

IN-Palm: an agri-environmental indicator to assess nitrogen losses in oil palm plantations

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Abstract

Oil palm, *Elaeis guineensis* Jacq., is currently cultivated on 19 M ha and palm oil represents more than one-third of the global vegetable oil market. Addition of nitrogen via legume cover crop and fertilizers is a common practice in industrial oil palm plantations. Part of this added nitrogen is prone to loss from the field, contributing significantly to environmental impacts. To improve the sustainability of palm oil production, it is crucial to determine which management practices minimize N losses. Continuous field measurements would be prohibitively costly as a monitoring tool, and in the case of oil palm, available models do not

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account for all the potential nitrogen inputs and losses or management practices. In this context, we developed IN-Palm, a model to help managers and scientists estimate nitrogen losses to the environment and identify best management practices. The main challenge was to build the model in a context of knowledge scarcity. Given these objectives and constraints, we developed an agri-environmental indicator, using the INDIGO® method and fuzzy decision trees. We validated the nitrogen leaching module of IN-Palm against field data from Sumatra, Indonesia. IN-Palm is implemented in an Excel® file and uses 21 readily available input variables to compute 17 modules. It estimates annual emissions and scores for each nitrogen loss pathway and provides recommendations to reduce nitrogen losses. IN-Palm predictions of nitrogen leaching were acceptable according to several statistics, with a tendency to underestimate nitrogen leaching. However, we highlighted necessary improvements to increase IN-Palm precision before use in plantations.

Core ideas

- We used INDIGO® method and fuzzy decision trees to develop IN-Palm indicator
- IN-Palm is run in Excel® using 21 input variables to estimate 6 loss pathways of N
- N leaching predictions against field data were acceptable, although underestimated
- IN-Palm outputs were sensitive to management changes and climate variability

1. Introduction

Oil palm is an important crop for global production of vegetable oil and for the economies of many tropical countries. The area of land under oil palm is currently about 19 M ha (FAOSTAT, 2014) and palm oil represents more than one third of the global vegetable oil market (Rival & Levang, 2014). Over the period 1990-2010, rapid expansion of the area cultivated to oil palm was associated with deforestation and oxidation of peat soils, contributing to greenhouse gases emission, mainly in Indonesia and Malaysia (Carlson et al., 2012; Koh, Miettinen, Liew, & Ghazoul, 2011; Miettinen et al., 2012).

Oil palm is very productive and addition of nitrogen (N) via legume cover and fertilizers is a common practice to maintain productivity and avoid depleting soil resources. Rates of N fertilizer application can amount to 100 to 200 kg N ha yr⁻¹ under adult palms, and application of fertilizers accounts for a large share of the production costs, ranging between 46 % and 85 % of field costs (Pardon, Bessou, Nelson, et al., 2016). A part of fertilizer-

derived N is prone to be transferred to be lost from the field and can contribute significantly to environmental impacts, such as eutrophication, acidification and climate change (Schmidt, 2010; Choo et al., 2011; Comte, Colin, Whalen, Gruenberger, & Caliman, 2012; Corley & Tinker, 2015). N compounds that are particularly important include ammonia (NH_3), nitrous oxide (N_2O), which is a potent greenhouse gas, and nitrate (NO_3^-), which is well known to affect aquatic ecosystem functioning.

To improve the sustainability of palm oil production systems, it is crucial to determine which management practices minimize N losses. Because N losses involve numerous compounds and impact pathways and are temporally and spatially highly variable, monitoring them with field measurements is prohibitively expensive. On the other hand, models can be useful to estimate potential losses based on current knowledge. However, in the case of oil palm plantations, there is insufficient knowledge to appraise all loss mechanisms. Available models do not account for all the potential N inputs and losses or management practices, such as residue and cover crop management. This leads to high uncertainty in N loss estimations (Pardon, Bessou, Saint-Geours, et al., 2016). In this context, we decided to develop a model specific to oil palm that estimates all potential N losses to the environment, as influenced by management practices, throughout the whole crop cycle.

Given our objectives and constraints, we decided to develop an indicator derived from the nitrogen indicator of the INDIGO® method for developing agri-environmental indicators (C. Bockstaller & Girardin, 2008; C. Bockstaller, Girardin, & van der Werf, 1997). Such indicators are more suitable than process-based models for use in conditions with knowledge scarcity, as they use a limited number of input variables, while harnessing readily accessible data from a range of sources, such as measured or modeled, qualitative or quantitative, empirical or expert knowledge (P. Girardin, Bockstaller, & Werf, 1999). In their typology of indicators, C. Bockstaller, Feschet, & Angevin (2015) described such indicators as predictive effect-indicators based on an operational model, differing from causal indicators using one or simple combination of input variables and measured effect indicators. This kind of indicator also has the advantage of being sensitive to practices and allowing ex-ante assessments in the form of simulations. Thus, even if estimates made by indicators are less precise than those made by the best process-based models, they may be sufficient to assess environmental risks and to support decisions based on site-specific practice levers.

This paper describes our development of an agri-environmental indicator, IN-Palm, designed to enable managers of oil palm plantations to answer the question: “what practices can I implement in this field, this year, to reduce N losses, given the environmental conditions, characteristics of the field, and long-term consequences of previous practices?”. IN-Palm

was derived from the INDIGO® indicator for N risk assessment in vineyards. A preliminary adaptation of the INDIGO® N indicator to oil palm had been done by Carcasses (2004), but it was incomplete as it estimated only three types of N loss, i.e. N leaching, NH₃ volatilization and N₂O emissions, and only for oil palm plantations older than 7 years. It did not use fuzzy logic and had not been validated against field data. In order to improve the extent and relevance of the risk assessment, we now account for all the loss pathways throughout the complete crop cycle. In order to address the lack of knowledge and to include all the available and relevant data, we used a decision tree modeling approach (Breiman, 1984) to design most of the indicator modules, combined with fuzzy logic (Zadeh, 2008) to obtain a more realistic and sensitive output space. Fuzzy decision tree modeling approach has already been used for agri-environmental modeling (e.g. van der Werf & Zimmer, 1998, for the pesticide indicator of the INDIGO® method; see Papadopoulos, Kalivas, & Hatzichristos, 2011, for a detailed example of the method applied to N balance in agriculture). Here, we present the design, calibration and validation of IN-Palm. We finally discuss the results of scenario testing aimed at assessing the sensitivity of the indicator to management practices, and hence its usefulness as a decision-making tool for field management.

2. Materials and methods

2.1. INDIGO® method and fuzzy decision tree modeling approach

The development of INDIGO® agri-environmental indicators started in the 90's (C. Bockstaller et al., 1997; P. Girardin & Bockstaller, 1997) and has resulted in a set of agri-environmental indicators (C. Bockstaller et al., 2009, 2008). The original concept was to build operational models that would be efficient to improve agricultural management practices, despite the lack of knowledge to model all soil-plant-atmosphere transfer mechanisms involved in agroecosystems.

INDIGO® indicators are generally structured as a set of risk (R) modules, each yielding an output, e.g. the R-N₂O module estimates the risk linked to nitrous oxide emissions. As indicators must be readily understandable by non-experts, it was proposed that the outputs be expressed not in physical units but in dimensionless scores on a scale of 0 to 10, calculated with respect to reference values. The reference values represent minimum values of the indicator output for which the agroecosystem is considered to be sustainable (C. Bockstaller et al., 1997).

To develop IN-Palm, we followed the five-step methodology proposed by Girardin et al. (1999): (1) identification of the objectives and end-users, (2) construction of the indicator,

(3) selection of reference values, (4) sensitivity analysis, and (5) validation of the indicator, i.e. demonstration that the indicator satisfies the target objectives. The objective of IN-Palm is to serve as a decision-support tool for oil palm plantation managers to help them minimize risks of N loss to the environment.

We also introduced the new approach of decision tree modeling for most of the modules. Decision tree modelling (Breiman, 1984) is particularly suitable here, as it enables quantitative outputs to be obtained without simulating the actual processes that are not fully understood, but by instead integrating expert knowledge as rules. One of the limits of standard decision trees, though, is that their output space is discontinuous. Indeed, the model may react abruptly to a small variation of input, i.e. with a threshold effect between limit of classes (Christian Bockstaller, Beauchet, Manneville, Amiaud, & Botreau, 2017), while the actual system may react more smoothly. Or it may not react, due to a too-coarse class structure, while the actual system does react. In order to obtain a more realistic output space, the modeller needs to increase the number of rules, which requires more knowledge and quickly increases the complexity of the model (Craheix et al., 2015). Application of fuzzy logic (Zadeh, 2008) to decision trees is a very efficient method in such a context, as continuous outputs can be obtained from exactly the same tree structure, without requiring more knowledge (Olaru & Wehenkel, 2003). Another advantage of the method is that this process of aggregation is transparent and reproducible.

To build and compute our fuzzy decision tree modules we used the same method as van der Werf & Zimmer (1998). First, for each module, the choice of the input variables, the structure of the tree, the conclusions of the rules, and the threshold values between classes were defined by expert judgment, using all available knowledge. Second, for each input factor, we defined two classes: Favourable and Unfavourable. More classes for each factor would require more knowledge to justify the threshold values, whereas preliminary tests, using the Fispro software (Guillaume & Charnomordic, 2010), showed that precision in outputs was not significantly improved. Third, we used a cosine function for all membership functions, because this produces a smoother and more realistic transition between the two classes than a linear function, without requiring more parameters (van der Werf & Zimmer, 1998). Fourth, to deduce the outputs of each module, we used Sugeno's inference method (Sugeno, 1985).

2.2. Modeled processes

Recent studies have identified important peculiarities of N dynamics and losses in oil palm plantations. First, published measurements show that N dynamics and N losses vary over the cycle, with highest losses reported under young plantations (Pardon, Bessou, Nelson, et al., 2016).

Second, a legume understorey, e.g. *Pueraria phaseoloides* or *Mucuna bracteata*, is generally sown at the beginning of the growth cycle, and the N fixed by the legume was identified as one of the largest N fluxes (Pardon, Bessou, Nelson, et al., 2016). The amount of legume understorey was also reported to be one of the most influential parameters on N losses before 7 years of age in a sensitivity analysis of APSIM-Oil palm simulation model (Pardon et al., 2017). Moreover, in a range of models compared, N fixation was always modeled with constant fixation rates (Pardon, Bessou, Saint-Geours, et al., 2016), while in the field, legumes usually have the capacity to regulate their N provision, by fostering N fixation or N uptake from soil, depending on soil mineral N content (Giller & Fairhurst, 2003).

Third, internal N fluxes within the agroecosystem, such as N released during decomposition of palm residues, were identified among the largest N fluxes (Pardon, Bessou, Nelson, et al., 2016). Moreover, the modeling, or not, of the kinetics of residue N release to the soil had a significant impact on the magnitude and timing of the first peak of losses simulated by several models (Pardon, Bessou, Saint-Geours, et al., 2016).

Fourth, N losses were reported to have a high variability, depending, among others, on management practices and spatial variability (Pardon, Bessou, Nelson, et al., 2016). For instance, the amount of understorey vegetation, or the placement of residues on the ground, may affect runoff and erosion.

We designed IN-Palm in order to account for the peculiarities of the oil palm system and obtain a complete estimate of N losses: (1) modeling of all loss pathways at all crop ages ; (2) modeling the contribution of the legume understorey in one specific module, with N fixation rate depending on mineral N available in soil; (3) modeling the kinetics of litter decomposition and N release in soil with two intermediate modules; and (4) accounting for the spatial effect of management practices, in a module estimating NH_3 volatilization and an intermediate module estimating the fraction of soil covered.

2.3. Data used for design, calibration, reference values and validation

Different sources of data were combined for four different purposes: (1) to design the structure of the indicator, (2) to calibrate modules, (3) to define reference values for losses,

and (4) to validate the R-Leaching module and test scenarios. For each of these purposes, one or several sources of data were used (Table 1).

For design of the structure, calibration of the modules, and definition of reference values, we mainly used three sources of data: measurements of N fluxes and losses in oil palm plantations synthesised in a literature review (Pardon, Bessou, Nelson, et al., 2016); qualitative and quantitative data from a range of models used for estimating N losses in oil palm and assessed in a model comparison (Pardon, Bessou, Saint-Geours, et al., 2016); and expert knowledge from a panel of experts.

For design of the structure and module calibrations, we also used existing models. We used two regression models, one for estimating NH_3 volatilization from organic fertilizer (Bouwman, Boumans, & Batjes, 2002a) and the other for NO_x emissions (Bouwman, Boumans, & Batjes, 2002b). To calibrate the N_2O emission modules we used the factors and classes defined in (Stehfest & Bouwman, 2006) model of N_2O emissions. Finally, we used a dataset of 58,500 simulations (Pardon et al., 2017), from the APSIM-Oil palm process-based model (Huth, Banabas, Nelson, & Webb, 2014), for the calibration of the Palm N Uptake module and estimation of evapotranspiration in the Soil Water Budget module. APSIM-Oil Palm was the only process-based model validated for oil palm production which also included a prediction of N fluxes and evapotranspiration. In the absence of studies monitoring the dynamics of palm N uptake and evapotranspiration over the whole growth cycle of palms, APSIM-Oil Palm hence appeared to be the most robust source available to estimate these fluxes for different ages.

For calibration of the R-Runoff-Erosion module, validation of the R-Leaching module, and the scenario testing, we used three measurement datasets from an oil palm plantation in Sumatra, Indonesia. The first dataset was from a 2-year-long trial investigating the response of N losses, via runoff and erosion, to slope and soil cover management under adult oil palms (Sionita, Pujiyanto, Bessou, Gervillier, & Caliman, 2014). The results of this trial were available in an aggregated format, and we used them for the calibration of the R-Runoff-Erosion module. The second dataset, described in more detail below, was from an 8-year-long trial in which N concentrations in soil solution were measured. We used this dataset for the validation of the R-Leaching module. The third dataset was a 16-year-long rainfall record and soil characteristics, already used in a model comparison (Pardon, Bessou, Saint-Geours, et al., 2016). We used this dataset to perform scenario testing of IN-Palm.

The trial in which N concentrations in soil solution were measured was conducted between 2008 and 2015 in a mature oil palm field. Nitrate and ammonium concentrations were

measured in soil solution at three depths (0.3, 1 and 3 m) under palms planted in 1993 on flat land with a sandy loam soil texture, less than 2% soil organic carbon (C) content, and average rainfall of 2,363 mm yr⁻¹. The plot was managed following standard industrial management practices, and urea was applied manually twice per year in weeded circles of, on average, 1.65 m of radius around the palms. A total of 48 tension lysimeters (porous ceramic cups) were installed in 2005 and the data began to be stable in 2008, under 15-year-old palms. Sixteen ceramic cups were located at each of the three depths to sample representatively the spatial variability of organic matter and fertilizer inputs within the plantation. For each ceramic cup, a suction of 80 kPa was applied twice a day and a composite sample was analyzed weekly to determine nitrate and ammonium concentrations. A total of 6465 soil solution samples were analyzed from 2008 to 2015. Weather data was recorded in an open area located 100 m from the experimental plot: rainfall and N concentration of rain were recorded daily; solar radiation, air temperature, air humidity and wind speed were recorded semi-hourly by a Davis automatic weather station. Urea application date and rate, as well as production of fresh fruit bunches, were also recorded.

Table 1 around here.

2.4. Validation of the R-leaching module

In order to assess the capacity of the indicator to reach the objectives, we validated the R-Leaching module. Three validation steps were proposed by C. Bockstaller & Girardin (2003): validation of the structure of the indicator by a panel of experts, validation of the soundness of indicator outputs, and validation of the utility by end-users. In this study, we performed the two first steps.

Structure of the indicator was validated by a panel of experts, who are either co-authors of this paper or acknowledged. Experts' fields of expertise were oil palm agronomy, N cycle and N emissions, and agri-environmental modeling. They evaluated the scientific validity of the indicator structure, the modeling approaches chosen, and the input variables and parameters selected. This evaluation was conducted several times during the development of the indicator.

Validity of outputs was evaluated for the R-Leaching module, comparing modelled values to values calculated from field measurements. From the soil solution N concentration dataset, we calculated weekly mean N concentrations measured in the soil solutions collected from ceramic cups at 3 m depth. The N measured at 3 m depth was considered lost for palms, as most of the fine roots from palms are generally assumed to be located above 1.5 m depth

(Corley & Tinker, 2015). The number of samples per week at 3 m depth was very variable, ranging from 0 to 11 depending on many factors, such as soil moisture or technical difficulties to maintain the vacuum in tension lysimeters. In order to perform a robust validation, we ignored the least certain periods, when less than 3 samples were recorded per week. This led to a series of 24 complete months, all within the 2008-2011 period, among 96 months in total in the 2008-2015 period. However, we checked that the concentrations of mineral N measured at other dates were in the same range as in the time series of 24 months selected for the validation of the R-Leaching module.

We calculated deep drainage using the water balance equation:

$$\text{Drainage} = W_{\text{initial}} - W_{\text{final}} + \text{Rain} - \text{Intercepted water} - \text{Runoff water} - \text{Evapotranspiration}$$

(adapted from Corley & Tinker, 2015), where W is the plant available water in soil. Calculations were done at a daily timestep, for a soil depth of 1.5 m, assumed to include nearly all the fine roots of palms (Corley & Tinker, 2015). A too-deep soil thickness would have led to an overestimation of evapotranspiration, and hence an underestimation of drainage. Initial soil water was assumed to be at plant available water capacity, i.e. 150 mm m^{-1} (Moody & Cong, 2008). Water intercepted by fronds, and eventually evaporated, was assumed to be 11% of rainfall (Banabas, Turner, Scotter, & Nelson, 2008; Kee, Goh, & Chew, 2000). Runoff water was estimated as a percentage of rainfall, using the equation from Sionita et al. (2014) relevant for this site's conditions. Evapotranspiration was estimated using the Penman-Monteith equation (R. G. Allen, Pereira, Raes, Smith, & others, 1998). Drainage was hence equal to the amount of water in excess of plant available water capacity, after computation of all other inputs and outputs. Daily input values necessary for calculations were rainfall, solar radiation, air temperature, air humidity and wind speed. Finally, we obtained daily values of N leaching by multiplying drainage by the average N concentration at 3 m depth. We cumulated these daily values in monthly values, to compare them to the monthly outputs of the R-Leaching module.

To compare modelled and measured N leaching values we used a set of four model efficiency statistics and their respective ranges to define satisfactory results, according to Moriasi et al. (2007): (1) the coefficient of determination of the linear regression between modeled and observed values, considered to be acceptable when it is higher than 0.5; (2) the Root Mean Square Error to Standard Deviation Ratio, satisfactory when it is lower than 0.7; (3) the Nashe-Sutcliffe efficiency, satisfactory when it is higher than 0.5; and (4) the Mean Error. Moreover, we completed these performance indicators with the method of the

probability area, using a likelihood matrix, which is particularly relevant for models yielding risk assessment, such as scores of losses (Aveline, Rousseau, Guichard, Laurent, & Bockstaller, 2009; C. Bockstaller & Girardin, 2003; Pervanchon et al., 2005).

2.5. Scenario testing

We also tested theoretical management scenarios, in order to check the sensitivity of the indicator to input variables, and its behaviour in different management conditions. This gave an idea of the indicator's utility for the end-users in terms of sensitivity of simulated N losses to changes in management.

The same soil characteristics and climate records were used as those in the model comparison performed by Pardon, Bessou, Saint-Geours, et al. (2016). We chose three scenarios: (1) standard management practices, as defined by Pardon, Bessou, Saint-Geours, et al. (2016); (2) composting of initial palm residues from the previous cycle, i.e. trunks and fronds at time of replanting, and recycling back to the field; and (3) adjustment of N fertilizer rates according to legume understorey and initial residue N inputs.

These scenarios involved changes in most of the management practice input variables. For scenario 2, composting of initial residues is not a common practice yet, but could become an option so that we wanted to test the sensitivity of IN-Palm to such innovative practices. For scenario 3, we estimated the monetary savings resulting from fertilizer adjustment. Fertilizer applications corresponded to 25% urea and 75% ammonium sulfate (Pardon, Bessou, Saint-Geours, et al., 2016), and fertilizer price paid by industrial oil palm plantations in Indonesia ranged from 0.16 to 0.57 US dollars kg^{-1} for urea, and from 0.14 to 0.25 US dollars kg^{-1} for ammonium sulfate (Bessou, unpublished data, November 2019).

In order to test the sensitivity to climate variations, we ran each scenario with five climate series, by offsetting the climate record against planting date by one year in each run (Pardon, Bessou, Saint-Geours, et al., 2016).

3. Results

3.1. General structure and outputs

IN-Palm is implemented in an Excel file and consists of 17 modules and needs 21 readily available input variables relating to the crop, understorey, soil, land, weather, and

management of fertilizer and residues (Table 2). IN-Palm uses oil palm yield as an input, rather than modeling it explicitly, as do most fertilizer calculation methods based on N budget approaches. In this regard, IN-Palm aims at being complementary to existing crop models which already predict yield. Seven of the 10 risk modules were developed in this work: R-Runoff-Erosion, R-NH₃-Organic, R-N₂-Mineral, R-NO_x-Mineral/Organic, R-N₂O-Baseline, R-NO_x-Baseline, and R-N₂-Baseline. Seven intermediate modules were also developed, in order to estimate intermediate variables needed to run the risk modules. Details of structure and operation are provided in a technical report in Supplementary Material.

IN-Palm calculates emissions and scores for each risk module, for one hectare of palms, 1 to 30 years old. All calculations are done monthly, except for 3 intermediate modules estimated annually, i.e. Litter Budget, Fraction of Soil Covered, and Palm N Uptake, as monthly calculations would increase complexity without improving precision. For each month, IN-Palm computes 5 main sets of calculations (Figure 1, Table 2). First, NH₃ volatilization from fertilizers is calculated. Second, intermediate variables on soil cover and water budget are calculated. Third, these intermediate variables are used to calculate denitrification from fertilizers (N₂O, N₂, NO_x), and N losses via runoff and erosion. Fourth, net N inputs released to soil and plant uptake are calculated to estimate soil mineral N. Fifth, soil mineral N is used to calculate baseline denitrification (N₂O, N₂, NO_x) and N leaching.

Table 2, around here. 2-column fitting table, black-and-white in print

Figure 1 around here. 2-column fitting figure, black-and-white in print

Most of the risk module outputs are monthly emission factors, i.e. a percentage of N inputs or soil mineral N which is lost in the environment. For a given loss pathway, the monthly emission factor is transformed into a monthly N loss. Monthly losses are summed to obtain an annual loss and then converted into an annual score between 0 and 10. To convert a loss into a score we used the same function as C. Bockstaller and Girardin (2008, p. 35) based on a reference value of loss. For each loss pathway, we defined the reference value as equal to 50 % of the N losses, measured or modelled, associated with standard practices in a range of soil and climate conditions (Pardon, Bessou, Nelson, et al., 2016; Pardon, Bessou, Saint-Geours, et al., 2016). A score of 10 corresponds to no loss; 7 corresponds to the reference value of loss, i.e. emissions reduced by 50 % compared to standard practices; 4 corresponds to emissions with standard practices; and 0 corresponds to a loss more than three times

higher than that associated with standard practices. As N losses are highly dependent on palm age, we calculated reference values for each age, in order to obtain more sensitive scores. Over the whole cycle, average reference values are, in kg N ha⁻¹ yr⁻¹: 5 for NH₃, 2.1 for N₂O, 0.8 for NO_x, 5.1 for runoff-erosion and 20 for N leaching.

IN-Palm also provides recommendations on possible management changes to reduce N losses. According to the N balance and N losses calculated, critical conditions are identified, such as a potential lack of available N to match the plant needs, or high N losses. Warning messages in the Excel tool are then parameterized to pop up when these critical conditions occur. First, recommendations are displayed in order to better adapt N inputs to plant needs. Second, for scores below 7, recommendations are provided for potential management changes specific to reduce N losses via specific pathways.

Recommendations for improvements were most difficult to define for fertilizer application rate and date. Potential combinations of rates and dates are numerous, and the associated losses depend on many interacting processes over several months. Therefore, IN-Palm provides two more indicators to identify *a priori* (1) the riskiest month in which to apply the mineral fertilizers, and (2) the optimal month in the year and rate to apply fertilizers, aimed at reaching the expected yield while minimizing losses. This calculation is done assuming only one application per year, due to computing limitations in Excel spreadsheets. This limitation is restricted to the optimization calculation, though, as IN-Palm handles multiple applications per year in regular runs. More details on the recommendations are provided in the technical report (Supplementary Material, section 4).

3.2. Calculation of the 17 modules

In the 17 modules, three calculation approaches were used. In 11 modules we used a fuzzy decision tree modeling approach. When no data was available to design decision trees, we used existing regression models (3 modules). When modeled variables depended on their own values in a previous time step calculation, such as for soil water content, we used a mass budget approach, so as to reduce uncertainty propagation over the 30 years of calculations (3 modules) (Table 2, Figure 1). Input/output variables, parameters, and references from the literature are listed for each module in Tables A.2, A.3 and A.4 of the technical report (Supplementary Material). The modules run in the following order.

First, 2 modules are run to calculate volatilization from fertilizers. R-NH₃-Mineral is calculated with a fuzzy decision tree, using five input variables: fertilizer type, fertilizer placement, rain frequency, palm age and soil texture. This module hence accounts for spatial effects by considering fertilizer placement as a spatial variable. The output is a

monthly emission factor, from 2 to 45 % of mineral N applied. R-NH₃-Organic is calculated with a regression model (Bouwman et al., 2002a), using the fertilizer rate as an input variable. The output is an emission factor of NH₃ from the N applied as organic fertilizer.

Second, 4 intermediate modules are run to calculate two main outputs, soil moisture and drainage; they are Litter Budget, Fraction of Soil Covered, Water Runoff, and Soil Water Budget. Litter Budget is calculated with a mass budget approach, accounting for inputs and decomposition kinetics of initial residues from the previous cycle, pruned fronds and organic fertilizer. The output is an annual quantity of litter. Fraction of Soil Covered is calculated with a fuzzy decision tree, using four input variables: litter amount, understorey biomass, and placement of pruned fronds and organic fertilizers. This module hence accounts for spatial effects by considering pruned fronds placement and organic fertilizer placement as spatial variables. The output is an annual percentage of soil covered, from 0 to 100 %. Water Runoff is calculated with a fuzzy decision tree, using 5 input variables: fraction of soil covered, rain amount, rain frequency, slope, and presence or absence of terraces. The output is a monthly runoff coefficient, from 1 to 20 % of rainfall. Finally, Soil Water Budget is calculated with a mass budget approach in the 1.5 m depth soil layer, accounting for all inputs to and outputs from the soil. The output values of this module are monthly soil moisture and drainage.

Third, 4 modules are run to calculate denitrification from fertilizers and N losses through runoff-erosion: R-N₂O-Mineral, R-N₂-Mineral, R-NO_x-Mineral/Organic, and R-Runoff-Erosion. R-N₂O-Mineral is calculated with a fuzzy decision tree, using five input variables: fertilizer rate, soil moisture, soil texture, soil organic C and litter amount. The output is a monthly emission factor, from 0.01 to 13 % of mineral N applied. R-N₂-Mineral is calculated with a fuzzy decision tree, using two input variables: N₂O emissions and soil moisture. The output is a monthly N₂/N₂O ratio, from 1.92 to 9.96. R-NO_x-mineral/organic is calculated with a regression model (Bouwman et al., 2002b), using six input variables: mineral and organic fertilizer type and rate, soil organic C and soil texture. This regression model directly calculates a quantity of NO_x without using an emission factor. Finally, R-Runoff-Erosion is calculated with a fuzzy decision tree, using six input variables: fraction of soil covered, rain amount, rain frequency, slope, soil texture and presence or absence of terraces. The output is a monthly emission factor, from 1 to 20 % of mineral N applied and N deposited from atmosphere. Indeed, in the main dataset used to design and calibrate this Runoff-Erosion module, N losses through runoff and erosion were calculated jointly, as a percentage of mineral N applied and N deposited from atmosphere, without explicitly differentiating the share of N coming from soil.

Fourth, 3 intermediate modules are run to calculate soil mineral N content: Palm N uptake, Understorey N Uptake/Fixation, and Soil Mineral N Budget. Palm N Uptake is calculated with a fuzzy decision tree, using two input variables: expected yield and palm age. The output is an annual value of N uptake from soil, from 2.2 to 321 kg N ha⁻¹ yr⁻¹. Understorey N Uptake/Fixation is calculated with a fuzzy decision tree, using three input variables: the understorey type, i.e. legume or natural vegetation, the understorey biomass, and the mineral N remaining in soil after palm uptake. The outputs are monthly values of N fixation rate, from 0 to 90 %, and N uptake from soil. Finally, Soil Mineral N Budget is calculated with a mass budget approach, accounting for all N inputs to, and outputs from, the soil mineral N pool. Thus, Soil Mineral N Budget is calculated in two steps: the first estimating the N available in soil after palm uptake, for Understorey N Uptake/Fixation calculation; and the second estimating the N available in soil after understorey uptake, to calculate the N available in soil for losses.

Fifth, 3 modules are run to calculate baseline denitrification, N leaching and net mineralization of soil organic N: R-N₂O-Baseline, R-N₂-Baseline, R-NO_x-Baseline and R-Leaching. R-N₂O-Baseline is calculated with a fuzzy decision tree, using the same input variables as R-N₂O-Mineral, except the fertilizer rate. The output of the module is a monthly emission factor, from 0.1 to 2.5 % of mineral N available in soil. R-N₂-Baseline uses the same decision tree as for R-N₂-Mineral, but the N₂/N₂O ratio is affected to baseline losses of N₂O, instead of losses from fertilizer. R-NO_x-Baseline uses the same regression model as R-NO_x-Mineral/Organic, but it accounts only for emissions not induced by fertilizers. R-Leaching is calculated with a fuzzy decision tree, using drainage as input variable. The output of the module is a monthly emission factor, from 0 to 5 % of mineral N available in soil. Finally, IN-Palm estimates the monthly net mineralization from soil organic N to soil mineral N. If the N budget resulting from previous calculations is higher than the soil mineral N equilibrium reported for oil palm (K. Allen, Corre, Tjoa, & Veldkamp, 2015), the net mineralization is assumed to be zero for this given month. If the N budget is lower than the soil mineral N equilibrium, the net mineralization is assumed to be equal to the missing amount of N to reach this equilibrium. The latter case corresponds to a situation where the soil organic N pool may be depleted to reach the expected yield.

3.3. Validation of the R-Leaching module against field data

Model efficiency was acceptable according to three of the statistics calculated, but there was a tendency to underestimate N leaching. The visual representation showed that IN-Palm predicted most of the time the months in which leaching was actually observed

(Figure 2a). The coefficient of determination of the linear regression (R^2) was 0.56 (Figure 2b), the Nash-Sutcliffe efficiency was 0.53, and the Root Mean Square Error to Standard Deviation Ratio was 0.68, the three of them indicating acceptable predictions (Moriasi et al., 2007). Moreover, in the likelihood matrix comparing scores obtained by IN-Palm to scores calculated from observed values, predicted values were good in 75 % of cases (Figure 2c). However, the slope of the linear regression line was 0.667, i.e. below 1, and its y-intercept was 0.1537, i.e. above 0. Thus, the linear regression line crossed the ideal line of slope 1 for $0.46 \text{ kg N ha}^{-1} \text{ month}^{-1}$. This indicated that IN-Palm tended to slightly overestimate N leaching for losses below $0.46 \text{ kg N ha}^{-1} \text{ month}^{-1}$, while underestimating N leaching for higher losses. Furthermore, this underestimation was quantified with a Mean Error index of about $-1.9 \text{ kg N ha}^{-1} \text{ yr}^{-1}$, i.e. 17 % of observed losses.

Figure 2 around here. 2-column fitting figure, black-and-white in print

3.4. Scenario testing and management for N loss reduction

IN-Palm estimated annual average losses of 78, 76 and $64 \text{ kg N ha}^{-1} \text{ yr}^{-1}$, for (1) standard management practices, (2) composting of initial palm residue from the previous cycle, and (3) fertilizer adjustment according to understorey and residue inputs, respectively (Figure 3). There was a high variability in annual losses, ranging from 12 to 242 kg N ha^{-1} , and depending on scenario, palm age, and weather. Over the 1st year under standard practices, the N release from the decomposition of initial palm residues contributed to 45 % of total N losses, while the N release from the decomposition of empty fruit bunches applied in the weeded circles contributed to 26 %. The indicator also estimated that 91, 266 and 151 kg N ha^{-1} were fixed from the atmosphere by the legume, for the 3 scenarios, respectively.

According to these simulations, the adjustment of fertilizer according to other N inputs (scenario 3) is the best option. Adjusting fertilizer rate according to N inputs from legumes and initial residues from the previous cycle could reduce annual average N losses by $14 \text{ kg N ha}^{-1} \text{ yr}^{-1}$, due to a possible 57 % reduction in fertilizer rate over the 3rd to the 10th year. This result suggested that fertilizer costs could be reduced by at least $274 \text{ US\$ ha}^{-1}$ per growth cycle, assuming minimum fertilizer prices and a reduction of fertilizers limited to the period from the 3rd to the 10th year. The relatively small mitigation of $14 \text{ kg N ha}^{-1} \text{ yr}^{-1}$ came from two main factors: (1) the buffering effect of the legume, and (2) the limitation of fertilizer adjustment to the period between the 3rd and the 10th year. (1) The legume reacted to the lower level of N in soil by fixing 61 kg of atmospheric N per ha more than

under standard practices. This N was then released to the soil, which partially compensated the lower addition of fertilizer. (2) The reduction of N losses is an average over the 25 years, while the fertilizer rate is adjusted only between the 3rd and the 10th year after planting. Lower rates for years 1 and 2 may have yielded less robust results (see section 4.2 in the discussion), and lower rates after the 10th year would have resulted in mining soil N. This reduction of 14 kg N ha⁻¹ yr⁻¹ over the whole cycle would hence correspond to a reduction of 43 kg N ha⁻¹ yr⁻¹ (- 38 %) over the 3rd to the 10th year. This suggests that there is a significant potential for N loss mitigation under young palms, even when mitigation actions focus on fertilizer rate only.

The composting of initial residues from the previous cycle (scenario 2) reduced the annual average N losses by only 2 kg N ha⁻¹ yr⁻¹, due to higher losses under adult palms when the spreading of compost was concomitant with standard rates of mineral fertilizer application. But the legume N fixation was enhanced by 175 kg N ha⁻¹ due to the reduction of N inputs at the beginning of the cycle. This fixation was twice more than in the case of fertilizer adjustment (scenario 3), because, in the latter case, high amounts of soil mineral N from initial residue were still inhibiting fixation over the first few years. This confirms the importance of modelling the legume understorey with a N fixation rate which depends on soil N status, in order to be able to capture such significant N fluxes. The composting of initial residues could hence be worthwhile to enhance legume fixation, but would also involve more logistical challenges and costs for the transport and composting processes, for small results in terms of N loss mitigation. These results suggest that combining the scenarios 2 and 3, by replacing part of the fertilizer by N fixation and compost application, could save fertilizer and help reduce N losses under young and adult palms.

Therefore, these results suggest that different strategies should be combined to address N losses over the whole cycle. Under young palms, mitigating N loss may require fertilizer rate adjustment, while under adult palms it would be more efficient to target specific N loss mechanisms. Moreover, these results show that IN-Palm estimates of N losses were sensitive to management changes and climate variability, as shown on Figure 3 by the different N loss patterns between the scenarios and the error bars, respectively.

Figure 3 around here. 2-column fitting figure, black-and-white in print

4. Discussion

4.1. Soundness of outputs

We showed that IN-Palm captured the dynamics of observed N leaching at an acceptable level, according to the statistics calculated. The validation of the N leaching module was strategic, given that leaching is one of the most uncertain N fluxes in oil palm (Pardon, Bessou, Saint-Geours, et al., 2016), and its calculation occurs after all other fluxes in IN-Palm, hence depending on the relevance of previous modeling steps.

However, we identified a tendency to underestimate N leaching compared to the measured data. There are two possible explanations for this underestimation. First, high and uncertain internal fluxes, such as palm N uptake, estimated at $267 \text{ kg N ha}^{-1} \text{ yr}^{-1}$ in 2009 by IN-Palm, may have been slightly overestimated. Errors in estimating such high and uncertain internal fluxes could impact significantly soil mineral N and hence N leaching calculations. Second, IN-Palm may not have captured the effect of short and intense weather events observed at the study site, due to its monthly time step calculations. When short and intense evapotranspiration occurs, IN-Palm may tend to overestimate soil moisture, soil water drainage and hence leaching (e.g. end of 2009, start of 2010). When short and intense rain occurs, IN-Palm may tend to underestimate soil water drainage and hence leaching (e.g. end of 2011). These short and intense events can also induce timing errors, where leaching events are predicted one month earlier or later than observed (e.g. end of 2008). For our specific study site, the tendency to underestimate dominated, due to a high underestimation at the end of 2011.

Nevertheless, this underestimation is likely to be restricted to adult palms, as, on the contrary, IN-Palm showed a tendency to overestimate N leaching under young palms during the calibration process. This overestimation is presumably due to an underestimation of soil N immobilization at young age, as IN-Palm does not model this potential immobilization of N. Moreover, the spatial and temporal variability in soil solution chemistry is high in agro-ecosystems with tree species, and N concentrations measured are dependent on the position of lysimeters (Laclau, Ranger, de Dieu Nzila, Bouillet, & Deleporte, 2003). This leads to uncertainties in N leaching measurements. In this context, a discrepancy of less than $2 \text{ kg N ha}^{-1} \text{ yr}^{-1}$ between observed and modeled values is probably lower than the uncertainty of the measurements of N leaching.

Given the significant effect of palm age on N fluxes and losses, a validation of the N leaching module with field measurements from a young plantation would be very helpful. Such measurements could record responses of leaching to different management scenarios

involving key practices, such as residue and soil cover management, and fertilizer placement. A validation of this module in industrial plantations managed in soils with contrasting textures would be also of interest to assess the robustness of IN-Palm. Finally, the validation of other modules of N loss would also be beneficial in order to further investigate the robustness of IN-Palm and/or highlight further areas for improvement.

Therefore, IN-Palm can already help to identify tendencies in N losses dynamics, while accounting for all the fluxes and practices along the whole crop cycle. However, it should be used carefully for more precise analyses of individual loss phenomenon until further validation is done against new available measured data.

4.2. Validity domain

IN-Palm (1) is suitable for application to a wide range of oil palm growing environments, (2) is applicable to palms of any age, (3) is suitable for testing common management practices, and (4) uses reference values logically related to current practices.

However, IN-Palm should be used carefully in some very specific conditions. IN-Palm is not parameterized to assess N losses in plantations on organic soils. Besides, due to its monthly time step calculations, IN-Palm is not much sensitive to very short and extreme weather events. In such cases, results should be used carefully.

IN-Palm can be applied at all ages of palms, but results should be interpreted with caution when assessing fertilizer management practices for very young palms of about 1-2 years, whose roots do not cover yet all the area. At that age the amount of soil mineral N actually available for palms may differ from IN-Palm predictions, as IN-Palm does not simulate the spatial distribution of N inputs and uptake within the plantation.

Finally, IN-Palm can test most of the common management practices in industrial plantations, except for the field application of palm oil mill effluents. We did not model this practice, as it applies to only a small proportion of plantation fields and is becoming less common as companies move to co-composting the effluent with empty fruit bunches. Moreover, very little knowledge was available, notably on emissions related to palm oil mill effluents during and after field application.

4.3. Further measurements to improve IN-Palm precision

The main uncertainties in module calculations were: (1) the emissions induced by compost application, (2) palm N uptake, (3) understorey N uptake and fixation, (4) soil N

immobilization and mineralization processes, and (5) the influence of spatial factors on leaching. New field measurements would help reduce these uncertainties and increase IN-Palm precision.

First, uncertainty of emissions from compost may be reduced with new field data on NH_3 volatilization and N_2O emissions. This improvement would be useful, as composting is becoming more common in oil palm plantations.

Second, palm N uptake is a very high internal flux, and also very uncertain, as no direct measurements are available. Measurements of N uptake at different ages, using for instance ^{15}N techniques, could help reduce uncertainty and underestimation of N leaching under adult palms.

Third, understorey N uptake and biological N_2 fixation is also a potentially high and very uncertain internal flux. To reduce uncertainty, useful measurements could involve the response of N fixation to soil mineral N in field conditions, and the testing of other factors potentially driving fixation rate, such as soil moisture and pH.

Forth, in IN-Palm, soil N immobilization and mineralization processes are accounted for by estimating a net soil N mineralization depending on a soil mineral N equilibrium parameter inferred from measurements in oil palm (K. Allen et al., 2015). Complementary field data quantifying immobilisation, storage and mineralization dynamics of organic N under oil palm would be very useful to reduce uncertainty in soil N dynamics modelling.

Lastly, leaching calculations could be better adapted to the oil palm system by accounting for fertilizer placement. However, this issue requires further investigations into the response of leaching to fertilizer placement, as the processes are complex, notably involving variable plant uptake depending on the relationship between long-term management and the development and distribution of palm roots. Thus, controversies emerge when trying to identify favourable and unfavourable placement.

4.4. Utility for decision-support and environmental assessment

IN-Palm can be used as a decision-support tool for management as well as an emission model for environmental assessments. For management, IN-Palm is easy to use and sensitive to most of the common management practices in industrial plantations. The scenario testing also showed that IN-Palm estimates of N losses were sensitive to management changes, accounting for important processes in oil palm agronomy, such as

legume N fixation or crop residues decomposition. IN-Palm can support decision-making about fertilizer management, by estimating the least risky months for applying fertilizer in a given field, and the optimal fertilizer rate, depending on soil characteristics, weather and other management practices implemented, such as the placement of pruned fronds and empty fruit bunches. A future test of the indicator by end-users in plantations could help to qualify and further improve its utility as management tool.

For environmental assessments, IN-Palm can help estimate all the important N loss pathways necessary to perform life cycle assessments for instance. The scenario testing also showed that IN-Palm estimates of N losses were sensitive to inter-annual climate variability, which is important to help reduce uncertainty in life cycle assessments. In complement to the N losses in the field assessed with IN-Palm, it is worthwhile noting that further investigation would be needed before concluding on management tracks to implement in order to reduce environmental impacts. Notably, environmental impact assessment should also account for emissions of N and other compounds induced out of the field, as done in life cycle assessments. For instance, N_2O , NO_3 and methane (CH_4) are emitted during the composting process (Peigné & Girardin, 2004), as well as non-renewable carbon dioxide (CO_2) and other fluxes during the production of fertilizers.

IN-Palm scores are calculated using as reference values 50 % of the losses under standard industrial management practices. This approach is assumed to be conservative given that standard industrial management practices are already optimized in order to avoid economically excessive application of fertilizer. We also tested other approaches to define reference values, e.g. minimum value for each loss pathway encountered in the literature, or the lower end of uncertainty ranges. However, those reference values could be very low. For instance, the lower end of (IPCC, 2006) uncertainty range of 0.3 % applied to a standard annual fertiliser rate of $140 \text{ kg N ha}^{-1} \text{ yr}^{-1}$ would lead to a reference value of $0.42 \text{ kg N ha}^{-1} \text{ yr}^{-1}$ for N_2O . In this case, the indicator score for N_2O emissions would be insensitive to any kind of practice change. However, depending on the context, those reference values maybe adapted in order to assess with a finer grain the room for improvement against best local or regional recorded performances for instance.

5. Conclusion

We developed an agri-environmental indicator, IN-Palm, to estimate all N losses throughout the oil palm crop cycle. The indicator uses 21 input variables readily available in most oil palm companies, and provides scores and management recommendations to reduce N

losses. Predictions of N leaching against measured data in Sumatra, Indonesia, were acceptable according to three standard statistical indicators and one dedicated evaluation method. We showed that IN-palm was sensitive to management changes, and was hence a potential tool for testing management scenarios and identifying practices likely to reduce N losses. We also highlighted the main uncertainties of IN-Palm, and we identified measurements and improvements necessary to increase IN-Palm precision before its use in commercial plantations. Field measurements are unsuitable to monitor large scale plantations, and the use of existing process-based models for oil palm is limited by the complexity of running them and getting the right parameters. Therefore, our indicator constitutes a useful tool for managers and scientists. This kind of agri-environmental indicator, easily adaptable to new crops in contexts of limited knowledge, can be of great utility to address the current need of reducing our global environmental impact. In particular, N fluxes could be used as inventory flows in palm oil life cycle assessments of environmental impacts.

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Figures

Figure 1. Fluxes and N losses calculated in IN-Palm. Five main steps of calculation are computed for one hectare of palms for each month of the chosen year (1 to 30 years of age): ① NH_3 volatilization from mineral and organic fertilizers; ② Soil cover and water budget estimations; ③ Denitrification from mineral and organic fertilizers, and N losses through runoff and erosion from mineral fertilizer and atmospheric deposition; ④ Soil mineral N estimation after net N release to soil and plant N uptake; ⑤ Baseline denitrification and N leaching, from soil mineral N, and net mineralization of soil organic N. EFB: Empty Fruit Bunches

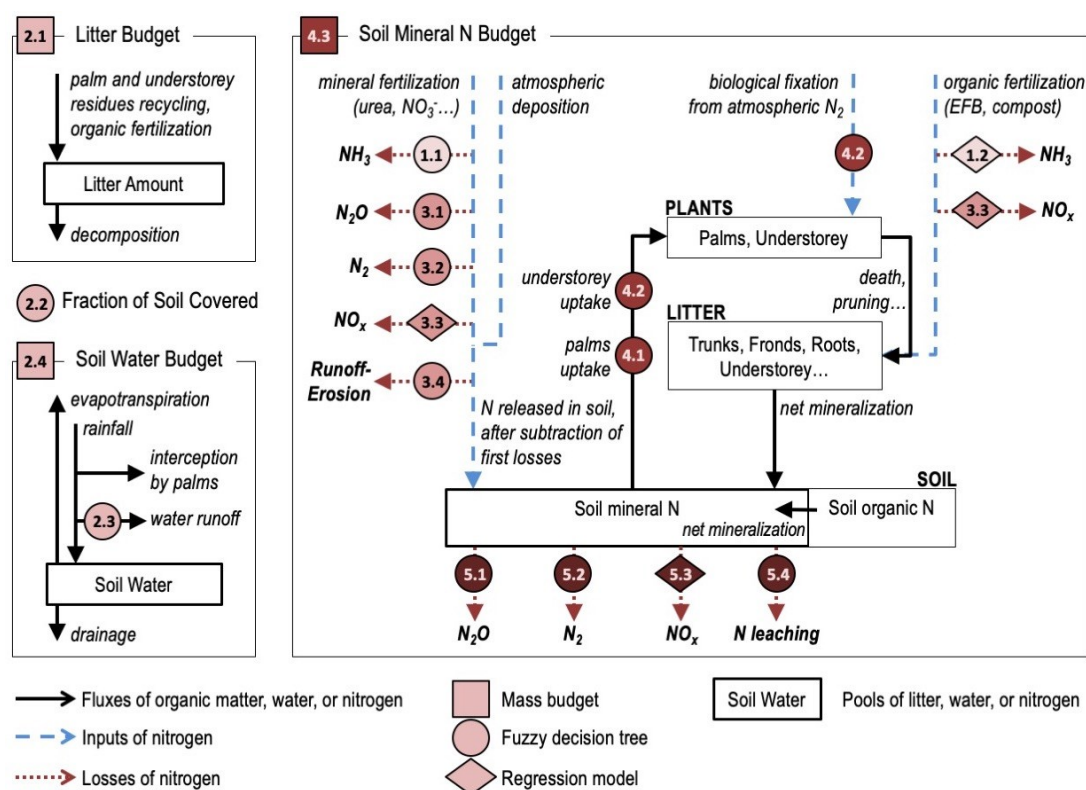


Figure 2. Modeled values from R-Leaching module vs. observed field measurements. (a) Visual representation of modeled and observed values of N leaching, for the 24-month period in which at least 3 samples were analysed per week. (b) Linear regression of modeled vs. observed values (solid line), ideal line of slope 1 (dotted line), and efficiency statistics: Nashe-Sutcliffe efficiency: 0.53, Mean Square Error to Standard Deviation Ratio: 0.68, Mean Error: $-1.9 \text{ kg N ha}^{-1} \text{ yr}^{-1}$. (c) The 24 scores distributed in the likelihood matrix.

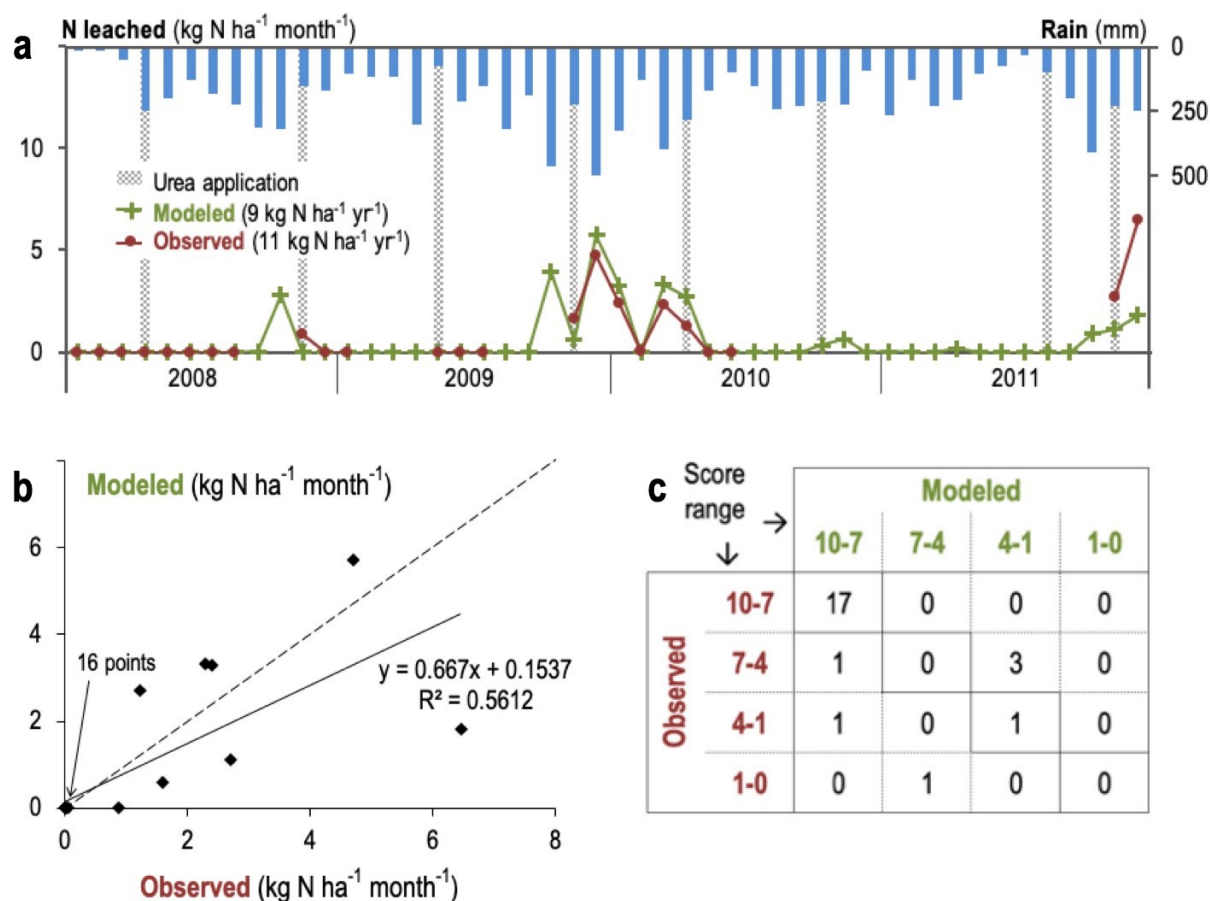
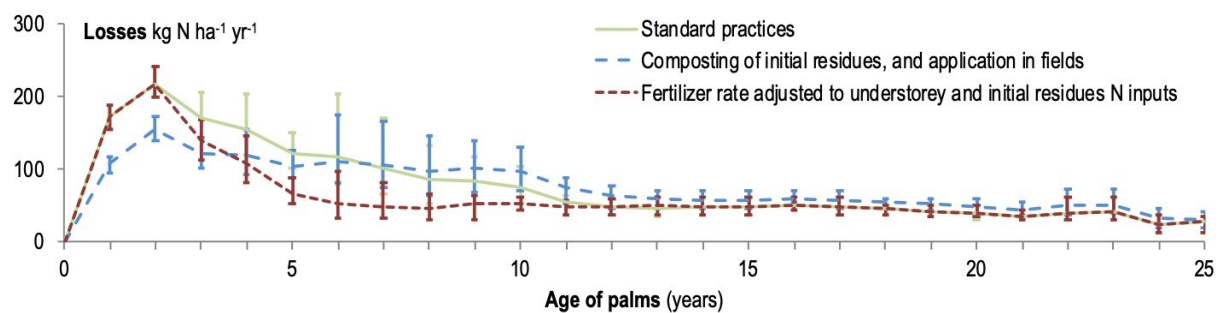


Figure 3. Nitrogen losses simulated by IN-Palm in three management scenarios. Losses include all N loss pathways: NH_3 volatilization, N lost through runoff-erosion, N_2O , N_2 , and NO_x emissions and N leached. Error bars represent minimum-maximum losses, depending on climate. N: Nitrogen



Tables

Table 1. Sources of data used in IN-Palm development and validation. Data from the literature, existing models, measurement datasets and expert knowledge, were used for (1) the design of the structure of the indicator, (2) the calibration of modules, (3) the reference values for scores, and (4) the validation of the R-Leaching module and the scenario testing.

Source	Type and availability	Use	References
Literature review (N fluxes and losses in plantations)	Quantitative and qualitative	1, 2, 3	(Pardon, Bessou, Nelson, et al., 2016)
Comparison of 11 models, specific regression models (NH ₃ volatilization, and N ₂ O and NO _x emissions)	Quantitative and qualitative, equations, classes for correction factors	1, 2, 3, 4	(Bouwman et al., 2002a, 2002b; Pardon, Bessou, Saint-Geours, et al., 2016; Stehfest & Bouwman, 2006)
Expert knowledge	Qualitative, meetings, review of documents	1, 2, 3	Panel of experts (oil palm agronomy, N cycle and N emissions, agri-environmental modeling)
APSIM-Oil palm model simulations	Quantitative dataset, 58 500 simulations, detailed data	2	(Pardon et al., 2017)
Runoff and erosion measurements	Quantitative dataset, 3-year-trial, aggregated data	2	(Sionita et al., 2014)
Measurements of N concentration in soil solution	Quantitative dataset, 8-year-trial, 7610 samples, detailed data	4	Unpublished data

Table 2. Overview of IN-Palm structure: IN-Palm consists of 21 inputs and 17 modules. Of the 17 modules, 11 use fuzzy decision trees, 3 use mass budget models, and 3 use regression models. Each module uses 1 to 33 inputs, being either user inputs or intermediate variables (*) calculated by other modules. C: Carbon, N: Nitrogen, FM: Fresh Matter, DM: Dry Matter, FFB: Fresh Fruit Bunches

Calculation steps		1		2			3				4			5					
		1.1	1.2	2.1	2.2	2.3	2.4	3.1	3.2	3.3	3.4	4.1	4.2	4.3	5.1	5.2	5.3	5.4	
10 risk modules		<div><div>R-NH₂-Mineral</div><div>R-NH₂-Organic</div><div>Litter Budget</div><div>Fraction of Soil Covered</div><div>Water Runoff</div><div>Soil Water Budget</div><div>R-N₂O-Mineral</div><div>R-N₂-Mineral</div><div>R-NO₃-Mineral</div><div>R-NO₃-Mineral</div><div>Palm N Uptake</div><div>Understorey N Uptake</div><div>Soil Mineral N Budget</div><div>R-N₂O-Baseline</div><div>R-N₂-Baseline</div><div>R-NO₃-Baseline</div><div>R-Leaching</div></div>																	
7 intermediate modules																			
Model type	Fuzzy decision tree																		
	Mass budget																		
	Regression model																		
Variable classes	Input variables	Units																	
Crop factors	Age of palms (1 to 25)	years	1												1	2	2	2	
	Yield	t FFB ha ⁻¹ yr ⁻¹													1	2	2	2	
Soil and land	Soil initial N total	kg N ha ⁻¹														2	1	2	
	Soil initial water	mm									1								
	Soil organic C	%										1	2	1		2	2	1	
	Soil texture	-	1								1	1	2	1	1	2	2	1	
	Slope	%									1	2	2	2	1	2	2	2	
	Terraces (yes or no)	-									1	2	2	2	1	2	2	2	
Weather	Number of rainy days	month ⁻¹	1									1	2	2	2	1	2	2	
	Monthly rainfall	mm										1	1	2	2	1	2	2	
	Atmospheric N deposition	kg N ha ⁻¹ yr ⁻¹														1	2	1	
Fertilizer management	Rate/Date of mineral fertilizer	kg ha ⁻¹	1										1	2	1	1	2	1	
	Type of mineral fertilizer	-	1										1	2	1		2	2	
	Placement of mineral fertilizer	-	1													2	2	2	
	Rate/Date of organic fertilizer	t FM ha ⁻¹		1	1	2	2	2	2	2	2	2	1	2		2	1	2	
	Type of organic fertilizer	-			1	2	2	2	2	2	2	2	1	2		2	2	2	
	Placement of organic fertilizer	-				1	2	2	2	2	2	2				2	2	2	
Understorey and residue management	Fronds (placement or exported)	-		1	1	2	2	2	2	2	2				2	1	2	2	
	Previous palms (yes or no)	-		1	2	2	2	2	2	2	2				2	1	2	2	
	Understorey biomass	-		1	1	2	2	2	2	2	2				2	2	2	2	
	Legume fraction	-														1	2	2	
	*Fraction of soil covered	-					3	1	2	2	2				1	2	2	2	
Soil & ecological processes	*Litter amount	t DM ha-1				3	1	2	2	1	2				2	2	1	2	
	*Water runoff	mm month ⁻¹							3	1	2	2				2	2	2	
	*Soil moisture	mm									3	1	1			2	2	1	
	*Palm N uptake	kg N ha ⁻¹ month ⁻¹														3	2	1	
	*Understorey N uptake/fixation	kg N ha ⁻¹ month ⁻¹														3	1	2	
	*Soil mineral N	kg N ha ⁻¹ month ⁻¹														1	3	1	
	*Water drained	mm month ⁻¹									3						2		
																		1	
N losses	*N ₂ O emissions	kg N ha ⁻¹ month ⁻¹										3	1				1	3	
	*N ₂ emissions	kg N ha ⁻¹ month ⁻¹											3				1		
	*NO _x emissions	kg N ha ⁻¹ month ⁻¹													3				
	*NH ₃ volatilization	kg N ha ⁻¹ month ⁻¹	3	3													2	1	
	*Runoff-Erosion	kg N ha ⁻¹ month ⁻¹														3			
	*N leaching	kg N ha ⁻¹ month ⁻¹																1	
* Intermediate variable																			
		1 Direct input 2 Indirect input 3 Output																	

* Intermediate variable

1 Direct input

2 Indirect input

3 Output