32. Fernandez-Mena, H.; MacDonald, G.K.; Pellerin, S.; Nesme, T. Co-benefits and Trade-Offs From Agro-Food System Redesign for Circularity: A Case Study With the FAN Agent-Based Model. Front. Sustain. Food Syst. 2020, 4, 41, doi:10.3389/fsufs.2020.00041.
33. Bonifacio, H.F.; Rotz, C.A.; Richard, T.L. A Process-Based Model for Cattle Manure Compost Windrows: Part 1. Model Description. Trans. ASABE 2017, 60, 877–892, doi:10.13031/trans.12057.

34. Lauwers, J.; Appels, L.; Thompson, I.P.; Degrève, J.; van Impe, J.F.; Dewil, R. Mathematical modelling of anaerobic digestion of biomass and waste: Power and limitations. Prog. Energy Combust. Sci. 2013, 39, 383–402, doi:10.1016/j.pecs.2013.03.003.

35. Walling, E.; Trémier, A.; Vaneckhaute, C. A review of mathematical models for composting. Waste Manag. 2020, 113, 379–394, doi:10.1016/j.wasman.2020.06.018.

36. Li, S.; Fang, Y.; Wu, X. A systematic review of lean construction in Mainland China. J. Clean. Prod. 2020, 257, 120581, doi:10.1016/j.jclepro.2020.120581.

37. Heyman, A.; Law, S.; Berghauer Pont, M. How is Location Measured in Housed Valuation? A Systematic Review of Accessibility Specifications in Hedonic Price Models. Urban Sci. 2019, 3, 3, doi:10.3390/urbanSci3010003.

38. Jia, F.; Peng, S.; Green, J.; Koh, L.; Chen, X. Soybean supply chain management and sustainability: A systematic literature review. J. Clean. Prod. 2020, 255, 120254, doi:10.1016/j.jclepro.2020.120254.

39. Wijewardhana, U.A.; Meyer, D.; Jayawardena, M. Statistical models for the persistence of threatened birds using citizen science data: A systematic review. Glob. Ecol. Conserv. 2020, 21, e00821, doi:10.1016/j.gecco.2019.e00821.

40. Harris, R.C.; Sumner, T.; Knight, G.M.; White, R.G. Systematic review of mathematical models exploring the epidemiological impact of future TB vaccines. Hum. Vaccin. Immunother. 2016, 12, 2813–2832, doi:10.1080/21645515.2016.1205769.

41. Downs, S.H.; Black, N. The feasibility of creating a checklist for the assessment of the methodological quality both of randomised and non-randomised studies of health care interventions. J. Epidemiol. Community Health 1998, 52, 377, doi:10.1136/jech.52.6.377.

42. Shiflet, A.B.; Shiflet, G.W. Introduction to Computational Science: Modeling and Simulation for the Sciences, 2nd ed.; Princeton University Press: Princeton, NJ, USA, 2014; ISBN 9781400850556.

43. Lin, Y.P.; Huang, G.H.; Lu, H.W.; He, L. Modeling of substrate degradation and oxygen consumption in waste composting processes. Waste Manag. 2008, 28, 1375–1385, doi:10.1016/j.wasman.2007.09.016.

44. Oudart, D.; Robin, P.; Paillat, J.M.; Paul, E. Modelling nitrogen and carbon interactions in composting of animal manure in naturally aerated piles. Waste Manag. 2016, 58, 588–598, doi:10.1016/j.wasman.2015.07.044.

45. Calisti, R.; Regni, L.; Priotti, P. Compost-recipe: A new calculation model and a novel software tool to make the composting mixture. J. Clean. Prod. 2020, 22427, doi:10.1016/j.jclepro.2020.122427.

46. Douglas, P.; Tyrrer, S.F.; Kimmersley, R.P.; Whelan, M.; Longhurst, P.J.; Walsh, K.; Pollard, S.J.T.; Drew, G.H. Sensitivity of predicted bioaerosol exposure during low wind window composting facilities to ADAMS dispersion model parameters. J. Environ. Manag. 2016, 184, 448–455, doi:10.1016/j.jenvman.2016.10.003.

47. Oudart, D.; Paul, E.; Robin, P.; Paillat, J.M. Modeling organic matter stabilization during windrow composting of livestock effluents. Environ. Technol. 2012, 33, 2235–2243, doi:10.1080/09593330.2012.728736.

48. Ge, J.; Huang, G.; Huang, J.; Zeng, J.; Han, L. Particle-Scale Modeling of Methane Emission during Pig Manure/Wheat Straw Aerobic Composting. Environ. Sci. Technol. 2016, 50, 4374–4383, doi:10.1021/acs.est.5b04141.

49. Vassiliadou, I.A.; Muktidirul Bari Chowdhury, A.K.M.; Akratos, C.S.; Tekerlekopoulou, A.G.; Pavlou, S.; Vayenas, D.V. Mathematical modeling of olive mill waste composting process. Waste Manag. 2015, 43, 61–71, doi:10.1016/j.wasman.2015.06.038.

50. Villaseñor, J.; Rodriguez Mayor, L.; Rodriguez Romero, L.; Fernández, F.J. Simulation of carbon degradation in a rotary drum pilot scale composting process. J. Environ. Manag. 2012, 108, 1–7, doi:10.1016/j.jenvman.2012.04.030.

51. Zhang, Y.; Lashermes, G.; Houot, S.; Doublet, J.; Steyer, J.P.; Zhu, Y.G.; Barriuso, E.; Garnier, P. Modelling of organic matter dynamics during the composting process. Waste Manag. 2012, 32, 19–30, doi:10.1016/j.wasman.2011.09.008.

52. Lashermes, G.; Zhang, Y.; Houot, S.; Steyer, J.P.; Fatoureaux, D.; Barriuso, E.; Garnier, P. Simulation of Organic Matter and Pollutant Evolution during Composting: The COP-Compost Model. J. Environ. Qual. 2013, 42, 361–372, doi:10.2134/jeq2012.0141.

53. St Martin, C.C.G.; Bekele, I.; Eudoxie, G.D.; Bristol, D.; Brathwaite, R.A.I.; Campo, K.-R. Modelling response patterns of physicochemical indicators during high-rate composting of green waste for suppression of Pythium ultimum. Environ. Technol. 2014, 35, 590–601, doi:10.1080/09593330.2013.839719.

54. Li, W.; Wu, C.; Wang, K.; Meng, L.; Lv, L. Nitrogen loss reduction by adding sucrose and beet pulp in sewage sludge composting. Int. Biodeterior. Biodegrad. 2017, 124, 297–303, doi:10.1016/j.ibiod.2017.03.013.

55. Huang, G.; Wang, X.; Han, L. Rapid estimation of nutrients in chicken manure during plant-field composting using physicochemical properties. Bioresour. Technol. 2011, 102, 1455–1461, doi:10.1016/j.biortech.2010.09.086.

56. Petric, I.; Mustafić, N. Dynamic modeling the composting process of the mixture of poultry manure and wheat straw. J. Environ. Manag. 2015, 161, 392–401, doi:10.1016/j.jenvman.2015.07.033.

57. Li, Z.; Lu, H.; Ren, L.; He, L. Experimental and modeling approaches for food waste composting: A review. Chemosphere 2013, 93, 1247–1257, doi:10.1016/j.chemosphere.2013.06.064.

58. Kabbashi, N. Sewage sludge composting simulation as carbon/nitrogen concentration change. J. Environ. Sci. 2011, 23, 1925–1928, doi:10.1016/S1001-0742(10)60642-0.

59. Boniecki, P.; Dach, J.; Pilarski, K.; Piekar ska-Boniecka, H. Artificial neural networks for modeling ammonia emissions released from sewage sludge composting. Atmos. Environ. 2012, 57, 49–54, doi:10.1016/j.atmosenv.2012.04.036.

60. Haug, R.T. The Practical Handbook of Compost Engineering; Lewis Publishers: Boca Raton, FL, USA, 1993; ISBN 0873713737.

61. Wang, Y.; Huang, G.; Zhang, A.; Han, L.; Ge, J. Estimating thermal balance during composting of swine manure and wheat straw: A simulation method. Int. J. Heat Mass Transf. 2014, 75, 362–367, doi:10.1016/j.ijheatmasstransfer.2014.03.083.
62. Hamelers, H.V.M. A Mathematical Model for Composting Kinetics; Rulkens, W.H., van Straten, G., Eds.; Wageningen University: Wageningen, The Netherlands, 2001; ISBN 90-5808-445-0.

63. Hamelers, H.V.M. Modeling composting kinetics: A review of approaches. Rev. Environ. Sci. Biotechnol. 2004, 3, 331–342, doi:10.1007/s11157-004-2335-0.

64. Bonifacio, H.F.; Rotz, C.A.; Richard, T.L. A Process-Based Model for Cattle Manure Compost Windrows: Part 2. Model Performance and Application. Trans. ASABE 2017, 60, 893–913, doi:10.13031/trans.12058.

65. Sun, W.; Huang, G.H.; Zeng, G.; Qin, X.; Yu, H. Quantitative effects of composting state variables on C/N ratio through GA-aided multivariate analysis. Sci. Total Environ. 2011, 409, 1243–1254, doi:10.1016/j.scitotenv.2010.12.023.

66. Bayram, A.; Kankal, M.; Ozsahin, T.; Saka, F. Estimation of the carbon to nitrogen (C:N) ratio in compostable solid waste using artificial neural networks. Fresenius Environ. Bull. 2011, 20, 3250–3257.

67. Hossein-zadeh, A.; Baziar, M.; Alidadi, H.; Zhou, J.L.; Altae, A.; Najafpoor, A.A.; Jafarpour, S. Application of artificial neural network and multiple linear regression in modeling nutrient recovery in vermicompost under different conditions. Bioresour. Technol. 2020, 303, 122926, doi:10.1016/j.biortech.2020.122926.

68. Diaz, M.J.; Eugenio, M.E.; López, F.; García, J.C.; Yañez, R. Neural Models for Optimizing Lignocellulosic Residues Composting Process. Waste Biomass Valor 2012, 3, 319–331, doi:10.1007/s12649-012-9121-y.

69. Mancebo, U.; Hettiaratchi, J.P.A. Rapid assessment of methanotrophic capacity of compost-based materials considering the effects of air-filled porosity, water content and dissolved organic carbon. Bioresour. Technol. 2015, 177, 125–133, doi:10.1016/j.biortech.2014.11.058.

70. Varma, V.S.; Kalamdhad, A.S.; Kumar, B. Optimization of waste combinations during in-vessel composting of agricultural waste. Waste Manag. Res. 2017, 35, 101–109, doi:10.1177/0734242X16678068.

71. Chen, H.; Sun, S.; Zhang, B. Forecasting N 2 O emission and nitrogen loss from swine manure composting based on BP neural network. MATEC Web Conf. 2019, 277, 1010, doi:10.1051/matecconf/201927701010.

72. Abdallah, M.; Abu Talib, M.; Feroz, S.; Nasir, Q.; Abdalla, H.; Mahfood, B. Artificial intelligence applications in solid waste management: A systematic research review. Waste Manag. 2020, 109, 231–246, doi:10.1016/j.wasman.2020.04.057.

73. Solle, D.; Hitzmann, B.; Herwig, C.; Pereira Remelhe, M.; Ulonska, S.; Wuerth, L.; Prata, A.; Steckenreiter, T. Between the Poles of Data-Driven and Mechanistic Modeling for Process Operation. Chem. Eng. Tech. 2017, 89, 542–561, doi:10.1002/ceat.201600175.

74. Roy, D.; Azaïs, A.; Benkarache, S.; Drogui, P.; Tyagi, R.D. Composting leachate: Characterization, treatment, and future perspectives. Rev. Environ. Sci. Biotechnol. 2018, 17, 323–349, doi:10.1007/s11157-018-9462-5.

75. Fernandez-Mena, H.; Gaudou, B.; Pellerin, S.; MacDonald, G.K.; Nesme, T. Flows in Agro-food Networks (FAN): An agent-based model to simulate local agricultural material flows. Agric. Syst. 2020, 180, 102718, doi:10.1016/j.agsy.2019.102718.

76. Rotz, C.A.; Corson, M.; Chianese, D.; Coiner, C. The Integrated Farm System Model; Pasture Systems and Watershed Management Research Unit Agricultural Research Service United States Department of Agriculture: Washington, DC, USA, 2012.