Modeling Ammonia Emissions from Dairy Farm:

Integration of Nitrogen Indicators and Farm Categories

MSc thesis

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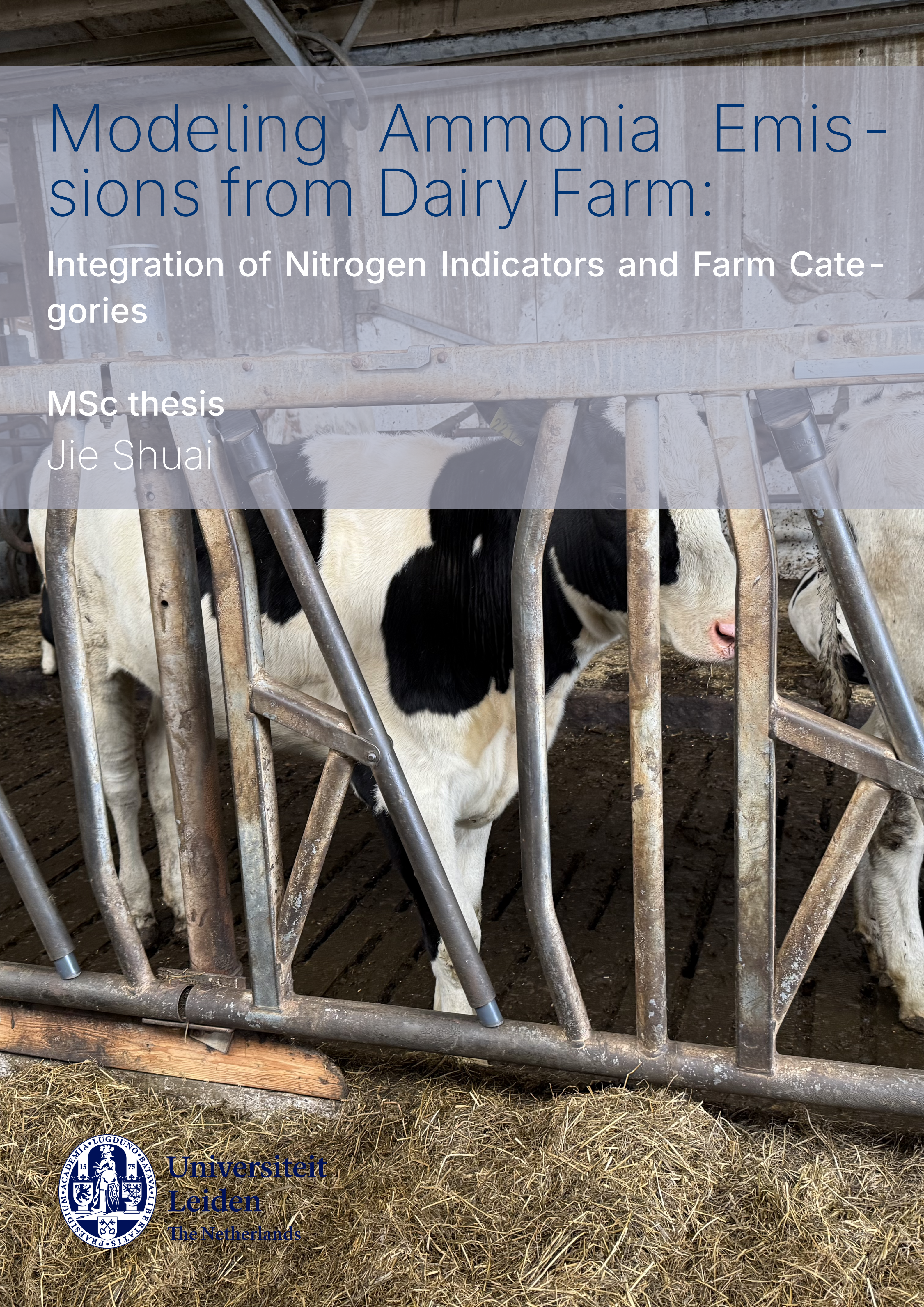

Universiteit Leiden
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Modeling Ammonia Emissions from Dairy Farm:

Integration of Nitrogen Indicators and Farm Categories

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Abstract

This study evaluates the feasibility of developing a farm-scale ammonia emission model for dairy farm using routinely measured parameters and management variables. Three regression models, each based on a different core predictor—Total Ammoniacal Nitrogen in manure (TAN), Milk Urea Nitrogen (MUN), and Ammonia Emission Potential (AEP)—were fitted to ammonia emissions measured using plume method. All models explained a substantial proportion of the overall variance in measured NH_3 emissions (R^2>0.68), with statistically significant fits. Strong positive correlations were found among the basic models adjusted for pH, temperature, and dry matter (DS), especially between the MUN and TAN models, underscoring the consistency and reliability of these approaches for estimating ammonia emissions at the farm scale. Model performance was further enhanced by incorporating farm and environmental factors such as manure C/N ratio, housing type, and management variables. In addition to these predictors, a clear seasonal emission pattern was detected, with peak ammonia emissions observed during the summer period, underscoring the role of environmental conditions in emission dynamics. Dietary factors—especially digestible protein in the small intestine (DVE) and the proportion of concentrate—were strong predictors of TAN and, indirectly, of ammonia emissions, highlighting feed management as an effective mitigation pathway. Despite the limited sample size, this research demonstrates the potential of combining direct measurements and key farm variables in ammonia emission modeling and emphasizes the importance of both feed and housing management for emission reduction. Future studies with larger datasets are needed to validate and further refine these findings.

Keywords: Ammonia Emission, **Multiple Linear Regression**, **Dairy Farms**, **Nitrogen Balance Analysis**, **Feed Management**

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I would also like to thank my parents and friends for always lifting my spirits and encouraging me, especially during periods of low productivity. Your unwavering support means everything to me.

Returning to campus after working for over ten years—and adapting to a new educational approach—has not been easy. I chose to study ESG because, after reaching a point where life's basics were no longer a concern, I wanted to understand more about the world and how I could make a difference, both personally and within industry. I am grateful for everything I have learned over the past two years in Industrial Ecology: not just about methods and tools, but also about myself. Looking back, I am glad I took this step and have no regrets about my decision. Although this thesis is not perfect and has its limitations, I am proud of having completed it and grateful to myself for the persistence.

Finally, I would like to thank ChatGPT. I believe that AI agents or LLM are a great invention, as they help reduce educational inequality. As a non-native English speaker, I'm truly thankful for ChatGPT's help in polishing my academic writing.

Acronyms

AEP	Ammonia Emission Potential
AEIG	Atmospheric Emission Inventory Guidebook
CP	Crude Protein
CP/kVEM	Crude Protein to Metabolizable Energy Balance Ratio
C/N ratio	Carbon to Nitrogen Ratio
DS	Dry Matter
DVE	Digestible Intestinal Protein
DMS	Dirksen Management Support B.V.
EF	Emission Factor
HBD	EU Habitats Directive and EU Bird Directive
IPCC	the Intergovernmental Panel on Climate Change
KDW	Critical Threshold Values
LU	Livestock Unit
NEMA	the National Emission Model for Agriculture
NPLG	the National Program for Rural Areas
MUN	Milk Urea Nitrogen
OLS	Ordinary Least Squares
OEB	Rumen Degradable Protein Balance
PAS	Programma Aanpak Stikstof
RIVM	the National Institute for Public Health and the Environment
SEM	Structural Equation Modeling
TAN	Total Ammoniacal Nitrogen
WSN	Nitrogen Reduction and Nature Improvement Act
WLS	Weighted Least Squares

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1. Introduction

1.1 The nitrogen issue in the Netherlands

Atmospheric nitrogen deposition has been identified as a primary driver of biodiversity decline through multiple mechanisms: eutrophication leading to floristic alterations, acidification resulting in potentially toxic metal mobilization, and elevated nitrate concentrations in groundwater systems (Feest, van Swaay, & van Hinsberg, 2014; Payne et al., 2017). The Netherlands experiences one of the world's highest atmospheric nitrogen deposition rates (Rubin et al., 2023), reaching a gross nitrogen balance of 165.8 kg N/Ha in 2017, approximately double the European Union average (*Statistics | Eurostat*, n.d.). Mitigating nitrogen deposition being essential for environmental protection is crucial for compliance with the EU Habitats Directive and EU Bird Directive (HBD). The HBD mandates EU Member States to preserve or restore threatened and endangered habitats, notably through the establishment of the EU-wide Natura 2000 protected areas network (Born, Cliquet, Schoukens, Misonne, & Hoorick, 2014). Within Dutch territories, 162 Natura 2000 areas exist, with 118 sites experiencing nitrogen deposits exceeding ecological risk thresholds by an average of 50% (Stokstad, 2019).

The Dutch government therefore has established ambitious targets to address this challenge, aiming to reduce nitrogen deposition below critical threshold values (KDW) across 74% of Natura 2000 areas by 2035 (Marra et al., 2023). Despite the implementation of multiple policies and measures, the latest report from the National Institute for Public Health and the Environment (RIVM) shows that although nitrogen deposition is decreasing, only 21% of areas had effectively reduced deposition to levels below the KDW by 2021. If this trend continues, instead of reaching 74%, only 40% of vulnerable nature conservation areas will fall below the KDW by 2035.

Several factors contribute to this delay, with one key argument focusing on the political incapability to manage the issue through current policies (Candel, 2023). For instance, the previous nitrogen policy, the 'Programma Aanpak Stikstof' (PAS), which was annulled by the Dutch Council of State, was criticized for focusing less on actually reducing nitrogen deposition and more on mitigating societal resistance by decreasing permit backlogs (Scheeringa, 2020). The newer policies aim to improve the situation by enabling farmers to directly observe the connection between mitigation measures and their outcomes. Therefore, in line with the recommendations of the Remkes Committee, the Nitrogen Reduction and Nature Improvement Act (WSN) incorporates the emission reduction target into its Explanatory Memorandum. This translates the deposition targets into explicit emission reduction goals—specifically, a 26% reduction by 2030 and a 50% reduction by 2035 (Stikstofproblematiek, 2020). The National Program for Rural Areas (NPLG) also calculates national emission reduction targets for agriculture, industry, and transport (Hazelhorst, van der Maas, & Romeijn, 2024).

1.2 Main nitrogen emission sources and monitoring challenges

According to recent inventories (CBS, 2022b), ammonia accounts for 67% of total Dutch nitrogen emissions to air in 2022, with 91% of these ammonia emissions originating from the agricultural sector. Within agriculture, cattle are responsible for 53% of ammonia emissions, meaning that dairy farms alone contribute to 32% of the total nitrogen emissions in the Netherlands. Given that intensive livestock operations—especially ammonia (NH_3) emissions from dairy and non-dairy cattle manure management and land application—constitute the principal source of atmospheric nitrogen deposition and emission (Stokstad, 2019; Wever et al., 2021), dairy farming represent a crucial intervention point.

In 2021, the RIVM calculated how much less nitrogen the agricultural sector would need to emit in order to meet legal targets, at the request of the Ministry of Agriculture, Nature, and Food Quality (LNV). Their assessment showed that to meet these targets, the agricultural sector needs to reduce ammonia emissions by 40% by 2035 compared to 2005 levels.

By introducing emission targets alongside deposition targets, it becomes possible for farmers to directly observe what requirements they must meet and to immediately see the effect of implemented measures. Nevertheless, achieving these targets requires highly accurate determination of ammonia emissions.

Currently, the Netherlands uses an approach based on the Atmospheric Emission Inventory Guidebook (AEIG) and the Intergovernmental Panel on Climate Change (IPCC) Guidelines to estimate NH_3 emissions from dairy farms and produce more accurate inventories. This method models emissions based on activity data, such as the average number of animals present, and emission factors (EF) (e.g., kg NH_3 emitted per animal per year). The National Emission Model for Agriculture (NEMA) is developed according to this methodology. While straightforward, this approach has its limitations. It does not accommodate innovative or farm-specific solutions. Additionally, the emission factors determined at a national scale may be inappropriate for farm specific estimations, as they often fail to accurately capture the specific conditions of individual farms (Yang et al., 2022), and are performed only for the primary, representative categories of livestock production and manure management systems. The study by Sommer, Webb, and Hutchings (2019) reveals significant variability in measured NH_3 emissions compared to EF calculated for barns, manure storage, or manure application within the main categories of livestock production and manure management systems.

The EFs provided exhibit a standard deviation as large as 50% of the estimated average for a given livestock category.

For more farm-specific estimates of ammonia emissions, the KringloopWijzer (KLW) model is employed. This scientific model, developed under standardized and EU-reviewed conditions, requires dairy farmers to track all nitrogen inputs to the farm (e.g., internally grown grass, purchased feed) and outputs from the farm (e.g., animal products, manure, losses, etc.), then uses a mass balance approach to estimate nitrogen use efficiency and emissions. The KLW methodology calculates digestible protein (VCRE) intake based on feed data, derives total ammoniacal nitrogen (TAN) in excretion, and subsequently estimates ammonia emissions by multiplying TAN by the national scale emission factor for the stable or grazing period (PPO/PRI AGRO Field Technology Innovations et al., 2022). This model provides valuable insights for farmers into their operational nitrogen cycles. However, several limitations exist: firstly, it relies heavily on precise farmer input and knowledge, making comprehensive validation impossible—this vulnerability to unintentional errors or even fraud makes it unsuitable as the basis for environmental policy instruments (Bestman & Erisman, 2016). Secondly, the KLW fails to include several key parameters—such as temperature and pH—which are critical to the chemical equilibrium between free ammonia and ammonium ions (Cai et al., 2021). As such, the KLW does not fully capture actual emissions at the farm level. Studies at two farms by LR - Veehouderij en omgeving et al. (2022) demonstrate that KLW may overestimate nitrogen use efficiency and thus underestimate real emissions compared to direct measurements. Thirdly, KLW calculates annual ammonia emissions using a national-scale EF, which means it cannot represent emission accumulation or dynamics over shorter timeframes. Additionally, similar to NEMA, KLW also suffers from the limitation of not being able to capture variations at the level of specific farms. Consequently, it cannot clearly link mitigation measures to emission reduction outcomes.

To ensure accuracy and reliability in farm-specific emission monitoring, directly measuring emissions is often seen as more dependable than relying on model-based estimates. For barns, measurement methods typically involve equipment that records air exchange rates and ammonia concentrations in both incoming and outgoing air; the difference indicates emissions generated by the livestock (Schep et al., 2024). However, this method requires a closed environment and is applicable primarily to indoor housing systems. Actual emissions from open barns or yards can also be measured using plume measurements—mobile stations are deployed to collect downwind ammonia concentration data from gas plumes, capturing emissions at the street level (Hensen et al., 2024). However, monitoring all farms with this technology would entail significant costs, and atmospheric measurements are further constrained by unsuitable weather conditions for data collection (Deru et al., 2018).

1.3 Research Gap, Research Question and Objective

Despite advances in both modeled and measured approaches for quantifying ammonia emissions, significant shortcomings remain. There is a pressing need for a method that is both affordable and reliable, capable of providing farm-level ammonia emission estimates with sufficient certainty. Such a technique is crucial not only for guiding effective emissions policy but also for enabling farmers to understand and manage their own emissions and to assess the impacts of mitigation measures in practice (LR - Veehouderij en omgeving et al., 2021). In addition, a reliable assessment method would help recognize and reward farmers who achieve substantial reductions in emissions.

This research addresses this gap by aiming to develop a practical farm-specific ammonia emission model for dairy farms in the Netherlands. The proposed model will be built on easily measured predictors or systematic classification of farms, reflecting key operational differences among them.

The model framework will use measured predictors as its foundation and will systematically integrate additional factors such as feed management, milk yield, manure composition, and manure management. The objective is to identify and categorize key farm characteristics that influence ammonia emission patterns, thereby improving emission estimation accuracy at the farm level.

Main Research Question:

Is it possible to develop an ammonia emission model for dairy farms based on measured parameters? Which farm characteristics and management practices have significant impacts on ammonia emissions during this phase?

Sub-Research Questions:

(a) Which widely used predictor variables and foundational model structures are most suitable as the basis for the development of a practical ammonia emission model for dairy farms?

(b) What additional farm characteristics or management variables significantly affect ammonia emissions, and how much do these factors improve the model's predictive ability compared to the base models?

(c) How do upstream feed management and nutritional parameters influence the intermediate predictors of ammonia emission, and indirectly affect emission outcomes? Can these relationships be quantified to inform mitigation strategies?

2. Method

2.1 Data source and collection

Field measurements used for the model derivation were performed at 23 confined dairy farms across the Netherlands under the combined program of Louis Bolk Instituut (LBI) and Dirksen Management Support B.V (DMS). These dairy farms possessed different locations (as seen in Figure 2.1), environmental conditions and management practices (feeding, housing, and manure storage and treatment practices), and therefore could represent a range of dairy production systems in the Netherlands. With the two-year program period, each of the farms were visited at according frequencies to get related sample and tested with according method to get required data.

Manure composition data. Manure samples are collected 5 times throughout the whole program period, the measuring rounds took place at the following times:

- R1: October 2023
- R2: February 2024
- R3: July 2024
- R4: November 2024
- R5: January 2025

During the sampling, a composite manure sample was collected from the dairy cows' manure pit by Peter Vanhoof (Pvf). The sample combined manure taken from at least 10 different spots underneath the slats. To ensure representative-ness, areas near the water trough, concentration box, or milking parlour/milking robot were avoided.

After sampling, the well mixed samples were sent to Pvf's mobile laboratory (Figure 2.2) for measuring manure compositions (Vanhoof, 2024). In the mobile lab, bioelectronic measurements (pH, EC, H_2S, etc.) were performed with a Consort C3050 multimeter. In addiiton, the Ammonia Emisison Potention (AEP) value was also measured using the J-AIM method (Keim, 2025). With this method, AEP was measured by pouring 400 grams of manure at 20 degrees

Figure 2.1: *Distribution of studied farms across the Netherlands*

Celsius into a plastic container. The container is then pressed into the test setup that is hermetically sealed. After this, air with a relative humidity of approximately 40% was sucked over the manure surface, while the NH_3 concentration (in ppm) was measured with a device from the company ExTox from Unna, Germany, the whole process takes 31 minutes. (Jong et al., 2025)

Figure 2.2: *Peter Vanhoof in his mobile lab*

Simultaneously with the mobile lab testing, a portion of the manure samples was sent to Eurofins, an independent clinical laboratory, for detailed analysis of the following manure composition parameters: pH, dry matter, organic matter, total nitrogen, Carbon/Nitrogen (C/N) ratio, TAN, organic nitrogen, and P_2O_5. Most of these key parameters were measured using infrared spectrometry. For instance, to determine TAN, the laboratory performs an extraction step using either water or HCl, depending on whether the sample is liquid or solid, applying an extraction ratio based on the method employed. Subsequently, the treated sample is analyzed according to ISO 15923-1 via spectrophotometry (Eurofins, 2025).

Feed Management data. During the week of manure measurements, farmers recorded the mixed feed provided to dairy cows using an APP developed by DMS. The feed was categorized by individual types, such as silage maize, concentrate, by-products, and total roughage. Farmers entered the nutritional values of each feed component and reported daily feed amounts in kilograms of dry matter per cow per day. Some farms utilized automatic feeding systems that automatically registered the quantities fed for each feed type, while others used feed mixers with weighing installations, allowing for accurate recording of rations. In some cases, farmers estimated feed weights due to the lack of weighing equipment. To ensure data accuracy and plausibility, DMS also collected the 2023 and 2024 Cycle Indicators from the participating farms (Jong et al., 2025).

Using these input data, the APP calculated nutritional quality parameters such as the average Crude Protein (CP or RE) value and the average metabolizable energy for maintenance and production (VEM or ME), based on the dry matter portion of the feed.

Milk composition data. Milk composition data were accessed through the Milk Production Registration (MPR) system, managed by Coöperatie Rundveeverbetering (CRV). Over the two-year period, the system tracked protein content, fat, lactose, and milk urea nitrogen (MUN) on a monthly basis, along with daily milk production. By combining milk composition data with feed intake data from the DMS APP, it became possible to calculate crude protein intake, the Mean Rumen Degradable Protein Balance (OEB), and Intestinal Digestible Protein (DVE).

Other farm foundational data. Foundational farm data were collected through questionnaires and on-site visits. During the program, DMS visited participating farms twice, in February 2024 and January 2025, gathering information including the number and type of cows housed, soil type, total farm area, housing system type (e.g., free-stall, low-emission flooring), bedding materials, manure additives used during storage, volume of manure pits, frequency of manure mixing, and other manure management practices (Jong, 2024).

Some of the collected company-specific data were processed in Excel to convert animal numbers into livestock units (LU) for standardized comparison between farms. Bedding materials and manure additives were assigned nominal numeric codes to facilitate analysis. For example, bedding types such as straw, sawdust, and others were coded as 1, 2, 3, etc., respectively; manure additives received numeric codes starting from 1 upward.

Measured ammonia emission. During the second (February 2024) and fifth (January 2025) measurement rounds, TNO conducted plume measurements outside the stables to quantify the actual ammonia emissions from the farms (Jong, 2024).

These measurement rounds, conducted at the end of the winter period (R2 and R5), were chosen to best represent stable period conditions, as manure pits are typically full during this time, reflecting the manure composition of the period. In round 2, measurements were performed at 18 farms, while round 5 covered 4 farms. The measurements employed a mobile measurement truck equipped with advanced gas analyzers. At each farm, a mobile wind meter was installed, and a cylinder containing nitrous oxide (N_2O) was placed downwind of the barn. Known volumes of N_2O were released, and the truck drove along public roads downwind to capture the resulting gas plume, as illustrated in Figure 2.3. Ammonia concentrations were measured directly in open air by the truck's roof-mounted Quantum Cascade Laser (QCL), avoiding adsorption losses commonly encountered in piping systems.

The plume air was sampled within the trailer by an Aerodyne laser trace gas analyzer using Tunable Infrared Laser Direct Absorption Spectroscopy (TILDAS) to measure concentrations of ammonia and nitrous oxide (N_2O). Ammonia emissions were estimated by comparing the measured dilution of the released N_2O with the ammonia concentrate in the plume, under the assumption that both gases exhibit similar atmospheric dispersion behavior. This relationship can be summarized by the following equation:

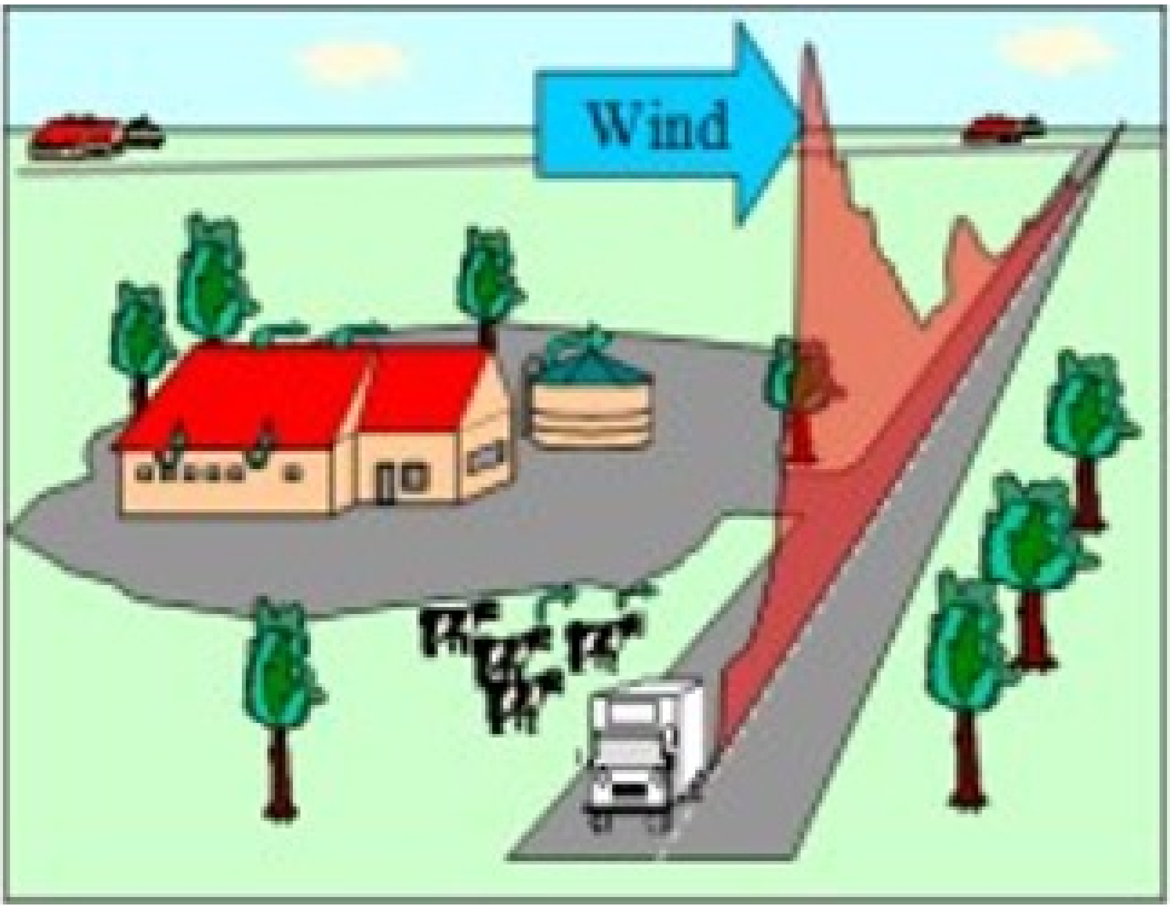

Figure 2.3: Illustration of a Plume Measurement

$$Q_{NH_3} = Q_{N_2O} \times \frac{C_{NH_3,\text{measured}}}{C_{N_2O,\text{measured}}} \tag{2.1}$$

- Q_{N_2O}: Known emission rate of N_2O (released volume per time)
- $C_{N_2O,\text{measured}}$: Measured concentration of N_2O in the plume
- Q_{NH_3}: Estimated ammonia emission rate (unknown, to be calculated)
- $C_{NH_3,\text{measured}}$: Measured concentration of ammonia in the plume

Data from the gas analyzers were synchronized with GPS and wind measurements, enabling identification of source plumes. Two calculation approaches were applied: one method used the N_2O tracer dilution to estimate ammonia emission rates, while the other employed the Gaussian plume model to mathematically estimate emissions based on wind speed, direction, and turbulence. Both methods yielded emission rates expressed in grams per second.(Hensen et al., 2024)

2.2 Data Preparation

2.2.1 Main predictor(s) and basic model(s) selection

To develop a comprehensive model that integrates various farm categories, we identified two to three key predictors as the foundation for the basic model.

AEP basic model. The primary predictor selected is the Ammonia Emission Potential (AEP). This metric serves as a practical indicator of ammonia emissions because it reflects the immediate capacity of manure to release ammonia. While ambient ammonia concentration remains the most reliable indicator for ammonia emission (van Jaarsveld, Bleeker, & Hoogervorst, 2000), the AEP value is obtained by measuring the ammonia concentration under controlled yet realistic environmental conditions. This method provides a “snapshot” or representative segment of the manure’s true emission behavior by simulating key physical and chemical factors influencing ammonia volatilization—such as temperature, moisture content, and air exchange. Essentially, AEP quantifies the potential amount of ammonia susceptible to release under these standardized conditions, making it a useful proxy for actual field emissions. Its reproducibility and sensitivity make AEP valuable for comparing emission potentials across different manure samples or treatments, thus supporting emission modeling efforts.

Since the measured AEP is determined at specific temperature conditions, and considering that actual temperature and pH are critical operational parameters influencing the chemical equilibrium between free ammonium nitrogen and ammonium ions (Cai et al., 2021; Srinath & Loehr, 1974; Guštin & Marinšek-Logar, 2011; Bonmatı & Flotats, 2003; Lei, Sugiura, Feng, & Maekawa, 2007), a temperature correction should be applied to the AEP based on the actual atmospheric temperature prior to its use as a predictor of ammonia emission.

Ammonia emissions depend on both the ammonia gas/liquid equilibrium and the dissociation equilibrium of ammonia in the liquid phase (Bonmatı & Flotats, 2003). The equilibrium of ammonia in aqueous solution is influenced by pH and temperature, and the relative concentrations of ammonium and ammonia can be expressed by the following Equation (2.2)(Srinath & Loehr, 1974):

$$f = \frac{[NH_3]}{[NH_3] + [NH_4^+]} = \frac{[NH_3]}{TAN} = \frac{1}{1 + 10^{pK_a - pH}} \tag{2.2}$$

where $[NH_3]$ is the free ammonia concentration, $[NH_3] + [NH_4^+]$ is the total ammonia nitrogen (TAN) concentration, and pK_a is the logarithmic acid dissociation constant. The pK_a can be expressed as a function of temperature (T in °C) by Equation (2.3), derived from polynomial regression based on the data from Bonmatı and Flotats (2003):

$$pK_a = 4 \times 10^{-8} \times T^3 + 9 \times 10^{-5} \times T^2 - 0.0356 \times T + 10.072 \tag{2.3}$$

The ammonia-fraction equation ($f_{NH_3}(T, pH)$) determines the equilibrium of the slurry solution under according temperature and pH environment, therefore the correction of the measured AEP could be done by below Equation (2.4):

$$\mathrm{AEP_{model}} = \mathrm{Corrected\_AEP} = \mathrm{AEP} \times \frac{f_{NH_3}(T_{\mathrm{measured}}, \mathrm{pH_{measured}})}{f_{NH_3}(20\,^\circ\mathrm{C}, \mathrm{pH_{measured}})} \tag{2.4}$$

For the final regression model, the above equation forms the basis of the AEP basic model.

TAN basic model. The second foundational model uses measured Total Ammoniacal Nitrogen (TAN) as the primary predictor. TAN represents the combined concentration of ammonium ions (NH_4^+) and ammonia (NH_3). Since NH_3 constitutes the non-ionized fraction of TAN, it is volatile and can transfer from the manure slurry to the headspace air above the slurry pit, serving as the direct source of ammonia emissions. This volatilization occurs throughout the nitrogen flow chain—from excretion in the stable or pasture, through manure storage (both indoors and outdoors), to the application of excreta on fields—while NH_4^+ remains dissolved in the liquid phase. NH_3 loss has been shown to correlate closely with TAN variations (Webb et al., 2006; S. Sheppard, Bittman, Swift, & Tait, 2011), making TAN a widely adopted fundamental predictor in ammonia emission estimation models worldwide (S. C. Sheppard & Bittman, 2012; S. Sheppard et al., 2011; Webb et al., 2006; Cowell & Apsimon, 1998; Webb, 2001; Dämmgen & Hutchings, 2008; Reidy et al., 2009; Velthof et al., 2012). Examples of TAN-based mass balance models include the NARSES model (UK), MARACCAS model (Europe), DNDC (US), and the NEMA and KLW models (Netherlands). Despite the limitations and variability discussed in the previous chapter, these models typically rely on calculated TAN, derived from animal feed composition and intake, nitrogen digestibility, and nitrogen retention, as well as the emission factors - rather than directly measured manure TAN. Consequently, since their primary input is feed-related data, these models are theoretically more accurately described as feed-based models rather than TAN-based models.

Other models that simulate emissions at the farm or more localized level often focus on the exchange of ammonia across the gas-film interface above the slurry. In Cortus and Lemay (2009), a comparison is made between models that predict NH_3 emission rates based on convective mass transfer from slurry surfaces. These models, illustrated in Figure 2.4, incorporate sub-models to estimate both the convective mass transfer coefficient and the NH_3 concentration within the gas film.

From these models, it is evident that most mechanistic approaches to ammonia volatilization from slurry start by expressing the mass transfer potential as a function of the dissolved free ammonia concentration in the liquid phase, typically calculated as $f \times \mathrm{TAN}$. For simplicity and due to data limitations, we adopt this formula as the basis for the TAN basic model. Although NH_3 and NH_4^+ are theoretically in chemical equilibrium in solution, this approach still effectively represents the emission potential.

Because the measured TAN in the database is given in grams per kilogram of manure excreted, it must be aligned with the units of our measured emission values which is gram per second. Thus, the TAN model can be formulated as:

$$\begin{aligned}\mathrm{TAN}_{\mathrm{model}} = \mathrm{TAN}_{\mathrm{measured}} &\times f_{\mathrm{NH_3}}(T_{\mathrm{measured}}, \mathrm{pH}_{\mathrm{measured}}) \\ &\times \mathrm{ManureExcretion} \times \mathrm{ManureDensity} \\ &/(365 \times 24 \times 3600)\end{aligned} \tag{2.5}$$

To apply this model, the annual manure excretion must first be estimated based on the production of fat and protein corrected milk yield (Jong et al., 2025):

$$\begin{aligned}\text{Manure excretion per year} = \Big(&6.6113 + 0.001 \times \mathrm{milkyield} \\ &\times \big(0.337 + 0.116 \times \%\text{fat in milk} \\ &+0.06 \times \%\text{protein in milk}\big)\Big) \\ &\times \frac{12}{7} \times \mathrm{milk\_cow\_number}\end{aligned} \tag{2.6}$$

And the manure density is then assumed as a constant value (American Society of Agricultural Engineers, 2003):

$$\text{Manure density} = 990\ \mathrm{kg/m^3} \tag{2.7}$$

MUN basic model. Milk urea nitrogen (MUN) is another predictor used to establish a basic model. The urea content in milk and TAN in manure strongly correlate with dietary protein levels (Frank & Swensson, 2002). Several studies have

Calculated variable	Variable calculations specific to each model: Zhang et al. (1994)	Aarnink and Elzing (1998)	Ni et al. (2000)	Liang et al. (2002)
Mass transfer coefficient (k)	$k = (5.3\times10^{-3} - 1.3\times10^{-2}\cdot v + 8.5\times10^{-4}\cdot v\cdot T_C + 2.3\times10^{-2}\cdot v^2)\cdot 1.16\times 10^{-5}$ (A1)	$k = 50.1\cdot v^{0.8}\cdot T_{film}^{-1.4}$ (B1)	$k = 4.78\times10^{-7}\cdot T_C^{0.8}\cdot v^{0.7}$ (C1)	$k = \left(\frac{1}{k_L} + \frac{1}{H''\cdot k_G}\right)^{-1}$ where $k_L = 2.229\times10^{-6}\cdot e^{0.236\cdot v}$ $k_G = 5.317\times10^{-5} + 2.012\times10^{-3}\cdot v$ (D1)
Fraction of TAN in unionized form (f) or Proportionality coefficient (P_{CO})	$f = \frac{10^{pH}}{10^{pH} + \frac{1}{K_a}}$ where $K_a = 0.2\cdot 10^{-\left(0.0897+\frac{2729}{T}\right)}$ (A2)	$f = \frac{10^{pH_E}}{10^{pH_E} + \frac{1}{K_a}}$ where $pH_E = pH + 1.1$ $K_a = 0.2\cdot 10^{-\left(0.0897+\frac{2729}{T_{film}}\right)}$ (B2)	$P_{CO} = \frac{K_a}{(q\cdot 10^{-pH_i} + K_a)\cdot H}$ where $K_a = 10^{-0.0897-\frac{2129}{T}}$ (C2)	$f = \frac{K_a}{K_a + 10^{-pH}}$ where $K_a = 0.5\cdot 10^{-\left(0.0897+\frac{2729}{T}\right)}$ (D2)
Henry Constant (H)	$H' = \frac{P_G}{C_L}$ $H' = 1.1561\cdot e^{-\frac{4151}{T}}$ (A3)	$H = \frac{C_L}{C_G}$ $H = 1431\cdot 1.053^{(293-T_{film})}$ (B3)	$H = \frac{C_L}{C_G}$ $H = 10^{\frac{1478}{T}-1.69}$ (C3)	$H'' = \frac{C_G}{C_L}$ $H'' = \frac{2.395\times10^5}{T}\cdot e^{\left(-\frac{4151}{T}\right)}$ (D3)
*Overall Emission (E_S)**	$E_S = k\cdot A\cdot\left(\frac{f\cdot TAN}{H'} - C_B\right)$ (A4)	$E_S = \frac{k\cdot A\cdot f\cdot TAN}{H}$ (B4)	$E_S = k\cdot A\cdot\left(\frac{17}{18}\cdot P_{CO}\cdot TAN - C_B\right)$ (C4)	$E_S = k\cdot A\cdot f\cdot TAN$ (D4)

Figure 2.4: *Comparison of ammonia emission from slurry (ES) models*

demonstrated a relationship between urinary nitrogen (UUN) and MUN (Burgos, Fadel, & DePeters, 2007; Jonker, Kohn, & Erdman, 1998; Kauffman & St-Pierre, 2001; Kohn, Kalscheur, & Russek-Cohen, 2002; Huhtanen, Cabezas-Garcia, Krizsan, & Shingfield, 2015), confirming that urinary nitrogen excretion—the primary direct source of ammonia—can be reliably estimated from MUN values. Moreover, MUN has been employed to estimate ammonia emissions (van Duinkerken et al., 2003; Powell, Broderick, & Misselbrook, 2008). Compared to UUN, MUN is a more stable predictor, though it may not fully capture the dynamic variations during transient, static, and reactive phases of ammonia emissions (Powell et al., 2008).

For this study, we use an MUN emission model adapted from the emission estimation table of Verbeek-Schilder and Verhoeven (2024), which correlates specific MUN levels with different grazing time categories (Jong et al., 2025). Additionally, this model was chosen because the range of milk urea nitrogen (MUN) in its experimental dataset closely matches our data, with the majority of milk urea values falling between 14 and 23 mg/dL.

$$E = 0.645 \times \mathrm{MUN} - 0.000673 \times G - 2.440 \tag{2.8}$$

where:
E = ammonia emission (kg NH_3/LU/year)
MUN = milk urea nitrogen (mg/dL)
G = grazing hours (hours/year)

This formula is based on pasture grazing management and milk urea concentrations and is intended for use across all dairy production levels. However, as it estimates annual emissions, the original source does not explicitly specify reference temperature and pH values. To enable consistent temperature and pH corrections, we assume the underlying data correspond to an average temperature of 11.8°C (*2024: record heat, rain, and storms in the Netherlands | NL Times*, 2024) and pH 7.5. Although these standard values may not precisely reflect the original conditions, this normalization facilitates fair comparison of model outcomes among farms.

After applying pH and temperature corrections and converting units to match our measured data, the MUN basic model is expressed as:

$$\begin{aligned} \mathrm{MUN}_{\mathrm{model}} = \; & (0.645 \times \mathrm{MUN}_{\mathrm{measured}} - 0.000673 \times G - 2.440) \\ & \times LU/(365 \times 24 \times 3600) \times \frac{f_{\mathrm{NH_3}}\left(T_{\mathrm{measured}}, \mathrm{pH}_{\mathrm{measured}}\right)}{f_{\mathrm{NH_3}}\left(11.8\,^{\circ}\mathrm{C}, 7.5\right)} \end{aligned} \tag{2.9}$$

2.2.2 Additional parameters selection

The predictors included in the basic model represent the potential for ammonia emissions but do not solely determine the final emission levels. Beyond the effects of pH and temperature incorporated into our models, various farm-related factors—such as climate, housing systems, and manure storage practices—either correlate with these predictors or directly influence the ultimate emissions.

For example, climate is known to influence ammonia emissions, which can vary by as much as 20% across different regions within the same country due to overall climatic differences (Skjøth & Geels, 2013). Elevated air temperatures (already included in our basic model given their significance) and low humidity generally increase volatilization by altering the ammonia-ammonium equilibrium and promoting ammonia gas formation (Beaudor, Vuichard, Lathière, & Hauglustaine, 2025). Additionally, higher wind speeds generally increase total ammonia emissions (Schrade et al., 2012); however, this effect is only observed within the first 0–12 hours after excretion, with emission rates stabilizing thereafter (Sommer, Olesen, & Christensen, 1991).

Components of manure composition also exhibit dynamic relationships with TAN levels, thereby affecting ammonia emissions. For example, the carbon/nitrogen (C/N) ratio in excretion interacts complexly with temperature during TAN volatilization; an increased C/N ratio can mitigate ammonia losses but requires specific temperature ranges to be effective (X. Wang, Lu, Li, & Yang, 2014). Whereas, the dry matter content in manure exhibits nonlinear relationships with the ammonia emission after 6 hours of the excretion, the dry matter factor can be expressed by the equation below (Sommer & Olesen, 1991):

$$F_{DS} = \frac{L}{f} = 0.38 + \frac{0.014}{0.0086 + 1.66 \times \exp(-0.654D)}$$

where

- L = updated loss rate from TAN,
- f = corrected equation included in previous equations (2.5), and (2.9),
- D = dry matter content in manure (percentage).

Therefore,

$$L = F_{DS} \times f,$$

which means by multiplying F_{DS} with the TAN and MUN basic models, we can include the impact of one more related parameter in the model. Since the manure composition effects were already accounted for in the experimental conditions, no correction for dry matter (DS) is necessary in the AEP model.

Once manure is deposited on the stable floor, additional farm characteristics affect TAN volatilization dynamics. Housing system factors such as loose housing versus tie stalls, barn ventilation type, the presence of solid or slatted floors, and water flushing practices significantly influence TAN volatility by modifying urea hydrolysis rates and air exchange within the barn and manure pits (Monteny & Erisman, 1998; Braam, Ketelaars, & Smits, 1997; Vitaliano, D'Urso, Arcidiacono, & Cascone, 2024). In the Netherlands, farms are classified using various RAV codes that correspond to the emission impacts of different housing systems. To quantify the differences between housing types, we introduce emission factors (EF) associated with each RAV code (Koninkrijksrelaties, 2023), expressed in units of kg NH_3 per animal place per year. The adjusted housing variable is then calculated as follows:

$$\text{housing\_variable} = \frac{EF_{\text{RAVcode}} \times \text{animal place} \times 1000}{365 \times 24 \times 3600}$$

During subsequent manure treatment and storage phases, various management practices—such as manure separation, incineration, pelleting/drying, and anaerobic digestion—have been shown to impact TAN volatilization (van der Zee et al., 2024). Interventions that modify pH, temperature, and C/N ratio are critical; for instance, anaerobic digestion and solid-liquid separation of dairy cow and buffalo manure may enhance mineralization of organic nitrogen to TAN, potentially increasing ammonia emissions. Conversely, covering manure with straw can reduce emissions by promoting immobilization of TAN as organic nitrogen (Cole et al., 2005).

Other influential factors include the total number of dairy cattle, as herd size determines the absolute quantity of nitrogen excreted.

2.2.3 Independent feed parameters

While the main emission model utilized direct predictors such as TAN, MUN, AEP, and some manure compositions, these factors themselves are, to a significant degree, influenced by upstream nutritional and feed management strategies on the farm.

For instance, feed intake strongly affects nitrogen excretion. Studies have shown that characteristics such as dry matter (DM), the average metabolizable energy for maintenance and production (VEM), dietary crude protein (CP), and the presence of minerals like potassium (K) and sodium (Na) influence nitrogen excretion by modifying nitrogen conversion efficiency and urine volume (Yan, Frost, Keady, Agnew, & Mayne, 2007; Madsen, Lund, Brask-Pedersen, & Johansen, 2023; de Boer, Smits, Mollenhorst, van Duinkerken, & Monteny, 2002; Waldrip, Todd, & Cole, 2013). VEM, DM, and CP positively correlate with TAN in manure and MUN levels, whereas the proportion of forage generally exhibits a negative correlation. The role of corn silage proportion in the diet, the effect of varying dietary protein relative to milk yield, and energy requirements for milk production (Feed Unit for Milk) also affect nitrogen excretion and the efficiency of nitrogen utilization for milk synthesis, thereby impacting TAN and MUN (Wattiaux & Karg, 2004; Groff & Wu, 2005; Chanda, Khan, Chanda, & Debnath, 2024). The concentrate proportion in the diet further reflects the intensity of animal management, where more intensive dairy systems have been linked to increased atmospheric NH_3/ammonium concentrations (Pain, Van der Weerden, Chambers, Phillips, & Jarvis, 1998). Intermediate nutritional parameters such as Digestible Intestinal Protein (DVE) and Metabolizable Energy Balance (OEB) also influence these predictors by reflecting nitrogen efficiency and consequently nitrogen excretion (van Duinkerken, Smits, André, Šebek, & Dijkstra, 2011).

These independent parameters were not included in the direct emisison model, however, as predictors like TAN and MUN are not usually modified directly in practice, feed composition and feeding strategies are active management levers available to farmers.

To integrate the predictors and parameters discussed in Sections 2.2.1, 2.2.2 and 2.2.3, and taking into account data availability, a summary of ammonia emission predictors alongside the farm categories that influence them and dynamically affect final emission outcomes is presented in Table 2.1. The sample size represents the number of observations or data points collected from the respective source and used in the analysis for each parameter.

As this study focuses on developing a barn emission regression model, parameters influencing emissions during grazing or manure application are excluded.

2.3 Statistic analysis

The statistical analysis in this chapter is organized into three interconnected sections. First, we develop weighted regression models to predict ammonia emissions using each of the basic underlying models (TAN-, MUN-, and AEP-based), incorporating additional farm and management parameters to improve predictive accuracy. Second, recognizing the availability of a larger dataset of model predictions, we perform a comparative analysis of the outputs from the three basic models, examining their mutual correlations and exploring temporal patterns across multiple experimental rounds. Finally, to better understand the underlying drivers of ammonia emission variability, we investigate the feed-to-predictor relationships by constructing ordinary least squares regression models that identify which feed characteristics significantly influence the selected predictors—and through them, ammonia emissions. This multifaceted approach enables us to both build robust emission prediction models and uncover biologically meaningful feed-related factors that can guide practical mitigation strategies. The potential correlations and causal relationships among the selected parameters are illustrated in Figure 2.5.

2.3.1 Direct Emission Model Development

To quantify and optimize the influence of selected parameters on ammonia emissions, we constructed regression models to simulate farm-level NH_3 emission based on key predictors. Measured ammonia emission served as the target for model calibration. The simulated emission was formulated as a function of selected variables, starting from a basic model and progressively incorporating additional paramters as per 2.2.2 representing farm management categories.

Given that measurement errors vary between farms, we employed Weighted Least Squares (WLS) regression to calibrate the simulation model(de Levie, 1986). In WLS, each observation is assigned a weight inversely proportional to the variance of its measurement error, such that more precise (lower-error) measurements have greater influence on parameter estimation. The mathematical forms

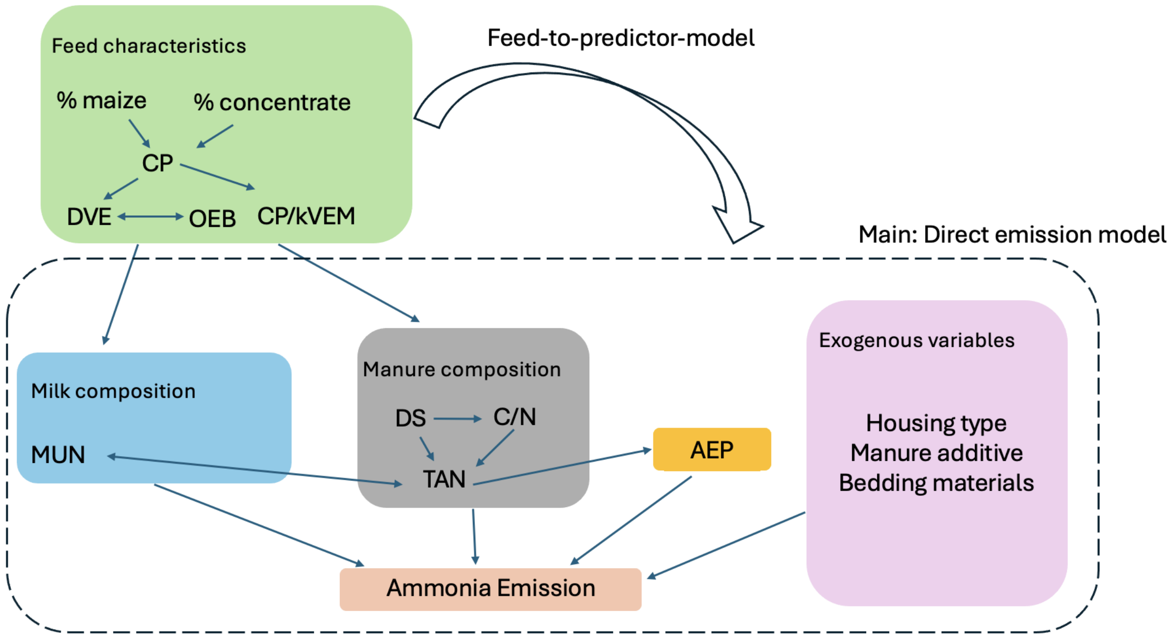

Figure 2.5: Potential Correlations and Causal Relationships Among Selected Parameters

are:

$$\begin{aligned}\text{TAN-based Simulated Ammonia Emission} = {} & \beta_0 + \beta_1 \times \text{TAN}_{\text{model}} \times F_{DS} \\ & + \beta_2 \times \text{C/N} \\ & + \beta_3 \times \text{Housing\_variable} \\ & + \beta_4 \times \text{manure\_additive\_variable} \\ & + \beta_5 \times \text{bedding\_materials\_variable}\end{aligned} \tag{2.10}$$

$$\begin{aligned}\text{MUN-based Simulated Ammonia Emission} = {} & \beta_0 + \beta_1 \times \text{MUN}_{\text{model}} \times F_{DS} \\ & + \beta_2 \times \text{C/N} \\ & + \beta_3 \times \text{Housing\_variable} \\ & + \beta_4 \times \text{manure\_additive\_variable} \\ & + \beta_5 \times \text{bedding\_materials\_variable}\end{aligned} \tag{2.11}$$

$$\begin{aligned}\text{AEP-based Simulated Ammonia Emission} = {} & \beta_0 + \beta_1 \times \text{AEP}_{\text{model}} \\ & + \beta_2 \times \text{Housing\_variable} \\ & + \beta_4 \times \text{bedding\_materials\_variable}\end{aligned} \tag{2.12}$$

The coefficients β_i are determined by minimizing:

$$\sum_{i=1}^{N} w_i \left(y_i - \left[\beta_0 + \sum_{j=1}^{n} \beta_j x_{ij} \right] \right)^2 \tag{2.13}$$

with y_i as the TNO measured emission for farm i, and weights $w_i = 1/\sigma_i^2$ where σ_i^2 is the variance (squared standard error) of each measurement.

2.3.2 Process-Based, Per-Cow emission normalization

Although all regression models were developed and calibrated using total farm-level ammonia emissions, a process-based perspective was introduced by normalizing both measured and predicted emissions to a per-cow basis. For each farm observation, per-cow NH_3 emission rates were calculated by dividing the total emission (g/s) by the number of lactating cows present at the time of sampling. This normalization facilitates direct, process-based comparison of emission intensities between individual farms, independent of herd size, and aligns the analysis with prevailing standards in emission inventory and mitigation literature (Velthof et al., 2012). Per-cow emission rates are subsequently used for benchmarking against literature values and for evaluating management efficiency across farms, providing additional context to the farm-level model evaluation.

2.3.3 Comparison of Basic Model Predictions and Temporal Patterns

To fully compare the behavior and consistency of alternative ammonia emission models, we utilized the complete dataset of model predictions—MUN_{model}, AEP_{model}, and TAN_{model}—spanning 105 experimental conditions, including all participated farms and experimental rounds. Pearson correlation analysis was applied to all pairwise combinations of model predictions to assess the degree of linear association among the three approaches and pairwise scatterplots were generated to graphically depict model agreement.

Beyond overall correlation, possible temporal or batch-wise effects were investigated by examining prediction patterns across the five experimental rounds recorded for each farm. For each round, model prediction distributions were compared using boxplots, and round-wise mean trends for each model were plotted. These analyses were conducted to identify consistent differences, trends, or sources of variability attributable to experimental rounds.

2.3.4 Feed Parameter Contributions to TAN or MUN Predictions

The feed-to-predictor model uses a simpler ordinary least squares (OLS) approach, where the TAN_i and MUN_i values for farm i are equally weighted due to the relatively consistent laboratory conditions and sampling procedures. The mathematical form is:

$$\text{Simulated TAN(or MUN)} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \gamma_1 (x_i \times x_j) + \cdots \beta_n x_n + \epsilon \tag{2.14}$$

where $x_1, x_2, ...$ are the selected input variables, $x_i \times x_j$ $x_i \times x_j$ represent the combined effect of two predictors on the outcome, capturing their potential non-linear influence on the final prediction (Aiken, West, & Reno, 1991). And coefficients β_i, γ_i are determined referring to the method ((2.3.1) used in WLS. All parameters and the target predictor(s) were aligned to same unit g/farm/s.

This section begins by fitting multiple linear regression models to investigate the associations between the selected feed parameters. This approach enables the evaluation of both direct effects and correlations (collinearity) among independent and dependent variables. Identifying pairs of highly correlated predictors is essential for ensuring correct model specification in subsequent analyses.

And then to identify the optimal set of explanatory variables, we used a stepwise forward selection process based on the adjusted coefficient of determination (R^2_{adj}). Starting from one of the chosen feed management, additional variables where justified by correlation analysis or biological reasoning.

At each step:

1. Add one new candidate variable or interaction term to the model.

2. Fit the OLS model using the updated variable set.

3. Calculate the new *adjusted* R^2:

$$R^2_{\text{adj}} = 1 - \frac{(1 - R^2)(n - 1)}{n - p - 1} \tag{2.15}$$

   where n is the number of observations, p is the number of predictors.

4. If R^2_{adj} increases, the new variable is retained; otherwise, it is excluded.

This process was repeated until no further increase in R^2_{adj} was observed.

Standardized Coefficients For interpretability, we also calculated standardized coefficients (Beta weights) for both the direct emission model as well as the feed-to-predictor model:

$$\beta_j^* = \beta_j \cdot \frac{\text{SD}(x_j)}{\text{SD}(y)} \tag{2.16}$$

where SD($\cdot$) denotes the standard deviation. Variables with the largest absolute standardized coefficients contribute most to explaining ammonia emission variation, regardless of their original scale.

2.3.5 Implementation and tools

All analyses were performed using Python 3.12.7 in the Visual Studio Code (VS Code) environment. Data manipulation and preprocessing were undertaken with pandas, regression analyses were carried out using the statsmodels library, and plots generated via matplotlib. Measurement errors were incorporated as weights in the WLS model to maximize the efficiency and validity of parameter estimates.

Table 2.1: Categories Data Description

Description	Parameter/Predictor	Sample Size	Source
Manure Composition	TAN	105	Eurofins
	AEP	105	Pvf
	Temperature	105	Pvf
	pH	105	Pvf
	C/N ratio	105	Pvf
	DS	105	Eurofins
Milk Composition	Milk Yield	105	CRV
	MUN	105	CRV
	Protein percentage	105	CRV
	Fat percentage	105	CRV
Feed Management / Nutritional Quality Parameters	% of maize	105	DMS
	% of concentrate	105	DMS
	CP	105	DMS
	DVE	105	DMS
	OEB	105	DMS
	CP/kVEM	105	DMS
	DS	105	DMS
Manure Management	Bedding materials	42	DMS
	Manure Additives	28	DMS
Others	avg.LU	24	DMS
	Dairy cow number	105	DMS
	Measured NH_3	22	TNO
	Standard error NH_3	22	TNO
	Animalplace	105	DMS
	RAV code	21	DMS
	Grazing day	21	DMS

3. Results

3.1 Model-based estimation of ammonia emissions

3.1.1 TAN based regression model

The best fit regression model established basing on TAN_{model} without adding manure management categories is displayed as Figure 3.1. The regression line (black) reflects the model's fit, while the red dashed line (identity) denotes perfect prediction.

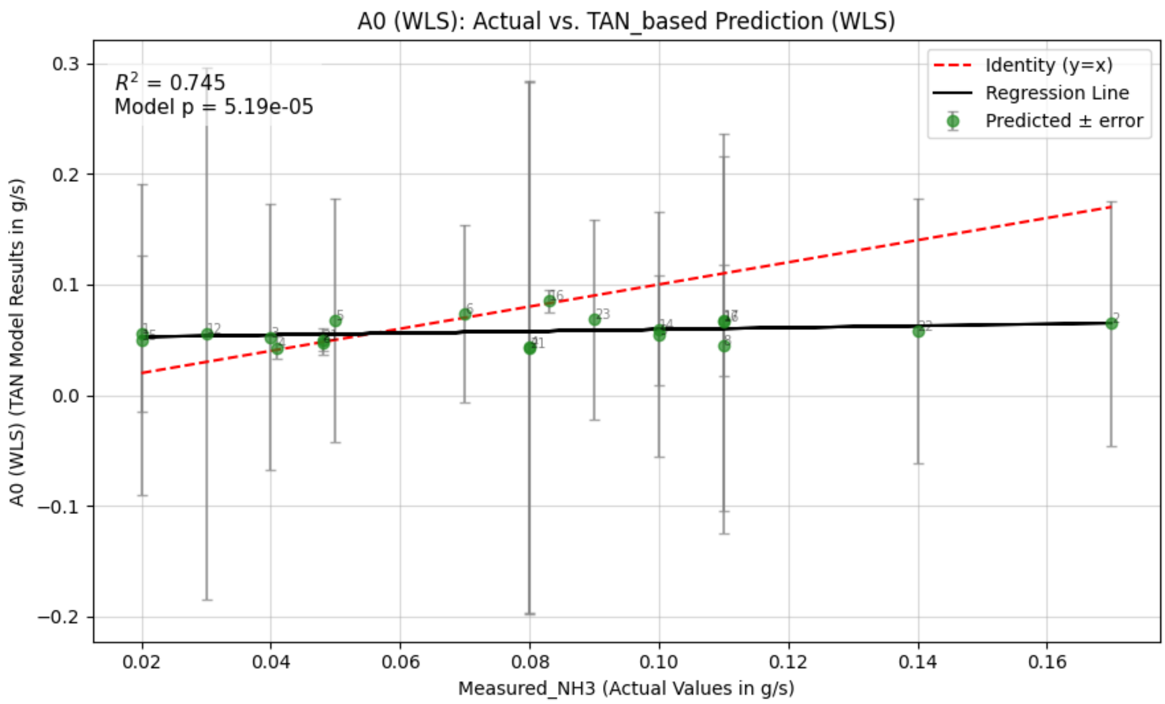

Figure 3.1: *Prediction Accuracy of TAN-Based Model for NH Emissions: Observed vs. Modeled Values, Including Uncertainty (WLS Regression)*

The regression model described in Equation (3.1) yields an R^2 value of 0.745 with a highly significant p-value. At first glance, this suggests that the model explains a large portion of the variance in measured NH_3 emissions. However, a more detailed inspection of Figure 3.1 reveals that the fitted regression line is nearly flat and fails to follow the identity line, particularly at the higher end of measured values. This indicates that, despite the presence of several explanatory variables, the model's predictions do not vary much across farms, often clustering around a similar range. This limited variation is likely due to the large uncertainties present in the estimated regression coefficients and/or a restricted range in the predictor values among the farms studied, effectively dampening the model's ability to distinguish emission differences between individual sites.

As a result, the apparently high R^2 reflects the model's ability to approximate the overall average emission level across all data points, rather than its capacity to provide accurate or meaningful predictions for individual farms. In practical terms, this means the model captures the baseline trend but does not effectively capture the farm-to-farm variability in NH_3 emissions. Therefore, care must be taken not to equate a high R^2 with strong predictive power for specific cases, especially when the fitted regression line lacks a significant slope. These findings highlight the importance of including more informative or farm-specific variables—particularly those related to manure management—to improve prediction accuracy and account for the variability observed in NH_3 emissions.

$$\begin{aligned}\text{TAN-based Simulated Emission}_1 = &-(0.0127 \pm 0.0216)\\ &+(0.4750 \pm 0.9679) \times \text{TAN}_{\text{model}} \times \text{F}_{\text{DS}}\\ &+(0.0067 \pm 0.0029) \times \text{C/N}\\ &+(0.3097 \pm 0.2195) \times \text{HousingVariable}\end{aligned} \tag{3.1}$$

Table 3.1: *TAN Model Coefficients, Standard Errors, and p-values*

Parameter	Coefficient ± SE	p-value
const	-0.012740 ± 0.021555	0.562753
$\text{TAN}_{\text{model}}$	0.475030 ± 0.967863	0.630230
C/N	0.006736 ± 0.002930	0.035305 *
HousingVariable	0.309669 ± 0.219524	0.177498

The regression model results in Table 3.1 indicate that none of the predictor variables, except the C/N ratio, reach conventional levels of statistical significance at the 0.05 level. The intercept (const) shows a small negative coefficient (-0.013) with a non-significant p-value (p = 0.563), suggesting no significant baseline effect. The basic model (extra corrected with DS) has a positive coefficient (0.475) but with high uncertainty and a non-significant p-value (p = 0.630), indicating weak evidence of its influence on the response. The C/N ratio exhibits a small positive effect (0.007) with a statistically significant p-value (p = 0.035), suggesting a modest but meaningful association with the outcome. The housing type variable has a positive coefficient (0.310) yet remains non-significant (p =

0.177), implying some potential influence but insufficient evidence to confirm it. Overall, while the model provides a statistically significant fit and appears to capture a substantial portion of the total variance in the data, it tends to underestimate higher observed values and exhibits considerable predictive uncertainty at the individual farm level. This highlights the need for further model refinement. In addition, due to large confidence intervals and limited statistical significance of the model coefficients, the specific impact of individual predictors remains difficult to interpret reliably.

In the case of including manure management parameters, such as bedding materials and manure additives, the regression model (Equation (3.2)) resulted in a substantial increase in the number of parameters due to the use of multiple dummy variables for each management category. As shown in Figure 3.2, this extended model achieves an exceptionally high R^2 value (0.993), indicating an almost perfect fit to the measured data. However, this apparent improvement comes at the cost of model generalizability. Since each dummy variable corresponds to a management practice found in only a small number of farms, the model tends to tailor itself to these limited data points rather than identifying generalizable relationships. This is a classic symptom of overfitting, especially when the total number of predictors (including more than a dozen dummy-coded variables as shown in Equation (3.2)) approaches or exceeds the number of observations per group. As a result, the model likely inflates its apparent predictive ability within the current dataset, but its performance on new data would be substantially less reliable. In summary, although the inclusion of detailed manure management information appears to enhance model fit, it also introduces a high risk of overfitting due to limited replicates for each dummy variable level and the proliferation of parameters relative to the sample size.

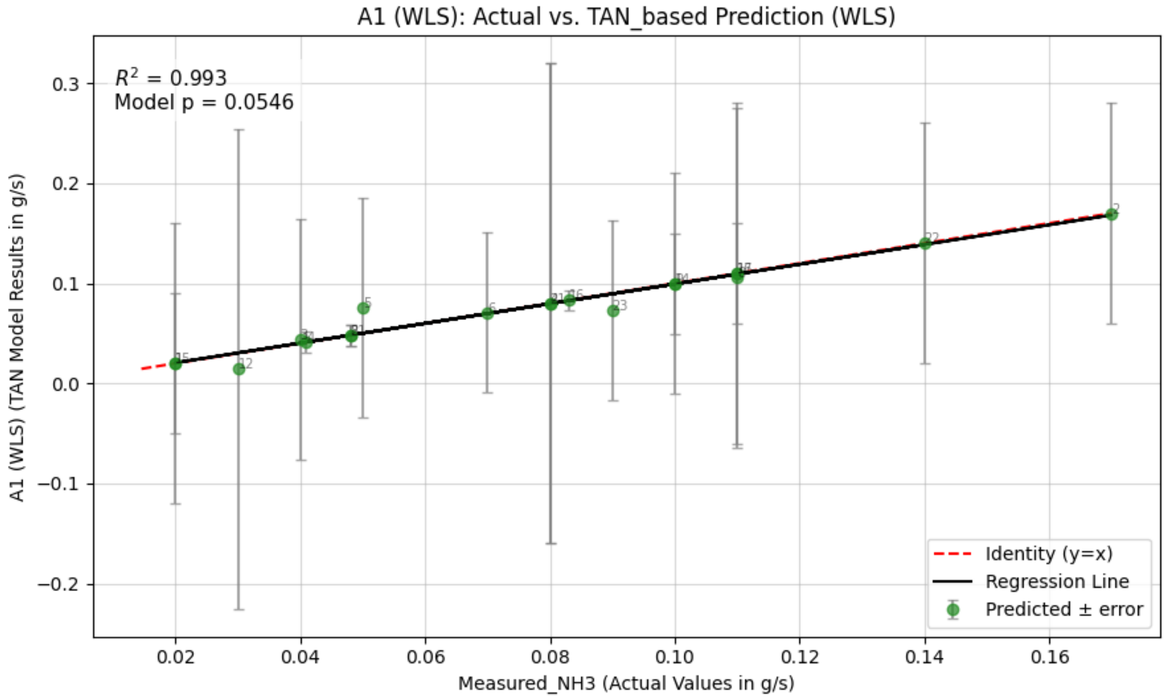

Figure 3.2: Effect of Including Manure Management (Bedding Materials and Additives) on TAN-Based Model Prediction of NH Emissions (WLS Regression, with Error Bars)

$$\begin{aligned}\text{TAN\_based Simulated Emission}_2 = {} & 0.0509 \pm 0.0399 - (3.8623 \pm 1.3605) \\ & \times \text{TAN}_{\text{model}} \times F_{DS} + (0.0106 \pm 0.0058) \times C/N \\ & - (0.0446 \pm 1.0039) \times \text{HousingVariable} \\ & - (0.0556 \pm 0.0130) \times \text{BeddingMaterials}_1 \\ & - (0.0194 \pm 0.0249) \times \text{BeddingMaterials}_2 \\ & + (0.0224 \pm 0.0392) \times \text{BeddingMaterials}_3 \\ & + (0.0646 \pm 0.0325) \times \text{BeddingMaterials}_4 \\ & + (0.0140 \pm 0.0282) \times \text{BeddingMaterials}_5 \\ & + (0.0403 \pm 0.0325) \times \text{BeddingMaterials}_6 \\ & + (0.0157 \pm 0.0152) \times \text{BeddingMaterials}_7 \\ & - (0.0311 \pm 0.0549) \times \text{BeddingMaterials}_8 \\ & + (0.0040 \pm 0.0127) \times \text{BeddingMaterials}_9 \\ & - (0.0040 \pm 0.0478) \times \text{BeddingMaterials}_{10} \\ & + (0.1249 \pm 0.0382) \times \text{ManureAdditive}_1 \\ & + (0.0644 \pm 0.0536) \times \text{ManureAdditive}_2 \\ & - (0.0695 \pm 0.0218) \times \text{ManureAdditive}_3 \\ & + (0.0040 \pm 0.0127) \times \text{ManureAdditive}_4 \\ & + (0.0000 \pm 0.0000) \times \text{ManureAdditive}_5 \\ & + (0.0284 \pm 0.0781) \times \text{ManureAdditive}_6 \\ & + (0.0000 \pm 0.0000) \times \text{ManureAdditive}_7 \\ & - (0.0502 \pm 0.0535) \times \text{ManureAdditive}_8 \end{aligned} \tag{3.2}$$

3.1.2 MUN and AEP-based regression models

MUN_based regression model

The best-fit regression model based on MUN_{model} is presented in Equation (3.3) and shown in Figure 3.3. With an R^2 value of 0.748 and a p-value of 0.0000478, it demonstrates explanatory power similar to that of the TAN-based approach. The model provides a statistically significant fit and accounts for a substantial proportion of the total variance in measured emissions.

$$\begin{aligned} \text{MUN-based Simulated Emission} = & -0.0117 \pm 0.0211 \\ & + (0.2012 \pm 0.3126) \times \mathrm{MUN_{model}} \times \mathrm{F_{DS}} \\ & + (0.0066 \pm 0.0029) \times \mathrm{C/N} \\ & + (0.2514 \pm 0.2591) \times \mathrm{HousingVariable} \end{aligned} \tag{3.3}$$

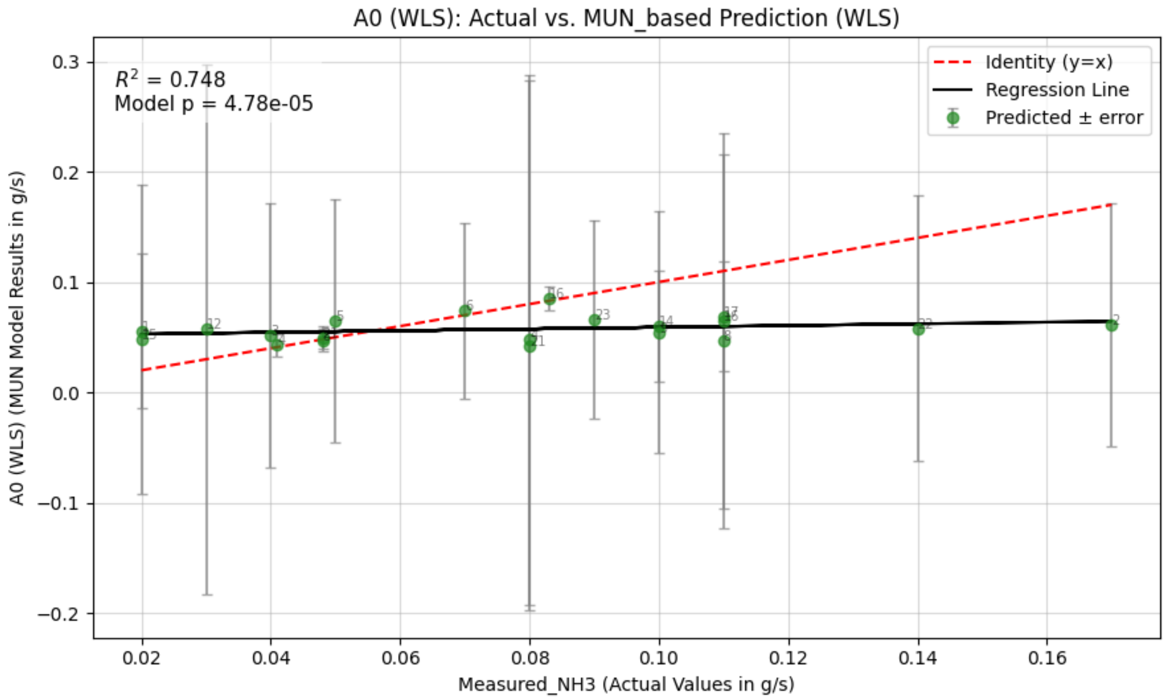

Figure 3.3: Prediction Accuracy of MUN-Based Model for NH Emissions: Observed vs. Modeled Values, Including Uncertainty (WLS Regression

Similar to the TAN model, the regression results (shown in Table 3.2 indicate that the C/N ratio is statistically significant (p = 0.0343). However, the basic model $MUN_{model} \times F_{DS}$ has a relatively large p-value of 0.529, suggesting there is no statistical evidence to support a strong effect of this term in the prediction model.

AEP_based Regression Model

The regression model based on AEP is represented in Equation (3.4) and illustrated in Figure 3.4. Compared to previous models, the performance of the AEP

Table 3.2: MUN Model Coefficients, Standard Errors, and p-values

Parameter	Coefficient ± SE	p-value
const	-0.011749 ± 0.021148	0.586189
$\text{MUN}_{\text{model}}$	0.201158 ± 0.312645	0.529074
C/N	0.006644 ± 0.002872	0.034340 *
HousingVariable	0.251445 ± 0.259128	0.346313

model is improved: $R^2 = 0.681$, indicating that AEP and housing type together explain approximately 68% of the variance in measured ammonia emissions. A p-value of 0.000006 indicates the model is highly statistically significant. Although the regression line still falls below the identity line at higher measured values, the model's predictions generally align more closely with the observed data. While some prediction uncertainty remains, as reflected by the substantial error bars, the overall fit better reflects actual emission patterns than previous models.

$$\begin{aligned} \text{AEP-based Simulated Emission} = {} & 0.0425 \pm 0.0073 \\ & - (0.0006 \pm 0.0004) \times \text{AEP}_{\text{model}} \\ & + (0.7547 \pm 0.1717) \times \text{HousingVariable} \end{aligned} \tag{3.4}$$

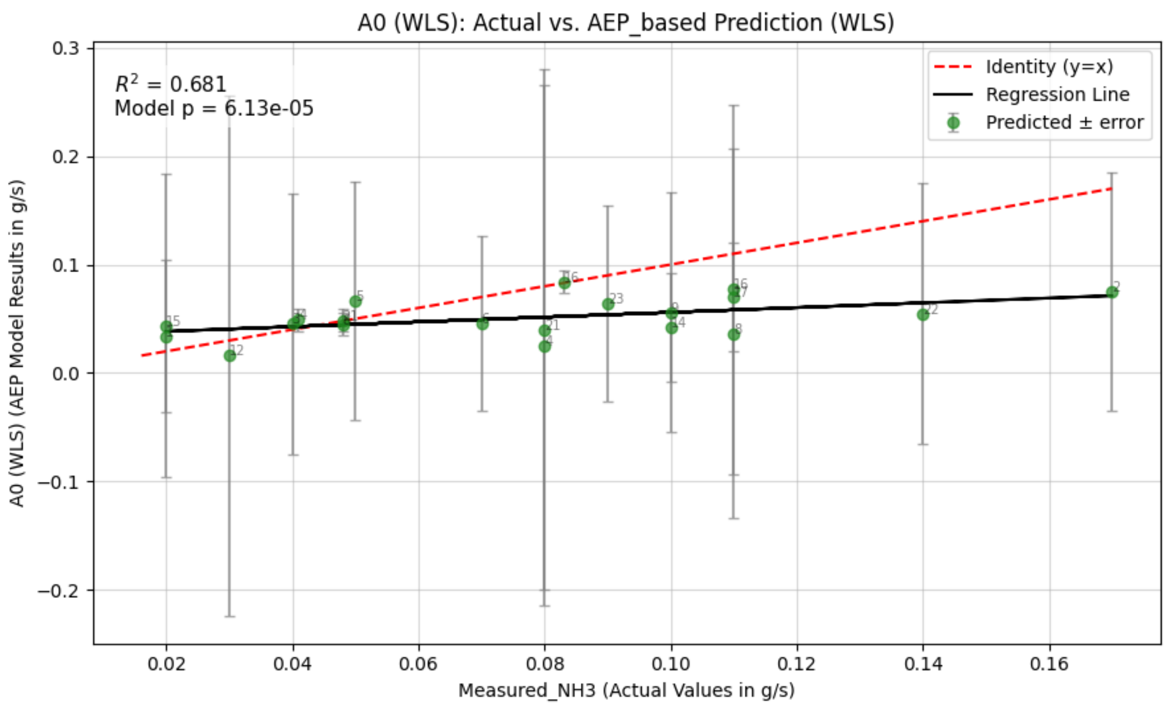

Figure 3.4: Prediction Accuracy of AEP-Based Model for NH Emissions: Observed vs.Modeled Values, Including Uncertainty (WLS Regression)

Table 3.3: AEP Model Coefficients, Standard Errors, and p-values

Parameter	Coefficient ± SE	p-value
const	0.042509 ± 0.007312	0.000021 ***
AEP_{model}	−0.000637 ± 0.000375	0.107143
HousingVariable	0.754659 ± 0.171710	0.000395 ***

The intercept(const) is statistically significant (p = 0.000021), indicating a meaningful baseline emission level contributing from parameters not included in our model. The coefficient for corrected AEP is negative and approaching significant (p = 0.107143), suggesting that higher Corrected AEP values are associated with a slight decrease emissions. The housing variable shows a positive effect and statistically significant (p = 0.000395).

Normalized coefficients of all parameters

The standardized coefficients analysis Table3.8 reveals the relative importance of parameters across the three regression models. The housing variable consistently emerges as the most significant predictor, particularly in the AEP-based model (= 0.4291*). In the AEP-based model, the AEP_{model} shows a negative association (= -0.3180), suggesting that higher AEP values might be linked to slightly lower ammonia emissions. The C/N ratio demonstrates statistically significant positive associations in both TAN-based and MUN-based models (0.16*). The pair of $TAN_{model} \times F_{DS}$ and $MUN_{model} \times F_{DS}$ show modest contributions, with standardized coefficients around 0.09-0.12.

Table 3.4: Standardized Coefficients (Beta) for Different Models

Parameters	AEP Model	TAN Model	MUN Model
HousingVariable	0.4291*	0.1761	0.1430
AEP_{model}	-0.3180	–	–
C/N	–	0.1650*	0.1627*
$TAN_{model} \times F_{DS}$	–	0.0877	–
$MUN_{model} \times F_{DS}$	–	–	0.1216

* Statistically significant coefficients

While the C/N ratio appears to be a relevant predictor, caution is warranted when interpreting the other variables due to their non-significant effects and uncertainty in their contributions. The limited significance of most predictors suggests further investigation with additional data may be needed.

3.1.3 Normalized per-cow emission

To enable comparison on a per-animal basis, the outputs from the three direct emission models were normalized to annual emissions per cow. This was achieved by dividing the 22 model-predicted emission values by the corresponding dairy cow numbers for each farm and round, and then applying the appropriate time conversion to yield results in kilograms of ammonia per cow per year. For a broader context, the 2022 national average inventory was used as a reference. This benchmark was calculated by dividing the national total ammonia emission from housing and storage (as reported by Van Bruggen et al. (2024)) by the country-wide average number of dairy cows for 2022 (CBS (2022a)). The results are summarized in Figure 3.5. Most individual farm-round results fall below the national average inventory line, with some variation between the three models at certain farm-rounds. For example, the three models produced slightly different estimates for Farm 4 in Round 1, which may reflect variability in model sensitivity to input parameters.

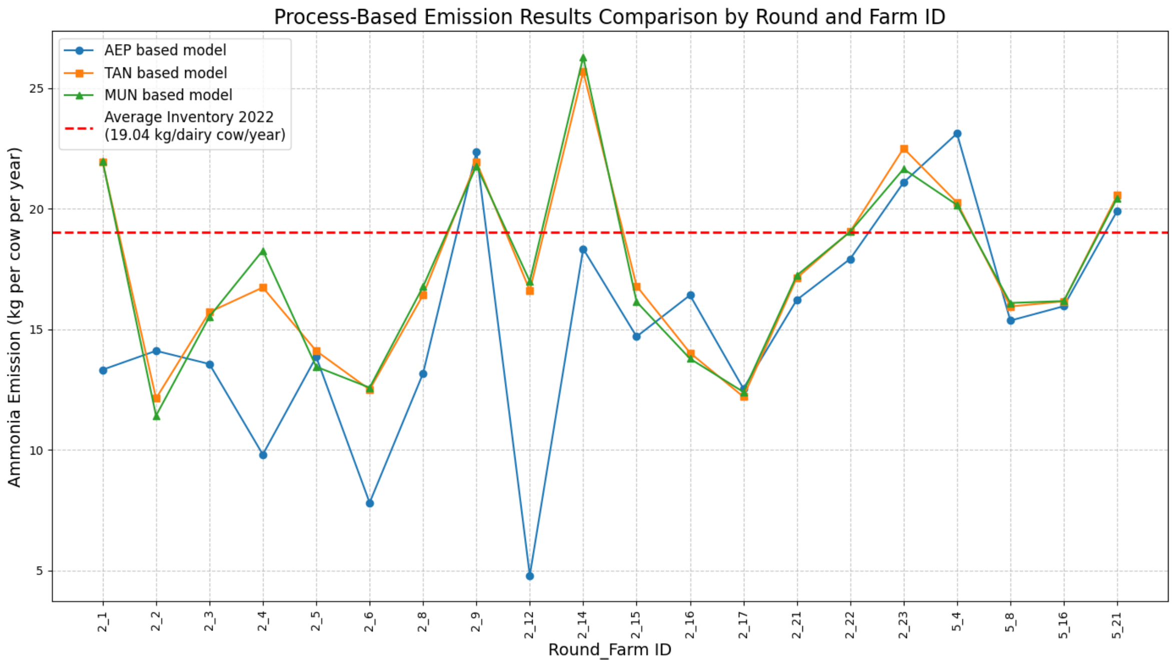

__Figure 3.5:__ Comparison of Model-Based Ammonia Emission Estimates per Cow per Year by Farm and Round, with Average Inventory Reference Line

3.2 Comparison among the Three Basic Models

All three regression models ((3.1), (3.3), (3.4)) explain a substantial portion of measured ammonia emissions. A direct comparison of the basic model outputs—$\text{TAN}_{\text{model}} \times F_{DS}$, $\text{MUN}_{\text{model}} \times F_{DS}$, and $\text{AEP}_{\text{model}}$—reveals a noteworthy degree of consistency, as summarized in Table 3.5.

Table 3.5: Pearson Correlation Matrix of Basic Models' Ammonia Emission Predictions

	$\text{TAN}_{\text{model}} \times F_{DS}$	$\text{AEP}_{\text{model}}$	$\text{MUN}_{\text{model}} \times F_{DS}$
$\text{TAN}_{\text{model}} \times F_{DS}$	1.000	0.62	0.92
$\text{AEP}_{\text{model}}$	0.62	1.000	0.62
$\text{MUN}_{\text{model}} \times F_{DS}$	0.92	0.62	1.000

As shown, $\text{TAN}_{\text{model}} \times F_{DS}$ and $\text{MUN}_{\text{model}} \times F_{DS}$ display an exceptionally strong positive correlation ($r = 0.92$), indicating that these two models simulate changes in NH_3 emissions in a remarkably similar, almost linear manner. By contrast, $\text{AEP}_{\text{model}}$ shows a moderate positive correlation ($r = 0.62$) with both $\text{TAN}_{\text{model}} \times F_{DS}$ and $\text{MUN}_{\text{model}} \times F_{DS}$. All correlations are positive, which indicates that higher values from one model generally correspond to higher values from the others.

Figure 3.6 further illustrates these relationships. In the pairwise scatterplots and marginal histograms, it is evident that the predictions of $\text{TAN}_{\text{model}} \times F_{DS}$ and $\text{MUN}_{\text{model}} \times F_{DS}$ are mostly concentrated at lower emission values, with moderate spread. Conversely, $\text{AEP}_{\text{model}}$ spans a broader range and includes some notably larger values, suggesting greater variability and outliers. In general, predicted emissions from $\text{TAN}_{\text{model}} \times F_{DS}$ are lower in absolute value compared to $\text{MUN}_{\text{model}} \times F_{DS}$.

Beyond overall correlation analysis, we examined potential temporal and batch effects by exploring the distribution of model predictions across five experimental rounds (Figure 3.7) and the round-wise mean emission trends (Figure 3.8). While the three models differ in variability—$\text{AEP}_{\text{model}}$ shows more fluctuations and outliers—their overall temporal trends are quite consistent. The medians and means of all three models rise from rounds 1 (Oct-23) through 3 (Jul-24), peaking in round 3, and then decline during rounds 4 (Oct-24) and 5 (Feb-25). This shared pattern suggests systematic effects of temporal factors, which may be attributable to management changes or environmental variations across seasons. Despite the higher variability in $\text{AEP}_{\text{model}}$, the consistency in trends across all models supports their complementary value in representing the temporal dynamics of NH_3 emissions.

In summary, while each basic model captures slightly different aspects of the emission dynamics, the strong correlations and consistent temporal patterns highlight their robustness for monitoring and comparison purposes.

3.2.1 Selection of feed parameters

Figure 3.9 shows the interactions between selected feed managements. The central hypothesis assumes the existence of interrelations between these parameters, as demonstrated in Figure 2.5. While our results can be summarized as follows:

The independent variables included maize proportion and concentrate pro-

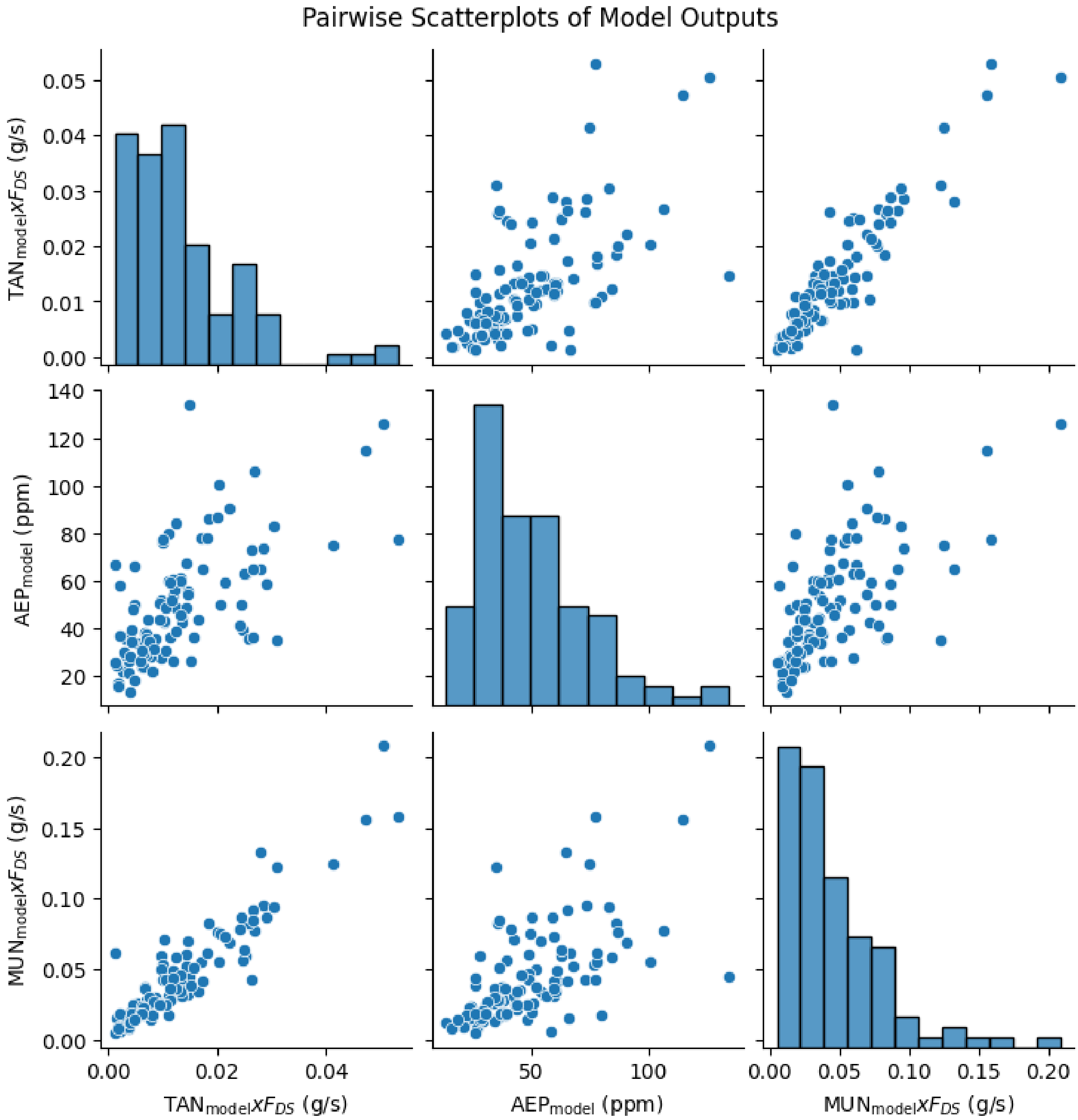

Figure 3.6: Pairwise relationships and distributions of basic model outputs: TAN$_{model}$ $\times$ F_{DS}, MUN$_{model}$ $\times$ F_{DS}, *and* AEP$_{model}$. *The diagonal panels display the distribution of each model output individually.*

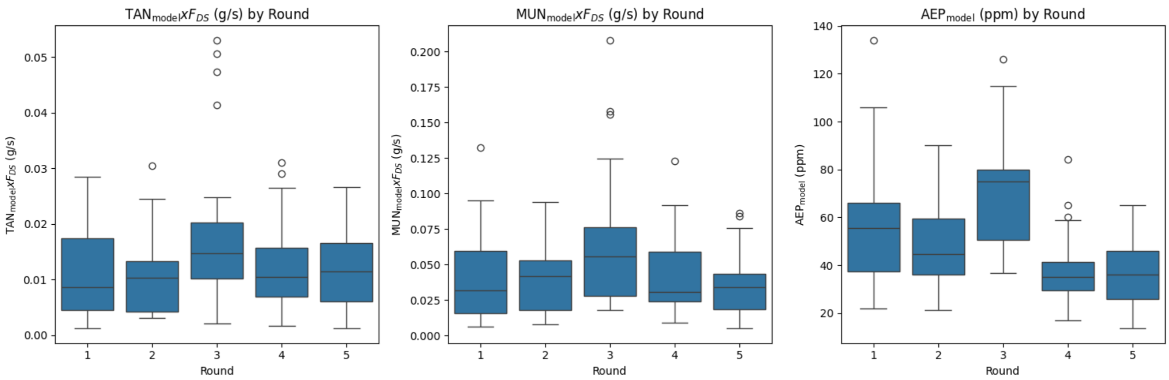

Figure 3.7: Distribution of emissions predicted by each basic model across experimental rounds.

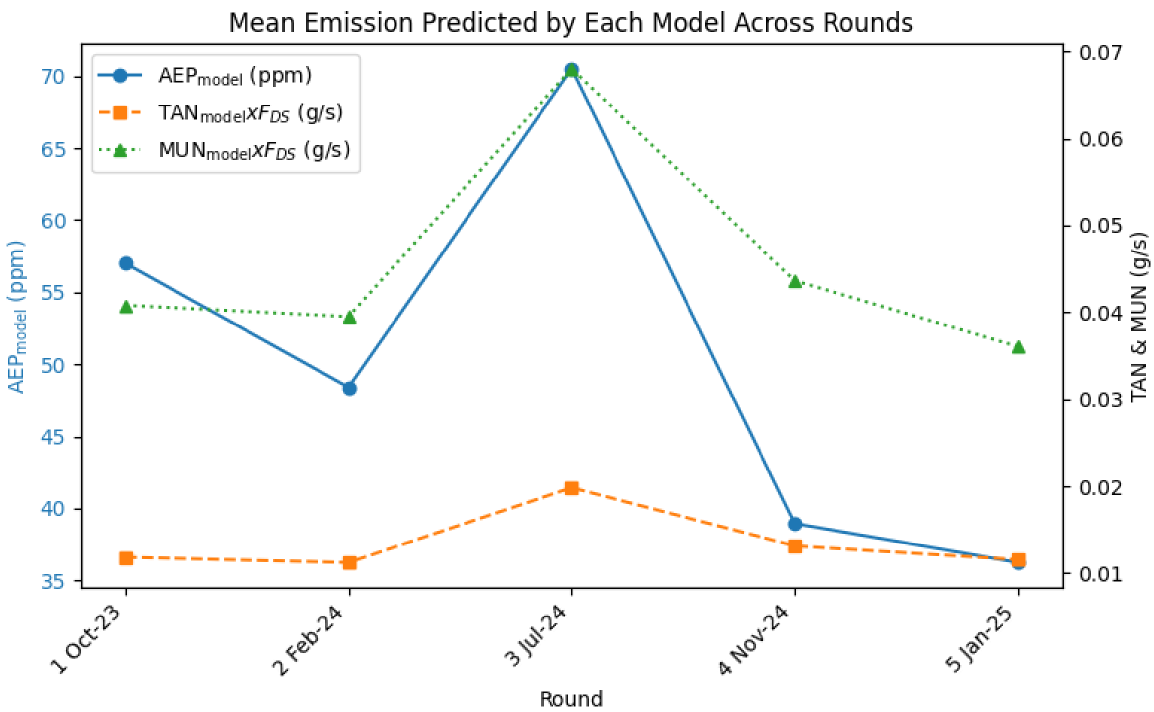

Figure 3.8: Round-wise mean emission trends for each model output. Each model exhibits a similar trajectory, with peak emissions in July 2024, followed by a decrease in later rounds.

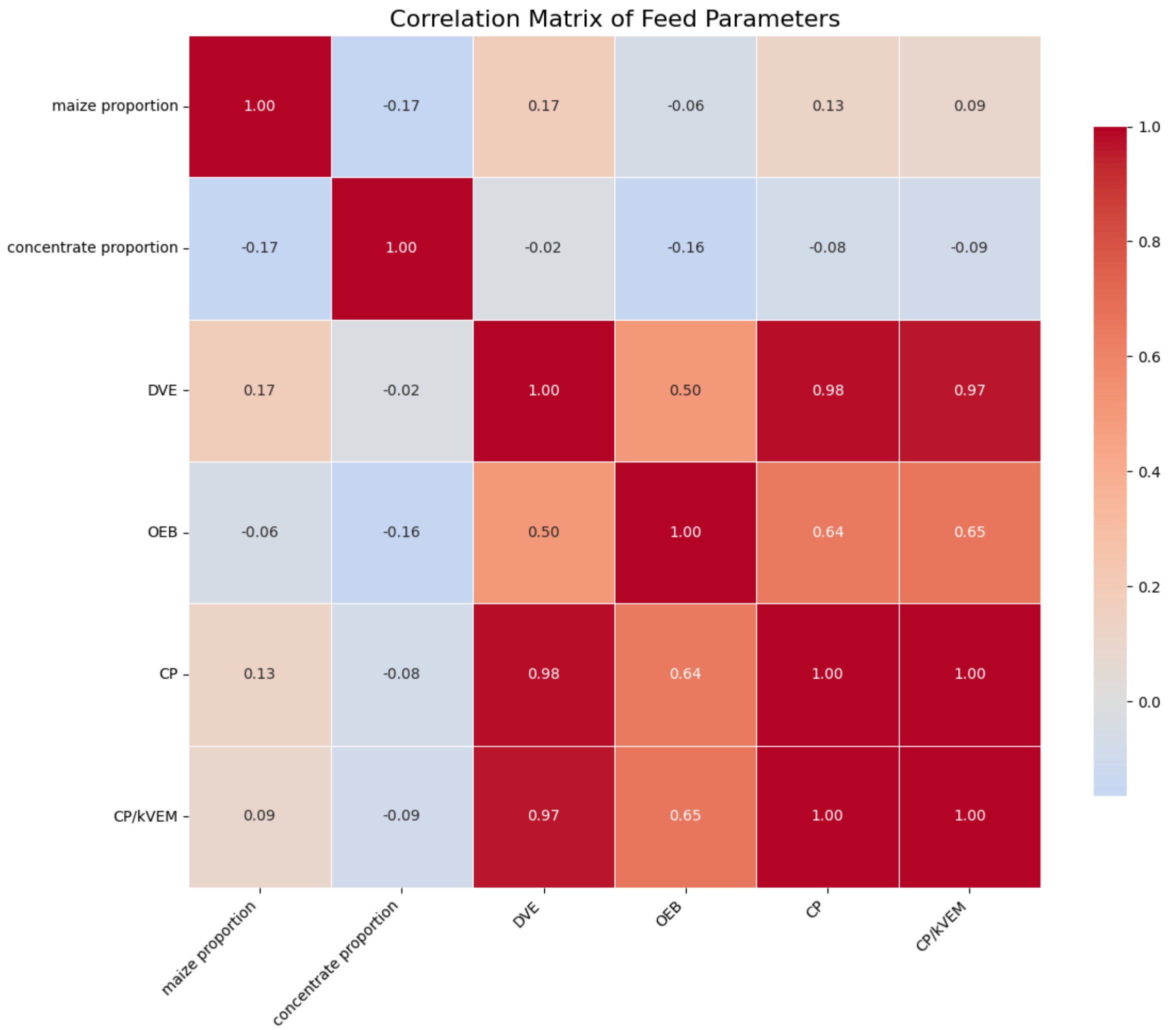

Figure 3.9: Correlation matrix of selected feed parameters. The heatmap visualizes Pearson correlation coefficients among key dietary components, including maize proportion, concentrate proportion, and nutritional indices (DVE, OEB, CP, CP/VEM). Higher (red) or lower (blue) color intensity reflects the strength and direction of the pairwise correlations. This matrix helps to identify potential multicollinearity and interdependencies among the feed variables, which are essential considerations for downstream regression analyses and model interpretation.

portion. Neither maize nor concentrate proportions showed strong statistical relationships with DVE, OEB, CP or CP_kVEM (all $p \geq 0.05$, $R^2 \leq 0.03$). However, within the intermediate variables, CP is a significant predictor for OEB ($p < 0.05$, $R^2 = 0.42$) and DVE ($p < 0.05$, $R^2 = 0.95$). Moreover, OEB and DVE serve as mutual significant predictors of one another ($p < 0.05$, $R^2 = 0.25$ for both regressions).

In summary, the following variable pairs demonstrated sufficiently strong correlations or reciprocal predictive relationships to warrant their consideration as potential interaction terms in the development of feed-to-key-predictor model:

- RE and OEB
- RE and DVE
- OEB and DVE

Based on these conclusions, the predicted TAN were constructed according to the feed elements listed in Table 3.6:

Table 3.6: Variables used in the regression models for simulated key predictor

Variable ID	Variable Name	Description
X_1	Maize Proportion	% maize in diet
X_2	Concentrate Proportion	% concentrate in diet
X_3	CP	Crude protein content in feed
X_4	OEB	Metabolizable energy balance (OEB)
X_5	DVE	Digestible protein in the small intestine
X_6	CP × OEB	Interaction term: crude protein × OEB
X_7	CP × DVE	Interaction term: crude protein × DVE
X_8	OEB × DVE	Interaction term: OEB × DVE
X_9	CP/kVEM	Ratio of crude protein to digestible energy in feed

3.2.2 Feed regression model

Based on the results presented in Table 3.7, most selected variables improved the adjusted R^2 of the models, with only minor decreases observed for X_4 (OEB), and X_9 (CP/kVEM). Nevertheless, we did not rely solely on adjusted R^2 as the criterion for variable selection. Given the established theoretical evidence supporting the linear contributions of OEB and DVE to UUN (Burgos et al., 2007), and recognizing the CP/kVEM ratio as a critical parameter for nitrogen efficiency, we retained these variables in the model.

The M9 model, encompassing 9 variables, ultimately demonstrated the highest R^2 and most favorable adjusted R^2, thus emerging as our definitive regression model for predicting TAN using feed management variables.

Table 3.7: Stepwise model R^2 summary and variables included for each $\text{TAN}_{\text{model}}$ *Prediction*

Model	Variables Included	R^2	R^2_{adj}	Nr of Predictors
M1	X_1 (Maize Proportion)	0.084	0.075	1
M2	X_1, X_2 (Concentrate Proportion)	0.095	0.078	2
M3	X_1, X_2, X_3 (CP)	0.682	0.673	3
M4	X_1, X_2, X_3, X_4 (OEB)	0.683	0.671↓	4
M5	X_1, X_2, X_3, X_4, X_5 (DVE)	0.710	0.696	5
M6	X_1, X_2, X_3, X_4, X_5, X_6 (CP × OEB)	0.716	0.698	6
M7	X_1, X_2, X_3, X_4, X_5, X_6, X_7 (CP × DVE)	0.721	0.701	7
M8	X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8 (OEB × DVE)	0.727	0.705	8
M9	X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8, X_9 (CP/kVEM)	0.729	0.703↓	9

The regression model can be expressed as below Equation (3.5), and illustrated with Figure3.10:

$$
\begin{aligned}
\text{Predicted TAN} = &-0.0377 \pm 0.0307 \\
&+ (0.0008 \pm 0.0003) \times \%\text{maize} \\
&+ (0.0014 \pm 0.0005) \times \%\text{concentrate} \\
&- (0.0506 \pm 0.0343) \times \text{CP} \\
&+ (0.1130 \pm 0.0582) \times \text{OEB} \\
&+ (0.1044 \pm 0.0284) \times \text{DVE} \\
&+ (0.0158 \pm 0.0139) \times \text{CP} \times \text{OEB} \\
&- (0.0007 \pm 0.0027) \times \text{CP} \times \text{DVE} \\
&- (0.0475 \pm 0.0324) \times \text{DVE} \times \text{OEB} \\
&+ (0.0209 \pm 0.0246) \times \text{CP\_kVEM}
\end{aligned}
\tag{3.5}
$$

The regression analysis reveals a strong positive correlation, with an R^2 value of 0.729 and a highly significant model p-value of 5.11e-23. The regression line demonstrates a near-linear relationship between the measured and predicted TAN values, indicating the model's predictive capability. The data points closely cluster around the identity line (red dashed line), suggesting that the predictive model closely approximates the actual measured TAN values. The spread of points suggests variability exist, but the overall trend confirms the model's reliability in estimating TAN across different farms, with most predictions falling within a narrow range of the actual measurements.

Standardised coefficient as shown in Table3.8 provide insights into the relative importance of each feed variables. The most substantial predictor is DVE which

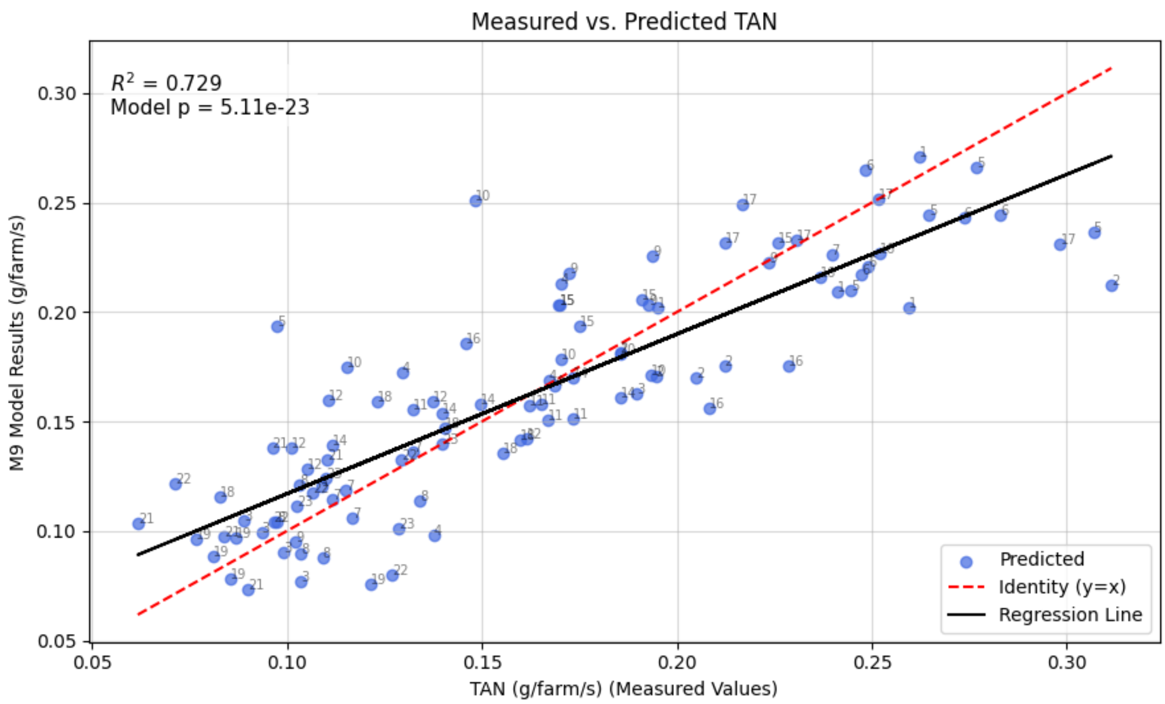

Figure 3.10: Comparison of measured and predicted TAN values. The plotted data show a near-linear relationship, with most points closely following the identity line (dashed red) and an overall R^2 of 0.729, highlighting the predictive strength of the model.

demonstrated a strong and highly significant relationship. It follows by CP shown as a notable negative coefficient, though the p-value (0.144) suggested the relationship might be attributed to random chance. Among the remaining parameters, the maize and concentrate proportions in feed show statistically significant positive associations with TAN, although the relatively modest β suggests that the impact may be limited.

Table 3.8: Regression Coefficients

Parameter	Standardized Beta	p-value	Significance
%maize	0.2087	0.0024	**
%concentrate	0.1627	0.0084	**
CP	-1.5711	0.1436	
OEB	0.6593	0.0552	
DVE	1.7782	0.0004	**
CP×OEB	0.8004	0.2594	
CP×DVE	-0.1212	0.8087	
DVE×OEB	-1.2050	0.1450	
CP/kVEM	0.6592	0.3969	

4. Discussion

4.1 Overall direct emission model performance

Overall, in modeling TNO-measured NH_3 emissions, the three regression models—Equations (3.1), (3.4), and (3.3)—each based on different underlying approaches, consistently captured the major patterns observed in the emission data. By incorporating pH- and temperature-corrected values (TAN_{model}, MUN_{model}, and AEP_{model}), together with dry matter content (DS), the C/N ratio in manure, and a housing type variable, these models provided a comprehensive framework for interpreting the primary drivers of emission potential. All three models yielded R^2 values greater than 0.68, with p-values below 0.0001, indicating statistically significant fits that explain a substantial proportion of the overall variance.

However, when zooming into individual model elements, neither basic model presents statistically significant contributions. Only the pH and temperature-corrected AEP shows an approaching significance (p= 0.1), yet its negative coefficient with the emission suggests that as AEP increases, the final emission tends to decrease — a counterintuitive relationship. The weak connection between our chosen basic models and the measured TNO emissions might be attributed to our limited sample size, with only 22 TNO-measured NH_3 emissions collected across two experimental rounds (Feb.24 and Feb.25). This sample size limitation is particularly problematic for robust statistical inference. According to the rule-of-thumb (Green, 1991), the recommended sample size (N) should be $N \geq 50 + m$ for reliable regression analysis, especially when the number of predictors (m) is less than 7 (which is our case). Small sample sizes not only reduce statistical power but also increase the likelihood of type II errors, where genuine relationships may remain undetected due to insufficient data points. Moreover, the limited sample size amplifies the risk of overfitting and reduces the generalizability of our statistical models, potentially masking true underlying relationships between basic model, other chosen additional parameters and ammonia emissions.

Other parameters such as the C/N ratio presents statistical significant while a positive but much smaller standardized coefficient. Previous research by X. Wang et al. (2014); Jiang, Schuchardt, Li, Guo, and Zhao (2011) indicates that a lower C/N ratio can increase NH_3 emission (negative correlation), but those findings were based on composted manure and observed under higher temperature regimes (e.g., 35°C) with C/N ratios above 25. In contrast, the C/N ratios in our dataset are much lower (6–11) and temperatures substantially cooler (6°C–16°C). At these lower temperatures and narrower C/N ranges, the microbial activity responsible for rapid nitrogen mineralization and ammonia production is likely constrained, and the direct influence of C/N ratio on ammonia volatilization is less pronounced.

The housing type variable in our model represents the unit-converted emission factor for each RAV code. Its positive correlation with measured emissions across all three regression models is logical, given that it inherently represents emissions per animal place. However, statistical significance was only observed in the AEP-based model.

In terms of manure management, including factors such as bedding material and the use of manure additives provided some improvement to model fit ((3.2)). However, these variables were highly imbalanced and sparse in our sample—for instance, out of 10 possible bedding materials type, types 6 ("Zaagsel kalk") and 10 ("Geperste gedroogde zonnebloempitten") were extremely rare, appearing only once each. And some manure additives do not appear in any farm's records. This limited variation means that the estimated effects for some categories are based on very few data points, resulting in large standard errors and limited statistical significance. Additionally, overfitting is a concern when numerous dummy variables are included relative to the number of observations, which in our case sometimes led to instability in the regression results and unreliable coefficient estimates. As such, while their inclusion may superficially increase the explanatory power of the models, we caution against drawing strong conclusions about the specific effects of individual manure management practices. Larger and more balanced datasets would be necessary to reliably evaluate these factors in future studies. Given the statistical constraints and potential for model instability, we strategically excluded manure management variables when constructing the MUN-based and AEP-based regression models.

Normalizing the results to a per-cow, per-year basis allows for direct comparison of ammonia emissions performance across individual farms and rounds. This horizontal comparison reveals distinct differences among farms, highlighting that certain farms consistently exhibit lower emissions per cow relative to others. Such differences may stem from a variety of factors, including but not limited to feeding strategies, housing types, and manure management approaches. These results emphasize the value of farm-level normalization for benchmarking and identifying operational best practices that may contribute to lower emissions. It is also noteworthy that the majority of the farm-level emission values are lower than the national average for 2022 (although our results are based on predictions from winter 2023 to spring 2024). This potential underestimation is likely linked to the exclusion of several parameters in our modeling approach. Although our models combine basic and additional parameters selected based on data availability, they do not include all variables known (or suspected) to affect ammonia emissions, as outlined in Section 2.2. Therefore, the direct emission models may lack important explanatory power with respect to both temporal and farm-specific variation, further highlighting the need for more comprehensive data collection and enhanced model complexity in future studies.

In general, despite deriving three statistically fitted regression models, our ability to accurately estimate ammonia emissions is severely constrained by profound methodological limitations. The TNO-measured NH_3 dataset, characterized by its minimal sample size, presents significant challenges to robust statistical inference. The measured emissions exhibit considerable variability, ranging from approximately 0.02 to 0.18 g/s, accompanied by standard errors spanning 0.004 to 0.07 g/s. This substantial variation introduces profound uncertainty, particularly for higher emission measurements. While the regression models demonstrate an initial statistical fit, the combination of small sample size, high measurement uncertainty, and significant standard errors fundamentally prevents us from making definitive claims about ammonia emission prediction accuracy.

4.2 Comparison of basic models

When comparing the predictive performance within the basic models, the analysis shows strong positive correlations between the different model-derived emission predictions, particularly between $\text{TAN}_{\text{model}}$ and $\text{MUN}_{\text{model}}$ (correlation coefficient = 0.92), which is consistent with the findings in Burgos et al. (2007); Kohn et al. (2002); Huhtanen et al. (2015) that TAN and MUN are strongly correlated. This demonstrates that despite relying on different predictor variables, these two models closely track similar emission dynamics. The generally lower absolute values predicted by the $\text{TAN}_{\text{model}}$ compared to the $\text{MUN}_{\text{model}}$ can be explained by the fact that the $\text{MUN}_{\text{model}}$ estimates emissions based on milk urea nitrogen, which serves as an indirect indicator of nitrogen use efficiency and ammonia emission potential, often leading to higher predicted values. Conversely, the TAN measurement represents the manure TAN level at a point of temporary compositional equilibrium, where a portion of ammonia has already undergone volatilization, consequently resulting in a potential underestimation of total ammonia emissions.

The results also presents moderately strong correlations between the $\text{AEP}_{\text{model}}$ and both $\text{TAN}_{\text{model}} \times F_{DS}$ and $\text{MUN}_{\text{model}} \times F_{DS}$ (correlation coefficients 0.62), suggesting the $\text{AEP}_{\text{model}}$ also effectively reflects key trends in ammonia emissions. This may be explained by the fact that the TAN- and MUN-basic models primarily consider only the TAN in the manure or Urea in milk, adjusted for pH, temperature, and dry matter, without accounting for the more complex dynamics within manure composition. In contrast, the AEP measurement method, aside from controlling experimental temperature, better reflects the potential interactions occurring within the manure during the TAN volatilization process. The less constrained prediction range in Figure3.6 of the $\text{AEP}_{\text{model}}$ might also indicate its greater sensitivity to other environmental factors which not involved in the other two basic models such as humidity, microbial activity, minerals in manure, etc..

This strong inter-model correlation implies significant shared information and complementary strengths, which reinforce confidence in their underlying representations of the emission processes. Even though adjustments are needed to improve alignment with measured values (for example: including more outdoor climate variables), the consistent trends and relational structure among the models indicate their capability to validate one another and provide robust predictive insights. Moreover, the stability of these correlations suggests that while absolute predicted values may deviate, the models reliably differentiate between low and high emission scenarios.

Temporal analyses across five monitoring rounds demonstrate that the trends predicted by all three models are concordant, peaking in round 3 (summer) and declining afterwards. This seasonal pattern align with the findings by Saha et al. (2014), that in summer the farm tends to have higher ammonia emission from barns comparing to spring, autumn and winter. The possible reason for the difference is because the temperature variations (Powell et al., 2008; Q. Wang, Flesch, Bai, Zhang, & Chen, 2024), although the specific contribution of temperature fluctuations to the observed emission changes was not explored in depth in this study, future research could focus on quantifying these effects in greater detail. Furthermore, the stable seasonal trends observed across models underscore their capability to provide dependable predictive insights into ammonia emissions.

4.3 Feed to predictor contribution

A reliable regression model using feed management in estimating TAN was sucessfully detrived. The near-linear relationship between measured and predicted TAN values validates the model's effectiveness in capturing the complex nitrogen dynamics in agricultural feed systems.

The standardrized coefficents shows that the Digestible Protein in the Small Intestine (DVE) emerges as the most significant predictor of TAN, with a strong and statistically significant relationship (= 1.7782, $p = 0.0004$). The Dutch DVE/OEB$_{1991}$ and DVE/OEB$_{2010}$ systems takes these two parameters as important criteria for nitrogen efficiency evaluation. Studies by de Boer et al. (2002); Van Dongen (1999) suggest that lower DVE intake could reduce urinary nitrogen excretion and thus ammonia emission, which do align with this positive relationship. Similarity, Rumen Degradable Protein Balance (OEB), is also typically recognized as positively associated with ammonia emissions (van Duinkerken et al., 2003; Van Dongen, 1999). Yet in our regression model, OEB only showed a marginally significant relationship ($p = 0.0552$), suggesting a potential, though not conclusive, association.

Additionally, maize and concentrate proportions demonstrate statistically significant positive associations with TAN, although with more modest effects (maize: = 0.2087, $p = 0.0024$; concentrate: = 0.1627, $p = 0.0084$). As anticipated, the percentage of concentrate, serving as a proxy for intensive farming management, demonstrated a positive correlation with emissions (Kelleghan, Hayes, Everard, & Curran, 2020; Dragosits et al., 2002). However, in contrast to established research indicating that with diets rich in readily fermentable carbohydrates (more maize) could mitigate ammonia emissions (Roberts, Xin, Kerr, Russell, & Bregendahl, 2007; Vogel & Humenik, 2017; van Duinkerken et al., 2003), our data unexpectedly demonstrated a positive association between maize proportion and total emissions. This might be attributable to the underlying biological complexity. For instance, Arndt, Powell, Aguerre, and Wattiaux (2015) demonstrated that while increasing alfalfa proportion and reducing corn proportion in feed, the total daily urinary urea increases, yet the urea concentration per liter of urine actually decreases. This absolute increase is primarily attributed to changes in total urine volume resulting from dietary mixture alterations. Given the complexity of feed composition, other feed proportion variations may also exert subtle influences on these biochemical dynamics.

Beyond the most influential predictors, crude protein (CP) emerged as a parameter of interest, notably showing a negative coefficient in our results. This contrasts with established research, which generally finds that higher dietary protein intake leads to increased nitrogen excretion (McGinn, Janzen, Coates, Beauchemin, & Flesch, 2016; Cole et al., 2005; Sajeev, Amon, Ammon, Zollitsch, & Winiwarter, 2018; Lynch, Sweeney, Callan, & O'Doherty, 2007). One possible explanation for this discrepancy lies in the complex interactions between dietary components represented in our multivariate model. When multiple, highly correlated nutritional variables are included simultaneously, the unique effect of CP—after controlling for total nitrogen intake and other confounding factors—may be isolated from its most direct biological pathway, occasionally resulting in counterintuitive coefficients due to multicollinearity. This suggests that CP alone, without considering dietary energy provision and other dietary factors, may not reliably reflect the true drivers of TAN excretion within the farm systems included in our dataset. In contrast, our findings for the CP/kVEM ratio revealed a positive correlation with nitrogen emissions, aligning well with prior studies. This ratio likely provides a better explanation of nitrogen dynamics because it reflects the balance between protein and energy supply. A high CP/kVEM ratio may indicate insufficient energy to digest crude protein efficiently, resulting in lower nitrogen utilization and consequently higher TAN excretion. Therefore, compared to CP alone, the CP/kVEM ratio offers a more reliable indicator of the complex relationship between diet composition and nitrogen emissions. These results highlight the importance of considering nutrient balance, not just absolute nutrient amounts, in predicting ammonia emissions and nitrogen excretion. Our results are consistent with earlier research (Arndt et al., 2015; LR - Veehouderij en omgeving, Plomp, Van Noord, Meerkerk, & De Haan, 2018) that also reported a positive association between CP/kVEM and TAN excretion. Taken together, these findings underscore the limitations of interpreting single nutrient effects without context and reinforce the need for integrated nutritional metrics in environmental modeling.

Regarding the regression coefficients for RExOEB, RExDVE, and DVExOEB, the results point to complex influences on TAN excretion. For example, the negative coefficient from the pair of term DVE*OEB suggests a phenomenon of diminishing returns or antagonism: when both DVE and OEB are high simultaneously, their combined effect on TAN emissions is less than the sum of their separate effects. Statistically, this negative interaction term essentially corrects for the "over-counting" that would result if the two variables simply added together without accounting for overlaps or dependencies in their effects on nitrogen metabolism.Nevertheless, none of the pairwise interaction terms show statistical significance, which means that while these trends hint at possible biological or metabolic interactions, the current data variability does not allow us to draw firm conclusions about the existence or strength of these effects.

4.4 Implications

The direct emission model developed in this study offers a cost-effective and practical solution for predicting ammonia emissions at the farm level. Unlike models that rely on national-scale emission factors—which often overlook important farm-specific differences—our approach incorporates measured on-farm predictors. This enables the model to better reflect the real-life management practices, feeding strategies, and environmental conditions unique to each farm. Compared to direct atmospheric ammonia measurement techniques, this model is considerably less resource-intensive, as it utilizes routinely collected farm data and does not require costly equipment or labor-intensive sampling, making it feasible for widespread monitoring and application.

Although the statistical significance of individual predictors in the direct emission model may be limited due to sample size and data quality constraints, the strong agreement between the three basic models ($\text{TAN}_{\text{model}} \times F_{DS}$, $\text{MUN}_{\text{model}} \times F_{DS}$, and $\text{AEP}_{\text{model}}$) underscores the model's robustness in capturing dynamic changes in ammonia emissions. This demonstrates that, even if absolute emission values are difficult to predict with precision, the modeling approach remains highly valuable for tracking emission trends and monitoring farm performance over time. It provides a practical framework for assessing the effects and sensitivity of mitigation actions and management interventions. Farms and policymakers can apply this tool to monitor progress, detect improvements or setbacks, and evaluate the real-world impacts of emission reduction strategies.

From a feed management perspective, our regression analysis provides clear, actionable recommendations for mitigating TAN excretion at the source. Specifically, strategies that reduce dietary DVE (digestible protein in the small intestine) and lower the proportion of concentrate in the ration are likely to yield direct reductions in ammonia emissions, as reflected by the standardized coefficients in the model. These insights can guide more targeted and effective feed interventions to improve nitrogen use efficiency and environmental outcomes.

Finally, all three predictive models consistently captured a pronounced seasonal pattern, with highest ammonia emissions recorded during the summer. This highlights the need for seasonally adaptive mitigation strategies, with increased efforts targeting periods of elevated risk, such as hot months. Regular, year-round monitoring can further help to identify when and how interventions are most effective, enabling timely responses—such as improved ventilation, timely manure removal, or cooling measures—that maximize the benefits of emission reduction efforts.

In summary, although the direct emission model alone may not be suitable for direct on-farm application, the combination of the basic models developed in this study offers a cost-effective and farm-specific approach for monitoring ammonia emission trends, guiding management interventions, and supporting policy evaluation in livestock production systems.

4.5 Scope and Data Limitations

Despite yielding important insights into the farm categories and other drivers of ammonia emission, several limitations of this study should be acknowledged.

First, the direct emission model's scope is confined exclusively to the stable period, primarily due to the availability of relevant and consistent TNO measured data. This temporal focus may limit the generalizability of results to other periods when feed management or environmental conditions differ—such as grazing seasons —where patterns of feed intake, manure output, and volatilization dynamics could diverge significantly.

Second, the dependent variable—ammonia emission rate—was estimated using the TNO plume method, which, in this study, was measured on a single day for each site rather than through continuous or frequent monitoring during the stable period. This "snapshot" approach cannot capture within-farm or between-day variability, which might arise from daily changes in weather, manure handling, animal behavior, or diet intake. Consequently, emission values used in model development may not fully represent typical or seasonal averages, possibly introducing measurement error or bias.

Third, such a small dataset of the measured NH_3 presents statistical limitations. Simple linear models were used in a two-step approach, which fits the scope and scale of available data. The low sample size not only restricts the complexity of models that can be reliably estimated, but also limits the applicability of the linear regression approach itself: with limited data, linear models provide interpretability and minimize overfitting, but they cannot capture possible nonlinear or more complex relationships in the system. Structural Equation Modeling (SEM), which would allow for a more sophisticated understanding of relationships and underlying mechanisms (Rex B., 2023), was not feasible here due to the increased risk of model overfitting, identification problems, and instability of parameter estimates under data scarcity. Therefore, both the choice of linear regression and the exclusion of more advanced modeling approaches were conservative responses to these data constraints.

Last important limitation is that although the simulation models demonstrated good fit to the measured ammonia emission data within our dataset, the lack of an independent external dataset precluded validation of model performance beyond the sampled farms. As a result, the predictive accuracy and generalizability of the derived regression models cannot be robustly assessed. This introduces the possibility of overfitting to the current sample and means further data collection or application to new farms would be necessary to confirm the reliability and applicability of these models in broader contexts.

In summary, while this study's design was shaped by significant practical constraints, it establishes clear foundational results and highlights priorities for future data collection. Expanding both the temporal depth and breadth of measurement, as well as the sample size and balance among management practices, will be essential to improve model precision and expand the applicability of research findings for on-farm emission mitigation.

5. Conclusion

This study aimed to investigate whether a measured-parameter-based ammonia emission model could be developed for dairy farms and which farm or management variables most significantly impact emissions. The following conclusions address the main research question and each sub-research question in turn, drawing upon results from regression analysis, model validation, and contextual discussion.st ammonia emission estimation models.

Main research question: Is it possible to develop an ammonia emission model for dairy farms based on measured parameters? Which farm characteristics and management practices have significant impacts on ammonia emissions?

The research successfully developed three regression models, each based on core predictors—Total Ammoniacal Nitrogen in manure (TAN), Milk Urea Nitrogen (MUN), and Ammonia Emission Potential (AEP)—to fit measured TNO ammonia emissions. All three models achieved statistically significant results, with R^2 alues exceeding 0.68, indicating good predictive performance within the available sample. The inclusion of additional farm and environmental variables—specifically manure pH, measurement temperature, dry matter content, C/N ratio, milk yield, grazing days, and housing type—helped account for variability in ammonia emissions.

However, it is important to acknowledge the model's statistical limitations, primarily due to a small sample size that falls below the generally recommended threshold for robust inference. As a result, while model fits are encouraging, some predictor effects (including those of the base models themselves) may be underpowered and findings should be interpreted with caution regarding general applicability.

Sub-RQ1: Which widely used predictor variables and foundational model structures are most suitable as the basis for the development of a practical ammonia emission model for dairy farms?

All three predictor constructs (TAN, MUN, and AEP) proved viable as bases for direct ammonia emission regression modeling. Among them, models based on MUN and TAN showed the strongest mutual agreement, with consistently higher R^2 and a more logical positive association with measured emission values. The AEP-based model performed slightly less well, even exhibiting a counterintuitive negative coefficient when controlling for local conditions, suggesting that while AEP can provide supplementary information, MUN and TAN are preferable as foundational predictors for practical applications in emission monitoring. Specifically, MUN reflects overall nitrogen loss, whereas TAN has a more direct connection to actual ammonia emissions.

Sub-RQ2: What additional farm characteristics or management variables significantly affect ammonia emissions, and how much do these factors improve the model's predictive ability compared to the base models?

Beyond the predictors and the parameters included in basic model such as manure pH and temperature and dry matter, several additional farm characteristics significantly improved model explanatory power. Statistically significant contributors included the C/N ratio in manure, as well as the housing type variable (linked to standard emission factors). These variables capture key site-specific or operational conditions influencing volatilization dynamics. By incorporating them, the models better account for environment- and management-driven variation, improving their performance and relevance for emission estimation at the farm scale.

Sub-RQ3: How do upstream feed management and nutritional parameters influence the intermediate predictors of ammonia emission, and indirectly affect emission outcomes? Can these relationships be quantified to inform mitigation strategies?

The study also demonstrates that upstream feed management exerts a quantifiable effect on ammonia emission potential, primarily via its impact on TAN. Regression analysis of dietary factors revealed that the content of digestible protein in the small intestine (DVE) and the share of concentrate feed are the most influential predictors of TAN. Both showed significant positive associations with TAN, suggesting that reducing DVE content and the proportion of concentrate in rations could be highly effective for mitigating direct ammonia losses from barns. These findings support feed-focused mitigation strategies: by optimizing protein sources and feed composition, farms can not only improve nitrogen use efficiency but also substantially lower their environmental ammonia footprint. Additionally, the moderate but significant impact of other nutritional ratios (such as the CP/kVEM ratio) supports the case for considering both macro- and micronutrient balancing in practical feed management.

In summary, while sample size limitations prevent definitive statements about all factors, this research establishes a practical foundation for farm-scale ammonia emission modeling based on measured parameters. Although the direct emission model alone may have limitations, the combination of basic models presents a feasible and cost-effective approach for monitoring emission trends and supporting targeted mitigation—particularly through dietary management and environmental controls. These tools are accessible for on-farm use and can guide both immediate management decisions and longer-term strategies to improve environmental performance.

Beyond the farm level, wider application of such models can contribute to meeting societal goals for reducing agricultural ammonia emissions, supporting compliance with environmental regulations, and informing policy evaluation. Future work with larger and more varied datasets is recommended to further validate and refine these approaches and expand their value for both producers and broader stakeholders.

References

2024: record heat, rain, and storms in the Netherlands | NL Times. (2024, December). Retrieved 2025-06-12, from https://nltimes.nl/2024/12/29/2024-record-heat-rain-storms-netherlands

Aiken, L. S., West, S. G., & Reno, R. R. (1991). *Multiple Regression: Testing and Interpreting Interactions*. Thousand Oaks, CA: SAGE Publications. Retrieved from https://books.google.nl/books?id=LcWLUyXcmnkC&printsec=frontcover&source=gbs_atb&redir_esc=y#v=onepage&q&f=false

American Society of Agricultural Engineers. (2003). *Manure Production and Characteristics.* American Society of Agricultural Engineers. Retrieved from https://www.asabe.org/ (Place: St. Joseph, MI, USA Published: ASAE Standard D384.1 FEB03)

Arndt, C., Powell, J., Aguerre, M., & Wattiaux, M. (2015, January). Performance, digestion, nitrogen balance, and emission of manure ammonia, enteric methane, and carbon dioxide in lactating cows fed diets with varying alfalfa silage-to-corn silage ratios. *Journal of Dairy Science*, *98*(1), 418–430. Retrieved 2025-06-29, from https://linkinghub.elsevier.com/retrieve/pii/S0022030214007747 doi: 10.3168/jds.2014-8298

Beaudor, M., Vuichard, N., Lathière, J., & Hauglustaine, D. A. (2025). Future Trends of Global Agricultural Emissions of Ammonia in a Changing Climate. *Journal of Advances in Modeling Earth Systems*, *17*(4), e2023MS004186. Retrieved 2025-06-22, from https://onlinelibrary.wiley.com/doi/abs/10.1029/2023MS004186 (_eprint: https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2023MS004186) doi: 10.1029/2023MS004186

Bestman, M., & Erisman, J. W. (2016). *Geschiktheid van de Kringloopwijzer als beleidsinstrument: Expert judgement* (Tech. Rep. No. 2015-052 LbD). Driebergen, Netherlands: Louis Bolk Instituut. Retrieved from https://orgprints.org/id/eprint/36683/1/3106.pdf

Bonmatı, A., & Flotats, X. (2003, January). Air stripping of ammonia from pig slurry: characterisation and feasibility as a pre- or post-treatment to mesophilic anaerobic digestion. *Waste Management*, *23*(3), 261–272. Retrieved 2025-06-06, from https://www.sciencedirect.com/science/article/pii/S0956053X02001447 doi: 10.1016/S0956-053X(02)00144-7

Born, C.-H., Cliquet, A., Schoukens, H., Misonne, D., & Hoorick, G. V. (2014). *The Habitats Directive in its EU Environmental Law Context: European Nature's Best Hope?* Routledge. (Google-Books-ID: G1acBQAAQBAJ)

Braam, C., Ketelaars, J., & Smits, M. (1997, July). Effects of floor design and floor cleaning on ammonia emission from cubicle houses for dairy cows. *Netherlands Journal of Agricultural Science*, *45*(1), 49–64. Retrieved 2024-

12-28, from https://library.wur.nl/ojs/index.php/njas/article/view/525 doi: 10.18174/njas.v45i1.525

Burgos, S., Fadel, J., & DePeters, E. (2007, December). Prediction of Ammonia Emission from Dairy Cattle Manure Based on Milk Urea Nitrogen: Relation of Milk Urea Nitrogen to Urine Urea Nitrogen Excretion. *Journal of Dairy Science*, *90*(12), 5499–5508. Retrieved 2025-06-12, from https://linkinghub.elsevier.com/retrieve/pii/S0022030207720234 doi: 10.3168/jds.2007-0299

Cai, Y., Gallegos, D., Zheng, Z., Stinner, W., Wang, X., Pröter, J., & Schäfer, F. (2021, October). Exploring the combined effect of total ammonia nitrogen, pH and temperature on anaerobic digestion of chicken manure using response surface methodology and two kinetic models. *Bioresource Technology*, *337*, 125328. Retrieved 2024-12-28, from https://linkinghub.elsevier.com/retrieve/pii/S0960852421006684 doi: 10.1016/j.biortech.2021.125328

Candel, J. (2023, June). *Nitrogen Wars: How the Netherlands Hit the Limits to Growth.* Retrieved 2025-07-10, from https://www.greeneuropeanjournal.eu/nitrogen-wars-how-the-netherlands-hit-the-limits-to-growth/

CBS. (2022a). *How many cattle and pigs in the Netherlands? - The Netherlands in numbers | CBS* [webpagina]. Retrieved 2025-07-15, from https://longreads.cbs.nl/the-netherlands-in-numbers-2023/how-many-cattle-and-pigs-in-the-netherlands (Last Modified: 2023-09-14)

CBS. (2022b). *Stikstofemissies naar lucht* [webpagina]. Retrieved 2025-05-07, from https://www.cbs.nl/nl-nl/dossier/dossier-stikstof/stikstofemissies-naar-lucht (Last Modified: 22-03-2024T11:27:48)

Chanda, T., Khan, M., Chanda, G., & Debnath, G. (2024, August). Correlation between Milk Urea Nitrogen (MUN) Levels with Metabolizable Energy (ME) and Crude Protein (CP) Provided with Ratio of Roughage Concentrate by Supplied Feed of Dairy Cattle and its Effect on Milk Yield and Milk Composition. *Agricultural Reviews*(Of). Retrieved 2025-06-19, from https://arccjournals.com/journal/agricultural-reviews/RF-280 doi: 10.18805/ag.RF-280

Cole, N. A., Clark, R. N., Todd, R. W., Richardson, C. R., Gueye, A., Greene, L. W., & McBride, K. (2005, March). Influence of dietary crude protein concentration and source on potential ammonia emissions from beef cattle manure1,2,3. *Journal of Animal Science*, *83*(3), 722–731. Retrieved 2025-06-19, from https://doi.org/10.2527/2005.833722x doi: 10.2527/2005.833722x

Cortus, E. L., & Lemay, S. P. (2009, January). Modelling ammonia emission from swine slurry based on chemical and physical properties of the slurry. *Canadian Biosystems Engineering*, *51*. Retrieved from https://www.researchgate.net/publication/228887708_Modelling_ammonia_emission_from_swine_slurry_based_on_chemical_and_physical_properties_of_the_slurry (Publisher: University of Minnesota)

Cowell, D., & Apsimon, H. (1998, February). Cost-effective strategies for the abatement of ammonia emissions from European agriculture. *Atmospheric Environment*, *32*(3), 573–580. Retrieved 2025-06-11, from https://linkinghub.elsevier.com/retrieve/pii/S1352231097002033 doi: 10.1016/S1352-2310(97)00203-3

de Boer, I. J. M., Smits, M. C. J., Mollenhorst, H., van Duinkerken, G., & Monteny, G. J. (2002, December). Prediction of Ammonia Emission from Dairy Barns Using Feed Characteristics Part I: Relation Between Feed Characteristics and Urinary Urea Concentration. *Journal of Dairy Science*, *85*(12), 3382–3388. Retrieved 2025-06-19, from https://www.sciencedirect.com/science/article/pii/S0022030202744251 doi: 10.3168/jds.S0022-0302(02)74425-1

de Levie, R. (1986). When, why, and how to use weighted least squares. *Journal of Chemical Education*, *63*(1), 10. Retrieved from https://doi.org/10.1021/ed063p10 doi: 10.1021/ed063p10

Deru, J., Hensen, A., van Dinther, D., Frumau, A., van den Bulk, P., & Antonissen, H. (2018). *Oriënterende ammoniak- en methaanmetingen in de Kwatrijnstal* (Tech. Rep. No. 2018-021 LbD). Bunnik, Netherlands: Louis Bolk Instituut. Retrieved from https://orgprints.org/id/eprint/36683/1/3106.pdf

Dragosits, U., Theobald, M. R., Place, C. J., Lord, E., Webb, J., Hill, J., . . . Sutton, M. A. (2002, April). Ammonia emission, deposition and impact assessment at the field scale: a case study of sub-grid spatial variability. *Environmental Pollution*, *117*(1), 147–158. Retrieved 2025-06-29, from https://www.sciencedirect.com/science/article/pii/S0269749101001476 doi: 10.1016/S0269-7491(01)00147-6

Dämmgen, U., & Hutchings, N. J. (2008, August). Emissions of gaseous nitrogen species from manure management: A new approach. *Environmental Pollution*, *154*(3), 488–497. Retrieved 2025-06-11, from https://linkinghub.elsevier.com/retrieve/pii/S0269749107001947 doi: 10.1016/j.envpol.2007.03.017

Eurofins. (2025). *Accreditatie.* Retrieved 2025-06-04, from https://www.eurofins-agro.com/nl-nl/over-eurofins-agro/accreditatie

Feest, A., van Swaay, C., & van Hinsberg, A. (2014, April). Nitrogen deposition and the reduction of butterfly biodiversity quality in the Netherlands. *Ecological Indicators*, *39*, 115–119. Retrieved 2024-11-22, from https://www.sciencedirect.com/science/article/pii/S1470160X13004986 doi: 10.1016/j.ecolind.2013.12.008

Frank, B., & Swensson, C. (2002, July). Relationship Between Content of Crude Protein in Rations for Dairy Cows and Milk Yield, Concentration of Urea in Milk and Ammonia Emissions. *Journal of Dairy Science*, *85*(7), 1829–1838. Retrieved 2024-12-28, from https://www.sciencedirect.com/science/article/pii/S0022030202742574 doi: 10.3168/jds.S0022-0302(02)74257-4

Green, S. B. (1991, July). How Many Subjects Does It Take To Do A Regression Analysis. *Multivariate Behavioral Research*, *26*(3), 499–

510. Retrieved 2025-06-28, from http://www.tandfonline.com/doi/abs/10.1207/s15327906mbr2603_7 doi: 10.1207/s15327906mbr2603_7

Groff, E. B., & Wu, Z. (2005, October). Milk Production and Nitrogen Excretion of Dairy Cows Fed Different Amounts of Protein and Varying Proportions of Alfalfa and Corn Silage. *Journal of Dairy Science*, *88*(10), 3619–3632. Retrieved 2025-06-12, from https://www.sciencedirect.com/science/article/pii/S0022030205730472 doi: 10.3168/jds.S0022-0302(05)73047-2

Guštin, S., & Marinšek-Logar, R. (2011, January). Effect of pH, temperature and air flow rate on the continuous ammonia stripping of the anaerobic digestion effluent. *Process Safety and Environmental Protection*, *89*(1), 61–66. Retrieved 2025-06-06, from https://www.sciencedirect.com/science/article/pii/S0957582010001102 doi: 10.1016/j.psep.2010.11.001

Hazelhorst, S., van der Maas, C., & Romeijn, P. (2024). *Effect van nieuwe inzichten op het bereiken van de NPLG stikstofdoelen* (Tech. Rep.). Rijksinstituut voor Volksgezondheid en Milieu RIVM. Retrieved 2025-05-15, from https://rivm.openrepository.com/handle/10029/627642 doi: 10.21945/RIVM-2024-0054

Hensen, A., Wintjen, P., Zhang, J., van Mamson, H., van den Bulk, P., Velzeboer, I., & van Dinther, D. (2024). *And finally... one more ammonia story.* (Published: PowerPoint presentation)

Huhtanen, P., Cabezas-Garcia, E., Krizsan, S., & Shingfield, K. (2015, May). Evaluation of between-cow variation in milk urea and rumen ammonia nitrogen concentrations and the association with nitrogen utilization and diet digestibility in lactating cows. *Journal of Dairy Science*, *98*(5), 3182–3196. Retrieved 2025-06-12, from https://linkinghub.elsevier.com/retrieve/pii/S0022030215001691 doi: 10.3168/jds.2014-8215

Jiang, T., Schuchardt, F., Li, G., Guo, R., & Zhao, Y. (2011, October). Effect of C/N ratio, aeration rate and moisture content on ammonia and greenhouse gas emission during the composting. *Journal of Environmental Sciences*, *23*(10), 1754–1760. Retrieved 2025-06-19, from https://www.sciencedirect.com/science/article/pii/S1001074210605918 doi: 10.1016/S1001-0742(10)60591-8

Jong, L. d. (2024). *The relation between slurry composition and ammonia emissions from the Dutch dairy sector* (Internship report). Beusichem, The Netherlands: Dirksen Management Support B. V.

Jong, L. d., Deru, J., Vanhoof, P., Hahn, K., Hensen, A., & Erisman, J. W. (2025). *Measuring is knowing? Determining ammonia emissions via feed trail, milk urea, manure samples and feather measurements on dairy farms* (Tech. Rep.). Kosterijland 3-53981 AJ Bunnik: Louis Bolk Institute. Retrieved from https://www.louisbolk.nl/publicaties

Jonker, J., Kohn, R., & Erdman, R. (1998, October). Using Milk Urea Nitrogen to Predict Nitrogen Excretion and Utilization Efficiency in Lactating Dairy Cows. *Journal of Dairy Science*, *81*(10), 2681–2692. Retrieved 2025-06-12, from https://linkinghub.elsevier.com/retrieve/pii/S0022030298758254 doi: 10.3168/jds.S0022-0302(98)75825-4

Kauffman, A., & St-Pierre, N. (2001, October). The Relationship of Milk Urea Nitrogen to Urine Nitrogen Excretion in Holstein and Jersey Cows. *Journal of Dairy Science*, *84*(10), 2284–2294. Retrieved 2025-06-12, from https://linkinghub.elsevier.com/retrieve/pii/S0022030201746759 doi: 10.3168/jds.S0022-0302(01)74675-9

Keim, J. (2025). *IG gesunde Gülle*. Retrieved 2025-06-04, from https://www.xn--ig-gesunde-glle-bwb.de/

Kelleghan, D. B., Hayes, E. T., Everard, M., & Curran, T. P. (2020, October). Assessment of the Impact of Ammonia Emissions from Intensive Agriculture Installations on Special Areas of Conservation and Special Protection Areas. *Environmental Protection Agency*. Retrieved from http://hdl.handle.net/10197/11627

Kohn, R., Kalscheur, K., & Russek-Cohen, E. (2002, January). Evaluation of Models to Estimate Urinary Nitrogen and Expected Milk Urea Nitrogen. *Journal of Dairy Science*, *85*(1), 227–233. Retrieved 2025-06-12, from https://linkinghub.elsevier.com/retrieve/pii/S002203020274071X doi: 10.3168/jds.S0022-0302(02)74071-X

Koninkrijksrelaties, M. v. B. Z. e. (2023). *Regeling ammoniak en veehouderij* [ministeriele-regeling]. Retrieved 2025-06-22, from https://wetten.overheid.nl/BWBR0013629/2023-04-01 (Last Modified: 2025-05-13)

Lei, X., Sugiura, N., Feng, C., & Maekawa, T. (2007, July). Pretreatment of anaerobic digestion effluent with ammonia stripping and biogas purification. *Journal of Hazardous Materials*, *145*(3), 391–397. Retrieved 2025-06-06, from https://www.sciencedirect.com/science/article/pii/S0304389406013951 doi: 10.1016/j.jhazmat.2006.11.027

LR - Veehouderij en omgeving, Plomp, M., Van Noord, T., Meerkerk, B., & De Haan, M. (2018). *Inzicht in ammoniakemissie op veenweidebedrijven : Analyse van bedrijfsresultaten van de KringloopWijzer (2013-2015)* (Tech. Rep.). Wageningen: Wageningen Livestock Research. Retrieved 2025-06-29, from https://research.wur.nl/en/publications/81e6b926-876b-4003-b352-32674875dce5 doi: 10.18174/432583

LR - Veehouderij en omgeving, PPO/PRI AGRO Field Technology Innovations, Animal Farming Systems, LR - PRC De Marke, WIAS, Lagerwerf, L., … Ogink, N. (2022). *Integrale modellering van emissies in de melkveehouderij : Metingen vs modellen* (Tech. Rep.). Wageningen: Wageningen Livestock Research. Retrieved 2025-02-05, from https://research.wur.nl/en/publications/22f3ebc5-04e3-4cff-a5d0-b3a7573c62ff doi: 10.18174/579200

LR - Veehouderij en omgeving, WIAS, Mosquera, J., Van Dooren, H., Ogink, N., Van Well, E., & Monteny, G. (2021). *Monitoring van methaan-, ammoniak-, en lachgasemissies uit melkveestallen : Praktijkmetingen in de periode oktober 2018-februari 2020* (Tech. Rep.). Wageningen: Wageningen Livestock Research. Retrieved 2025-02-13, from https://research.wur.nl/en/publications/44067f71-5955-4c56-9f22-16e256eca73f doi: 10.18174/

536752

Lynch, M. B., Sweeney, T., Callan, B. F., J. J., & O'Doherty, J. V. (2007, January). The effect of high and low dietary crude protein and inulin supplementation on nutrient digestibility, nitrogen excretion, intestinal microflora and manure ammonia emissions from finisher pigs. *Animal*, *1*(8), 1112–1121. Retrieved 2025-06-19, from https://www.sciencedirect.com/science/article/pii/S1751731107000407 doi: 10.1017/S1751731107000407

Madsen, P., Lund, P., Brask-Pedersen, D., & Johansen, M. (2023, January). Effect of age and dietary crude protein level on nitrogen excretion in Holstein bull calves. *Livestock Science*, *267*, 105139. Retrieved 2024-12-28, from https://linkinghub.elsevier.com/retrieve/pii/S1871141322003122 doi: 10.1016/j.livsci.2022.105139

Marra, W., Hazelhorst, S., Brandt, K., Wichink Kruit, R., Schram, J., & de Jongh, L. (2023). *Monitor stikstofdepositie in Natura 2000-gebieden 2023. Monitoring van de Wet stikstofreductie en natuurverbetering* (Tech. Rep.). Rijksinstituut voor Volksgezondheid en Milieu RIVM. Retrieved 2024-12-26, from https://rivm.openrepository.com/handle/10029/627028 doi: 10.21945/RIVM-2023-0239

McGinn, S. M., Janzen, H. H., Coates, T. W., Beauchemin, K. A., & Flesch, T. K. (2016). Ammonia Emission from a Beef Cattle Feedlot and Its Local Dry Deposition and Re-Emission. *Journal of Environmental Quality*, *45*(4), 1178–1185. Retrieved 2025-06-19, from https://onlinelibrary.wiley.com/doi/abs/10.2134/jeq2016.01.0009 (_eprint: https://acsess.onlinelibrary.wiley.com/doi/pdf/10.2134/jeq2016.01.0009) doi: 10.2134/jeq2016.01.0009

Monteny, G., & Erisman, J. (1998, December). Ammonia emission from dairy cow buildings: a review of measurement techniques, influencing factors and possibilities for reduction. *Netherlands Journal of Agricultural Science*, 225–247. Retrieved 2024-12-28, from https://library.wur.nl/ojs/index.php/njas/article/view/481 doi: 10.18174/njas.v46i3.481

Pain, B. F., Van der Weerden, T. J., Chambers, B. J., Phillips, V. R., & Jarvis, S. C. (1998, February). A new inventory for ammonia emissions from U.K. agriculture. *Atmospheric Environment*, *32*(3), 309–313. Retrieved 2025-06-13, from https://www.sciencedirect.com/science/article/pii/S1352231096003524 doi: 10.1016/S1352-2310(96)00352-4

Payne, R. J., Dise, N. B., Field, C. D., Dore, A. J., Caporn, S. J., & Stevens, C. J. (2017). Nitrogen deposition and plant biodiversity: past, present, and future. *Frontiers in Ecology and the Environment*, *15*(8), 431–436. Retrieved 2024-11-22, from https://onlinelibrary.wiley.com/doi/abs/10.1002/fee.1528 (_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/fee.1528) doi: 10.1002/fee.1528

Powell, J., Broderick, G., & Misselbrook, T. (2008, February). Seasonal Diet Affects Ammonia Emissions from Tie-Stall Dairy Barns. *Journal of Dairy Sci-*

ence, *91*(2), 857–869. Retrieved 2025-06-12, from https://linkinghub.elsevier.com/retrieve/pii/S0022030208714309 doi: 10.3168/jds.2007-0588

PPO/PRI AGRO Field Technology Innovations, LR - Veehouderij en omgeving, PPO/PRI AGRO Multifunctioneel Landgebruik, Van Dijk, W., De Boer, J., Schils, R., ... Verloop, J. (2022). *Rekenregels van de KringloopWijzer 2022 : Achtergronden van BEX, BEA, BEN, BEP en BEC: actualisatie van de 2021-versie* (Tech. Rep.). Wageningen: Stichting Wageningen Research, Wageningen Plant Research, Business Unit Agrosystems Research. Retrieved 2025-01-05, from https://research.wur.nl/en/publications/34a08e60-dfbb-4d92-ac3a-0ad7fe9ff4d3 doi: 10.18174/582185

Reidy, B., Webb, J., Misselbrook, T., Menzi, H., Luesink, H., Hutchings, N., ... Dämmgen, U. (2009, March). Comparison of models used for national agricultural ammonia emission inventories in Europe: Litter-based manure systems. *Atmospheric Environment*, *43*(9), 1632–1640. Retrieved 2025-06-11, from https://linkinghub.elsevier.com/retrieve/pii/S1352231008011291 doi: 10.1016/j.atmosenv.2008.12.015

Rex B., K. (2023). *Principles and Practice of Structural Equation Modeling: Fifth Edition.* Retrieved 2025-06-13, from https://www.guilford.com/books/Principles-and-Practice-of-Structural-Equation-Modeling/Rex-Kline/9781462551910

Roberts, S. A., Xin, H., Kerr, B. J., Russell, J. R., & Bregendahl, K. (2007, August). Effects of Dietary Fiber and Reduced Crude Protein on Ammonia Emission from Laying-Hen Manure1. *Poultry Science*, *86*(8), 1625–1632. Retrieved 2025-06-19, from https://www.sciencedirect.com/science/article/pii/S0032579119403751 doi: 10.1093/ps/86.8.1625

Rubin, H. J., Fu, J. S., Dentener, F., Li, R., Huang, K., & Fu, H. (2023, June). Global nitrogen and sulfur deposition mapping using a measurement–model fusion approach. *Atmospheric Chemistry and Physics*, *23*(12), 7091–7102. Retrieved 2025-01-05, from https://acp.copernicus.org/articles/23/7091/2023/ (Publisher: Copernicus GmbH) doi: 10.5194/acp-23-7091-2023

Saha, C. K., Ammon, C., Berg, W., Fiedler, M., Loebsin, C., Sanftleben, P., ... Amon, T. (2014, January). Seasonal and diel variations of ammonia and methane emissions from a naturally ventilated dairy building and the associated factors influencing emissions. *Science of The Total Environment*, *468-469*, 53–62. Retrieved 2025-06-26, from https://www.sciencedirect.com/science/article/pii/S0048969713009297 doi: 10.1016/j.scitotenv.2013.08.015

Sajeev, E. P. M., Amon, B., Ammon, C., Zollitsch, W., & Winiwarter, W. (2018, January). Evaluating the potential of dietary crude protein manipulation in reducing ammonia emissions from cattle and pig manure: A meta-analysis. *Nutrient Cycling in Agroecosystems*, *110*(1), 161–175. Retrieved 2025-06-19, from https://link-springer-com.tudelft.idm.oclc.org/article/10.1007/s10705-017-9893-3 (Company: Springer Distributor: Springer Institution: Springer Label: Springer Number: 1 Publisher: Springer Netherlands) doi: 10.1007/s10705-017-9893-3

Scheeringa, T. (2020). *Nitrogen emissions in the Netherlands: a policy conundrum* (Unpublished master's thesis). Wageningen University, The Netherlands.

Schep, C., Vermeulen, E., Van Dooren, H., Keuskamp, J., Van Well, E., & Van Deest, K. (2024). *Emissies van ammoniak en methaan uit melkveestallen in het netwerk praktijkbedrijven : Tussenresultaten van praktijkmetingen op 15 onderzoeksbedrijven* (Tech. Rep.). Wageningen: Wageningen Livestock Research. Retrieved 2025-01-05, from https://research.wur.nl/en/publications/93dc0f09-6d3e-4569-8c1e-ba07fc4ec75b doi: 10.18174/659372

Schrade, S., Zeyer, K., Gygax, L., Emmenegger, L., Hartung, E., & Keck, M. (2012, February). Ammonia emissions and emission factors of naturally ventilated dairy housing with solid floors and an outdoor exercise area in Switzerland. *Atmospheric Environment*, *47*, 183–194. Retrieved 2025-05-01, from https://www.sciencedirect.com/science/article/pii/S1352231011011782 doi: 10.1016/j.atmosenv.2011.11.015

Sheppard, S., Bittman, S., Swift, M., & Tait, J. (2011, December). Modelling monthly NH_3 emissions from dairy in 12 Ecoregions of Canada. *Canadian Journal of Animal Science*, *91*(4), 649–661. Retrieved 2025-06-11, from http://www.nrcresearchpress.com/doi/10.4141/cjas2010-005 doi: 10.4141/cjas2010-005

Sheppard, S. C., & Bittman, S. (2012, December). Farm practices as they affect NH_3 emissions from beef cattle. *Canadian Journal of Animal Science*, *92*(4), 525–543. Retrieved 2025-06-11, from http://www.nrcresearchpress.com/doi/10.4141/cjas2012-055 doi: 10.4141/cjas2012-055

Skjøth, C. A., & Geels, C. (2013, January). The effect of climate and climate change on ammonia emissions in Europe. *Atmospheric Chemistry and Physics*, *13*(1), 117–128. Retrieved 2025-06-22, from https://acp.copernicus.org/articles/13/117/2013/ (Publisher: Copernicus GmbH) doi: 10.5194/acp-13-117-2013

Sommer, S. G., & Olesen, J. E. (1991, July). Effects of Dry Matter Content and Temperature on Ammonia Loss from Surface-Applied Cattle Slurry. *Journal of Environmental Quality*, *20*(3), 679–683. Retrieved 2025-06-22, from https://acsess.onlinelibrary.wiley.com/doi/10.2134/jeq1991.00472425002000030029x doi: 10.2134/jeq1991.00472425002000030029x

Sommer, S. G., Olesen, J. E., & Christensen, B. T. (1991, August). Effects of temperature, wind speed and air humidity on ammonia volatilization from surface applied cattle slurry. *The Journal of Agricultural Science*, *117*(1), 91–100. Retrieved 2025-06-25, from https://www.cambridge.org/core/product/identifier/S0021859600079016/type/journal_article doi: 10.1017/S0021859600079016

Sommer, S. G., Webb, J., & Hutchings, N. D. (2019, November). New Emission Factors for Calculation of Ammonia Volatilization From European Livestock Manure Management Systems. *Frontiers in Sustainable Food Systems*, *3*. Retrieved 2025-06-03, from https://www.frontiersin.org/journals/sustainable-food-systems/articles/10.3389/fsufs.2019.00101/full (Publisher: Frontiers) doi: 10.3389/fsufs.2019.00101

Srinath, E. G., & Loehr, R. C. (1974). Ammonia Desorption by Diffused Aeration. *Journal (Water Pollution Control Federation)*, *46*(8), 1939–1957. Retrieved 2025-06-06, from https://www.jstor.org/stable/25038213 (Publisher: Water Environment Federation)

Statistics | Eurostat. (n.d.). Retrieved 2024-12-08, from https://ec.europa.eu/eurostat/databrowser/view/aei_pr_gnb/default/table?lang=en

Stikstofproblematiek, A. (2020, June). *Niet alles kan overal - Rapport - Rijksoverheid.nl* [rapport]. Retrieved 2024-12-23, from https://www.rijksoverheid.nl/documenten/rapporten/2020/06/08/niet-alles-kan-overal (Last Modified: 2021-11-16T15:19 Publisher: Ministerie van Algemene Zaken)

Stokstad, E. (2019, December). Nitrogen crisis threatens Dutch environment—and economy. *Science*, *366*(6470), 1180–1181. Retrieved 2024-12-08, from https://www.science.org/doi/full/10.1126/science.366.6470.1180 (Publisher: American Association for the Advancement of Science) doi: 10.1126/science.366.6470.1180

Van Bruggen, C., Bannink, A., Bleeker, A., Bussink, D., Dooren, H., Groenestein, C., … Van Der Zee, T. (2024). *Emissies naar lucht uit de landbouw- berekend met NEMA voor 1990-2022* (Tech. Rep.). Wageningen: WOT Natuur & Milieu. Retrieved 2025-07-15, from https://research.wur.nl/en/publications/bb84932f-57bb-44b3-8576-d6c6b114c40c doi: 10.18174/672550

van der Zee, T., Bleeker, A., van Bruggen, C., Bussink, W., van Dooren, H., & Groenestein, C. (2024). *Methodology for the calculation of emissions from agriculture* (Tech. Rep.). Rijksinstituut voor Volksgezondheid en Milieu RIVM. Retrieved 2024-12-26, from https://rivm.openrepository.com/handle/10029/627510 doi: 10.21945/RIVM-2024-0015

Van Dongen, C. F. J. (1999). Dairy cattle feeding and ammonia emission on practical farms. *Meststoffen (Netherlands)*.

van Duinkerken, G., André, G., Smits, M. C. J., Monteny, G. J., Blanken, K., Wagemans, M. J. M., & Šebek, L. B. J. (2003, March). Relatie tussen voeding en ammoniakemissie vanuit de melkveestal.

van Duinkerken, G., Smits, M. C. J., André, G., Šebek, L. B. J., & Dijkstra, J. (2011, January). Milk urea concentration as an indicator of ammonia emission from dairy cow barn under restricted grazing. *Journal of Dairy Science*, *94*(1), 321–335. Retrieved 2025-05-12, from https://www.sciencedirect.com/science/article/pii/S0022030210006995 doi: 10.3168/jds.2009-2263

Vanhoof, P. (2024). *Bepaling van drijfmestkwaliteit.* Retrieved 2025-06-04, from https://www.organic-forest.org/bepaling-van

-drijfmestkwaliteit

van Jaarsveld, J. A., Bleeker, A., & Hoogervorst, N. J. P. (2000). Evaluation of ammonia emission abatement on the basis of measurements and model calculations. *RIVM rapport 722108025*. Retrieved from https://www.pbl.nl/uploads/default/downloads/722108025.pdf

Velthof, G. L., van Bruggen, C., Groenestein, C. M., de Haan, B. J., Hoogeveen, M. W., & Huijsmans, J. F. M. (2012, January). A model for inventory of ammonia emissions from agriculture in the Netherlands. *Atmospheric Environment*, *46*, 248–255. Retrieved 2024-12-12, from https://www.sciencedirect.com/science/article/pii/S1352231011010387 doi: 10.1016/j.atmosenv.2011.09.075

Verbeek-Schilder, Y., & Verhoeven, F. (2024). *The low-emission business operation: A practical and substantiated approach to reduce ammonia emissions on land-based dairy farms* (Research Report). Utrecht, The Netherlands: BV Boerenverstand, Wageningen UR, Leiden University. Retrieved from www.boerenverstand.nl

Vitaliano, S., D'Urso, P. R., Arcidiacono, C., & Cascone, G. (2024, July). Ammonia Emissions and Building-Related Mitigation Strategies in Dairy Barns: A Review. *Agriculture*, *14*(7), 1148. Retrieved 2025-05-07, from https://www.mdpi.com/2077-0472/14/7/1148 (Number: 7 Publisher: Multidisciplinary Digital Publishing Institute) doi: 10.3390/agriculture14071148

Vogel, K. P., & Humenik, F. J. (2017). *Ammonia Emissions from Cattle Feeding Operations* (Extension Publication E-632). Texas A&M University: Texas A&M AgriLife Extension Service. Retrieved 2025-06-19, from https://college.agrilife.org/baen/wp-content/uploads/sites/24/2017/01/E-632.-Ammonia-Emissions-from-Cattle-Feeding-Operations.pdf

Waldrip, H. M., Todd, R. W., & Cole, N. A. (2013, September). Prediction of nitrogen excretion by beef cattle: A meta-analysis1,2,3. *Journal of Animal Science*, *91*(9), 4290–4302. Retrieved 2024-12-28, from https://academic.oup.com/jas/article/91/9/4290/4717369 doi: 10.2527/jas.2012-5818

Wang, Q., Flesch, T. K., Bai, M., Zhang, M., & Chen, D. (2024, February). Seasonal ammonia emissions from an intensive beef cattle feedlot in Victoria Australia. *Journal of Environmental Management*, *351*, 119898. Retrieved 2025-06-27, from https://www.sciencedirect.com/science/article/pii/S0301479723026865 doi: 10.1016/j.jenvman.2023.119898

Wang, X., Lu, X., Li, F., & Yang, G. (2014, May). Effects of Temperature and Carbon-Nitrogen (C/N) Ratio on the Performance of Anaerobic Co-Digestion of Dairy Manure, Chicken Manure and Rice Straw: Focusing on Ammonia Inhibition. *PLoS ONE*, *9*(5), e97265. Retrieved 2024-12-28, from https://dx.plos.org/10.1371/journal.pone.0097265 doi: 10.1371/journal.pone.0097265

Wattiaux, M. A., & Karg, K. L. (2004, October). Protein Level for Alfalfa and Corn Silage-Based Diets: I. Lactational Response and Milk Urea Nitrogen. *Journal of Dairy Science*, *87*(10), 3480–3491. Retrieved 2025-06-12, from https://www.sciencedirect.com/science/

article/pii/S0022030204734839 doi: 10.3168/jds.S0022-0302(04)73483-9

Webb, J. (2001). Estimating the potential for ammonia emissions from livestock excreta and manures. *Environmental Pollution*, *111*(3), 395–406. Retrieved 2025-06-11, from https://linkinghub.elsevier.com/retrieve/pii/S0269749100000907 doi: 10.1016/S0269-7491(00)00090-7

Webb, J., Ryan, M., Anthony, S. G., Brewer, A., Laws, J., Aller, M. F., & Misselbrook, T. H. (2006, December). Cost-effective means of reducing ammonia emissions from UK agriculture using the NARSES model. *Atmospheric Environment*, *40*(37), 7222–7233. Retrieved 2025-06-11, from https://www.sciencedirect.com/science/article/pii/S1352231006006923 doi: 10.1016/j.atmosenv.2006.06.029

Wever, D., Coenen, P., Dröge, R., Geilenkirchen, G., van Huijstee, J., 't Hoen, M., ... van der Zee, T. (2021). *Informative Inventory Report 2021. Emissions of transboundary air pollutants in the Netherlands 1990–2019* (Tech. Rep.). Rijksinstituut voor Volksgezondheid en Milieu. Retrieved 2024-12-23, from https://rivm.openrepository.com/handle/10029/624861 doi: 10.21945/RIVM-2021-0005

Yan, T., Frost, J. P., Keady, T. W. J., Agnew, R. E., & Mayne, C. S. (2007, August). Prediction of nitrogen excretion in feces and urine of beef cattle offered diets containing grass silage1. *Journal of Animal Science*, *85*(8), 1982–1989. Retrieved 2024-12-28, from https://academic.oup.com/jas/article/85/8/1982/4778272 doi: 10.2527/jas.2006-408

Yang, F., Han, Y., Bi, H., Wei, X., Luo, W., & Li, G. (2022, November). Ammonia emissions and their key influencing factors from naturally ventilated dairy farms. *Chemosphere*, *307*, 135747. Retrieved 2025-05-18, from https://www.sciencedirect.com/science/article/pii/S0045653522022408 doi: 10.1016/j.chemosphere.2022.135747