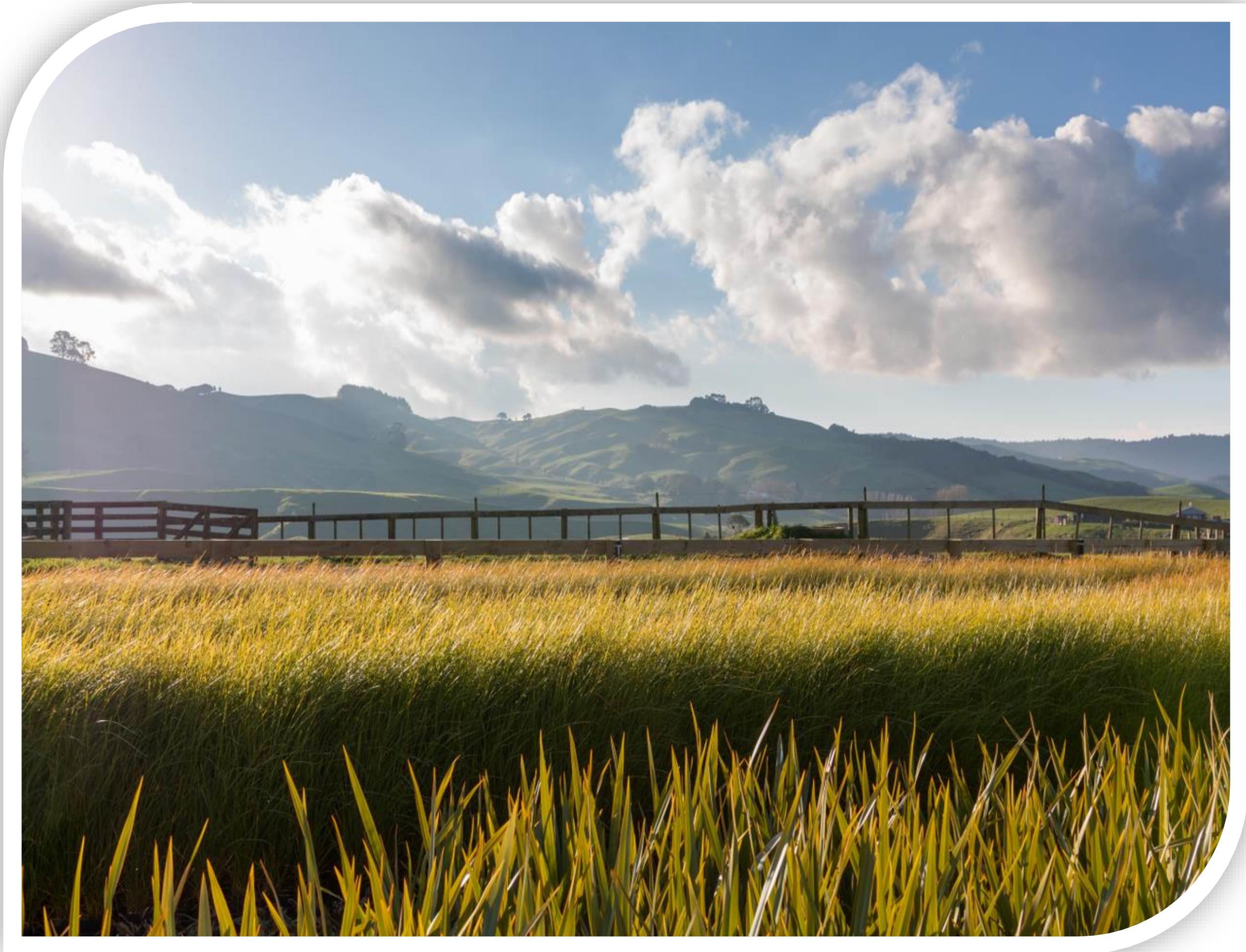

Assessment of the impact of using different temporal climate data on the N-loss estimated by the Overseer science model

Jean-Paul Tavernet and Jacquie Harper

August 2022

Report for:

Overseer Limited
August 2022

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Summary

Background

Overseer provides site-specific annual nutrient budgets at the farm and block scale. It uses a combination of inputs accessible to users for a wide range of farm management systems across New Zealand, and location-specific climate datasets provided by NIWA (National Institute of Water & Atmospheric). The aim of this study was to assess the impact of using climate datasets with different temporal resolutions on the N-loss estimates for farms in the OverseerFM database.

Approach

The impact of changing the temporal resolution and averaging approach of the climate dataset on the Overseer long-term N-loss estimate was investigated using three climate dataset scenarios provided by NIWA for the 30-year climate period 1991-2020. N-loss estimates for farms in the OverseerFM database were calculated and the results compared using:

- The 30-year long term average *monthly scale* climate dataset (current)
- The average of 30 individual climate years of N-loss estimates using *monthly scale* climate data
- The average 30 individual climate years of N-loss estimate using *daily scale* climate data.

The study focused on the impact of using daily climate resolution data within the hydrology sub-model. Working to the requirement that data inputs for the end user should not increase, the study focused on changes in the climate datasets i.e., current (average monthly) management practice information was note altered.

Findings

The N-loss estimates using different datasets were statistically comparable in relation to previously determined output uncertainties. Inputs for individual year-to-year management practices will be required to address potential artifacts in the N-loss results observed when average management practices are used with annual climate datasets.

1. Introduction

OverseerFM is a long-term decision support tool designed to provide a long-term average farm-scale nutrient loss estimate from a farm, assess the impact of changes in long-term farm management practices on that nutrient loss estimate, and support farm management decision making to support environmental planning.

The Overseer science model (Overseer) is based on the premise that inputs are in equilibrium with production and that management and site characteristics (soil and climate) are relatively consistent over multiple years. This approach serves to limit the number of inputs requested from users, as described in the introduction chapter of the Overseer Technical Manual (Wheeler et al., 2022). In the case of climate, Overseer uses a 30-year long-term average climate database, in line with the internationally recognised timeframe for defining average climate (Tait 2022).

Overseer currently uses location-specific climate conditions from its long-term climate database. Following a recent review of the N-loss component of the Overseer Model (MPI, 2021) there is increased interest in assessing the impact of using higher temporal resolution climate data on Overseer's N-loss estimate. More specifically, investigation into the difference between using the current long-term monthly average climate dataset to determine N-loss estimates and averaging the N-loss estimates of 30 individual years of daily climate data.

This study was undertaken to assess the impact of using climate datasets of different resolution in the Overseer model on the N-loss estimate for different farm setups in OveseerFM. In line with the request not to increase data input requirements with increased temporal resolution of the climate datasets, only the climate datasets were modified.

2. Setup

The Technical Manual Chapters and wiring diagram (Appendix 1, Figure 7) describing the Overseer model can be found online[1]. The model currently runs on a monthly time step except for the hydrology sub-model (water balance) which uses a daily time step pattern. Therefore, the analysis focused on inputting daily climate into the hydrology model in the first instance.

2.1 Model version

The current version of the model code (6.4.1) was used for the analyses.

[1] http://www.overseer.org.nz/our-model; http://www.overseer.org.nz/our-science

2.2 Current climate dataset

The Overseer model uses a long-term monthly average climate dataset generated by NIWA and is based on 30 years of climate observations (1991 to 2020) collected at climate stations located around New Zealand. The climate data are produced by interpolating these climate observations on a 500 m spatial resolution grid across New Zealand (Wratt 2006). It provides long-term monthly average climate (L-Av) data for rainfall, potential evapotranspiration (PET) and temperature.

Mandatory farm geolocation in OverseerFM ensures monthly climate data used for a given farm are those of the nearest point on the grid from the L-Av climate dataset. Most of the Overseer sub-models run on monthly timesteps, therefore the monthly data is inputted directly. However, the hydrology sub-model, which calculates the soil water balance, uses daily timesteps to model, amongst other features, drainage, overland flow, and wetlands.

The hydrology sub-model derives “daily patterns” for rainfall and PET data by distributing monthly values from the climate dataset into daily values using 15 pseudo climatic regions – based on the amount of precipitation and the strength of seasonality (Wheeler, 2022; Rutherford et al. 2008). This allows monthly precipitation and PET values to be broken down into a pattern of typical daily values based on the pseudo region in which a farm is located. Water budgets from the hydrology sub-model are then aggregated up to monthly values for further calculations to align with the monthly time step in the other sub-models.

Daily temperatures are not used in Overseer. All sub-models using temperature progress in monthly timesteps.

2.3 Climate datasets

This study investigated the impact of using three different climate datasets (1991-2020) from NIWA on the Overseer N-loss estimate.

- Current 30-year average monthly dataset into a 500 m spatial grid across New Zealand. **(L-Av)**
    - Generated by interpolating observations made at climate stations located around the country to generate estimated climate data overlaying a spatial 500 m resolution grid across NZ (Tait, 2022)
    - Long-term, 30-year average of monthly estimates of rainfall, PET and temperature.
- Thirty individual years of monthly climate data into a 500 m spatial grid across New Zealand. **(M-Val)**
    - Monthly data were generated by interpolation, as outlined for the L-Av dataset above
    - Total monthly estimates of rainfall, PET, and average monthly temperature.
- Thirty years of daily climate data into a 5 km (*) spatial grid across New Zealand. **(D-Val)**
    - NIWA’s daily VCSN dataset, generated as described in Tait et al. (2006)
    - Daily estimates of rainfall, PET, and the average temperature.

(*) Expert advice was that accurate interpolation of daily climate observations datasets with a spatial resolution of 500 m could not be guaranteed (Tait, 2022). Generation of the monthly datasets at 5 km resolution for comparison with the VSCN data was not possible within the project timeframe.

Table 1*: Description of the different climate datasets.*

Acronym	Description	Contents	Grid spatial resolution	Number of N-loss estimates per farm
L-Av	Long-term values of climate data	Average over 30 years of monthly rainfall, PET, and temperature	500 m	1 ($NLeaching_{longterm}$)
M-Val	30 years of monthly climate values	30 years of monthly rainfall, monthly PET, and average monthly temperature	500 m	30 ($NLeaching_{monthly_i}$)
D-Val	30 years of daily climate values	30 years of daily rainfall, daily PET, and average daily temperature	5 km	30 ($NLeaching_{daily_i}$)

2.4 Farm dataset

6178 anonymised farms with similar sources of inputs were selected using the following criteria:

- Inputs farm-specific climate data from the climate database
- Excludes farm scenarios
- Most recent farm setup >2018.

2.5 Methods

This study focused on investigating the use of climate data with different temporal resolutions. To assess the impact of different climate datasets on the N-loss estimates of farms, only the input climate data was modified e.g., year-to-year management decisions (fertiliser application, irrigation, animal distribution) were not used. Any interpretation of results should account for the temporal disconnect between climate and management data. For example: using monthly irrigation management with the daily climate dataset.

N-loss was estimated using each of the climate datasets described in Table 1. For the different estimates, the input climate dataset, and the year, if necessary, we changed while the other inputs remained unchanged.

The process for inputting the different datasets and calculating the different N-loss estimates is summarised below (see also Figure 1):

- L-Av: Average long-term monthly climate data (1991-2020):
  - Current daily climate pattern method. The model is run once, and a single N-loss estimate is obtained per farm, denoted $NLeaching_{longterm}$
- M-Val: 30 years of actual monthly climate data (1991-2020):
  - As for the current method, except that each year of monthly climate data is run through the model.
  - There are 30 N-loss estimates calculated per farm, one per year, denoted $NLeaching_{monthly_i}$ where *i* is a year from 1991 to 2020.
  - The 30-year average of these estimates is denoted $\overline{NLeaching_{daily}}$.
- D-Val: 30 years of daily climate data (1991-2020):
  - The model is run 30 times, running each year of daily climate data through the model.
  - There are 30 N-loss estimates per farm, one per year, denoted $NLeaching_{daily_i}$ where *i* is a year from 1991 to 2020.
  - The 30-year average of these estimates is denoted $\overline{NLeaching_{daily}}$.
  - As the hydrology sub-model uses the daily climate data directly; the monthly values required by the other sub-models were obtained by aggregating the daily values. The monthly rainfall and PET are the monthly sum of the daily rainfall and PET, respectively. The monthly temperature is the monthly average of the mean daily temperature.

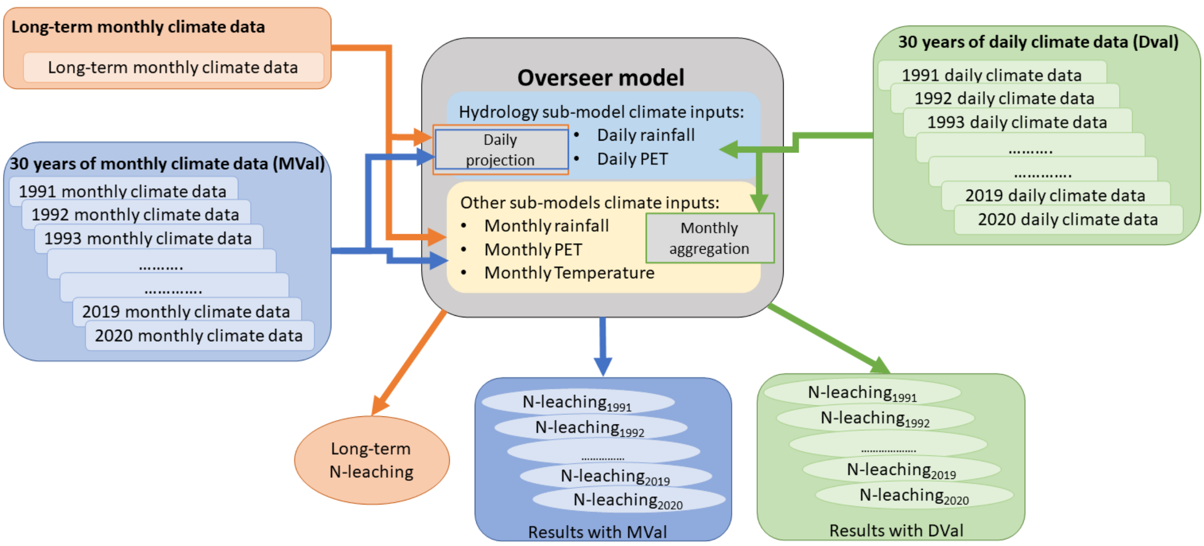

***Figure 1**: Description of the process to calculate the different N-loss estimates obtained with the different climate datasets.*

3. Results

3.1 Comparison of N-loss results

Farm N-loss estimates were calculated by the Overseer model using each of the three climate datasets. For the M-Val and D-Val datasets, N-loss estimates were calculated both annually (1991-2020) and as the average of the 30 individual years to assess the impact of using different climate datasets on the N-loss estimate, including comparison with the L-Av dataset currently used in OverseerFM.

3.1.1 N-loss comparisons with L-Av dataset

3.1.1.1 Comparison with the averaged N-loss estimates using the M-Val dataset

To investigate the impact on N-loss estimate of averaging annual N-loss estimates, the N-loss estimates using the M-Val and L-Av datasets were compared (Figure 2).

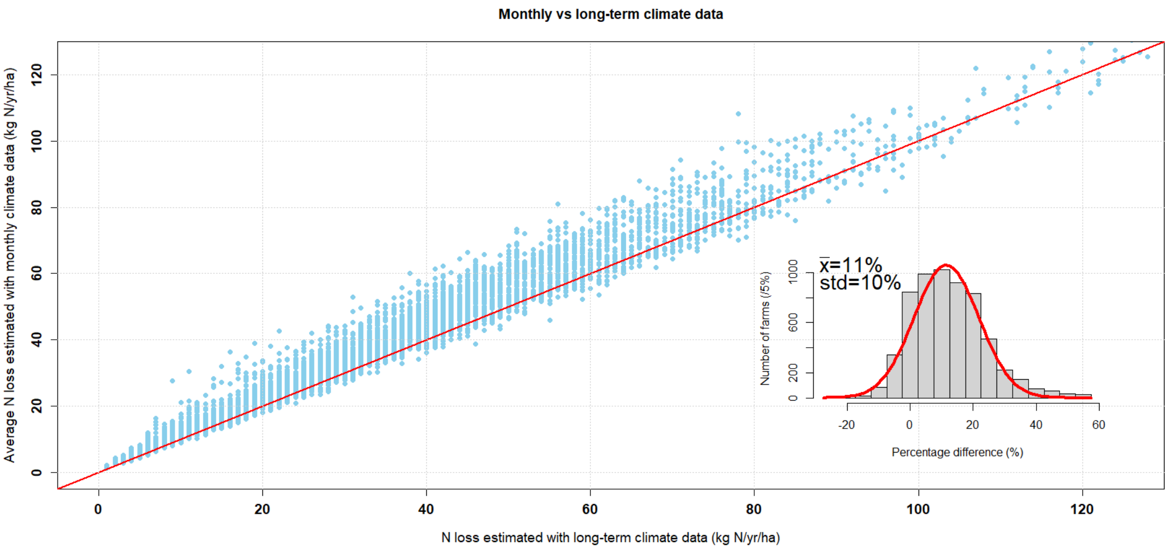

Figure 2: *Comparison of the long-term annual N-loss estimate (L-Av) for 6178 farms with averaged estimates using the M-Val dataset. Inset: Percentage difference of the distribution.*

The percentage difference in distribution of the N-loss estimates (Figure 2, inset) was defined as:

$$\Delta_{ratio}(\%) = \frac{\overline{NLeaching_{monthly}} - NLeaching_{longterm}}{NLeaching_{longterm}} * 100$$

where $NLeaching_{longterm}$ is the N-loss estimate based on the L-Av dataset (current use), and $\overline{NLeaching_{monthly}}$ is the average of the N-loss estimates based on the M-Val dataset.

As rainfall has been identified as the most influential parameter on the N-loss estimate (Overseer, 2022b), the evolution of the percentage difference for each farm relative to the total annual rainfall, including the mean and the standard deviation for different rainfall ranges was also assessed (Figure 3 and Table 2).

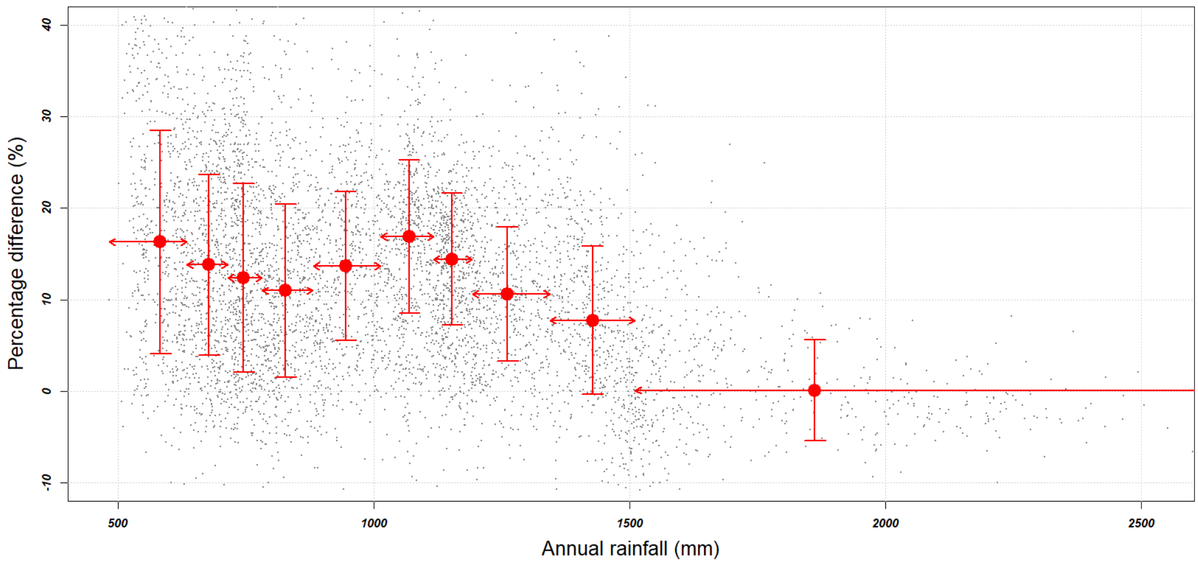

Figure 3: *Percentage difference (M-Val cf. L-Av) versus the long-term average annual rainfall. Each point represents a selected farm. The red crosses represent the mean and the standard deviation of the percentage difference when points are stratified into 10 groups with an equal number of farms.*

Table 2: *Mean and standard deviation of the percentage difference for different rainfall ranges.*

Rainfall range (mm)	Mean (%)	Standard deviation (%)
[453,624]	16	12
(624, 703]	13	10
(703, 769]	12	9
(769, 864]	10	8
(864, 998]	12	7
(998, 1110]	14	6
(1110, 1190]	13	6
(1190, 1340]	10	6
(1340, 1510]	7	7
(1510, 4200]	0.5	6

The analyses showed no bias on the N-loss estimate for farms experiencing >1500 mm of rainfall per annum, meaning that year-to-year variation does not significantly impact the averages N-loss estimate. This also indicates that drainage, a main driver of N-loss in the Overseer model, does not change significantly in regions with consistently high rainfall.

Below 1500 mm rainfall per annum, the comparison with the M-Val showed in positive average bias of 11% with a 10% deviation. As such, the M-Val dataset gave N-loss estimates 11% higher than those obtained using the current climate dataset (L-Av).

3.1.1.2 Comparison with the averaged N-loss estimates using the D-Val dataset

The long-term annual N-loss estimates (L-Av) were then compared with the averaged N-loss estimates obtained with the 30 years of daily climate data (D-Val) (Figure 4).

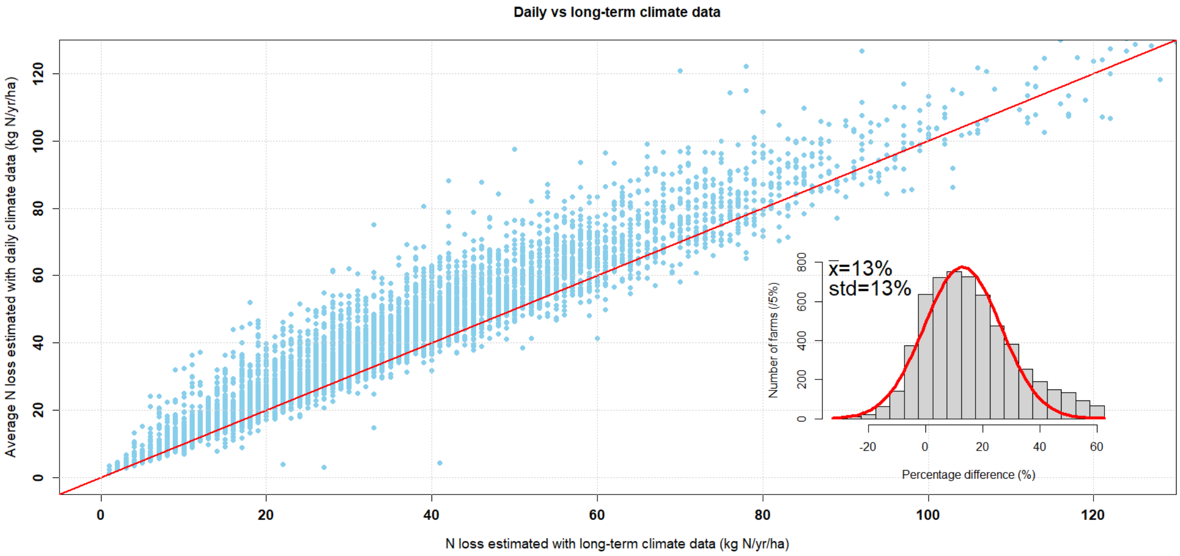

Figure 4: *Comparison of the long-term annual N-loss estimate (L-Av) for 6178 farms with the average annual estimates using the D-Val dataset. Inset: Percentage difference of the distribution.*

The percentage difference in the distribution of the N-loss estimates (Figure 4, insert) was defined as:

$$\Delta_{ratio}(\%) = \frac{\overline{NLeaching_{daily}} - NLeaching_{longterm}}{NLeaching_{longterm}} * 100$$

where $NLeaching_{longterm}$ is the annual N-loss estimate based on the long-term average climate data and $\overline{NLeaching_{daily}}$ is the average of the estimated N-loss results based on 30 years of actual daily climate data. The distribution is characterised by a standard deviation of 13% with a bias of +13%. As for the monthly comparison, the evolution of the percentage difference for each farm relative to the total annual rainfall was also determined (Appendix 2, Figure 11); the analyses show no bias on the N-loss estimate for farms experiencing >1500 mm of rainfall per annum and a positive average bias below 1500 mm rainfall per annum.

Possible explanations for the observed difference in N-loss values (M-Val:L-Av and D-Val:L-Av) below 1500 mm rainfall include:

1. N-loss is a threshold-nature event whereby the minimum of N-loss is zero. For this reason, Overseer, like other tools modelling N-loss, is a nonlinear model. This translates mathematically into *Jensen's inequality* (Jensen 1906) which states that, if $F(x)$is a nonlinear function, the function average is expected to differ from the value of the nonlinear function at the average of the variable quantity, i.e., $\overline{F(x_i)} \neq F(\bar{x})$ where $\bar{x}$ is the average of $x_i$values. Any significant positive deviation from the average value is not offset by a negative balance, therefore it is

expected that the average on 30 annual N-loss estimates will be greater than the single long-term result. This naturally leads to lower estimates when climate event values are averaged (long-term climate dataset).

2. To avoid the requirement for additional inputs from users, the long-term average management practices (fertiliser application, irrigation, animal distribution etc.) were retained for the analysis with the M-Val dataset which could contribute to bias. For example, the long-term schedule of fertiliser applications is constant, even if a specific month of a given year experiences higher than average rainfall, this will result in an artificial increase in the N-loss estimate. To test whether this bias is an artifact that results in higher N-loss estimates using the M-Val and D-Val datasets, further work looking at 30 individual years of monthly and/or daily management practices is recommended.

3.1.1.3 N-loss comparison of the M-Val and D-Val datasets

Due to the similarities observed in the bias when the averaged N-loss estimates using the M-Val and D-Val datasets were compared to the estimates from the current L-Av dataset, the N-loss estimates using the M-Val and D-Val datasets were directly compared. Figure 5 shows the results for 0.1th and 99.9th percentile of the distributions, representing the comparison of the averaged N-loss estimates for 6146 farms.

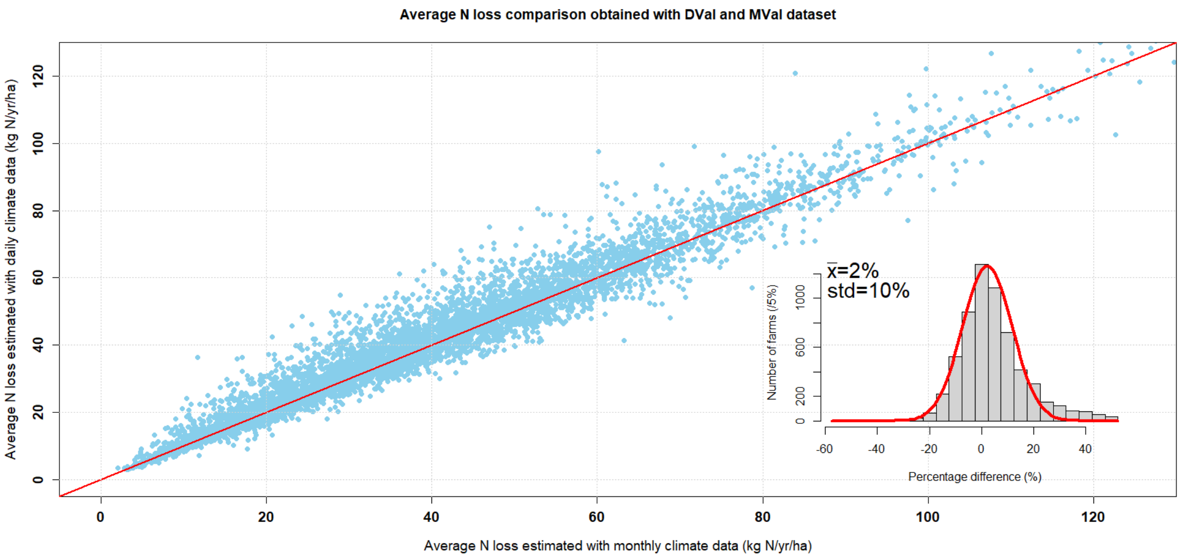

Figure 5: *Comparison of the averaged N-loss estimates for 6178 farms using the D-Val and M-Val datasets. Inset: Percentage difference of the distribution.*

The percentage difference in the distribution of the N-loss estimates (Figure 5, insert) was defined as:

$$\Delta_{ratio}(\%) = \frac{\overline{NLeaching_{daily}} - \overline{NLeaching_{monthly}}}{\overline{NLeaching_{monthly}}} * 100$$

$\overline{NLeaching_{daily}}$ and $\overline{NLeaching_{monthly}}$ are the N-loss averages obtained using the D-Val and M-Val datasets, respectively.

The results show a narrow distribution around the 1:1 ratio; with a standard deviation of 10% and a bias of 2%. As such, the averaged N-loss estimates obtained with the two sets of climate data are statistically comparable. This was further confirmed by a p-value of 10^{-4}, obtained using the Kolmogorov-Smirnov test (Williams, 2001). It was noted that the percentage difference values were not completely normally distributed. A positive distribution tail was observed, whereby the N-loss estimates for 11% of farms were ≥ 20% higher using the D-Val dataset compared to the M-Val dataset.

Figure 6 presents the comparison of the individual annual N-loss estimates obtained using the D-Val dataset and M-Val datasets. The results for 0.1th and 99.9th percentile of the distributions are shown representing the comparison of the annual N-loss estimates for 6178 farms (184,357 estimated per dataset).

The percentage difference in the distribution of the N-loss estimates (Figure 6, inset) was defined as:

$$\Delta_{ratio}(\%) = \frac{NLeaching_{daily_i} - NLeaching_{monthly_i}}{NLeaching_{monthly_i}} * 100$$

$NLeaching_{daily_i}$ and $NLeaching_{monthly_i}$ are the N-loss values estimated with the daily and monthly climate dataset, respectively, and *i* the year of the estimate.

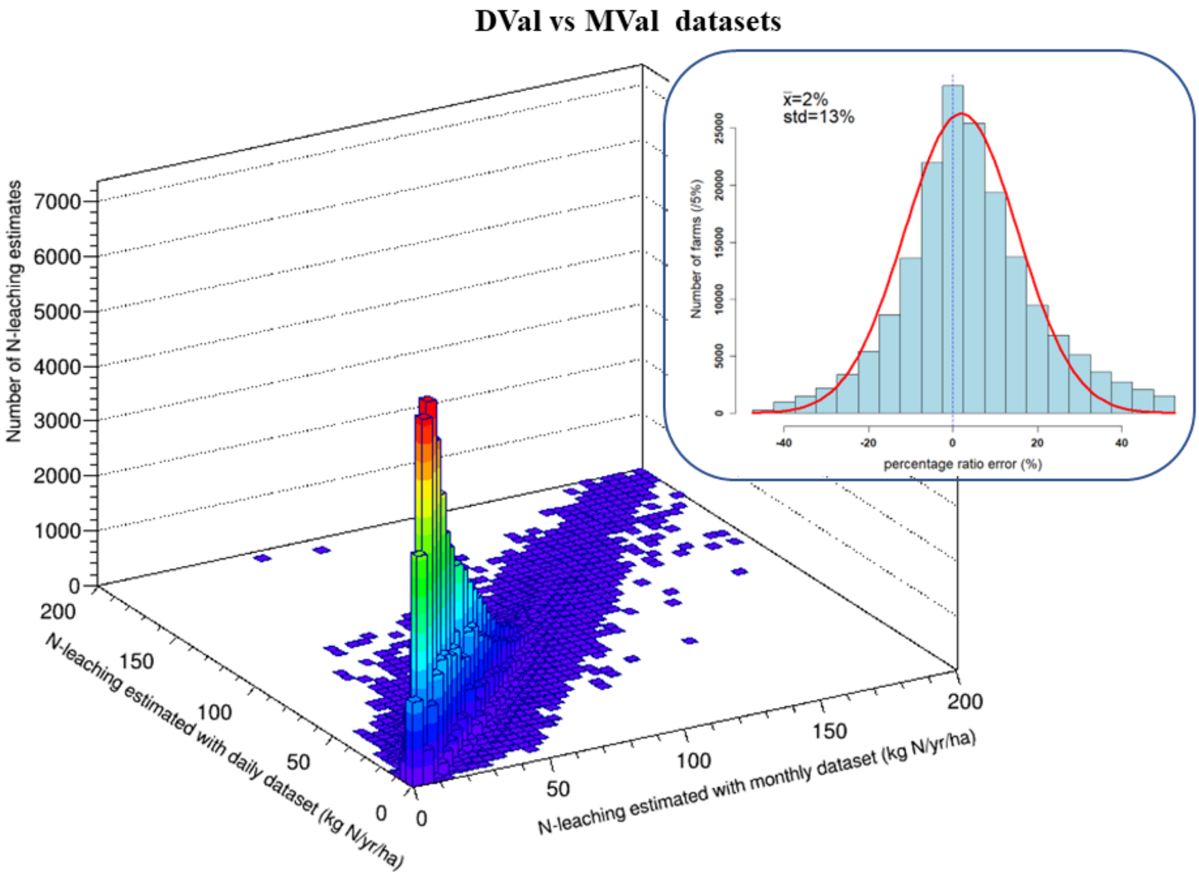

Figure 6: *Comparison of the annual N-loss estimates for 6178 farms using the D-Val and M-Val datasets. Inset: Percentage difference of the distribution.*

Consistent with the comparison of the averaged N-loss estimates using the M-Val and D-Val datasets, the distribution was found to be narrow around the 1:1 ration (standard deviation 13% and 2% bias) with the presence of a similar tail structure. More specifically, 15% of farms were ≥ 20% higher using the D-Val dataset compared to the M-Val dataset.

Possible reasons for the observed tail in the D-Val:M-Val comparisons include:

- The spatial resolution of the D-Val dataset is 5 km (0.05 degrees in latitude and longitude), while it is 500 m for the M-Val dataset. The impact of the difference in resolution is difficult to quantify because the landscape profile must be considered farm by farm.
- Inputs and management practices are described as being in quasi-equilibrium 'steady state' with the farm production and the model is calibrated for typical climate conditions over 30 years (Wheeler, 2022). As such, the model is not calibrated for extreme episodic daily climatic events or atypical weekly climatic patterns.
- Source of daily values for the M-Val (daily patterns) compared to D-Val (interpolated daily data).

Further studies of the impact of extreme daily events on N-loss or on the interactions between management practices and climate data would be required to determine the origin of the tail distribution.

3.1.1.4 Impact of the daily projections (M-Val vs D-Val)

The similarity of the 30-year N-loss estimates (annual averages and individual years) using the D-Val and M-Val datasets was measured with a correlation coefficient. The resulting coefficient of 0.99 (±0.0001 at a 95% confidence interval), confirmed the strong correlation between the year-to-year pattern of N-loss estimates for the two datasets. The principal difference in the application of these two datasets is the use of the ''daily pattern'' mechanism by the M-Val to distribute monthly data into daily data. The significant correlation between the N-loss estimates using the daily pattern (M-Val) compared with daily data (D-Val) provides some confidence in the ''daily pattern'' mechanism currently used by the model to generate daily data. These findings also indicate that increasing the temporal resolution of the input climate dataset from monthly to daily is unlikely to result in significant changes to the N-loss estimate.

3.1.1.5 Year-to-year variation

To interrogate the correlation between the N-loss estimates from the D-Val and M-Val datasets, 30 years of annual N-loss estimates were plotted for three farms representing low, medium and high N-loss estimated alongside the current long-term average N-loss (L-Av) (Figure 7). The annual N-loss estimates using the D-Val and M-Val datasets followed a similar pattern from year-to-year and had comparable 30 year mean values, consistent with the high correlation coefficient calculated.

The dispersion of the estimated N-loss from year-to-year ($NLeaching_{monthly_i}$ or$NLeaching_{daily_i}$) for each farm (6178) was then measured by Relative Standard Deviation-RSD (or coefficient of variation), defined as the ratio of the standard deviation by the mean of the modelled N-loss distribution.

The distribution of RSD values when using the M-Val and D-Val datasets is presented in Figure 8 with average RSD values of 23±7% and 24±8% respectively. This means that the dispersion of values around the averaged N-loss estimate $\overline{NLeaching_{monthly}}$ for a specific farm is also equal to 23% ($or\ \overline{NLeaching_{daily}}$, 24%) if the distribution of the $NLeaching_{monthly_i}$ ($or\ NLeaching_{daily_i}$) can be considered normal in the first approximation. According to the Shapiro-Wilk test (Shapiro & Wilk, 1965), the distribution of the 30 estimates obtained with the M-Val or D-Val datasets can be considered normal for 86% of the farms studied.

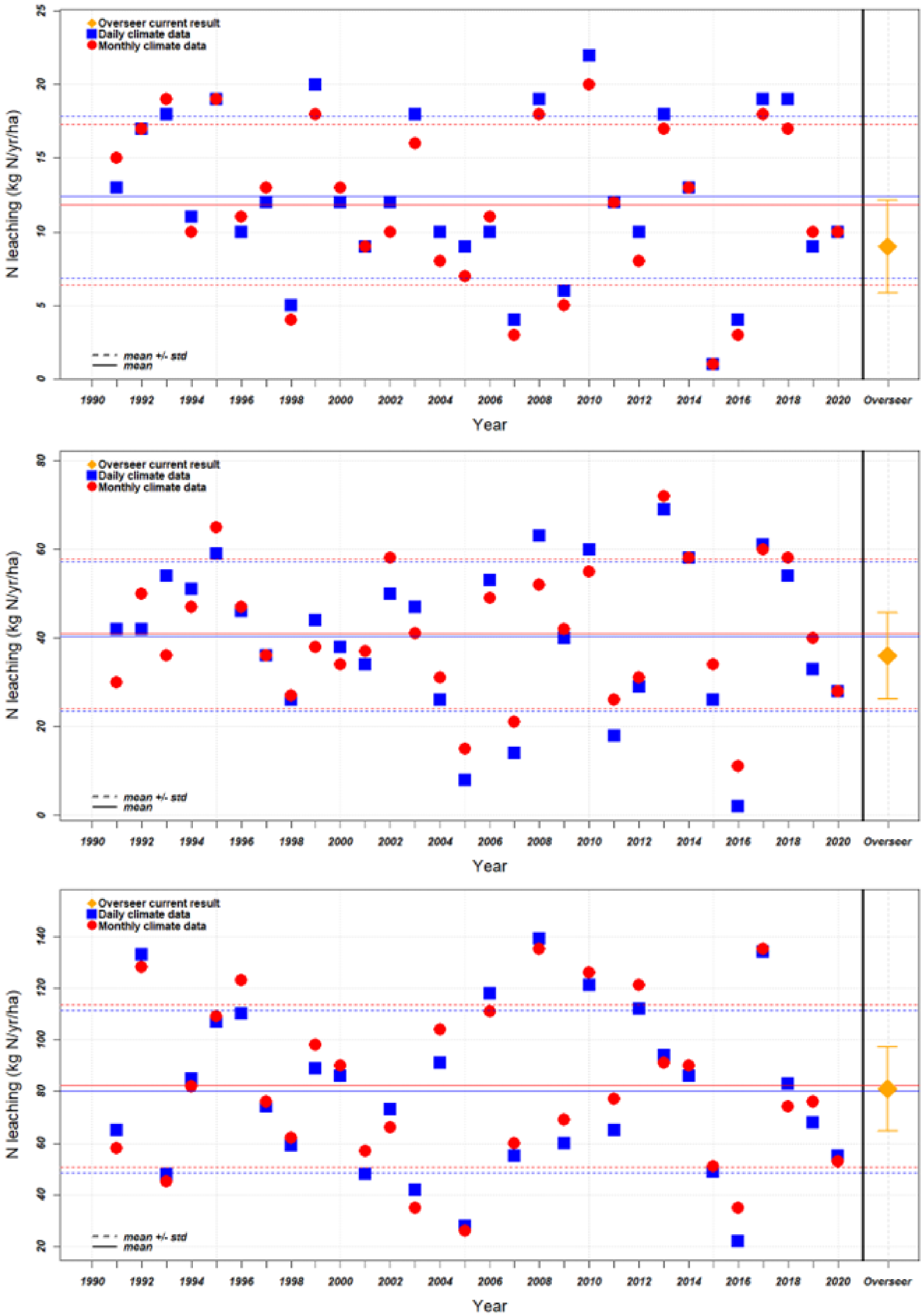

Figure 7: *Overseer estimates of N-loss per hectare for each year in the D-Val and M-Val datasets for three farms representing (a) low, (b) medium and (c) high level of N-loss. Means (solid lines) and RSD (dotted lines) are represented by the different coloured lines. The long-term N-loss estimate with uncertainty (Overseer, 2022a) is indicated in orange.*

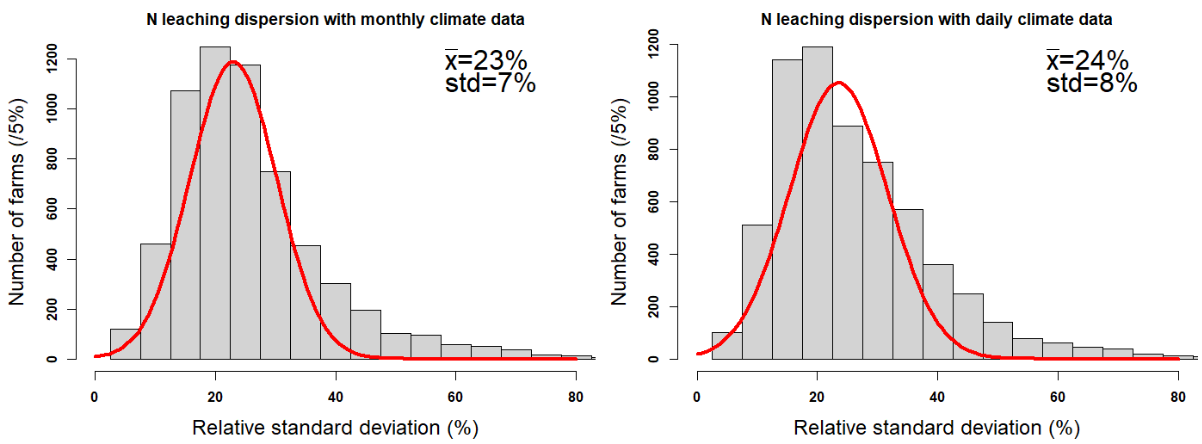

Figure 8: *Distribution of coefficients of relative standard deviation RSD (%) for the M-Val and D-Val datasets.*

Input uncertainty information for the M-Val and D-Val climate datasets was not available for this analysis however, it is possible to use the RSD values as an indicator of uncertainty for the averaged N-loss estimates (M-Val, D-Val). Previous uncertainty analyses (Overseer, 2022a) calculated ~28% average uncertainty on the long-term $NLeaching_{longterm}$. Consequently, the "uncertainties" relating to the three distributions (M-Val, D-Val and L-Av) can be considered statistically comparable. This could be tested further if uncertainty data for the M-Val, D-Val becomes available.

It is possible to apply the RSD values calculated for the M-Val (Figure 2) and D-Val (Figure 4) datasets to the comparative analyses of the N-loss estimates with L-Av. In this context, the 10% (RSD 23%) and 13% (RSD 24%) higher N-loss estimates for M-Val and D-Val respectively are statistically comparable to the N-loss estimates (28% uncertainty) using L-Av.

The most likely origin of the year-to-year variability illustrated in Figure 9 is annual rainfall, previously identified in the sensitivity studies as one of the parameters most influencing the N-loss estimate (Overseer, 2022b). This was investigated by calculating the correlation coefficient between the annual rainfalls and the N-loss estimates using M-Val for all the selected farms.

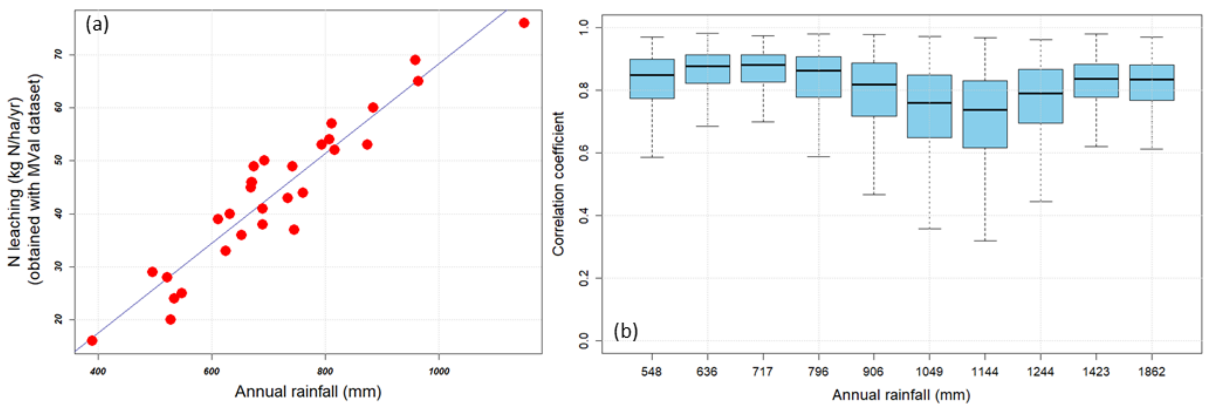

Figure 9: *(a) Comparison of the N-loss estimates (M-Val) with the annual rainfalls for a single farm. (b) Boxplot of the correlation coefficients of all selected farms (6178) against rainfall ranges.*

The boxplot of the correlation coefficients between the annual N-loss and the total rainfall for each farm over the rainfall range (Figure 9b) shows a significant correlation between N-loss estimates and annual rainfall; with an average correlation coefficient of 0.8±0.1. This result confirms that the year-to-year variability of the N-loss estimates can be largely explained by the year-to-year variation of the annual rainfall. A similar pattern was also observed using the D-Val dataset (Appendix 3, Figure 12).

3.2 Impact of different climate datasets on N-loss estimates

The climate parameters have a key influence on the N-loss estimated by the Overseer model. They are currently defined at the month level at the location of a farm from a long-term monthly climate dataset (L-Av) provided by NIWA. We studied the impact of different temporal-resolution input climate data on the N-loss estimated by Overseer. The N-loss estimates provided using 30 years of interpolated monthly climate data (M-Val), 30 years of interpolated daily climate data (D-Val) and the L-Av climate data were compared, with the following main findings:

- The averaged N-loss estimates using 30 individual years of monthly and daily interpolated climate datasets are statistically comparable to the N-loss estimates using the current L-Av climate dataset based on the output uncertainty assessments of 23%, 24% and 28% respectively.
- The M-Val and D-Val N-loss estimates (annual and averaged) are statistically comparable. This provides confidence in the use of “daily climate patterns” for the generation of daily climate data used in the hydrology model and indicated that the use of interpolated daily climate data is unlikely to deliver material benefit over monthly data to the model output.
- The trend towards higher N-loss estimates using the M-Val and D-Val datasets was not statistically significant and is likely to be an artifact due to:
    I. N-loss being a threshold process (Jensen) i.e., a stochastic process with only positive results and
    II. The difference in the temporal resolution between the long-term average management practices and annual climate datasets. Adjustment for year-by-year management practices could be investigated to ascertain the impact of the latter on these averaged, annual N-loss estimates.

4. Summary

The average N-loss distributions obtained with the actual climate data (D-Val and M-Val) are consistent with the long-term N-loss distribution (L-Av) when the uncertainties are considered. This means that there is no evidence of significant benefits in switching from the current long-term average dataset, at this time. Furthermore, switching from the current option to using one of the two other climate datasets examined is likely to require input of 30 years of management practices to avoid potential artifacts in the N-loss estimates due to differences in the temporal resolution (annual climate and average management inputs).

5. Acknowledgements

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7. Appendices

Appendix 1

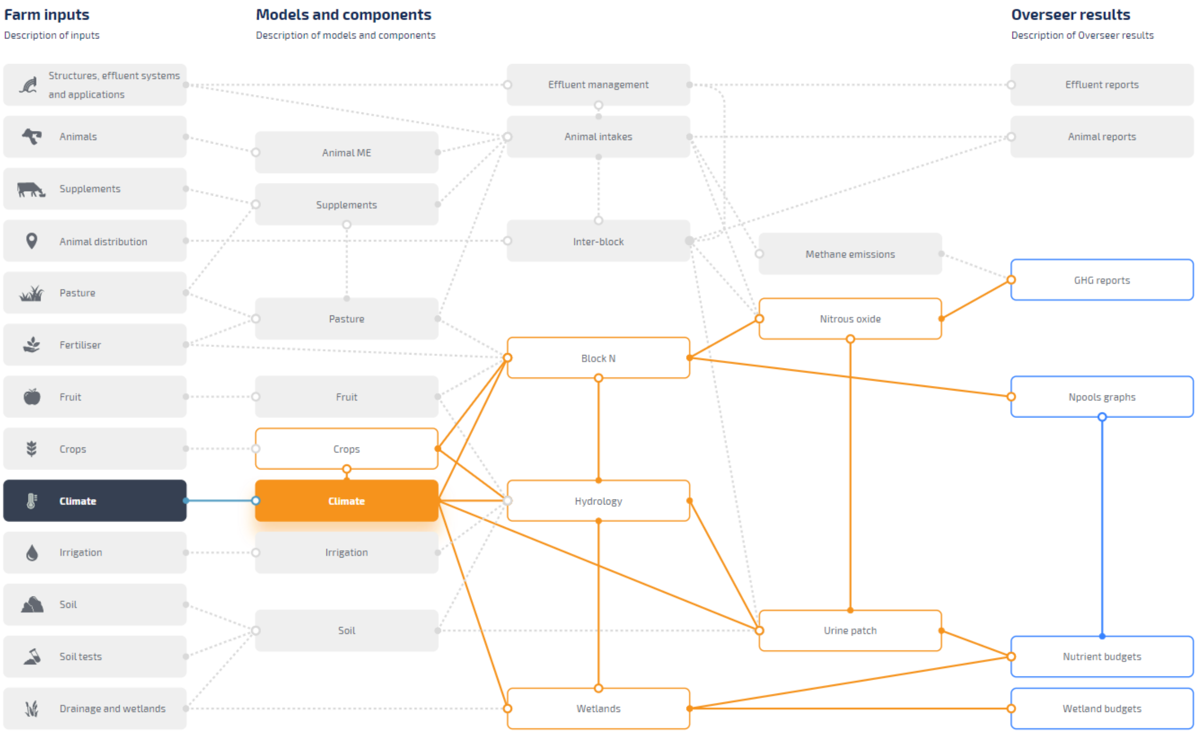

Figure 10: *Diagram of science models and components that work together to model nutrient flows, including greenhouse gas emissions for a farm system. The inputs of the model are described in the first column on the left, the model components using climate records are represented in orange, and the results depending on climate data are highlighted in blue.*

Appendix 2

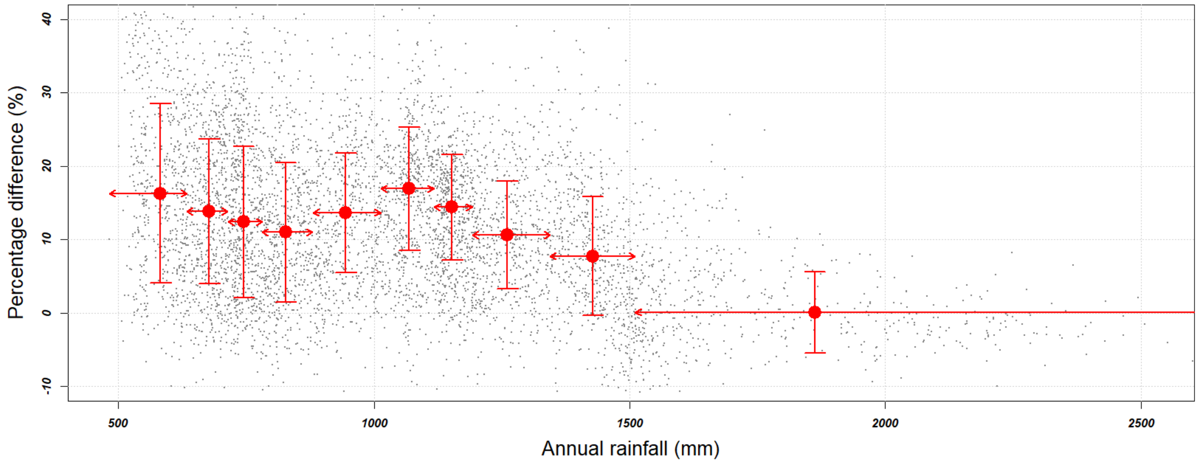

Figure 11: *Percentage difference (D-Val cf. L-Av) versus the long-term annual rainfall. Each point represents a selected farm. The red crosses represent the mean and the standard deviation of the percentage difference when points are stratified into 10 groups with an equal number of farms.*

Appendix 3

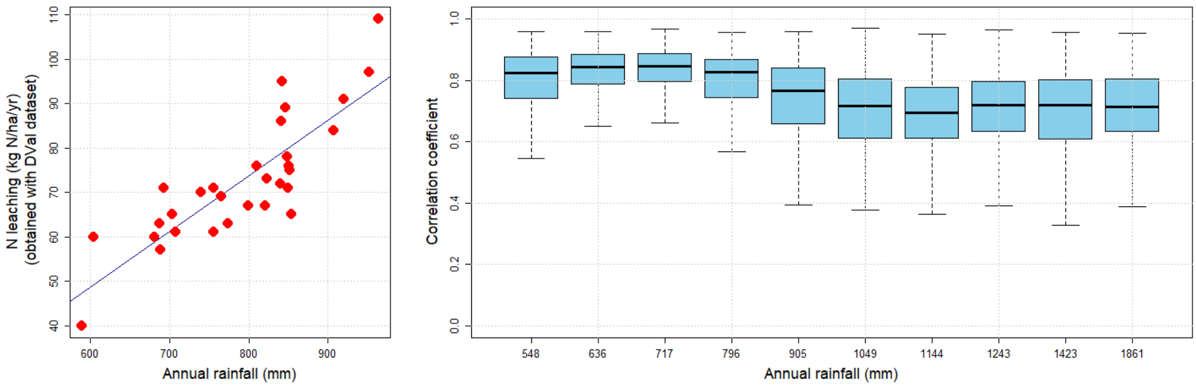

Figure 12: *(a) Comparison of the N-loss estimates (M-Val) with the annual rainfalls for a single farm. (b) Boxplot of the correlation coefficients of all selected farms (6178) against rainfall ranges.*

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