Towards a measurement-based approach to estimate farm-specific ammonia emissions

With feed management parameters and the slurry manure composition as indicators of the AEP

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The first thing I discovered was my limited knowledge of the dairy sector. I was surprised by its complexity and diversity. It is such an important part of our society, but it felt distant because I had hardly encountered it in my city life. While working at DMS, I often asked how something worked or what the conventional way of making a certain management decision was. The answer was always: it depends...

Firstly, I would like to thank everyone at DMS for making me feel so welcome. Thanks to Robin, Robin, Bert, Hans and Joyce for answering all my questions and helping me with the data. Kim, I really appreciated your feedback and academic insight. It helped a lot! Special thanks to Tim and Reidze for the good times in the evenings at DMS, exchanging ideas about the agricultural sector, but also about many other random topics. Thanks to Jan Willem and José for the critical feedback and for reminding me that anything is possible. And of course thanks to all my family and friends for their support throughout the whole process.

Abstract

The research focuses on a novel measurement-based approach to estimate the farm-specific ammonia emission potential (AEP) in the dairy sector. By measuring and evaluating the feed-manure chain, feed management strategies and manure parameters influencing AEP can be identified. Ammonia emissions from dairy farms are not only considered to be an important driver of biodiversity loss, but are also responsible for nutrient losses in the farm cycle. Currently, farm-specific ammonia emissions are calculated using the Kringloopwijzer model, which tends to over- or underestimate actual ammonia emissions. Therefore, the possibilities of a measurement-based approach are evaluated.

This study analyses the relationships within the feed-manure-AEP sequence. A comprehensive approach is used, involving 23 manure parameters and 12 feed management parameters. The most important predictors of the AEP include N, TAN, Norg, N90, and the C/N ratio, whilst urea in milk, pH, and DS showed low significance. Silage maize and VEM are identified as feed management parameters with a positive indirect relationship with the AEP, whereas other roughage and fresh grass exhibit a negative indirect relationship. The calculated TAN value plays a central role in the emission calculations of the Kringloopwijzer model. There are concerns about the accuracy of this value as well as the absence of other manure parameters in the calculation, highlighting the need for further research. Currently, it is uncertain whether the AEP measurements will be suitable for an emissions-based policy, due to the incapacity to directly represent actual ammonia emissions and the uncertainty regarding the interpretation of the results caused by the period prior to the measurements. Nonetheless, the measurements are valuable in assessing the influence of the manure composition on the AEP, and how it has been affected by feed management strategies.

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1. Problem introduction

1.1 Ammonia emissions and closing the nutrient cycle

The agricultural sector is the backbone of our society, providing food for an ever-growing global population. However, it also has had a significant negative impact on biodiversity and the natural environment. Not only the loss of natural habitats, but also the intensification of land-use, the increased use of synthetic chemicals and monoculture cropping practices are some examples of drivers of biodiversity loss in the agricultural sector (The Royal Society, 2021). In the Netherlands, 54% of the total area (including open and inland water) is used for agricultural land (CBS, 2021), giving farmers an important role as stewards of the natural-agricultural environment.

The Dutch nitrogen emissions consist of 60% ammonia (NH_3) and 40% of nitrogen oxides (NO_x) (Schollaardt, 2019). An important driver of biodiversity loss is caused by the deposition of ammonia in mature natural areas, resulting in an excess of nitrogen. Fast-growing species thrive much better and take over the area, leading to major biodiversity losses (Lu et al., 2008). Research has been carried out on ammonia deposition in designated nature areas, known as Natura 2000 areas. It is estimated that about 40% originates from the agricultural sector, 10% from transport, 10% from industry, 5% from the sea and 35% from neighbouring countries (Schollaardt, 2019). Due to the Habitats Directive (Dutch: Habitatrichtlijn), which was agreed upon by European law in 1992, the Netherlands has been obliged to preserve the quality of the Natura 2000 areas. The Netherlands encompasses 162 of those areas. Many of these areas are in bad condition, with ammonia deposition identified as an important driver (Ministerie van Economische Zaken, Landbouw en Innovatie, 2022).

The dairy sector is responsible for about half of the total ammonia emissions caused by the agricultural sector (Schollaardt, 2019). Ammonia originates from nitrogen which is introduced into the agricultural system by means of fodder and fertilisers. A major part of the nitrogen remains in the nutrient cycle of a farm system, as manure is applied to land to stimulate grass and crop growth. It leaves the cycle either as losses such as emissions, as products like milk and meat, or by means of exported manure. In the agricultural sector, nutrient losses are an indication of a less efficient system. Losses have to be compensated by external inputs, reducing the nutrient efficiency and increasing the costs. Therefore, the reduction of ammonia emissions is not only an environmentally attractive objective, but it is also of economic concern (Ondersteijn, 2002).

The first step in the formation of ammonia takes place when urea and faeces start to interact after excretion. Ammonium (NH_4^+) is formed when enzymes in manure break down urea in urine (Smits & Bokma, 2008), which is called hydrolysis and is described in the following formula:

$$CO(NH_2)_2 + 2\ H_2O \rightarrow (NH_4)_2CO_3 \leftrightarrow 2\ NH_4^+ + CO_3^{2-}$$

After ammonium is formed, it can convert into ammonia which is able to volatilise under the right circumstances:

$$NH_4^+ \leftrightarrow NH_3 + H^+ \text{ (liquid)} \leftrightarrow NH_3 \text{ (dissolved gas)} \leftrightarrow NH_3 \text{ (airborne gas)}$$

The total amount of inorganic nitrogen present in a solution in the form of NH_3 and NH_4^+ is referred to as the total ammonia nitrogen (TAN). The volatilisation potential depends on physical factors (airspeed, surface area, temperature, etc.) and chemical factors (NH_4^+ concentration, pH, etc.) moving the equilibrium of the formula (Velthof et al., 2009). During storage, organically bound nitrogen can convert to NH_4^+, which is called mineralisation. Mineralisation tends to increase with higher temperatures and a higher pH. It is currently very difficult to quantify these processes (Velthof et al., 2009). With a high C/N ratio (e.g. straw-rich manure), some of the ammonia will be immobilised; it will transfer back to organic nitrogen. Inorganic nitrogen is directly available to plants, but it can more easily be leached or volatilised. Plants cannot take up organic nitrogen. Organic nitrogen can be converted into soil, where it becomes available only after mineralisation in the soil by soil microorganisms (Eghball et al., 2002).

Emissions take place during storage, in the stables, during grazing and during manure applications. Therefore, farmers have invested in emission reduction measures such as low-emission housing systems, air purifiers (luchtwassers) and low-emission field application techniques. However, recent research has shown that current low-emission housing systems do not function as intended (Bremmer et al., 2022).

1.2 From a deposition-based towards an emission-based policy

The Dutch government has been aware of the problems caused by ammonia deposition for a long time, and effective measures have been taken since the 90s. However, the emission reduction has come to a standstill in the last decade. Therefore, the government introduced Programma Aanpak Stikstof (PAS). PAS has not had the desired effect, resulting into a lock-in at national level (Remkes et al., 2019). Companies are not able to obtain permits for building projects and uncertainties arise in the agriculture sector, making it difficult to make investments and create development perspectives. At the moment, the government uses critical deposition loads (KDW) to set deposition targets and to grant building permits (Vink et al., 2021). The KDW is the deposition load above which the risk of effects in nature areas increase, which is established in the law since 2021. Right now, the government is unable to translate the deposition-based policy into management pathways for individual farmers (Erisman et al., 2023). Recently, a study from the UvA has put into question the relation between emitted ammonia in stables and the deposition in surrounding areas. It stated that the contribution to the ammonia deposition of a farm, outside the range of 500m, is relatively low compared to the contribution of the background concentration of NH_3 in the air (Dutch: stikstofdeken) (Tietema et al., 2023). In other words, the share of the contribution of an individual farm to the deposited NH_3 is very difficult to determine. To be able to improve this situation in terms of policies, an emission-based policy should be considered. The idea of an emission-based policy is to focus on farm and company-specific emission reduction goals. Once these goals are set, monitored and enforced, management pathways for farmers will be created. Companies will be responsible for their individual goals, whilst the responsibility to meet the Nature Conservation Act will remain with the government. This creates a clear action perspective for farmers and other stakeholders (Erisman et al., 2023).

One of the hurdles of such an emission-based policy is the difficulty of measuring and enforcing the exact emission values at farm-level. This is important, because the differences between individual farms are significant (Mollenhorst & De Haan, 2021). Under current circumstances, farmers outperforming the average cannot be rewarded, and those performing below average cannot be effectively motivated or steered. (Remkes et al., 2020). Information regarding farm-specific ammonia emissions will provide important insights not only into the environmental performance of individual farms, but also into their nutrient efficiency.

1.3 Models vs measurements

The Dutch nitrogen legislation is based on scientific models. These are used to provide insights about mineral management, emissions and depositions. On a national level, AERIUS is used to determine the location and severity of depositions on national level. In June 2020, the advisory committee (adviescollege Meten en Berekenen) concluded that this model is unsuitable for determining farm-specific depositions with the required accuracy of 0.005 mol/ha (Hordijk et al., 2020). Although not used for any regulations, the Kringloopwijzer (KLW model) is used to estimate farm-specific emissions (Vellinga & De Haan, 2022). It is beneficial for farmers, as it provides information on mineral efficiency: crop yields, mineral losses and mineral cycles (Vellinga & De Haan, 2022). The KLW model is a scientific model, developed under standardized conditions and reviewed within the EU (Netwerk Praktijkbedrijven, 2023). Nevertheless, a model will always have its limitations. Like every model, the KLW is very prone to ‘the garbage in = garbage out’ principle. Incorrect input values will most likely result in output values that do not meet the expectations. The accuracy of the input data of the KLW depends on the precision of measured approximations of e.g. silage compositions as well as the farmers’ commitment to provide correct values (DMS, personal communication, 12 December, 2023). It is impossible to validate all these numbers, making the model unsuitable for (environmental) policies (Bestman & Ersiman, 2016). Other input values in the KLW model are based on experimental standardized conditions and substitute values, leading to an over- or underestimation of the actual situation and ultimately the emission potential (Netwerk Praktijkbedrijven, 2023; Vellinga & De Haan, 2022). Currently, measuring these farm-specific emissions is simply too complex and expensive (Netwerk Praktijkbedrijven, 2023; Van Dijk et al., 2020), let alone monitoring and enforcing the correctness of these emission values. Although the KLW model is detailed, it remains to be under development. Every year, the model is adjusted and relationships are changed, with the goal to refine it (Van Dijk et al., 2022; Velthof et al. 2009).

This research looks into the possibilities of a novel and cost-effective method to monitor on-farm ammonia emissions by means of measurements. Meanwhile, the possibilities will be explored to alter the measured emissions by influencing the manure composition through feed-management strategies, giving individual farmers the perspective to move towards a greener dairy sector.

2. Academic knowledge gap

Influencing the measured emissions using the novel measurement approach involves decoupling from the annual emission values, as well as taking into account multiple feed management and manure parameters. These components are discussed in this chapter, whilst the measurement approach is explained in the methods section.

2.1 The ammonia emission potential

Differences in ammonia emission between farms occur due to two reasons. First of all, the manure composition. Parameters such as the amount of dry matter (DS), TAN and pH influence the potential emissions of the manure (Hafner et al., 2017; Visser et al., 2005). Secondly, environmental factors impact the final emissions. According to the literature, temperature, wind and precipitation are considered as influential environmental factors (Hafner et al., 2017; Li et al., 2012). Specific measures can be taken to alter the way manure interacts with its environment, such as the use of low-emission housing systems or specific field application techniques (Hristov et al., 2011). On the other hand, feed management and manure additives can impact the manure composition. This research will look into the first aspect: the effect of the manure composition on the measured ammonia emission potential (AEP). The AEP does not represent the final emission, but describes how much ammonia could potentially be emitted based on the manure composition. Manure with a low AEP provides a good foundation for reducing final ammonia emissions as the initial emission potential is lower. The AEP of slurry manure in the pit can change over time as the composition changes, either due to biochemical processes, the addition of new manure and urine to the existing mix, or due to manure additives. The relationship between the manure composition and the AEP is commonly used in the literature (Hristov et al., 2011; Lee et al., 2012). The advantage of the AEP is that it is more closely related to the effect of feed management choices, whereas the disadvantage is that it does not represent the actual final emission.

2.2 The manure-feed cycle

Currently, the KLW model calculates ammonia emissions based on annual averages. Information is collected on, among other things, the annual ransom, digestion coefficients, number of grazing days and livestock composition. However, due to seasonal-bound conditions, farmers have to adjust the composition of the ransom, as the availability of fresh grass changes. Even the content of grass changes throughout the year; for instance, grass is considered more nitrogen-rich in spring (DMS, personal communication, 2 October, 2023), which influences the composition of the excreted manure. Additionally, farmers are only allowed to apply manure to land from February to August, which affects the fullness of the slurry manure pit, affecting its composition and subsequently its emission potential. The manure-feed cycle is illustrated in Figure 1.

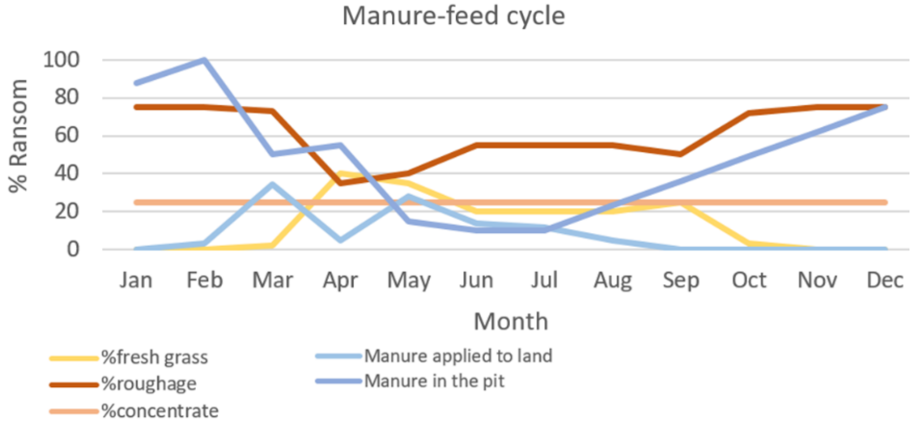


Figure 1: The manure-feed cycle shows the yearly pattern of the ransom distribution and the relation between slurry manure which is stored in the pit and slurry manure being applied to land (DMS, personal communication, 19 December, 2023).

As can be seen in the manure-feed cycle, the measured AEP will most likely be determined by the composition and age of the manure, which fluctuates throughout the year. Additionally to grass, the supplementary ransom consists of roughage and concentrate, both with enormous variations regarding their content. By following the manure-feed cycle, as will be done in this study, more insight can be gained regarding the relation between feed management choices and seasonal fluctuation of the AEP. This can add more nuance to the currently generated farm-specific emission values. To date, limited studies include these annual fluctuations. Lagerwerf et al. (2022) describe the ammonia emissions (so not the AEP) together with the TAN excretions of two stables throughout the year. In this study, they concluded that the ammonia emission in stables fluctuates throughout the year, being slightly correlated with the temperature, but not with the excreted TAN. However, the two farms showed large variations in the volatilised TAN, concluding that it is not yet possible to extrapolate the results to other farms.

Reducing the emission potential and the related the final ammonia emissions of slurry manure by targeting the nitrogen input is considered to be a measure with high potential (Velthof et al. 2009). Figure 2 shows the location of such an input measure in a simplified nitrogen cycle of a dairy farm system. Feed management decisions can reduce the amount of nitrogen entering the system, resulting in less nitrogen leaving the system (Vellinga & De Haan, 2022). Of course, feed management is only one of the many possible mechanisms to reduce the final emissions (Mosquera et al., 2017). However, this approach still lacks scientific validation, which is crucial for the implementation into the Dutch environmental legislation (Vellinga & De Haan, 2022).

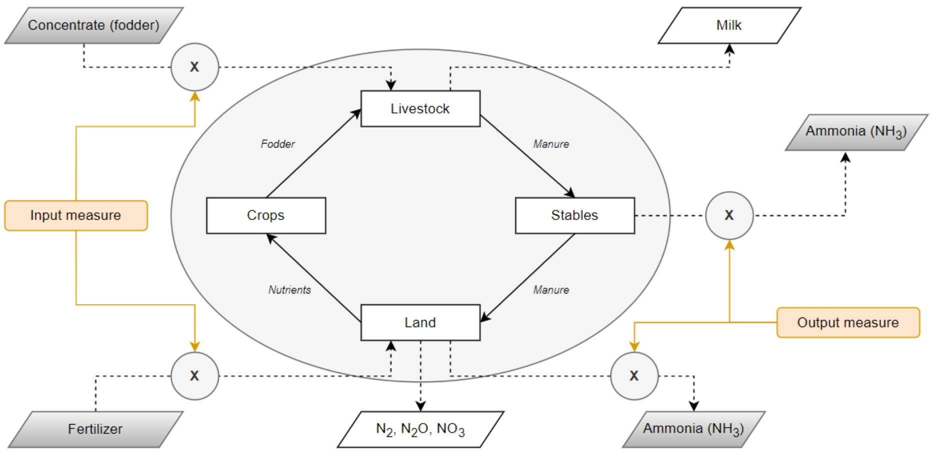


Figure 2: A simplified representation of the nitrogen-flow through a dairy farm system, leading to the deposition of ammonia (NH_3), with input measures and output measures located. The figure is based on Van Dijk et al. (2022).

2.2 The manure composition as an emission predictor

Manure is a valuable material within the agricultural system. It does not only affects the (potential) emission, but is a critical component in the entire nutrient cycle. Within the current KLW model, the calculations of the farm-specific ammonia emissions make use of the annually calculated total ammonia nitrogen (TAN) of manure, a calculation that includes mineralisation and immobilisation constants. All phases in the nutrient cycle where emissions could take place are included in the model: grazing, storage, stables and field applications (Van Dijk et al., 2022). The stable emissions are determined by multiplying the calculated TAN with emission factors (EFs) which vary depending on the stable type. Similar steps are taken to calculate the emissions during field application, as shown in Figure 3 on the next page.

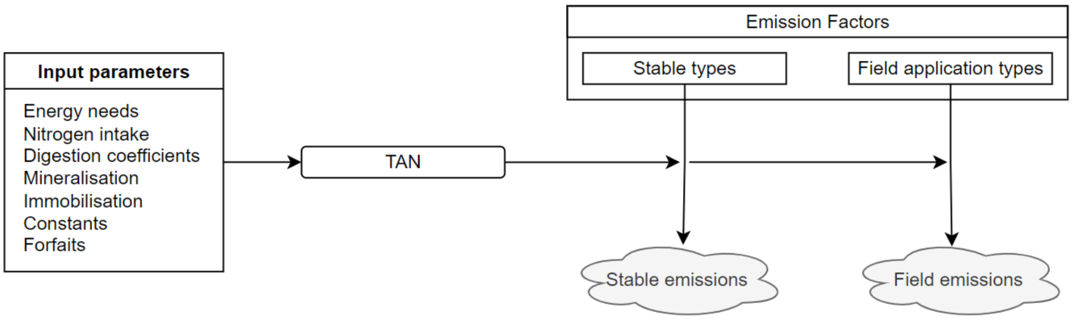


Figure 3: Visualisation of the calculated ammonia emissions in the KLW model with TAN in central position, based on Van Dijk et al. (2022

Although TAN is seen as an important parameter for predicting ammonia emissions, research has shown that it is not quite conclusive enough. Statistics Netherlands (CBS) argues that ammonia emissions calculated with TAN may underestimate the actual emission (Van Bruggen et al., 2019). Therefore, the N/P_2O_5 ratio is suggested as a more precise indicator of emissions. The ratio is taken at the moment of excretion and at the moment after storage. Since phosphate is not able to volatilise, the change in ratio indicates the amount of ammonia which has been volatilised. Using this method, Van Bruggen et al. (2019) argued that the effect of low-emission housing systems may be underestimated, while regular housing systems are less prone to this. Furthermore, the reliability of the EFs of these stables has been questioned, as the EFs are only based on a limited number of measurements (Ogink et al., 2017).

In addition to TAN and the N/P_2O_5 ratio, other measurable components in manure but also in milk have been identified for their predictive capabilities; e.g. urea in milk, C/N ratio, pH and the amount of dry matter (DS) in manure (Table 1). Urea in milk is urea that has diffused through cell walls into the udder and is in balance with the amount of urea excreted. (Van Duinkerken et al., 2003). Data of urea in milk is easy to obtain and is already part of the data from the Milk Production Registration (MPR). The C/N ratio[1] in manure can be of predictive value, because it affects the mineralisation process, which influences the equilibrium between organic nitrogen and TAN (Zanen et al., 2003). The pH is known to increase the conversion of nitrogen into ammonia: a lower pH shifts the equilibrium from ammonium to ammonia $NH_3 \leftrightarrow NH_4^+$ (Bussink et al., 1994; Li et al., 2012), which is why acidification of manure is proven to be an effective manure treatment strategy (Park et al., 2015). The amount of dry matter is also considered to have a relation with the emissions. A reduced dry matter content indicates a relative increase in water content, which reduces the concentration of TAN and the associated emissions (Van Dooren et al., 2022).

Parameter	*Description*	*Source et al.*
TAN	NH_3 and NH_4^+ in the manure	(Velthof et al., 2009)
Milk urea	Urea which is able to transfer into milk, in balance with excreted as urea	(Van Duinkerken et al., 2003)
C/N ratio	Carbon-nitrogen ratio	(Külling et al., 2001)
pH	Acidic/basic state of the solution	(Bussink et al., 1994; Park et al., 2015)
N/P_2O_5 ratio	Nitrogen-phosphate ratio	(Van Bruggen et al.,, 2019)
DS	The concentration of the manure solution	(Van Dooren et al., 2022)

Table 1: Potential measurable ammonia emission predictors.

Combining these parameters into one predictive set could not only improve the AEP predictions, but also improve the overall understanding of variation between AEP values and the ability of farmers to act upon it. To facilitate interventions, the next step is to identify feed management strategies which influence the manure parameters with a predictive value. This will contribute to a better understanding of the overall feed-manure-AEP sequence.

[1] The C/N ratio is also known to be very important for soil life and a healthy and stable soil (Zanen et al., 2003).

2.3 Feed management parameters

Numerous studies describe the positive effect of feed management on ammonia emissions and TAN in manure (PBL, 2020; Mollenhorst et al., 2023). However, a more comprehensive feed-manure relationship including a wider range of parameters is rarely described. Existing research is limited to the nitrogen components in the ransom (e.g. Sørensen et al., 2003; Lagerwerf et al., 2022). The set of feed parameters which could influence the emissions might be more diverse, based on the theory that the AEP is caused by a more nuanced set of parameters than merely TAN in manure. In addition to feed management, manure additives can also influence the manure composition (Van Boxmeer & Ogink, 2023). This is beyond the scope of this study.

According to the literature, crude protein (RE) has been identified as a predictive emission parameter (Schrade et al., 2023; Lee et al., 2012; Hristov et al., 2011). The amount of crude protein in the ransom is the absolute nitrogen intake per cow, and therefore directly affects the ammonia emission. RE is critical for milk production, but there is an optimum a cow can process. Another important parameter is the RE/kVEM ratio. In the rumen, microbes break down a major part of the proteins. To support the process, the microbes need energy. A good ratio is critical for efficient nitrogen utilization. Of course, the cow also needs energy for all other internal processes, ensuring the overall health of the cow. When the amount of energy is too low compared to the RE, the cow is not able to utilize the proteins in the diet. According to multiple studies, the RE/kVEM ratio directly influences TAN and the related emission (Plomp et al, 2018; Reijs et al., 2021). According to DMS, the optimal RE/kVEM ratio is 150 to 160, depending on the milk production and the milk urea level.

Although several manure parameters are known to have a direct effect on AEP, and certain feeding parameters have an effect on the TAN and consequently on the AEP, there is still limited knowledge of the overall relationship between feed, manure and AEP. In addition, research on the effect of manure composition, including more than one manure component, is relatively limited and has therefore not been included in the current farm-specific KLW model.

3. Research approach and research questions

This study is part of an overarching research, with the ultimate goa to explore the possibilities of facilitating an emission-based policy using measured emission data. Subsequently, the influence of feed management on the AEP can be determined, with the additional aim to monitor the impact of such a strategy. Feed management is considered an easily applicable and cost-effective measure. By doing so, farmers are given a wider range of levers to reduce ammonia emissions. Such farm-specific management measures will be more viable if a) the AEP is measurable at farm level and b) if the emission reduction strategy (influencing the manure composition by means of feed management) is effective. Understanding the effect of feed management on manure and the related AEP is essential. The reliability of the measurements can be evaluated by comparing them with results from the KLW model. This leads to the main research question of this study:

"To what extent can measurements of the slurry manure composition serve as a reliable indicator for the ammonia emission potential, and how can we influence it by feed-management strategies?"

The proposed research has a deductive approach and is predominantly quantitative. Figure 4 locates the emphasis of the different sub-questions (numbers) within the feed-manure sequence that help to answer the main research question. The upper box displays the measured approach, whilst the lower box displays the modelled approach. Regarding the measured approach, AEP data is collected using the novel measurement method, which is supplemented with measured feed and manure parameters from the same moment in the manure-feed cycle. The modelled approach follows the same sequence, as far as the design of the KLW model allows it, using annual data. The relationships in the measurement-based sequence are tested by comparing it with the modelled sequence. By doing so, the modelled sequence will be automatically reflected upon as well, as both approaches remain to be approximations of reality with their own advantages and disadvantages.

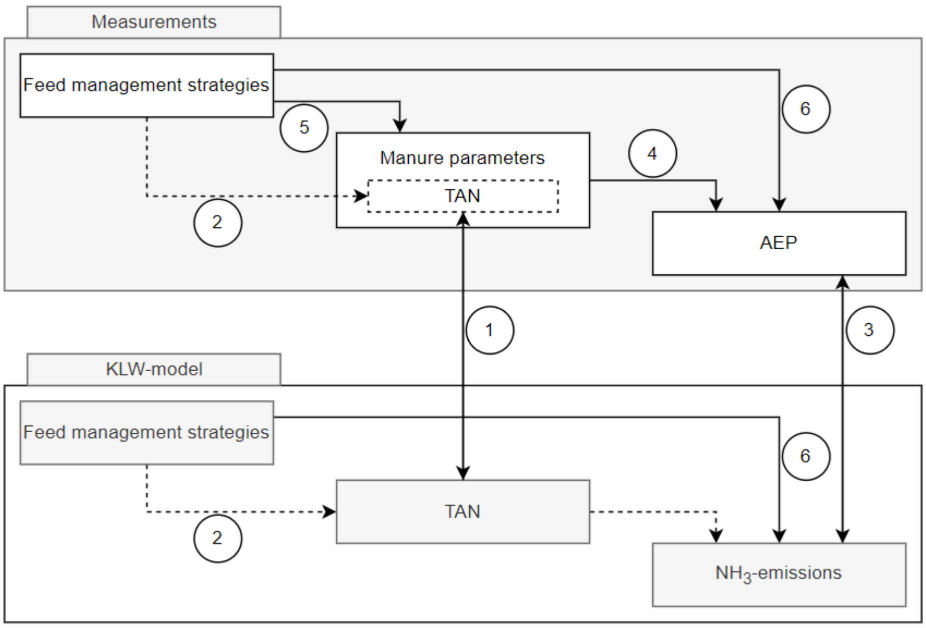


Figure 4: The research flow, with the different sub questions (numbers) localised in the feed-manure-emission chain of both the modelled and the measured approach. Double numbers imply that the question relates to both approaches.

The first question tests whether TAN in slurry manure in the pit, when approximated either by the KLW model or by measurements, will give the same results. In the literature, TAN is identified as the most important manure parameter for determining ammonia emissions. Therefore the calculated TAN plays a central role in the ammonia emission calculations in the KLW model:

1. *To what extent is there a difference between TAN in manure being calculated by the KLW model and TAN in manure being obtained from manure samples?*

To shed a different light on the TAN comparison, the relationships of both TAN approximations with a set of feed management parameters will be analysed:

2. *To what extent is there a difference in the relationships between feed parameters and the two TAN approaches as proposed in the previous question?*

Next, it is desired to gain a better understanding of the measured AEP values. Since these values are derived from a novel measurement method, it is meaningful to analyse whether they make sense. Based on the data availability, it is most informative to relate the AEP values with related emission values derived from the KLW model:

3. *To what extent are the measured AEP values in line with emission values derived from the KLW model?*

As has been mentioned in the literature, TAN alone is not considered sufficient enough as an emission predictor. Therefore, it is necessary to find out whether a set of manure parameters covers a larger part of the variance. Due to the absence of parameters in the modelled approach, only the measured approach will be analysed:

4. *Which measured manure parameters have the strongest predictive power to determine the AEP?*

At the moment that the AEP and manure parameters are sampled, the feeding parameters of the corresponding period within the feed-manure cycle are obtained. To gain a comprehensive overview of the feed-manure-emission sequence, the relationships between feed and manure will be analyzed, including their indirect relationships:

5. *Which measured feed management strategies have the strongest predictive power to determine the manure parameters, and indirectly determine the AEP?*

Finally, the relationships between feed management strategies and the AEP are tested, using both the modelled and the measured approach. Both approximations are based on a different method. The extent of the differences can be insightful to better evaluate the meaning of the identified relationships:

6. *Which measured feed management strategies have the strongest predictive power to determine the AEP, and to what extent does this differ from the KLW model?*

4. Methods

This chapter explains the research methods. Firstly, the general data collection is discussed. Then the approach to the measured and modelled feed-manure-AEP sequence is explained, supplemented by the justification of the chosen statistical analysis.

4.1 General data collection

In this study, data from different sources has been used. An overview can be seen in Table 2. For all KLW-data, the database of DMS has been used (source: DMS-KLW). DMS is in possession of a large database containing many dairy farms throughout the Netherlands. It is a unique database due to its richness of data and the quantity of farms being present. Farmers have authorized DMS to use their data for, among other things, consultancy purposes. All KLW data is by definition annual data. The group of farms where the measurements are made consists of 23 farms spread across the Netherlands (the AMMONI group in the DMS database). This group is composed by its characteristics to have an expected distribution of ammonia emissions. The manure samples are taken by Vanhoof, Eurofins and the MPR-data is derived from the CRV (Coöperatie Rundveeverbetering). Eurofins is a qualified biochemical analytical institute and access to MPR-data was possible through authorizations granted to DMS. The combination of manure and MPR data is sometimes mentioned as ‘manure data’ or ‘manure parameters’ in the report. Access to daily feed management data used to analyse the measured feed-manure-AEP sequence, taking into account the feed-manure cycle, has been made possible by a feeding app developed by DMS. This app allows farmers to fill in their daily ransom. All data formats have been converted into Excel files, after which they have been analysed in Python. The sample sizes remained low, mainly due to a limited amount of available measured data. Especially data from the feeding app was incomplete, as some farmers haven't filled in the app. Additionally, data losses occurred due to mismatches in occasions where measured and modelled sets had to be merged.

Research question	*Description*	*Sample size*	*Source*
RQ1	Measured manure (TAN) data	37	Eurofins
	Calculated manure data from the KLW model	37	DMS-KLW
RQ2	Measured manure (TAN) data	25	Eurofins
	Calculated manure data from the KLW model	25 / 81	DMS-KLW
	KLW feed management data	25 / 81	DMS-KLW
RQ3	AEP data	15	Vanhoof
	KLW emission data	15	DMS-KLW
RQ4	AEP data	25	Vanhoof
	Measured manure data	25	Vanhoof
	Measured manure data	25	Eurofins
	MPR data	25	CRV
RQ5	Measured manure data	13	Vanhoof
	Measured manure data	13	Eurofins
	Feed management data (feeding-app)	13	DMS
RQ6	AEP data	13	Vanhoof
	Feed management data (feeding-app)	13	DMS
	KLW emission data	4656	DMS-KLW
	KLW feed management data	4656	DMS-KLW

Table 2: Data sources and sample sized divided among the sub questions.

4.2 The measured feed-manure-AEP sequence

The measurements of the ammonia emission potential (AEP) are executed by Peter Vanhoof from Organic Forest. In addition, manure parameters and feed parameters are sampled to complete the data needs for the comprehensive feed-manure-AEP sequence. The strategy is to measure four times a year over a period of two years, following the manure-feed cycle (Figure 5, next page). At the moment of this research, only the first sample round (from a total of 8 rounds over 2 years) has taken place.

This sample round is indicated by the black vertical line in the Figure. During this moment the slurry manure pit is relatively empty.

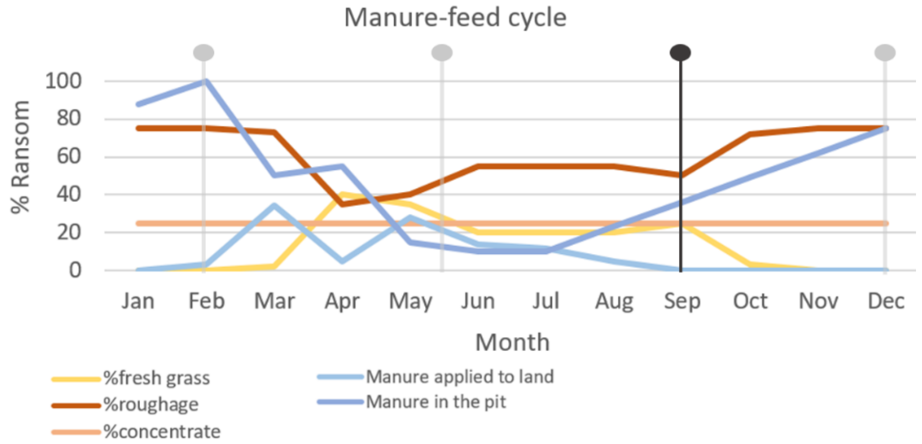


Figure 5: The manure-feed cycle shows the yearly pattern of the ransom distribution as well as the relation between slurry manure being in storage and manure being applied to land (DMS, personal communication, December 19, 2023). The four vertical lines indicate the measurements moments. The black line indicate the measuring moment used in this research.

The four measuring moments can be characterised accordingly:

i. September, during the end of the summer, just before the cows are kept in the stables.
ii. December, when the manure pit starts to fill.
iii. February, when the pit is the fullest.
iv. May/June, when nitrogen-rich spring grass is fed.

AEP and manure parameters

The day before manure sampling and AEP measurements, the manure is mixed in the pit to create a more homogeneous mixture and to obtain a sample that is more representative of the previous period. Vanhoof took multiple manure samples on the same farm, as some farmers deal with multiple pits. Also, the depth of the pits vary influencing the mixture throughout the pit. These measurement locations are recorded to enable identical measurements later in the research. The samples are combined and mixed, of which one part is measured by Vanhoof and the other part is sent to Eurofins for laboratory analysis. Vanhoof measures the AEP in his 'driving lab' in a controlled environment (Figure 6). His measuring method is the low-cost method proposed by DMS, which could potentially be used in a future emission policies. The measurements on all farms in the AMMONI group are taken in the period from 26th September to 3rd October.

Figure 6: Vanhoof measuring the AEP of liquid manure in his 'driving lab' (Vanhoof, 2019).

During the measurements of Vanhoof, a more extensive list of manure parameters is examined than only the 6 parameters described in Chapter 2. These additional parameters are included into the analysis, to obtain a more complete overview of all potential emission drivers in the manure. The whole list of manure parameters measured by Vanhoof, Eurofins together with the MPR data are listed in

Table 3. Some of these parameters potentially give additional information, while others may create noise.

Vanhoof strongly advocates circular agriculture, with high-quality manure consisting of a high C/N ratio and organic-rich contents together with a low nitrogen content to support soil life. This could be influenced by a relatively nitrogen-poor and carbon-rich diet. Vanhoof also states that emission-rich manure not only contains a lot of TAN but also potassium oxide. This results in aggressive and decaying manure, which contains less oxygen, being rich in salt and containing a high pH and EC (Vanhoof, 2020; Vanhoof, 2019). Although his ideas may lack extensive scientific support, Vanhoof's reasoning follows logic and should be taken into account.

Parameter	*Abbr.*	*Description*	*Collected by:*
Ammonia emission potential	AEP	The potential ammonia	Vanhoof
pH	pH	The acidity or basicity of manure (measured by Vanhoof)	Vanhoof
Electrical conductivity	EC	The electrical resistance of manure, describing the amount of dissolved mineral salts	Vanhoof
Redox potential	Eh	How aerobic the manure is, affecting the conditions for aerobic and anaerobic micro-organisms. Manure is anaerobic, which mans	Vanhoof
Protein content in milk	-	Nitrogen converted into milk protein (avg. 3,6%)	CRV
Fat:protein ratio in milk	-	Describes the health (energy and rumen condition) of the cow. <1,1 can mean rumen acidosis while higher than 1,5 could mean sickness. Therefore, it can impact the manure	CRV
Phosphate content in milk	-	Strongly related with the protein content in milk, and describes the redundancy of phosphate.	CRV
Urea in milk	-	Nitrogen which is not utilized by the cow	CRV
Dry matter	DS	Liquidity of manure	Eurofins
Rough ash	RAS	All inorganic material	Eurofins
Organic material	OS	All organic material	Eurofins
Nitrogen	N	All forms of nitrogen	Eurofins
Nitrogen (DS=9%)	N90	All forms of nitrogen, if DS is set to 9%	Eurofins
Carbon-nitrogen ratio	C:N	Carbon content over nitrogen content	Eurofins
Total ammonia nitrogen	NH_3-N + NH_4-N	Mineral nitrogen in forms of ammonia or ammonium	Eurofins
Organic nitrogen	NORG	All organic nitrogen	Eurofins
Phosphorus pentoxide	P_2O_5	Phosphorus pentoxide, when dissolved in water, it forms an acidic solution	Eurofins
Phosphate (DS=9%)	$P_2O_5$90	Phosphate, if DS is set to 9%	Eurofins
Potassium oxide	K_2O	Potassium oxide, when dissolved in water, it forms a basic solution	Eurofins
Magnesium oxide	MgO	Magnesium oxide, when dissolved in water, it forms a basic solution	Eurofins
Sodium oxide	Na_2O	Sodium oxide, when dissolved in water, it forms a basic solution	Eurofins
pH	pHWater	The acidity or basicity of manure (measured by Eurofins)	Eurofins
Nitrogen-phosphate ratio	N:P_2O_5	Nitrogen content over phosphate content	Eurofins

Table 3: The selection of all manure and milk parameters, measured by Eurofins, Vanhoof and CRV.

Milk parameters

As mentioned, MPR data is used as well. Every third day, milk which is stored in containers is being collected, to be processed centrally and used for consumption. Each batch undergoes sampling, including measurements of urea in milk, the fat content, the protein content and the phosphate content. This data is primarily used to give farmers a better understanding of the efficiency of their feeding strategy. Since MPR data is already being measured, including them into the set requires limited effort and it has the potential to be a valuable additional component of AEP prediction. As previously explained, urea in milk has already been identified as an emission predictor with a lot of potential. Milk protein content is the protein richness of milk (amount of nitrogen converted), representing the nitrogen which is utilized into milk production by the cows (Goselink et al., 2016). The phosphate content in milk is also included in the analysis. Although it is not expected to be of any impact, the data availability justifies its inclusion in the study. The fat-protein ratio indicates whether the amount of energy and structure in the ransom is adequate, and therefore may also be informative (Smolder & Wagenaar, 2009). The average MPR value from the previous month of manure sampling is taken, as it best represents the composition of the manure during that period (DMS, personal communication, December 20, 2023).

Feed management parameters

In this study, a set of feed management parameters are proposed, covering a wider range of information about the ransom than just the nitrogen components, as has been done in the literature. The suggested feed management parameters can be divided into three subcategories: feed content, feed type and feed efficiency. The complete list is described in Table 4.

The category feed content consists of VEM, RE, P, RE/kVEM and P/kVEM. The parameters RE, VEM and RE/kVEM are included because of their direct link with ammonia emissions, as has been described in Chapter 2. The phosphorus-related parameters are not expected to have an impact, but are included in the analysis due to their presence in the selected manure parameters set. In case of any significant effects, these parameters could be traced back to feed management choices.

The feed type category is based on five ransom categories as is being described by the KLW model: fresh grass, grass silage, maize silage, concentrates and other roughage & by-products. The unit is in percentage of dry matter of the total ransom (% ds). These feeding types are the tools of farmers to optimize i.e. the RE/kVEM ratio, the ransom structure and more (Van Duinkerken et al., 2007). Fresh grass contains more protein (and thus nitrogen). Autumn grass in particular is high in protein. The quality of grass silage can vary a lot, influencing the feed content. Maize contains more VEM and less RE, which is used to balance a predominantly nitrogen-rich grass diet. Grass and silage maize account for most of the ransom (Velthof et al., 2020). To complement the ransom, farmers use concentrates and by-products, which contain a wide range of nutrients. Literature does not clearly show to what extent these ransom categories contribute to the composition of liquid manure and its related AEP.

The remaining two parameters describe the feed efficiency: the amount of produced milk and the amount FPCM[2] produced, both related to one kg dry matter feed intake. The hypothesis is that an increased efficiency correlates with a reduction of all components in manure including nitrogen components, resulting in a reduced AEP.

Feed management parameters	*Description*
Kg milk per kg ds intake	Kg milk produced per kg ds feed intake
Kg FPCM per kg ds intake	Kg FPCM produced per kg ds feed intake
VEM	Net energy in all feed
RE	Protein in all feed
P	Phosphor in feed
RE/kVEM	Protein-energy ratio
P/kVEM	Phosphor-energy ratio
% ds grass silage	% ds of total feed accounted to grass silage
% ds other roughage & by-products	% ds of total feed accounted to other roughage and by-products
% ds silage maize	% ds of total feed accounted to silage maize
% ds concentrates	% ds of total feed accounted to concentrates
% ds grass	% ds of total feed accounted to fresh grass

Table 4: The selected feed parameters for the feed-manure-AEP sequence.

To analyse the relationship between feeding strategies and the manure parameters within the measure feed-manure-AEP sequence, feed management data should represent the manure samples taken in the period 26 September to 3 October. According to DMS, the manure which is sampled is most strongly affected by the feed-management strategy of September. Data from this period can be obtained through the feeding app. Not all farmers had filled in the app, resulting into a dataset of only 12 farmers, as can be seen in Table 5 on the next page.

[2] Fat and protein corrected milk: milk converted to 4% fat and 3.3% proteins, facilitating comparison between milk samples.

Farmer code	Days of feeding data	Completeness of feeding types	Sufficient?
AMMONI-01	1	Incomplete	No
AMMONI-02	0	Incomplete	No
AMMONI-03	45	Complete	Yes
AMMONI-04	3	Incomplete	No
AMMONI-05	0	Incomplete	No
AMMONI-06	1	Complete	Yes
AMMONI-07	0	Incomplete	No
AMMONI-08	7	Complete	No
AMMONI-09	1	Incomplete	No
AMMONI-10	0	Incomplete	No
AMMONI-11	21	Complete	Yes
AMMONI-12	45	Compete	Yes
AMMONI-13	45	Compete	Yes
AMMONI-14	45	Compete	Yes
AMMONI-15	0	Incomplete	No
AMMONI-16	0	Incomplete	No
AMMONI-17	4	Complete	Yes
AMMONI-18	1	Complete	Yes
AMMONI-19	29	Complete	Yes
AMMONI-20	0	Incomplete	No
AMMONI-21	25	Complete	Yes
AMMONI-22	1	Complete	Yes
AMMONI-23	1	Complete	Yes

Table 5: Feed data of the AMMONI-project farms, with farmers with complete data in green.

The initial dataset is increased by allowing feeding data from 1 September up to 15 October. According to DMS, the ransom has been very stable for dairy farms during this extended period. After 15 October, a lot of precipitation has taken place, causing many farmers to end the grazing season, significantly impacting the ransom.

Before the feeding app data can be used, all data had to be converted into a proper format. Data was organized per day per farmer. It had to be merged in order to use monthly averages and be able to calculate the percentages of the different feeding types. The data conversion was done in Python. Lastly, the completeness of the data was verified by checking whether the sum of the percentages of the feeding types was 100%. Also, all days were checked for completeness regarding the ransom composition. To analyse the relationships between feed management and the manure parameters, simple linear regression has been used. The p-values, R-squared values and the direction of the relationships were calculated. The complete set of consists of 21 dependent variables (manure parameters) and 12 independent variables (feed parameters), resulting in 252 possible relationships. The significant relationships are isolated.

4.3 The modelled feed-manure-AEP sequence

The modelled approach follows the same sequence as the measured approach, as far as the design of the KLW model allows it. The exact same feed management parameters can be used. Because TAN is the only manure parameter in the emission calculations of the KLW model, no comparison can be made between the two approaches regarding the set of manure parameters. Nevertheless, measured TAN values are compared with modelled TAN values, which will be elaborated on in chapter 4.4.

To be able to evaluate the measured AEP values by the KLW model, emission values approximating the measured AEP are used. The raw output emission values generated by the model cannot simply be used for comparison. After all, the AEP is not an emission; the units are different (AEP is measured in parts per million [ppm], whilst the KLW model indicates emissions in kilograms [kg] per year), and the moment within the manure-feed cycle is different. Therefore, to evaluate the AEP, steps should be taken to find a modelled emission value closely related to the measured AEP. The modelled emission used for the comparison is described as NH3-stable emissions in kg/GVE, excluding farms prone to stable emission reduction factors. The exclusion is done by only including data of farms with 'stalemreddrijf = 0', which confirms that no stable EFs have been utilised. By doing so, the size of the farm and possible emission factors impacting the emissions are eliminated in the comparison. Only the relative order and size of the two approaches will be considered in the evaluation. Because this approach has its drawbacks, an additional method is used to evaluate the AEP. TAN from the same sample as the AEP is used as an AEP-proxy, since the emissions values in the KLW model are based on the calculated TAN.

4.4 The two TAN approximations

The KLW model calculates annual emission values. A large set of parameters are used to calculate TAN within the model (Figure 3, chapter 2.2). The calculation steps are described in the BEA section (company-specific ammonia emission) of *Rekenregels van de Kringloopwijzer*, which has been aligned with the NEMA (national emission model for ammonia) (Van Dijk et al., 2022). To make a reliable comparison between calculated and measured TAN values, TAN from the same moment in the nitrogen cycle within the farm should be taken. After all, TAN represents an equilibrium which can change over time. The following requirements are chosen: TAN is from slurry manure in the pit which is about to be applied to land, which means the measured TAN should be from manure samples in January. The manure composition has been building up for a long time, representing a ransom and production period of about 5 months, approximating the annual value. The requirements are summarised in Table 6.

Manure code	14 (slurry manure)
Location	In the pit
Time	January (Just before being applied to land)
Years	2018, 2019, 2020, 2021, 2022
Farmers set	AMMONI

Table 6: Requirements of the measured and calculated TAN

Modelled TAN

The previously described TAN is not available in the DMS database. The only available value is the gross TAN: the TAN in manure directly after excretion. Since there are no measurements available of the gross TAN, it cannot be used. The TAN value described in Table 5 is the Net TAN: the remaining TAN after volatilisation, mineralisation and immobilisation during storage, representing the TAN content in manure before it is being applied to land. Therefore, the Net TAN should be derived from the Rekenregels van de Kringloopwijzer (Van Dijk et al., 2022). The model refers to this as 'TAN applied to land' (Dutch: TAN-aanwending), which cannot be taken directly from the model and must therefore be calculated according to the principles of the model. Some values used to calculate the Net TAN are unavailable because they are interim values. These are interim outcomes of the calculation in the model. Therefore, these values needed to be copied manually from individual KLW models, restricting the dataset to 23 farms of the AMMONI group and restricting the years to 2018-2022 (see table 6). Prior to 2018, the required values were not yet available in the KLW model. The formula to determine the Net TAN is:

*TAN-applied to land = %TAN-manure * kg N manure applied to land*

Two values are needed: '%TAN-manure' and 'kg N manure applied to land'. %TAN-manure can be deduced from the database, where it is named 'PcTan_uitrmst'. Kg N manure applied to land can be calculated using the formula:

Kg N manure applied to land = Net N-excretion + N-manure supplied – N-manure discharged

'Kg N manure applied to land' and 'Net N-excretion' cannot be extracted. Kg N manure applied to land has four subcategories: applied to cornfield, arable land, natural land, and grassland, of which the kg N applied to grassland is an interim value and should be copied manually from the KLW-models. After the TAN-applied to land [kg] is defined, the next step is to convert the values into g/kg manure, to be able to use the same unit as the measured manure. Because the total amount of liquid manure applied to land is an interim value, it should also be added manually to the database. Figure 6 describes a flow chart of the calculation based on the KLW model, used to approximate the measured TAN value.

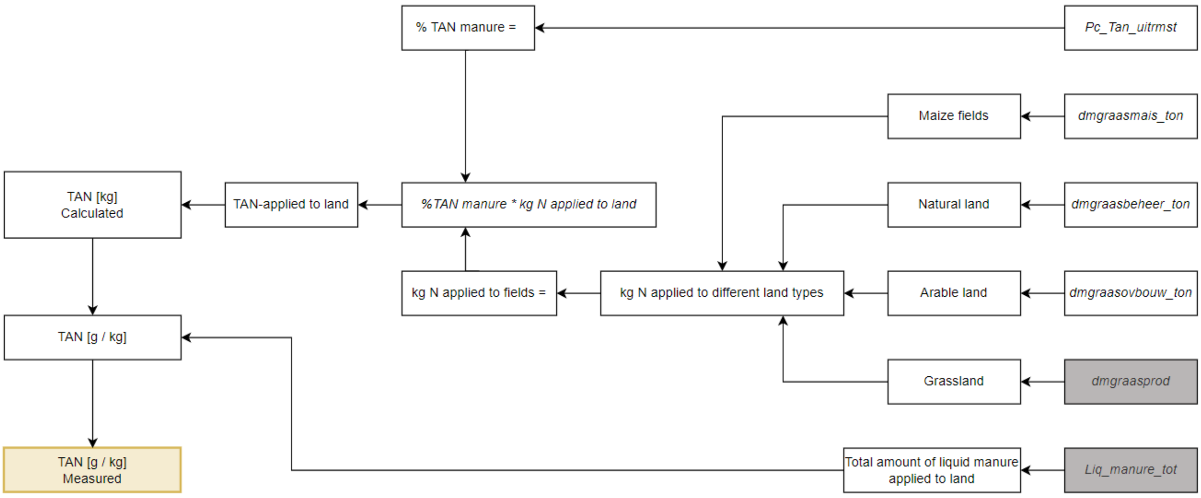


Figure 7: The method used to calculate the TAN value which complies with the measured TAN. The input data is located on the far right side. The grey boxes represent the manually added data. The yellow box represent the final TAN value complying with the measurements.

Measured TAN

The measured TAN values originate from samples taken by Eurofins and must comply with Table 6. The manure descriptions in the database have been checked to ensure the correctness of the data. Instead of the sample year, the 'seizoensjaar' is of the sample is used. This refers to the year prior to the year in which the measurements were taken, which better represents the January measurements. Once the two datasets are created, the KLW-values of the two datasets were matched according to the unique farmer code-year combination, resulting in 37 matches.

Feed management parameters related to the two TAN approximations

To shed a different light on the TAN comparison, the relationships of both TAN approximations with a set of feed management parameters are analysed. The feed management data consists of 12 parameters divided into three sub-categories as explained in chapter 4.2. To analyse the differences in relationships, the matching feed data obtained from the KLW model is merged with the two TAN approximations according to their unique year-farmer code combination. This results in a list of 25 feed parameter sets matching 25 modelled TAN values and an equal amount of measured TAN values. The three sets contain identical year-farmer code combinations. The analysis is done in Python and consists of a simple linear regression, resulting in p-values, R-squared and direction of the relationship.

Not all farmers took a manure sample in January as it is not mandatory. This is the limiting factor for the size of the dataset in the comparison, reducing the sample size to 25 farmers. If the requirement for the comparison that both TAN approaches contain the same year-farmer code combination was ignored, the sample size of the modelled approach could easily be increased. This was therefore done in addition, as it may improve the results of the analysis of the modelled approach.

4.5 Manure parameters to predict the AEP

As has been shown in Table 3 of Chapter 4.2, manure and MPR data originating from different sources have to be collected and merged. Once the dependent variable (AEP) and the independent variables (manure and MPR parameters) are obtained, statistical analysis can be conducted. Finding the parameters with the strongest predictive power is done in three steps, as described below. The overview of the method is visualised in Figure 8.

i. Data exploration: By means of a simple linear regression, an overview of the different parameters and their individual relationships (p-value, R-squared and direction) with the AEP was made. A linear relationship is assumed. Due to the possible presence of multicollinearity, a correlation matrix and a VIF analysis were applied. Multicollinearity means that independent parameters can also interact with each other e.g. more RAS automatically means more nutrients, and more N means more Norg. An increase in AEP might seem to be caused by an increase in variable X and Z, but the increase in X might not be related to the AEP but only with variable Z. In other words, multicollinearity creates noise in the results. Additionally, analysing multicollinearity it is insightful to better understand the interactions within manure. A correlation matrix is a visual representation of two-sided interaction between independent variables, while VIF (Variance Inflation Factor) indicates the amount of variance of a regression coefficient that is affected by multicollinearity (Shrestha, 2020).
ii. Data analysis: By means of ridge regression. The findings of the first two steps lead to the following conclusions: There exists high multicollinearity, making the results of the simple linear regression less reliable. The chosen statistical analysis is ridge regression. This analysis is effective for addressing multicollinearity. Also, it is suitable in situations when datasets contain a higher number of independent variables than observations (which is the case). Also can penalize less important parameters without completely removing them (Schreiber-Gregory, 2018). Another option would be to remove parameters responsible for multicollinearity in the dataset. It was decided not to do so, as it could lead to a loss of information. The design decisions regarding the ridge regression analysis are described in Appendix A.
iii. Sensitivity analysis: The analysis is prone to the chosen statistical analysis as well as the settings within the analysis. The sensitivity analysis is three-folded: 1) a regression analysis with two reduced sets of parameters, of which the new set is based on literature and a combination of results from the simple linear regression and multicollinearity analysis. 3) Lasso regression with the reduced sets of parameters. Lasso regression is an analysis which can also deal with highly correlated values. The difference between Lasso and ridge regression is that Lasso can shrink coefficients of parameters to zero, completely excluding certain parameters.

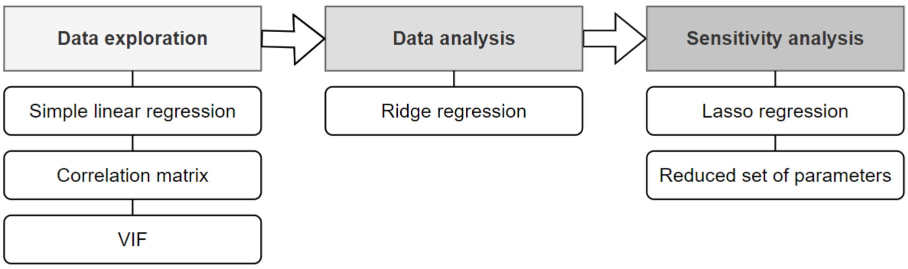


Figure 8: The research method used to analyse the relationship between manure parameters and the AEP

4.6 Feed management parameters to predict the two emission approximations

To determine the relationships between feed-management strategies (independent variable) and the AEP (dependent variable), and thus excluding manure in the analysis, feed management and emission parameters are required. The modelled and measured approaches are compared. This results in a dataset of 13 farms due to the limited availability of the feeding app data. For the modelled approach, there is an abundance of data. This dataset contains data from the years 2018 to 2022, resulting in a maximum of 5 data points per farm. This resulted in a dataset of n = 4656 for the modelled approach. Using simple linear regression, the p-values, R-squared values and the direction of the relationships were calculated.

5. Results

In this chapter, the results of all sub questions are reported. For the regression analyses, the R-squared represents the proportion of the variance which is predicted by the independent variable. The P-value explains the statistical significance of an independent variable. The direction indicates whether an independent variable positively (+) or negatively (-) affects the dependent variable. Commonly, a higher significance (lower p-value) results in an increase in the explained variance (higher R-squared).

5.1. The two TAN approximations

Figure 9 shows the distances of the matching farmer code-year combinations (n = 37) of the two TAN approximations. Every combination is connected with a grey line. Large distances are visible

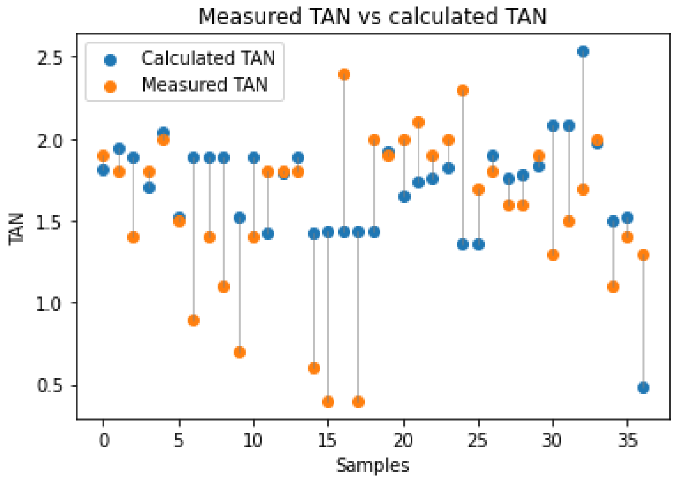


Figure 9: The distance between the two TAN approaches per farmer code-year combination. The grey line indicates connects the matching values.

Table 7 shows the distances between the two TAN approaches. A positive distance indicates a higher calculated value (blue) and a negative distance indicates a higher measured value (orange). Only the largest 11 values are shown in this table, because the distances are significantly smaller from the 12th place onwards. The complete list can be seen in Appendix B. The relative spacing, considering the size of the TAN values is very large. As shown in the table, three farmers (AMMONI-05, -07 and -21) account for a total of 9 outliers in the group of 11 largest outliers. Plots of the two complete datasets of TAN values, before the two datasets were merged, can also be found Appendix B.

Nr.	*Farmer code*	*Year*	*Distance*
1.	AMMONI-07	2019	1,04
2.	AMMONI-07	2021	1,03
3.	AMMONI-05	2019	0,99
4.	AMMONI-07	2019	-0,96
5.	AMMONI-18	2019	-0,94
6.	AMMONI-21	2021	0,83
7.	AMMONI-05	2018	0,83
8.	AMMONI-05	2021	0,82
9.	AMMONI-23	2018	-0,81
10.	AMMONI-05	2019	0,79
11.	AMMONI-21	2018	0,78

Table 7: List of largest differences between measured and calculated TAN values, including the farmer codes and years.

5.2 Feed management parameters related to modelled and measured TAN

To analyse whether there is a difference between the relationships of annual feed management strategies and modelled or measured TAN approximations, two linear regression analyses were done (n = 25). Table 8 shows the relationships using the measured TAN and Table 9 shows the relationships using the calculated TAN. Table 10 shows an additional analysis with the relationships using modelled values with an extended dataset (n = 81). The independent variables displayed in bold are the feeding parameters with a significant relationship with the used TAN approximation (p-value < 0.05).

Independent Variable	*P-Value*	*R-squared*	*Direction*
RE	0,000	0,452	+
VEM	0,021	0,211	+
Fresh grass	0,026	0,197	-
Kg milk per kg ds intake	0,030	0,188	+
REkVEM	0,032	0,186	+
Kg FPCM per kg ds intake	0,068	0,138	+
Concentrates	0,162	0,083	+
Other roughage	0,411	0,030	+
Grass silage	0,427	0,028	+
P	0,485	0,021	+
Silage maize	0,856	0,001	+
PkVEM	0,937	0,000	-

Table 8: The relationship between measured TAN and yearly feed parameters.

According to Table 8, the relationships between measured TAN and the feed parameters RE, VEM, fresh grass and RE/kVEM are significant, of which fresh grass has a negative relationship. The explained variance is only moderate for RE.

Feed parameters	*P-Value*	*R-squared*	*Direction*
RE	0,12	0,10	+
P/kVEM	0,20	0,07	-
RE/kVEM	0,25	0,06	+
Grass silage	0,29	0,05	+
P	0,38	0,03	-
VEM	0,39	0,03	+
Fresh grass	0,47	0,02	-
Kg FPCM per kg ds intake	0,59	0,01	-
Silage maize	0,72	0,01	-
Concentrates	0,76	0,00	+
Kg milk per kg ds intake	0,93	0,00	+
Other roughage	0,97	0,00	+

Table 9: The relationship between calculated TAN and yearly feed parameters.

According to Table 9, no significant relationships can be found between calculated TAN and the feed parameters. Two parameters show a different direction in relationship compared to the measured TAN. Additionally, the order of parameters differs according to their magnitude.

Independent Variable	*P-Value*	*R-squared*	*Direction*
RE/kVEM	0,00000	0,23822	+
Silage maize	0,00002	0,20677	-
RE	0,00002	0,20410	+
Grass silage	0,00003	0,19792	+
P	0,00225	0,11212	+
P/kVEM	0,00340	0,10351	+
Other roughage	0,01184	0,07752	-
Fresh grass	0,02674	0,06060	+
Concentrates	0,14903	0,02618	+
VEM	0,85658	0,00042	-
Kg milk per kg ds intake	0,95013	0,00005	+
Kg FPCM per kg ds intake	0,95226	0,00005	-

Table 10: The relationship between calculated TAN and yearly feed parameters, using the extended dataset.

According to Table 10, the significant relationships between calculated TAN and the feed parameters using the extended dataset are: RE/kVEM, silage maize, RE, silage grass, phosphorus, P/kVEM, other feed types and fresh grass are significant, of which silage maize and other feed types have a negative relationship. The maximum explained variance is 0.2, which is low.

There are large differences in results between the three approaches, when looking at the order of magnitude, significant relationships and directions. With a smaller dataset, the relationships between measured TAN and feed parameters are stronger than the relationships between the calculated TAN and feed parameters. When the dataset is increased for the calculated approach, the significance improves. For all approaches, RE and RE/kVEM score relatively high, which matches with the literature.

5.3 Evaluation of the measured AEP-values

The measured AEP value is evaluated by means of two approaches. For the first approach AEP is compared to NH_3 emissions generated by the KLW model (Figure 10). For the second approach, TAN is used as a proxy of the AEP, derived from the same measurement set (Figure 11). The values are scaled, enabling a comparison between the relative magnitudes per farm as well as the order of magnitude. The scaling factors are chosen with the aim to equalise the maximum values of both approaches, assigning less weight to the outliers. For both Figures, the farms are ordered according to the order of magnitude of the calculated NH_3 emissions.

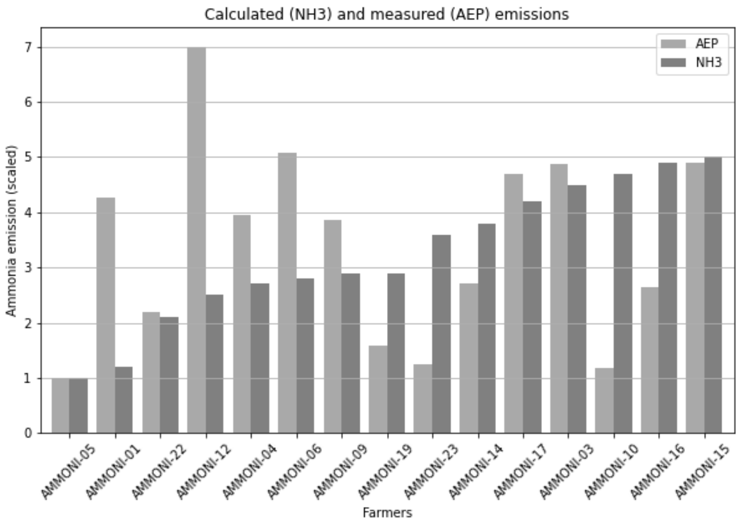


Figure 10: The comparison between measured AEP and NH_3 emissions calculated by the KLW.

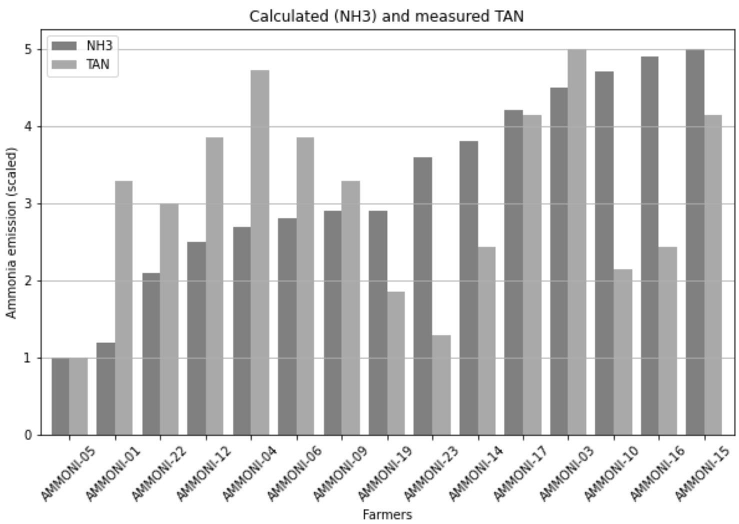


Figure 11: The comparison between measured TAN and NH_3 emissions calculated by the KLW.

For both approaches, a large difference between measured and calculated emission values can be identified. Furthermore, the order of magnitude shows a large variance. The two measured approaches (light grey bars) follow a more similar trend.

5.4 Manure parameters: strongest predictors of the AEP

In this chapter, the results of the relationship between manure parameters and AEP (n = 23) are shown. Firstly, the results of the data exploration are show, secondly the data analysis, and finally the sensitivity analysis.

Data exploration

Table 11 shows the p-value, R-squared and direction, as result of a linear regression analysis, with the significant parameters in bold. Figure 12 shows a more visual representation. The significant parameters (in bold) are TAN, N, with K_2O, N/P_2O_5, Norg and DS being slightly less significant. They all have a positive relationship. The explained variance of TAN and N are significantly higher. K_2O scores high as well. Urea in milk is not identified as significant. Two pH measurement have been taken: pH1 and pH2. pH1 (Vanhoof) has a higher significance compared to pH2 (Eurofins). The direction of pH1 is positive which matches with the literature, while pH2 is negative. More information regarding the two pH values can be found in Appendix C. The direction of C/N ratio and the redox potential are negative, which matches with the literature. The related scatter plots can be seen in Appendix D.

Manure parameter	*P-value*	*R-squared*	*Direction*
TAN	0,0007	0,399	+
N	0,0018	0,351	+
K2O	0,0150	0,231	+
N:P2O5	0,0173	0,222	+
NORG	0,0218	0,208	+
DS	0,0385	0,173	+
OS	0,0688	0,137	+
RAS	0,0716	0,134	+
Redox potential	0,1529	0,087	-
Phosphate content milk	0,1844	0,075	+
pH1	0,1897	0,074	+
P2O5	0,1907	0,073	+
NA2O	0,2718	0,052	+
Electical conductivity	0,2962	0,047	+
C:N	0,3533	0,038	-
MGO	0,4278	0,028	+
P2O590	0,4522	0,025	-
pH2	0,5775	0,014	-
Urea milk	0,6453	0,009	+
Fat:protein ratio milk	0,6500	0,009	-
N90	0,6584	0,009	+
Protein content milk	0,7154	0,006	+

Table 11: List of P-values and R-squared values of all independent variables resulting from the simple linear regression, listed from strongest to weakest.

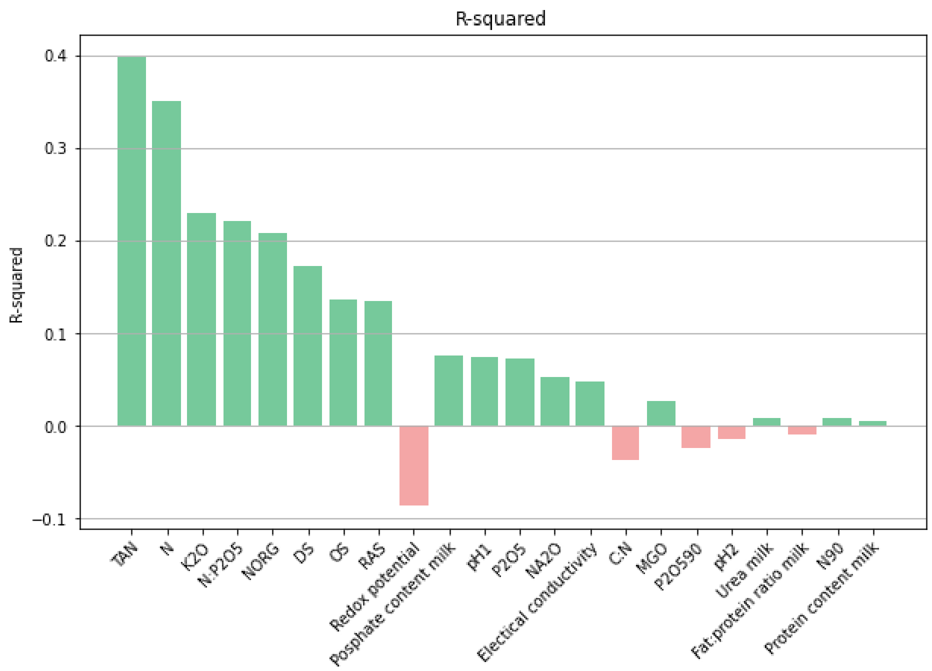


Figure 12: Bar chart showing the parameters in order of magnitude according to the R-squared multiplied with the direction.

Table 12 on the next page shows the VIF values. If the value of VIF is 1 with no correlation, 1 < VIF < 5 shows a moderate correlation and a VIF value higher than 10 indicates a high degree of correlation (Shrestha, 2020). All parameters deal with a high up to a very high degree of correlation, of which RAS, DS and OS have an infinitely high VIF score. The correlation matrix (Figure 13, next page), shows relationships between two independent parameters. Darker blue indicates a negative relationship and darker red shows a positive relationship. Interesting observations are:

- The MPR parameters have weak correlations among themselves and with other parameters.
- The redox potential and the electrical conductivity both have opposing strong relationships with TAN, K_2O and MgO, but also with urea in milk. Their mutual relation is negative. This can also explain the high ranking of K_2O in the simple linear regression analysis.
- K_2O, P_2O_5 and MgO behave similarly. K_2O and MgO are expected to increase the pH while P_2O_5 would decrease the pH. This is faintly noticeable.
- DS, RAS and OS behave almost identically and are strongly correlated with each other.
- The nitrogen components (N, TAN and Norg) behave similarly. TAN is strongly correlated with K_2O. According to DMS, this might be due to the richness of both nitrogen and K_2O in grass.
- The C/N ratio has a very strong negative relation with N90 and a moderate negative relation with TAN.
- N90 is strongly negatively related with DS, RS and OS, which is in contrast with its relation with N. The same contrast can be seen between P_2O_5 and P_2O_590

Manure parameter	*VIF*
NA2O	34
MGO	69
Urea milk	188
Redox potential	578
Electical conductivity	1,E+03
C:N	2,E+03
K2O	2,E+03
P2O590	3,E+03
Fat:protein ratio milk	3,E+03
N:P2O5	7,E+03
TAN	7,E+03
Protein content milk	8,E+03
N90	9,E+03
NORG	1,E+04
Posphate content milk	1,E+04
P2O5	2,E+04
pH1	3,E+04
N	4,E+04
pH2	6,E+04
RAS	inf
DS	inf
OS	inf

Table 12: The correlation matrix of all manure parameters

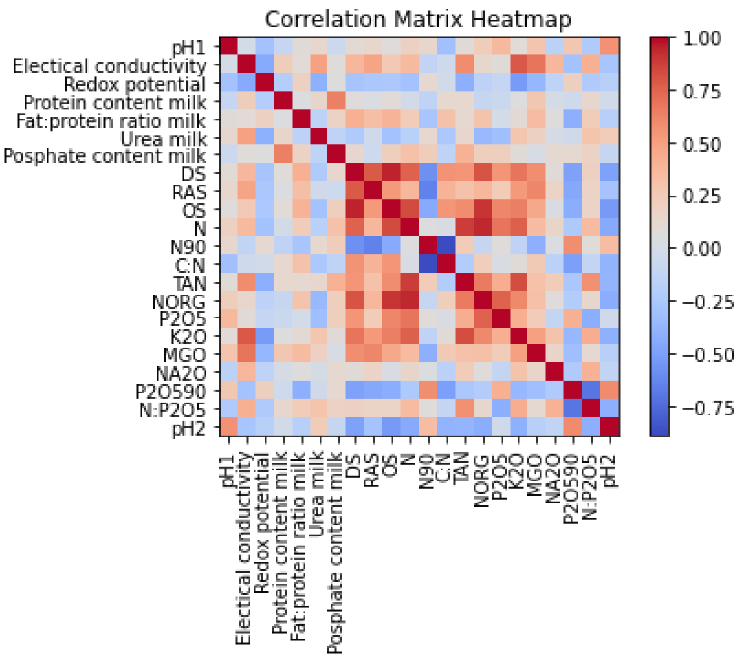


Figure 13: The VIF values of all manure parameters.

Data analysis

Before performing ridge regression, choices were made. Based on the results of the simple regression analysis, the pH measured by Eurofins was excluded. No other parameters were excluded, to prevent a loss of information. To perform a ridge regression, a set of choices have been made which impact the analysis: the regularization parameter (alpha) and the relation ratio between training set and testing set. These are further elaborated in Appendix A.

The results of the ridge regressions are displayed in Table 13 and Figure 14. The five strongest parameters resulted to be: N, TAN, Norg, N90 and the C/N-ratio. N, TAN and Norg were also present in the top 5 strongest parameters of the simple linear regression (bold in the table). Urea in milk, pH and DS score very low. The direction of C/N is negative. K2O, RAS, redox potential and OS are identified as less important compared to the simple linear regression. According to DMS, K_2O and nitrogen components in manure are both related to a plant-based ransom. K_2O scored significantly lower after the ridge regression, because multicollinearity is dealt with. The mean squared error (MSE) indicates how well the model preforms on the test-set. The MSE is 1154, indicating a poor performance. This can be a result of a high alpha-value, which has been chosen to prevent overfitting which is important when using a small dataset.

Manure parameters	*Coefficient*
N	2,41
TAN	2,35
NORG	2,04
N90	1,99
C:N	-1,84
NA2O	1,62
N:P2O5	1,51
MGO	-1,48
P2O5	1,43
Posphate content milk	1,30
K2O	1,27
pH1	1,09
OS	0,91
Protein content milk	0,88
DS	0,81
Electical conductivity	-0,76
P2O590	0,36
Protein:fat ratio milk	-0,24
RAS	0,23
Urea milk	-0,10
Redox potential	0,09

Table 13: The numerical list of coefficients.

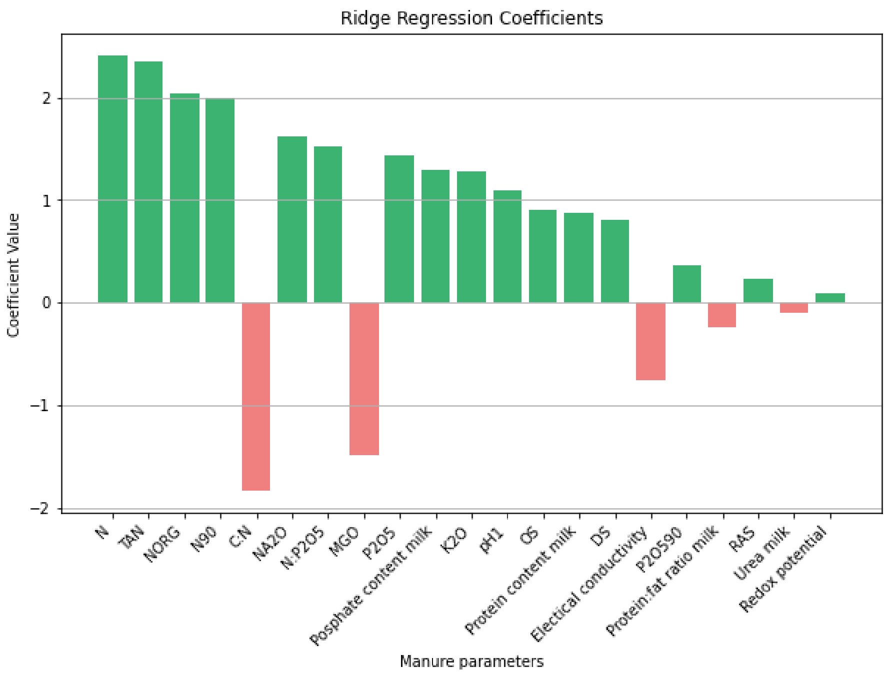


Figure 14: The list of coefficients displayed in a bar chart, in order of magnitude.

Sensitivity analysis

The sensitivity analysis is three-folded: 1) Regression analysis with two reduced sets of parameters. The reduced set is based on literature and a combination of results from the simple linear regression and multicollinearity analysis. 2) Lasso regression analysis with the full set of parameters. 3) Lasso regression with the reduced sets of parameters.

i. The regression analysis performed with a reduced set of parameters

The first reduced set of parameters consists of: pH, DS, N, C/N, TAN, N/P2O5 and K2O (Figure 15). As Norg is closely related to N, the second reduced set of parameters consists of the same set but replaces N with Norg (Figure 16).

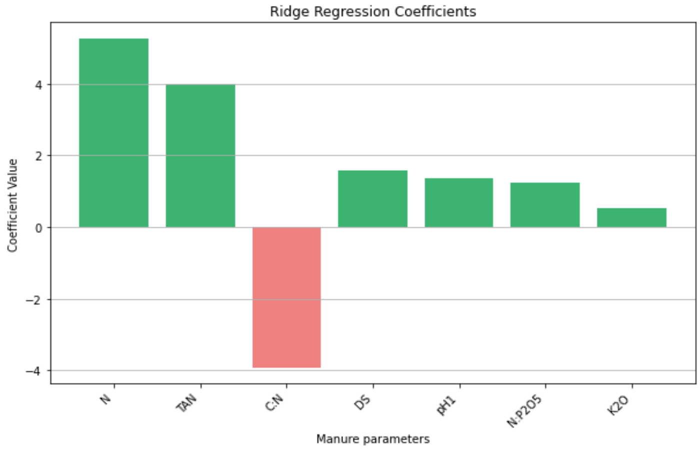


Figure 15: The reduced coefficient set (with N) displayed in a bar chart using ridge regression.

Figure 16: The reduced coefficient set (with Norg) displayed in a bar chart using ridge regression.

ii. Lasso regression analysis with the full set of parameters (Figure 17).

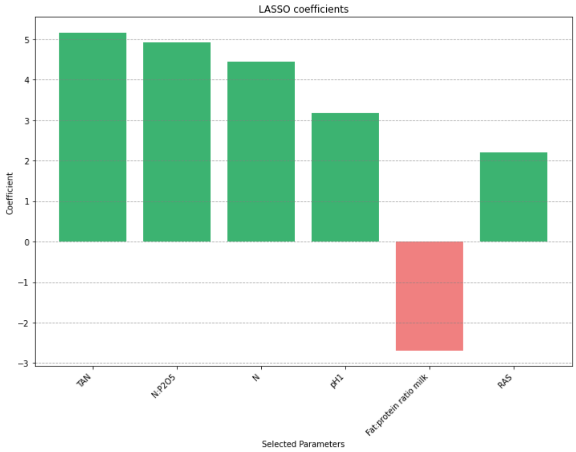
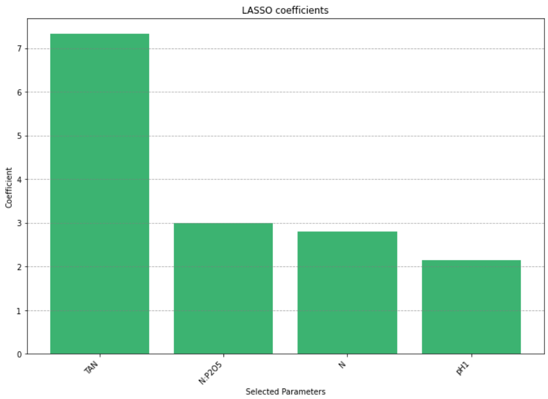


Figure 17: The list of the coefficient based on Lasso regression.

iii. Lasso regression with the reduced set of parameters (Figure 18 & 19).



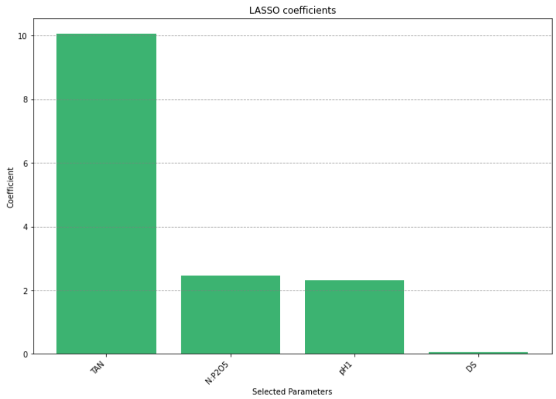


Figure 18 (left): The list of reduced coefficient (with N, without Norg) based on Lasso regression.
Figure 19 (right): The list of reduced coefficient (with Norg, without Norg) based on Lasso regression.

The results of the reduced regression analysis are similar to the original ridge regression analysis with the full set of parameters. However, DS, pH and N/P_2O_5 are assigned a higher value. The magnitude and order do not differ significantly. In both cases, TAN is considered the second strongest independent variable. According to the Lasso regression, TAN stands out as the most dominant parameter. The C/N ratio is excluded by the analysis and the N/P_2O_5-ratio together with pH are identified as much more important. This corresponds slightly to the ride regression analysis with the reduced set of parameters.

5.5 Measured feed management strategies related to manure parameters

All the feed parameters (12 independent variables) are linked to the complete set of manure parameters (21 dependent variables) for the 13 farms of the AMMONI-project (n=13) which had sufficient data regarding their feed management strategies. A linear regression analysis is performed resulting in 273 relationships. All the significant relationships (p-value < 0.05) are displayed in Table 14 on the following page. The top 5 manure parameters which are identified by the regression analysis to be the strongest predictors of the AEP are displayed in bold. The complete matrices with all relationships can be found in Appendix E.

Feed_Parameter	Manure_Parameter	P_Value	R_Squared	Direction
RE/kVEM	*Urea milk*	0,004	0,538	+
Silage maize	***NORG***	0,006	0,506	+
Silage maize	*Urea milk*	0,009	0,473	-
Other roughage	***N***	0,010	0,469	-
RE	*Urea milk*	0,010	0,463	+
Other roughage	***NORG***	0,012	0,450	-
RE/kVEM	*Redox potential*	0,017	0,417	-
Silag emaize	*Fat:protein ratio milk*	0,018	0,412	+
Fresh grass	***NORG***	0,022	0,393	-
RE	*Redox potential*	0,025	0,378	-
P/kVEM	***N***	0,026	0,375	-
Concentrates	*Redox potential*	0,029	0,364	+
Concentrates	*Urea milk*	0,031	0,358	-
Fresh grass	*OS*	0,031	0,358	-
Grass silage	*K2O*	0,031	0,356	+
Silage maize	***N***	0,032	0,353	+
VEM	***N***	0,032	0,353	+
Grass silage	*OS*	0,033	0,352	+
Other roughage	*OS*	0,033	0,349	-
Fresh grass	*Fat:protein ratio milk*	0,034	0,347	-
Other roughage	*K2O*	0,037	0,338	-
Silage maize	*Posphate content milk*	0,047	0,312	+
Other roughage	***TAN***	0,049	0,308	-
Other roughage	*P2O5*	0,050	0,306	-

Table 14: All significant food-manure relationships, with the top 5 manure parameters from the ridge regression in bold.

RE/kVEM and RE are strongly positively related to urea in milk, whilst maize silage has a negative relationship. Silage Maize and VEM are positively related to the manure parameters and therefore positively related to the AEP. P/kVEM, fresh grass and other roughage are negatively related to the manure parameters and therefore negatively related to the AEP. RE/kVEM and RE are not significantly correlated with the Nitrogen components in manure. They do show a significant relationship with urea in milk. Figure 20 on the next page shows the cascading effect of the feed management parameters with the strongest indirect predictive value for the AEP. The selection is based on their relationships with the top 5 important manure parameters identified by the ridge regression. The significance of fresh grass can be tricky, because fresh grass can either be taken up by the cow during grazing, or the farmer has chosen to mow the grass and bring it into the stables. These management choices have large effect on the actual relationship with manure parameters, and should be considered. This distribution can be seen in Table 15. It shows that 5/12 have a grass intake which is purely based on grazing, 3/12 is purely based on mowing, 1/6 has a marginal percentage of grass intake via grazing and 1/6 has nog grass intake.

Farmer code	*03*	*06*	*11*	*12*	*13*	*14*	*17*	*18*	*19*	*21*	*22*	*23*
% Grazing	0	-	100	-	0	11	100	0	100	100	100	14

Table 15: The percentage of fresh grass intake via grazing. The symbol (-) means an absence of fresh grass in the ransom.

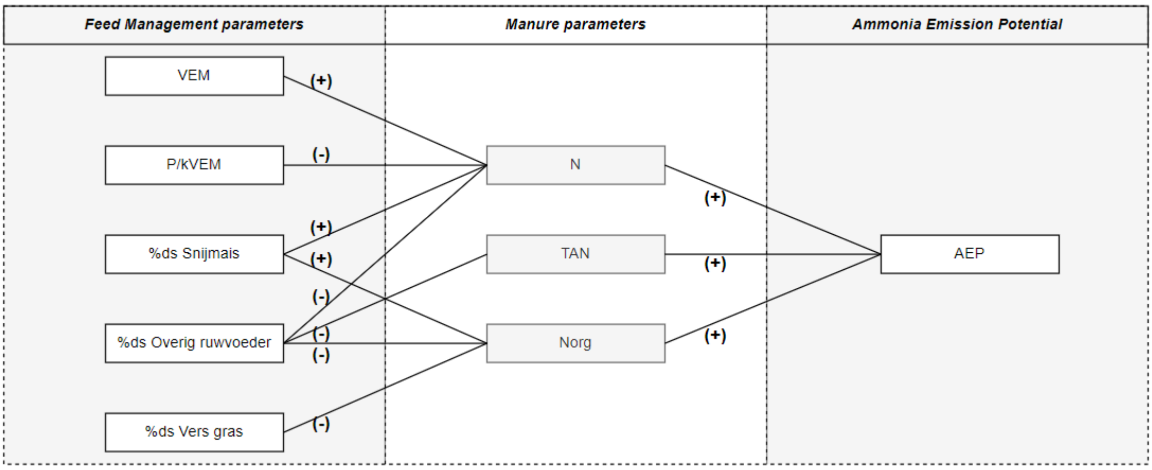


Figure 20: The significant feed parameters which are related to the strongest manure parameters influencing the AEP.

5.6 Feed parameters related to modelled and measured emission values

Two identical linear regression analyses are performed. One following the measured data from the feed-AEP sequence (n=13) and one following modelled sequence (n=4656). The linear regression analysis resulted into p-values, R-squared values and directions of every feed-emission relationships. The results of the measured approach are presented in Table 16. The calculated approach is presented in Table 17. The independent variables displayed in bold are the feeding parameters with a significant relationship with the emission values (p-value < 0.05). Appendix F illustrates the regression plots for all individual relationships.

Independent Variable	*P-Value*	*R-squared*	*Direction*
P/kVEM	0,20	0,14	-
P	0,24	0,13	-
Grass silage	0,31	0,09	+
VEM	0,35	0,08	+
Other roughage	0,49	0,04	-
Kg FPCM per kg ds intake	0,52	0,04	-
Fresh grass	0,53	0,04	-
Kg milk per kg ds intake	0,53	0,04	-
Concentrates	0,77	0,01	+
RE	0,89	0,00	+
Silage maize	0,91	0,00	-
RE/kVEM	0,94	0,00	-

Table 16: The feed – AEP relationships according to the measured approach

Independent Variable	*P-Value*	*R-squared*	*Direction*
RE	0,00E+00	0,48	+
RE/kVEM	0,00E+00	0,33	+
Kg FPCM per kg ds intake	1,70E-199	0,18	+
Fresh grass	1,85E-186	0,17	-
Kg milk per kg ds intake	5,22E-171	0,15	+
Concentrates	1,75E-123	0,11	+
VEM	1,77E-76	0,07	+
P	4,00E-43	0,04	+
Grass silage	1,19E-33	0,03	+
P/kVEM	2,17E-14	0,01	+
Silage maize	0,13	0,00	+
Other roughage	0,29	0,00	+

Table 17: The feed- NH_3 relationships, according to the modelled approach.

Conclusively, there is a large difference between the results of the measured and calculated approach. None of the feed parameters in the measured approach show a significant relationship, which is in contrast with the KLW model approach, showing a very high significance for almost all relationships. Also, the explained variance of RE and RE/kVEM are large. Only silage maize and other roughage are considered significant. Finally, there is also a difference in direction and order of magnitude of the relationships.

6. Discussion

Following the results in Chapter 5, this section reflects on the key findings and discusses the limitations and recommendations of this study.

6.1 The identified relationships in the measured feed-manure-AEP sequence

When analysing the measured feed-manure-AEP sequence, several findings stand out. Literature describes TAN, the N/P2O5 ratio, urea in milk, C/N ratio, pH and DS as manure parameters with the most potential to predict the emission potential of manure, with TAN as the most important predictor. According to the ridge regression analysis, N, TAN, Norg, N90 and the C/N ratio have been identified as the five most important predictors, in the aforementioned order. All these manure parameters are N-related components. In contrast to the literature, urea in milk, pH, and DS score were surprisingly low. As TAN alone did not emerge as the sole primary predictor parameter, it raises further questions whether the KLW model can sufficiently cover the variance when including only one manure parameter (TAN) in its emission calculations, as argued by Van Bruggen et al. (2019). However, the sensitivity analysis showed a strong dependence on the chosen statistical method, which reduces the robustness of the results.

Furthermore, only a very limited number of relationships between feed management parameters and manure parameters are observed to be significant. Of those relationships, only ten feed-manure relationships include the five strongest predicting manure parameters, as identified by the ridge regression analysis. The most important feed parameters impacting the AEP positively are maize silage and VEM. Feed parameters with a negative relationship are other roughage, P/kVEM, and fresh grass. The direct effect of these feed management parameters on the AEP remains small; the feed management parameters only explain a part of the variation in the manure parameters, which only partly explains the AEP. According to the literature, the important feeding parameters are RE and RE/kVEM, which are not confirmed by the results of the sequence analysis. It is difficult to evaluate these indirect relationships by the model, due to the absence of additional manure parameters in the KLW model. When comparing the direct relationships of the feed management parameters with both the measured AEP and the modelled emission approximation, large differences can be noted. The direct relationship with the measured AEP is not significant, whereas the modelled approach showed very strong significance. This could be due to the size of the dataset, but also due to the embedded relationships in the KLW model; it is notable that almost all feed parameters show a relationship with extremely high significance, in stark contrast to the insignificance of silage maize and other roughage.

6.2 Evaluation of the measured feed-manure-AEP sequence using the KLW model

The measured feed-manure-AEP sequence is analysed using the KLW model. However, as the KLW model is also an approximation to the truth, the model will also be evaluated. To begin with, TAN derived from the KLW model is evaluated by means of measured TAN values. After all, the calculated TAN is an important parameter in the model to determine the ammonia emission values. This resulted in large differences between the two approaches, possibly due to several reasons. Firstly, the measurements might insufficiently fit the comparison, as the manure samples were not taken to serve the purpose of this particular comparison. A single sample might not represent the composition of the entire pit, as a farmer often deals with multiple pits. Also, TAN samples from January are taken, whilst February 16th is the first day farmers are permitted to apply manure on land. On the other hand, it is possible that the model has failed to capture the TAN values due to generalisations in the model, i.e. mineralisation, immobilisation and digestion constants. It is noteworthy that not only one type of TAN approach scores systematically higher or lower than the other. This may indicate that there is no constant over- or under-fitting, supporting the calculation method used in this study. In addition, the TAN approximations are evaluated by examining their corresponding relationships with feed management parameters. This evaluation also resulted in limited similarities. Whether this is due to limitations of the model or the samples remains to be seen and should be further assessed in future studies. Both methods did show a significant relationship between TAN and both RE and RE/kVEM, aligning with the literature.

The measured AEP was evaluated through the KLW model. There were significant differences in the relative magnitudes per farm, as well as the order of magnitude of the compared emission values. These differences could be due to the fact that neither the AEP nor its proxy reflects the annual modelled emission value with enough accuracy. The moment within the feed-manure cycle in September might be too far off compared to the annual data. Nevertheless, at least a similar trend in the order of magnitude would be expected, because the modelled value does approximate the AEP. If both the measured AEP and the KLW model would be taken as true, the results would indicate that high annual emitters can perform relatively well in September probably having their emission peak at a different time of year. It cannot mean that the higher emitters have very effective emission reduction strategies, because the EFs responsible for emission reductions in the model are excluded in the emission values used in this specific comparison. Possibly, the KLW model might be too generalized, not being able to capture the variance in emissions which characterizes the AMMONI group, an argument based on the criticism made earlier in this chapter. Since the AEP measurements are also criticised (next section), the truth may lie somewhere in between.

6.3 Evaluation of the measured AEP for an emission-based policy

It is important to critically assess whether the AEP measurements are an appropriate tool in an emissions-based policy. This remains questionable as the AEP doesn't represent the actual ammonia emission. Instead, it indicates whether the composition of the manure sample has a relatively high or low potential to emit ammonia at the moment of measuring. The AEP can vary over time as the manure composition changes due to added manure and biochemical processes in the mixture. Furthermore, ammonia which was emitted in the period prior to the measurements affects the measured AEP as well. A low AEP value could mean that the manure has a very low emitting potential, but it could also mean that a major part of the ammonia has already been volatilised, which introduces uncertainty into the conclusions drawn from the measurements. The extent of this uncertainty is currently unclear. Moreover, it is challenging to determine how well the specific manure sample(s) represents the emission potential of the entire slurry manure composition of the pit. Even if the method is validated and standardized, additional procedures will still be needed to limit the uncertainty introduced by the period prior to the measurements. When comparing the results to other farms, exported manure, external storages but also the number of days the pit is being filled can influence the interpretability. Also, if such measurement were to be applied in an emission-based policy, additional steps would need to be taken to identify the gap between the AEP and the final ammonia emissions. Lagerwerf et al. (2022) already showed large fluctuations between the excreted TAN and the actual ammonia emission.

Nevertheless, the measurements can be useful for evaluating the effect of the manure composition on the AEP, and how it has been influenced by feed management strategies. Feed management, manure and the AEP are directly linked. The reliability of the results will improve if measurements are taken immediately after excretion, thus removing the impact of the period prior to the measurements. However, this will limit the applicability of the results to merely the feed management strategies of the specific day. Nonetheless, information regarding the manure composition and the AEP will be useful for farmers, as it will improve their understanding of the nutrient efficiency of their livestock. Currently, the AEP measurement method is at its starting phase. The method will continue to improve and the measurements themselves still need to be validated by TNO.

As has been stated, measuring is not by definition better than modelling. The full potential of both the measured and modelled approaches should be considered when assessing their applicability to an emissions-based policy. Disadvantages of using a model such as the KLW model are based on the dependence on reliable input data, the use of standardised values and, in addition, the use of TAN as the only manure component in the model. Therefore, the model may not be able to account for farmers who exceed average emission levels. On the other hand, the applicability of the AEP measurements has also been questioned. If the 'relatively cheap' measurements were validated, the correctness of such measurement method would still be prone to human error. Furthermore, it would remain very costly to be able to measure systematically and correctly on all dairy farms in the Netherlands.

Continuing from the previous paragraphs, it is reasonable to ask whether we actually want to use such emission approximations to establish a boundary indicating whose emissions are acceptable and whose emissions are unacceptable. It remains very difficult to either correctly model or measure a complex farm system, as there are numerous factors influencing the system and its related emission values. Potentially, it is fairer to set boundaries based on (emission) values which cannot be questioned. For example, an undisputable number related to the intensity of a farm could offer such boundary. However, guaranteeing a fair transition based on such numbers would still need larger system change. Large emitters form other sectors should be included, but also retailers, banks and other stakeholders linked to the dairy sector. As the political events in the Netherlands have proven, this remains to be very challenging.

6.2 Recommendations and limitations

The results of the feed-manure-AEP sequence are based on the first measurement round of a total of eight measurements over a period of two years. As the research continues, the dataset will be increased, giving more reliable results regarding the set of most predictive manure parameters and the related feed management parameters. Measurements of one year will not only show possible fluctuation linked to the manure-feed cycle, but will also the comparison with results from the KLW model. Nevertheless, it will remain to be tricky to compare the AEP with the ammonia emission calculated by the KLW model.

The slurry manure samples were measured by Eurofins and Vanhoof. When comparing the two results, there was a remarkable difference between the pH values, as the pH values of Eurofins are consistently higher. This may be due to the fact that Vanhoof's measurements were taken when the AEP was also sampled, whereas it took several days before Eurofins measured the samples. According to literature, an increase in pH would mean an increase in TAN, creating a mismatch between the AEP and the manure parameters measured by Eurofins. It is recommended to use only one method to measure the manure parameters, preferably as close in time as possible to the AEP measurements. The difference in the results highlights the dependence of the results on the chosen measurement method.

This study only briefly touches on feed parameters and their effects. A more extended analysis of how feed management influences the manure composition will be insightful to better understand the feed-manure relationship. Not only VEM and RE should be included, but also other components that influence the internal system of a cow, such as OEB, DVE and NDF. The current analysis showed surprising results regarding the effect of fresh grass and silage maize. These components account for most of the ransom, and also highly impact the agricultural-natural landscape in the Netherlands. Maybe, the effect of a more grass-rich diet is more nuanced than just the fact that the diet is more protein-rich. The relationship between fresh grass and manure composition can be particularly tricky, as fresh grass from grazing would automatically be linked with manure excreted outside the stables. Finally, ensuring a complete feeding dataset for the remaining rounds of measurements is of great value. The size of the current dataset was very small.

The measuring method used to sample the AEP with the novel measuring technique was already decided on and was beyond the scope of this study. The chosen method did have its limitations. The measurements were not conducted in a controlled experimental environment, in which the majority of the conditions are regulated. As this was not the case, it will be challenging to conduct identical measurements during the remaining measurement rounds. Also, it is more difficult to be certain about the observed relationships, as other factors which do not take part in the measurements could have an influence on the results. On the other hand, a controlled environment is very difficult to regulate in a stable.

In order to critically assess the TAN values used in the KLW model, it is recommended to use manure samples that have been specifically measured to facilitate the comparison between measured and calculated TAN values. This may lead to a strong confirmation or rejection of the ability of the KLW to calculate the TAN values of slurry manure, and automatically the associated emission values. Possibly, the results will strengthen the tendency to support a measurement-based approach used to determine the ammonia emissions. Additionally, a more in-depth analysis of the reasons for the differences found is needed, an aspect that was not extensively addressed in this study. Depending on these results, a new method of calculating the gross TAN in the KLW model can be considered. This could be achieved by developing a model, based on the measured feed-manure-AEP sequence.

7. Conclusion

In this study, the aim was to answer the following research question:

"To what extent can measurements of the slurry manure composition serve as a reliable indicator for the ammonia emission potential, and how can we influence it by feed-management strategies?"

By following measurements of the feed-manure-AEP sequence of a selected group of farms, the relationships in the sequence were analysed. A set of 23 manure parameters and 12 feed management parameters are used. Literature described TAN, the N/P2O5 ratio, urea in milk, C/N ratio, pH and DS as manure parameters with most potential to predict the emission potential of manure, with TAN as the most dominant predictor. In this study, N, TAN, Norg, N90, and the C/N ratio are identified as the most important predictors. Urea in milk, pH and DS score score surprisingly low. The sensitivity analysis revealed some uncertainty in the results. The most important feed parameters positively impacting the AEP are maize silage and VEM. Feed parameters with a negative relationship are P/kVEM, other roughage, and fresh grass. The direct effect of these feed management parameters on the AEP remains small. Since fresh grass and silage maize account for most of the ransom and impact the agricultural-natural landscape in the Netherlands, it is recommended to conduct additional research regarding these parameters. The direct relationship with the measured AEP showed no significant relationships, which is in contrast with the results of the modelled approach. The results of the feed-manure-AEP sequence are based on the first measurement round of a total of eight measurements over a period of two years. As the research continues, the dataset will be increased, giving more reliable results.

The measured feed-manure-AEP sequence is evaluated using the KLW model. To begin with, measured TAN is evaluated by comparing it with modelled TAN values. This resulted in large differences between the two approaches. Consequently, it is recommended to repeat the comparison with manure samples which have been measured to facilitate the comparison. Evaluating the AEP using the KLW model resulted in large differences regarding the relative magnitudes per farm as well as the order of magnitude of the compared emission values. Nevertheless, a similar trend in order of magnitude was expected. It remains challenging to determine whether the model or the measurements are incorrect.

It is questionable whether the AEP measurements will be an appropriate tool in an emissions-based policy, due to the inability to directly represent the final ammonia emissions. AEP values can fluctuate over time due to changes in manure composition and prior ammonia emissions, introducing uncertainty into their interpretation. Nevertheless, the measurements are suitable for assessing the effect of the manure composition on the AEP, and how it has been influenced by feed management strategies. The reliability of the results will be improved when the measurements are taken immediately after excretion. The information regarding the manure composition and the AEP will remain to be useful for farmers, as it will improve their understanding regarding the nutrient efficiency of their livestock.

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Appendices

The appendices referred to in the text are located on the next pages.

Appendix A. Ridge regression: design choices

Performing ridge regression requires multiple design choices impacting the analysis. Influential parameters are: The regularization parameter, the ratio between training-set and testing-set and the number of cross-validations.

Regularization parameter

The regularization parameter (in the code = alpha) creates bias in the data. The alpha influences the mean squared error (MSE) on the testing set: how well the combination of coefficients fit the data. Since the dataset is limited (n=23), it is likely that the coefficient will over fit the data without including a regularization parameter. The regularization parameter creates a deviation from the sum of the squared residuals (the minimum sum of the total distances of all data points to the created regularization line). The hypothesis is that an increase in data points will lead to a change in results. The goal is that the regression line will not change too much if extra data would have been added in the future. Choosing the alpha can be tricky as it highly influences the results. The following choices have been made

1. In the code, 1000 possible alphas are chosen within the range of 10^-3 – 10^3.
2. Cross-validation is a machine learning method and is used to identify the best fitting alpha: the data is split into a training set and a test set. The part of the data which is the test-set is changes every time, looking for the optimum alpha. Finally, the optimum alpha turned out to be **31.6**.

Ratio training-set and testing-set

The ratio is based on prior knowledge about the manure parameters. According to literature and the simple linear regression, a relatively high scoring TAN would indicate a logical ratio. By trial and error, the ratio training: testing turned out to be 70:30. 30% considers of testing data.

Cross-validation

The amount of cross-validation is set to 10, due to the same trial-and-error method as explained above.

Evaluating the model using negative mean squared error

In the code, it can be seen that the model uses the negative mean squared error. Normally, a measure of a well performing regression model aims to find a low mean squared error (MSE). Scikit-learn (a library used) is looking for maximizing scoring function, which would be in conflict with the goal. By doing so, lower negative values indicate a better performance. Therefore, a negative MSE is used to find the best alpha.

Appendix B. The two TAN-approaches: the complete dataset

Figure B1 shows the two complete datasets of TAN. The two graphs on the left-side display the measured set, the right side shows the more calculated set. The colour codes define the different farms. The vertical line in the two upper graphs visualise the connected points, which means they derive from the same farm. The lines in the lower to graph visualise the TAN values of the same farm within the same year, using a colour code. This is why there are no lines the graph on the right-bottom corner, since the calculated TAN values are annual. On the left-bottom side, it is visivle that one farm has 4 slurry manure samples in the same year in January, complying with the requirements.

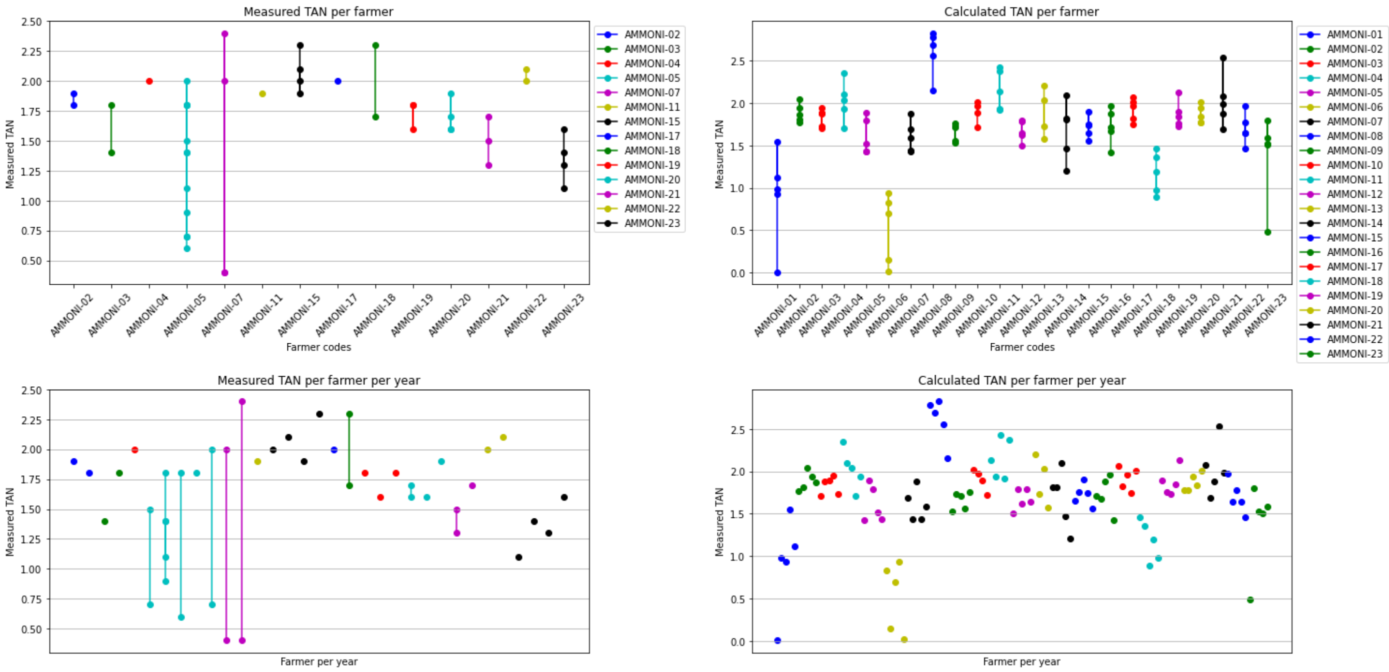


Figure A1: The comparison between measured AEP and NH_3 calculated by the KLW.

From Figure B1, several conclusion can be made. First of all, there is a large spread in measured TAN values taken within the same year within the same farm. Secondly, there are some outliers visible in the calculated set, but the majority is located between a value of 1.5 and 2.0. At last, without directly comparing individual values, the magnitude of the values seem to match well.

Table B1 (next page) shows the complete lists of distances from the different TAN combinations. The top 11 is made bold.

Nr.	*Farmer code*	*Year*	*Distance*
1.	**AMMONI-07**	**2019**	**1,04**
2.	**AMMONI-07**	**2021**	**1,03**
3.	**AMMONI-05**	**2019**	**0,99**
4.	**AMMONI-07**	**2019**	**-0,96**
5.	**AMMONI-18**	**2019**	**-0,94**
6.	**AMMONI-21**	**2021**	**0,83**
7.	**AMMONI-05**	**2018**	**0,83**
8.	**AMMONI-05**	**2021**	**0,82**
9.	**AMMONI-23**	**2018**	**-0,81**
10.	**AMMONI-05**	**2019**	**0,79**
11.	**AMMONI-21**	**2018**	**0,78**
12.	AMMONI-21	2018	1,04
13.	AMMONI-07	2021	1,03
14.	AMMONI-03	2020	0,99
15.	AMMONI-05	2019	-0,96
16.	AMMONI-05	2019	-0,94
17.	AMMONI-23	2021	0,83
18.	AMMONI-05	2018	0,83
19.	AMMONI-15	2021	0,82
20.	AMMONI-15	2018	-0,81
21.	AMMONI-18	2019	0,79
22.	AMMONI-17	2019	0,78
23.	AMMONI-20	2018	1,04
24.	AMMONI-19	2019	1,03
25.	AMMONI-15	2019	0,99
26.	AMMONI-02	2021	-0,96
27.	AMMONI-23	2020	-0,94
28.	AMMONI-19	2018	0,83
29.	AMMONI-03	2018	0,83
30.	AMMONI-02	2019	0,82
31.	AMMONI-05	2019	-0,81
32.	AMMONI-20	2021	0,79
33.	AMMONI-04	2020	0,78
34.	AMMONI-22	2018	1,04
35.	AMMONI-05	2021	1,03
36.	AMMONI-11	2021	0,99
37.	AMMONI-05	2020	-0,96

Table A1: The list of distances from between the two TAN approximations.

Appendix C. pH comparison: Vanhoof and Eurofins

Figure C1 visualizes the difference between the two pH measurements, with the measurements of Eurofins systematically giving higher values. This might be caused by the fact that the manure sample has aged before it has sampled. It could potentially mean an increase in the TAN values as well, which is also measured by Eurofins. Additionally, pH measurements by Eurofins are more expensive. Therefore, it could be economically interesting to continue with only the pH measurements of Vanhoof.

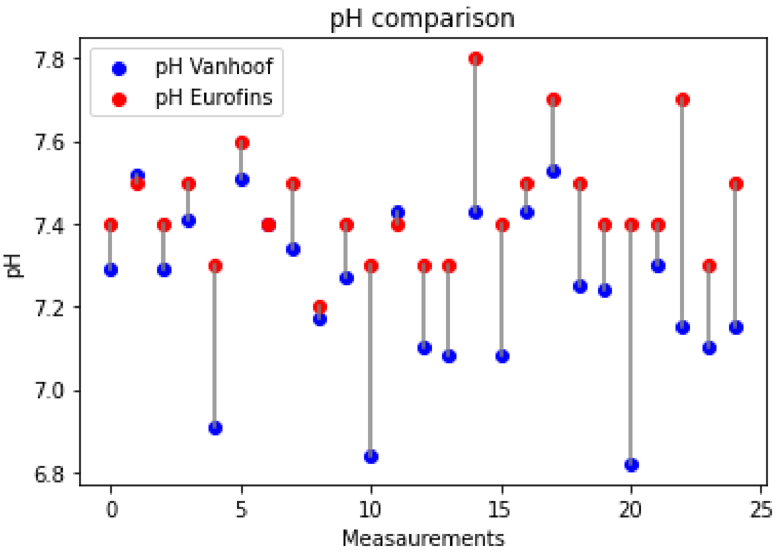
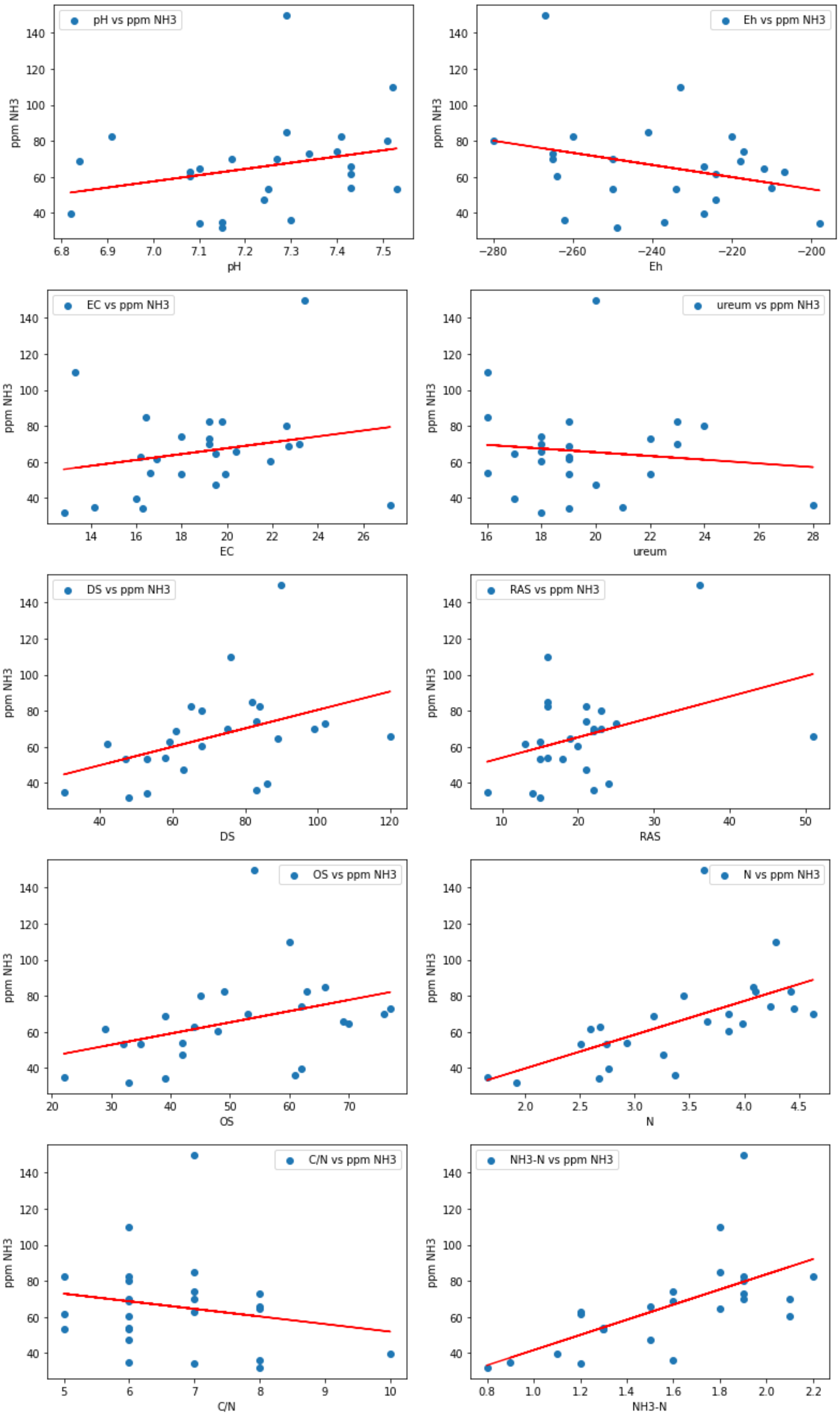
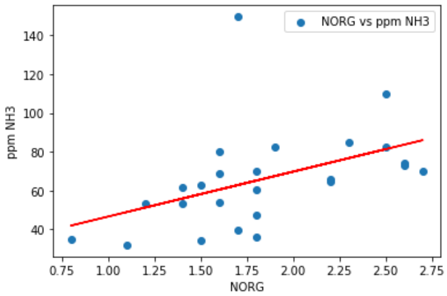
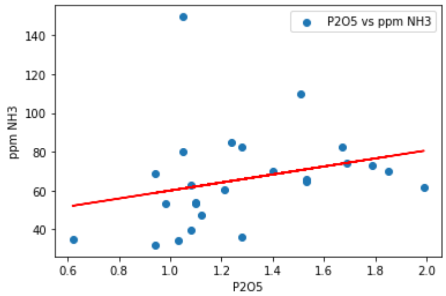


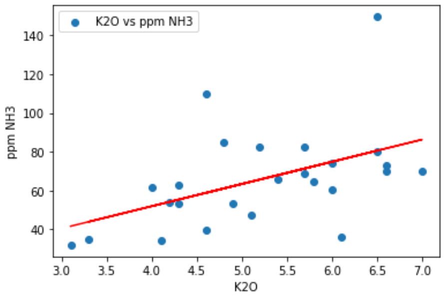
Figure C1: The comparison between the two measured pH values.

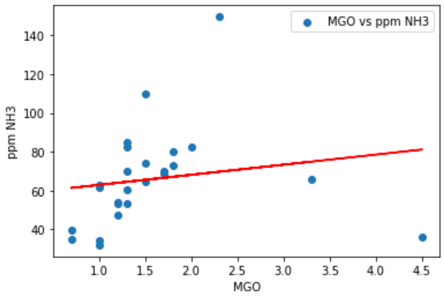
Appendix D. Regression lines of the manure-AEP relationship

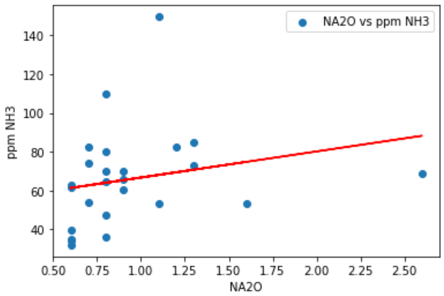


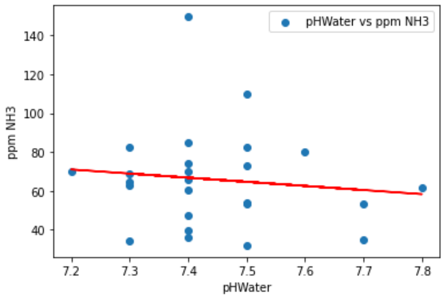

NORG vs ppm NH3
ppm NH3
NORG

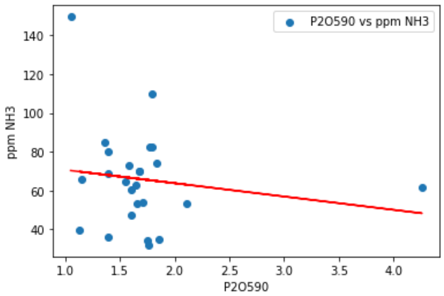

P2O5 vs ppm NH3
ppm NH3
P2O5

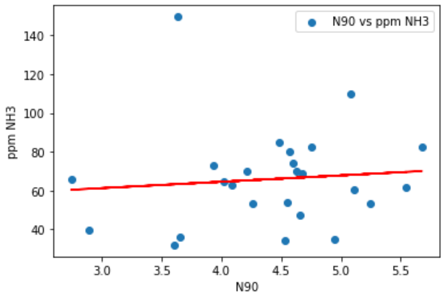

K2O vs ppm NH3
ppm NH3
K2O


MGO vs ppm NH3
ppm NH3
MGO


NA2O vs ppm NH3
ppm NH3
NA2O


pHWater vs ppm NH3
ppm NH3
pHWater


P2O590 vs ppm NH3
ppm NH3
P2O590


N90 vs ppm NH3
ppm NH3
N90

Appendix E. Manure-feed relationship matrices

The matrices placed on the next three pages.

Primary page: P-value

Secondary page: R-squared

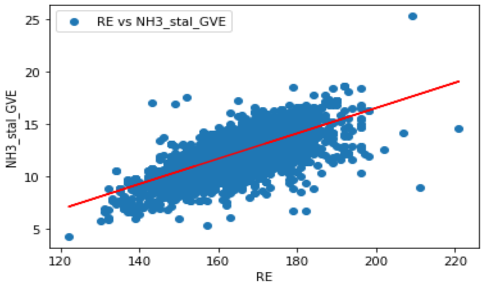
Tertiary page: Directional R-squared

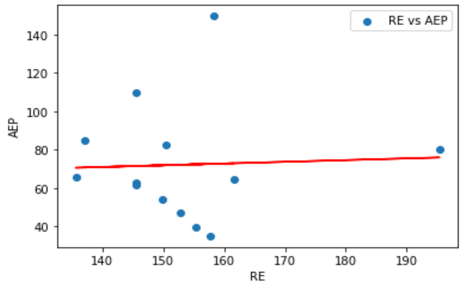
	kg_melk_kg_ds_opna	kg_meetmelk_kg_ds	RE	P	VEM	RE/kVEM	P/kVEM	per_ds_VersGras	per_ds_Snijmais	per_ds_Kuilgras	per_ds_Overigruwv	per_ds_Krachtvoer	per_ds_ijproduct
N:P2O5	0,752	0,750	0,265	0,507	0,451	0,388	0,477	0,218	0,823	0,227	0,776	0,092	0,238
P2O590	0,836	0,825	0,605	0,650	0,925	0,665	0,657	0,191	0,687	0,215	0,827	0,147	0,539
NA2O	0,897	0,858	0,605	0,296	0,738	0,582	0,297	0,115	0,303	0,313	0,307	0,429	0,555
MGO	0,817	0,836	0,842	0,276	0,560	0,907	0,346	0,882	0,879	0,601	0,318	0,676	0,989
K2O	0,678	0,673	0,086	0,213	0,931	0,131	0,244	0,891	0,760	0,031	0,037	0,064	0,745
P2O5	0,847	0,859	0,241	0,313	0,401	0,193	0,256	0,960	0,219	0,905	0,050	0,120	0,053
NORG	0,814	0,786	0,298	0,114	0,076	0,167	0,062	0,022	0,006	0,295	0,012	0,660	0,138
TAN	0,942	0,937	0,504	0,085	0,053	0,830	0,052	0,354	0,271	0,345	0,049	0,543	0,912
C:N	0,709	0,730	0,818	0,969	0,732	0,863	0,967	0,220	0,714	0,200	0,568	0,639	0,829
N90	0,844	0,862	0,818	0,734	0,256	0,983	0,864	0,642	0,916	0,219	0,546	0,550	0,886
N	0,872	0,854	0,771	0,055	0,032	0,474	0,026	0,074	0,032	0,281	0,010	0,993	0,359
OS	0,774	0,805	0,498	0,174	0,197	0,342	0,117	0,031	0,033	0,214	0,033	0,946	0,361
RAS	0,958	0,943	0,771	0,241	0,308	0,909	0,350	0,943	0,907	0,222	0,252	0,594	0,720
DS	0,872	0,901	0,562	0,142	0,748	0,506	0,140	0,177	0,217	0,157	0,052	0,763	0,444
Posphate content milk	0,264	0,289	0,218	0,620	0,105	0,135	0,438	0,338	0,047	0,673	0,129	0,199	0,276
Urea milk	0,499	0,508	0,010	0,578	0,142	0,004	0,404	0,118	0,009	0,449	0,658	0,031	0,106
Protein:fat ratio	0,733	0,773	0,261	0,645	0,542	0,226	0,563	0,034	0,018	0,992	0,988	0,763	0,652
Protein content milk	0,055	0,066	0,564	0,453	0,842	0,558	0,489	0,792	0,926	0,821	0,777	0,558	0,387
Redox potential	0,596	0,605	0,025	0,677	0,258	0,017	0,554	0,803	0,078	0,144	0,981	0,029	0,037
Electical conductivity	0,503	0,506	0,114	0,182	0,565	0,120	0,277	0,391	0,385	0,155	0,154	0,064	0,724
pH1	0,987	0,994	0,813	0,965	0,314	0,665	0,919	0,398	0,789	0,828	0,849	0,940	0,843

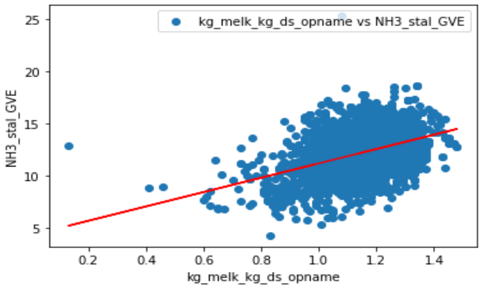
	kg_melk_kg_ds_op	kg_metmelk_kg_	RE	P	VEM	RE/kVEM	P/kVEM	per_ds_VersGras	per_ds_Snijmais	per_ds_Kuilgras	per_ds_Overigruwv	per_ds_Krachtvoer	per_ds_Bijproduct
N:P2O5	0,009	0,010	0,111	0,041	0,053	0,068	0,047	0,134	0,005	0,130	0,008	0,237	0,124
P2O590	0,004	0,005	0,025	0,019	0,001	0,018	0,019	0,150	0,015	0,136	0,005	0,181	0,035
NA2O	0,002	0,003	0,025	0,099	0,011	0,028	0,098	0,210	0,096	0,092	0,095	0,058	0,033
MGO	0,005	0,004	0,004	0,107	0,032	0,001	0,081	0,002	0,002	0,026	0,090	0,017	0,000
K2O	0,016	0,017	0,244	0,137	0,001	0,195	0,121	0,002	0,009	0,356	0,338	0,278	0,010
P2O5	0,004	0,003	0,122	0,092	0,065	0,149	0,115	0,000	0,134	0,001	0,306	0,205	0,299
NORG	0,005	0,007	0,098	0,211	0,259	0,166	0,281	0,393	0,506	0,099	0,450	0,018	0,189
TAN	0,001	0,001	0,042	0,245	0,298	0,004	0,301	0,078	0,109	0,081	0,308	0,035	0,001
C:N	0,013	0,011	0,005	0,000	0,011	0,003	0,000	0,133	0,013	0,144	0,031	0,021	0,004
N90	0,004	0,003	0,005	0,011	0,116	0,000	0,003	0,020	0,001	0,134	0,034	0,033	0,002
N	0,002	0,003	0,008	0,295	0,353	0,048	0,375	0,261	0,353	0,105	0,469	0,000	0,077
OS	0,008	0,006	0,043	0,161	0,146	0,082	0,208	0,358	0,352	0,137	0,349	0,000	0,076
RAS	0,000	0,000	0,008	0,122	0,094	0,001	0,080	0,000	0,001	0,132	0,117	0,027	0,012
DS	0,002	0,001	0,032	0,185	0,010	0,041	0,187	0,159	0,135	0,173	0,302	0,009	0,054
Posphate content milk	0,112	0,101	0,134	0,023	0,221	0,191	0,056	0,084	0,312	0,017	0,197	0,145	0,107
Urea milk	0,042	0,041	0,463	0,029	0,186	0,538	0,064	0,207	0,473	0,053	0,018	0,358	0,220
Protein:fat ratio milk	0,011	0,008	0,113	0,020	0,035	0,130	0,031	0,347	0,412	0,000	0,000	0,009	0,019
Protein content milk	0,295	0,274	0,031	0,052	0,004	0,032	0,045	0,007	0,001	0,005	0,008	0,032	0,069
Redox potential	0,026	0,025	0,378	0,016	0,115	0,417	0,033	0,006	0,256	0,184	0,000	0,364	0,337
Electical conductivity	0,042	0,041	0,212	0,156	0,031	0,206	0,106	0,068	0,069	0,175	0,176	0,279	0,012
pH1	0,000	0,000	0,005	0,000	0,092	0,018	0,001	0,066	0,007	0,004	0,003	0,001	0,004

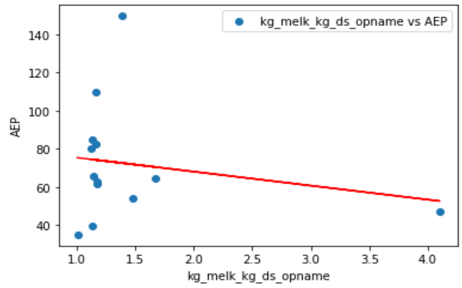
	kg_me	kg_me	RE	P	VEM	RE/kV	P/kVE	per_ds	per_ds	per_ds	per_ds	per_ds	per_ds
N:P2O5	0,009	0,010	0,111	-0,041	0,053	0,068	-0,047	-0,134	0,005	0,130	-0,008	-0,237	0,124
P2O590	-0,004	-0,005	-0,025	0,019	-0,001	-0,018	0,019	0,150	-0,015	-0,136	0,005	0,181	-0,035
NA2O	0,002	0,003	-0,025	-0,099	0,011	-0,028	-0,098	-0,210	0,096	0,092	-0,095	-0,058	0,033
MGO	-0,005	-0,004	-0,004	-0,107	-0,032	-0,001	-0,081	0,002	0,002	0,026	-0,090	-0,017	0,000
K2O	0,016	0,017	0,244	-0,137	0,001	0,195	-0,121	-0,002	-0,009	0,356	-0,338	-0,278	0,010
P2O5	-0,004	-0,003	-0,122	-0,092	0,065	-0,149	-0,115	0,000	0,134	-0,001	-0,306	0,205	-0,299
NORG	0,005	0,007	-0,098	-0,211	0,259	-0,166	-0,281	-0,393	0,506	0,099	-0,450	0,018	-0,189
TAN	0,001	0,001	0,042	-0,245	0,298	0,004	-0,301	-0,078	0,109	0,081	-0,308	-0,035	-0,001
C:N	-0,013	-0,011	-0,005	0,000	-0,011	-0,003	0,000	-0,133	0,013	0,144	-0,031	-0,021	-0,004
N90	0,004	0,003	0,005	0,011	0,116	0,000	0,003	0,020	0,001	-0,134	0,034	0,033	0,002
N	0,002	0,003	-0,008	-0,295	0,353	-0,048	-0,375	-0,261	0,353	0,105	-0,469	0,000	-0,077
OS	-0,008	-0,006	-0,043	-0,161	0,146	-0,082	-0,208	-0,358	0,352	0,137	-0,349	0,000	-0,076
RAS	0,000	0,000	-0,008	-0,122	-0,094	-0,001	-0,080	0,000	-0,001	0,132	-0,117	-0,027	-0,012
DS	-0,002	-0,001	-0,032	-0,185	0,010	-0,041	-0,187	-0,159	0,135	0,173	-0,302	-0,009	-0,054
Posphate content milk	-0,112	-0,101	-0,134	-0,023	0,221	-0,191	-0,056	-0,084	0,312	-0,017	-0,197	0,145	-0,107
Urea milk	0,042	0,041	0,463	0,029	-0,186	0,538	0,064	0,207	-0,473	0,053	0,018	-0,358	0,220
Protein:fat ratio milk	-0,011	-0,008	-0,113	-0,020	0,035	-0,130	-0,031	-0,347	0,412	0,000	0,000	-0,009	-0,019
Protein content milk	-0,295	-0,274	0,031	0,052	-0,004	0,032	0,045	0,007	-0,001	-0,005	-0,008	-0,032	0,069
Redox potential	0,026	0,025	-0,378	-0,016	0,115	-0,417	-0,033	-0,006	0,256	-0,184	0,000	0,364	-0,337
Electical conductivity	0,042	0,041	0,212	-0,156	-0,031	0,206	-0,106	0,068	-0,069	0,175	-0,176	-0,279	0,012
pH1	0,000	0,000	0,005	0,000	-0,092	0,018	0,001	0,066	-0,007	-0,004	-0,003	-0,001	0,004

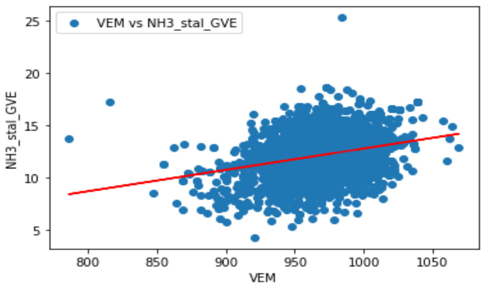
Appendix F Regression lines of relationship between feed parameters and emission values

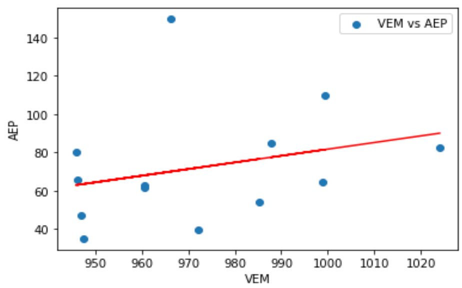


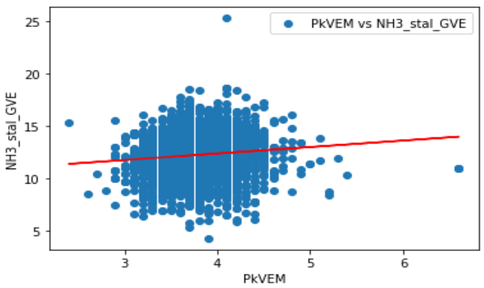


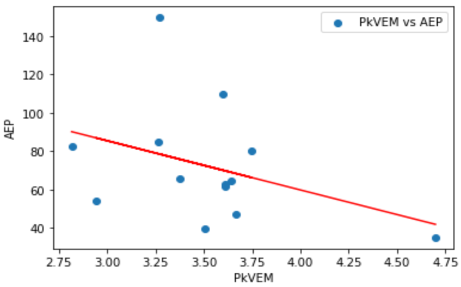


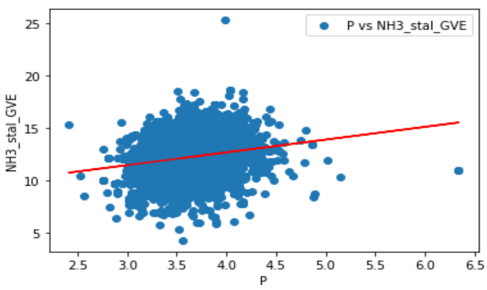


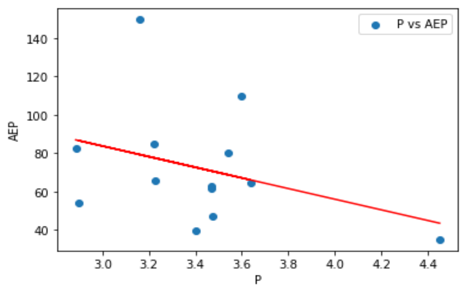


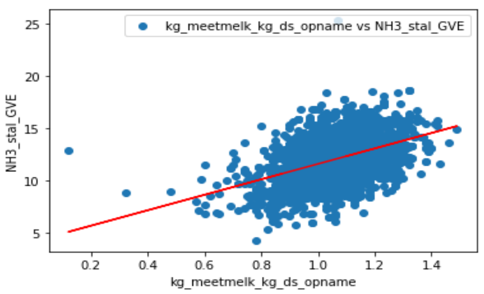


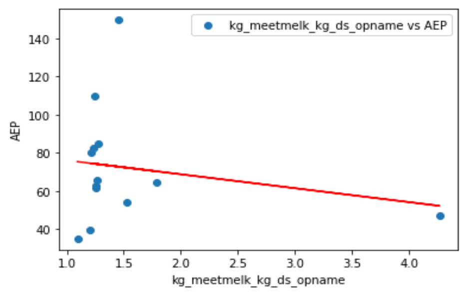


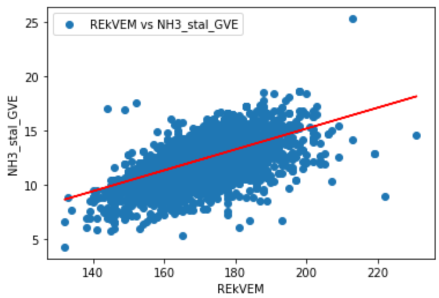


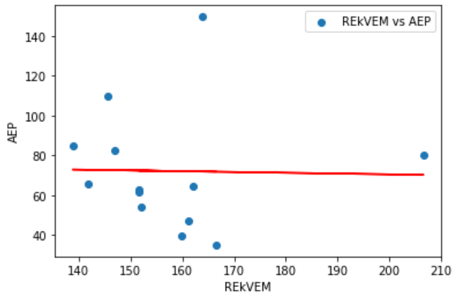


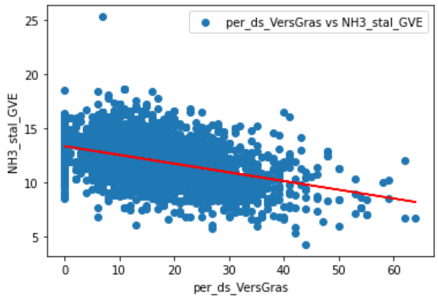


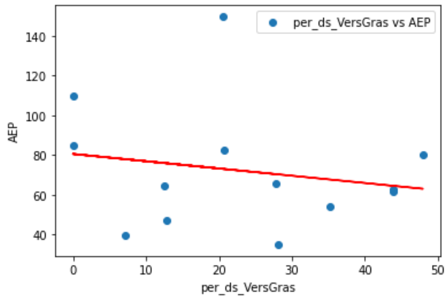


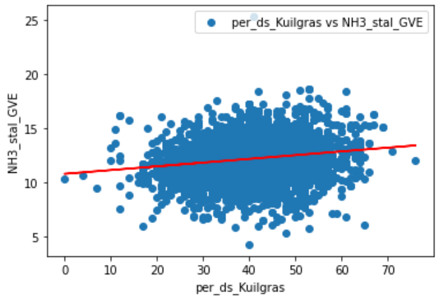


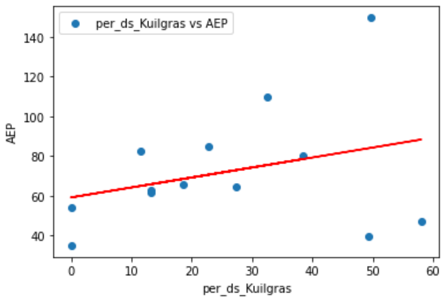

REkVEM vs NH3_stal_GVE
NH3_stal_GVE
REkVEM

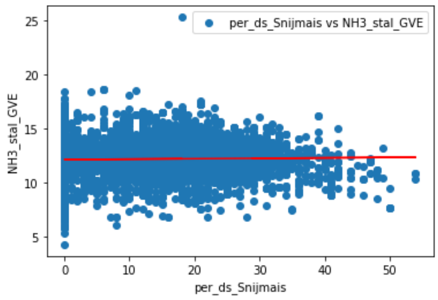

REkVEM vs AEP
AEP
REkVEM

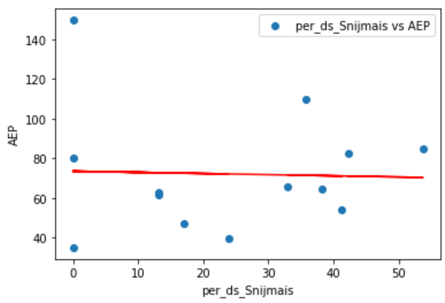

per_ds_VersGras vs NH3_stal_GVE
NH3_stal_GVE
per_ds_VersGras

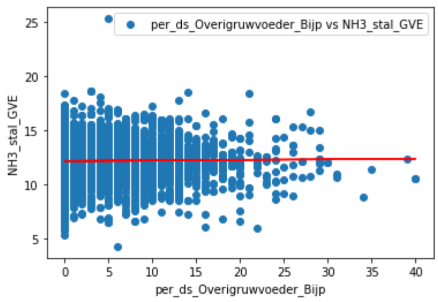

per_ds_VersGras vs AEP
AEP
per_ds_VersGras

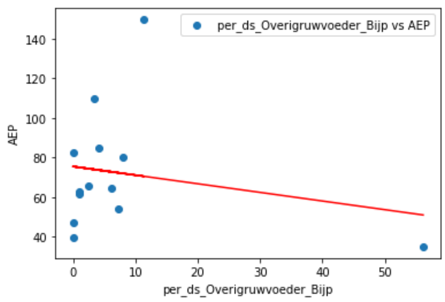

per_ds_Kuilgras vs NH3_stal_GVE
NH3_stal_GVE
per_ds_Kuilgras

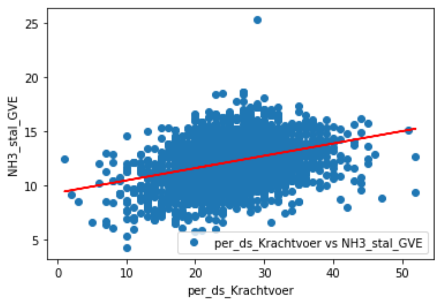

per_ds_Kuilgras vs AEP
AEP
per_ds_Kuilgras

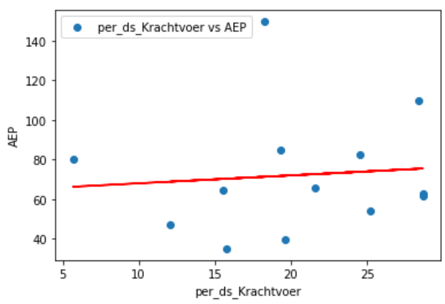

per_ds_Snijmais vs NH3_stal_GVE
NH3_stal_GVE
per_ds_Snijmais


per_ds_Snijmais vs AEP
AEP
per_ds_Snijmais


per_ds_Overigruwvoeder_Bijp vs NH3_stal_GVE
NH3_stal_GVE
per_ds_Overigruwvoeder_Bijp


per_ds_Overigruwvoeder_Bijp vs AEP
AEP
per_ds_Overigruwvoeder_Bijp


per_ds_Krachtvoer vs NH3_stal_GVE
NH3_stal_GVE
per_ds_Krachtvoer


per_ds_Krachtvoer vs AEP
AEP
per_ds_Krachtvoer