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REGULAR ARTICLE

Comparison between observed and DeNitrification-DeComposition model-based nitrous oxide fluxes and maize yields under selected soil fertility management technologies in Kenya

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Abstract
Aims Process-based biogeochemical models can be used to simulate soil nitrous oxide (N_2O) fluxes and maize yields and draw insights on yields improvement and climate change mitigation options. We compared both observed and DeNitrification-DeComposition (DNDC) simulated soil N_2O fluxes and maize yields.
Methods We used DNDC model to simulate soil N_2O fluxes and maize yields under four soil fertility treatments (inorganic fertiliser, animal manure, animal manure + inorganic fertiliser and control,) replicated thrice for 1 year in Central Highlands of Kenya. We sampled soil N_2O fluxes using static chambers installed in each plot. We analysed soil N_2O using gas chromatography and calculated cumulative fluxes using trapezoidal rule linear interpolation between sampling dates.
Results DNDC showed poor results in simulating daily N_2O fluxes (157.16% ≤ normalised root mean square error (nRMSE) ≤ 324.01% and 0.90 ≤ modelling efficiency (NSE) ≤ 0.96), good to excellent performance in simulating cumulative annual soil N_2O fluxes (6.16 ≤ nRMSE ≤12.86 and 0.63 ≤ NSE ≤ 0.86) and good to excellent performance in simulating maize yields (1.15% ≤ nRMSE ≤13.86% and 0.51 ≤ NSE ≤ 0.88) across all soil fertility treatments.
Conclusion The DNDC model had good to excellent performance in simulating cumulative soil N_2O fluxes and crop yields across treatments. Though the model

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captured yield-scaled N_2O fluxes and N_2O emission factors across treatments, they were underestimated under manure treatment. There is a need to continue calibrating the DNDC model for improved capture of daily N_2O fluxes and uptakes on Kenyan soils.

Keywords DeNitrification-DeComposition model · Sub Saharan Africa · Yield-scaled N_2O emission · Emission factors · Central highlands of Kenya

Introduction

The main challenge in global agricultural systems is producing enough food to feed future generations while containing greenhouse gas emissions (FAO 2017; Kc et al. 2018). Agricultural ecosystems are the primary source of nitrous oxide (N_2O) fluxes accounting for approximately 60% of the total anthropogenic N_2O emissions (Smith et al. 2007). Nitrous oxide is a potent greenhouse gas with a global warming potential of 265 times that of carbon dioxide (CO_2) (IPCC 2014). The N_2O fluxes result from complex biogeochemical processes mainly produced through nitrification and denitrification process (Butterbach-Bahl et al. 2013). The N_2O fluxes are impacted by soil properties, including carbon, nitrogen, temperature, moisture, pH, bulk density, and oxygen concentration (Signor and Cerri 2013; Smith 2017). Agricultural management practices such as applying organic and inorganic fertiliser aimed at increasing agricultural production alter soil properties. Hence, to enhance food security while augmenting climate change mitigation and adaptation, there is a pressing need to quantify the trade-offs of different soil management technologies and soil greenhouse gas emissions.

Application of external inputs, including organic and inorganic fertiliser, contributes to soil N_2O fluxes (Hickman et al. 2014; Kihara et al. 2020). The contribution of organic or inorganic fertiliser on soil N_2O fluxes is mainly driven by soil texture and carbon concentration (Pelster et al. 2012). Macharia et al. (2020) recorded higher soil N_2O fluxes under animal manure treatment on coarse-textured soils, while Musafiri et al. (2020a) found higher soil N_2O fluxes under inorganic fertiliser treatment on fine-textured soil of the Central Highlands of Kenya. The increased N_2O fluxes under manure treatments on coarse-textured, which primarily have low C concentration, could be due to the addition of C substrate and enhanced soil respiration, thus increasing soil denitrification N_2O production (Rochette et al. 2008). Despite manure application producing lower soil N_2O fluxes in the fine-textured soils, *a* prolonged application could lead to long-term high emissions due to carbon accumulation (Deng et al. 2016).

Accurate documentation of Intended Nationally Determined Contributions (INDCs) of GHG emissions is essential in meeting Kenya's obligation to the United Nations Framework Convention on Climate Change (UNFCCC) and 2015 Paris agreement on climate change (Pauw et al. 2018). Quantifying soil greenhouse gas emissions under different soil fertility management technologies is essential in choosing the best technology that improves crop yields while lowering the fluxes. However, only a few direct soil GHG quantification studies in smallholder farming systems have been conducted in Kenya (e.g., Ortiz-Gonzalo et al. 2018; Macharia et al. 2020; Musafiri et al. 2020a). This has resulted in a dearth of accurate soil GHG data among smallholder farming systems (Rosenstock et al. 2016). Direct quantification of the soil N_2O fluxes is impractical and expensive under national and regional scales (Giltrap et al. 2010). Therefore, exploring cheaper soil GHG quantification methodologies, including process-based biogeochemical models, is imperative.

Process-based biogeochemical models offer an alternative by simulating greenhouse gas emissions and crop yields from agricultural systems as influenced by different soil fertility management technologies. One of the commonly used biogeochemical models in simulating soil N_2O fluxes and maize yields is the DeNitrification DeComposition (DNDC) model. The DNDC model was initially developed to simulate soil tracer emissions following rainfall events in the USA (Li et al. 1992, 2010). However, the model has been modified and widely used across the globe to simulate crop yields and N_2O fluxes, for instance, in New Zealand (Giltrap et al. 2008) in Canada (Uzoma et al. 2015), China (Abdalla et al. 2020), and in Africa (Budiman et al. 2020). Previous studies have indicated that DNDC model performance is acceptable in simulating soil N_2O fluxes and maize yields (Deng et al. 2016; Zhang et al. 2018; Lv et al. 2020). However, there is still limited information on model performance in Kenya and SSA at large. Cognisant of the DNDC model's applicability in simulating soil N_2O fluxes and maize yields in other regions, there is a need for its calibration and validation under different soil fertility management practices on Humic Nitisols in Kenya.

In this study, we aimed at achieving two objectives, i.e., i) calibrate, validate and assess the accuracy of the DNDC model in simulating daily/cumulative soil N_2O fluxes and maize yields as grain, leaf, stem, and root under different soil fertility management technologies and ii) to compare both DNDC simulated and measured yield-scaled N_2O emissions and N_2O emissions factors under different soil fertility management technologies in Kenya.

Materials and methods

Experimental site description

We carried out soil GHG quantification in three farms from March 2018 to March 2019 in three smallholder maize farms located at 1436 m a.s.l, S 0.3561° & E 37.6333°, 1439 m a.s.l, S 0.3878° & E 37.6173°, and 1434 m a.s.l, S 0.3888° & E 37.6314° in Tharaka-Nithi County Kenya. The site is in the Upper Midland 3 (UM3) agro-ecological zone on the eastern slopes of Mount Kenya (Jaetzold et al. 2007). The predominant soil type in the region is Humic Nitisol (8% sand, 14% silt, and 78% clay), Ngetich et al. 2014). The average long-term (30-year period) annual air temperature in the site is 20 °C (Jaetzold et al. 2007). The site receives bimodal rainfall with a long rains season (LR) between March and June and a short rain season (SR) occurring between October and December, thus two cropping seasons annually. The average long-term seasonal rainfall amount ranges from 420 to 750 mm and 250 to 450 mm for LR and SR seasons, respectively, with long-term annual rainfall ranging between 1200 and 1400 mm per annum (Jaetzold et al. 2007).

Experimental set-up and agronomic management

We laid out the experiment in a randomised complete block design with four treatments replicated thrice. The treatments were: i) control (No fertiliser input), ii) inorganic fertiliser (NPK, 23.23.0120 kg N ha^{-1} yr^{-1}), iii) animal manure (goat manure, 120 kg N ha^{-1} yr^{-1}), and iv) animal manure + inorganic fertiliser (120 kg N ha^{-1} yr^{-1}), Table 1). We used a checklist to identify previous soil fertility management practices on the three selected smallholder farms. The farmers used low quantities of inorganic fertiliser and animal manure (less than 50 kg N ha^{-1} yr^{-1}), Musafiri et al. 2020b). We used HB 516, the commonly used maize (Zea may L.) variety, as the test crop. Selection of soil fertility management treatment and test crop was informed by our baseline survey Musafiri et al. (2020b), that documented maize was the main crop grown in the area with animal manure, inorganic fertiliser, or a combination of inorganic manure and inorganic fertiliser as major soil fertility management technologies practised by smallholder farmers in the area. A detailed description of this experiment's design and agronomic management has been reported by Musafiri et al. (2020a).

Plot dimensions were 6 m by 4.5 m. We spaced maize planting holes at 0.75 m between rows and 0.50 m within rows hence 180 maize plants per plot. We manually prepared land and incorporated manure using a hand hoe a week before planting. We analysed the animal manure's nitrogen concentration sourced from the local farmers using a C/N analyser (Thermal Scientific, Flash 2000 Analyser, Waltham, MA 180 USA). The animal manure total nitrogen content was 1.9 ± 0.2% (Musafiri et al. 2020a). Therefore, we incorporated 3158 kg ha^{-1} and 1579 kg ha^{-1} of animal manure per season for animal manure and animal manure + inorganic fertiliser treatments to meet the recommended N requirement (Fertiliser Use Recommendation Project (FURP) 1987). Planting corresponded with fertiliser application, and therefore, we applied 260.8 kg ha^{-1} per season of NPK (23.23.0) for inorganic fertiliser treatment and for the animal manure + inorganic fertiliser treatment, the amount of NPK applied was based on the goat manure analysis report. To ensure weed-free plots, we did weeding manually using hand hoe twice a cropping season.

Soil N_2O fluxes measurement and gas chromatography

We conducted forty-six (46) soil N_2O fluxes sampling campaigns from March 2018 to March 2019 using the static chamber technique. The chamber had two components a lid and a base (Rosenstock et al. 2016; Musafiri et al. 2020a). We installed three chambers in each sampling plot to a depth of 7 cm. We collected soil N_2O fluxes weekly at the start of each cropping season, biweekly during the off-season and following key events, including planting, rainfall event, fertiliser, and manure application. We collected four gas samples at the chamber headspace closure of 30 min at 0, 10, 20 and 30 min during each sampling event. We sampled 20 ml using 60 ml propylene syringes fitted with Luer

Table 1 Soil fertility management technologies implemented during long and short rain seasons 2018 in Tharaka-Nithi County, Central Highlands of Kenya

Soil fertility management technology	Abbreviation	Fertiliser rate (kg N ha^{-1} yr^{-1})	
		Inorganic	Organic
No external input	Control	0	0
Inorganic fertiliser (NPK, 23.23.0)	Fertiliser	120	0
Goat Manure	Manure	0	120
Goat manure+ Inorganic fertiliser	Man+Fert	60	60

NPK is Nitrogen, Phosphorous and Potassium concentration

locks from each of the three chambers. We used gas pooling techniques following Arias-Navarro et al. (2013), the first 20 ml was used to pre-evacuate a 20 ml glass vial, and the remaining 40 ml pressurised in the vial. The samples were then transported to International Livestock Research Institute – Nairobi laboratory for soil N_2O analysis.

The soil N_2O concentration was analysed using an SRI 8610C gas chromatography (GC), SRI Instruments, Torrance, CA, USA) fitted with a ^{63}Ni-electron capture detector (ECD). We operated the GC with Hayesep D-packed columns (3 m, 1/8″) and an oven temperature of 65 °C. The N_2O fluxes are sporadic, and we set the detection limit at ±2.96 μg N2O-N m^{-2} h^{-1} for the linear model and ± 10.21 μg N2O-N m^{-2} h^{-1} for non- linear model following Parkin et al. (2012). We calculated hourly soil N_2O fluxes (μg N_2O-N m^{-2} h^{-1}) by converting the concentrations to mass per volume accounting for auxiliary measurements such as actual air temperature, chamber volume, and ambient pressure as per ideal gas law (Musafiri et al. 2020a). Since soil N_2O fluxes sampling was done between 0830 and 1200 h to minimise diurnal variation in N_2O fluxes (Parkin and Venterea 2010), we extrapolated chamber soil N_2O hourly fluxes to daily soil N_2O fluxes (g N_2O-N ha^{-1} day^{-1}). We used linear interpolation between sampling days based on the trapezoidal rule to calculate cumulative seasonal/annual soil N_2O fluxes from each sampling plot following Barton et al. (2015).

Soil sampling and maize crop production

At the beginning of the experiment (March 2018), we collected soil samples for baseline soil properties determination (Table 2). At each plot, three samples were collected from 0 to 20 cm depth using an Eijkelkamp Gouge auger (Eijkelkamp Agrisearch Equipment, Giesbeek, The Netherlands) and pooled together in a labelled ziplock bag. Samples were oven-dried at 40 °C for 72 h, ground using a ball mill (Retsch ball mill, Haan, Germany), and sieved through a 2 mm sieve. We used a sub-sample of 1:2 soil: water ratio and a glass probe pH meter (Crison Instruments, Barcelona, Spain) for pH and a C/N analyser (Thermal Scientific, Flash 2000 Analyzer, Waltham, MA USA) for soil nitrogen and carbon determination. At each plot, we collected three samples (0–5 cm depth) using 100 cm^3 core rings (Eijkelkamp Agrisearch Equipment, Giesbeek, The Netherlands). We oven-dried at 105 °C for a day to determine soil bulk density (Okalebo et al. 2002). Initial soil ammonium and nitrates were determined using a photometric analyser (Aquakem200: Thermo Scientific, Wilmington, DE, US).

During harvesting, we portioned maize yields to grain, leaf, stem, and roots. Briefly, we harvested leaf, stem, and roots from a net plot of 1.5 m^2 (eight plants) and the grains from a net plot of 21 m^2. We recorded both wet and dry weight and extrapolated the dry weight to 10,000 m^2. We adjusted maize grain yields to 12.5% moisture content (Ngetich et al. 2014).

The DNDC model description

DeNitrification-Decomposition is a process-based biogeochemical model developed by Li et al. (1992) to simulate C and N turnover in agricultural ecosystems. The model can predict crop yields, soil environmental factors, C sequestration, and C and N trace gas fluxes. The model has six sub-models categorised into two broad components. The first component consists of soil, climate, crop growth, and decomposition sub-model, simulating soil temperature, pH, moisture, and substrate

Table 2 Mean (± 1 standard error of the mean) measured soil physiochemical properties in Tharaka-Nithi County

Treatment[1]	Bulk density (gcm^{-3})	pH	Total Nitrogen (%)	SOC (%)	C/N Ratio	NH_4^+-N (mg N kg^{-1})	NO_3^--N (mg N kg^{-1})
Control	0.98±0.01	5.06^{a2}±0.02	0.20±0.01	2.26±0.09	11.12±0.07	2.05^{d}±0.62	5.70^{d}±0.34
Fertiliser	0.96±0.01	5.04^{a}±0.08	0.21±0.01	2.33±0.13	11.28±0.17	2.30^{c}±0.13	6.58^{b}±0.39
Manure	0.97±0.01	4.70^{b}±0.04	0.20±0.01	2.48±0.31	12.59±1.41	3.37^{a}±0.62	6.90^{a}±0.14
Man+Fert	0.97±0.01	4.73^{b}±0.06	0.25±0.03	2.79±0.30	11.17±0.23	2.96^{b}±0.42	6.14^{c}±0.35
P value	0.3	0.002	0.2	0.4	0.5	<0.001	<0.001

[1] Treatments Control = (No external input), fertiliser = (inorganic fertiliser NPK. 23.23.0, 120 kg N ha^{-1} yr^{-1}), Manure = (animal manure, 120 kg N ha^{-1} $yr^{-1)}$ and Man + Fert = (animal manure+ inorganic fertiliser, 120 kg N ha^{-1} yr^{-1})

[2] Same superscript letters in the same column denote no significant difference between treatments means at $P \leq 0.05$

concentration, such as ammonium, nitrates, and dissolved organic carbon. The second component consists of nitrification, denitrification, and fermentation submodel and simulates trace gases (NO, N_2O, CH_4, and NH_3) fluxes. Functional equations for six sub-models are derived from basic physical, chemical, and biological theories or empirical associations between measured and simulated values. Various studies have used the model to predict tracer gas emissions (e.g., Rafique et al. 2011; Giltrap et al. 2013; Deng et al. 2016).

The DNDC modelling and input parameters

We used the DNDC model version 9.5; http://www.dndc.sr.unh.edu, downloaded in April 2020 to simulate crop growth and N_2O fluxes. To simulate site-specific tracer N_2O fluxes and crop yields, we used climatic conditions, vegetation, soil properties, and farm management practices as input parameters published in our previous study, Musafiri et al. (2020a). We used both observed parameters, that is., parameters recorded during the experiment (Table 2), and from the previous research in the study site by Ngetich et al. (2014), Table 3) and model default parameters (model inbuilt) soil properties. The soil properties used in DNDC modelling include texture, bulk density, soil organic carbon, mineral N, wilting point, field capacity, porosity, and hydraulic conductivity (Tables 2 and 3). We obtained weather data from a nearby automated Hobo weather station (1434 m a.s.l, S 0.3868° & E 37.6271°). The weather data, including precipitation, minimum and maximum air temperature, solar radiation, relative humidity, and wind velocity, were averaged every 15 min and then uploaded to a HOBO U30 NRC station data logger (Onset Computer Corporation, Bourne, MA, USA). We downloaded the data quarterly for analysis. Farm management practices such as manure amendments, fertilisation, and tillage were obtained from the experimental set-up. Details of farm management practices, including land preparation, manure and fertiliser application and planting dates were captured throughout the experimentation (Table 3).

Model calibration, sensitivity and validation

We calibrated the DNDC model to predict the observed nitrous oxide fluxes and maize yields (grain, leaf, stem, and root) from the control treatment across the three replicates. We first ran the model with observed and default inputs parameters (Tables 2 and 3). The DNDC model was then calibrated by optimising soil properties, including soil organic carbon, texture, pH, bulk density and C: N ratio and crop growth parameters such as maximum biomass production, shoot: root ratio, thermal degree days, water demand and optimum temperature. Following the DNDC guide, we converted maize yields to kg C ha^{-1} equivalence by multiplying harvested yields with 0.4 (Li 2012). We ran the calibrated DNDC model to simulate soil N_2O fluxes and maize yields across the three nitrogen fertilised soils.

We performed a sensitivity analysis to determine the performance of the model. The sensitivity analysis was used to determine the parameters that had a greater influence on the soil N_2O fluxes. Sensitivity analysis is an important modelling procedure providing insights into the model structure that could guide its improvement (Rafique et al. 2013). During sensitivity analysis, we changed one input parameter at a time while others kept constant. We assessed the changes in soil N_2O fluxes when daily rainfall, soil texture, bulk density, pH and soil organic carbon (SOC) were increased or decreased by 10%, 20% and 30%. Sensitivity analysis was also performed to assess how the soil N_2O fluxes were influenced by changing daily air temperature in the range of -3 °C to +3 °C.

We run the DNDC model using optimised input parameters such as climate, soil, crop and management data (e.g., quantity animal or inorganic fertiliser applied). The DNDC model was run across the three fertilised treatments. We validated the model by comparing observed and simulated soil N_2O fluxes, maize yields, yield scaled N_2O emissions and N_2O emission factors.

Model evaluation

We evaluated the DNDC model's performance in simulating soil N_2O fluxes and maize yields using four mathematical matrices. The matrices were mean error (ME) (Eq. 1), root mean squared error (RMSE) (Eq. 2), normalised root mean squared error (nRMSE) (Eq. 3), and model efficiency the Nash-Sutcliffe efficiency (NSE), (Eq. 4).

$$\mathrm{ME} = \frac{\sum_{i-1}^{n}(\mathrm{P_i}-\mathrm{O_i})}{\mathrm{n}} \tag{1}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i-1}^{n}(\mathrm{P_i}-\mathrm{O_i})^2}{n}} \tag{2}$$

$$\mathrm{nRMSE}(\%) = \frac{100}{o}\sqrt{\frac{\sum_{i-1}^{n}(\mathrm{P_i}-\mathrm{O_i})^2}{n}} \tag{3}$$

$$\mathrm{NSE} = 1-\frac{\sum_{i-1}^{n}(P_i-\mathrm{O_i})^2}{\sum_{i-1}^{n}\left(\mathrm{O_i}-\overline{\mathrm{O}}\right)^2} \tag{4}$$

Where $\mathrm{P_i}$ is the prediction value, n is the number of observed values, and $\overline{O}$ is the mean value of the observed data. Though each matrix was calculated independently, using various matrices to evaluate the model shows overall performance. Mean error (ME) and root mean square error (RMSE) give the overall deviation from the observed value. The normalised root square mean error (nRMSE) shows the percentage deviation from the average. We computed Nash-Sutcliffe efficiency (NSE), Nash and Sutcliffe (1970), referred to as modelling efficiency in our study. The NSE ($-\infty$ to 1) is a normalised statistic that determines the relative magnitude of the residual variance compared to measured data variance (Nash and Sutcliffe 1970; Moriasi et al. 2007). We considered our model to have excellent performance when the nRSME RSME ≤10%; good when 10% < nRMSE ≤20%; fair when 20% < nRMSE ≤30; and when nRMSE was >30, model was termed to have performed poorly (Dutta et al. 2017; Jiang et al. 2019; Smith et al. 2020). We considered model to be perfect when NSE = 1, good 1 > NSE ≥ 0.5, fair 0.5 > NSE ≥ 0 and poor NSE < 0 (Moriasi et al. 2007). We also used the coefficient of determination (R^2) between observed and simulated values to assess the agreement between observed and simulated. We fitted observed and simulated N_2O fluxes and maize yields in zero to intercept linear regression. The observed and simulated values were subjected to analysis of variance in SAS 9.4 software. The mean differences between soil fertility management technologies were separated using the least significant difference at $p \le 0.05$.

Yield-scaled N_2O emissions and N_2O emission factors

We calculated yield-scaled N_2O emission (g N_2O-N kg^{-1} grain yield) by dividing soil N_2O fluxes (g N_2O-N ha^{-1} yr^{-1}) with annual grain yields (Mg ha^{-1} yr^{-1}), Van Groenigen et al. 2010). We also determined N_2O emission factors for inorganic fertiliser, animal manure, and inorganic fertiliser + animal manure following Giltrap et al. (2013).

$$Yield\ scaled\ N_2O\ emission = \frac{Annual\ N_2O\ emission}{Grain\ yield} \tag{5}$$

$$N_2OEF = 100 \times \frac{\left\{\left(N_2O\ flux\ fertilised\right)-\left(N_2O\ flux\ control\right)\right\}}{N\ applied} \tag{6}$$

Where *N_2O EF* is a percent (%) nitrous oxide emission factor, *N_2O flux fertilised* (g N_2O-N ha^{-1} yr^{-1}) is annual nitrous oxide emission from nitrogen fertilised treatments, *N_2O flux control* is annual nitrous oxide emission from 0 nitrogen fertilised treatment (control),

Table 3 Climatic, crop management, and default DNDC input parameters used in simulation of nitrous oxide fluxes and maize yields in Tharaka-Nithi County

Parameter	Value/unit
Climatic	
Annual precipitation amount	1815 mm
Average daily minimum air temperature	15.7 °C
Average daily maximum air temperature	25.4 °C
Average daily wind speed	0.53 m/s
Average daily relative humidity	79.72%
Average daily solar radiation	17.92 Mj/M^2/day
Soil parameters	
Land use type	Upland crop filed
Crop	Maize (Variety-HB 516)
Soil texture[a]	Clay (78% clay, 14% silt and 8% sand)
Field capacity[a]	Observed
Wilting point[a]	Observed
Porosity[a]	Observed
Hydrological conductivity[a]	Observed
SOC portioning (fraction of resistant litter, humads and humus)	DNDC default values
CN ratio (of resistant litter, humads and humus)	DNDC default values
Depth of water retention	DNDC default values
Slope[a]	4.5
Field activities	
Land preparation and manure incorporation	LR 2018 season: 7th March 2018 SR 2018 season: 17th October 2018
Planting and fertiliser application	LR 2018 season: 13th March 2018 SR 2018 season: 24th October 2018
Harvesting	LR 2018 season: 9 August 2018 SR 2018 season: 28th February 2019

[a] Data previously derived in the same study area by Ngetich et al. (2014)

and N applied is the annual nitrogen application rate of 120 $kg\ N\ ha^{-1}\ yr^{-1}$.

Results

Soil characteristics and weather data

Observed soil bulk density ranged from 0.96 to 0.98 g cm^{-3}, soil pH 4.70–5.06, total nitrogen 0.20 to 0.23%, soil organic carbon (SOC) 2.26 to 2.52%. Soil C: N ratio ranged from 11.12 to 12.59, ammonium 2.05 to 3.37 mg N kg$^{-1,}$ and nitrates 5.70 to 6.90 mg N kg^{-1} (Table 2). The annual rainfall amount was 1815 mm, with 1193.5 mm and 621.5 mm received during LR 2018 and SR 2018 season, respectively (Table 3).

Model calibration

We calibrated the DNDC model using input parameters under control treatment (Tables 2 and 3). The calibrated DNDC model performed excellently in simulating soil N_2O fluxes (Fig. 1a and Table 4). The simulated cumulative annual N_2O fluxes of 0.20 kg N_2O-N ha $^{-1}$ yr^{-1} during calibration were close to the observed value of 0.21 kg N_2O-N ha $^{-1}$ yr^{-1} (Table 5). The performance of the DNDC calibrated model in simulating maize yields was good.

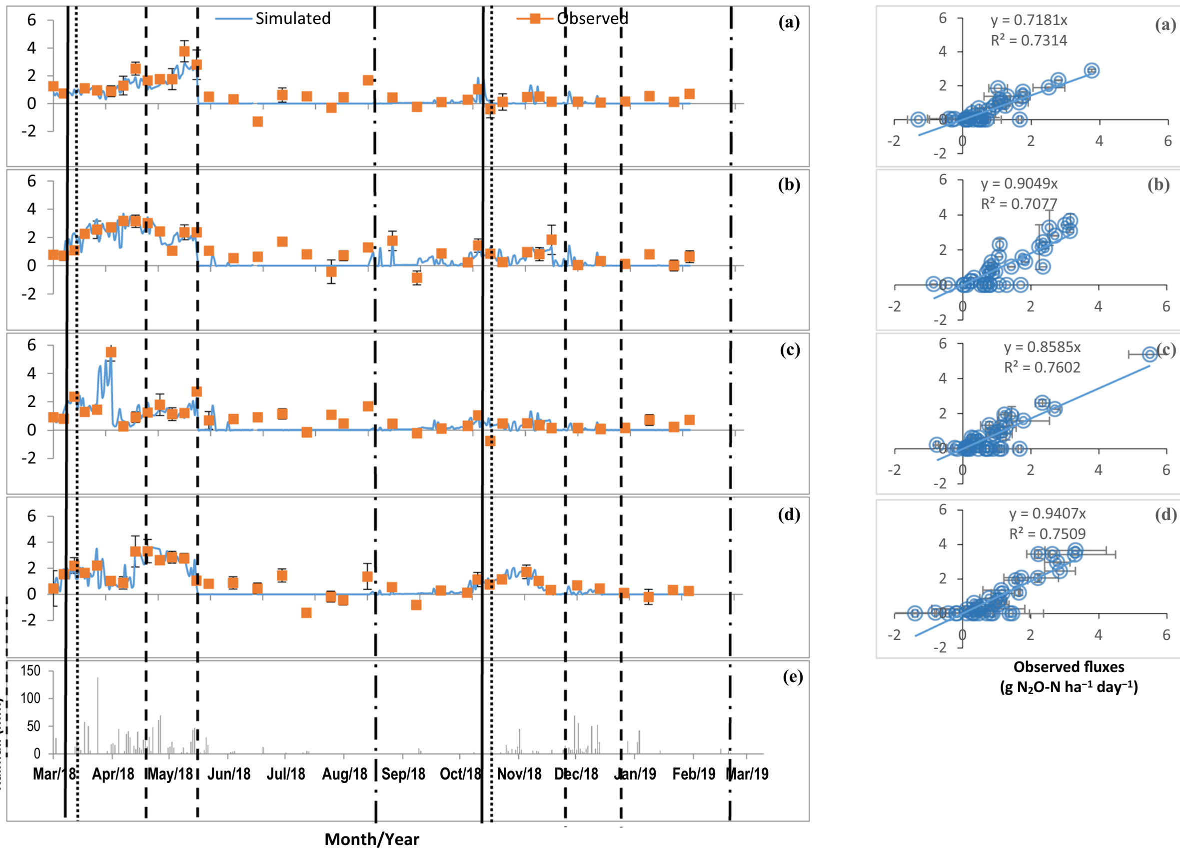

Fig. 1 Comparison between observed and simulated daily N_2O fluxes (g N_2O-N ha^{-1} day^{-1}) from the calibration (**a**) control (no external input), and validation (**b**) inorganic fertiliser (NPK 23.23.0, 120 kg N ha^{-1} yr^{-1}), (**c**) animal manure (goat manure, 120 kg N ha^{-1} yr^{-1}) and (**d**) animal manure + inorganic fertiliser (120 kg N ha^{-1} yr^{-1}) in Tharaka-Nithi County, Central highlands of Kenya for two cropping seasons (long rain and short rain, 2018). The vertical lines correspond to land preparation and manure application (continuous), planting and fertiliser application (dotted), weeding (dashed), and harvesting (long dashed). The Zero to intercept linear regression and R^2 are shown. The vertical error bars indicate simulated standard deviations while the horizontal error bars indicate observed (measured) standard deviations

Model sensitivity

The DNDC model was highly sensitive to daily rainfall, soil pH, bulk density, and soil organic carbon (Fig. 2). The greatest sensitivity was observed under rainfall, changing daily rainfall in the range of −30% to +30% change the cumulative N_2O fluxes from −48% to 65%. Changing soil pH from −30% to +30% varied cumulative annual soil N_2O fluxes from −50% to 56%. Changing soil bulk density and SOC from −30% to +30% changed cumulative N_2O fluxes from −31% to +28% and − 32% and + 30%, respectively. Changing the daily air temperature range from -3 °C to 3 °C had a moderate influence on cumulative N_2O fluxes that ranged from −13% to +16%. The DNDC model was less sensitive to soil texture, where changing soil texture from −15 to 15% change cumulative N_2O fluxes in the range from +3% to −2%.

Model evaluation in predicting daily soil N_2O fluxes

Observed daily soil N_2O across soil fertility technologies ranged between −1.40 and 5.51 g N_2O-N ha^{-1} day^{-1}. Simulated daily N_2O fluxes ranged between 0 and 5.37 g N_2O-N ha^{-1} day^{-1} (Fig. 1b-d). We observed peak N_2O fluxes following precipitation and fertiliser application. We infrequently observed soil N_2O uptakes (9.5%) of the totals sampling events. The model underestimated the soil N_2O peak on 16th May 2018 under control treatment (Fig. 1a). Both

Table 4 The model evaluation matrices comparing between simulated and observed daily and cumulative seasonal/annual soil N_2O fluxes Tharaka-Nithi County

Season[a]	Treatment[b]	ME	RMSE	nRMSE (%)	NSE
Daily	Control	−0.70	2.47	324.01	0.90
(g N_2O-N ha^{-1} day^{-1})	Fertiliser	−1.07	2.67	224.69	0.96
	Manure	−0.79	2.10	241.09	0.94
	Man+Fert	−0.90	1.58	157.16	0.95
LR 2018	Control	1.95	22.58	15.05	0.92
(g N_2O-N ha^{-1})	Fertiliser	−12.13	15.42	6.18	0.89
	Manure	−22.55	33.53	16.89	0.96
	Man+Fert	−18.09	25.91	11.88	0.81
SR 2018	Control	−8.14	8.89	13.44	0.97
(g N_2O-N ha^{-1})	Fertiliser	19.72	28.96	22.94	0.94
	Manure	−5.46	7.12	9.79	0.71
	Man+Fert	18.47	26.31	28.74	0.89
Annual	Control	−6.19	21.77	10.07	0.86
(g N_2O-N ha^{-1} yr^{-1})	Fertiliser	7.59	31.49	8.38	0.71
	Manure	−28.01	34.89	12.86	0.63
	Man+Fert	0.39	19.07	6.16	0.76

[a] Daily is sampling events, LR 2018 is long rain 2018 season, SR 2018 is short rain 2018 season and annual is the two cropping season March 2018 through March 2019

Evaluation matrices where ME is Mean Error, RMSE is Root Mean Square Error, nRMSE is normalized Root Mean Square Error, NSE is Nash-Sutcliffe efficiency

[b] Treatments: Control = (No external input), fertiliser = (inorganic fertiliser - NPK. 23.23.0, 120 kg N ha^{-1} yr^{-1}), Manure = (animal manure, 120 kg N ha^{-1} yr^{-1}) and Man + Fert = (animal manure+ inorganic fertiliser, 120 kg N ha^{-1} yr^{-1})

observed and simulated soil N_2O fluxes followed a similar pattern (Fig. 1b-d).

The model performance in simulating daily N_2O fluxes was poor, as shown by high nRMSE ranging from 157.16 to 324.01% across treatments (Table 4). The comparison between simulated and observed daily soil N_2O fluxes using zero to intercept regression resulted in a slope that ranged from 0.72 to 0.94, and R^2 ranged from 0.71 to 0.76 across treatments (Fig. 1a-d). Across all the four treatments, the model performance resulted in calculated matrices that ranged between ME = −1.07 and − 0.70 g N_2O-N ha^{-1} day^{-1}, RMSE = 1.57 and 2.67 g N_2O-N ha^{-1} day^{-1}, and NSE = 0.90 and 0.96 (Table 4).

Model performance in predicting cumulative seasonal and annual soil N_2O fluxes

Apart from inorganic fertiliser and animal manure + inorganic fertiliser, which had fair prediction using nRMSE during the SR 2018 season, the model's overall performance was good and excellent (Table 4). The DNDC model overestimated soil N_2O fluxes during SR 2018 season. During LR 2018 season, the model had a slope of 1.07, $R^2 = 0.94$, ME ranged between −22.55 and 1.95 g N_2O-N ha^{-1}, RMSE ranged between 15.42 and 33.53 g N_2O-N ha^{-1}, 6.18 ≤ nRMSE ≤16.89, and 0.81 ≤ NSE ≤ 0.96 (Table 4). During SR 2018 season, model performance ranged from excellent under manure treatment to fair under manure + fertiliser treatment. The DNDC model had slope = 0.90, $R^2 = 0.80$, E ranged between −8.14 and 19.72 g N_2O-N ha^{-1}, RMSE ranged between 7.12 and 28.98 g N_2O-N ha^{-1}, 9.76 ≤ nRMSE ≤28.74, and 0.71 ≤ NSE ≤ 0.97 across treatments (Fig. 3 and Table 4). Overall, DNDC model performance in simulating cumulative annual soil N_2O fluxes ranged between good and excellent across treatments (Table 4). The DNDC model had slope = 0.98, $R^2 = 0.96$, RMSE ranged from 19.07 to 34.89 g N_2O-N ha^{-1}, 6.16 ≤ nRMSE ≤12.86, and 0.63 ≤ NSE ≤ 0.86 (Table 4).

Table 5 Mean (±1 standard error of the mean) observed and simulated cumulative seasonal/annual soil N_2O fluxes under different soil soil fertility management technologies in Tharaka-Nithi County

Season [1]	Treatment [2]	Nitrous oxide fluxes (kg N_2O-N ha^{-1})	
		Observed	*Simulated*
LR 2018	Control	0.15^{c3}±0.01	0.15d
	Fertiliser	0.25^{a}±0.01	0.24a
	Manure	0.20^{b}±0.01	0.18c
	Man+Fert	0.22^{ab}±0.01	0.20b
	P value	0.001	<0.001
SR 2018	Control	0.07^{b}±0.01	0.06^{c}
	Fertiliser	0.13^{a}±0.01	0.15^{a}
	Manure	0.07^{b}±0.01	0.07^{c}
	Man+Fert	0.09^{ab}±0.02	0.11^{b}
	P value	0.031	<0.001
Annual	Control	0.21^{c}±0.01	0.20^{d}
	Fertiliser	0.38^{a}±0.02	0.38^{a}
	Manure	0.27^{b}±0.01	0.24^{c}
	Man+Fert	0.31^{b}±0.03	0.31^{b}
	P value	<0.001	<0.001

[1] LR 2018 is the long rain 2018 season, SR 2018 is the short rain 2018 season and annual is the two complete cropping season March 2018 through March 2019

[2] Treatments Control = (No external input), fertiliser = (inorganic fertiliser - NPK. 23.23.0, 120 kg N ha^{-1} yr^{-1}), Manure = (animal manure, 120 kg N ha^{-1} yr^{-1}) and Man + Fert = (animal manure+ inorganic fertiliser, 120 kg N ha^{-1} yr^{-1})

[3] Mean cumulative soil N_2O fluxes followed by the same superscript in the same column for the same season indicate no significant difference at $p = 0.05$

Simulated and observed cumulative annual soil N_2O fluxes significantly varied across treatments (Table 5). The cumulative observed and simulated annual soil N_2O fluxes ranged between 0.21 ± 0.01 and 0.38 ± 0.02 kg N_2O-N ha^{-1} yr^{-1} and 0.20 to 0.38 kg N_2O-N ha^{-1} yr^{-1}, respectively (Table 5). The highest soil N_2O fluxes were observed under fertiliser treatment and the lowest under control treatment (Table 5). Though observed and simulated soil N_2O fluxes were similar, the DNDC model underestimated fluxes in control and manure treatments (ME = −6.19 and − 28.01 g N_2O-N ha^{-1} yr^{-1}) while overestimating in fertiliser and manure + fertiliser treatments (ME = 7.59 and 0.39 g N_2O-N ha^{-1} yr^{-1}), respectively (Tables 4 and 5).

Model performance in simulating maize yields

The DNDC simulated maize crop yields (grain, leaf, stem, and root) were strongly correlated with the observed yields (Fig. 4). During the LR 2018 season, the R^2 ranged between 0.49 and 0.97, while zero to intercept linear regression slope ranged between 0.81 and 1.26 (Fig. 4a). The zero to intercept linear regression slope and R^2 ranged from 0.77 to 1.18 and 0.38 to 0.93, respectively, during the SR 2018 season (Fig. 4b).

Except for roots yields during LR 2018 season, which had a good performance, simulated maize yields (grain, leaf, stem, and root) across all soil fertility management technologies agreed with observed values (Table 6). Overall, evaluation matrices revealed that ME and RMSE of grain, leaf, stem, and root yields were relatively small, ranging from −322.00 to 164.74 kg ha^{-1} and 23.17 to 632.18 kg ha^{-1},

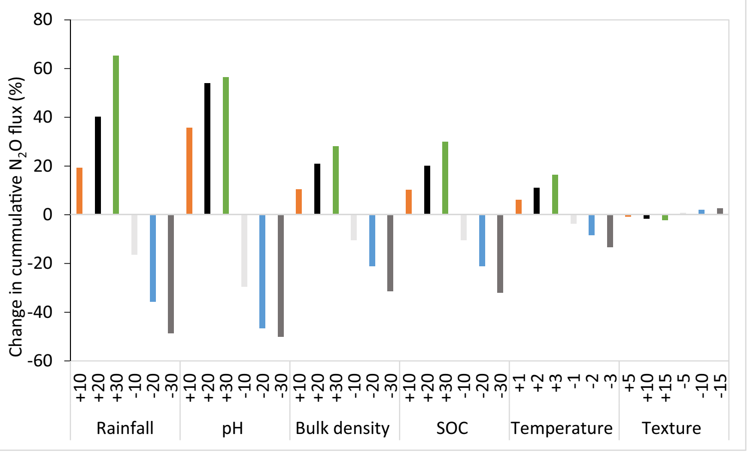

Fig. 2 Sensitivity analysis of the DNDC model to changes in the input parameters (i.e. daily rainfall, soil pH, soil bulk density, soil organic carbon (SOC), daily air temperature and soil texture)

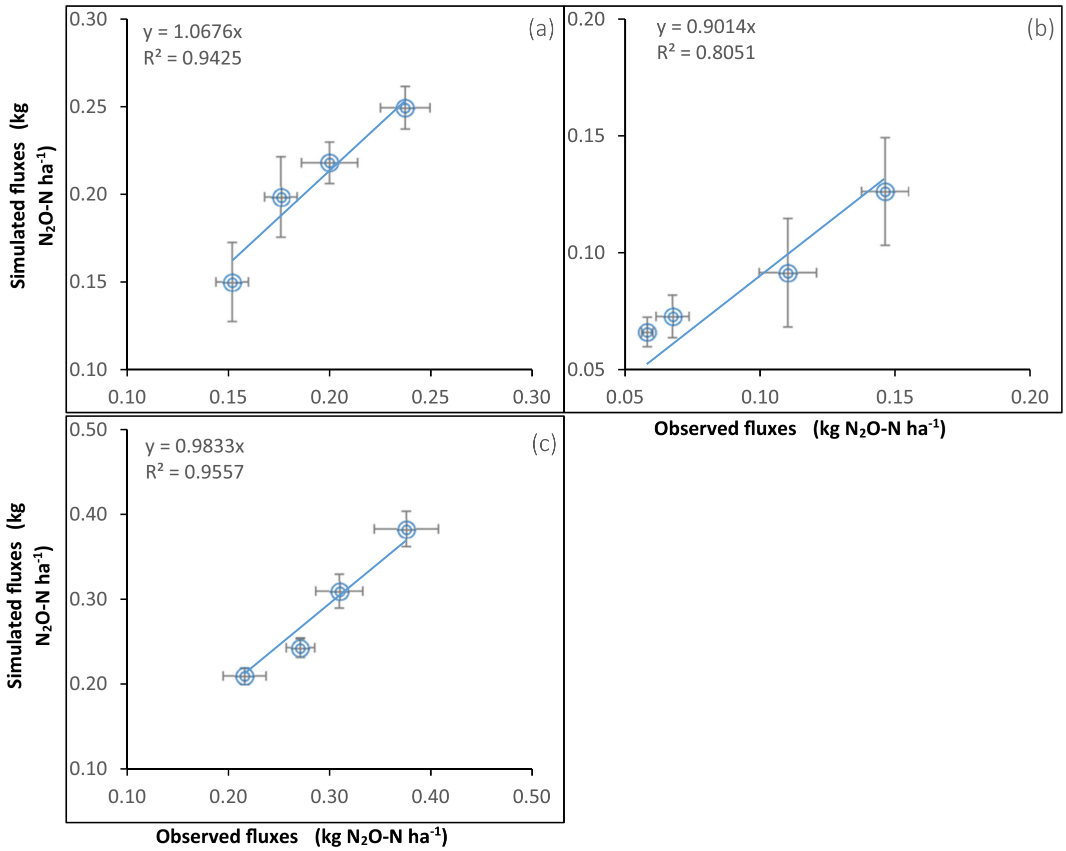

Fig. 3 The Zero to intercept linear regression between observed and simulated cumulative seasonal and annual N_2O fluxes, **a** long rain 2018 season cumulative N_2O fluxes, **b** short rain 2018 season cumulative N_2O fluxes, and **c** annual cumulative N_2O fluxes. The vertical error bars indicate simulated standard deviations while the horizontal error bars indicate observed (measured) standard deviations

respectively. The nRMSE (1.15 to 13.34%) and NSE (0.51 to 0.88) for all biomass components were good to excellent.

Observed grain yields ranged between 3.53 ± 0.23 and 7.24 ± 0.22 Mg ha^{-1}), and the simulated ranged from 3.34 ± 0.16 to 7.06 ± 0.18 Mg ha^{-1}), Table 7). Though the model captured the treatment means of grain yields, it underestimated grain yields (ME ranged between −322.00 and – 34.72 Kg ha^{-1}) across all soil fertility management technologies during the two cropping seasons (Table 6). Except for root prediction, the model performed better during the LR 2018 season than the SR 2018 season reason.

Comparison between observed and simulated yield-scaled N_2O emissions and N_2O emission factors

The DNDC model captured soil fertility management technologies' influence on yield-scaled N_2O emission and emission factors (Table 8). The DNDC model underestimated the yield-scaled N_2O under manure treatment (Table 8). Simulated yield-scaled N_2O emission ranged from 0.022 to 0.029 g N_2O-N kg^{-1} grain yield (Table 8). The DNDC model captured nitrous oxide emission factors (N_2O EFs) across treatments (Table 8). The simulated soil N_2O EFs were significantly ($p = 0.001$) different across treatments.

Discussion

Model calibration and sensitivity

The DNDC model's calibration using control treatment was necessary due to uncertainty in the environment since the model was initially developed to simulate C and N turnover in the US environments (Li et al. 1992). To simulate soil N_2O fluxes and crop yields, previous

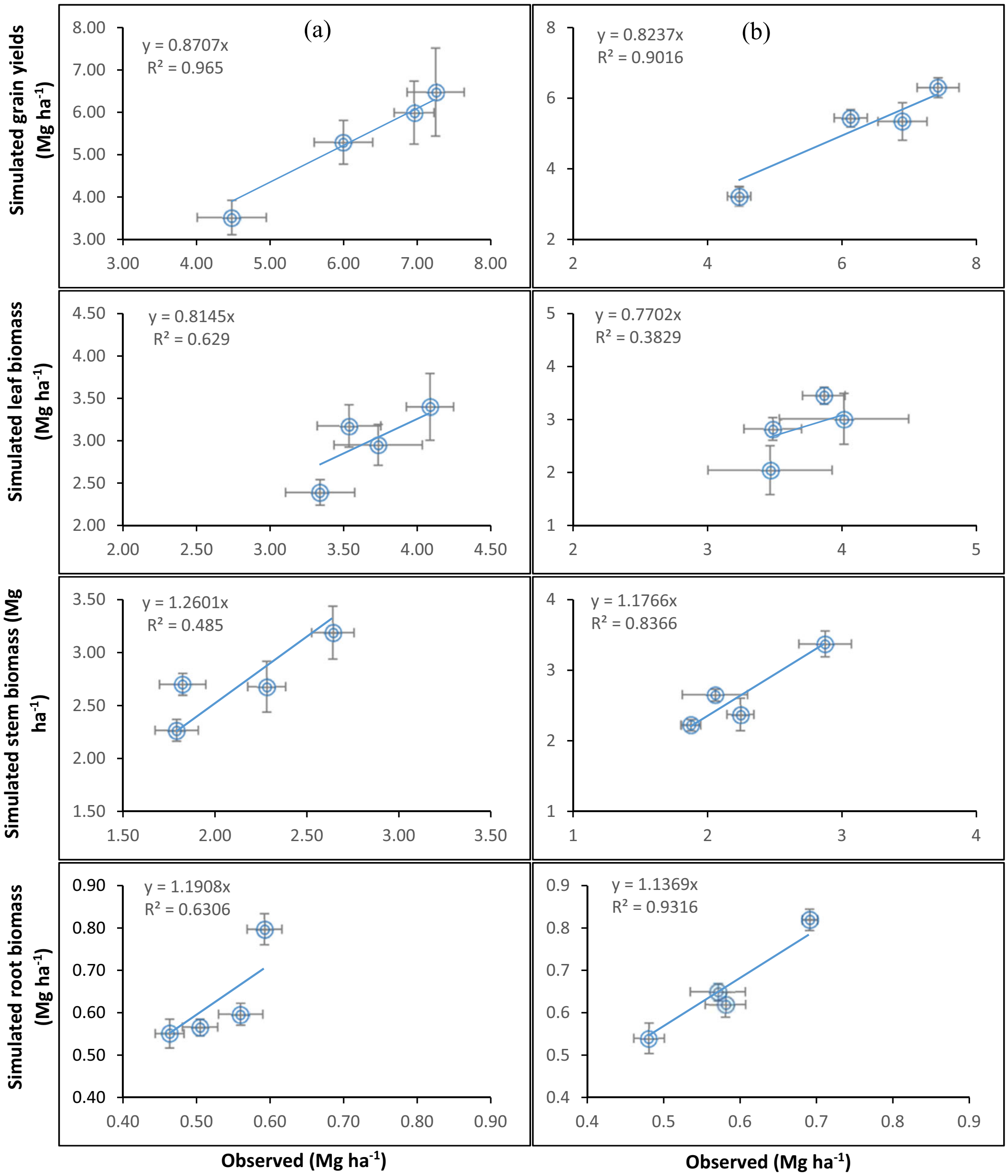

Fig. 4 Zero to intercept linear regression between observed and simulated maize yields (grain, leaf, stem and root), **a** long rain 2018 season and **b** short rain 2018 season under different soil fertility management technologies in Tharaka-Nithi County. The vertical error bars indicate simulated standard deviations while the horizontal error bars indicate observed (measured) standard deviations

studies suggest the DNDC model be calibrated to improve the prediction of biogeochemical processes (Rafique et al. 2011; Li et al. 2014; Abdalla et al. 2020). The calibrated DNDC successfully predicted the observed soil N_2O fluxes and maize yields (Fig. 1a, Tables 4, 5 and 6). Our findings agreed with previous studies (Cui et al. 2014; He et al. 2020; Lv et al. 2020) that reported the DNDC model to predict soil N2O fluxes and maize yields accurately.

The sensitivity analysis revealed that the DNDC model was sensitive to daily rainfall, soil pH, SOC, bulk density and daily air temperature (Fig. 2). Our findings underscore the importance of climatic and soil properties in predicting soil N_2O fluxes. Our findings

Table 6 Evaluation matrices comparing between simulated and observed maize yields (grain, leaf, stem, and root) under different soil fertility management technologies for two cropping seasons in Tharaka-Nithi County

Season[a]	Treatment[b]	Grain				Leaf			
		ME	RMSE	nRMSE (%)	NSE	ME	RMSE	nRMSE (%)	NSE
LR 2018	Control	−161.21	324.71	7.53	0.56	−69.26	82.49	2.53	0.82
	Fertilizer	−182.41	193.71	2.74	0.70	54.00	98.61	2.38	0.73
	Manure	−101.98	202.01	3.43	0.68	21.11	119.97	3.38	0.54
	Man+Fert	−322.00	331.44	5.00	0.85	−84.07	84.56	2.32	0.88
SR 2018	Control	−193.77	221.66	6.64	0.67	66.67	292.13	9.88	0.82
	Fertilizer	−116.07	632.18	9.91	0.54	82.22	153.04	4.39	0.69
	Manure	−107.58	243.40	4.68	0.67	107.41	135.21	4.11	0.56
	Man+Fert	−34.72	179.00	3.00	0.59	−21.48	33.62	1.15	0.97
		Stem				Root			
		ME	RMSE	nRMSE (%)	NSE	ME	RMSE	nRMSE (%)	NSE
LR 2018	Control	164.74	169.68	8.69	0.68	37.41	44.92	8.98	0.87
	Fertilizer	35.67	144.49	5.40	0.58	88.44	90.70	13.34	0.75
	Manure	−51.44	130.91	7.40	0.65	56.00	64.39	11.50	0.91
	Man+Fert	−135.11	148.52	6.93	0.68	50.81	70.94	11.63	0.88
SR 2018	Control	−106.67	109.78	5.07	0.51	18.89	23.17	4.07	0.85
	Fertilizer	−10.00	165.29	5.19	0.52	18.89	52.53	6.43	0.67
	Manure	−34.44	84.09	3.15	0.72	23.33	31.80	5.39	0.74
	Man+Fert	−78.89	92.72	3.56	0.59	36.30	52.49	8.29	0.84

[a] LR 2018 is the long rain 2018 season; SR 2018 is the short rain 2018 season

[b] Treatments Control = (No external input), fertiliser = (inorganic fertiliser NPK. 23.23.0, 120 kg N ha^{-1} yr^{-1}), Manure = (animal manure, 120 kg N ha^{-1} yr^{-1}) and Man + Fert = (animal manure+ inorganic fertiliser, 120 kg N ha^{-1} yr^{-1})

Evaluation matrices: ME is Mean Error, RMSE is Root Mean Square Error, nRMSE is normalized Root Mean Square Error, NSE is Nash-Sutcliffe efficiency

were in agreement with Smith et al. (2010) and Hu et al. (2011), who reported that the DNDC model was sensitive to soil organic carbon (SOC), pH, and bulk density. Given the ability to alter soil properties through different agricultural management practices, the soil N_2O fluxes could be mitigated. In agreement with our findings, Abdalla et al. (2020) reported high DNDC sensitivity to daily precipitation, soil organic carbon and daily air temperature.

Model performance in simulating daily soil N_2O fluxes

In this study, the negative soil N_2O fluxes meant that soil acted as a sink, while positive indicated a source of the emissions. The observed and simulated peak soil N_2O fluxes occurred following soil fertilisation and precipitation event similar to other DNDC studies, including Uzoma et al. (2015) and Giltrap et al. (2010). The Peaks under control treatment occurred following precipitation events, in agreement with Abdalla et al. (2020), who reported peak N_2O fluxes under control treatment following rainfall events in Hebei, China. The model failure to capture soil N_2O uptakes was inconsistent with field observations reported in the Central Highlands of Kenya that recorded small N_2O uptakes (Ortiz-Gonzalo et al. 2018; Macharia et al. 2020; Musafiri et al. 2020a). Similar to our findings, Rafique et al. (2011) documented soil N_2O negative fluxes that the DNDC model did not capture. The occasional uptake was ascribed to high water-filled pore space that could dissolve the soil N_2O into the water.

The ocassional soil N_2O uptakes was mainly observed under control treatment (10.8% of the total observations) and could be attributed to low nitrogen concentration (Chapuis-Lardy et al. 2007). Consentient with our study, Rafique et al. (2011) found that the DNDC model poorly captured daily soil N_2O fluxes during the off season. Soil N_2O uptake is not common

Table 7 Mean (±1 standard error of the mean) observed and simulated maize yields (grain, leaf, stem, and roots) Mg ha^{-1} under different soil fertility management technologies for two cropping seasons in Tharaka-Nithi County

Season[1]	Treatment[2]	Grain yields (Mg ha^{-1})		Leaf biomass (Mg ha^{-1})	
		Observed	Simulated	Observed	Simulated
LR 2018	Control	4.47^{c3}±0.27	4.31^{c}±0.10	3.27^{b}±0.16	3.30^{b}±0.07
	Fertiliser	7.24^{a}±0.22	7.06^{a}±0.18	4.14^{a}±0.09	4.06^{a}±0.13
	Manure	5.99^{b}±0.23	5.89^{b}±0.14	3.55^{b}±0.16	3.48^{b}±0.09
	Man+Fert	6.94^{a}±0.16	6.63^{a}±0.21	3.65^{ab}±0.18	3.53^{b}±0.23
	P value	<0.001	<0.001	0.023	0.020
SR 2018	Control	3.53^{b}±0.23	3.34^{c}±0.16	2.39^{b}±0.09	2.46^{b}±0.27
	Fertiliser	6.49^{a}±0.60	6.38^{a}±0.16	3.40^{a}±0.23	3.49^{a}±0.28
	Manure	5.31^{a}±0.30	5.20^{b}±0.14	3.18^{a}±0.06	3.29^{a}±0.09
	Man+Fert	6.01^{a}±0.43	5.97^{a}±0.32	2.95^{a}±0.14	2.93^{ab}±0.12
	P value	0.005	<0.001	0.010	0.035
		Stem biomass (Mg ha^{-1})		Root biomass (Mg ha^{-1})	
		Observed	Simulated	Observed	Simulated
LR 2018	Control	1.79^{c}±0.07	1.95^{c}±0.04	0.46^{b}±0.01	0.50^{d}±0.01
	Fertiliser	2.64^{a}±0.07	2.67^{a}±0.11	0.59^{a}±0.01	0.68^{a}±0.01
	Manure	1.82^{c}±0.07	1.77^{bc}±0.14	0.50^{b}±0.01	0.56^{c}±0.02
	Man+Fert	2.28^{b}±0.06	2.14^{b}±0.06	0.56^{a}±0.02	0.61^{b}±0.02
	P value	<0.001	0.001	0.001	<0.001
SR 2018	Control	2.27^{c}±0.06	2.16^{c}±0.04	0.55^{b}±0.02	0.57^{c}±0.02
	Fertiliser	3.19^{a}±0.14	3.18^{a}±0.11	0.80^{a}±0.02	0.82^{a}±0.01
	Manure	2.70^{b}±0.06	2.67^{b}±0.05	0.57^{b}±0.01	0.59^{bc}±0.02
	Man+Fert	2.68^{b}±0.14	2.60^{b}±0.13	0.60^{b}±0.01	0.63^{b}±0.01
	P value	0.002	<0.001	<0.001	<0.001

[1] LR 2018 is the long rain 2018 season; SR 2018 is the short rain 2018 season

[2] Treatments Control = (No external input), fertiliser = (inorganic fertiliser NPK. 23.23.0, 120 kg N ha^{-1} yr^{-1}), Manure = (animal manure, 120 kg N ha^{-1} yr^{-1}) and Man + Fert = (animal manure+ inorganic fertiliser, 120 kg N ha^{-1} yr^{-1})

[3] Mean maize yields followed by the same superscript in a column for the same season are not significantly different at $p \leq 0.05$

in tropical soils, which are net sources of N_2O fluxes (Hickman et al. 2011). Globally, the soil N_2O uptakes are low, mostly from wetlands and peat ecosystems, thus could not significantly contribute to large N_2O sink (Schlesinger 2013). Further, Kim et al. (2013), in their review, found that the soil N_2O uptakes are infrequent and of low magnitude thus could have a limited contribution to the global budget. The poor DNDC performance in capturing temporal trends in soil N_2O fluxes (Table 4) was consistent with 76 to 275% reported by He et al. (2020) and 192 to 328% reported by Lv et al. (2020). The high nRMSE could be attributed to the differences in the timing of daily peaks between observed and simulated, similar to Lv et al. (2020). Further, the poor performance in simulating daily soil N_2O fluxes could be attributed to inaccurate prediction of NO_3^--N and NH_4^+-N oxidation (Giltrap et al. 2015). Underestimation of daily soil N_2O fluxes in the off-season season could be attributed to model underestimation of soil water content (Smith et al. 2008).

Model performance in simulating cumulative soil N_2O fluxes

Our finding on cumulative soil N_2O fluxes agreed with various studies that reported the DNDC model had high discrepancies in simulating daily soil N_2O fluxes but accurately captured the magnitude of cumulative fluxes (e.g., Uzoma et al. 2015; He et al. 2020). The overestimation of soil N_2O fluxes during SR 2018 season could

Table 8 Mean (±1 standard error of the mean) observed and simulated yield-scaled N_2O emissions and N_2O emission factors from maize production under different soil fertility management technologies in Tharaka-Nithi County

Treatment[1]	Yield-scaled N_2O emission[2] (g N_2O-N kg^{-1} grain yield)		N_2O Emission factors[3] (%)	
	Observed	Simulated	Observed	Simulated
Control	0.027±0.001	0.028±0.001	–	–
Fertiliser	0.028±0.003	0.029±0.001	0.14^{a4}±0.02	0.14^{a}±0.01
Manure	0.024±0.002	0.022±0.001	0.05^{b}±0.01	0.03^{c}±0.01
Man+Fert	0.024±0.001	0.025±0.001	0.08^{b}±0.02	0.08^{b}±0.01
P value	0.4	0.2	<0.001	0.001

[1] Treatments Control = (No external input), fertiliser = (inorganic fertiliser NPK -23.23.0, 120 kg N ha^{-1} yr^{-1}), Manure = (animal manure, 120 kg N ha^{-1} yr^{-1}) and Man + Fert = (animal manure + inorganic fertiliser, 120 kg N ha^{-1} yr^{-1})

[2] Yield-scaled N_2O emission calculated by dividing maize grain yield with cumulative annual N_2O emission

[3] N_2O emission factors calculated by subtracting N_2O emissions control treatment from N_2O emissions in N applied treatments then dividing by annual N application rate (120 kg N ha^{-1} yr^{-1})

[4] Mean N_2O emission factors followed by the same superscript in the same column show no significant difference between treatments at $p \leq 0.05$

be attributed to the overestimation of soil N mineralisation from inorganic fertiliser.

We attributed the underestimation of cumulative annual soil N_2O fluxes under control treatments (Table 5) to the underestimation of the peak on 16th May 2018 (Fig. 1a). This could be ascribed to model difficulties in predicting soil nitrates and water content. The underestimation of cumulative annual soil N_2O fluxes under manure treatment resulted from poor prediction of soil NO_3^--N, especially during the SR season. It is noteworthy that, though manure treatment had lower cumulative annual soil N_2O fluxes possibly due to low N release, continuous application of animal manure could lead to a long term increase in N_2O fluxes due to accumulation of soil organic carbon (Wang et al. 2012; Deng et al. 2016).

The DNDC model overestimation of cumulative annual soil N_2O fluxes under inorganic fertiliser and manure + inorganic fertiliser (Table 5) could be attributed to model overestimation of soil N mineralisation from inorganic fertiliser applied (NPK, 23.23.0). Further, annual observed cumulative fluxes were calculated based on linear interpolation between sampling events Barton et al. (2015); however, the N_2O emissions are sporadic hence high uncertainty. Further, sampling following fertiliser application and rainfall event was done the following day (next 24 h), and hence we could have missed key peak emissions leading to overestimation by the DNDC model.

The low soil N_2O fluxes under control treatment could be attributed to low soil organic carbon and nitrogen, similar to Ri et al. (2003), who reported a decrease in soil N_2O fluxes with a decrease in organic carbon and N pool. The high simulated soil N_2O fluxes recorded under fertiliser treatment that was similar to our field observation could be attributed to enhanced nitrification and denitrification by the inorganic fertiliser (Abdalla et al. 2012). However, other studies, for example, Deng et al. (2016) and Abdalla et al. (2020), reported that splitting fertiliser application and avoiding its application during rainfall events can significantly reduce observed and simulated soil N_2O fluxes.

Model performance in simulating maize yields

Our findings on zero to intercept linear regression (1:1) R^2 were consistent with Abdalla et al. (2020) study, which reported an R^2 of 0.89 to 0.92 from maize and wheat grain yields under different N application rates in Hebei, China. The DNDC model was able to simulate different maize yields components across different soil fertility management technologies. Our results agreed with other studies that reported well to excellent agreement between simulated and observed maize crop biomass under different soil fertility management technologies (Cui et al. 2014; Jiang et al. 2019; Lv et al. 2020). Underestimation of maize crop yields across soil fertility management treatments can be ascribed to the overestimation of evapotranspiration and the DNDC model difficulties in predicting soil water content and nitrates. Jiang et al. (2019) noted underestimation of maize yields attributed to the possibility of DNDC underestimating N mineralisation and dissolved inorganic N pool under N stress.

In this study, the model performed better during the LR 2018 season compared with the SR 2018 season reason consistent with Zhang et al. (2018), who revealed the possibility of underestimation of crop yields under low precipitation periods. Further, the model's low performance during the SR 2018 season that had 47% lower precipitation compared with LR season 2018 season could be endorsed to the model overestimation of evapotranspiration. Nevertheless, the model's accurate simulation of root biomass under low rain season (SR 2018) can be ascribed to its ability to accurately predict root distribution and soil water content (Uzoma et al. 2015).

Simulation of yield-scaled N_2O emissions and N_2O emission factors

Yield-scaled N_2O emission can evaluate trade-offs between crop production and environmental impacts under different soil fertility management technologies (Van Groenigen et al. 2010). Though simulated yield-scaled N_2O emissions were low, they were close to the observed values (Musafiri et al. 2020a). We attributed the underestimation of yield-scaled N_2O under manure treatment to the underestimation of cumulative annual soil N_2O fluxes. Our simulated yield-scaled N_2O emission (Table 8) was lower than the 0.5 to 2.2 g N_2O-N kg^{-1} grain yield reported in the Central Highlands of Kenya (Macharia et al. 2020). The low yield-scaled N_2O emissions in this study can be attributed to high potential Humic nitisols, which have higher grain production and low nitrous oxide emissions possibility due to high crop nitrogen uptake (Musafiri et al. 2020a). It is noteworthy that though manure treatment had the lowest yield-scaled N_2O emissions, the overall grain yields were significantly lower during SR 2018 season. Therefore, combining animal manure and inorganic fertiliser yielded reasonable trade-offs between crop production and greenhouse gas emissions.

The simulated N_2O EFs were 0.14% under fertiliser treatment, 0.08% under manure + fertiliser treatment, and 0.03% under manure treatment. Though the DNDC model accurately captures N_2O EFs, it underestimated factors under manure treatment (Musafiri et al. 2020a). Simulated N_2O EFs though consistent with several field-measured values reported in Central Highlands of Kenya Ortiz-Gonzalo et al. (2018), Macharia et al. (2020), and Musafiri et al. (2020a), were 7 to 33 times lower than IPCC Tier 1 default EFs of 1%. Therefore, using IPCC Tier 1 default, EFs could overestimate soil N_2O fluxes in the range of 86 to 97%.

Conclusion

Our study revealed that the DNDC model did not accurately simulate daily soil N_2O fluxes. The DNDC simulated cumulative soil N_2O fluxes, maize yields, yield-scaled N_2O fluxes, and emission factors were close to observed values. The DNDC model captured the influence of all four soil fertility management on soil N_2O fluxes, maize yields, yield-scaled emission, and emission factors in the central highlands of Kenya. Given that direct quantification of soil GHG emissions is expensive and impractical for accurate reporting INDCs, especially in developing countries, including Kenya, use of the DNDC model could be a plausible alternative. However, the DNDC model needs to be further improved to accurately predict daily emissions and occasional uptakes in tropical soils. Upon development, the DNDC could be used to report N_2O emissions in Kenyan soils. We recommend long term soil greenhouse gas quantification experiments to increase understanding of different soil fertility management technologies implications on sustainable production. We also recommend further research on the implication of split fertiliser application on soil N_2O fluxes in Kenya.

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Availability of data and material All data generated or analysed during this study are included in this published article.

Code availability Not applicable.

Authors' contributions CMM, JMM, and FKN conceived this research and designed experiments; CMM performed experiments and analysis; CMM, OKN, CAS, JMO, EAO, MNK participated in the design and interpretation of the data. CMM, JMM, MNK, FKN wrote the paper and participated in the revisions of it. All authors read and approved the final manuscript.

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Declarations

Conflicts of interest/competing interests The authors declare that they have no potential conflict of interest in relation to the study in this paper.

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