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# Modelling nitrous oxide emissions from grazed grassland systems

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A B S T R A C T

Grazed grassland systems are an important component of the global carbon cycle and also influence global climate change through their emissions of nitrous oxide and methane. However, there are huge uncertainties and challenges in the development and parameterisation of process-based models for grazed grassland systems because of the wide diversity of vegetation and impacts of grazing animals. A process-based biogeochemistry model, DeNitrification-DeComposition (DNDC), has been modified to describe $N_2O$ emissions for the UK from regional conditions. This paper reports a new development of UK-DNDC in which the animal grazing practices were modified to track their contributions to the soil nitrogen (N) biogeochemistry. The new version of UK-DNDC was tested against datasets of $N_2O$ fluxes measured at three contrasting field sites. The results showed that the responses of the model to changes in grazing parameters were generally in agreement with observations, showing that $N_2O$ emissions increased as the grazing intensity increased.



## 1. Introduction

Agriculture plays an important role in the UK economy, landscape and environment, accounting for 5% of the gross domestic production (GDP) in 2007. It is a major source of nitrous oxide ($N_2O$) and methane ($CH_4$) emissions, accounting for c. 79% of the total UK emissions of $N_2O$ and 41% of the total UK $CH_4$ emissions in 2009 (MacCarthy et al., 2011). Nitrous oxide is an important greenhouse gas (GHG) because it has approximately 300 times the global warning potential of carbon dioxide ($CO_2$) on a mass basis (IPCC, 2006). Nitrous oxide is produced naturally in soils through the microbial processes of nitrification and denitrification. Agricultural practices, such as nitrogen (N) amendments with fertiliser or manure, cultivation, legume cropping and irrigation, can increase $N_2O$ production and emissions above background levels. Application of synthetic N fertiliser directly increases the pool of mineral N available for nitrification and denitrification. Various biogeochemical factors influence mineral N supply, plant N demand and abiotic soil conditions which affect $N_2O$ emissions from soils. Since soils represent one of the largest reservoirs of terrestrial N and carbon (C) on the global scale, quantifying the change of the C and N storage in soil is a central challenge for understanding C and N cycle dynamics and a prerequisite for reliable prediction of climate change. Therefore, the potential of the soil to act as a sink or source of atmospheric GHGs is of great interest (Lal, 2004; Davidson and Janssens, 2006; Heimann and Reichstein, 2008; Schlesinger, 1999; Mosier and Kroeze, 2000; Richter et al., 2010).

The UK ratified the United Nations Framework Convention on Climate Change (UNFCCC) in December 1993 and the Convention came into force in March 1994. Parties to the Convention are committed to developing, publishing and regularly updating national inventories of GHG emissions. The inventory methods developed by the Intergovernmental Panel on Climate Change (IPCC) for estimating national-level GHG inventories are comprehensive, globally-applicable and empirical (IPCC, 2006; Wang et al., 2011a). The IPCC inventory methodology is a practical, first-order approach that uses simple default emission factors (EFs) and addresses the anthropogenic effects on sources and sinks of GHGs. A series of default EFs are used for estimating GHG emissions. However, emissions from livestock depend on a range of factors, such as animal type, their weight and age, proportion of time spent grazing, type of animal housing, type of manure and its storage and application, weather and soil type. The variability of all these controlling factors, both in time and space, results in very heterogeneous GHG emissions. Thus, the emissions exhibit a high degree of temporal and spatial variability. An accurate inventory

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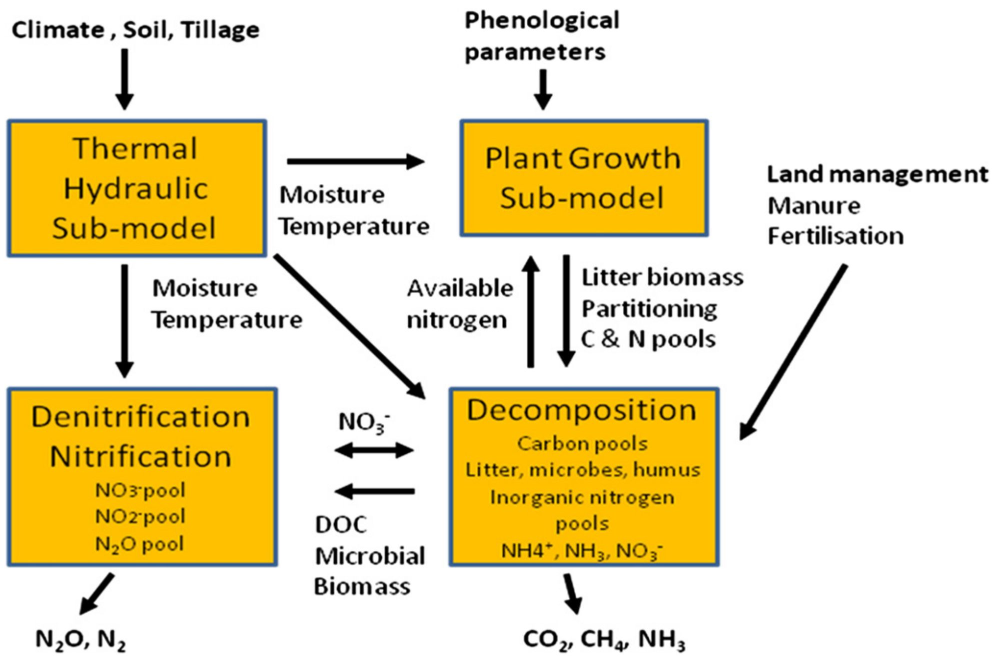


**Fig. 1.** Structure of the UK-DNDC model.

should calculate total national emissions, identify the major sources and spatial variations, and hence help to develop effective abatement policies. Assessing the accuracy of such an inventory requires an evaluation of the accuracy of the estimated $N_2O$ emissions.

Field experiments play a key role in obtaining first-hand information about the effects of alternative management practices on crop yield and various C or N pools or fluxes in particular fields. However, most field experiments require extensive time and resources. Therefore, field measurements will always be limited in space and time for the sake of practical and financial reasons. In particular, direct measurement of GHG emissions for inventory purposes is impractical as it would require many measurements to be made over a large scale and for long periods of time. To extrapolate the experimental data gained at a limited number of field sites to regional scales, process-based models have been developed and adopted to assist the policy making process in agricultural studies. Many process-based simulation models for estimating $N_2O$ emissions have been developed, such as DNDC (Li et al., 1992a, 1992b, 2006; Brown et al., 2002), NGAUGE (Brown et al., 2005), SIMSdairy (del Prado and Scholefield, 2008), MOTOR (Whitmore, 2007), CENTURY (Parton et al., 1988; Melillo et al., 1995) and Daycent (Parton et al., 1998). Agro-ecosystem models generally operate at a scale that simulates soil biogeochemical processes at a particular site, and this can then be upscaled through a regular or irregular grid.

The DNDC model has received much attention because it has more functions and is more widely applicable than some other ago-

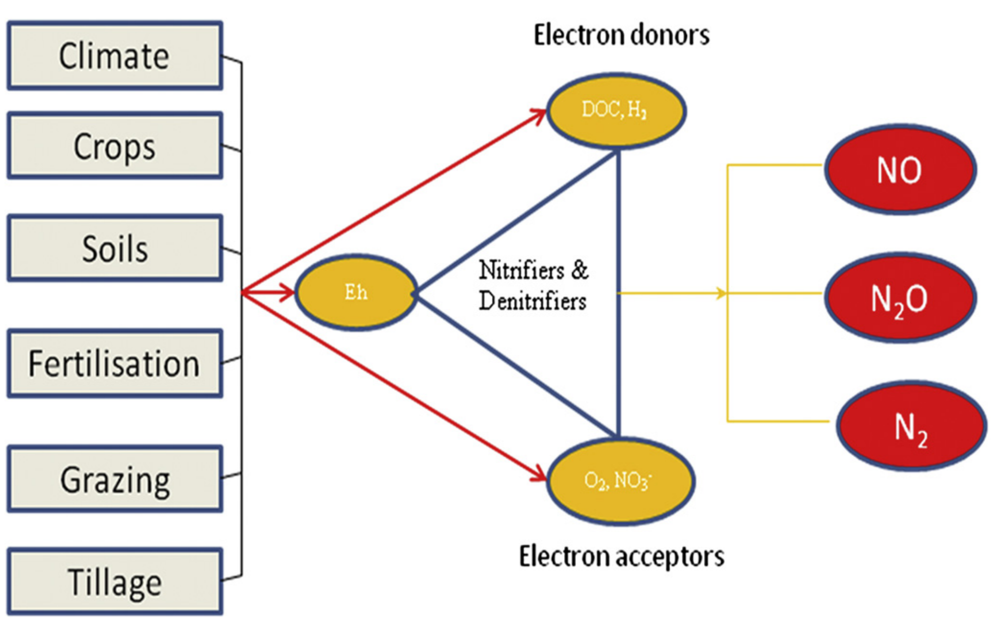


**Fig. 2.** Schematic representation of nitrification and denitrification processes at a soil microsite as modelled in UK-DNDC.

**Table 1**
Characteristics of the three field sites in England and Wales.

| Location | Rowden | Cae Banadl | High Mowthorpe |
|---|---|---|---|
| Latitude | 50:46 | 52:26 | 54:06 |
| Average temperature (°C) | 10.66 | 10.86 | 9.6 |
| Soil bulk density | 1.0 | 0.9 | 0.93 |
| Soil texture | Clay loam | Loam – fine loam | Silty clay loam |
| Soil pH | 5.8 | 6.4 | 7.4 |
| Total soil C (%) | 6.7 | 3[a] | 4.2 |
| Soil $NO_3^-$ (mg N $kg^{-1}$) | 0.06 | 10.5 | 0.06[a] |
| Soil $NH_4^+$ (mg N $kg^{-1}$) | 6.42 | 1.85 | 6[a] |
| 2006 rainfall (mm $yr^{-1}$) | 922 | 1047 | 813 |
| Atmos. background $NH_3$ (ppm) | 0.06[a] | 0.06[a] | 0.06[a] |
| Atmos. $CO_2$ (ppm) | 350[a] | 350[a] | 350[a] |

[a] Note that data were estimated.

ecosystem models. Butterbach-Bahl et al. (2001, 2004) developed the model for forest modelling. It was used by Miehle et al. (2006) to analyse the uncertainty in large-scale model predictions of forest C dynamics. Cui et al. (2005) analysed the $CO_2$ and $CH_4$ emissions of forest wetland using Wetland-DNDC. The forest version was used for estimating the $N_2O$ emissions of tropical rainforests in the Wet Tropics of Australia (Kiese et al., 2005). Frolking et al. (2004) simulated short- and long-term GHG emissions in rice paddies. Li et al. (2005) modelled impacts of farming practices on $CO_2$, $CH_4$ and $N_2O$ emissions from rice paddy fields in China. Fumoto et al. (2008) modified the model to simulate methane emission from rice paddy fields under various residue management and fertiliser regimes. Li et al. (2010) simulated impacts of alternative farming managements on GHG emissions from a winter wheat-maize rotation in China. Qiu et al. (2009) studied C sequestration in agricultural soils in China.

Most validations of the DNDC model have been performed on arable or forest fields with relatively few on grazing systems. Grasslands cover approximately 140 million ha within Europe west of the Urals, accounting for 18% of the land area in the EU-15 (Levy et al., 2007). In spite of their importance, the source strength of grazing systems for $N_2O$ emissions is still poorly characterised, due to the lack of data or their poor quality in respect to spatial and temporal factors. Saggar et al. (2004, 2007) and Giltrap et al. (2010a, 2010b) simulated GHGs from grazing systems in New Zealand. Levy et al. (2007) simulated fluxes of GHGs emissions from European grassland. Despite many improvements to incorporate grazing systems in their frameworks, these models are still not sufficiently detailed to resolve temporal and spatial variations from agricultural grazed sources.

There are huge uncertainties in the development of process-based models for grazed systems. This arises from the wide diversity of vegetation and root systems in grassland and the growth of vegetation required to be described and parameterised for different regions. Furthermore, because of the movement of animals when grazing, their impacts are non-uniform and difficult to parameterise. To contribute towards more reliable estimates of $N_2O$ emissions from grazing systems it will be necessary to follow a dual approach. Detailed measurements of rates of $N_2O$ emissions from different grazing ecosystems are required. These should be both spatially representative and provide long-term coverage in order to better understand seasonal variability and to identify the major environmental drivers that control the magnitude of $N_2O$ emissions (Kiese et al., 2005; Cardenas et al., 2010). These data are also needed to further develop and validate biogeochemical models, which provide a useful tool for integrating our knowledge of key processes and driving variables to estimate N and C trace gas emissions from grazed pastures.

The primary aims of the present study were to (1) further parameterise the grazing systems for the UK-DNDC model to allow it to cope with grazed conditions and their impacts on $N_2O$ emissions, (2) validate the revised UK-DNDC against measured data from three UK sites and (3) estimate the influence of animal grazing practices on $N_2O$ emissions with the modelling tool. We expected that the study would improve our understanding of soil biogeochemical processes in grazed systems.

## 2. Materials and methods

### 2.1. The UK-DNDC model

DNDC (Li et al., 1992a and 1992b) is a mechanistic simulation model of C and N biogeochemistry in agricultural soils. DNDC contains four interacting submodels: soil thermo-hydraulic, denitrification, decomposition and plant growth as shown in

**Table 2**
Timing and rates of ammonium nitrate fertiliser applications (kg N $ha^{-1}$) in 2006.

| Location | | Plot 1 | Plot 2 | | Plot 3 | | Plot 4 | |
|---|---|---|---|---|---|---|---|---|
| | Date | Fertiliser kg $ha^{-1}$ | Date | Fertiliser kg $ha^{-1}$ | Date | Fertiliser kg $ha^{-1}$ | Date | Fertiliser kg $ha^{-1}$ |
| Rowden | | | 19/04 | 40 | 19/04 | 60 | 19/04 | 80 |
| | | | 30/05 | 35 | 10/05 | 50 | 10/05 | 70 |
| | | | | | 30/05 | 35 | 30/05 | 60 |
| | | | | | 20/06 | 30 | 20/06 | 50 |
| | | | | | | | 11/07 | 50 |
| | | | | | | | 01/08 | 40 |
| | Total | 0 | | 75 | | 175 | | 350 |
| Cae Banadl | | | 26/04 | 40 | 26/04 | 60 | 26/04 | 80 |
| | | | 13/06 | 35 | 22/05 | 50 | 22/05 | 70 |
| | | | | | 13/06 | 35 | 13/06 | 60 |
| | | | | | 05/07 | 30 | 05/07 | 50 |
| | | | | | | | 31/07 | 50 |
| | | | | | | | 30/08 | 40 |
| | Total | 0 | | 75 | | 175 | | 350 |
| High Mowthorpe | | | 27/04 | 50 | 27/04 | 75 | 27/04 | 101 |
| | | | 19/06 | 26 | 02/06 | 33 | 02/06 | 50 |
| | | | | | 19/06 | 37 | 19/06 | 68 |
| | | | | | 24/07 | 31 | 24/07 | 71 |
| | | | | | | | 22/08 | 60 |
| | Total | 0 | | 75 | | 175 | | 350 |


**Fig. 3.** Location of the three field study sites.

Fig. 1. The soil thermal-hydraulic submodel uses soil texture, air temperature, and precipitation data to calculate soil temperature and moisture profiles. This information is fed into both the denitrification and the decomposition submodels. The decomposition submodel tracks various C and N pools in soil as plant residues decompose and soil microbes grow and die. The denitrification submodel, driven by rainfall events, calculates hourly denitrification processes and $N_2$, NO and $N_2O$ production. All organic components are divided into four major soil organic C (SOC) pools, namely residues, microbial biomass, humads, and humus. Each of the SOC pools consists of two or three sub-pools representing the relatively labile and resistant fractions of the pool. The humus pool is defined as the passive humus, which is relatively resistant and can stay for decades to centuries in the soil. The plant growth submodel calculates daily crop growth, N uptake by vegetation, plant biomass partitioning, and root respiration driven by the climate and soil conditions. Effects of agricultural practices (fertilisation, irrigation, tillage, crop rotation, and manure amendments) on the soil C and N dynamics have been incorporated into the model. Rothamsted Research (North Wyke) has been involved in the development of the UK version of DNDC (Brown et al., 2002) and assessing its potential in compiling a GHG inventory for UK agriculture (Brown et al., 2001; Wang et al., 2011a). The UK-DNDC keeps the structures and main functions of original DNDC but incorporates the UK-calibrated crops and soil characteristics, livestock and farming practice. The UK-DNDC is also developed for the requirement of the UK, such as biogas digestate for use as fertiliser (Wang et al., 2010b).

In DNDC, $N_2O$ production/consumption is directly regulated by three factors, namely soil redox potential (Eh), dissolved organic C (DOC) concentration and available N i.e., ammonium ($NH_4^+$) or nitrate ($NO_3^-$) concentration. When natural processes or management practices change, they can alter one or more of the three driving factors and hence affect $N_2O$ production. If any of the three factors becomes limiting, the $N_2O$ production will be reduced or stopped (Fig. 2). DNDC tracks the soil redox potential evolution and calculates production and consumption of $CO_2$, $N_2O$ and $CH_4$ sequentially for grassland, arable or forest ecosystems (Li et al., 1992, 2005 and Li, 2007). In DNDC, DOC concentration is calculated on the basis of the SOC decomposition rate using the decomposition submodel and controls $N_2O$, $CO_2$, or $CH_4$ production by fuelling the relevant microbial activities in conjunction with other substrates (e.g., $NH_4^+$, $NO_3^-$ or $H_2$). By precisely simulating the soil microbial activities, DNDC links $N_2O$ emissions to C sequestration and $CH_4$ emissions. A complete set of farming management practices such as tillage, fertilisation, manure amendment, irrigation, flooding, grazing, etc. have also been parameterised in UK-DNDC to regulate the soil environmental factors (e.g., temperature, moisture, pH, redox potential and substrate concentration gradients).

### 2.2. Modification of the model for grazing

To simulate the GHG impacts of grazing, UK-DNDC has been modified by integrating an enhanced livestock grazing function. For grazed pastures, animal grazing was parameterised according to grazing intensity and timing. The amount of dung and urine from each animal was summed to obtain the total amount of dung and urine produced for a site. Grazing intensity per hectare was defined as the number of grazing animals × the number of grazing days during each grazing event.

A scheme can be written based on the grazing intensity for each type of animal:

For Grazing Numbers
{ For Grazing days
{ C = $k_1$ *C_Dung/365
N = $k_2$ * N_Dung/365
U = $k_3$ * Urine/365
N_surf = $k_4$ * head/365 (Surface Loss due to $NH_3$ volatilisation)
Grazing C = head * C
Grazing N = head * N − $k_5$ * N_surf
Grazing C/N = Grazing C/Grazing N
Grazing U = $k_6$ * U * head − $k_7$ * N_surf
Allocation to very labile, labile and resistant C pools of the litter and microbes
}
}

C_Dung and N_Dung denote the C and N content of animal dung per animal each year, respectively. Urine is the quantity of urine-N per animal each year. N_surf is N loss from the pasture surface due to $NH_3$ volatilisation. Head is the number of animals per hectare. The coefficients, $k_1$ to $k_7$, are correction factors related to animal weight, age and food and environmental conditions.

Any change in grazing practices mostly affects the quantity and quality of the animal waste input and grass litter incorporation, which eventually redefines the soil C and N balance with the local climate and soil conditions. The grazing intensity

**Table 3**
Start date and grazing intensity (head $ha^{-1}$ × days) for individual grazing events at the three field sites.

| Location | Plot 1 | | Plot 2 | | Plot 3 | | Plot 4 | |
|---|---|---|---|---|---|---|---|---|
| | Date | Grazing head.days $ha^{-1}$ | Date | Grazing head.days $ha^{-1}$ | Date | Grazing head.days $ha^{-1}$ | Date | Grazing head.days $ha^{-1}$ |
| Rowden | 10/05 | 3.34 × 42 | 10/05 | 4.46 × 23 | 10/05 | 5.57 × 17 | 10/05 | 6.69 × 17 |
| | 06/07 | 3.34 × 12 | 06/06 | 4.46 × 15 | 06/06 | 5.57 × 15 | 06/06 | 6.69 × 7 |
| | 11/08 | 3.34 × 15 | 06/07 | 4.46 × 12 | 06/07 | 5.57 × 12 | 04/07 | 6.69 × 14 |
| | 04/09 | 3.34 × 10 | 11/08 | 4.46 × 15 | 11/08 | 5.57 × 15 | 11/08 | 6.69 × 15 |
| | 02/10 | 3.34 × 10 | 04/09 | 4.46 × 10 | 04/09 | 5.57 × 10 | 04/09 | 6.69 × 10 |
| | 08/11 | 3.34 × 6 | 02/10 | 4.46 × 10 | 02/10 | 5.57 × 10 | 02/10 | 6.69 × 10 |
| | | | 08/11 | 4.46 × 6 | 08/11 | 5.57 × 6 | 08/11 | 6.69 × 6 |
| | Total | 317 | | 406 | | 474 | | 529 |
| Cae Banadl | 11/05 | 4.6 × 23 | 11/05 | 7.8 × 23 | 11/05 | 9 × 23 | 11/05 | 9.6 × 23 |
| | 21/06 | 3.7 × 17 | 21/06 | 3.8 × 24 | 21/06 | 5.7 × 22 | 21/06 | 7.3 × 20 |
| | 05/09 | 3.7 × 5 | 05/09 | 3.7 × 5 | 17/08 | 7.3 × 9 | 17/08 | 3.7 × 6 |
| | 16/09 | 3.7 × 6 | 16/09 | 3.7 × 7 | 09/09 | 3.7 × 6 | 05/09 | 4.9 × 10 |
| | 06/10 | 4.9 × 8 | 26/09 | 3.7 × 4 | 16/09 | 3.7 × 11 | 21/09 | 6.9 × 9 |
| | | | 11/10 | 3.7 × 7 | 06/10 | 3.7 × 8 | 06/10 | 3.7 × 8 |
| | Total | 249 | | 356 | | 491 | | 530 |
| High Mowthorpe | 04/05 | 13.33 × 34 | 04/05 | 16.67 × 34 | 04/05 | 18.18 × 34 | 04/05 | 15.38 × 34 |
| | 12/06 | 13.33 × 8 | 07/06 | 16.67 × 13 | 07/06 | 18.18 × 13 | 07/06 | 15.38 × 13 |
| | 26/06 | 13.33 × 10 | 26/06 | 16.67 × 10 | 26/06 | 18.18 × 10 | 26/06 | 15.38 × 10 |
| | 07/08 | 13.33 × 9 | 07/08 | 16.67 × 12 | 07/08 | 18.18 × 12 | 07/08 | 15.38 × 12 |
| | 04/09 | 13.33 × 15 | 04/09 | 16.67 × 15 | 04/09 | 18.18 × 15 | 04/09 | 15.38 × 15 |
| | Total | 1013 | | 1400 | | 1527 | | 1292 |

determines the dung and urine from animal grazing and these are linked to the C pools of the litter and microbes which control the biogeochemical reactions. Thus, the parameterised grazing intensity was integrated into the decomposition and denitrification/nitrification submodels. It should be mentioned that the weight, diet and age of animals also change the quantity and quality of the excreta. The coefficients, $k_1$ to $k_7$, can be used for adjusting these factors when data are available. The model is capable of estimating GHG emissions and predicting impacts of alternative grazing managements on GHG mitigation for a wide range of farm types using the grazing intensity.

### 2.3. Model validation input data

The revised UK-DNDC model was validated using data taken from Cardenas et al. (2010). Nitrous oxide measurements had been carried out at three field sites in the UK with climate and soil conditions representative of the agricultural regions where the sites are located, and provide suitable datasets for testing the sensitivity of the UK-DNDC model to changes in environmental and management factors at a regional scale. Locations of the three sites are shown in Fig. 3 and characteristics are listed in Table 1.

UK-DNDC was tested against the grazing treatments at these three sites. The same four treatments of fertilisation (Table 2) had been applied to grazed plots at each site: Plot 1 was a control plot that received no N fertiliser; Plots 2, 3 and 4 received ammonium nitrate ($NH_4NO_3$) fertiliser at application rates of 75, 175 or 350 kg N $ha^{-1}$, respectively. The measured $N_2O$ fluxes from these plots were used for the model validation (see details of methods in Cardenas et al., 2010). The model was used to simulate daily $N_2O$ emissions over a full year. Annual total grazing intensity was aggregated by summing up the grazing intensities from all the grazing events for each plot. Grazing timing and intensity are listed for all the plots in Table 3. Further details can be found in Cardenas et al. (2010).

## 3. Results

Fig. 4 shows a comparison between the simulated $N_2O$ emissions and the measured daily rainfall for the plots at the three sites without both any application of fertiliser and grazing. However, Fig. 4 keeps same conditions of weather and soils at the three sites. The modelled timing and intensity of $N_2O$ pulses generally followed the rainfall events for all three sites. Simulated $N_2O$ emissions between January and early March were higher than those for the other months. The high $N_2O$ fluxes in the spring time could be explained as an influence of the high concentrations of inorganic N in the soils as well as the wetter soil conditions.

Figs. 5–7 show the measured and simulated $N_2O$ emissions for the grazed plots at the three field sites. To compare the effects of grazing, the figures also show the results without grazing but all other parameters left unchanged. The simulated emissions of $N_2O$ from grazed plots show the same trends in all four plots at the Rowden site. The model generally captures the timing of grazing events and fertiliser applications and the pattern and magnitude of $N_2O$ losses. Fig. 5a shows measured and simulated $N_2O$ emissions for Plot 1, the control plot without fertiliser application and with a grazing intensity of 317 head.days $ha^{-1}$. Compared to the measurements, UK-DNDC overpredicted $N_2O$ emissions in spring and underestimated $N_2O$ in late autumn. The $N_2O$ emissions increased with increasing fertiliser application rate and grazing intensity (Fig. 5b–d). The simulated $N_2O$ emissions were mostly the same order of magnitude as the measured emissions (Fig. 5b) for a low fertiliser rate and grazing intensity. However, the model underestimated peak emissions by a factor of almost four times for the high fertiliser rate and grazing intensity (Fig. 5d). The peak $N_2O$ flux on Day 110 was measured as 559 g N $ha^{-1}$ $day^{-1}$, compared with a simulated value of 112 g N $ha^{-1}$ $day^{-1}$. The current UK-DNDC did not match the high peaks and short duration of $N_2O$ emissions at the high fertiliser rate and grazing intensity.

The simulated results showed the influence of animal grazing on $N_2O$ emissions in all the four plots. Nitrous oxide emissions increased with the grazing intensity, although the increase was less at the high fertiliser application rates. Grazing intensity took account of animal numbers and grazing days but it in the model did not include age and feed factors.

For the Cae Banadl site, representing a high rainfall UK region, the simulated emissions of $N_2O$ showed the same trends in all the four plots (Fig. 6). The model generally captured the timing of grazing events and fertiliser applications and the patterns of $N_2O$ loss. Plot 1 was the control plot without fertiliser application and with a grazing intensity of 249 head.days $ha^{-1}$. In the absence of fertiliser, the simulated $N_2O$ emissions were the same order of

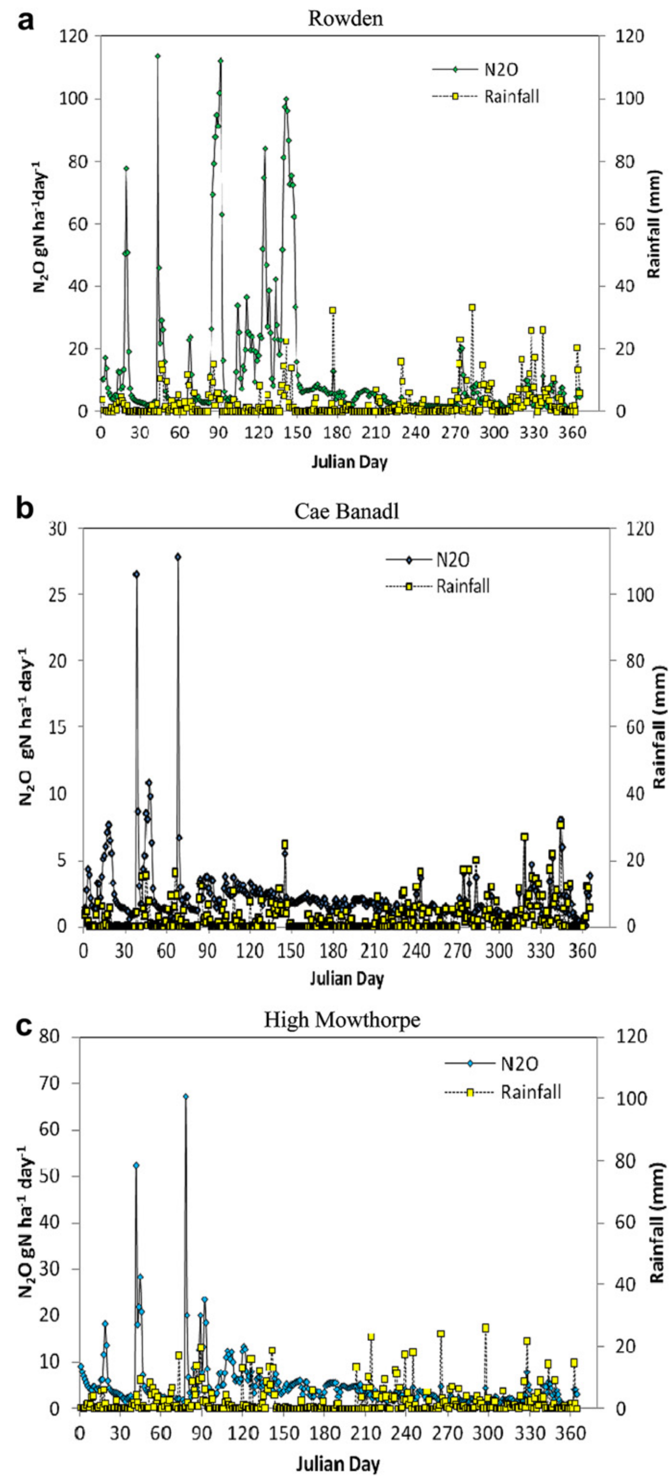


**Fig. 4.** A comparison between simulated $N_2O$ fluxes and rainfall events without grazing for the 0-N treatment (Plot 1) at the three field sites.

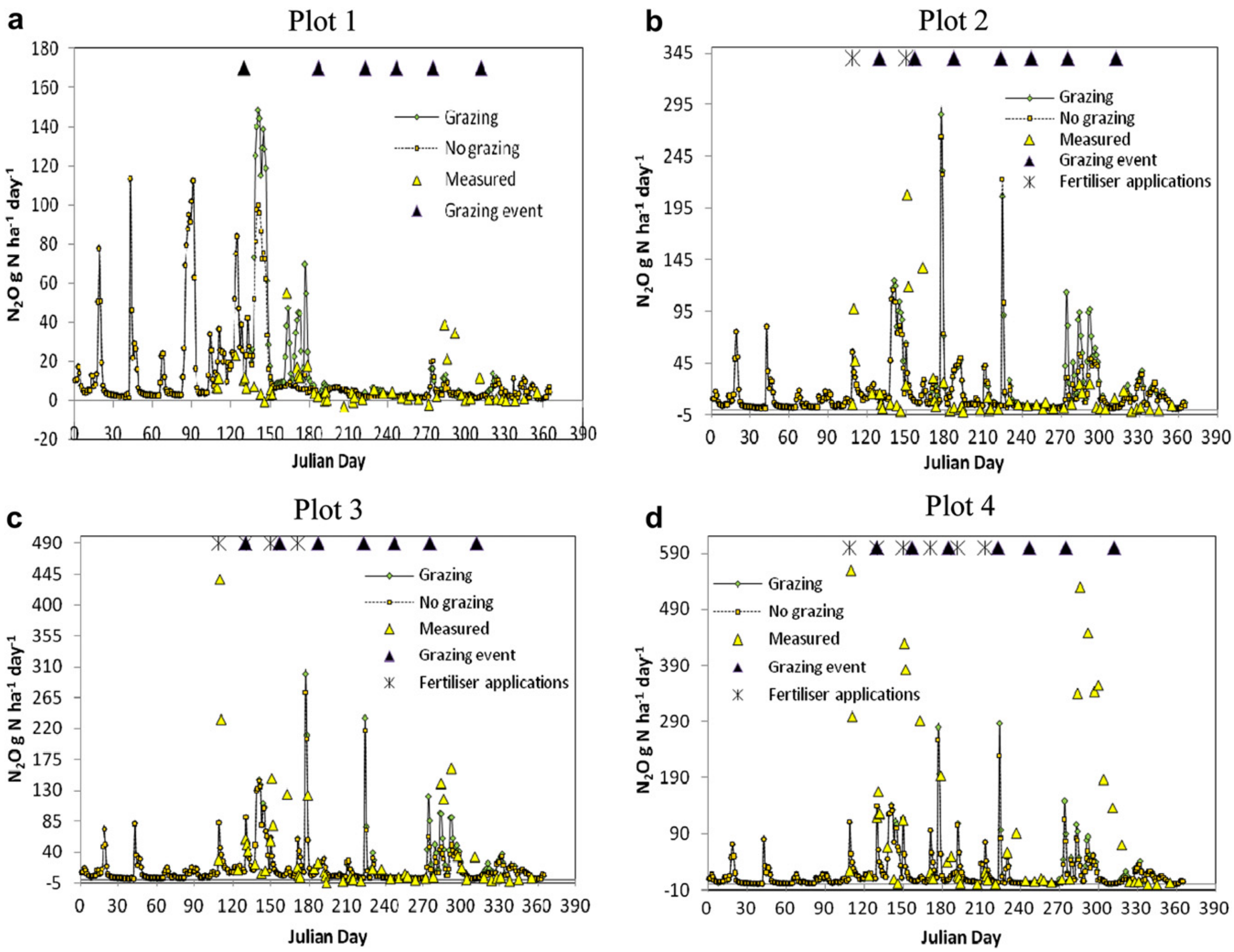


**Fig. 5.** Simulated vs. observed $N_2O$ emissions at the Rowden site: a) Plot 1: 0N and grazing intensity (GI) 317 head.days ha$^{-1}$, b) Plot 2: 75 N and GI 405 head.days ha$^{-1}$, c) Plot 3: 175 N and GI 473 head.days ha$^{-1}$ and d) Plot 4: 350N and GI 528 head.days ha$^{-1}$ (Measured emissions are shown as yellow triangles. Solid lines are values from simulations with grazing; dotted lines are from simulations where grazing has been omitted. Asterisks represent the dates of fertiliser applications and blue triangles the start of grazing events.). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

magnitude as the observed ones (Fig. 6a). The UK-DNDC model underestimated $N_2O$ emission in spring and winter, and overestimated $N_2O$ in summer. The $N_2O$ emissions increased with increasing fertiliser application rates and the grazing intensity (Fig. 6b–d). The fertiliser rate had the greatest effect on $N_2O$ emissions although animal grazing also contributed. Generally, the modelled $N_2O$ emission was consistent with the observation for fertiliser rates and intensive grazing (Fig. 6b and c). However, the model underestimated emissions at high fertiliser rates (Fig. 6d). In particular, it missed several large emission peaks; for example, peaks of 196 g N ha$^{-1}$ day$^{-1}$ at Day 117 (Fig. 6b), 1257 g N ha$^{-1}$ day$^{-1}$ at Day 144 (Fig. 6c) and 1615 g N ha$^{-1}$ day$^{-1}$ (Fig. 6d) at Day 143. It is uncertain what caused these high peak emissions although one reason could have been the wet weather: the accumulated precipitation was 94 mm between Day 135 and Day 147. The other reasons for these discrepancies also appear to be similar as those at the Rowden site.

At High Mowthorpe, the driest of the three sites, simulated emissions of $N_2O$ showed similar trends in all the four plots. The simulated $N_2O$ emissions are of the same order of magnitude as the measured ones for all the plots. The model generally captured the timing of grazing events and fertiliser applications and the patterns of $N_2O$ emissions. For Plot 1 (Fig. 7a) and Plot 2 (Fig. 7b), UK-DNDC overpredicted the $N_2O$ emission in spring. However, for the high fertiliser rate (Plot 4), the model underestimated the $N_2O$ emissions in spring and overestimated them in summer (Fig. 7d). The grazing intensity at High Mowthorpe was double or three times that at the Rowden and Cae Banadl sites. The last peak in the simulated values (Day 270) was attributed to the very intensive grazing. However, this last peak did not correspond to the measured data (Fig. 7d). In contrast, the peak of 33 g N ha$^{-1}$ day$^{-1}$ without grazing at Day 270 corresponds to 464 g N ha$^{-1}$ day$^{-1}$ with grazing. It was clear that the grazing contributed greatly to the simulated $N_2O$ emission. Similarly, the applied fertiliser also affected $N_2O$ emissions. The $N_2O$ emissions increased as the applied fertiliser increased in Fig. 7a–d. Generally, the modelled $N_2O$ emission was consistent with the observation for high fertiliser application and intensive grazing (Fig. 7a–d).

Fig. 8 shows the effect of changing the grazing intensity (head. ha$^{-1}$ day$^{-1}$) on simulated $N_2O$ emissions. These additional simulations were carried out for Plot 2 at High Mowthorpe, in all cases keeping the same timing of fertiliser and grazing events as in the field experiment but changing the grazing intensity. It can be seen that all the $N_2O$ peaks increased with increasing grazing intensity. It is clear that the grazing intensity affected $N_2O$ emissions. The model generally captured the timing and relative magnitude of $N_2O$

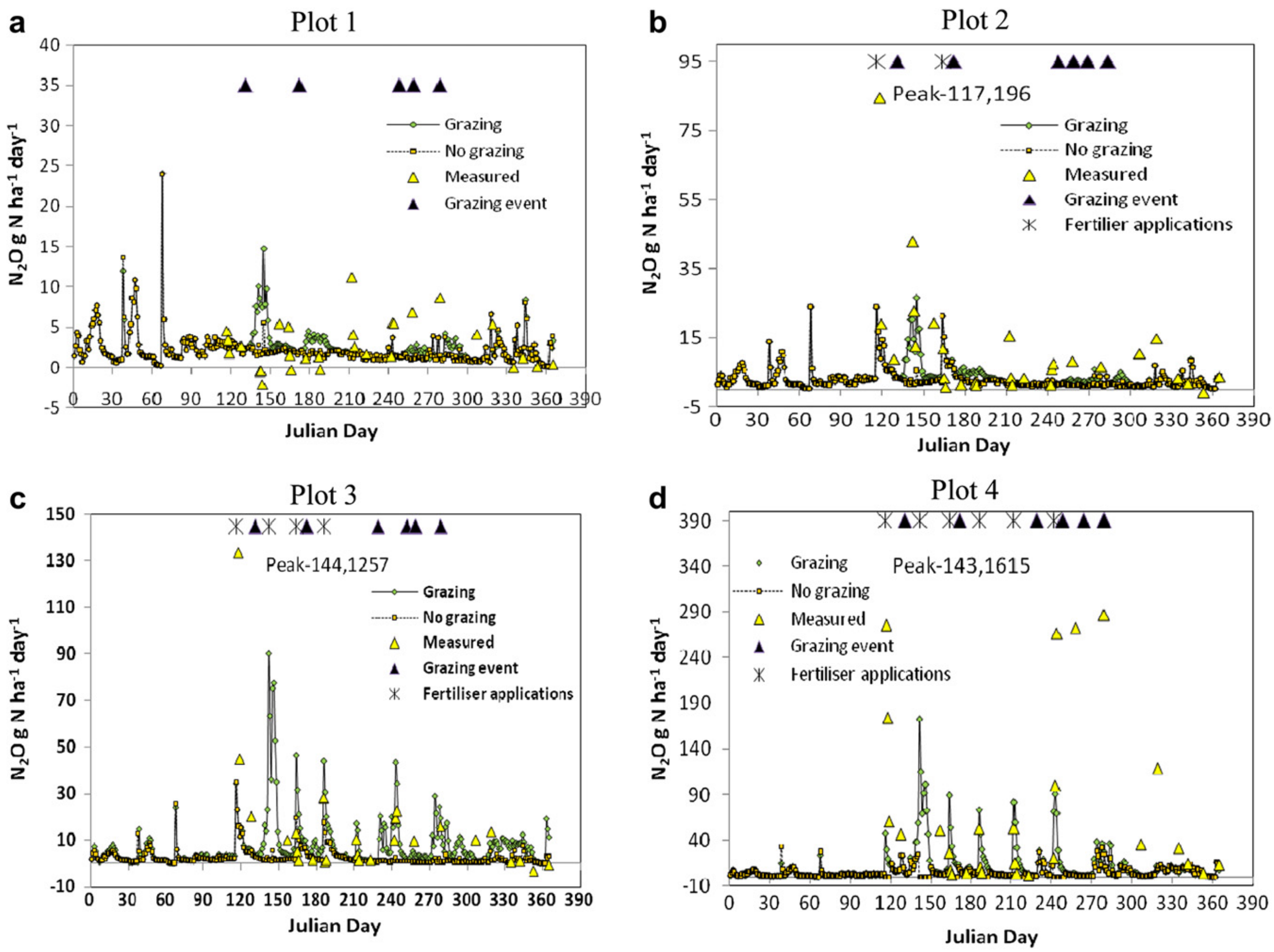


**Fig. 6.** Simulated vs. observed $N_2O$ emissions at the Cae Banadl site: a) Plot 1: 0 N and grazing intensity (GI) 249 head.days $ha^{-1}$, b) Plot 2: 75 N and GI 356 head.days $ha^{-1}$, c) Plot 3: 175 N and GI 491 head.days $ha^{-1}$ and d) Plot 4: 350N and GI 530 head.days $ha^{-1}$ (Measured emissions are shown as yellow triangles. Solid lines are values from simulations with grazing; dotted lines are from simulations where grazing has been omitted. Asterisks represents the dates of fertiliser applications and blue triangles the start of grazing events). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

pulses following animal grazing events. There was a strong linear relationship between simulated cumulative annual $N_2O$ emissions and the dummy grazing intensities (Fig. 9).

## 4. Discussion

In this study, simulated $N_2O$ emissions from 12 grazed plots at three sites obtained using the revised UK-DNDC model were generally in good agreement with observations. The model generally captured the timing and intensity of $N_2O$ pulses following rainfall, fertiliser application and grazing events. This implies that the external parameters adopted for UK-DNDC take into account the major factors that influence regional variations in $N_2O$ emissions. However, the current model did not accurately capture the observed high peaks of $N_2O$ emissions. In particular, the model greatly underestimated the measured $N_2O$ peaks following the applications of high fertiliser rates and high grazing intensities at Cae Banadl. Fig. 10 shows relationship between simulated and measured data with 95% confidence limits at Rowden site. Blue lines represent the region of 95% confidence limits. Fig. 10a shows the relationship of Plot 2 between simulated and measured data with correlation coefficient, 0.33; and Fig. 10b those of Plot 3 with correlation coefficient, 0.64. It is clear that Plot 3 is much better correlation than those of Plot 2. This implies that nonlinear relationships between main factors were not captured. Some of the internal parameters or processes in the model may not be properly set to cover the nonlinear relations between fertiliser use, grazing and $N_2O$ emissions. For example, in the current model the C and N from dung and urine from grazing were calculated using constants which represent a linear relationship with the number of animals in the field. In practices, the amount of C and N excreted by each animal is dependent on many factors, such as age, weight, diet and environmental factors. Furthermore, C and N were proportionally distributed to C and N pools. This did not take into account environmental factors, such as temperature and rainfall, which influence the allocation to the different C pools. However, we did not try making any adjustments to the internal parameters or processes in the model. We believe that fitting a model to experimental data is not necessary if the model is mainly used for predicting rather than describing. It is clear that these internal coefficients need to be integrated with local environmental factors and animal conditions when data are available.

There are major challenges to improving the accuracy of the livestock components of the model, associated both with the quality of the available input data and in the representation of the hydro-biogeochemical processes in the soil. Firstly, emissions from livestock are dependent on many factors, such as the type of animal, age, weight, diet and proportion of time housed or grazing.

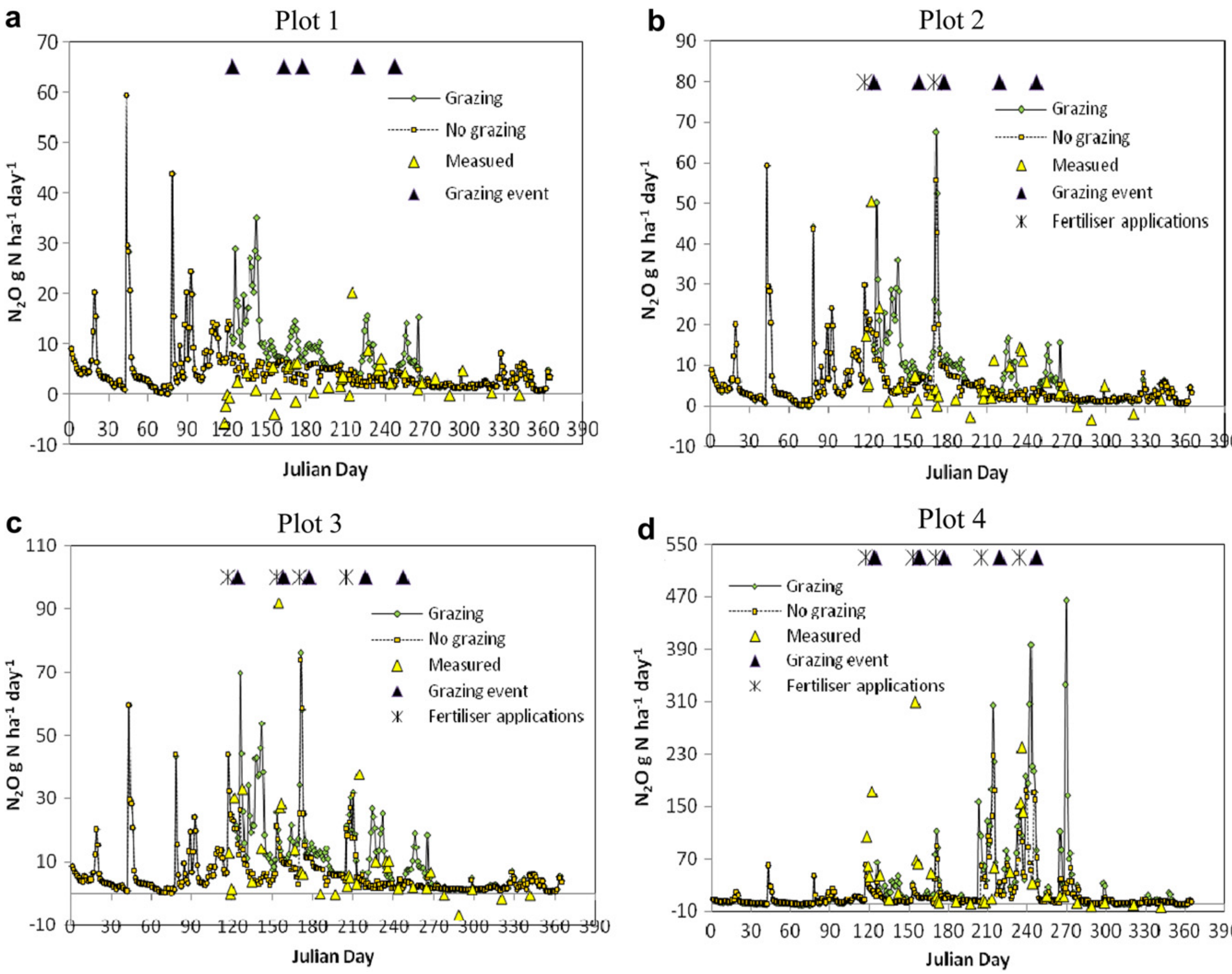


**Fig. 7.** Simulated vs. observed $N_2O$ emissions at the High Mowthorpe site: a) Plot 1: 0N and grazing intensity (GI) 1013 head.days ha$^{-1}$, b) Plot 2: 75 N and GI 1400 head.days ha$^{-1}$, c) Plot 3: 175 N and GI 1527 head.days ha$^{-1}$ and d) Plot 4: 350N and GI 1292 head.days ha$^{-1}$ (Measured emissions are shown as yellow triangles. Solid lines are values from simulations with grazing; dotted lines are from simulations where grazing has been omitted. Asterisks represent the dates of fertiliser applications and blue triangles the start of grazing events). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

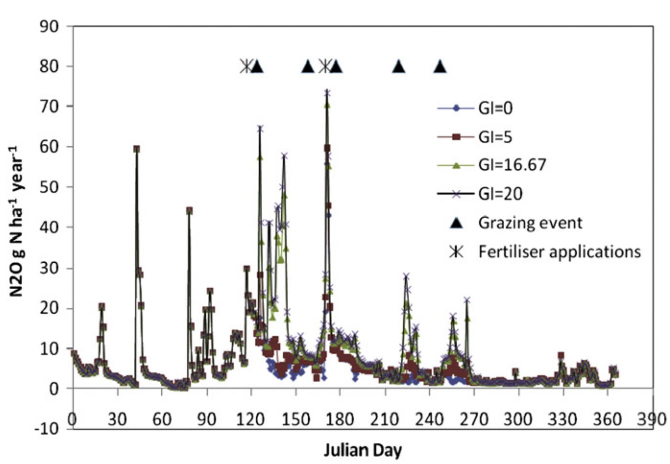


**Fig. 8.** Effect of changing the grazing intensity (head ha$^{-1}$ day$^{-1}$) in simulations of daily $N_2O$ emissions for Plot 2 at the High Mowthorpe site (Asterisks represent the dates of fertiliser applications and the filled triangles the start of grazing events).

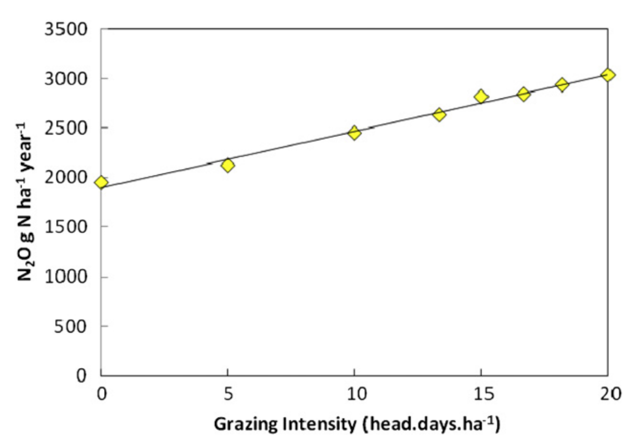


**Fig. 9.** Relationship between grazing intensity (head ha$^{-1}$ day$^{-1}$) and annual cumulative-$N_2O$ emissions as determined from simulations with different grazing intensities for Plot 2 at the High Mowthorpe site.

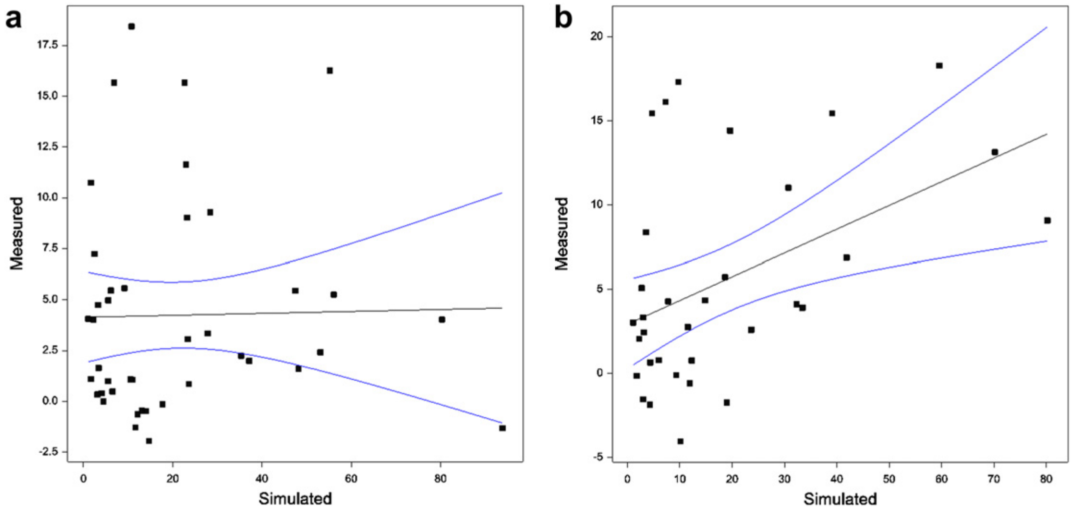


**Fig. 10.** Fitted and observed relationship with 95% confidence limits at Rowden: a) Plot 2 with correlation coefficient, 0.33; b) Plot 3 with correlation coefficient, 0.64.

Although information is available about numbers of different classes of livestock on a regional basis, much of this information is generally amalgamated for modelling purposes and, in practise, parameterisation is a compromise between reality and simplicity.

Secondly, emission measurements of $N_2O$ from grazing are particularly difficult due to the uneven distribution of excreta, both in space and time, which leads to heterogeneity in the measurements. Saggar et al. (2007) used 18 chamber replicates for each measurement to cover the influence of spatial excretal N distribution on $N_2O$ emissions. Their results showed that the measured fluxes had coefficients of variation ranging between 56 and 262%. This implies that the accuracy of the measurements will be greatly dependent on the number and distribution of measurement points. It is also possible that the field measurements of $N_2O$ fluxes may themselves be misrepresenting the detailed shape of the $N_2O$ pulse, which clearly varies rapidly with time and space. The UK-DNDC model is very sensitive to climate, soil, and crop inputs, so in some cases errors may be introduced when auxiliary inputs are not measured on-site. In spite of the complexity and difficulty, a rational yet tractable process-based model of this type can contribute to the shared goal of cutting the currently high cost of estimating and assessing GHG emissions and improving understanding of biogeochemical processes.

Thirdly, UK-DNDC differentiates between soil types according to clay content and bulk density but field soils are very heterogeneous in their distribution of pore sizes and tortuosities and these are not represented in the model. The recent modelling of micro-processes in porous media showed that pore sizes and tortuosities have a strong influence on permeability and adsorption and desorption (Young and Crawford, 2004; Wang et al., 2005, 2008; Zhang et al., 2008). The soil structure determines the ease with which plants may extract water, the rate of flow in unsaturated conditions, and the rate of diffusion of compounds and gases into and out of the soil matrix. Small changes in soil moisture can change the associated rate coefficients by orders of magnitude, sensitively dependent on the fine-scale structure. This may affect both the diffusion of $N_2O$ out of soil microsites and the movement of water and oxygen to microsites within soil aggregates, where the microbial activity takes place. The difference between soil structures appears to dominate all fertile soils and is possibly a key diagnostic for C and N dynamics because it represents an important functional bridge between the micro-processes of soils (Kaiser and Guggeneberger, 2007; Baveye, 2009). The horizontal transports of water and substrates were not represented in the model (Zhang et al., 2002). Young and Crawford (2004) and O'Donnell et al. (2007) indicated that soil microbes were a self-organising system, growing in patches in soil architectures rather than uniformly. Although the soil is teeming with life, only about $10^{-6}$% of the surface area is covered by soil microbes. The important point here is that microorganisms are heterogeneous in coverage, which can vary with soil structure, moisture, and substrate availability. Currently, UK-DNDC does not account for these heterogeneities.

In addition, the soil redox potential, *Eh*, is calculated according to the Nernst equation and is determined by the product of the concentrations of all the oxidising species versus the product of the concentrations of all the reducing species in the soil liquid phase. Transfer of an electron from a reducing species to an oxidising species is regulated by the change in the Gibbs free energy in the model. Fumoto et al. (2008) showed that the contents of other electron acceptors in the soil, such as $Fe^{3+}$, $Mn^{4+}$, and $SO_4^{2-}$, will strongly affect $CH_4$ emissions. This is also likely to influence the production of $N_2O$. However, UK-DNDC does not take account of the variations in the content of these electron acceptors in soils at the small scale. Instead, these factors were set to estimated national averages for modelling $CH_4$ emissions. The accessibility of the reactive sites and retention time of solution near an exchange site is dictated by the fine-scale structure and the hydraulic connectivity and conductivity of the habitat. Comparisons between cation exchange capacities in homogenized and structured soils show that the amount of exchangeable cations is reduced by 10% in the structured system, where mass flow dominates. Similarly, UK-DNDC simulates $N_2O$ emissions at a national scale without accounting for the effects of variations in the contents of these electron acceptors. In reality, the contents of electron acceptors will strongly affect $N_2O$ emissions from grassland.

It should be noted that the present work do not include field sites in Northern Ireland and Scotland. Future development should include the sites in the two countries to represent wider climatic, soil and environmental conditions across the UK.

## 5. Concluding remarks

In this study, the UK-DNDC model was enhanced by the addition of an animal grazing component, which was parameterised using animal grazing intensity. The new version of UK-DNDC was validated against the observed $N_2O$ fluxes from three grazed grassland sites in the UK. The model basically captured the $N_2O$ emissions measured at the grazing sites, showing that $N_2O$ emissions increased as the grazing intensity increased. In addition, the model generally captured the timing and intensity of $N_2O$ pulses following rainfall, N fertiliser application or grazing events. The results imply that the external parameters used as inputs to run UK-DNDC take into account the main factors dominating variations of $N_2O$ emissions from the grazed plots. However, discrepancies exist between the modelled results and observations. For example, the model missed some observed high peaks of $N_2O$ emissions, especially the high peaks related to the high fertiliser rates and grazing intensity at the Cae Banadl site. Future improvements in the scientific processes of the model could provide opportunities to reduce the uncertainties in modelling $N_2O$ emissions from grazing systems. Understanding the uncertainties or challenges is critically important for us to accurately address questions regarding the impact of land-management practices and future climate changes on GHG emissions.

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