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Review

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

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Citation: Yang, Z.; Muhayodin, F.; Larsen, O.; Miao, H.; Xue, B.; Rotter, V. A Review of Composting Process Models of Organic Solid Waste with a Focus on the Fates of C, N, P, and K. *Processes* **2021**, *9*, 473. https://doi.org/10.3390/pr9030473

Academic Editor: Antoni Sánchez

Received: 16 February 2021
Accepted: 3 March 2021
Published: 6 March 2021

Table S1. Code list of target variables related to modeling objects.

No.	Target Variables Related to Modeling Objects	Description
1	C	Carbon
2	OC	Organic carbon
3	CO_2	Carbon dioxide
4	TC	Total carbon
5	TN	Total nitrogen
6	MC	Microbial carbon
7	ON	Organic nitrogen
8	MN	Microbial nitrogen
9	CH_4	Methane
10	NH_3	Ammonia
11	N_2O	Nitrous oxide
12	NH_4^+	Ammonium
13	NO_3^-	Nitrate
14	P	Phosphorus
15	N	Nitrogen
16	C/N	Carbon to nitrogen ratio
17	TOC	Total organic carbon
18	TKN	Total Kjeldahl nitrogen
19	TP	Total phosphorus
20	TK	Total potassium

Table S2. Code list of mechanism-derived model types.

No.	Mechanism-Derived Model Types	Description
1	MK	Monod kinetics model
2	FK	First-order kinetics model
3	MB	Mass balance model
4	HB	Heat (energy) balance model
5	MM	Michaelis–Menten kinetics model
6	SE	Semi-empirical model
7	MS	Multi-stage model
8	PB	Process-based model

Table S3. Code list of data-driven model types.

No.	Data-Driven Model Types	Description
1	GA	Genetic algorithm aided by the stepwise cluster analysis method
2	LR	Linear regression analysis
3	MLR	Multiple linear regression
4	ANN	Artificial neural network
5	ANFIS	An adaptive network-based fuzzy inference system
6	CEF	Critical exponential function
7	RHF	Rectangular hyperbola function
8	FF	Fourier function
9	BN	Bayesian network model
10	RM	Regression model
11	RBFNN	Radial basis functional neural network model

12	BPNN	Backpropagation neural network model

Table S4. Code list of applied scale types.

No.	Applied Environment Types	Description
1	LS	Lab scale
2	IpS	Industrial plant scale
3	FmS	Farm scale

Table S5. Summary of 22 models.

No.	Types	Target Variables Related to Modeling Objects	Applied Environment	Characteristics and Features	References
1	ANN MLR	C/N	LS	7 input variables (the proportions of food and yard, ash and scoria waste, the moisture content, the fixed carbon content, the total amount of organic matter, high calorific value, and pH) of 52 waste samples were collected for modeling.	Bayram et al. 2011 [66]
2	LR	TN, TP, and TK	IpS	A total of 147 samples were collected in different stages during composting. pH, EC, and dry matter content were selected as input variables.	Huang et al. 2011 [55]
3	SE MS	TC and TN	LS	4 equations and 7 parameters were included for modeling.	Kabbashi 2011 [58]
4	GA	C/N	LS	5 input variables such as $NH_4{}^+-N$ concentration, moisture content, ash content, mean temperature, and mesophilic bacteria biomass of 198 samples were included.	Sun et al. 2011 [65]
5	ANN	NH_3	LS	Models contain 7 input variables (chemical and physical parameters of composting) and 1 output (ammonia emission). 550 cases of data were included.	Boniecki et al. 2012 [59]
6	ANFIS	CO_2	LS	4 input variables (aeration, moisture, particle size, composting time) 48 groups data were collected for modeling	Díaz et al. 2012 [68]
7	MK FK MB	CO_2	LS	10 equations and 42 parameters were included.	Oudart et al. 2012 [47]
8	FK	C	LS	5 equations were included.	Villaseñor et al. 2012 [50]
9	MK FK MB	CO_2	LS	7 equations were included.	Zhang et al. 2012 [51]

10	MK FK MB	OC and CO_2	LS	10 equations, 21 parameters and 12 variables were included.	Lashermes et al. 2013 [52]
11	CEF RHF FF MLR	TOC and TKN	LS	Composting formula, time and composting formula interacting through the time of 54 groups data were selected as input variables.	St Martin et al. 2014 [53]
12	RM	CH_4	LS	3 input variables, such as air-filled porosity, moisture content, and dissolved OC content of 14 groups of data, were included.	Mancebo and Hettiaratchi 2015 [69]
13	SE PB	CO_2, N_2O and NH_3	FmS	10 equations and 55 parameters were included.	Oudart et al. 2015 [44]
14	MK MB HB	CO_2	LS	27 (8 ordinary differential equations) and 35 parameters were included.	Petric and Mustafić 2015 [56]
15	MK FK MB HB	N and P, and CO_2	IpS	22 equations were included.	Villaseñor et al. 2012 [50]
16	BN	TN, TP, and TK	LS	68 composts and vermicomposts that were analyzed for their C, lignin and NPK contents throughout the composting process.	Faverial et al. 2016 [15]
17	FK MM HB MB	CH_4	LS	10 equations were included.	Ge et al.2016 [48]
18	SE PB	OC, MC, ON, MN, $NH_4{}^+$, $NO_3{}^-$, CO_2, N_2O, and NH_3	FmS	26 equations and 96 parameters were included.	Bonifacio et al. 2017 [33,59]
19	RM	TN	LS	3 input variables, such as sucrose-adding ratio, adding time, sucrose concentration of 15 groups of data, were included.	Li et al. 2017 [54]
20	RBFNN	CO_2	LS	Data from 2 combinations of 20-day duration experiments were analyzed for modeling. Input variables included moisture content, pH, EC, TOC, TKN, soluble biochemical oxygen demand, $NH_4{}^+-N$ concentration, available phosphorous, C/N, total phosphorous, oxygen uptake rate, Na, K, Ca.	Varma et al. 2017 [70]
21	BPNN LR	N_2O	LS	68 groups data from 11 published papers were collected for modeling. 4 inputs were selected as input variables; they are C/N, moisture	Chen et al. 2019 [71]

				content, aeration rate, and superphosphate content.	
22	ANN MLR	TN and TP	LS	pH, EC, C/N, $NH_4{}^+/NO_3{}^-$, water-soluble carbon, dehydrogenase enzyme, and total phosphorus are selected as variables. 20 groups of data were included.	Hosseinzadeh et al. 2020 [67]

EC (electrical conductivity); **DM** (dry matter).

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