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# OVERSEER MODEL: FARM-SPECIFIC MODELLING OF NITROUS OXIDE EMISSION FACTORS FROM ANIMAL URINE AND MODEL IMPROVEMENT

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## Abstract

Nitrous oxide ($N_2O$) – a highly impactful greenhouse gas (GHG) with a significant warming effect – is a byproduct released from agricultural practices, especially from animal urine deposition on pastures and manure management. Accurate estimates of $N_2O$ emission factors (EFs) are crucial for assessing the impact of mitigation strategies required for achieving environmental sustainability. The main aim of this study was to use New Zealand experimental data to develop a farm-specific methodology for estimating $N_2O$ EFs from animal urine.

A predictive algorithm in the Overseer environment for modelling farm-specific EFs of dairy cattle urine was developed utilising an $N_2O$ database. This database contained EF data produced from field experiments conducted under various agricultural environments that spanned a range of soil characteristics, climatic conditions, and urine application rates. Through statistical analysis, the key parameters that influence $N_2O$ EFs were identified and integrated in a predictive algorithm for dairy cattle urine. The $N_2O$ database did not contain enough data to develop separate algorithms for sheep, beef, and deer urine, or for sloped land. Instead, an adjustment was made to the predictive algorithm for cattle urine, using the relative difference in EFs for different livestock species and slope classes that are used in New Zealand's national agricultural inventory model (AIM). The new algorithms were integrated into the Overseer model, therefore allowing estimates of $N_2O$ EFs to be farm- and livestock-specific and sensitive to slope.

We also assessed the need to refine the current Overseer approach for estimating $N_2O$ emissions from manure management systems (MMS) by comparing it with the AIM methodology. Based on this, it was recommended that Overseer retain its current framework for characterising MMS, but carefully review the associated algorithms and emission factors. Updates should be made when sufficient new data is available.

Finally, several other changes and improvements were made to the $N_2O$ emissions sub-model to better align with the AIM model (EF for dung and the inclusion of emissions from roots following cultivation), or to make a correction (imported organic fertilisers).

The refined methods and adjustments to the Overseer $N_2O$ model collectively increased the precision and confidence in the EFs used by Overseer, and support users to make more informed

decisions regarding nutrient management practices and mitigation strategies that influence $N_2O$ emissions.

## Introduction

Overseer, a tool for estimating farm-level nutrient budgets and greenhouse gas emissions, previously offered a "farm-specific" option for calculating nitrous oxide ($N_2O$) emissions from animal urine. This option adjusted $N_2O$ emission factors (EFs) based on soil temperature and moisture content in the top 10 cm (SM100) of the soil profile. However, concerns arose as this method could lead to EFs exceeding values observed in New Zealand field trials. This discrepancy was attributed to the assumed relationship between EFs and SM100 (de Klein et al., 2017). Consequently, the option was disabled, leaving Overseer reliant on the national average EF value (1%) from New Zealand's Agricultural Inventory Model (AIM; MPI, 2022), potentially compromising accuracy at the farm-scale.

Recent studies (e.g., van der Weerden et al. 2019) highlighted the influence of specific soil properties (water content, density, clay content, and organic carbon) on $N_2O$ emissions from dairy cattle urine. Predictive algorithms based on these parameters provide an opportunity to develop a farm-specific method for estimating urinary $N_2O$ EFs within Overseer. The aim of this study was to:

- Utilise the New Zealand $N_2O$ database for dairy cattle urine to develop an algorithm for implementation within Overseer that accurately predicts block-specific EFs.
- Build upon the developed algorithm for dairy cattle urine and explore its applicability to other animal enterprises and sloping land, enabling farm-specific or block-specific $N_2O$ EF estimation for other livestock types and topographies.

While $N_2O$ emissions are highly sensitive to SM100, the SM100 values directly available in Overseer have limitations, including an inability to exceed field capacity, compromising their effectiveness in $N_2O$ estimations. This study offers an alternative approach. Instead of relying on directly available SM100 values, the new algorithm will base its estimations on readily available input parameters known to influence SM100, such as rainfall, temperature, and specific soil properties.

The development of an algorithm for estimating farm-specific $N_2O$ emission factors for animal urine in Overseer is fully reported in Simon et al. (2021). Here we provide a summary of this study and describe the impact of the improved methodology for urinary $N_2O$ EFs on the Overseer $N_2O$ estimates.

## Method

### *Data sourcing*

The data collection carried out by Simon et al. (2021) involved two key steps:

- Field trial data collection ($N_2O$ database): identified suitable $N_2O$ EF measurements from dairy cattle urine in field trials across New Zealand (including that in de Klein et al, 2003, 2004, 2014a,b; Hoogendoorn et al., 2013; Luo et al., 2008, 2010, 2013, 2019; Ledgard et al., 2014; Sherlock et al., 2003a,b; Sprosen et al., 2016; Simon et al., 2019; van der Weerden and Rutherford., 2015; van der Weerden et al., 2011). These trials covered flat land and low-slope hill land and included a diverse range of soil types.

- Overseer data: linked the measured EFs with corresponding soil and climate variables available within the Overseer database:
    - Soil data: by using trial site coordinates, the appropriate S-map soil types to each site were assigned to each measurement.
    - Climate data: the site-specific climate data for the exact period of each field trial was obtained. This involved identifying the closest virtual climate station near each trial site, requesting data for the last 20 years from NIWA, and extracting the relevant climate data for the specific trial period.

This approach resulted in a dataset of 68 EF measurements of $N_2O$ and their associated soil and climate variables from 31 sites across New Zealand, representing a significant portion of the diversity of the country's agricultural land. The field sites were on soils belonging to soil orders representing 82% of New Zealand's agricultural land: allophanic, brown, gley, pallic and recent soils.

### *Data analysis*

The dataset was analysed to determine the main drivers of $N_2O$ emissions and to develop a best-fit model describing the EFs of $N_2O$ in dairy cattle urine. Statistical analyses were conducted using mean EF values per site, as soil and climatic variables were only available per site, not for each replicate measurement. The data distribution was skewed, requiring a natural log-transformation for variance stabilisation. A linear modelling approach was then used to derive a predictive algorithm based on variables explaining the variability in $N_2O$ emission factors.

Initially, ‘soil type’ was included as a random effect in the linear predictive algorithm but was later discarded as it only accounted for a very small amount of the variance. Subsequent investigation focused on fixed effects only.

## Key results

### *Selected variables*

The analysis aimed at identifying variables that best explain the variability in measured $N_2O$ emission factor values is detailed in Simon *et al.* (2021). Linear algorithms combining 36 variables, describing different soil and climatic characteristics, were explored. Given the interdependent nature of several variables, the objective was to identify the most impactful variable within each group of characteristics. Three single variables – cumulative rainfall in the 30 days ($Rain_{0\text{-}30}$) following the trial start, profile available water (*PAW*) in the top 30 cm, and soil clay content (*Clay*) of the top 30 cm – were found to best explain the variability.

Simon *et al.* (2021) further investigated the interaction between $Rain_{0\text{-}30}$ and *PAW*, as these factors influence each other. The ratio ($PAW/Rain_{0\text{-}30}$) was created to reflect this collinearity, with higher values of this ratio indicating better soil moisture conditions (low rainfall, high available water). Additionally, a significant effect of land use (flat land vs. low-slope hill land) was observed, with flat land having generally higher emission factors (van der Weerden *et al.*, 2020). This binary variable (flat land vs. low-slope hill land) was retained, leading to the development of separate algorithms for each land type.

Different linear algorithms with 2, 3, or 4 variables were tested. Algorithms were evaluated not only based on their goodness-of-fit, but also on the scientific logic of the relationships. Algorithms with good fit but inconsistent with scientific evidence were rejected, ensuring that both statistical and scientific validity were assessed in the selection.

## Algorithms

### *Dairy cattle methodology*

The optimal linear model produced two equations tailored to topography and land use: one for flat land, based on 48 observations, and one for low slope areas (<12°), based on 20 observations. Although the coefficients of the variables in the two algorithms showed no significant difference, the constant term varied significantly, indicating distinct but parallel relationships:

For flat land:

$$Log\left(N_2O\ EF_{urine,dairy,flat}\right) = -1.24484 * \frac{PAW}{Rain_{0-30}} + 0.08076 * Clay - 1.96674$$

For hill land - low slope:

$$Log\left(N_2O\ EF_{urine,dairy,hill}\right) = -1.24484 * \frac{PAW}{Rain_{0-30}} + 0.08076 * Clay - 2.95716$$

It's worth noting that using a back-transformed mean as an estimate of the mean on the original scale introduces bias (Rothery, 1988). This bias in back-transformed means was corrected by using the variance of transformed residuals ($\sigma^2$) (Neyman and Scott, 1960).

$$EF_{urine,dairy}(\%) = exp\left(Log\left(N_2O\ EF_{urine,dairy}\right)\right) * \exp\left(\frac{0.9489363}{2}\right)$$

Figure 1 presents a comparison between modelled and measured values using the best algorithm derived from available data, demonstrating a level of agreement considered "reasonable".

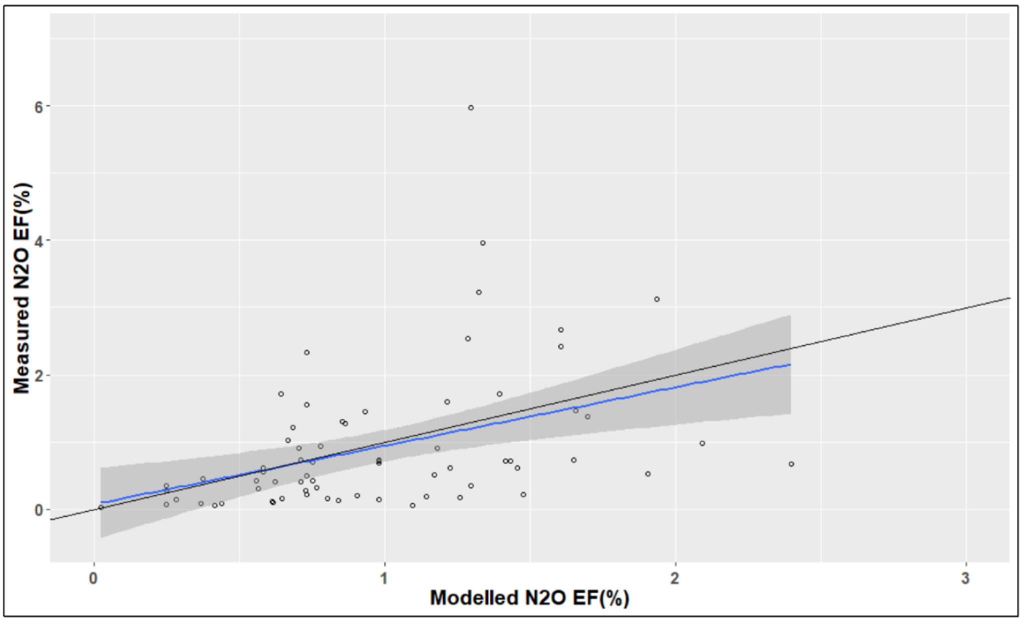


*Figure 1: Comparison of modelled and measured EF values using the proposed algorithm. The shaded area represents the 95% confidence interval for the mean of each model.*

Sensitivity tests detailed in Simon *et al.* (2021) were conducted with the aim of evaluating the EF values for $N_2O$ from urine and comparing them to the expected ranges. In total, 13 different soil and climate combinations, spread over five regions, were selected, and the respective soil classifications and climate information were collected. In general, the EF values matched expectations well, apart from one soil type with high clay content that exceeded the upper limit used in the algorithm development. As a result, lower (15%) and upper limits (32.5%) were imposed on the clay content in the algorithm, based on the values from the original dataset. Statistical analysis of the algorithm's performance will be refined as additional testing is performed and new measured $N_2O$ EF values become available.

***Animals and hill country methodology***

Although separate algorithms have been developed for flat land and hill land-low slopes with similar offsets, the flat land algorithm is considered more robust and can be applied with greater confidence as it is based on a greater number of observations. Therefore, the flat land algorithm is used for dairy cattle urine deposited on land blocks with slopes less than 15 degrees.

For slopes greater than 15 degrees, the hill country approach of the AIM model was employed. In the AIM approach, $N_2O$ emissions from sheep and cattle urine are estimated for different slope classes. Adopting this approach in the Overseer model results in an estimate of the EF in each block of land. Therefore, the EF for animal urine deposited on different slope classes is estimated as follows:

$$EF_{urine,animal,slope}\ (\%) = EF_{urine,dairy,flat} * R_{animal,slope}$$

Where $R_{animal,slope}$ is adjusted based on the ratio of EF values used in AIM for other animals and slopes, and *slope* is the slope of the land block where urine is deposited. Since land blocks are defined based on common physical and management characteristics, slope is a consistent attribute within each block in Overseer. Table 1 presents the values of $R_{animal,slope}$ for various animal species and slope block classifications. These values are based on analyses provided in van der Weerden *et al.* (2020) and additional research presented in van der Weerden *et al.* (2019).

| Animals and slope class | | $R_{animal,slope}$ |
|---|---|---|
| Dairy cattle | - Slopes < 15° | 1.00 |
| | - Slopes ≥ 15° | 0.69 |
| Beef cattle | - Slopes < 15° | 0.90 |
| | - Slopes ≥ 15° | 0.32 |
| Sheep cattle | - Slopes < 15° | 0.48 |
| | - Slopes ≥ 15° | 0.077 |
| Deer cattle | - Slopes < 15° | 0.71 |
| | - Slopes ≥ 15° | 0.19 |

*Table 1: Ratio for scaling EF algorithm for dairy urine on flat land, to estimate block-specific emission factors for hill country beef, deer and sheep on low and medium/steep topography, based on values used in the AIM model that are published in van der Weerden et al. (2020) and additional analysis provided in van der Weerden et al. (2019).*

Flat land/low slope class definitions differ between the $N_2O$ database (and AIM) and Overseer. The $N_2O$ database uses a limit of 12° and Overseer uses a limit of 15° for the flat land/low slope classes class. Given that the analyses are based on data collected for average slopes greater than 15°, the $R_{animal,slope}$ values remain applicable to the ≥ 15° definition used by Overseer for this class.

## Impact on Overseer analyses

The implementation of the new methodology to estimate $EF_{urine,animal,slope}$ at the block (or sub-block) level within Overseer influences the estimation of total $N_2O$ emissions at the farm-level. A comprehensive analysis of the Overseer database was conducted to assess this impact. This involved running the most recent analyses of each of the 11,000 farms available in the database (one analysis per farm, or 11,000 analyses), providing an understanding of the potential consequences of this new methodology.

The average farm-level $EF_{urine,animal,flat}$ for the flat land is calculated for all farms defined in the Overseer database. EFs are visualized in Figure 2 using boxplots for the different farm types defined in Overseer. The average $EF_{urine,dairy,flat}$ of dairy farms located on flat land is close to 1%, which corresponds to the previously well-established national average for flat land. This consistency suggests that the new EF estimation algorithm is consistent with existing knowledge. However, significant variability is observed around this average, highlighting the diversity of agricultural landscapes across New Zealand. Factors such as different soil types (affecting PAW and clay content) and climates (affecting $Rain_{0\text{-}30}$) contribute to this distribution of EF values.

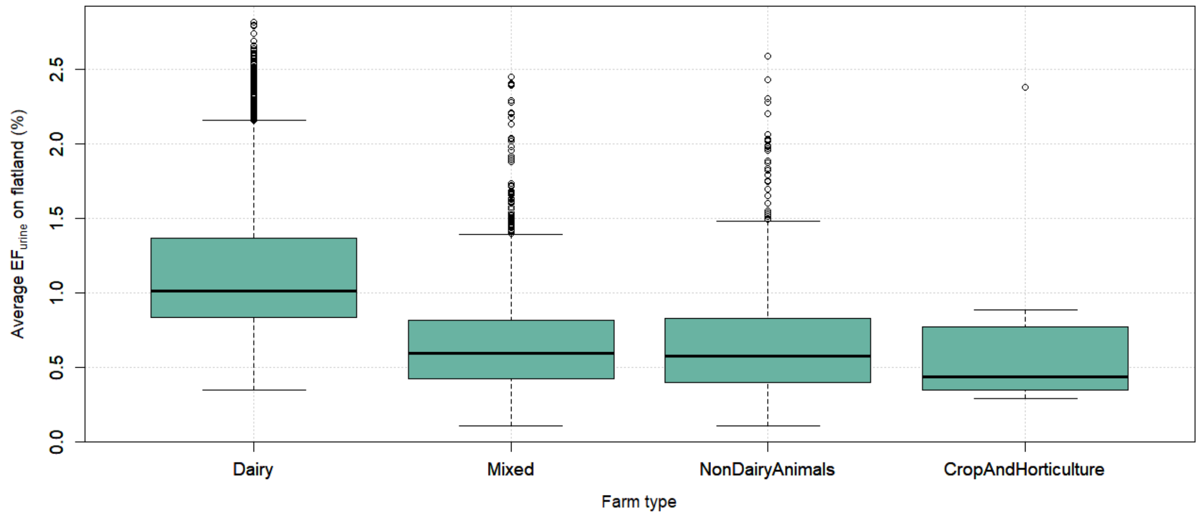


*Figure 2: Boxplots of farm average emission factors for urine deposited on flat land (slopes < 15°) across Overseer farm types. These types include "dairy cattle" (dairy cattle only), "mixed" (dairy and non-dairy cattle), "non-dairy" (non-dairy animals only), and "crops" (external animals grazing on crops).*

Likewise, $EF_{urine,animal,flat}$ for all farm types exhibit significant variability (Figure 2), likely also due to block-specific factors such as soil diversity and climatic variations. Comparing farm-level $N_2O$ emissions from urinary deposition estimated using the new methodology with those obtained using the original static emission factor of 1%, reveals this variability (Figure 3). This reflects the diversity of agricultural soils and climate, suggesting that the new methodology more accurately describes $N_2O$ emissions from urine.

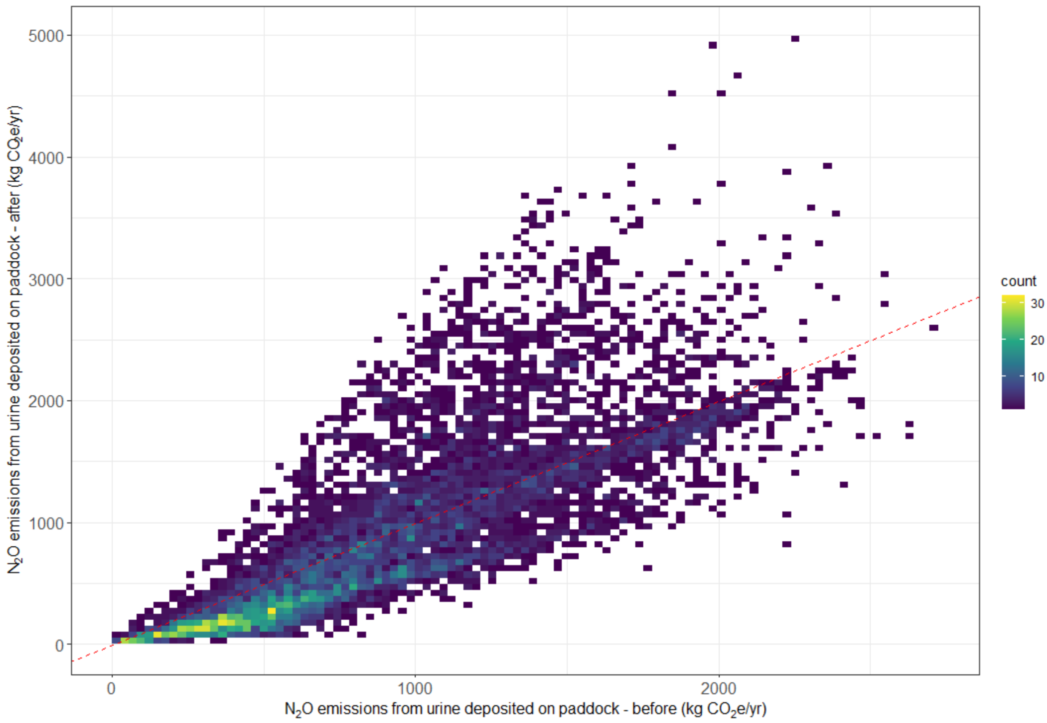


*Figure 3: Comparison of farm-level $N_2O$ emissions from urinary soil deposition: new methodology (after update) versus old 1% emission factor (before update) estimation.*

### Other changes in the $N_2O$ sub-model

In addition to the introduction of the new methodology for estimating $N_2O$ emissions from urinary soil deposition, several other changes and improvements have been made to the $N_2O$ emissions sub-model. The EF for dung deposited on soil has been adjusted from 0.0025 to 0.0012 to align with the AIM model. In addition, the calculation of $N_2O$ emissions from imported organic fertilisers has been corrected and $N_2O$ emissions from roots in the case of ploughing (cultivation/end-of-crop) are now included.

The need to refine the Overseer approach to estimating GHG emissions from manure management systems (MMS) was assessed by de Klein *et al.* (2021). The authors compared the current Overseer framework for describing MMS with a proposed update of the AIM framework. Based on the findings, it was recommended that Overseer retains its current framework for characterising MMS, but carefully reviews the associated algorithms and emission factors to ensure these are scientifically robust. Revisions will be made once sufficient research data becomes available.

### Total impact of all improvements

Figure 4 illustrates the combined impact of all the changes, with an overall reduction in $N_2O$ emissions of 8% on average. A 30% standard deviation is observed, mainly attributable to the consideration of farm- or block-specific soil characteristics and climatic conditions in the calculation of $EF_{urine,animal,slope}$.

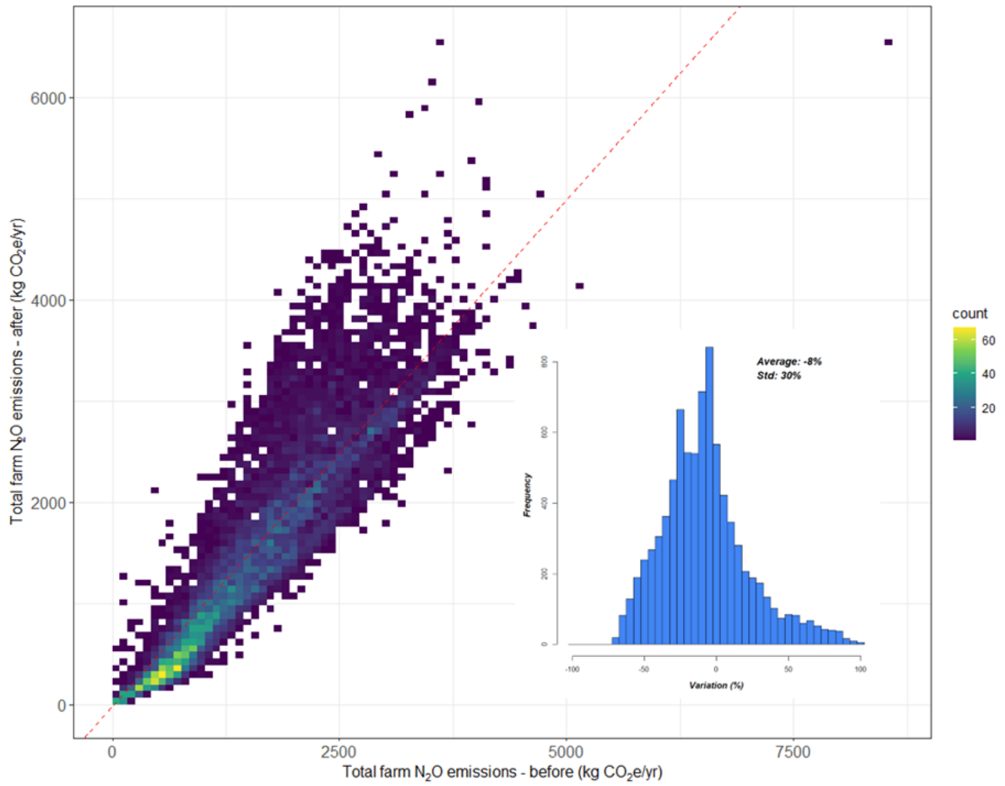


*Figure 4: Comparison of total farm-level $N_2O$ emissions: new methodology (after update) versus old 1% emission factor (before update) estimation. Inset: histogram of the variation defined by the ratio of (New Total $N_2O$ Emission - Old Total $N_2O$ Emission) / Old Total $N_2O$ Emission.*

## Conclusions

This study presents significant advancements in refining nitrous oxide ($N_2O$) emission estimations within the Overseer model, a tool for farm-level nutrient budgeting and greenhouse gas (GHG) assessment. We developed a novel method for estimating urinary $N_2O$ emission factors (EFs) within Overseer. The method leverages a comprehensive New Zealand $N_2O$ database to create algorithms to estimate EFs.

Statistical analyses identified key drivers of $N_2O$ emissions from dairy cattle urine, informing the development of algorithms which incorporate soil and climatic characteristics at the block-level. Results indicated that variables such as cumulative rainfall, profile available water, and soil clay content significantly influenced $N_2O$ EFs. The algorithms developed for dairy urine on flat land demonstrated good agreement with measured values; sensitivity tests validate their performance within expected ranges.

Furthermore, for different animal types and slope classes, adjustments were made based on EF values used in AIM. These adjustments accounted for discrepancies in slope class definitions between the $N_2O$ database and Overseer. Adjustments were also made to EF for dung ensuring consistency with the AIM model, and to the emissions calculations from imported organic fertilisers and crop root residues.

The combined impact of these changes resulted in an overall decrease in estimated $N_2O$ emissions at farm-level by 8%, with variations attributable to block-specific soil and climate characteristics (Figure 4).

This study's findings represent a significant step forward in improving the precision and reliability of $N_2O$ EF estimations within Overseer. By incorporating the diversity of agricultural landscapes in Aotearoa New Zealand, the new methodology offers a more realistic $N_2O$ emission estimate from deposited urine. Ongoing and future research will further refine the model as additional data become available.

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