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Quantifying nitrogen losses in oil palm plantations: models and challenges

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Abstract. Oil palm is the most rapidly expanding tropical perennial crop. Its cultivation raises environmental concerns, notably related to the use of nitrogen (N) fertilisers and the associated pollution and greenhouse gas emissions. While numerous and diverse models exist to estimate N losses from agriculture, very few are currently available for tropical perennial crops. Moreover, there is a lack of critical analysis of their performance in the specific context of tropical perennial cropping systems. We assessed the capacity of 11 models and 29 sub-models to estimate N losses in a typical oil palm plantation over a 25-year growth cycle, through leaching and runoff, and emissions of NH_3, N_2, N_2O, and NO_x. Estimates of total N losses were very variable, ranging from 21 to 139 kg N ha^{-1} yr^{-1}. On average, 31 % of the losses occurred during the first 3 years of the cycle. Nitrate leaching accounted for about 80 % of the losses. A comprehensive Morris sensitivity analysis showed the most influential variables to be soil clay content, rooting depth, and oil palm N uptake. We also compared model estimates with published field measurements. Many challenges remain in modelling processes related to the peculiarities of perennial tropical crop systems such as oil palm more accurately.

1 Introduction

Oil palm is the most rapidly expanding tropical perennial crop. The area of land under oil palm, currently amounting to approximately 19 Mha, has been rising at 660 000 ha yr^{-1} over the 2005–2014 period (FAOSTAT, 2014), and this trend is likely to continue until 2050 (Corley, 2009). This increase raises significant environmental concerns. Beside issues related to land use changes and the oxidation of peat soils when establishing plantations, the cultivation of oil palm can generate adverse environmental impacts, in particular through the use of nitrogen (N) fertilisers. The latter are associated with pollution risks for ground and surface waters, and emissions of greenhouse gases (Choo et al., 2011; Comte et al., 2012; Corley and Tinker, 2003). As a result, an accurate estimation of N losses from palm plantations is critical to a reliable assessment of their environmental impacts. Models appear necessary in this process because comprehensive direct measurements of N losses are too difficult and resource-intensive to be generalised.

While a number of models exist to estimate N losses from agricultural fields, they mostly pertain to temperate climate conditions and annual crops. N losses under perennial tropical crops are expected to follow specific dynamics, given, for instance, the higher ranges of temperature and rainfall experienced in these climatic zones, and the high amount of crop residues recycled over the growth cycle. However, few models are available for tropical crops, and even fewer for perennial tropical crops (Cannavo et al., 2008). Such models, in particular mechanistic ones, were primarily developed for research purposes, in order to simulate crop growth as affected by biogeochemical processes, and to gain insight into the underlying processes. Nowadays, models are also widely used to estimate the emission of pollutants for the purpose of environmental assessment, aiming either at more accurate estimates of mean emissions, or at evaluation of the impact of certain management practices on emissions. Different types of models are used, ranging from highly complex process-based models to more simple operational models such as empirical regressions. Despite some consensus and recommendations regarding best practices for the modelling of field emissions, notably within the framework of life cycle assessment (e.g. IPCC, 2006; EC ILCD, 2011), there has not been any comprehensive review and comparison of potentially useful models for environmental assessment. Moreover, various publications pinpointed the need for models that are better adapted to tropical crops in the estimation of field emissions (Basset-Mens et al., 2010; Bessou et al., 2013; Cerutti et al., 2013; Richards et al., 2016). To improve field emissions modelling in oil palm plantations, we need to determine the potential applicability and pitfalls of state-of-the art models regarding N cycling and losses in these systems.

Most environmental impact assessment methods, such as life cycle assessment, consider perennial systems to behave similarly to annual ones. Following this assumption, the inventory data on the farming system are generally based on one productive year only, corresponding to the time the study was carried out or the year for which data were available (Bessou et al., 2013; Cerutti et al., 2013). However, models of annual cropping systems do not account for differences in N cycling that occur during the growth cycle of perennial crops such as oil palm. Some key parameters in these dynamics, such as the length of the crop cycle, the immature and mature stages, and inter-annual yield variations, are thus not accounted for. This also applies to other long-term eco-physiological processes, such as the delay between inflorescence meristem initiation and fruit bunch harvest. To improve the reliability and representativeness of the environmental impacts of oil palm, we thus need to better account for the spatio-temporal variability of both the agricultural practices and the eco-physiological responses of the plant stand throughout the perennial crop cycle (Bessou et al., 2013). Since most of these impacts hinge on N management and losses, modelling the N budget of palm plantations is a key area for improvement and is the focus of this work.

Here, we assess the capacity of existing models to estimate N losses in oil palm plantations, while accounting for the peculiarities of oil palm plantations related to the N dynamics over the course of the growth cycle. We start with a review of models that could be used for oil palm, and we detail how they were selected, calibrated, and run with relevant input data for a particular case study. Outputs from the models were subsequently compared to each other and to previously reported field measurements. Key model parameters were identified using a Morris sensitivity analysis (Morris, 1991). Finally, we discuss the relevance of existing models and the remaining challenges to adequately predict N fluxes in oil palm plantations.

2 Material and methods

2.1 Model selection and description

Among existing models, we first selected those that appeared most comprehensive and relevant. We then also selected partial models, in order to cover the diversity of current modelling approaches as much as possible, and to explore potential complementarities between them. By “partial models” we mean models that simulate only one or a few N losses.

The selection criteria were (i) the possibility of estimating most of the N losses of the palm system; (ii) the applicability to the peculiarities of the oil palm system; and additionally, for partial models, (iii) those most widely used in environmental assessments, e.g. EMEP (2013). In total, we selected 11 comprehensive plus 5 partial models.

We compared models at two levels. At the first level the aim was to compare the 11 comprehensive models, to obtain an overview of their abilities to estimate the various N fluxes constituting the complete N budget of the plantations. The second level involved the partial models and aimed at better understanding the factors governing the variability of each type of N loss. Most of the 11 comprehensive models were actually a compilation of sub-models. We hence included these sub-models in the second-level comparison, in addition to the 5 partial models originally selected. In total, 29 partial models, hereafter referred to as sub-models, were compared at this second level.

2.1.1 Description of comprehensive models

Following the typology defined by Passioura (1996), three of the comprehensive models were classified as mechanistic, dynamic models (WANULCAS from van Noordwijk et al., 2004; SNOOP from de Barros, 2012; APSIM from Huth et al., 2014). The others were simpler static models mainly based on empirical relationships (Mosier et al., 1998; NUTMON from Roy, 2005; IPCC, 2006, from Eggleston et al., 2006; Banabas, 2007; Schmidt, 2007; Brockmann et al., 2014; Meier et al., 2014; Ecoinvent V3 from Nemecek et al., 2014)[1]. Other mechanistic models commonly used in crop modelling, such as DNDC (Li, 2007) and Century (Parton, 1996), were not adapted for oil palm modelling and could not be used within our model comparison without proper pre-

[1]The models are hereafter referred to by their name or their first author in order to ease reading of both the text and figures.

liminary research and validation work, which fell beyond the scope of this work.

The mechanistic models were built or adapted explicitly for oil palm. The other models were developed or are mainly used for environmental assessment. Among the latter, some were explicitly built for oil palm or proposed parameters adaptable to oil palm (Banabas, Schmidt, Ecoinvent V3), some involved parameters potentially adaptable to perennial crops (NUTMON, Brockmann, Meier-2014), while others were designed to be used in a wide range of situations, without specific geographical or crop-related features (Mosier and IPCC-2006, which are often used in Life Cycle Inventories).

Most of the models distinguished between mineral and organic fertiliser inputs, some included symbiotic N fixation, and a few considered atmospheric deposition and non-symbiotic N fixation (Table 1). All models required parameters related to soil, climate, and oil palm physiology, except for two of them (Mosier and IPCC-2006), which only required N input rates. Management parameters were mainly related to fertiliser application, i.e. the amount and type applied, and the date of application. The splitting of application was considered in APSIM, SNOOP, and WANULCAS, and the placement of the fertiliser was only taken into account in WANULCAS.

All models considered the main internal fluxes of N, either modelling them or using them as input data. The most common fluxes were transfer from palms to soil, via the mineralisation of N, in the residues left by the palms of the previous cycle and pruned fronds, followed by oil palm uptake and root turnover. The least considered fluxes were cycling of N through the other oil palm residues such as male inflorescences and frond bases, and uptake and recycling by legumes (accounted for by only five models).

Finally, the main losses modelled were leaching (all models), N_2O emissions (10 models), and NH_3 volatilisation from fertilisers (9 models). NO_x emissions and runoff were taken into account by fewer models (7 and 8 models, respectively). Emissions of N_2, erosion, and NH_3 volatilisation from leaves were the least modelled losses. In some cases, several losses were modelled jointly and it was not possible to differentiate the contribution of each loss. For instance, erosion was always combined into the calculation of leaching and runoff, except for NUTMON, which used the mechanistic erosion sub-model LAPSUS (Schoorl et al., 2002). However, we could not run LAPSUS since it required precise local parameters to run its digital terrain model component that were not available.

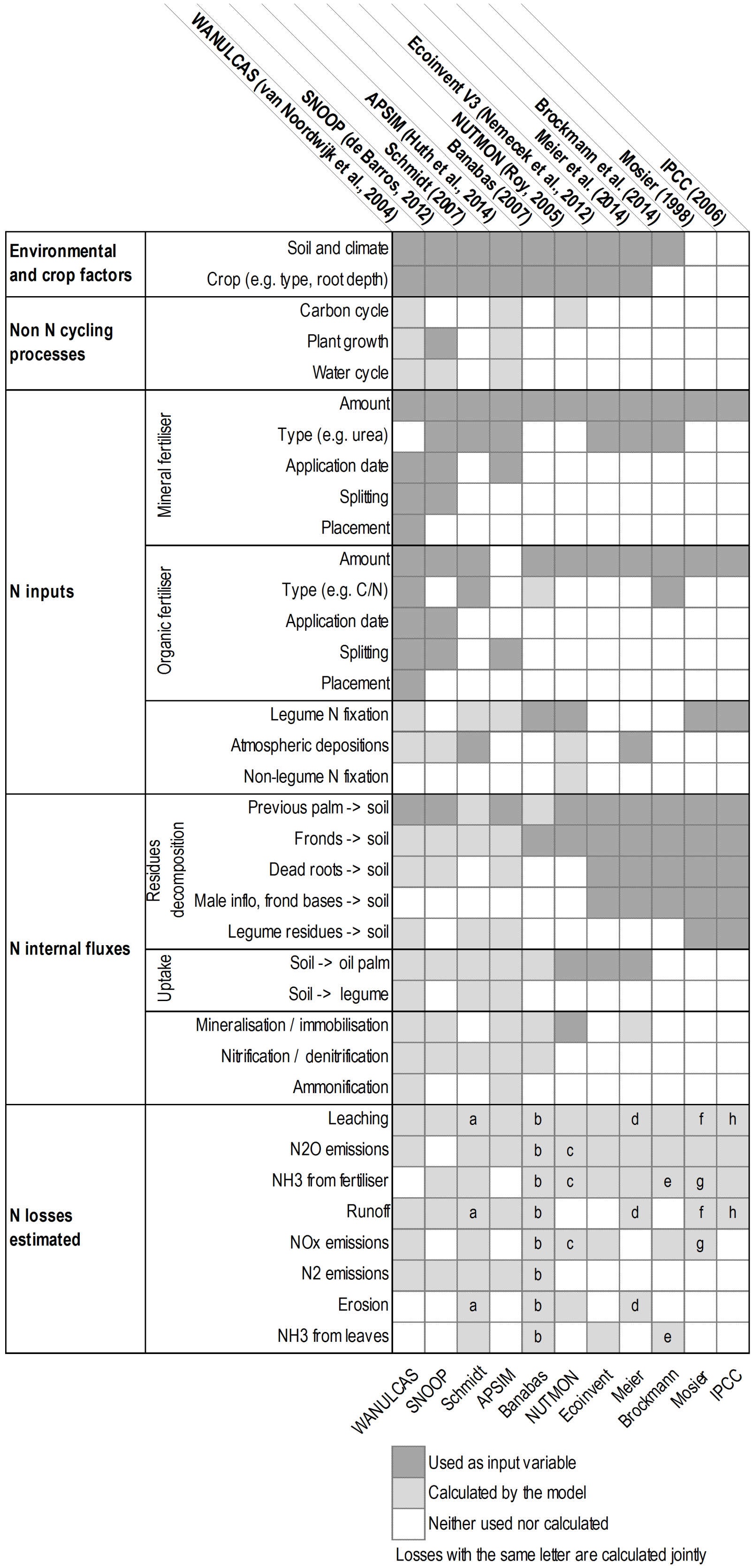
2.1.2 Description of sub-models

Each of the 29 sub-models modelled N losses from the soil–plant system via one of the following three types of pathways: loss via leaching and runoff (8 sub-models); loss by emission of NH_3, commonly referred to as volatilisation (9 sub-models); and loss by emission of the gaseous products of nitrification and denitrification: N_2, N_2O, and NO_x (12 sub-models).

For the first pathway (leaching and runoff), eight sub-models were tested. Leaching concerned inorganic N losses (NO_3^-, NH_4^+), whereas runoff included inorganic and organic N losses without separating between the dissolved and particulate forms. Leaching was taken into account by all eight sub-models. Runoff was calculated jointly with leaching in two sub-models (Mosier and IPCC-2006), and separately in modules of APSIM, SNOOP, and WANULCAS. None of the eight models calculated erosion losses. The Mosier and IPCC-2006 sub-models calculated losses as a linear function of N inputs via mineral and organic fertiliser applications and crop and legume residues. Both used an emission factor of 30 % of N inputs in our test conditions. Smaling (1993), SQCB-NO3 (Faist-Emmenegger et al., 2009) and de Willigen (2000) used regressions and calculated losses taking into account N inputs, soil such as soil N organic content and soil clay content, climate data such as annual rainfall, and some physiological parameters such as root depth and N uptake rates. The input variables used depended on the sub-models. APSIM, SNOOP, and WANULCAS used a soil N module coupled with a water budget module to calculate the losses through leaching and runoff. In these three cases, a cascading layered approach was used to model the soil, and N transformation rates and water flows were calculated for each layer on a daily time step. The other five sub-models used a yearly time step.

For the second pathway (the volatilisation of NH_3), nine sub-models were tested. They modelled NH_3 emissions from mineral and organic fertilisers, with three sub-models accounting for emissions from leaves. All sub-models calculated the emissions from mineral fertiliser, except for Agrammon Group (2009), and four sub-models calculated the emissions from organic fertiliser. For the emissions from leaves, Agrammon used a constant rate of 2 kg N ha^{-1} yr^{-1}, whereas EMEP (2009, 2013) calculated them jointly with emissions from mineral fertiliser. For emissions from organic and mineral fertilisers, the sub-models assumed linear relationships between fertiliser application rate and N losses. The emission factors were modulated depending on the fertiliser type. For mineral fertilisers, emission factors ranged from 0 to 15 % of N inputs for ammonium sulfate and 10 to 39 % of N inputs for urea. For organic fertilisers, emission factors ranged from 20 to 35 % of N inputs. For Mosier and IPCC-2006, emission factors differed only between mineral and organic fertilisers. In some sub-models, these factors were also modified by other parameters. For instance, the Bouwman et al. (2002a) model took into account soil pH, soil temperature, and cation exchange capacity, whereas in the Agrammon model emission factors were affected by factors specific to the type of animal manure considered (e.g. pig vs. cattle manure) and the application method. However, this was not relevant to

Table 1. Main input/output variables and processes modelled in the 11 comprehensive models.



empty fruit bunches, the main organic fertiliser used in oil palm plantations.

For the third pathway (gaseous losses of N_2 and N oxides), 12 sub-models were tested. N_2O emissions were estimated by eight sub-models. NO_x emissions were estimated by four sub-models. N_2 emissions were estimated by four sub-models but were calculated jointly with other gases, except for WANULCAS and APSIM. Mosier, IPCC-2006, EMEP-2013, Crutzen et al. (2008), and Nemecek et al. (2007) sub-models calculated losses as a linear function of N inputs, using fixed emission factors for N_2O, from 1 to 4 % of N inputs, or NO_x with 2.6 % of N inputs in EMEP-2013. Meier (2012) also used a linear relationship, but with an emission factor that could be modified. However, its correction factors were applicable to annual crops under temperate climate and not here, e.g. impact of tillage. Bouwman et al. (2002b), Shcherbak et al. (2014), and SimDen (Vinther and Hansen, 2004) sub-models used non-linear relationships between N inputs and N losses. The Bouwman-2002b model took into account various parameters for the calculation, mainly of drainage, soil water content, and C organic content. Shcherbak and SimDen took into account only N inputs and baseline emissions. APSIM and WANULCAS calculated the losses by combining a soil N module and a water budget module, plus a carbon module for APSIM.

2.2 Model runs and sensitivity analysis

2.2.1 Model calibration and input data

Oil palm plantations are usually established for a growth cycle of approximately 25 years. Palms are planted as seedlings and the plantation is considered immature until about 5 years of age, when the palm canopy closes and the plantation is considered mature. Harvesting of fresh fruit bunches starts after about 2–3 years. The models were run over the whole growth cycle, including changes in management inputs and output yields between immature and mature phases. We considered replanting after a previous oil palm growth cycle. Potential impacts of land use change on initial conditions were hence not considered. However, when possible, the initial decomposing biomass due to felling of previous palms was included in the models.

In order to compare the models, we kept calibration parameters and input variables consistent across models as much as possible. However, all models did not need the same type of parameters and input data. In particular, for some static models, input variables were initially fixed and could be considered as calibrated parameters based on expert knowledge. For instance, NUTMON and Ecoinvent V3 needed the oil palm uptake rate as an input value, but Schmidt and APSIM used their own calculations for uptake.

We considered a 1 ha plantation located in the Sumatra region of Riau, Indonesia. For climate during this period, the dataset contained daily rain, 2407 mm yr^{-1} on average, as well as temperature and solar radiation. As the dataset was only 16 years long, from 1998 to 2013, we had to repeat an average year to complete the last 9 years of the simulation. The soil was a typical Ultisol, with four layers (0–5, 5–15, 15–30, and 30–100 cm). The main characteristics, averaged over the upper 30 cm, were bulk density (1.4 t m^{-3}), drainage (good), clay content (31 %), initial organic C content (1.65 %, i.e. 0.0165 g g^{-1}), initial organic N content (5.5 t ha^{-1}), pH (4.5), and rate of soil organic N mineralisation (1.6 % per year) (USDA, 1999; Khasanah et al., 2015; Corley and Tinker, 2003; Roy, 2005).

Regarding management input variables, we used a set of values representing a standard average industrial plantation (Pardon et al., 2016). These values were consistent and based on a comprehensive review of available measurements. For oil palm the main peculiarities were the yield (25 t of fresh fruit bunches ha^{-1} yr^{-1} after 10 years, i.e. 73 kg N ha^{-1} yr^{-1}), the uptake (222 kg N ha^{-1} yr^{-1} after 10 years), and the depth where most of the active roots are found (set at 1 m). For the management of the field, the input variables were the slope (0°), planting density (135 palms ha^{-1}), presence of a legume cover sown at the beginning of the cycle (e.g. *Pueraria phaseoloides* or *Mucuna bracteata*), and presence of the biomass of felled palms from the previous growth cycle (550 kg N ha^{-1}, corresponding to the above- and below-ground biomass of felled palms). For fertiliser, the application of mineral fertiliser increased from 25 kg N ha^{-1} yr^{-1} the first year up to 100 kg N ha^{-1} yr^{-1} after the fifth year. It was assumed to be 25 % of urea and 75 % of ammonium sulfate. Organic fertiliser, i.e. empty fruit bunches, was applied around the palms for the first 2 years at a typically used rate of 184 kg N ha^{-1} yr^{-1}. This amount, over 2 years, corresponds to the number of empty fruit bunches generated from 1 ha over 25 years, assuming a yield of 25 t of fresh fruit bunches ha^{-1} yr^{-1}. Atmospheric deposition of N through rain was set at 18 kg N ha^{-1} yr^{-1}. Biological N fixation by the legume cover was set at 635 kg N ha^{-1} fixed over the first 7 years, and released to the soil during the same period. The release of N through the decomposition of the organic residues from palms was set at an annual average of 108 kg N ha^{-1} yr^{-1} going to the soil. These residues correspond to fronds and some inflorescences that are regularly pruned, naturally falling frond bases, and dead roots.

For model comparison, we calculated the annual estimated losses, considering the relative contributions of leaching, runoff, and erosion; NH_3 volatilisation; and N_2, N_2O, and NO_x emissions. Besides the inter-model comparison, we also compared the simulated losses with previously reviewed measurements from the literature (Pardon et al., 2016). Most of the models are static ones and do not account for variations in processes during the crop cycle. To model the whole cycle, we ran these models on a yearly basis accounting for annual changes in some input variables from the scenario, such as fertiliser application rates, biological N fixation, crop N uptake, N exported in fresh fruit bunches, temperature, and rainfall. One model (SNOOP) simulates specific years of the crop cycle one by one, using a daily time step. For this model, the calculation was repeated 25 times, taking into account the year-to-year changes. The other models were built to simulate the whole growth cycle with a daily time step, as for WANULCAS and APSIM, or with a yearly time step, as for Banabas and Schmidt.

For the sub-model comparisons, we compared the three groups of sub-models separately: (1) leaching, runoff, erosion; (2) NH_3 volatilisation; (3) N_2, N_2O, and NO_x emissions. For these comparisons, we used the same input data and the same calibration as for the previous one.

We compared the magnitude of the losses estimated by the various sub-models, and when possible, we also identified the contribution of the various N input sources to the losses estimated, i.e. the influence of mineral and organic fertiliser inputs, biological N fixation, plant residues, and atmospheric depositions.

2.2.2 Sensitivity analysis

Sensitivity analysis investigates how the uncertainty of a model output can be apportioned to different sources of uncertainty in the model inputs (Saltelli et al., 2008). Sensitivity analysis aims at ranking sources of uncertainty according to their influence on the model outputs, which helps to identify inputs that should be better scrutinised in order to reduce the uncertainty in model outputs.

We conducted a Morris sensitivity analysis (Morris, 1991) for the three groups of sub-models in order to identify the input variables that have the most effect on the magnitude of the losses. We used RStudio software to code and run the models (R Development Core Team, 2010), and the "morris" function from the "sensitivity" package version 1.11.1. Process-based models were not included in the sensitivity analysis as the source code of SNOOP was not accessible and APSIM and WANULCAS were not directly programmable without adapting the model structure to run the sensitivity analysis, which fell beyond the scope of this study.

Each model used n input variables. For each input variable X_i ($i \in [1; n]$), we defined a nominal, minimum, and maximum value. For climate, soil, oil palm characteristics, and N input fluxes, the ranges were determined based on literature references. For emission factors and other parameters, some ranges were directly provided by some sub-models (e.g., IPCC-2006). Other parameters were varied within a -90 to $+90$ % range relative to their nominal values. The ranges and references are listed in Table SM1 in the Supplement. For the analysis, each range was normalised between 0 and 1 and then split into five levels by the morris function.

The Morris sensitivity analysis technique belongs to the class of "one-at-a-time" sampling designs. For each model, we carried out $400 \times (n+1)$ runs, with each set of $n+1$ runs called a "trajectory". For each trajectory, an initial model run was carried out in which each input variable was randomly set to one of the five possible levels. For the second run, one variable X_1 was changed to another random level differing from the initial one, and the difference in output between the first and second runs was recorded. That difference, divided by the normalised change in input level, is called an "elementary effect" of variable X_1. For the third run, another variable X_2 was changed, keeping all other input variable values the same as in the second run. The elementary effect of X_2 was recorded, and so on, until the $(n+1)$th run. Each trajectory was initiated using a new random set of input variable values, and each trajectory generated one elementary effect value for each X_1.

Then, following Morris's method, we calculated two sensitivity indices for each variable X_i: the mean of absolute values of the 400 elementary effects (μ_i^*), being the mean influence on the output when the input varies in its minimum/maximum range, and their standard deviation (σ_i). The higher the μ_1^* is, the more influential the variable X_i. The higher the σ_i is, the more important the interaction between the variable X_i and the other input variables in the model, or the influence of X_i is non-linear. The mean of the absolute values of the elementary effects (μ_i^*) was used rather than the mean of the actual values (μ_i) because the effects could be positive or negative.

3 Results

3.1 Comparison of the 11 comprehensive models

Estimations of total losses of N were very variable, ranging from 21 to 39 kg N ha^{-1} yr^{-1} around an average of 77 kg N ha^{-1} yr^{-1} (Fig. 1a). Annual estimates were 20–25 t of fresh fruit bunches ha^{-1} yr^{-1} for yield and 132–147 kg N ha^{-1} yr^{-1} of N inputs (mineral fertiliser, atmospheric deposition, biological N fixation, empty fruit bunches, and previous felled palms), with 2407 mm yr^{-1} of rainfall and 932–1545 mm yr^{-1} of evapotranspiration. Two main factors contributed to the variability of N losses: some pathways were not taken into account by some of the models (see Table 1); and estimates of leaching, runoff, and erosion, which greatly contributed to the total losses, were particularly variable across models.

According to the models, the leaching and runoff pathway was the most important of the three, with an average loss of 61 kg N ha^{-1} yr^{-1}, i.e. about 80 % of the losses, ranging from -12 to 135 kg N ha^{-1} yr^{-1}. A negative leaching loss was estimated with NUTMON after the sixth year, when oil palm N uptake exceeded 160 kg N ha^{-1} yr^{-1}. NH_3 volatilisation was the next most important pathway with 11 kg N ha^{-1} yr^{-1} on average, ranging from 5 to 13 kg N ha^{-1} yr^{-1}. Emissions of N_2, N_2O, and NO_x had the lowest magnitude, but considerable variability, with 6 kg N ha^{-1} yr^{-1} on average, ranging from 0 to 19 kg N ha^{-1} yr^{-1}.

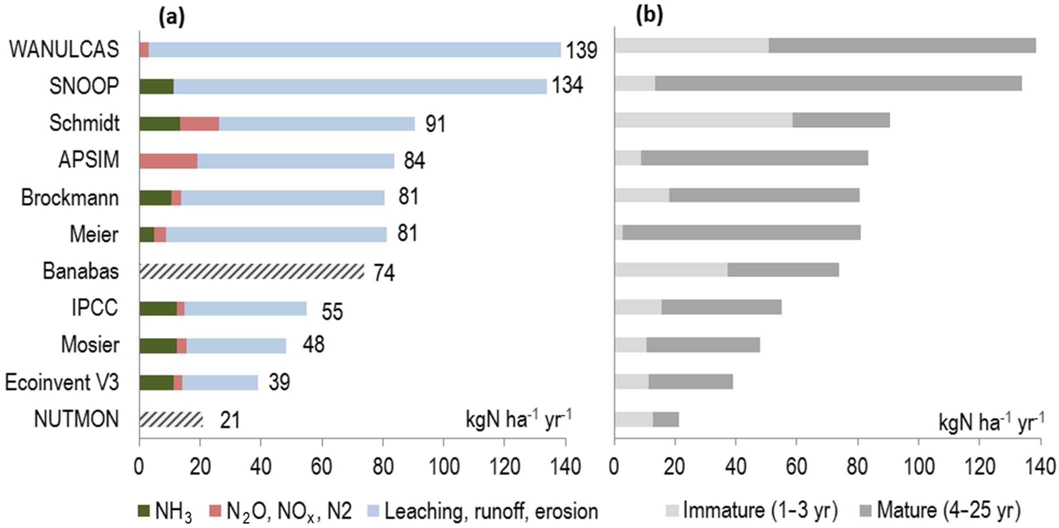


Figure 1. Estimates of N losses by 11 models. **(a)** Distribution of the annual average losses between the three pathways: leaching and runoff; NH_3 volatilisation; N_2O, NO_x, N_2 emissions. Overall losses of N were very variable, with an average of 77 kg N ha^{-1} yr^{-1}, ranging from 21 to 139 kg N ha^{-1} yr^{-1}. The leaching and runoff pathway was the most important of the three, corresponding to about 80 % of the losses. The hatched bars represent calculations including several pathways at once: Banabas estimated the three pathways jointly, NUTMON estimated jointly all gaseous emissions and leaching losses were negative. SNOOP estimated N_2, N_2O, and NO_x emissions as null, and APSIM and WANULCAS did not model the NH_3 volatilisation. **(b)** Distribution of the annual average losses between the immature and the mature phases, corresponding to 1–3 years, and 4–25 years after planting; respectively. On average, 31 % of the losses occurred during the immature period, which represents 12 % of the cycle duration.

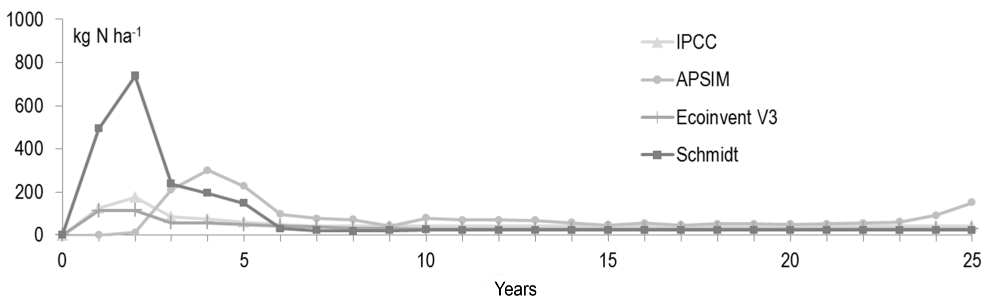


Figure 2. Temporal patterns of N losses along the growth cycle for four approaches selected to illustrate the variability of the results. Most of the models simulated maximum losses near the beginning of the cycle. The timing of the peak depended on the model, occurring between the first and the fourth year. The magnitude of the peak was very variable, up to 738 kg N ha^{-1} yr^{-1} for Schmidt.

According to the models, N losses varied substantially along the growth cycle. On average, 31 % of the losses occurred during the immature period, which represents 12 % of the cycle duration (Fig. 1b). Most of the models simulated maximum losses near the beginning of the cycle. The magnitude of this peak was very variable, up to 738 kg N ha^{-1} yr^{-1} for Schmidt. Its timing in the cycle depended on the model, occurring for instance during the first, second, or fourth year for Ecoinvent V3, IPCC-2006, and APSIM, respectively (Fig. 2: for clarity, only four examples are shown, to illustrate the variability of the results). This high loss of N toward the beginning of the growth cycle was due to the large amount of N entering the soil at this time, via the felled palms from the previous cycle, the spreading of empty fruit bunches, and biological N fixation. The high variability in the magnitude and timing of the peak was due to differences in modelling approaches, especially the inclusion or otherwise of various N inputs and internal fluxes.

3.2 Comparison of the 29 sub-models

3.2.1 Losses through leaching and runoff

For this pathway, eight sub-models were tested (Fig. 3), which were all sub-models integrated in the comprehensive models. There were no stand-alone models focusing on this pathway. Banabas, Schmidt, and Meier-2014 models were not included in this comparison because they did not use specific sub-models but calculated leaching, runoff, and erosion as the surplus of the N budget. The average loss estimate of the eight sub-models was 59 kg N ha^{-1} yr^{-1}, with a −12 to 135 kg N ha^{-1} yr^{-1} range.

All eight sub-models considered leaching. Five models considered runoff, but this flux was very low, i.e. < 0.06 kg N ha^{-1} yr^{-1}, due to the assumption of a zero field slope. None of these models considered erosion. Therefore, the fluxes calculated for this pathway could be considered as leaching losses, and their variability mainly hinged on the way leaching was modelled. In comparison, field measurements of this pathway type range from 3.5 to 55.8 kg N ha^{-1} yr^{-1} (Fig. 4).

Without accounting for N inputs via empty fruit bunches application, atmospheric deposition, and biological N fixation, the average annual losses were estimated at 26 kg N ha^{-1} yr^{-1}. There was a substantial variation between sub-models, which spanned an overall range of −17 to 60 kg N ha^{-1} yr^{-1} (mean of six sub-models). When empty fruit bunches application was taken into account, the losses increased by an average of 3 kg N ha^{-1} yr^{-1} (mean of five sub-models). When biological N fixation was taken into account, the losses increased by an average of 18 kg N ha^{-1} yr^{-1} (mean of two sub-models).

In terms of temporal patterns (Fig. SM1 in the Supplement), APSIM estimated peak losses through leaching and runoff of up to 251 kg N ha^{-1} in the fourth year, when biological N fixation was taken into account. The peak losses through leaching estimated by SQCB-NO3 more than doubled (up to 103 kg N ha^{-1}) when empty fruit bunches application was taken into account. This peak of losses through leaching at the beginning of the cycle has also been observed in field measurements (Pardon et al., 2016).

In terms of spatial patterns, WANULCAS calculated that, of the 135 kg N ha^{-1} yr^{-1} lost through leaching, about 88 kg N ha^{-1} yr^{-1} came from the weeded circle surrounding the palm stem, where the mineral and organic fertilisers were applied; and about 31 kg N ha^{-1} yr^{-1} originated from the windrow where the trunks from the previous palms were left.

3.2.2 NH_3 volatilisation

For this pathway, nine sub-models were tested (Fig. 5). In this comparison, two sub-models were partial models not used in the 11 comprehensive models (EMEP-2013 and Bouwman-2002a). Two sub-models were used by several comprehensive models: Asman (1992) was used by Ecoinvent V3 and Meier-2014, and Agrammon was used by Ecoinvent V3 and Brockmann. Modelled estimates averaged 10.0 kg N ha^{-1} yr^{-1}, with a range of 5.4–18.6 kg N ha^{-1} yr^{-1}.

Whenever possible, we differentiated the influence of mineral fertiliser, empty fruit bunches, and leaves on the emissions. The average emissions from mineral fertiliser were estimated at 9.2 kg N ha^{-1} yr^{-1} (mean of eight sub-models). The emission factors for urea and ammonium sulfate differed considerably between models, ranging from 10 to 39 % and 1.1 to 15 %, respectively. However, in several cases these differences compensated for each other when total emissions from mineral fertiliser were calculated. For instance, emissions calculated using the Schmidt and Asman models were close, with 8.4 and 9.1 kg N ha^{-1} yr^{-1}, respectively, whereas their emission factors were very different, being 30 and 2 % in Schmidt and 15 and 8 % in Asman, for urea and ammonium sulfate, respectively. The average emissions from empty fruit bunches were estimated at 3.7 kg N ha^{-1} yr^{-1} (mean of four sub-models). However, these estimates were done with emission factors more adapted to animal manure than to empty fruit bunches. The emissions from leaves were estimated separately only by Agrammon, with a constant rate set by definition in the model at 2 kg ha^{-1} yr^{-1}. For comparison, field measurements of losses as NH_3 range from 0.1 to 42 kg N ha^{-1} yr^{-1} (Fig. 4).

In terms of temporal patterns, only the sub-models considering emissions from empty fruit bunches presented a peak which occurred over the first 2 years.

3.2.3 N_2O, N_2, NO_x emissions

For this pathway, 12 sub-models were tested (Fig. 6). Three of these sub-models were partial models not used in the 11 comprehensive models (Crutzen, EMEP-2013, and Shcherbak). Four sub-models were used in several comprehensive models: Nemecek-2007 was used in Ecoinvent V3 and Brockmann; and IPCC-2006 was used in Schmidt, Ecoinvent V3, Meier-2014 and Brockmann. The average estimate of combined N_2, N_2O, and NO_x emissions was 5.2 kg N ha^{-1} yr^{-1}, with a wide range from 0 to 19.1 kg N ha^{-1} yr^{-1}. This wide range could be explained partly because some sub-models estimated only N_2O or NO_x, while others calculated two or three of these gases jointly. Therefore, we did comparisons for N_2O and NO_x separately, in order to better understand the variability of the results. Emissions of N_2 were always calculated jointly with another gas, except for WANULCAS and APSIM. When possible, we also determined the influence of mineral fertiliser, empty fruit bunches, biological N fixation, plant residues, and soil inorganic N on emissions.

For N_2O, the average estimate of the outputs was 3.4 kg N ha^{-1} yr^{-1}, ranging from 0.3 to 7 kg N ha^{-1} yr^{-1} across eight sub-models (Fig. 7). The average contributions were estimated at 2.0 kg N ha^{-1} yr^{-1} for mineral fertiliser (mean of six sub-models), 0.8 for empty fruit bunches (mean of four sub-models), 0.5 for biological N fixation (mean of three sub-models), 1.6 for plant residues (mean of three sub-models), and 1.6 for soil inorganic N (one sub-model). In this range of results, it was difficult to identify the most suitable models. For instance, the Bouwman-2002b model seemed

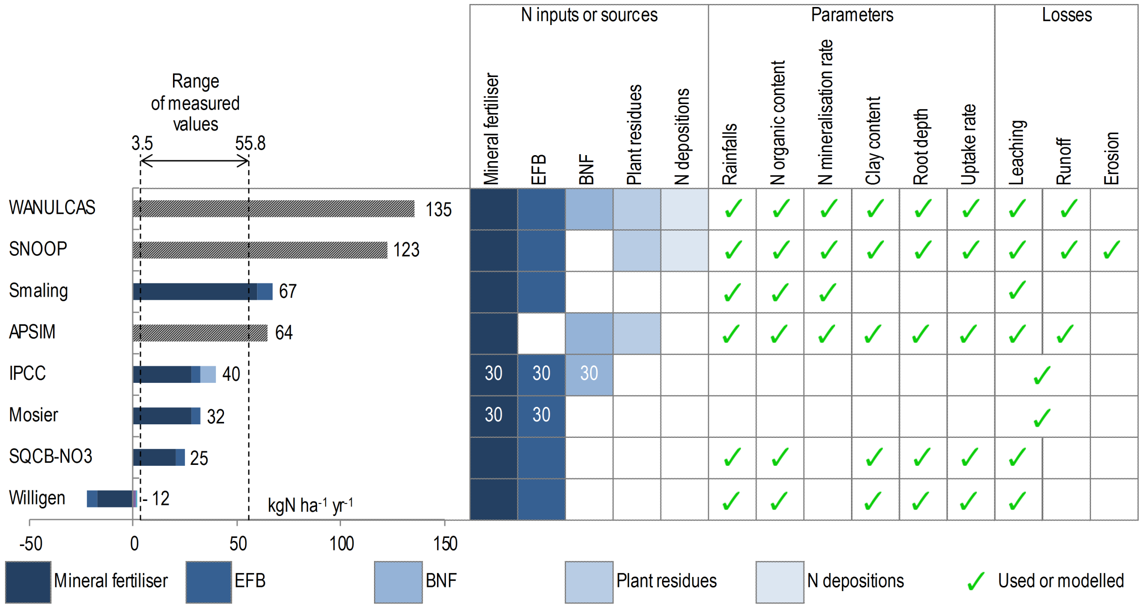


Figure 3. Comparison of annual average losses through leaching and runoff, estimated by eight sub-models. The average loss estimate was 59 kg N ha^{-1} yr^{-1}. The results represented mostly losses through leaching due to low values for runoff losses (< 0.06 kg N ha^{-1} yr^{-1}). The hatched bars represent calculations which include several sources at once: in WANULCAS, SNOOP, and APSIM, all sources are considered in the same calculation. Measured values are from Pardon et al. (2016). The table shows the N inputs and parameters used by the sub-models, and emission factors for linear relationships. Emission factors are in %; e.g. in IPCC-2006, leaching and runoff are 30 % of mineral N applied. BNF: biological N fixation; EFB: empty fruit bunches, i.e. organic fertiliser.

relevant as it used a climate parameter for the subtropical context. Shcherbak's model seemed relevant for oil palm management as it calculated losses as a non-linear function of N inputs, which avoids overestimating emissions when mineral fertiliser inputs were less than 150 kg N ha^{-1} yr^{-1}. However, the results were very different, being the highest for the former, with 7 kg N ha^{-1} yr^{-1}, and one of the lowest for the latter, with 0.8 kg N ha^{-1} yr^{-1}. For NO_x, the average estimate of the outputs was 1.4 kg N ha^{-1} yr^{-1}, ranging from 0.3 to 2.4 kg N ha^{-1} yr^{-1} across four sub-models (Fig. 8). In comparison, measurement-based estimates of the losses as N_2O range from 0.01 to 7.3 kg N ha^{-1} yr^{-1} (Fig. 4).

In terms of temporal patterns (Fig. SM2), the sub-models that included mineral fertiliser inputs only did not show any peak of emissions over the crop cycle, e.g. in Bouwman et al. (2002b), whereas the ones taking into account at least one other N input, such as felled palms, empty fruit bunches, and biological N fixation, showed a peak during the immature period, e.g. in Crutzen and APSIM. In field measurements, higher levels of losses through N_2O have also been observed at the beginning of the cycle (Pardon et al., 2016). With some sub-models the peak occurred during the first 3 years of the cycle, e.g. at 10 kg N ha^{-1} yr^{-1} in the second and third years in Crutzen, but in APSIM it occurred later, at 9 kg N ha^{-1} yr^{-1} in the fourth year.

3.3 Sensitivity analysis

For the leaching and runoff pathway, five out of eight sub-models were tested (Fig. 9). None of these sub-models took erosion into account. We therefore did not test the influence of slope. On average for the five sub-models, the most influential input variables were clay content, rooting depth, oil palm N uptake, and the IPCC emission factor, resulting in values of $\mu^* > 200$ kg N ha^{-1} yr^{-1}. For clay content, rooting depth, and oil palm N uptake, there were also high non-linearities and/or interactions with other variables, with $\sigma > 250$ kg N ha^{-1} yr^{-1}. In the case of clay content, the variability was substantial. It was very influential for SQCB-NO3 and de Willigen, with $\mu^* > 395$ kg N ha^{-1} yr^{-1} and $\sigma > 1200$ kg N ha^{-1} yr^{-1}, but had no influence on Smaling, which was not sensitive to clay content when it was less than 35 % (μ^* and σ being zero). Nitrogen inputs, through mineral fertiliser application, empty fruit bunches application, and biological N fixation, and rainfall had lower mean influence and lower non-linearities and/or interaction indices, μ^* ranging from 64 to 110 kg N ha^{-1} yr^{-1} and σ ranging from 40 to 141 kg N ha^{-1} yr^{-1}. Other input variables related to soil characteristics, such as carbon content and bulk density, had lower mean influences with $\mu^* < 45$ kg N ha^{-1} yr^{-1}.

For NH_3 volatilisation, seven out of nine sub-models were tested (Fig. 10). The influences of input variables were lower for this pathway than for leaching and runoff, with $\mu^* < 80$

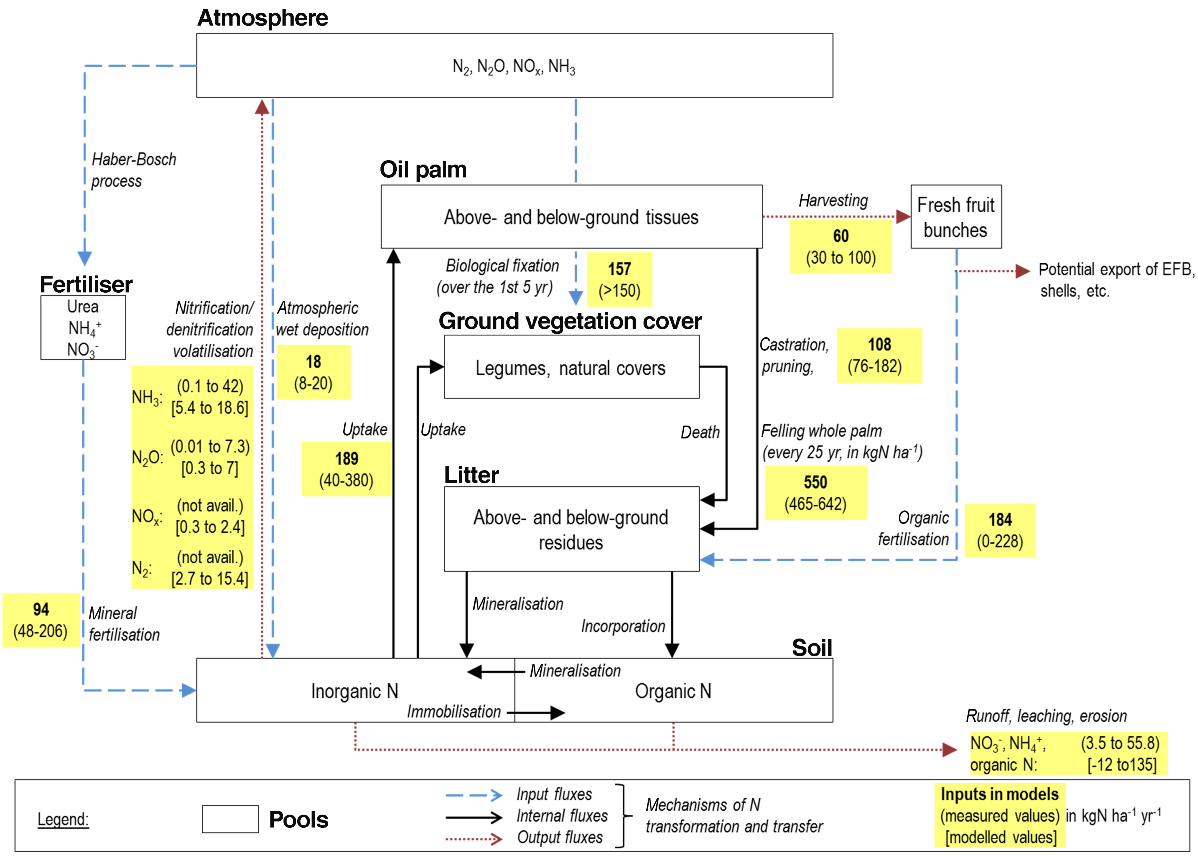


Figure 4. Comparison of measured and modelled N losses in oil palm plantations. The range of modelled values for leaching and runoff was wider than the one of measured values of leaching, runoff, and erosion. Modelled NH_3 volatilisation seemed underestimated; however the maximum value of 42 kg N ha^{-1} yr^{-1} was measured for mineral fertiliser applications of solely urea, while the rate of urea in our scenario was of 25 % of mineral fertiliser. Modelled N_2O emissions were similar to field measurements, although the minimum value was not as low. The pools are represented by the rectangles, and the main fluxes are represented by the arrows. Flux values are ranges given in kg N ha^{-1} yr^{-1}. Measured values are from Pardon et al. (2016). POME: palm oil mill effluent; EFB: empty fruit bunches.

and $\sigma < 35$ kg N ha^{-1} yr^{-1}. For the seven sub-models, the mean influences of variables related to organic fertiliser, i.e. emission factor and rate of application, were on average higher than for mineral fertiliser, i.e. emission factor, rate of application, and urea rate in fertiliser applied, with μ^* being 38–78 and 12–32 kg N ha^{-1} yr^{-1}, respectively. The interaction indices were also higher for organic fertilisers than for mineral fertilisers. Temperature and soil pH were less influential with $\mu^* < 2$ kg N ha^{-1} yr-^{1}.

For N_2, N_2O, and NO_x emissions, 7 out of 12 sub-models were tested (Fig. 11). The influences of input variables were lower for this pathway type than for the other two, with $\mu^* < 44$ and $\sigma <$ 19 kg N ha^{-1} yr^{-1}. However, the mineral fertiliser rate had a very high mean influence compared to the other pathway types, being μ^*: 44 kg N ha^{-1} yr^{-1} because one sub-model was very sensitive to the fertiliser application rate, i.e. μ^*: 283 kg N ha^{-1} yr^{-1} for Shcherbak. Most of the N inputs had a lower mean influence on emissions than emission factors, except for biological N fixation.

Across the three pathways, i.e. 19 sub-models, the five most influential variables were related to leaching and runoff losses (Fig. 12). These variables, which had μ^* greater than 100 kg N ha^{-1} yr^{-1}, were clay content, oil palm rooting depth, oil palm N uptake, and emission factors of IPCC-2006 and Mosier. Their interaction indices were also very high, except for the two emission factors. Mineral and organic fertiliser application rates and biological N fixation were the only input variables not specific to one pathway but used to simulate losses in all the three pathways. Soil pH, temperature, and other N inputs in soil, such as atmospheric N deposition, residues of legume, and oil palm, had lower influences on losses.

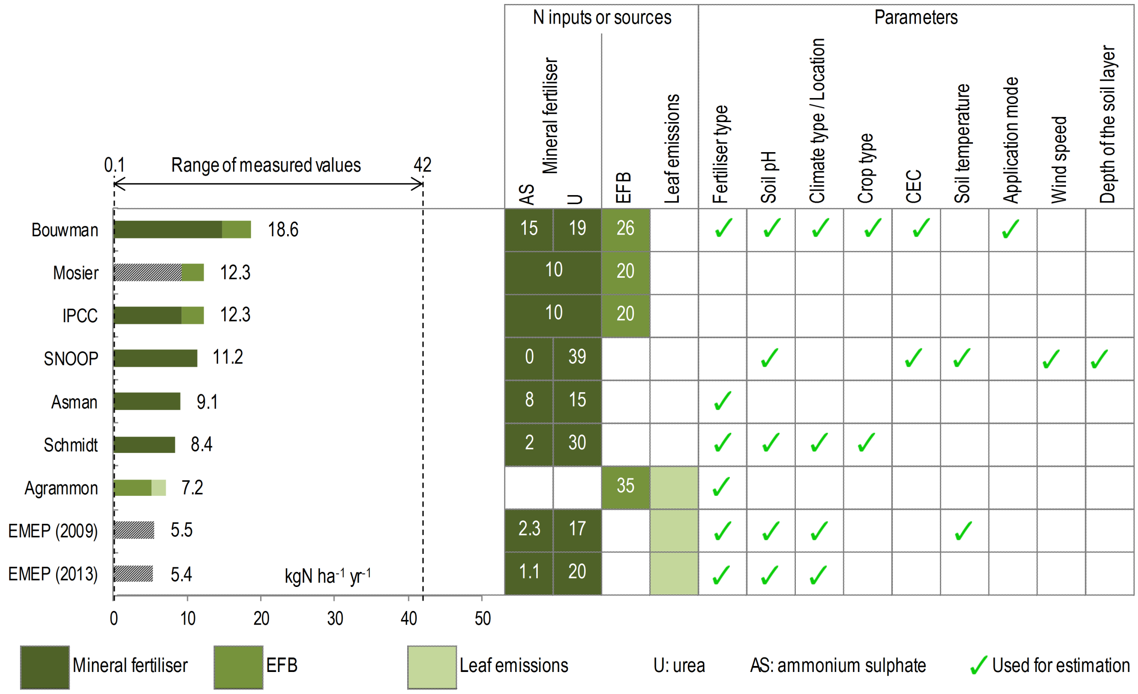


Figure 5. Comparison of annual average losses through NH_3 volatilisation, estimated by nine sub-models. The average emissions from mineral fertiliser were estimated at 9.2 kg N ha^{-1} yr^{-1}. The emission factors for urea and ammonium sulfate differed considerably between models, ranging from 10 to 39 % and 1.1 to 15 %, respectively. The hatched bars represent calculations that include several sources at once: in Mosier, NH_3 emissions from mineral fertiliser include NO_x emissions, and in EMEP-2009 and EMEP-2013, emissions from mineral fertiliser include those from leaves. Measured values are from Pardon et al. (2016). The table shows the N inputs and parameters used by the sub-models, and emission factors for linear relationships. Emission factors are in % of N inputs. EFB: empty fruit bunches, i.e. organic fertiliser.

4 Discussion

4.1 Relevance of model comparisons and flux estimates

The model comparison revealed large variations between models in the estimation of N losses from oil palm plantations. This variability was apparent a priori in the structures of the models, which were process-based or regression-based, had a yearly or daily time-step, and were more or less comprehensive in terms of processes accounted for. We may assume that other models exist, which we could not access or calibrate, but those tested very likely provide a representative sample of modelling possibilities for simulating the N budget of oil palm plantations. Some models were clearly operated beyond their validity domains, especially regression-based models for leaching. As this study did not aim to validate the robustness of the models, we did not filter out any of them as the overall set of model outputs helped highlight key fluxes and uncertainties. Further modelling work across contrasting plantation situations might be worthwhile to further test the validity of the models. In particular, nutrient, water, or disease stresses, or the impact of the previous land use, may critically influence the overall crop development and associated N budget.

The variability in model type or structure resulted in a large range of model outputs for the oil palm case simulated. There was an approximate 7-fold difference between the lowest and the highest overall N loss estimates. In order to investigate the plausibility of these estimates, we used a simple budget approach. Assuming that soil N content remained constant over the cycle, N inputs would equal N exported in fresh fruit bunches plus the increase in N stock in palms plus N lost. The assumption of constant soil N appears reasonable because soil N dynamics are closely related to soil C dynamics, and soil C stocks in plantations on mineral soil have been shown to be fairly constant over the cycle, especially when oil palm does not replace forest (Smith et al., 2012; Frazão et al., 2013; Khasanah et al., 2015). In our scenario based on measured values (Pardon et al., 2016), average N inputs, N exports, and N stored in palms were 156, 60, and 22 kg N ha^{-1} yr^{-1}, respectively. Assuming a constant N stock over the cycle, these values imply N losses of 74 kg N ha^{-1} yr^{-1}.

Based on this plausible estimate of 74 kg N ha^{-1} yr^{-1}, it was possible to identify three groups among comprehensive models: models which likely underestimated losses (IPCC-2006, Mosier, Ecoinvent V3, NUTMON), models which likely overestimated losses (SNOOP, WANULCAS),

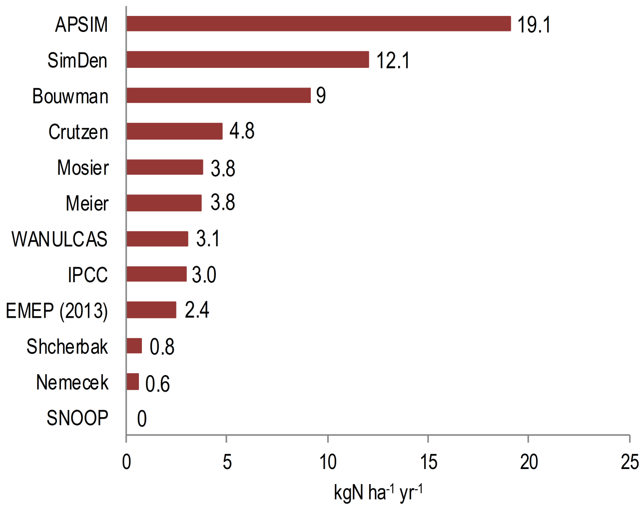


Figure 6. Comparison of annual average losses through N_2O, N_2, and NO_x emissions, estimated by 12 sub-models. The average estimate of combined N_2, N_2O, and NO_x emissions was 5.2 kg N ha^{-1} yr^{-1}. The wide range of 0 to 19.1 kg N ha^{-1} yr^{-1} could be explained partly because some sub-models estimated only N_2O or NO_x, while others calculated two or three of these gases jointly.

and models simulating a plausible amount of loss (Banabas, Meier-2014, Brockmann, APSIM, Schmidt).

Underestimates may be due to simulated leaching losses being too low. This was particularly clear for SQCB-NO3 and NUTMON, which used regressions not adapted to the high N uptake rates of oil palm, resulting in negative leaching losses in some instances. However, IPCC-2006, Mosier, and SQCB-NO3 estimated leaching losses within the of 3.5–55.8 kg N ha^{-1} yr^{-1} range of measured losses when considering leaching, runoff, and erosion combined (Fig. 4). All models seemed to underestimate NH_3 volatilisation compared with measured values (Fig. 4). However, this was due to the fact that the higher measured value of 42 kg N ha^{-1} yr^{-1} was for mineral fertiliser applications of solely urea, whereas the rate of urea in our scenario was 25 % of mineral fertiliser. For the IPCC-2006, Mosier, and SQCB-NO3 models, the underestimation may also be explained by the fact that none of them were complete in terms of N budgets. They accounted neither for all gaseous emissions, such as emissions of N_2, nor for all inputs, such as atmospheric deposition.

Overestimates of losses were primarily related to leaching losses, which were very high for both WANULCAS and SNOOP. This could result from interactions developing between modules in process-based models. For instance, the zoning of the palm plantation might have interacted with N inputs in WANULCAS, as the mineral N input from fertiliser was applied close to the palm trunks where water infiltration is likely to be higher due to stemflow. Another potentially important interaction involves N immobilisation and mineralisation in soil. Indeed, in WANULCAS, the mineralisation of residues and empty fruit bunches caused high losses through leaching in the first years of the crop cycle, while in APSIM, the immobilisation of N dominated the dynamics over several years and leaching losses were delayed and reduced to a large extent. However, more work is necessary to better understand how the structure of the models can lead to overestimate leaching.

Lastly, the models that came up with a plausible estimate of overall N losses, i.e. close to 74 kg N ha^{-1} yr^{-1}, showed large differences in single N flux sizes. APSIM estimated a plausible overall loss of 84 kg N ha^{-1} yr^{-1}, but its prediction of leaching seemed too large compared to measured values. This was very probably because some other fluxes were not taken into account, such as NH_3 volatilisation and N input through empty fruit bunches. Similarly, Meier-2014 and Brockmann output plausible overall loss estimates, but large leaching losses, while neither N_2 emissions nor N input through biological N fixation were taken into account. Schmidt and Banabas estimates seemed plausible and they accounted for most of the fluxes. Modelled N_2O emissions were similar to field measurements, although the minimum modelled emissions were still higher than the minimum losses measured in the field. Therefore, our results call for caution with regard to the choice of a single model to simulate N losses in oil palm. In absence of further empirical studies available to test these models, we would recommend using several models to predict N losses.

Some notable patterns differentiated process-based vs. regression-based models, and more comprehensive vs. less comprehensive models. The process-based models tended to predict higher overall losses and appeared to overestimate leaching losses. The less comprehensive models either seemed to underestimate overall losses, or tended to overestimate leaching losses, which counterbalanced missing fluxes in the N budget. Regarding leaching losses, the process-based models produced similar estimates to those that deduced these losses from the total balance.

Process-based models have the advantage of being able to simulate the impact of management practices, such as the timing, splitting, and placement of fertilisers. They also take into account other processes related to the N cycle, such as carbon cycling, plant growth, and water cycling. However such models need more data, e.g. related to soil characteristics. Furthermore, the interactions between modules may generate unexpected behaviours, e.g. for simulating leaching, and they are generally not easily handled by non-experts. On the other hand, simple models, such as IPCC-2006 and Mosier, have the potential to provide plausible results if some N fluxes were supplemented, without requiring a lot of data. However they cannot take into account peculiarities of oil palm or the effects of management practices. One way forward is the development of simple models, such as agro-ecological indicators based on the Indigo© concept (Girardin

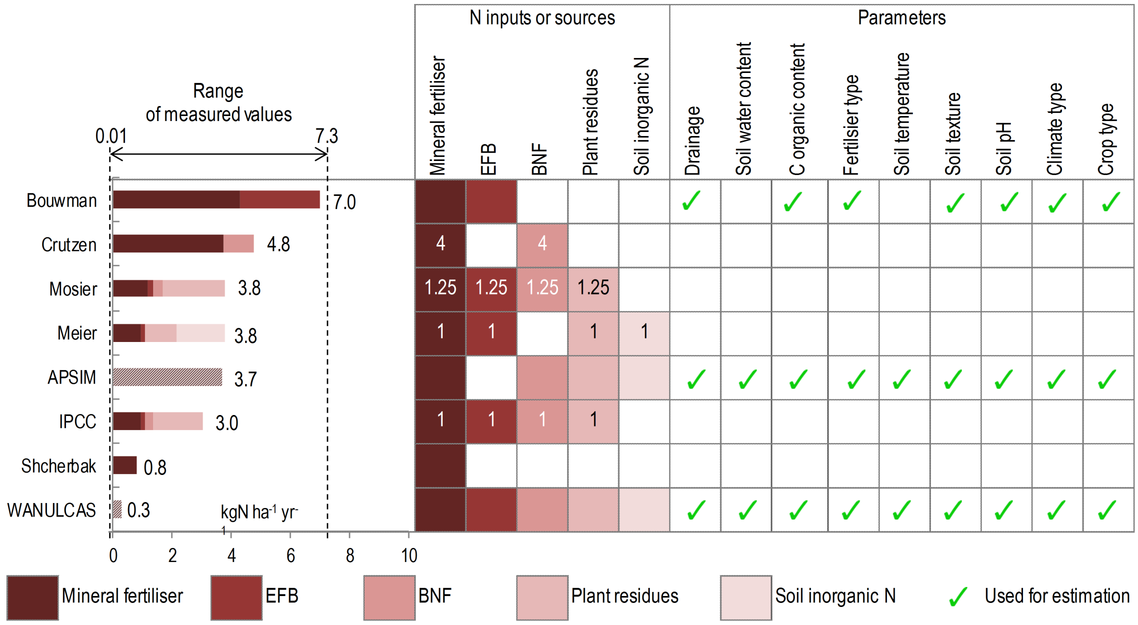


Figure 7. Comparison of annual average losses through N_2O emissions, estimated by eight sub-models. The average estimate was 3.4 kg N ha^{-1} yr^{-1}, ranging from 0.3 to 7 kg N ha^{-1} yr.$^{-1}$. For APSIM, all sources are considered in one calculation. Measured values are from Pardon et al. (2016). The table shows the N inputs and parameters used by the sub-models, and emission factors for linear relationships. Emission factors are in % of N inputs. BNF: biological N fixation; EFB: empty fruit bunches, i.e. organic fertiliser.

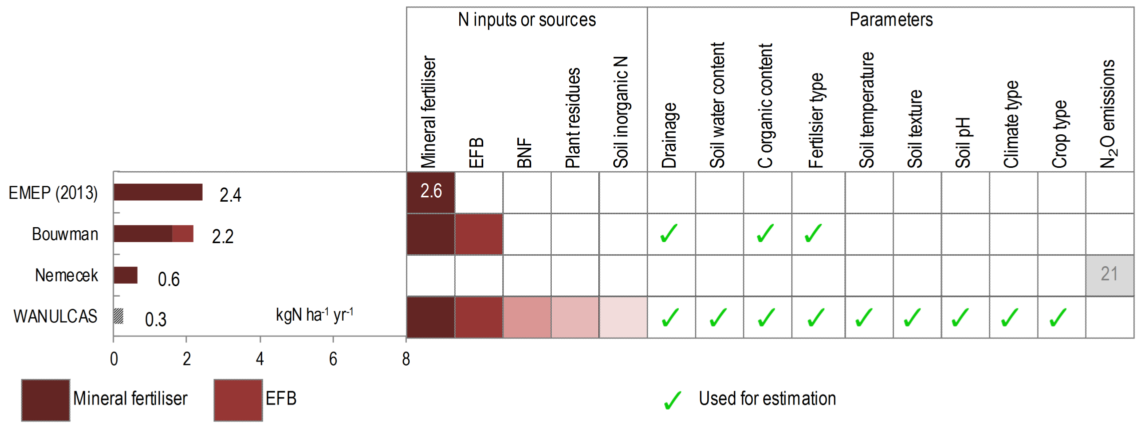


Figure 8. Comparison of annual average losses through NO_x emissions, estimated by four sub-models. The average estimate was 1.4 kg N ha^{-1} yr^{-1}, ranging from 0.3 to 2.4 kg N ha^{-1} yr^{-1}. For Nemecek-2007, all sources are considered in one calculation. The table shows the N inputs and parameters used by the sub-models, and emission factors for linear relationships. Emission factors are in % of N inputs. EFB: empty fruit bunches, i.e. organic fertiliser.

et al., 1999). These indicators are designed to be easy to use, while incorporating some specificities of crop systems such as management practices.

4.2 Challenges for modelling the N budget in oil palm plantations

We identified two important challenges for better modelling the N cycle in oil palm plantations: (1) to model most of the N inputs and losses while accounting for the whole cycle, and (2) to model particular processes more accurately by accounting for the peculiarities of the oil palm system (Table 2).

Given the changes in N dynamics, management practices, and N losses through the growth cycle of oil palm, it is important for models to be built in a way that accounts for this whole cycle. In particular, the immature phase is an important period to consider, as about a third of the N losses occurred during this phase according to the models. Measurements in the field have also shown losses to peak during this phase (Pardon et al., 2016), which involves large inputs of N

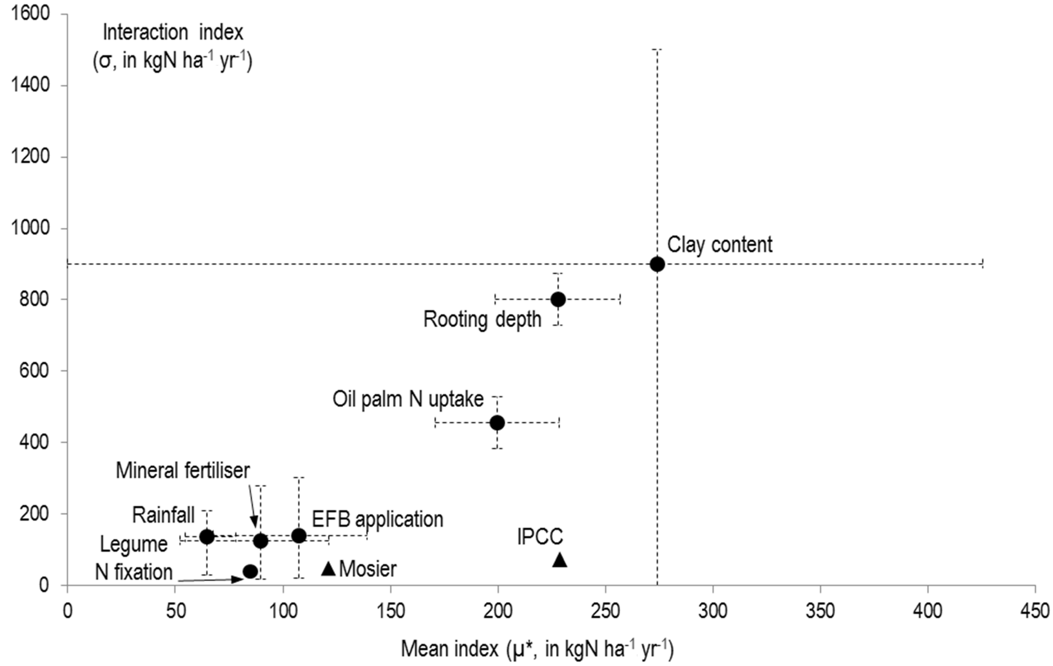


Figure 9. Morris's sensitivity indices for five sub-models calculating leaching and runoff losses. Clay content, rooting depth, and oil palm N uptake had high interaction indices, and they had the most important mean indices with IPCC (2006) emission factor. Sub-models tested: IPCC-2006, Mosier, Smaling, de Willigen, and SQCB-NO3. Indices lower than 50 kg N ha^{-1} yr^{-1} are not represented. Triangles: emission factors; circles: N inputs, oil palm and environment characteristics. EFB: empty fruit bunches, i.e. organic fertiliser.

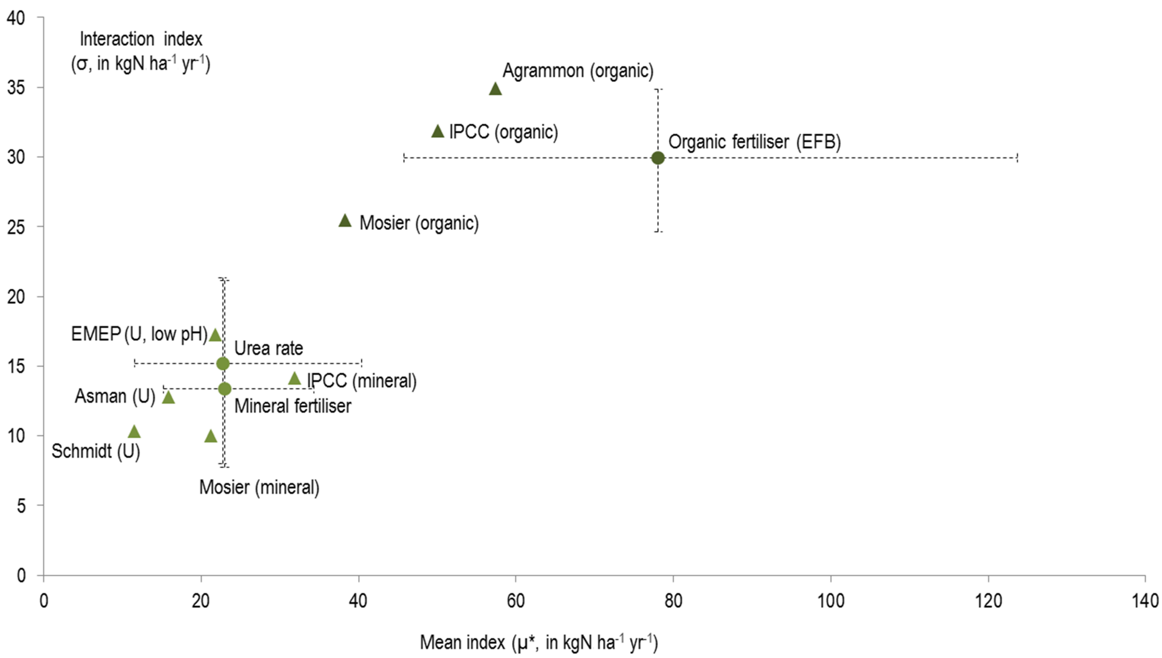


Figure 10. Morris's sensitivity indices for sub-models calculating NH_3 volatilisation. The input variables related to organic inputs (dark green) had higher Morris indices than mineral inputs (clear green). Sub-models tested: IPCC-2006, Mosier, Asman, Schmidt, Agrammon, EMEP-2009 and EMEP-2013. Indices lower than 10 kg N ha^{-1} yr^{-1} are not represented. Triangles: emission factors; circles: N inputs. AS: ammonium sulfate; U: urea; EFB: empty fruit bunches, i.e. organic fertiliser.

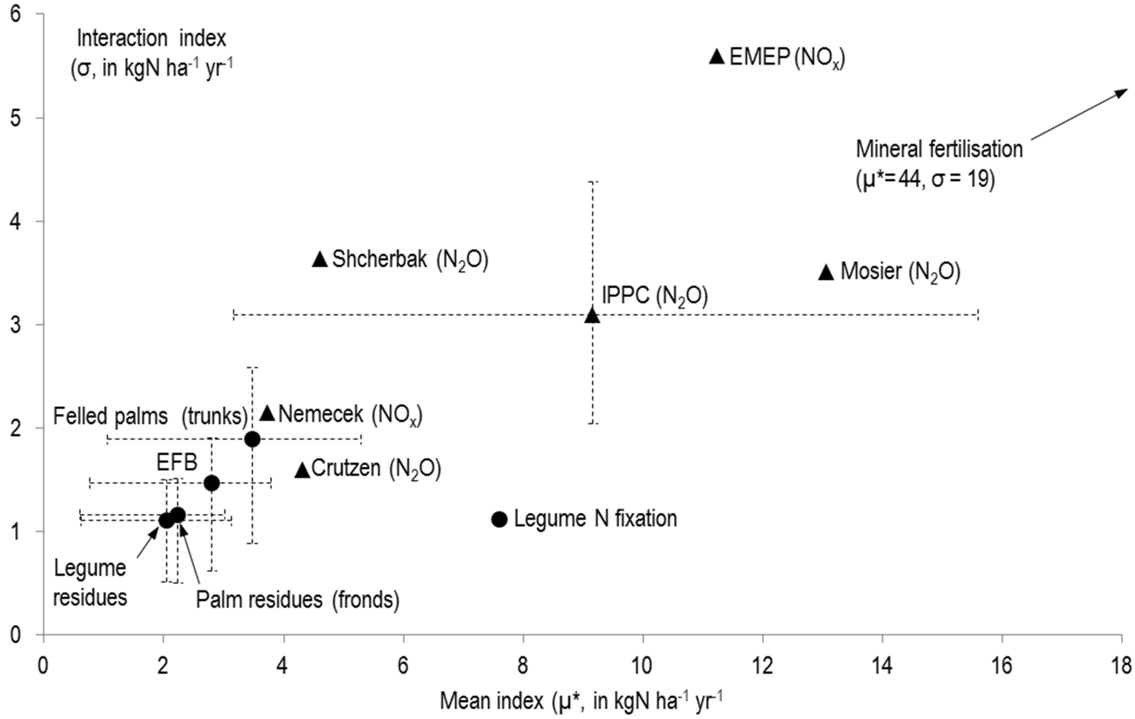


Figure 11. Morris's sensitivity indices for sub-models calculating N_2O, NO_x, and N_2 emissions. Mineral fertiliser application had the highest indices (out of this graph). For other input variables, emission factors (triangles) had higher Morris indices than N inputs (circles). Sub-models tested: Mosier, IPCC-2006, Crutzen, Meier-2014, EMEP-2013, Nemecek-2012. Indices lower than $2\,kg\,N\,ha^{-1}\,yr^{-1}$ are not represented. EFB: empty fruit bunches, i.e. organic fertiliser.

from the felled palms, the spreading of empty fruit bunches, and biological N fixation. This results in complex N dynamics on the understorey crop, litter, and soil components of the ecosystem. Regarding N inputs, it seems important to also account for biological N fixation and atmospheric deposition since their contributions to the N budget were not negligible, besides fertiliser applications. Internal fluxes, such as the decomposition of felled palms and residues of oil palm and groundcover, are among the largest fluxes in the oil palm system, and their influence on N dynamics is substantial (Pardon et al., 2016). In the case of a new planting, the impacts of land use change and land clearing might also need to be further investigated to better quantify the input fluxes due to decomposition as well as the influence of transitional imbalance state of the agroecosystem on N loss pathways.

For N losses, further model development is also needed to close the N budget. First, it would be worthwhile to model erosion without requiring detailed input data, while accounting for changes in erosion risk through the crop cycle and the effects of erosion control practices on N dynamics. Erosion was not modelled independently of other losses in most of the reviewed models. Further, NH_3 emissions from leaves could easily be included. Finally, despite the difficulties of understanding and simulating the complexity of processes driving N_2O emissions (Butterbach-Bahl et al., 2013), N_2O, NO_x, and N_2 should be modelled in a more comprehensive and systematic way. In particular, N_2O emissions, and thus presumably NO_x and N_2 emissions, have high spatial and temporal variability (Ishizuka et al., 2005). Parameters related to fertiliser application are therefore not the only drivers of these emissions, as surmised in the simple models. Since the time resolution of N_2O measurements in the field influences the cumulative emissions recorded for this gas significantly (Bouwman et al., 2002b), it is paramount to model those N losses accounting for the changes in driving parameters over the whole crop cycle.

Finally, losses should not be calculated jointly if the objective is to assess the environmental impacts of the plantation and to identify those practices most likely to reduce N losses and impacts. Indeed, different N fluxes may lead to different N pollution risks. N losses through erosion, runoff, or leaching do not end up in the same environmental compartments, e.g. surface water vs. groundwater. They hence do not contribute in the same way to potential environmental impacts such as eutrophication. For the purpose of environmental assessment, models should hence be as comprehensive and detailed as possible. Regarding these criteria, the Schmidt model appeared the most comprehensive and detailed one, as it distinguishes between six N fluxes. However, this model could be improved by separately modelling losses

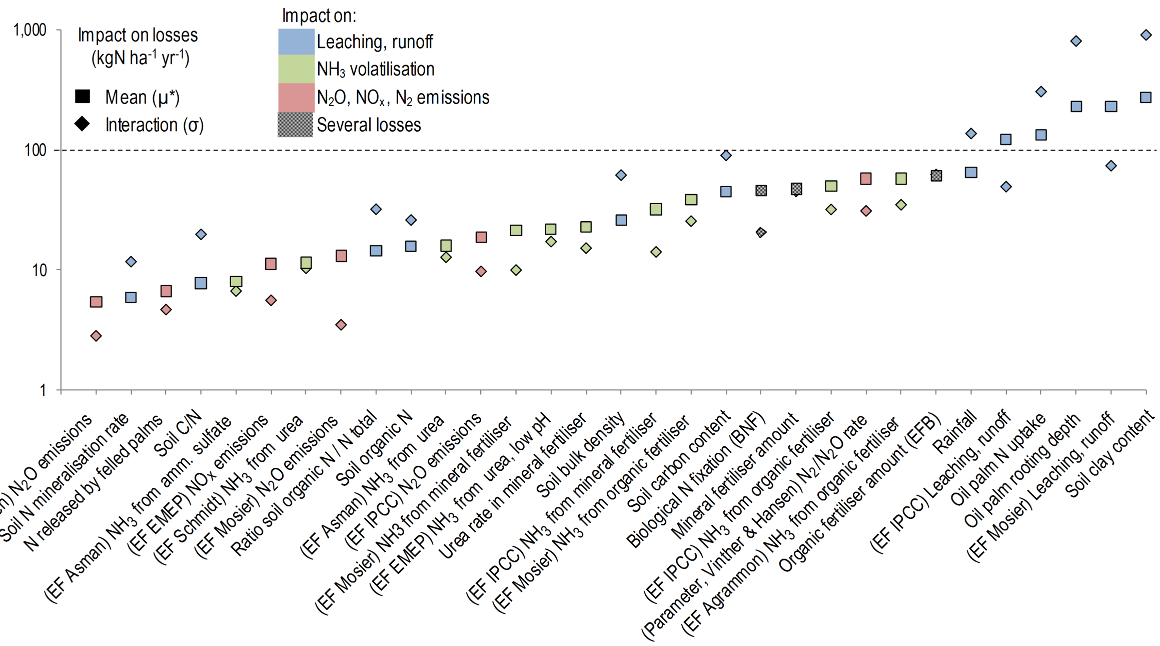


Figure 12. Average Morris indices for 31 variables of the 19 sub-models. The five variables with the highest influence ($\mu^* > 100\,\mathrm{kg\ N\,ha^{-1}\,yr^{-1}}$) were related with leaching and runoff losses (logarithmic scale). Variables were ranked by increasing mean sensitivity index (μ^*). The mean effect (μ^* squares) was an estimation of the linear influence of the variable on losses. The interaction effect (σ, diamonds) was an estimation of non-linear and/or interaction effect(s) of the variable on losses. Variables with $\mu^* < 5\,\mathrm{kg\ N\,ha^{-1}\,yr^{-1}}$, i.e. 16 variables, are not represented. EF: emission factor; BNF: biological N fixation; EFB: empty fruit bunches, i.e. organic fertiliser.

through erosion, runoff, and leaching, i.e. calculating a total of eight N fluxes.

The second challenge is to improve the modelling of some of the key N cycling processes, while accounting for the peculiarities of the oil palm system. Regarding internal fluxes, a better representation of the interaction between legumes and soil N dynamics is an important challenge, as the actual role of legumes during the immature period is complex and not fully understood yet. Indeed, legumes have the capacity to regulate their N provision, by fostering N fixation or N uptake, depending on soil nitrate content (Pipai, 2014; Giller and Fairhurst, 2003). They may contribute to the reduction of N losses through immobilisation or to their increase through N fixation and release.

Reducing the uncertainty in the modelling of leaching is an important challenge, as about 80 % of the total losses came from leaching, according to the models, and results were very variable across models. Models should be better adapted to the oil palm systems, as some regression models clearly appeared out of their validity domain. Further research on leaching prediction should focus on the effects of soil clay content, oil palm rooting depth and oil palm N uptake, since they emerged as the most influential variables according to the sensitivity analysis. The −90 to +90 % relative variation range used in the latter for the parameters that were not given a specific range may appear as a rather extreme set of values, but it made it possible to encompass a wide range of conditions. The sub-models included in the sensitivity analysis were regression models that did not explicitly simulate N cycling processes, resulting in a lack of influence of some parameters that may affect leaching in practice and in process-based models. Therefore, it could be interesting to perform complementary sensitivity analyses focused on process-based models, such as APSIM.

In order to take into account the influence of management practices on internal fluxes and losses, it would be necessary to use a daily step approach, to account for the timing or splitting of N fertiliser applications. Modelling approaches that incorporate spatial heterogeneity, as in WANULCAS, should be favoured, to assess the effect of fertiliser or empty fruit bunch placements. For gaseous losses, emission factors could be adapted to the oil palm system, as all of them, i.e. for NH_3 or N_2O / NO_x fluxes, were based on data from temperate areas on mineral soils, including mostly animal manure as reference for organic fertilisers. On a general note, more field measurements and model development are needed to account for the peculiarities of palm plantation management on peat soils. They involve substantial and potentially widespread areas, notably in Indonesia (Austin et al., 2015). Those plantations require specific management, including complex drainage systems, and may entail severe pollution risks, notably leaching, which are not yet properly accounted for in current models, e.g. IPCC-2006.

Table 2. Synthesis of the challenges identified in modelling the N cycle in oil palm plantations. BNF: biological N fixation.

Challenges	Recommendations for modellers	Data available and lacking
To better understand and model the N cycle during the immature period	– To better model the magnitude and the timing of the peak of emissions – To better understand and model the dynamics of N release from the residues, and the dynamics of legume N fixation, uptake, and release	– Measurements of kinetics are available for residue decomposition (Pardon et al., 2016) – Knowledge is lacking concerning fluxes of N between legumes and soil, and actual losses over this period (Pardon et al., 2016)
To better model the main losses through leaching, runoff, NH_3 volatilisation, and N_2O emissions	Leaching and runoff: – To favour a modelling approach using soil layers to obtain more precise estimates – To favour a daily step approach to model the influence of timing and splitting of fertiliser application – To focus on the most influential variables: soil clay content, oil palm rooting depth, and oil palm N uptake NH_3 volatilisation: – To select emission factors more relevant to tropical conditions and perennial crops	N_2O emissions: data are still lacking for tropical conditions (Pardon et al., 2016) to allow evaluation of the models
To model most of the N fluxes in order to complete the N cycle	– For input fluxes: include atmospheric N deposition and BNF – For internal fluxes: include felled palms from the previous cycle, and all the palm residues (fronds, inflorescences, roots) – For losses: to model erosion without requiring too much data, to consider NH_3 emissions from leaves, to model NO_x and N_2 even with simple models already available	– Measurements of quantities and kinetics of decomposition are already available for internal fluxes (Pardon et al., 2016). – Measurements under oil palm are lacking for NO_x and N_2 (Pardon et al., 2016)
To favour ways of modelling adapted to oil palm specificities and to the objectives of the modelling	– To favour models accounting for the whole cycle – To favour a daily step approach and to integrate the spatial heterogeneity, in order to account for the influence of fertiliser management better – To favour low data requirement models so they can be run easily – To estimate the losses separately via each pathway to calculate its impact and to identify potential mitigation practices	

4.3 Implications for management

The main levers that managers can use to reduce N losses involve the level of inputs, including fertiliser management, but also the handling of the immature phase. To manage fertiliser inputs, managers need to know the economic response, which is the main driver of practices, and the environmental response, to type, rate, timing, and placement. They may decide on the optimum fertiliser management practices based on these two dimensions. Models that include both N losses and fresh fruit bunch production in relation to management scenarios can provide the information needed to evaluate both responses.

The model comparison showed the importance of the immature phase with respect to N losses, and suggested field research lines and modelling approaches to improve our understanding of loss processes and their estimation. There are also direct implications of our results for crop management during this phase. Light, water, and N are not fully used by the young palms, as their canopies and root systems do not cover the available ground in the field. Thus, in the current systems, the combination of high input rates with suboptimal resource capture capacity of the growing oil palms in the immature period results in high losses and negative environmental impacts. There are two possible approaches for reducing those. One is to reduce the inputs: for instance, it might be better to plant a non-legume cover crop and to manage N supply to the palms only with fertilisers. An alternative approach would be to grow another crop during this phase, which would use the surplus N and either export it in product or take it up in biomass so that it would decompose later. For instance, for fast-growing trees like balsa, trunks could be harvested after 5 years and exported, whilst leaving some branches, leaves, and roots to decompose on the soil.

There are also re-planting systems that make it possible to combine old and young palm trees in the same plantation block. The advantage can be both economic and agroecological as the immature phase actually becomes productive thanks to the remaining old palm trees and the nutrient cycling potentially more competitive. However, there is still limited data available to quantify and model the potential competition and adapt fertiliser management. Moreover, potential reduction in N losses should not come at the cost of increased use of herbicides, which may be used to kill the old palm trees without damaging the newly planted ones.

From the environmental point of view, it is also important to consider fertiliser management and N losses within a wider system and value chain. First, fertilisers encompass residues from the mill, whose environmental costs and benefits to the plantation should be considered from a whole life cycle perspective. This would include the production of waste, transport, or avoided impact through the substitution of synthetic fertilisers, etc. This can be done using life cycle assessments. Second, the carbon balance, i.e. the balance of carbon sequestration and release, is closely coupled to the N balance. Thus, models that include both cycles are warranted to fully evaluate the environmental impacts of oil palm production.

5 Conclusions

N losses are a major concern when assessing the environmental impacts of oil palm cultivation, and management practice targeted at reducing N losses and costs is critical to this industry. Modelling N losses is crucial because it is the only feasible way to predict the type and magnitude of losses, and thus to assess how improved management practices might reduce losses. Our study showed that there were considerable differences between existing models, in terms of model structure, comprehensiveness, and outputs. The models that generate N loss estimates closest to reality were the most comprehensive ones, and also took into account the main oil palm peculiarities, irrespective of their calculation time step. However, in order to be useful for managers, a precise modelling of the impact of management practices on all forms of N losses seems to require the use of a daily time step or the modelling of spatial heterogeneity within palm plantations. The main challenges are to better understand and model losses through leaching, and to account for most of the N inputs and outputs. Leaching is the main loss pathway and is likely to be high during the young phase when inputs are high due to decomposition of felled palms and N fixation by legumes. Field data are still needed to better understand temporal and spatial variability of other losses as well, such as N_2, N_2O, and NO_x emissions, in the context of oil palm investigations. These improvements could allow managers to evaluate the economic and environmental impacts of changes in management, such as, for instance, modifying fertiliser inputs or the plant cover type during the immature phase.

6 Data availability

Research data may be made available upon request to the corresponding author.

The Supplement related to this article is available online at doi:10.5194/bg-13-5433-2016-supplement.

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