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A model to identify entry points to curb emissions from complex manure management chains

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ABSTRACT

Livestock operations deploy increasingly complex facilities and technologies in manure management to reduce negative environmental impacts and to improve the agronomic value of manures. To capture and quantify processes of degradation, conversion and emission of manure constituents in these complex systems, this study presented a newly developed modular manure management (FarmM3) model. Using this model, we simulated flows and losses of manure organic matter (OM), carbon (C), nitrogen (N), phosphorus (P) and potassium (K) from manure management chains (MMCs) with deep litter, anaerobic lagoon, solid-liquid separation (SLS), anaerobic digestion (AD), and combinations of SLS and AD. The sensitivity of degradation and losses of manure constituents to changes in the configuration and parameters of MMCs was assessed. Results showed the MMCs with deep litter and AD led to higher OM degradation, C losses and greenhouse gas (GHG) emissions due to the substantial amounts of straw added to bedding and the digester. A trade-off between GHG and ammonia emissions was identified in the MMCs with deep litter. Application of SLS could reduce GHG emissions by 40% to 60% due to reduced methane and nitrous oxide emissions from separated liquid fraction storage. A stronger reduction of ammonia emission was observed when applying SLS to digested slurry than to raw slurry. Sensitivity analysis showed that the N loss was most sensitive to N transformation in the MMC with deep litter, and was most affected by the loss coefficients of ammonia during liquid manure storage and application in MMCs with SLS and AD. Losses of P and K from MMCs with SLS were influenced by separation efficiencies from SLS and loss coefficients from solid fraction storage. The impact of model input parameters on GHG emissions highly depended on the selected manure management facilities. This study shows that manure management facilities have a strong influence on the fate of manure constituents. The FarmM3 model can be used to quantify the degradation and losses of different manure constituents in complex MMCs and the effects of manure treatment facilities, and to identify the most important parameters determining these losses.

1. Introduction

The intensification and specialization of dairy production resulted in the decoupling of crop and dairy farming. With a substantial amount of produced manure but few available lands, these intensive dairy farming systems posed detrimental impacts on the environment, such as gaseous emissions, groundwater and surface waters pollution, and excessive use of feed additives (e.g., heavy metals, antibiotics, micronutrients) (Oenema et al., 2007; Kuppusamy et al., 2018). To reduce the environmental risk of gaseous emissions and other nutrient losses and to increase operational flexibility in manure management, various emerging manure management facilities are available and prioritized in dairy farms with high animal density (Hou et al., 2018; Tan et al., 2021; Niles et al., 2022). For example, solid-liquid separation (SLS) can be used to separate slurry into a diluted liquid fraction and a nutrient-rich solid fraction using different types of mechanical separators, which not only could increase manure fertilizer value but also facilitate exporting solid fractions to avoid nutrient surpluses within farms (Hjorth et al., 2010; Sommer et al., 2013). Anaerobic digestion (AD) has been used to produce biogas (a mixture of methane and carbon dioxide) as a source of alternative energy by breaking down manure OM in the absence of oxygen (Foged et al., 2011), and has been proven to reduce GHG emissions

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(Aguirre-Villegas and Larson, 2017; Holly et al., 2017).

Application of these management facilities may induce changes in physical, chemical and/or biological properties of manure and hence influence the decomposition of OM and carbon (C), and the fate of nutrients within manure management chains (MMCs) (Hou, 2016; Khalil et al., 2016). Aguirre-Villegas et al. (2019) found that applying SLS could retain more total solids and volatile solids but much less total ammoniacal nitrogen and total potassium in separated solid fractions, which resulted in both greenhouse gas (GHG) and ammonia (NH_3) reductions from storage and land application compared to a scenario without SLS. AD alone and combined AD and SLS could reduce GHG emissions due to reduction of the quantity of volatile solids in liquid manure storage but could also lead to increased NH_3 emissions due to the increased total ammoniacal nitrogen from mineralization of organic nitrogen during digestion.

Given the possible interactive effects of manure management facilities on emissions, the importance of integrated modelling approaches in estimating gaseous emissions and nutrient flows from a whole chain perspective has been pointed out (Hou, 2016; Sajeev et al., 2018; Wei et al., 2021). Table A.1 provides a list of existing integrated modelling approaches. However, most of these approaches mainly focus on traditional manure management facilities, i.e., a linear process of manure excretion, manure storage and application. Few of them allow to integrate the emerging on-farm manure management facilities (e.g., SLS, AD, composting, etc.) and enable to evaluate the impacts of these new manure management facilities on nutrient losses along the whole MMC. Pardo et al. (2017) designed a module ($SIMS_{WASTE\text{-}AD}$) to calculate gases emissions from AD processes, but the new module was aimed to be applied within the $SIMS_{DAIRY}$ modelling framework (Del Prado et al., 2011) to account for potential effects of AD on nutrient flows. Dairy-CropSyst developed by Khalil et al. (2019) allowed to evaluate the effects of diverse manure management facilities (AD, separation and nutrient recovery) on nutrient fate through MMCs with liquid manure handling systems with lagoons, while not addressing solid manure handling systems in MMCs. Sefeedpari et al. (2019) introduced a process-based analysis model that can be used to calculate degradation and losses of manure constituents through MMCs with different manure management facilities. However, Sefeedpari et al. (2019) only quantified the quality of final products to applied fields without estimating the losses of manure constituents from manure application, which might not be able to fully capture the interactive effects of manure management facilities on nutrient losses since the reduced losses before application might lead to increased losses after application (Shah et al., 2013).

The approaches listed in Table A.1 focus on only one or a few manure constituents or gaseous emissions (NH_3, N_2O, CH_4, GHG, etc.), and conversions and losses of manure OM and C, phosphorus (P) and potassium (K) from MMCs are sparsely considered. It was reported that over 50% of the excreted manure P and K could be lost from MMCs (Bai et al., 2016). Knowledge of degradation of OM and losses of P and K along various MMCs could contribute to a more comprehensive assessment of the performance of MMCs.

As discussed above, there is lack of a model that has more flexibility of integrating various emerging manure management facilities and could comprehensively evaluate flows and losses of different manure constituents (OM, C, N, P and K) of diverse MMCs. We address this issue by introducing a newly developed modular manure management (FarmM3) model. It has the advantage of being able to integrate more alternative manure management facilities from excretion to application to cover complex MMCs in a modular way. It can assess the effects of emerging manure treatment technologies on different manure constituents (OM, C, N, P and K).

In this paper, we firstly describe this newly developed, flexible and extendable FarmM3 model for quantifying conversions and losses of OM, C, N, P and K along dairy MMCs with different complexity. Then with the FarmM3 model, we assess different MMCs with diverse manure management facilities and evaluate environmental impacts by comparing nutrient losses, NH_3 and GHG emissions. Finally, a global sensitivity analysis is performed to investigate how the system level losses of OM, C, N, P and K from MMCs are influenced by variations in configurations of manure management facilities and loss coefficients.

2. Material and methods

2.1. Model description

A modular approach developed by Qu et al. (2022) allows to estimate N flows and losses along diverse MMCs in a flexible way. In this study, we further extended this approach to quantify degradation of OM and C, losses of P and K by integrating loss coefficients from the literature and developed a modular manure management (FarmM3) model. Fig.A.1 shows the main data window of FarmM3 model. This model includes four types of components: Inputs, Pools, Separators and Applications. The Inputs components specify the quantities of materials added such as the excreted manure, amendments of bedding materials or crop residues for co-digestion with a given composition (dry matter (DM) content, ash content, and C, N, P, K contents). Conversion and loss coefficients of OM, C, N, P and K are established from experiments or literature reviews for each manure management Pool in which manure is deposited or maintained. Separators split a Pool in two new Pools and for each nutrient the fraction allocated to the new Pools can be specified. Applications should be the endpoints of the MMC, in which the loss coefficients of manure nutrients during application are specified. Table A.2 lists the input parameters of different components in the FarmM3 model.

Any number of these types of components can be combined into MMCs that start with Inputs and finish with Applications of manure fractions in fields or barns. Within each component, flows and losses of OM, C, organic N, inorganic N, P and K are quantified using a mass balance approach by calculating input from the previous component, conversion and loss within the component and output to the next component. The accumulated degradation and losses of manure constituents from the whole MMC are derived by summing up the losses in different types of components. Also, losses of different N species (i.e., NH_3-N, N_2O-N, NO-N, N_2-N, leaching and runoff N) and different C species (CO_2-C and CH_4-C) through the MMC are presented. These losses are also expressed per cow and per unit of area by dividing by the number of cows and the total surface area of the farm. The detailed calculation procedures are presented in the supplementary material.

2.2. Model visualization

The FarmM3 modelling tool was developed in MS Visual Studio using the C# programming language. The flows of manure constituents along the whole chain of MMC were visualized using DOT language in Graphviz software that allows to create diagrams with code and have them automatically drawn (Ellson et al., 2004). As shown in Fig. 1 with a flow diagram of inorganic N through an example MMC as generated by the FarmM3 model. The nodes were labelled with different types of inputs, manure management facilities, or loss pathways of manure constituents along the MMC. The amounts of flows and losses of manure constituents were added to vertices between nodes.

2.3. Analysis of manure management scenarios

A hypothetical dairy farm with 100 cows was developed with several contrasting manure management scenarios as shown in Table 1. Manure management facilities included deep litter with farmyard manure (FYM) storage, anaerobic lagoon, exercise yard, SLS, AD and combinations of SLS and AD. The annual amount of manure excreted is 1,201,018 kg/year, with different quantities of added straw for bedding or co-digestion, as shown in Table A.3.

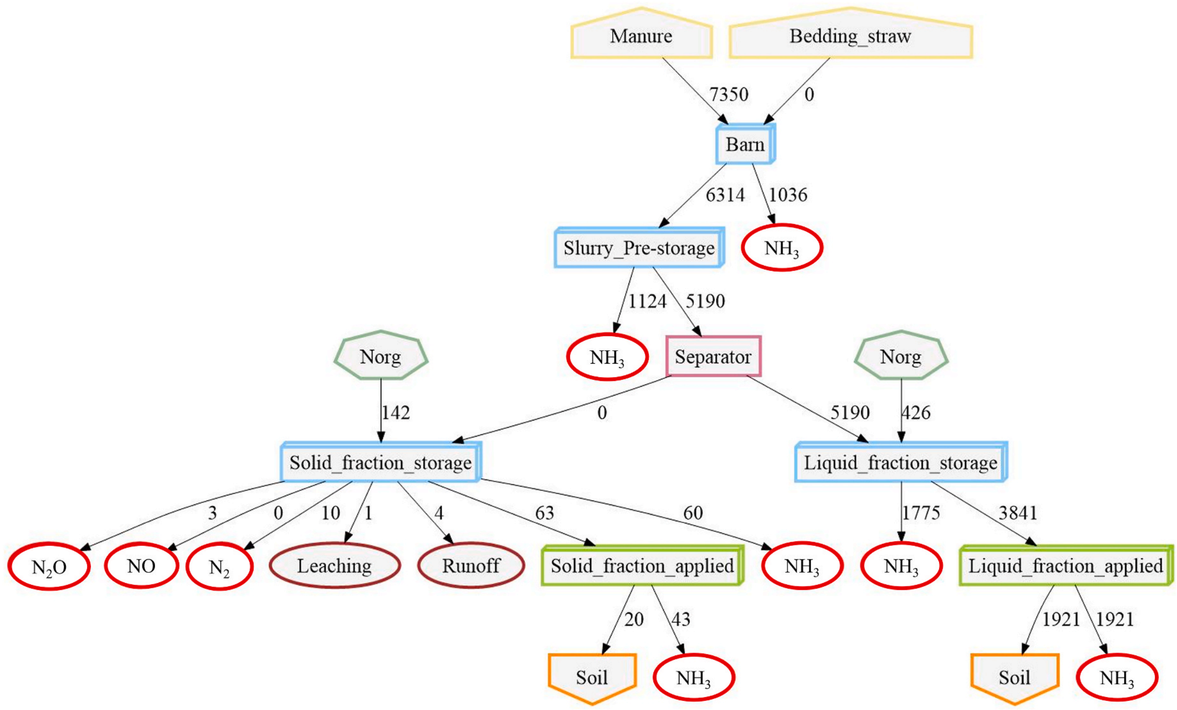

Fig. 1. The flow of inorganic nitrogen (Nmin) through the manure management chain (MMC) with a mechanical solid-liquid separation (SLS). The golden house shapes represent Inputs, the blue boxes denote Pools, the pink rectangle indicate Separators and the green boxes represent Applications. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Table 1
Description of manure management scenarios. The arrows indicated the flows of manure constituents among management facilities..

Scenarios	Scenario description	Manure management chains
S1	Deep litter and FYM storage	Dairy barn → Deep litter → Farmyard manure storage → Broadcast spreading Milking parlor → Flushing system → Slurry storage tank → Broadcast spreading Grazing pasture
S2	Anaerobic lagoon storage	Dairy barn → Combined scraping and flushing system → Anaerobic lagoons → Broadcast spreading
S3	Anaerobic lagoon and yard manure storage	Dairy barn → Combined scraping and flushing system → Anaerobic lagoons → Broadcast spreading Exercise yards → Scraping system → Solid manure in heap → Broadcast spreading
S4	SLS	Dairy barn → Flushing system → Slurry pre-storage → Separator → Separated liquid fraction storage tank → Broadcast spreading → Separated solid fraction composting → Broadcast spreading
S5	AD	Dairy barn → Scraping system → Slurry pre-storage → Anaerobic digester → Digested slurry storage → Broadcast spreading
S6	AD and SLS	Dairy barn → Scraping system → Slurry pre-storage → Anaerobic digester → Digested slurry storage → Separator → Separated liquid fraction storage tank → Broadcast spreading → Separated solid fraction composting → Broadcast spreading
S7	SLS and AD	Dairy barn → Flushing system → Slurry pre-storage → Separator → Separated liquid fraction storage tank → Anaerobic digester → Digested slurry storage tank → Broadcast spreading → Separated solid fraction composting → Broadcast spreading

Note: FYM represents farmyard manure; SLS represents solid-liquid separation; AD represents anaerobic digestion.

2.4. Winding Stairs sensitivity analysis

Variations in manure management facilities, and the inherent uncertainties associated with emission factors, can have substantial implications for estimated results. A variance-based Winding Stairs sensitivity analysis was performed to assess the effects of variations in loss coefficients on the expected degradation of OM, nutrient flows and emissions from MMCs. Given the complexity of MMCs and potential interactions between loss coefficients of manure management facilities, in this study, we selected manure management scenarios 1, 4 and 6 in Table 1 as examples to analyse the effects of variations in loss coefficients on output variables. Results of the sensitivity analysis of scenarios 2, 3, 5 and 7 are presented in Tables A.4 to A.7.

The Winding Stairs algorithm incorporated in the FarmM3 modelling tool is based on Monte-Carlo sensitivity analysis but performs a systematic sampling of random parameter values within user-defined ranges. Output variables Y_i are decided by input parameters X_1, X_2, …, X_k based on a developed deterministic function f ($Y_i = f(X_1, X_2, …, X_k)$), here represented by the model calculations as described in the supplementary material. Sampling of parameter values occurs in a cyclical order. In the first step of cycle 1, X_{11} is randomly adjusted, in the second X_{21}, etc. thereby producing new values {X_{11}, X_{21}, …, X_{k1}}. Thus, each cycle contains K steps that constitute one Winding Stairs sample or 'winding' (Jansen et al., 1994). The number of random Winding Stairs samples generated (R) can be set as a parameter of the algorithm. The total number of observations generated is $N = K \times (R+1)$, where 1 represents the original parameter set that is used at the start of the first cycle. For each sample of parameter values the model output variables are calculated using the function f. This results in a matrix with K columns and R+1 rows, see Fig.A.2 for an example from Chan et al. (2000) with $K = 3$ and $R = 4$.

In our case, the system level losses of OM, inorganic N, P, K and GHG emissions from MMCs were selected as output variables. We excluded NH_3 emissions and total C losses as output variables due to strong correlations between NH_3 emissions and inorganic N losses (Pearson correlation coefficients = 0.856 to 0.999), and between total C losses and OM degradation (Pearson correlation coefficients = 0.954 to 1.000). The Pearson correlation coefficients among output variables in different MMCs are listed in Table A.8. The original parameter values, minimum and maximum values of selected input parameters were specified based on empirical values from publications. These input factors were sampled randomly within the set ranges through 5000 windings (R = 5000).

The variance of model output variables was decomposed into the first-order sensitivity index (FSI) and total sensitivity index (TSI). The FSI, also called top marginal variance, is defined as the variance reduction due to fixing factor X_k while varying the other factors. Conversely, the TSI, also denoted as bottom marginal variance, is the variance caused when only X_k is uncertain (Jansen et al., 1994; Chan et al., 2000). These indices can be used to evaluate the main effects (FSI values) and the total effects (TSI values), including main and interactive effects, of these parameters on the system level losses of OM, inorganic N, P, K and GHG emissions. Small differences between FSI and TSI values indicate that there is no interaction between parameters.

3. Results

3.1. Degradation and losses of manure constituents from MMCs

As shown in Table 2, the amounts of OM degradation, C and nutrient losses, NH_3 and GHG emissions from seven manure management scenarios were compared. For the hypothetical dairy farm with 100 cows, the MMC with deep litter and FYM storage (Scenario 1) had the lowest NH_3 emissions and total N loss. In contrast, the amounts of OM degraded and C lost in Scenario 1 were five to seven times higher than losses in Scenarios 2, 3 and 4. Additionally, the GHG emissions from Scenario 1 were much higher than emissions from Scenarios 2, 3 and 4. The results indicated the pollution swapping of NH_3 emissions and OM degradation, C loss and GHG emissions from the MMC with deep litter. The substantial amount of added straw to deep litter provided more substrate for degradation of OM but could absorb urine N quickly and promoted the immobilization of inorganic N to organic N, thereby reducing NH_3 emissions.

We compared the degradation and losses of manure constituents in Scenarios 2, 3 and 4 because they all have the same amounts of manure and bedding straw input (Table A.3). In comparison with Scenarios 2 and 3, the larger amounts of degraded OM degradation and C loss in Scenario 4 were caused by the higher degradation rate of OM under aerobic conditions during separated solid manure storage. The SLS in Scenario 4 helped reduce GHG emissions by around 60%, due to lower total CH_4 and N_2O emissions compared to Scenarios 2 and 3. Small differences in N losses and NH_3 emissions in Scenarios 2 and 4 were observed. Scenario 3 presented higher environmental risk of losing nutrients (N, P and K) by leaching and runoff, compared to Scenarios 2 and 4 (the MMCs without exercise yards).

In Scenarios 5, 6 and 7, the OM degradation, C losses, and GHG emissions were relatively higher compared to other scenarios, due to the substantial amounts of straw added to AD. Applying SLS after AD (Scenario 6) reduced GHG emissions by 44% compared to applying AD only (Scenario 5). This was due to the lower CH_4 emissions from separated liquid fraction storage in Scenario 6 (Fig. A.3). Additionally, Scenario 6 resulted in slightly lower N loss and NH_3 emissions. Changing the sequence of manure management facilities might influence flows and losses of manure constituents. Applying SLS before AD (Scenario 7) resulted in lower OM degradation and C loss, but higher GHG emissions than applying SLS after AD (Scenario 6). The main differences between the GHG emissions in Scenarios 6 and 7 were due to the higher CH_4 emissions from the digested slurry storage, compared to the separated liquid fraction from digestate in Scenario 6 (Fig. A.3). This can be further explained by the larger quantity of volatile solids in the digested slurry storage in Scenario 7 due to a large amount of straw added to the digester with the separated liquid fraction. Scenario 6, on the other hand, only had a small percentage of volatile solids from digestate which can be retained in the liquid fraction after separation. Although the total losses of P and K from both Scenarios 6 and 7 were small, about 60% lower P loss was observed from Scenario 7. This was because the higher separation efficiency of P in digested slurry (Scenario 6) than in raw slurry (Scenario 7) led to more P retained in the solid fraction, thereby increasing leaching and runoff losses of P. Different from P, the higher separation efficiency of K in raw slurry than in digested slurry led to 40% more K loss in Scenario 7, compared to Scenario 6. These results show that there are contrasting effects of separation efficiency of SLS on total P and K losses.

Table 2
Amounts of OM degradation, nutrient losses and GHG emissions from different manure management scenarios. The added straw for animal bedding and anaerobic digester were also included in material flows.

Scenarios	Scenario description	OM degraded, (kg/cow)	Total C loss, (kg/cow)	GHG emissions, (kg CO_2-eq/cow)	Total N loss, (kg/cow)	NH_3-N loss, (kg/cow)	Total P loss, (g/cow)	Total K loss, (g/cow)
1	Deep litter and FYM storage	2297.1	1148.5	5765.5	44.6	30.5	24.9	3273.7
2	Anaerobic lagoon storage	291.2	145.6	2561.7	63.7	57.3	0.0	0.0
3	Anaerobic lagoon storage and yard manure storage	370.4	185.2	2507.0	72.4	60.0	3088.9	62956.3
4	SLS	422.3	211.1	1060.0	60.2	59.6	7.5	721.7
5	AD	5760.1	2880.0	1974.9	120.3	120.3	0.0	0.0
6	AD and SLS	5724.8	2862.4	1101.4	110.1	109.7	19.8	514.1
7	SLS and AD	5380.0	2690.0	1768.3	117.9	117.4	7.5	721.7

Note: FYM represents farmyard manure; SLS represents solid-liquid separation; AD represents anaerobic digestion.

3.2. Sensitivity of system level losses from MMCs to variations of loss parameters

3.2.1. Degradation of organic matter

The most important variables influencing degradation of OM differed among scenarios and depended on applied manure management facilities in MMCs. The Winding Stairs sensitivity analysis showed that degradation rates of OM under aerobic conditions in deep litter and in FYM storage contributed more than 80% of variance to total OM degradation from Scenario 1, whereas the contribution of degradation rates of OM in slurry storage was almost negligible (Table 3). In Scenario 4, both the degradation rate of OM in separated solid manure storage and in separated liquid fraction storage were influential, with two times higher FSI value for degradation rate of OM in separated solid manure storage than in separated liquid manure storage (Table 3). In Scenario 6 with a digester and a separator, the degradation of OM was the most sensitive to the degradation rate of OM in the digester (Table 3). The effects of these input parameters on degradation of OM from MMCs in Scenarios 1, 4 and 6 are presented in Fig. 2, with higher parameter values leading to more degradation of OM from MMCs. It should be noted that the contribution of input parameters to total variance of OM degradation from MMCs depends on the range of input parameters and the degree of influence of these parameters represented by regression coefficients (Fig. 2). A small range but large value of regression coefficient might lead to a small fraction of explained variance, and consequently a small value of coefficient of determination (R^2) and FSI and TSI values (Fig. 2d and i).

3.2.2. Total inorganic N losses

In Scenario 1, changes of mineralization rate of organic N in FYM storage contributed more than 50% variance of total inorganic N losses, with higher mineralization rate leading to larger inorganic N losses (Fig. 3b). Conversely, the immobilization rate of inorganic N in deep litter had a negative effect on total inorganic N losses (Fig. 3a). In total, these two parameters contributed more than 70% of variance of total inorganic N losses, much higher than contributions of loss coefficients of NH_3-N during manure storage and application (Table A.9). On the contrary, in Scenarios 4 and 6, the total inorganic N losses were more sensitive to changes in loss coefficients of NH_3-N during storage and application than mineralization rates of organic N. In total, loss coefficients of NH_3-N during liquid fraction storage and application resulted in more than 60% of variance, which was four times higher than the contribution of mineralization rates of organic N (Table A.9). We did not observe significant contribution of separation efficiency of N to variance of total inorganic N losses in Scenarios 4 and 6 because only a small percentage of inorganic N (less than 10%) would be allocated to the solid fraction.

3.2.3. Total P and K loss

Runoff and leaching losses during solid manure storage are the primary loss pathways of P and K from MMCs. We observed significant contribution of loss coefficients of leaching and runoff from solid manure storage to variance of total P and K losses from the MMCs, with FSI values ranging from 40% to 99%. In MMCs with SLS (Scenarios 4 and 6), both separation efficiency of P of separator and loss coefficient of P from solid fraction storage were influential, with two times higher FSI value for loss coefficient of P from solid fraction storage than separation efficiency of P (Table A.10). The separation efficiency of K was as important to total K losses as the loss coefficient of runoff and leaching from solid fraction storage. The differences between FSI and TSI values of separation efficiency of P or K and loss coefficient of P or K from solid fraction storage indicated interactions between these two parameters, contributing more than 10% of variance to total P or K losses from MMCs with SLS. The amounts of P or K in solid fractions are the prerequisite for the losses of P or K, with the more P or K staying in solid fractions leading to the more P or K losses by runoff and leaching during storage.

Table 3
Sensitivity index (%), including first-order sensitivity index (FSI) and total sensitivity index (TSI), of input parameters on total OM degradation from MMCs of Scenarios 1, 4 and 6.

Manure management facility	Parameters	Scenario 1			Scenario 4			Scenario 6		
		Range	FSI	TSI	Range	FSI	TSI	Range	FSI	TSI
Deep litter	Fraction of substrate stored under oxic conditions	0.5–1.0	2.9	6.5						
	Degradation rate of OM under oxic conditions	0.3–0.6	**40.5**	**42.1**						
	Degradation rate of OM under anoxic conditions	0.2–0.4	−0.3	2.6						
FYM storage	Fraction of substrate stored under oxic conditions	0.5–1.0	5.3	6.6						
	Degradation rate of OM under oxic conditions	0.3–0.6	**41.3**	**42.7**						
	Degradation rate of OM under anoxic conditions	0.2–0.4	−0.3	2.6						
Slurry storage	Fraction of substrate stored under oxic conditions	0.0–0.1	−1.6	0.0	0.0–0.2	−0.8	0.2	0.0–0.2	0.0	0.0
	Degradation rate of OM under oxic conditions	0.0–0.1	−1.6	0.0	0.0–0.1	−0.8	0.4	0.00–0.05	−1.2	0.0
	Degradation rate of OM under anoxic conditions	0.05–0.15	−1.3	0.2	0.00–0.05	5.6	6.4	0.00–0.05	−1.3	0.1
Anaerobic digester	Degradation rate of OM under anoxic conditions							0.3–0.5	**56.1**	**56.2**
Digested slurry storage	Fraction of substrate stored under oxic conditions							0.0–0.1	0.1	0.0
	Degradation rate of OM under oxic conditions							0.0–0.1	1.4	0.0
	Degradation rate of OM under anoxic conditions							0.0–0.1	5.0	5.3
Liquid fraction storage	Fraction of substrate stored under oxic conditions				0.0–0.1	0.9	0.1	0.0–0.1	0.0	0.0
	Degradation rate of OM under oxic conditions				0.0–0.1	0.8	0.0	0.0–0.3	0.1	0.1
	Degradation rate of OM under anoxic conditions				0.05–0.20	**25.2**	**25.9**	0.0–0.1	3.0	2.1
Solid fraction storage	Fraction of OM to Solid fraction				0.3–0.6	1.6	4.8	0.3–0.6	2.9	3.7
	Fraction of substrate stored under oxic conditions				0.5–1.0	3.7	7.6	0.5–1.0	1.5	2.8
	Degradation rate of OM under oxic conditions				0.05–0.40	**53.9**	**59.7**	0.0–0.6	**29.7**	**31.4**
	Degradation rate of OM under anoxic conditions				0.00–0.15	2.1	1.6	0.0–0.2	0.6	0.5

Notes: The parameters with FSI and TSI values higher than 10% are indicated in bold.

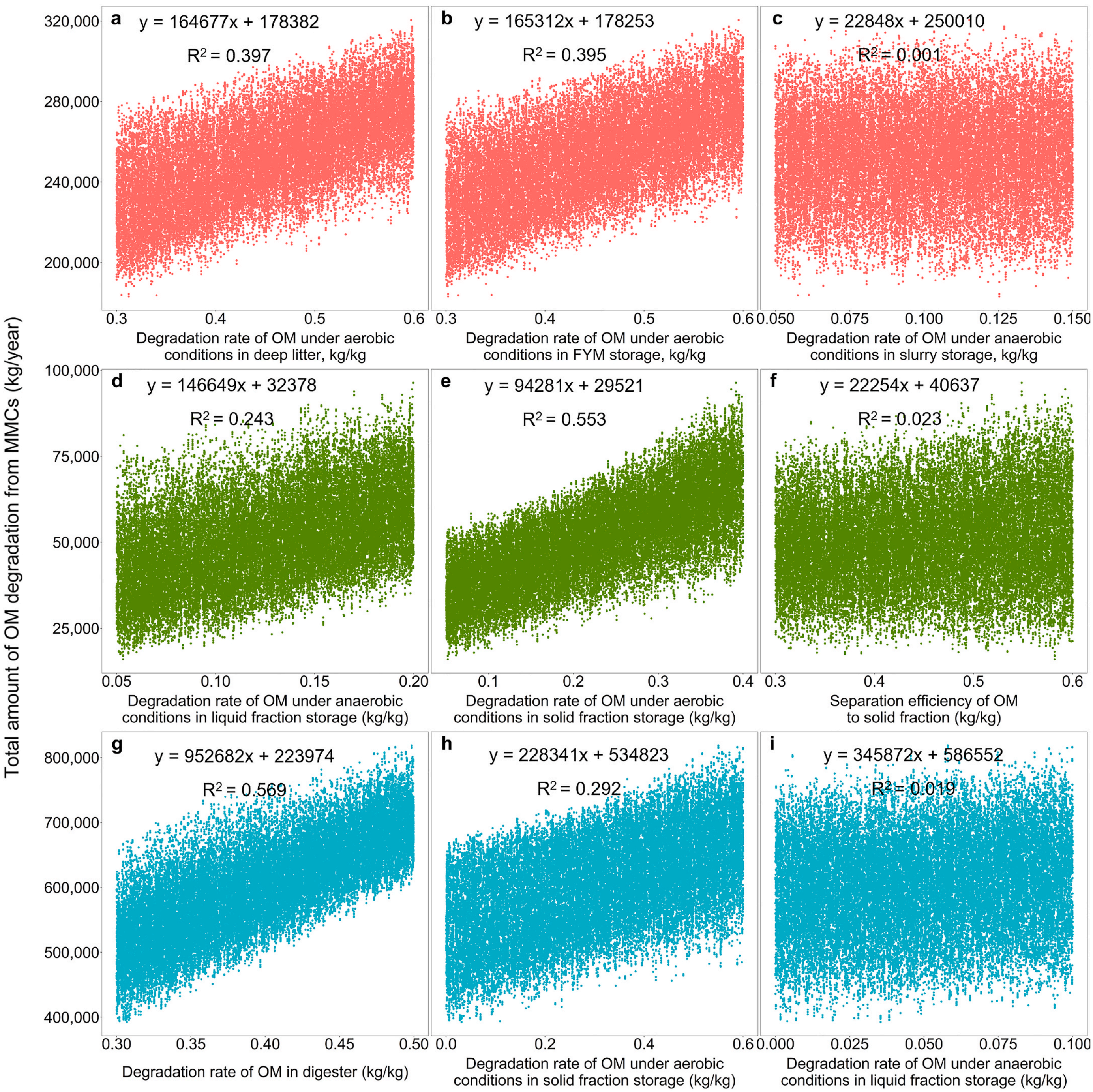

Fig. 2. Relationships between input parameters of different manure management facilities and total organic matter (OM) degradation from manure management chains (MMCs). Different colors represent different MMCs of Scenarios 1 (red, a-c), 4 (green, d-f) and 6 (blue, g-i). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

The parameters relating to AD in Scenario 6 did not influence system level losses of P and K.

3.2.4. *GHG emissions*

The emissions of GHG from MMCs are related to C losses by emissions in the form of CH_4, and to N_2O emissions. Configurations of the manure management facilities in MMCs had important effects on GHG emissions, with stronger effects of parameters in earlier facilities of MMCs than in later facilities. In Scenario 1, we observed important effects of degradation of C in deep litter on GHG emissions from the whole MMC. About more than 70% of variance of total GHG emissions could be explained by changes of degradation rate of OM under aerobic conditions in deep litter and changes of fraction of CH_4-C in total C loss from deep litter. In Scenario 4, a larger contribution of loss coefficient of N_2O during separated liquid fraction storage to total variance of GHG emissions from the MMC was observed even with a small varying range from 0.0 to 0.1 for the loss coefficient (Table A.11). The degradation rate of C under anaerobic conditions in separated liquid fraction and the fraction of C lost as CH_4-C emissions were also influential, in total contributing about 40% of variance to total GHG emissions from the MMC. The AD in Scenario 6 played the most important role in determining the uncertainty of GHG emissions from the MMC. The highest TSI was observed

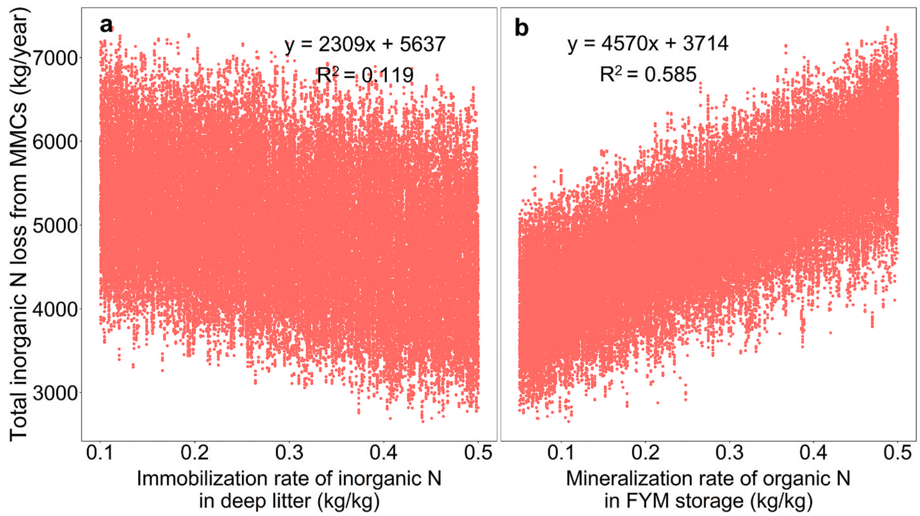

Fig. 3. Influence of the immobilization rate of inorganic N in deep litter (a, with FSI and TSI values of 13.6% and 12.6%, respectively) and the mineralization rate of organic N in farmyard manure storage (b, with FSI and TSI values of 57.5% and 58.8%, respectively) on total inorganic N losses from the MMC of Scenario 1.

for the effect of the fraction of CH_4 produced in a digester that would be combusted (Table A.11), with higher fraction of CH_4 combusted resulting in lower GHG emissions (Fig. A. 4b). Besides, the degradation rate of C in AD could be influential, with higher values resulting in larger variations of GHG emissions from the MMC (Fig. A. 4a).

4. Discussion

4.1. Impacts of manure management facilities on the fates of manure constituents

With the newly developed FarmM3 model we quantified the degradation and losses of OM, C, N, P and K from several contrasting manure management scenarios. Comparisons among these manure management scenarios demonstrated the impact of choice and configurations of manure management facilities on flows and losses of manure constituents throughout the whole MMCs. The MMCs with deep litter and AD had higher OM degradation, C losses and GHG emissions because of the added straw. Application of SLS could reduce GHG emissions by 40–60%. These reductions were due to the lower CH_4 and N_2O emissions from separated liquid fraction storage as less volatile solids entered the liquid fraction, so no natural crust formed during the storage (Aguirre-Villegas et al., 2014; Holly et al., 2017). The influence of SLS on NH_3 emissions from MMCs was affected by manure management facilities before and after SLS. We observed a greater reduction in NH_3 emissions when applying SLS to digested slurry than to raw slurry. The decrease of NH_3 emissions from MMCs with SLS might be because of less NH_3 emissions from separated solid fraction storage and from separated liquids application due to the quick infiltration of ammoniacal N in liquids to the soil (Aguirre-Villegas et al., 2014). In contrast, Kupper et al. (2020) found that SLS caused higher losses for NH_3 due to the absence of a surface crust during separated liquid fraction storage (Baldé et al., 2018). The balance between increased NH_3 emissions from separated liquid fraction storage and reduced NH_3 emissions from solid fraction storage and from liquid manure application resulted in different effects of SLS on NH_3 emissions from the whole MMC. This study also showed that, compared to the MMCs without SLS, separated solid fraction storage might increase the risks of P and K losses through leaching and runoff. This highlights the importance of improving management of solid manure storage to reduce nutrient losses.

4.2. The important parameters of determining losses of manure constituents in complex MMCs

The FarmM3 model enabled the identification of the most important parameters determining losses of manure constituents in complex MMCs through WS sensitivity analysis. The degradation rates of OM under aerobic conditions during solid manure storage and under anaerobic conditions during liquid manure storage were the most important influencing parameters. The important parameters for determining GHG emissions varied among MMCs, indicating the effects of configurations of manure management facilities in MMCs on GHG emissions.

In the MMCs with solid manure storage (e.g., the deep litter system), the immobilization and mineralization rate between inorganic and organic N were more influential than the loss coefficients of NH_3-N. Various studies have highlighted the importance of considering N transformations in solid manure storage when using a inorganic N flow approach to estimate N losses from MMCs (Dämmgen and Hutchings, 2008; Velthof et al., 2012). But the quantitative effects of immobilization and mineralization rates of organic N and inorganic N on total N losses from MMCs were rarely investigated, which prevents us from comparing with other studies. For liquid manure management systems with SLS or AD, the loss coefficients of NH_3-N during liquid manure storage and application contributed more to the variance of total N losses, which is in accordance with the study of Aguirre-Villegas et al. (2014). The separation efficiencies of organic N and inorganic N did not influence the total N losses from MMCs, which agrees with the study of Perazzolo et al. (2017). This was mainly because of the low separation efficiency (0–10%) of inorganic N to solid fraction and the negligible inorganic N losses from solid fraction storage (Aguirre-Villegas et al., 2019). Different from N, total losses of P and K from MMCs were sensitive to changes of separation efficiencies of P and K from SLS, with more contribution of separation efficiency of K to total losses than separation efficiency of P.

4.3. Comparison with other modelling approaches

The FarmM3 model in this study was developed based on a modular concept and a mass balance approach. Compared to existing modelling approaches that only considered the traditional manure management strategies (e.g., storage and application), this model has more flexibility that allows to integrate more alternative manure management facilities in a desired and feasible sequential order from excretion to application to cover complex MMCs. The results of quantifying flows of manure constituents along MMCs with contrasting manure management facilities in this study verified the feasibility of applying the FarmM3 model in various MMCs in on-farm settings. Besides, this model is able to quantify flows of different manure constituents (i.e., OM, C, N, P and K) throughout MMCs, which might make it as a helpful tool for comprehensively evaluating the effects of manure management options on degradation and losses of different manure constituents and for identifying trade-offs among these manure constituents.

4.4. Limitations

The developed FarmM3 model quantified the flows and losses of manure OM, C, N, P and K throughout MMCs based on empirical values of input parameters from publications. However, in practical situations, these input parameters, including loss coefficients, emissions factors and performance parameters of manure management facilities might be affected by management practices and environmental factors (i.e., temperature, rainfall etc.). In this regard, this model still has its limitations regarding selecting suitable parameters to specifically meet the on-farm situation although the simplicity of calculations with emission factors might make it easy to use. These limitations can be reduced further by identifying the most influential input parameters through sensitivity analysis, and by improving the accuracy of these important parameters by developing mechanistic estimation models or by validating estimated results using data from farm measurements.

4.5. Implications

The developed FarmM3 model can be used as a helpful tool for quantifying degradation and losses of different manure constituents (OM, C, N, P and K) in complex MMCs. The results can contribute to understanding the effects of various manure management facilities on the flows and losses of manure OM, C, N, P and K through the whole MMCs. It can support farm managers in decision making on designing and optimizing manure management strategies by assessing trade-offs among these different environmental indicators. By identifying the most important parameters determining losses from various MMCs, it also helps researchers to identify future research priorities in estimating loss coefficients of different manure constituents from various manure management facilities.

4.6. Future research

To further validate and improve the accuracy of model estimates, on-farm measurements on degradation and losses of different manure constituents from whole MMCs might be necessary and helpful. For future works, the FarmM3 model can be integrated into whole-farm models such as the FarmDESIGN model (Groot et al., 2012) to improve flexibility of model application in dairy farming systems with complex MMCs. In addition to evaluating environmental performance in terms of degradation of OM, nutrient losses and gaseous emissions from MMCs, this model could be extended to allow a multi-criteria decision-making analysis for design and optimize manure management scenarios considering economic aspects, such as investment and operation costs of management facilities.

5. Conclusions

This study developed the FarmM3 model, and quantifiably compared diverse manure management facilities, and the relative degradation and losses of OM, C, N, P and K throughout their MMCs. The results showed that, compared to other MMCs, the MMCs with deep litter and AD yielded higher OM degradation, C losses and GHG emissions due to the more added straw. This implied the positive relationships between the quantity of manure dry matter and OM degradation, and GHG emissions. Further, the MMC with deep litter showed reduced NH_3 emission, but increased GHG emissions due to the pollution swapping caused by adding straw. Application of SLS could reduce GHG emissions, but its effect on NH_3 emissions varied depending on the characteristics of the separated slurry. A larger reduction in NH_3 emissions was observed when applying SLS to digested slurry than to raw slurry. The sequence of manure management facilities in MMCs influenced the flows and losses of constituents. For example, our results showed greater reductions in GHG and NH_3 emissions when applying SLS after AD than applying SLS before AD.

Results of WS sensitivity analysis showed the most important parameters for determining GHG emissions varied among MMCs, indicating the effects of configurations of manure management facilities in MMCs on GHG emissions. For N losses, the immobilization and mineralization rates between inorganic and organic N were more influential than loss coefficients of NH_3-N in the MMC with deep litter. In liquid manure systems, the loss coefficients of NH_3-N from liquid manure storage and application were more influential than from solid fractions. The separation efficiencies of organic N and inorganic N did not influence total N losses from MMCs with SLS. In contrast, the separation efficiencies of P and K from SLS were influential to total losses of P and K from MMCs with SLS.

Our modelling approach could contribute to understanding the role of manure management facilities in farm nutrient management planning and could be helpful for farmers, researchers and policy makers to decide how to improve manure management systems at farm level.

CRediT authorship contribution statement

Qingbo Qu: Conceptualization, Data curation, Formal analysis, Visualization, Writing – original draft. **Keqiang Zhang:** Funding acquisition, Supervision, Conceptualization, Writing – review & editing. **Jeroen C.J. Groot:** Conceptualization, Methodology, Software, Supervision, Writing – review & editing.

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.

Data availability

I have shared the link to my data at the Attach file step.

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Appendix A. Supplementary data

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