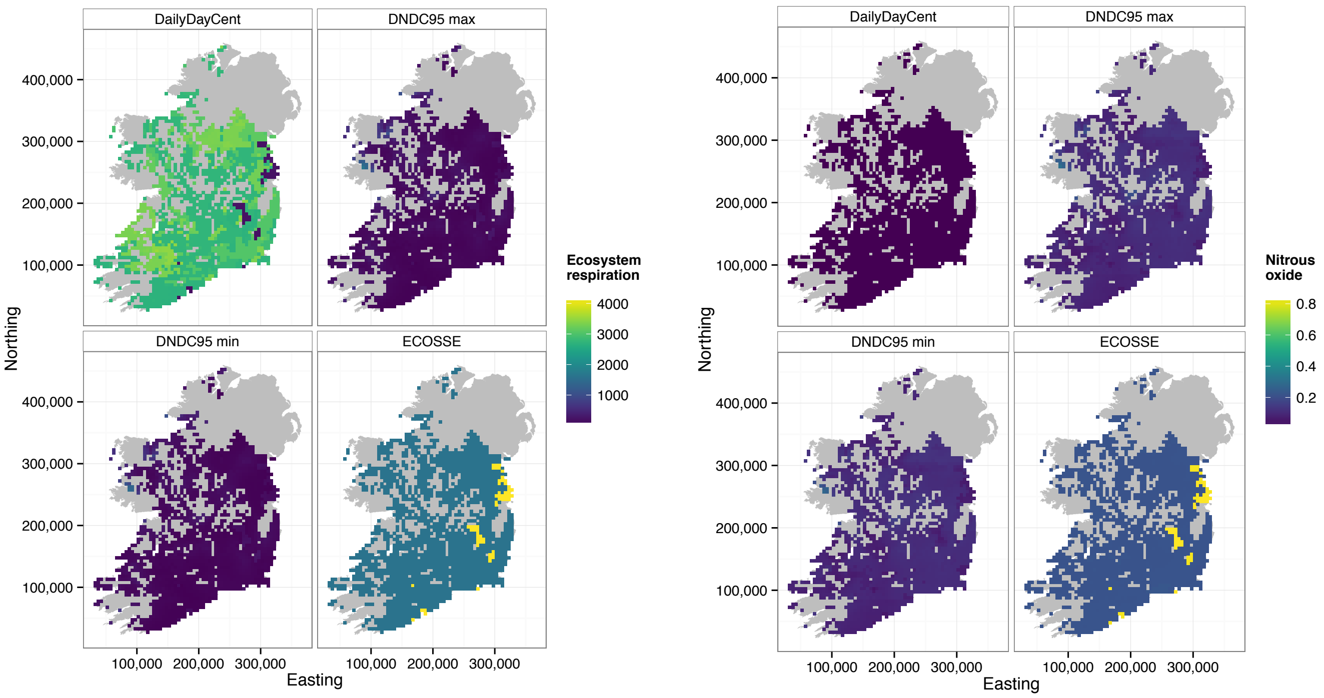
Report No. 304

epa Research
Climate - Water - Sustainability
Identifying pressures • Informing policy • Developing solutions

Scaling Soil Greenhouse Gas Emissions to the National Level

Authors - Mike G. Whitfield, Mohamed Abdalla, Giuseppe Benanti, William Burchill, Dru Marsh, Bruce Osborne, Brendan Roth, Matthew Saunders, Pete Smith and Mike Williams



www.epa.ie

Rialtas na hÉireann
Government of Ireland

ENVIRONMENTAL PROTECTION AGENCY

The Environmental Protection Agency (EPA) is responsible for protecting and improving the environment as a valuable asset for the people of Ireland. We are committed to protecting people and the environment from the harmful effects of radiation and pollution.

The work of the EPA can be divided into three main areas:

Regulation: *We implement effective regulation and environmental compliance systems to deliver good environmental outcomes and target those who don't comply.*

Knowledge: *We provide high quality, targeted and timely environmental data, information and assessment to inform decision making at all levels.*

Advocacy: *We work with others to advocate for a clean, productive and well protected environment and for sustainable environmental behaviour.*

Our Responsibilities

Licensing

We regulate the following activities so that they do not endanger human health or harm the environment:

- waste facilities *(e.g. landfills, incinerators, waste transfer stations)*;
- large scale industrial activities (*e.g. pharmaceutical, cement manufacturing, power plants)*;
- intensive agriculture *(e.g. pigs, poultry)*;
- the contained use and controlled release of Genetically Modified Organisms *(GMOs)*;
- sources of ionising radiation *(e.g. x-ray and radiotherapy equipment, industrial sources)*;
- large petrol storage facilities;
- waste water discharges;
- dumping at sea activities.

National Environmental Enforcement

- Conducting an annual programme of audits and inspections of EPA licensed facilities.
- Overseeing local authorities' environmental protection responsibilities.
- Supervising the supply of drinking water by public water suppliers.
- Working with local authorities and other agencies to tackle environmental crime by co-ordinating a national enforcement network, targeting offenders and overseeing remediation.
- Enforcing Regulations such as Waste Electrical and Electronic Equipment (WEEE), Restriction of Hazardous Substances (RoHS) and substances that deplete the ozone layer.
- Prosecuting those who flout environmental law and damage the environment.

Water Management

- Monitoring and reporting on the quality of rivers, lakes, transitional and coastal waters of Ireland and groundwaters; measuring water levels and river flows.
- National coordination and oversight of the Water Framework Directive.
- Monitoring and reporting on Bathing Water Quality.

Monitoring, Analysing and Reporting on the Environment

- Monitoring air quality and implementing the EU Clean Air for Europe (CAFÉ) Directive.
- Independent reporting to inform decision making by national and local government *(e.g. periodic reporting on the State of Ireland's Environment and Indicator Reports)*.

Regulating Ireland's Greenhouse Gas Emissions

- Preparing Ireland's greenhouse gas inventories and projections.
- Implementing the Emissions Trading Directive, for over 100 of the largest producers of carbon dioxide in Ireland.

Environmental Research and Development

- Funding environmental research to identify pressures, inform policy and provide solutions in the areas of climate, water and sustainability.

Strategic Environmental Assessment

- Assessing the impact of proposed plans and programmes on the Irish environment *(e.g. major development plans)*.

Radiological Protection

- Monitoring radiation levels, assessing exposure of people in Ireland to ionising radiation.
- Assisting in developing national plans for emergencies arising from nuclear accidents.
- Monitoring developments abroad relating to nuclear installations and radiological safety.
- Providing, or overseeing the provision of, specialist radiation protection services.

Guidance, Accessible Information and Education

- Providing advice and guidance to industry and the public on environmental and radiological protection topics.
- Providing timely and easily accessible environmental information to encourage public participation in environmental decision-making *(e.g. My Local Environment, Radon Maps)*.
- Advising Government on matters relating to radiological safety and emergency response.
- Developing a National Hazardous Waste Management Plan to prevent and manage hazardous waste.

Awareness Raising and Behavioural Change

- Generating greater environmental awareness and influencing positive behavioural change by supporting businesses, communities and householders to become more resource efficient.
- Promoting radon testing in homes and workplaces and encouraging remediation where necessary.

Management and structure of the EPA

The EPA is managed by a full time Board, consisting of a Director General and five Directors. The work is carried out across five Offices:

- Office of Environmental Sustainability
- Office of Environmental Enforcement
- Office of Evidence and Assessment
- Office of Radiation Protection and Environmental Monitoring
- Office of Communications and Corporate Services

The EPA is assisted by an Advisory Committee of twelve members who meet regularly to discuss issues of concern and provide advice to the Board.

EPA RESEARCH PROGRAMME 2014–2020

Scaling Soil Greenhouse Gas Emissions to the National Level

(2012-CCRP-MS.6)

EPA Research Report

Prepared for the Environmental Protection Agency

by

Department of Botany, Trinity College Dublin

Authors:

Mike G. Whitfield, Mohamed Abdalla, Giuseppe Benanti, William Burchill, Dru Marsh, Bruce Osborne, Brendan Roth, Matthew Saunders, Pete Smith and Mike Williams

ENVIRONMENTAL PROTECTION AGENCY
An Ghníomhaireacht um Chaomhnú Comhshaoil
PO Box 3000, Johnstown Castle, Co. Wexford, Ireland

Telephone: +353 53 916 0600 Fax: +353 53 916 0699
Email: info@epa.ie Website: www.epa.ie

ACKNOWLEDGEMENTS

This report is published as part of the EPA Research Programme 2014–2020. The EPA Research Programme is a Government of Ireland initiative funded by the Department of Communications, Climate Action and Environment. It is administered by the Environmental Protection Agency, which has the statutory function of co-ordinating and promoting environmental research.

The authors would like to acknowledge the members of the project steering committee, namely Phillip O'Brien (EPA) and Marc Kierans (ex-EPA).

The EPA Research Programme addresses the need for research in Ireland to inform policymakers and other stakeholders on a range of questions in relation to environmental protection. These reports are intended as contributions to the necessary debate on the protection of the environment.

EPA RESEARCH PROGRAMME 2014–2020

Published by the Environmental Protection Agency, Ireland

ISBN: 978-1-84095-878-2 December 2019

Price: Free Online version

Project Partners

Mike Williams
Department of Botany
Trinity College Dublin
Dublin
Ireland
Tel.: +353 1 896 2421
Email: willimsm@tcd.ie

Pete Smith
Biological Sciences
University of Aberdeen
Aberdeen
UK
Tel.: +44 1224 272 702
Email: pete.smith@abdn.ac.uk

Bruce Osborne
School of Biology and Environmental Sciences
University College Dublin
Dublin
Ireland
Tel.: +353 1 716 2249
Email: bruce.osborne@ucd.ie

Contents

List of Figures

List of Tables

Executive Summary

Agricultural soils are a major source of greenhouse gas (GHG) emissions globally. In Ireland, 81% of the land is devoted to agriculture, which means that there is potential for significant mitigation of agricultural GHG emissions through land-use change. However, current tools for assessing GHG emission savings through land-use change – Intergovernmental Panel on Climate Change Tier 1 and Tier 2 – are limited; Tier 3 approaches, in which process-based models are used to estimate GHG emissions for given land-use and climatic scenarios, are more flexible. This project was concerned with improving the national inventory of GHG emissions from Irish soils through the use of Tier 2 and 3 methodologies, effectively upscaling regional data on N_2O and CO_2 (ecosystem respiration, R_{ecos}) fluxes to the national level through a combined process-based model and geographic information system (GIS) approach.

A 5 × 5 km GIS map framework for Ireland has been successfully developed that will allow calculation of nationwide annual emissions of N_2O and CO_2 (R_{ecos}) from grasslands and arable soils. This has been linked to climate, land use and soil type using the Irish Soil Information System (SIS). Preliminary runs for background emissions of N_2O and CO_2 have been carried out using soil and climate parameters as the main drivers and using DailyDayCent, DeNitrification-DeComposition (DNDC 9.5) and ECOSSE (Estimation of Carbon in Organic Soils – Sequestration and Emissions) as simulation models. The total area of grassland and cropland calculated from the GIS maps was 3 and 0.3 million hectares, respectively, which is in close agreement with the total area of cropland and pasture land recorded in the 2016 census (3.9 million hectares). Upscaling DNDC 9.5 outputs using the GIS map gave combined R_{ecos} and N_2O background emissions of between 0.45 and 0.5 Mt CO_2e for grassland and between 0.074 and 0.08 Mt CO_2e for arable land. These are in broad agreement with inventory values, considering that the effects of fertiliser additions and management were not considered.

Using an extensive validation dataset, we evaluated the capability of the four process-based models representative of the current ecosystem of biogeochemical models – DailyDayCent, DNDC 9.4 and 9.5, and ECOSSE – for simulating soil N_2O emissions and R_{ecos} at a range of arable and grassland agricultural sites. The majority of model simulations underestimated cumulative N_2O emissions and many performed poorly when used to simulate sites with no fertiliser additions. Simulation performance was highly site specific but, in general, a combination of the DailyDayCent and ECOSSE models performed well at arable sites, whereas both versions of the DNDC model were useful for simulating grassland N_2O emissions.

The model performance of DNDC 9.4 and 9.5 was significantly better for R_{ecos} than for N_2O, producing low root mean square error values, correlation coefficients approaching 90% and final simulated cumulative fluxes that followed measured values closely. In this case, we suggest a combination of DNDC 9.4 and 9.5 as suitable for providing the most reliable estimates of R_{ecos} flux.

We performed Monte Carlo simulations and determined that, in general, the variation in precipitation and temperature made the greatest contribution to uncertainty in the model outputs.

Although we have successfully produced a workable GIS map framework for calculation of nationwide fluxes of N_2O and CO_2 from grassland and arable systems, the fit of modelled to measured N_2O emissions is so poor as to suggest that a simpler empirical approach should be used to upscale N_2O fluxes to the national level.

This study is the first of its kind in Ireland and represents a useful objective baseline from which to establish priorities for model parameterisation and improvements for application in Irish agricultural systems.

1 Introduction

1.1 Objectives

This project was concerned with improving the national inventory of greenhouse gas (GHG) emissions from Irish soils by developing Tier 2 and 3 methodologies, to effectively upscale regional data on soil processes to the national level through a combined process-based model and geographic information system (GIS) approach. It relied on an extensive database of GHG emissions provided by Trinity College Dublin and University College Dublin through their partnership with the Environmental Protection Agency (EPA), Council for Forest Research and Development (COFORD), the Department of Agriculture, Food and the Marine and the European Union (EU) Framework Programmes. Modelling of GHG emissions was linked to a spatial assessment using regional climate, land-use and soil C stocks data linked to the Irish Soil Information System (SIS).

Three process models, DailyDayCent, DeNitrification-DeComposition [DNDC (version 9.4 and 9.5)] and ECOSSE (Estimation of Carbon in Organic Soils – Sequestration and Emissions), were used for simulating N_2O emissions from agricultural soils in Ireland, with the aim of determining the most suitable model for simulating N_2O emissions from a range of agricultural land uses and management regimes based on the coincidence and association of simulated data with measured data. Contribution analysis was carried out to determine the contribution of variation in climatic (temperature, precipitation) and edaphic (bulk density, clay content, pH) factors to uncertainty in model simulations.

Model simulations were presented in a GIS map format, allowing a proof-of-concept analysis of the upscaling of N_2O and CO_2 (ecosystem respiration, R_{ecos}) emissions to the national level. These GIS maps will link model simulations to land use, climate and soil type using a resolution of 5 km^2.

1.2 Soils As a Source of Greenhouse Gases

Agricultural soils represent a significant source of GHGs through the combined microbial processes of soil respiration, nitrification and denitrification, with wetland soils adding an extra burden to the atmosphere through methane production. Soils are the largest C pool in terrestrial systems, containing more than two-thirds of the total C. Current global estimates indicate that soils emit ≥ 350 Pg CO_2e (CO_2e = CO_2 equivalent = total effect of all GHGs normalised to CO_2), equivalent to 21% of the global soil C and N pools (Bahn *et al*., 2010; Oertel *et al*., 2016). In comparison, the amount of CO_2 emitted each year from fossil fuel combustion and the cement industry is approximately 33.4 Pg CO_2 (Oertel *et al*., 2016). As a result, small changes in soil CO_2 flux across large areas can have a pronounced impact on global atmospheric CO_2 concentrations. In terms of nitrous oxide, soils have been estimated to emit approximately 7 million metric tonnes of N per year globally, with agricultural soils providing anywhere between 30% and 60% of this total (Mosier *et al*., 1998; Oertel *et al*., 2016). This soil component of the global GHG budget represents a serious challenge in mitigating GHG emissions through manipulation of C sinks.

In Ireland, agriculture represents the largest source of GHG emissions to the atmosphere, with 19.6 Mt CO_2e being emitted from this sector in 2016, representing 31.8% of the total national emissions in 2016 (EPA, 2019). This is the highest national proportion of agricultural emissions in the EU (www.epa.ie), reflecting the importance of agriculture within the Irish economy. Agricultural land accounted for approximately 81.2% of the total land of Ireland in 2016, with grassland constituting 61%, forestry 10.7% and croplands 9.5% (CSO, 2018). Emissions consist primarily of non-CO_2 gases (methane – CH_4 – and N_2O) from enteric fermentation (49%), management of animal manure (13%) and agricultural soil metabolism related to N fertiliser inputs (38%).

1.3 National Climate Policy and Food Wise 2025

Ireland faces significant challenges in reducing its GHG emissions. Although Ireland, as a signatory to the Kyoto Protocol, complied with the Kyoto Protocol (KP1) emission targets in 2012, this was more the result of economic downturn post 2008 than management. EU policy requires far more stringent reductions in the post-Kyoto 2013–2020 period, particularly in the non-Emissions Trading Scheme (non-ETS) sector, representing 72% of national emissions (EPA, 2019). Under the terms of the Climate and Energy Package adopted by the European Council in 2008, more specifically the EU Effort Sharing Decision (Decision No. 406/2009/EC), Ireland is to reduce non-ETS emissions by 20% by 2020 compared with 2005 levels. There is a significant possibility, given ongoing EU policy, that this mitigation target may increase significantly. Post-2020 mitigation targets for the EU overall may rise to 80–95% of 1990 levels, achieved through domestic actions and not C trading (EC, 2011).

Through the National Climate Change Strategies of 2000 and 2007, reductions in GHG emissions from Irish agriculture were envisaged through Common Agricultural Policy (CAP) reform, sequestration of C by grasslands and forestry, planting of energy crops and better manure management. However, the launch of Food Harvest 2020 in 2010, the first government strategy to increase production in the agri-food and fishery sectors as a response to the economic downturn, has effectively led to increases in GHG emissions from this sector, of 8.9% by 2017 (EPA, 2019), an increase of 1.9% over initial emission projections of 7% published in 2012 (EPA, 2012). Food Wise 2025, the successor to Food Harvest 2020, was launched in 2015 (DAFM, 2015). This new strategy projects that the export market in the Irish agri-food sector will grow to €19 billion per year by 2025, driven chiefly by expansion in the "low" sustainability food groups of dairy and beef (Poore and Nemecek, 2018; Willet *et al.*, 2019), with the danger of increasing agricultural GHG emissions further. The contrasting strategies of increasing economic growth and progress to a low-C economy have been considered in the latest national GHG emissions projections report (EPA, 2018). Here, two scenarios are included: "with existing measures" and "with additional measures". The first scenario assumes that there are no additional policies and measures post 2016, whereas the second scenario assumes further implementation of renewables, energy efficiency policies and measures set out in both the National Renewable Energy Action Plan (NREAP)[1] and the National Energy Efficiency Action Plan (NEEAP).[2] In both scenarios Ireland's emissions will meet neither 2020 nor 2030 emission reduction targets. Ireland will exceed its 2013–2020 compliance obligations by approximately 17 Mt CO_2e under the "with existing measures" scenario and by 16.3 Mt CO_2e under the "with additional measures" scenario (EPA, 2018), with the non-ETS sector being particularly at fault. For the 2021–2030 compliance period, Ireland's non-ETS sector has been projected to exceed these future targets by between 47 Mt CO_2e (with additional measures) and 52 Mt CO_2e (with existing measures), with agriculture accounting for approximately 44% of these values (EPA, 2018).

Clearly there are significant challenges ahead for Ireland to progress to a low-C economy. Central to this transition is the requirement for comprehensive and scientifically sound data on national GHG emissions and sinks to support policy decisions, which must be underpinned by rigorous scientific analysis of an international standard (Environmental Protection Agency Review Group, 2011). This, by necessity, means a move away from default Intergovernmental Panel on Climate Change (IPCC) methodologies towards a peer-reviewed, scientifically robust Tier 3 approach. The aim of this project, therefore, is to use established, process-based models to upscale soil processes to the national level in order to produce a map of GHG emissions that may be used to test mitigation strategies inherent in approaching a low-C economy.

1.4 Tier 1, 2 and 3 IPCC Methodologies

A coherent strategy for reduction of GHG emissions requires data that are as accurate as possible on C stocks, changes in C stocks as a result of land use, land-use change and forestry (LULUCF) and annual estimates of GHG emissions. In Ireland's 2018 National Inventory Report (Duffy *et al.*, 2018), the LULUCF sector accounts for annual GHG emissions of approximately 4.9 Mt CO_2e, primarily from grasslands

1 http://www.dcenr.gov.ie/energy/en-ie/Renewable-Energy/Pages/Action-Plan.aspx (accessed 21 August 2019).

2 https://www.dccae.gov.ie/en-ie/energy/topics/Energy-Efficiency/energy-efficiency-directive/national-energy-efficiency-action-plan-(neeap)/Pages/National-Energy-Efficiency-Action-Plan-(NEEAP).aspx (accessed 21 August 2019).

and wetlands. Forestland, harvested timber products and cropland constitute collectively an estimated annual sink for C of approximately 4.6 Mt CO_2e (Duffy *et al*., 2018). In calculating national GHG emissions, however, significant uncertainties exist, dependent on which methodology is used (O'Brien, 2007). In the absence of direct measurements of GHGs from agriculture, the IPCC good practice guidelines (Hirashi *et al*., 2014) recommend a Tier 1 approach using default values derived from international research. In the case of N_2O, this assumes a fixed proportion of applied mineral/organic N being released as N_2O, an emission factor, requiring a calculation of the total amount of mineral/organic N applied to the soil. This baseline approach to GHG reporting ignores variations in agronomic, edaphic and climatic factors critical in driving N_2O production and release, such as crop type, soil C levels and rainfall and temperature. Tier 1 calculations on their own provide no mechanism to assess the potential impacts of future climate and land-use change. A considerable improvement therefore is to incorporate "local" plot-/field-scale measurements of GHG emissions in the determination of how emission factors may vary according to soil, crop and regional climate. This Tier 2 approach has been applied in the UK for agricultural soils (Skiba *et al*., 1996) and farmed livestock (Chadwick *et al*., 1999); it has also been applied in Scotland using regional Scottish and UK field data by Flynn *et al*. (2005). The study by Flynn *et al*. (2005) illustrates clearly the potential for significant under-reporting of GHG emissions on the national scale using the default IPCC methodology alone, again using N_2O as an example (Table 1.1).

The Tier 2 approach, although still reliant on default values in part, provides a better estimation of regional emissions. By far the preferred option would be a Tier 3 approach. These methodologies are highly country-specific, using peer-reviewed simulation models developed from national datasets to achieve process-driven estimates of GHG emissions.

Recognising the need to move to a Tier 2 methodology, Ireland has invested considerable funds into establishing datasets for GHG emissions from grasslands, croplands and forestry, and to a lesser extent peatlands, most notably through the EPA Science, Technology, Research and Innovation for the Environment (STRIVE) programme, COFORD and Department of Agriculture, Food and the Marine Research Structural funds, meaning that for the first time a proof of concept for a Tier 3 approach is now possible.

1.5 Process-based Biogeochemical Models for Simulating GHG Emissions from Soils

The current ecosystem of process-based biogeochemical models includes, among others,

Table 1.1. Contributions of land-use and fertiliser type to total annual N_2O emissions in Scotland (tN_2O-N $year^{-1}$): IPCC default values (Tier 1) compared with a Tier 2 approach incorporating climate and crop-responsive emission factors

Land-use category and N source	IPCC default methodology	New methodology
Arable (cereals, oilseed rape)		
Mineral N	743	357
Organic N	422	169
Total	1165	526
Cut grassland		
Mineral N	403	867
Organic N	702	281
Total	1105	1148
Grazed grassland (managed)		
Mineral N	983	4250
N deposited by animals	3383	4568
Total	4366	8818

Source: adapted from Flynn *et al*. (2005).

DailyDayCent, DNDC and ECOSSE. All three models were initially developed and parameterised in environments not representative of Irish agricultural systems. It is therefore pertinent to evaluate the performance of these models when simulating GHG emissions from Irish agricultural systems, to determine their suitability as tools for estimating the impact of management, land-use change and climate change on Irish agricultural GHG emissions. We selected these models based on their usage in the literature and the availability of expertise in running them. We evaluated two versions of the DNDC model – 9.4 and 9.5 – to determine the effect that changes in the model code between versions has had on the ability of the model to simulate GHG fluxes.

The DNDC model was developed to simulate GHG emissions from agricultural soils in the USA and has been used for regional-scale simulations in the USA (Li *et al*., 1996), China (Li *et al*., 2001) and Europe (Dietiker *et al*., 2010). The DNDC model has been extensively tested and shows reasonable agreement between measured and simulated data for many ecosystems, including grassland (Levy *et al*., 2007; Giltrap *et al*., 2010), cropland (Cai *et al*., 2003; Tang *et al*., 2006) and forests (Lu *et al*., 2008; Kurbatova *et al*., 2009). The model has also been applied to Irish grasslands and croplands (Abdalla *et al*., 2009, 2010, 2011). DailyDayCent is a widely-used ecosystem biogeochemical model for simulating GHG emissions. It is the daily timestep version of the CENTURY biogeochemical model (Parton *et al*., 1994). Comparison of model results and observed data have shown that DailyDayCent reliably simulates crop yield, soil organic matter and trace gas flux for various native and managed systems, including grasslands and arable crops (Del Grosso *et al*., 2002, 2009; Smith *et al*., 2008). ECOSSE is a simulation model recently developed for organic soils in Scotland (Smith *et al*., 2007). The model includes the major processes of C and N turnover, with material exchange between soil organic matter pools controlled at rates modified by temperature, soil moisture, soil pH and crop cover. The advantage of ECOSSE is that, because of simplified data requirements, regional and national emission estimates are easier to produce than in other “data heavy” models.

2 Methodology

2.1 Simulation of GHG Emissions

2.1.1 Model input and data validation

Table 2.1 illustrates the data used for this study, including land use (arable or grassland), measuring period (2003–2011), soil type, pH, bulk density, crop type, management and fertiliser applied. All sites listed provided N_2O data from chamber measurements. R_{ecos} data from eddy covariance installations were further provided from the arable and grassland sites at Carlow and Mount Lucas.

Daily weather data were derived from Met Éireann weather stations. Input data and management scenarios were represented in the same way across all models, to ensure that the simulations were equivalent. The models being compared all require differing numbers of parameters, in addition to input data. Parameters were left at the developers' default values unless there were measured data to inform a change. In doing so, we tried to ensure a fair test between models, explicitly driving models only using inputs for which measured data were available, and avoiding altering parameters without a valid reason. All flux data were converted to common units (kg ha^{-1} day^{-1}) and then summarised to daily means and standard errors to correspond to the timestep used by the models. None of the models compared had the ability to simulate N_2O uptake, so observed negative N_2O fluxes were coded as missing values and excluded from model evaluation. Observed cumulative fluxes were estimated over periods for which flux measurements existed (the measurement period) by interpolating measured fluxes on a daily basis using a constant (stepwise) method. Observed negative fluxes were converted to zero for cumulative flux comparisons.

2.1.2 Model spin-up

Each model required a spin-up simulation to be executed prior to the simulation run itself, in order to determine the correct balance of C and N between various substrate pools used to simulate decomposition and mineralisation. The developers' recommended spin-up period was used for each model (DailyDayCent: approximately 2000 years; DNDC: 20–30 years). In ECOSSE, an analytical process was used to set up the pools prior to the start of the simulation, so an explicit spin-up period is not required. Spin up periods were driven using 40 years of daily weather data from Carlow, using a scenario based on the transition from mixed forest, to grassland, then system-specific land management derived from historical land-use data.

2.1.3 Model evaluation

Model simulations were evaluated by comparison with all available measured data, using an R implementation of the MODEVAL tool, originally developed in Microsoft Excel by Smith and Smith (2007). The MODEVAL tool calculates several statistics that describe various aspects of model fit (coincidence and association). The root mean square error (*RMSE*) is the total percentage difference between simulated and measured data and can be compared with its 95% confidence interval ($RMSE_{95}$) to determine whether the fit between simulated and observed data could be improved using the data available (Smith and Smith, 2007). *RMSE* and $RMSE_{95}$ are calculated as follows:

$$RMSE = \frac{100}{\bar{O}} \times \sqrt{\frac{\sum_{i=1}^{n}\left(O_i - P_i\right)^2}{n}} \tag{2.1}$$

$$RMSE_{95} = \frac{100}{\bar{O}} \times \sqrt{\frac{\sum_{i=1}^{n}\left(SE_i \times t_{m,95}\right)^2}{n}} \tag{2.2}$$

where $\bar{O}$ is measured data, *P* is simulated data, *SE* is the standard error of the measured data, $t_{m,95}$ is the Student's *t* value for *m* replicates and 95% probability, and *n* is the number of data points being compared. Relative error (*E*) is a measure of bias in the difference between simulated and observed data, the significance of which can be assessed against its 95% confidence

Table 2.1. Datasets used for model validation

Site	Measurement period	Soil type	Soil pH	Bulk density ($g\ cm^{-3}$)	Crop type	Treatments	Fertiliser applied ($kg\ N\ year^{-1}$)
Arable							
Carlow – cover crop comparison	2010–2012	Brown earth/ Eutric Cambisol/ sandy loam	6.8	1.28	Spring barley	Bare fallow (control and fertilised); mustard or radish cover crops	Control bare fallow: 0. Other treatments: 2010: 133; 2011: 62; 2012: 0
Carlow – conventional tillage, reduced tillage with cover crops, varying N addition	2007–2009	Brown earth/ Eutric Cambisol/ sandy loam	7.0	1.12	Spring barley	Conventional tillage with varying N addition; non-inversion tillage with varying N addition and mustard cover crop	Unfertilised control: 0; low N: 70; high N: 140
Carlow – conventional or reduced tillage with varying N addition	2003–2005 (R_{ecos} in addition to N_2O)	Brown earth/ Eutric Cambisol/ sandy loam	7.0	1.4	Spring barley	Conventional tillage with varying N addition; non-inversion tillage with varying N addition	Unfertilised control: 0; 2004: low N: 70, high N: 140; 2005: low N: 79, high N: 159
Grassland							
Carlow – cut/ grazed pasture	2003–2005 (R_{ecos} in addition to N_2O)	Brown earth/ Eutric Cambisol/ sandy loam	7.3	1.0	Mix: *Lolium perenne* L. cv. Cashel, *Trifolium repens* L. cv. Aran	Grazing and cutting, unfertilised control	Unfertilised control: 0; 2003: 200; 2004: 200; 2005: 140
Carlow – unmanaged grassland	2008–2009	Brown earth/ Eutric Cambisol/ sandy loam	6.8	0.76	*L. perenne*	None	None
Dooary – semi-natural, unimproved grassland	2008–2009	Low humic mineral gley	5.3	0.49	*Juncus effusus* L.-dominated sward	None	None
Mount Lucas	2010–2011 (R_{ecos} in addition to N_2O)	Brown earth	6.9	1.06	*Alopecurus pratensis* L.-dominated sward	None	None
Solohead	2008–2012	Poorly drained gleys (90%); grey-brown podzolics (10%)	6.2	0.87	Mix: *L. perenne* L., *T. repens* L.	Grazed and fertilized; cut and unfertilised	2008: 0; 2009: 62.4; 2010: 57.5; 2011: 86.4; 2012: 86.4

interval (E_{95}) (Smith and Smith, 2007). E and E_{95} are calculated as follows:

$$E = \frac{100}{\bar{O}} \times \frac{\sum_{i=1}^{n}(O_i - P_i)}{n} \quad (2.3)$$

$$E_{95} = \frac{100}{\bar{O}} \times \frac{\sum_{i=1}^{n}(SE_i \times t_{m,95})}{n} \quad (2.4)$$

The significance of the association between simulated and observed data is calculated using the sample correlation coefficient (r) and an F-test (Smith and Smith, 2007).

2.1.4 Contribution analysis

A contribution analysis, to quantify the contribution of uncertainty in model inputs to uncertainty in the simulated fluxes, was carried out for each combination of site and management regime. Our uncertainty ranges (Table 2.2) and statistical approach follow similar methods to those used by Fitton *et al*. (2014a,b) and Hastings *et al*. (2010). Different approaches were required for each model. The simulations required to perform sensitivity analyses in DNDC were performed using an internal Monte

Table 2.2. Model input uncertainty ranges used in sensitivity and uncertainty analyses

Variable	Uncertainty range
Daily temperature	±1°C
Daily precipitation	±10%
Soil pH	±1 pH unit
Soil clay content	±20%
Bulk density	±0.2 g cm^{-3}

Carlo routine, whereas those in DailyDayCent and ECOSSE were performed as follows. Latin hypercube sampling was used to generate random samples of input conditions across all tested inputs, with the resulting uniform distributions used to run each model iteratively. We ensured that the sensitivity analyses between models were as equivalent as possible, within the limitations imposed by the design of the software.

The percentage contribution of each input to the overall uncertainty in simulations was quantified using the contribution index (c_i) (Vose, 2000; Gottschalk *et al.*, 2007):

$$\left[c_i = \frac{\sigma_g - \sigma_i}{\sum_{i=1}^{i_{max}} \left(\sigma_g - \sigma_i \right)} \times 100 \right] \tag{2.5}$$

where σ_g is the standard deviation representing the total uncertainty in simulations as a result of varying all inputs simultaneously (the global uncertainty) and σ_i is the standard deviation derived from holding each input, *i*, constant in turn while varying all other inputs. Each model was run 4096 times (the default for DNDC) for each of the six tests, yielding a total of 24,576 runs per model per site. We were limited to five test variables by the availability of central processing unit (CPU) time required to perform model runs. We selected test variables to allow comparison with other studies (Hastings *et al.*, 2010; Fitton *et al.*, 2014a,b).

2.2 Geographic Information System

2.2.1 Creating the 5 km grid

In order to map Tier 3 default model runs at the country level, a 5 km grid comprising 3758 cells was created inside the ArcGIS 10.1 environment (ArcMap software) for Ireland. Maximum and minimum *x* and *y* co-ordinates for Ireland were used (extrapolated from a census boundary map for Ireland from http://www.cso.ie/en/census/census2011boundaryfiles), together with the specified cell size, to calculate the number of rows and columns to use for the grid. Unneeded cells outside the Irish boundaries were eliminated, utilising the census boundary layer as a source layer. The resulting grid uses the projected co-ordinate system TM75 Irish Grid (Transverse Mercator).

2.2.2 Collection and geoprocessing of soil data

The soil data used in the spatial modelling of GHG emissions were collected from the official EPA website (http://erc.epa.ie/safer/iso19115/displayAllAttachments.jsp?isoID=7) and the Irish SIS (http://gis.teagasc.ie/soils/downloads.php).

Soil pH and soil organic carbon

Basic soil information, such as pH and soil organic carbon (SOC), sourced from the EPA, was extracted from 2 km-based raster grids onto the 5 km grid, utilising a combination of conversion and intersection tools using ArcGIS 10.1 and the statistical language R. Specifically, the original 2 km grids (raster format with flt extensions) were first converted into GRID format in order to proceed with the intersection geoprocessing in the Geospatial Modelling Environment (GME). The next step involved the intersection of the newly converted raster with the 5 km polygon-based map grid using the "Isectpolyrst" tool. The computation of metrics such as mean and standard deviation for each 5 km cell was specified using R code within GME. The resulting polygon-based grid had a total of 3758 cells, with four new data fields for each cell specifying the mean and standard deviation for pH and SOC, and is illustrated in Figure 2.1.

Soil associations, classes and bulk densities

Soil association and soil class polygon-based maps sourced from SIS were statistically converted into a 5 km grid format utilising zonal statistical tools inside the ArcGIS 10.1 environment, coupled with polygon/raster conversions and intersections in GME to determine the "mode" (i.e. the most commonly occurring soil association for each 5 km grid).

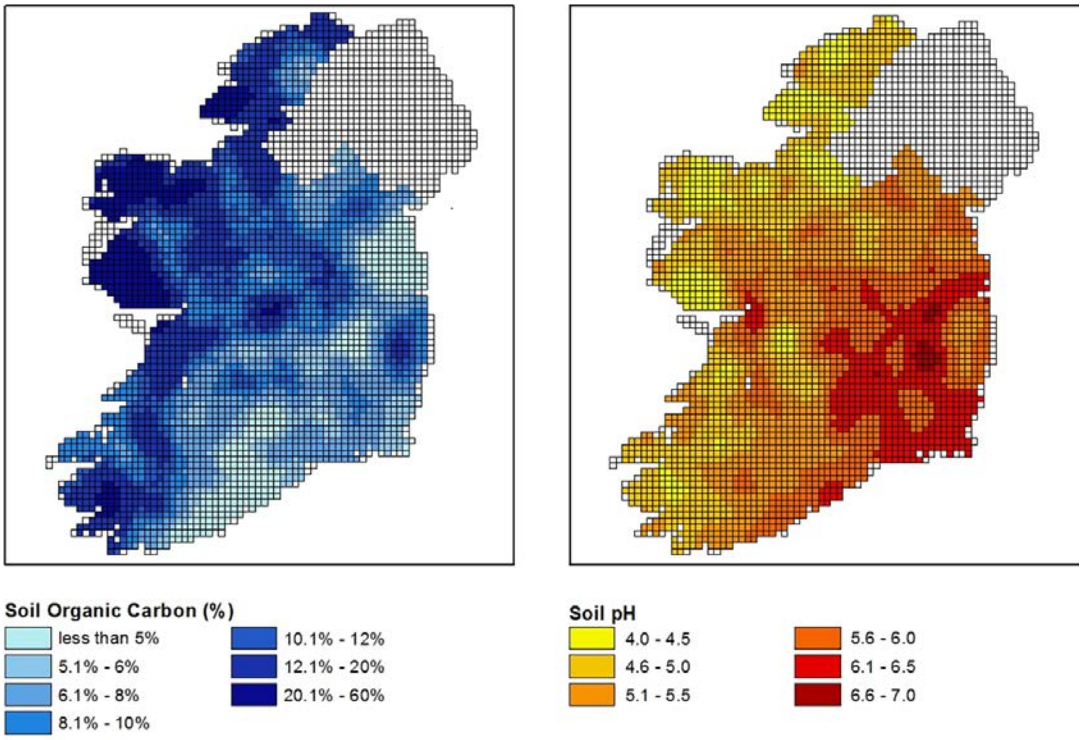


Figure 2.1. Maps showing SOC and soil pH for Ireland. Each cell in the grid represents an area of 5 × 5 km = 25 km^2.

The original SIS map on soil associations was a polygon-based map layer composed of more than 20,000 polygons, subdividing the national territory in circa 60 different soil associations. Each soil association is defined as a group of soil classes, amongst which one is considered the most important and gives the name to the corresponding association. For each soil class the SIS website also provides basic soil information such as bulk density, texture and particle size distribution.

The procedure illustrated in the previous section for the determination of soil pH and SOC for each cell in the grid utilised numeric data for these variables, so that estimation of means and standard deviations was relatively straightforward. When dealing with nominal or categorical data, as is the case for soil associations (i.e. data in strings of text), determination of averages equals the specification of the most commonly occurring category for a defined region (i.e. the mode), and the process is more complex. Here, the mode for each region (5 km^2 cell) was determined by transforming irregular polygons defining the soil associations into smaller, regular squares (0.5 km^2) and then counting each association (as illustrated in Figure 2.2). Here, the polygon-based map of soil associations sourced from SIS was initially converted into a 0.5 km raster format inside the ArcGIS environment, using the "polygon to raster" tool. This new raster was a File Geodatabase Raster and so was converted into a GRID format to allow for further geoprocessing. Zonal statistics were performed on this newly created raster, allowing for the calculation of statistics on values of a raster within specified zones (the cells of the 5 km grid). The "zonal statistics" tool was used inside the ArcGIS 10.1 environment and "majority" was indicated as the statistic type, allowing for the identification of the most commonly occurring category in each zone.

The outcome of the zonal statistics step was again a File Geodatabase Raster dataset, which was transformed to a GRID format prior to further geoprocessing, as above. Finally, in GME the new raster dataset was intersected to the 5 km polygon-based grid and the new dataset was used for the simulation of GHG emissions and the generation of the GIS maps of the main soil types, illustrated in Figure 2.3.

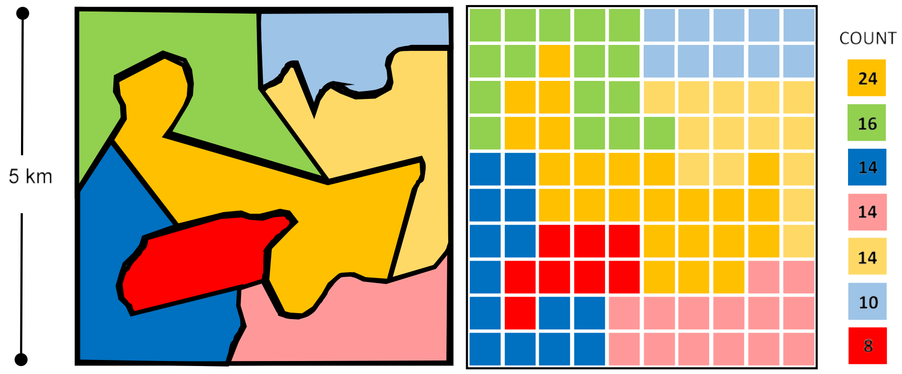


Figure 2.2. Simplified diagram showing the spatial statistical method used to geoprocess soil association and land cover data. Irregular polygons were transformed into a raster grid 0.5 km in size and the squares were counted to determine the most commonly occurring category (mode) for the selected predefined area (5 × 5 km cell).

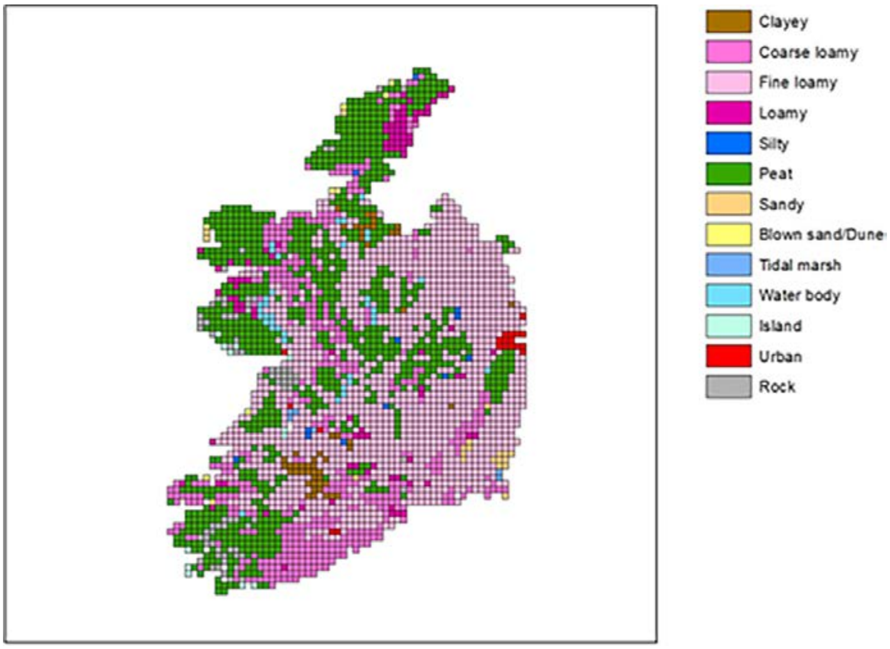


Figure 2.3. Macro-aggregations of soil associations on the basis of soil type. This does not represent the actual soil data used in the modelling process, in which a sub-categorisation into circa 60 different soil associations was used. For clarity of representation here, similar soil types were aggregated into only 13 categories.

2.2.3 Collection and geoprocessing of land cover data

A similar approach to the one outlined in section 2.2.2 was used for land cover data collected from the CORINE programme through the EPA portal (http://gis.epa.ie/GetData). The CORINE polygon-based maps were converted into 0.5 km grids and subsequently zonal statistics procedures were used to estimate the modal best representative soil cover type for each of the 3758 5 km-based cells, utilising a combination of GIS tools inside the ArcGIS 10.1 and GME environments (Figure 2.4).

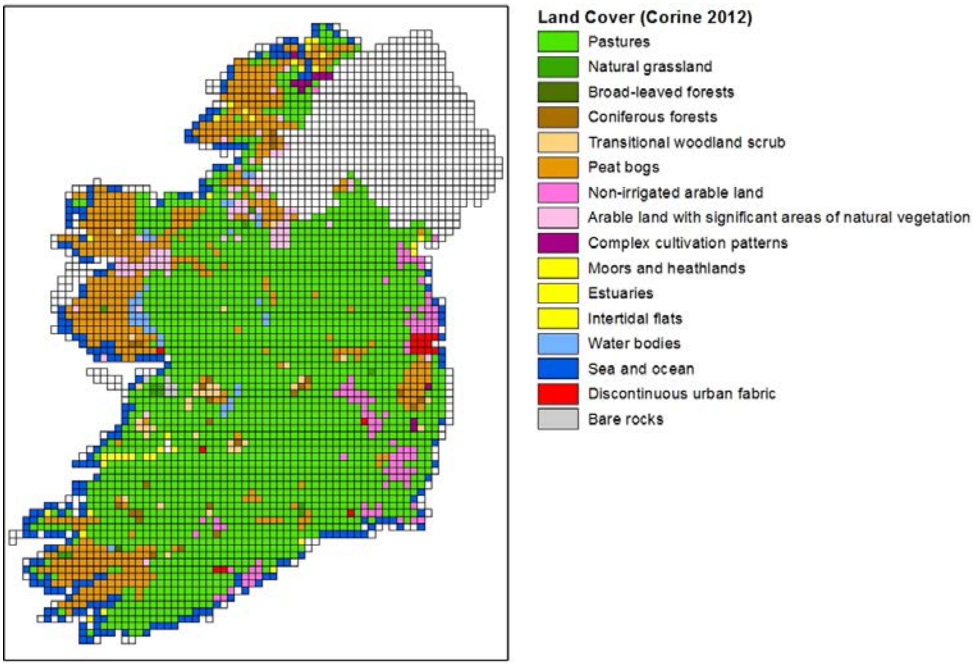


Figure 2.4. GIS map showing soil cover data for Ireland. Each cell in the grid represents an area of 5 × 5 km = 25 km^2.

3 Results and Discussion

In order to move towards more comprehensive, precise estimates of agricultural GHG budgets, process-based simulation models are necessary for simulating soil GHG emissions, which form a large component of the agricultural GHG budget. The value of using process-based models to estimate agricultural GHG emissions lies in their ability to accurately simulate GHG emissions from a range of soils, under a variety of contemporary management scenarios, and the extension of this ability to future climate and management scenarios. We set out to evaluate the capability of four process-based biogeochemical models – DailyDayCent, DNDC versions 9.4 and 9.5 and ECOSSE – for simulating soil N_2O and CO_2 emissions from a range of common agricultural land uses in Ireland. Importantly, we used existing crop parameterisations and the minimum set of inputs required by the models under evaluation in order to test the suitability of the models for use outside their original parameterisation environment, i.e. their transferability.

The fit of simulated data to observed data was assessed both on a daily (*RMSE*, *E* and Pearson's *r*) and a cumulative (percentage difference between observed and simulated cumulative emissions) basis, with annual cumulative values of N_2O and R_{ecos} being the most important for GHG reporting through upscaling to the national level.

3.1 Simulation of N_2O Emissions

A consistent observation was that no single process model was suitable for all land-use categories. DailyDayCent and ECOSSE produced a better fit of modelled to measured data for arable systems, with DNDC version 9.5 being more suited to simulating N_2O flux from grasslands. The overall fit of modelled to measured data was poor, particularly in low emission/low fertiliser sites. Individual site analysis data are presented in Appendix 1 (see section A1.1), with the overall analysis statistics presented here.

3.1.1 Daily N_2O emissions

As an example of the disparity between model output and land-use type, Figure 3.1 illustrates the fit of modelled to daily measured data for an arable and a grassland site at Carlow (see sections A1.1.1 and A1.2.1 for the full analysis). ECOSSE appears to be best suited to modelling arable data, both capturing the spring fertiliser peaks in N_2O flux and illustrating a reasonable representation of background emissions. This is in extreme contrast to the grassland site, where ECOSSE fails to reproduce any of the major peaks in N_2O flux. In contrast, DNDC versions 9.4 and 9.5 seem best suited to modelling daily emissions from the grassland site, capturing fertiliser peaks and background emissions that the other two models fail to capture.

One significant limitation in assessing the suitability of process-based models to simulate soil GHG fluxes at the national level would be the small number of datasets used (Flynn *et al*., 2005; Cowie *et al*., 2012; Myrgiotis *et al*., 2019). Our study incorporated arable and grassland flux data from eight separate experimental sites, representing three differing soil types and a variety of management options and covering the time period from 2003 to 2011 (see Table 2.1). Although biased towards free-draining soils, our analysis represents the first major study of its kind in Ireland.

Goodness of fit of the models to measured data was analysed using three different procedures: *RMSE*, relative error (*E*) and Pearson's *RMSE*, and Pearson's correlation coefficients (*r*).

Figure 3.2 illustrates Pearson's *r* coefficients between simulated and measured fluxes for the arable and grassland sites using the four individual process-based models.

The mean values for Pearson's *r* coefficients between simulated and measured fluxes were generally low, indicating a poor representation of N_2O flux dynamics by all of the models. This is also illustrated in the calculation of the *RMSE* (Figure 3.3) and *E* (Figure 3.4).

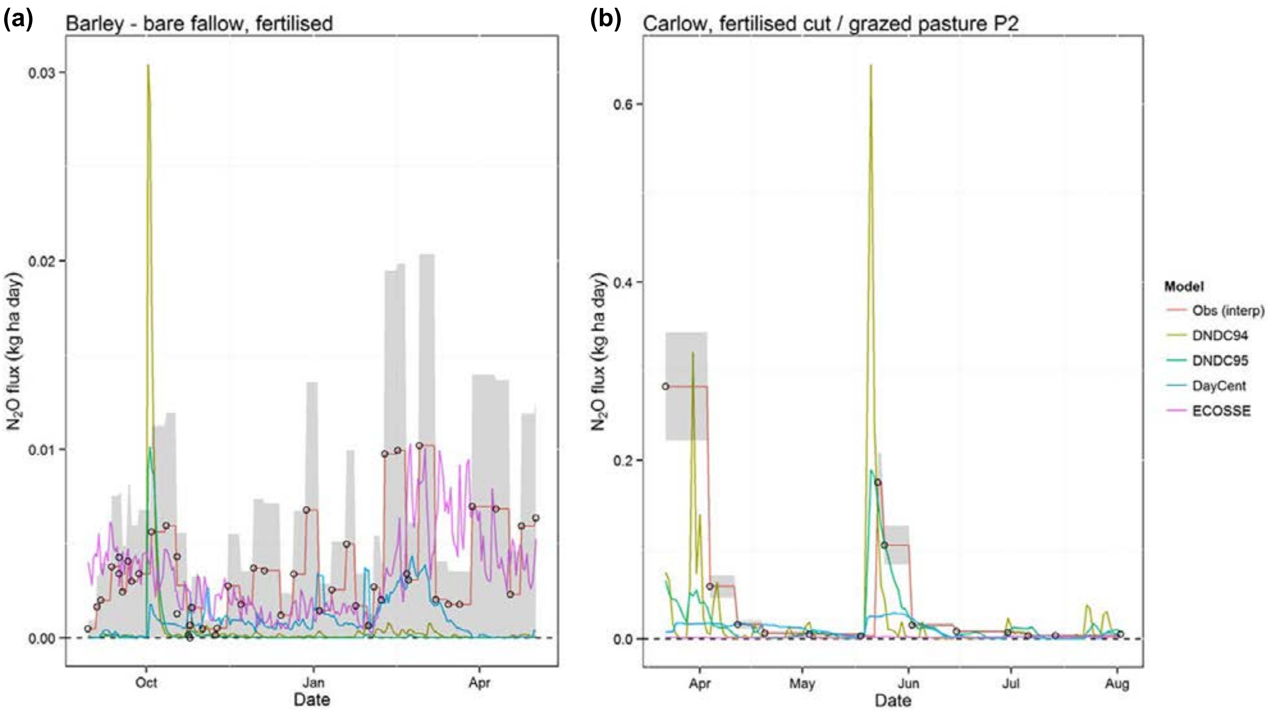


Figure 3.1. Simulated and measured daily fluxes of N_2O from two representative arable (a) and grassland (b) sites. The orange line highlights the observed, interpolated data and the grey bars indicate the standard deviation of the interpolated, measured data. P2, second period.

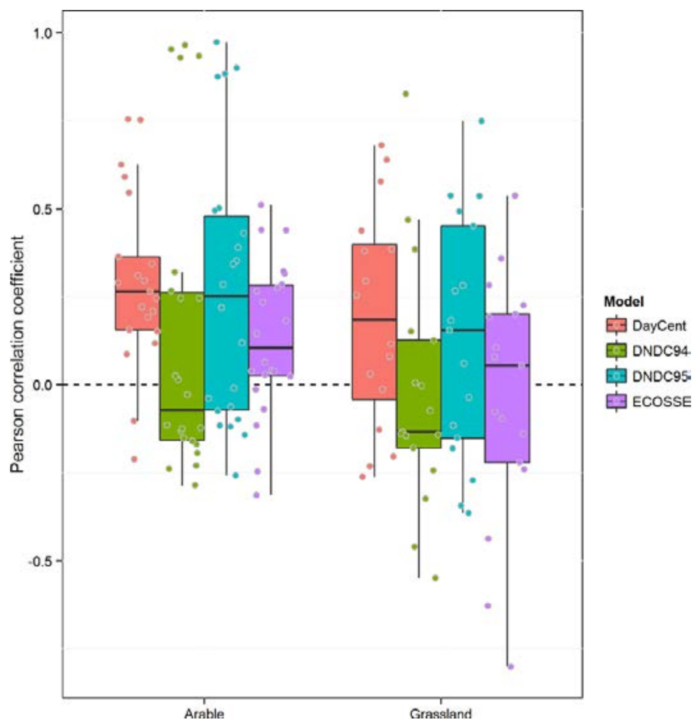


Figure 3.2. Pearson's correlation coefficients (*r*) for each model within each system. Box plots indicate the distribution of the data. Each point represents a correlation coefficient for an individual simulation.

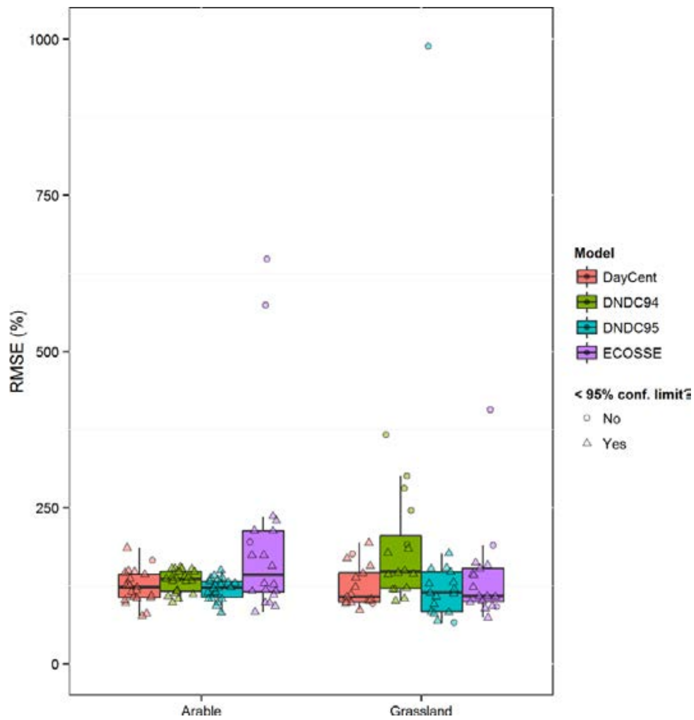


Figure 3.3. Simulation of the *RMSE* for each model within each system. Box plots indicate the distribution of the data. Overlaid points represent individual *RMSE* values for each simulation; the shape of the point indicates whether the *RMSE* for that simulation was within the 95% confidence interval. Three simulations with very high *RMSE* values are excluded from this plot for ease of interpretation: ECOSSE simulations of sites Barley C_0 (*RMSE* = 2316.61%) and Barley C_1 (*RMSE* = 1190.34%) and the DNDC 9.4 simulation of the unmanaged grassland at Dooary (*RMSE* = 8346.52%).

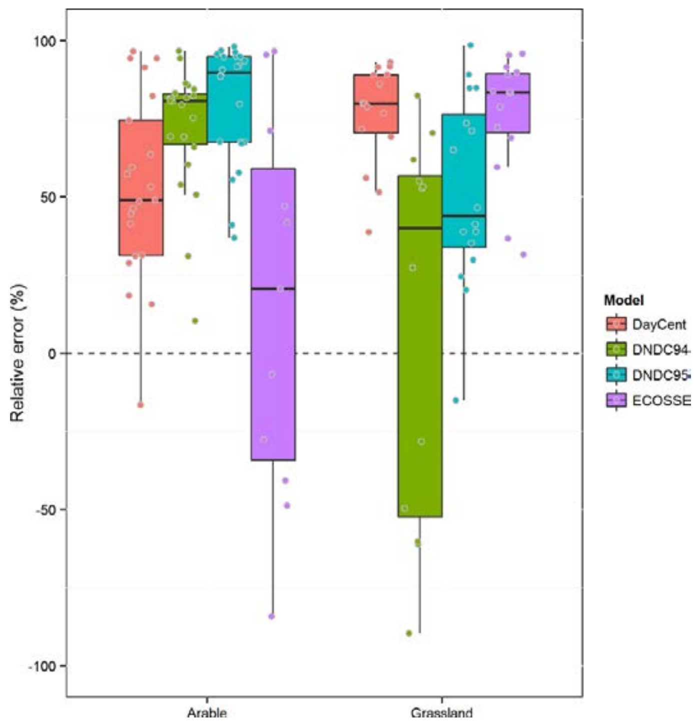


Figure 3.4. Relative error (*E*) for each model within each system. Box plots indicate the distribution of the data. Each overlaid point represents an *E* value for an individual simulation.

The majority of the overall simulation errors, expressed as the *RMSE*, were not statistically significant at the 95% level. Of all of the models, ECOSSE produced the highest number of statistically significant *RMSE* values.

However, although many of the *RMSE* values were within the 95% confidence intervals for their associated sites, simulation errors on a daily basis were generally large and frequently greater than 100% of the measured emission value. The high 95% confidence intervals reflect the frequently large standard errors associated with the measured N_2O fluxes and are a symptom of the methodological difficulties associated with measuring N_2O fluxes. The large confidence intervals associated with the *RMSE* may be interpreted as being overtly forgiving in this regard because, although model performance can be considered statistically acceptable, it is unlikely that simulations with such large deviations from the measured data could be used to reliably predict the dynamics of N_2O emissions in response to future climate and land-use management scenarios.

A simplified means of illustrating the fit of modelled to measured data for each individual site is illustrated in Figure 3.5. To enable comparison, we generated scores to describe model fit in terms of coincidence and association, by standardising *RMSE* and *E* within sites to the range [0, 1], with higher scores indicating a better model fit (i.e. *RMSE* and *E* closer to zero). These overall simulation scores ("simscore") were used to rank the ability of each model to simulate N_2O emissions from each site on a daily timestep, with rankings listed for each site in Appendix 1.

In terms of coincidence ("diffscore") alone, DailyDayCent and ECOSSE produce higher values for the arable sites and DNDC version 9.5 produces higher values for the grassland sites. Association scores ("cor") are lower and show no overall pattern between the land-use categories. Taking both coincidence and association into consideration, therefore, the pattern of distribution of the overall simulation scores ("simscore") suggests that the DailyDayCent and ECOSSE models are best suited for simulating daily N_2O emissions for the arable land-use category, whereas DNDC versions 9.4 and 9.5 are best suited for simulating daily N_2O emissions for grasslands.

3.1.2 Cumulative N_2O emissions

Annual cumulative emissions of N_2O are a requirement for GHG reporting. As with daily N_2O emissions, the ability of the four simulation models to predict cumulative fluxes of N_2O was highly variable across land use, site, management and year. This is illustrated clearly in Figure 3.6, where the percentage differences between measured and simulated cumulative fluxes, using outputs from all four models, have been arranged in numerical order between −400% and +250%. Here, the models tested underestimated cumulative N_2O emissions over the site-specific measurement periods in 75% of cases.

Consideration of differences from 50% to 0% between modelled and measured cumulative fluxes illustrates a consistent theme: at these values ECOSSE and DailyDayCent are best at simulating arable cumulative emissions of N_2O and DNDC versions 9.4 and 9.5 are best at simulating cumulative emissions of N_2O from grasslands. To illustrate this point further, Figure 3.7 provides linear regression plots of simulated versus measured cumulative fluxes of N_2O from the grassland and arable data.

The extent to which models underestimated emissions varied between agricultural land-use types. At arable sites, DNDC versions 9.4 and 9.5 underestimated cumulative N_2O emissions to a greater extent than DailyDayCent, whereas ECOSSE tended to overestimate emissions. At grassland sites, DailyDayCent and ECOSSE simulations underestimated cumulative N_2O emissions more than DNDC 9.4, which had a greater tendency to overestimate emissions, and DNDC 9.5. Model performance tended to be poorer at sites with lower levels of fertiliser application, in large part because of the inability of any of the models to simulate negative fluxes of N_2O, resulting in poor scores for both coincidence and association between simulated and modelled data when evaluated on a daily basis. Despite the poor overall fit, ECOSSE and DailyDayCent seem better than DNDC for simulating cumulative fluxes of N_2O from arable sites, whereas DNDC 9.5 produces a better correlation between simulated and measured fluxes for the grassland data.

Temporal resolution of measured N_2O emissions introduces a major source of error when estimating cumulative fluxes at a daily timestep, in order to

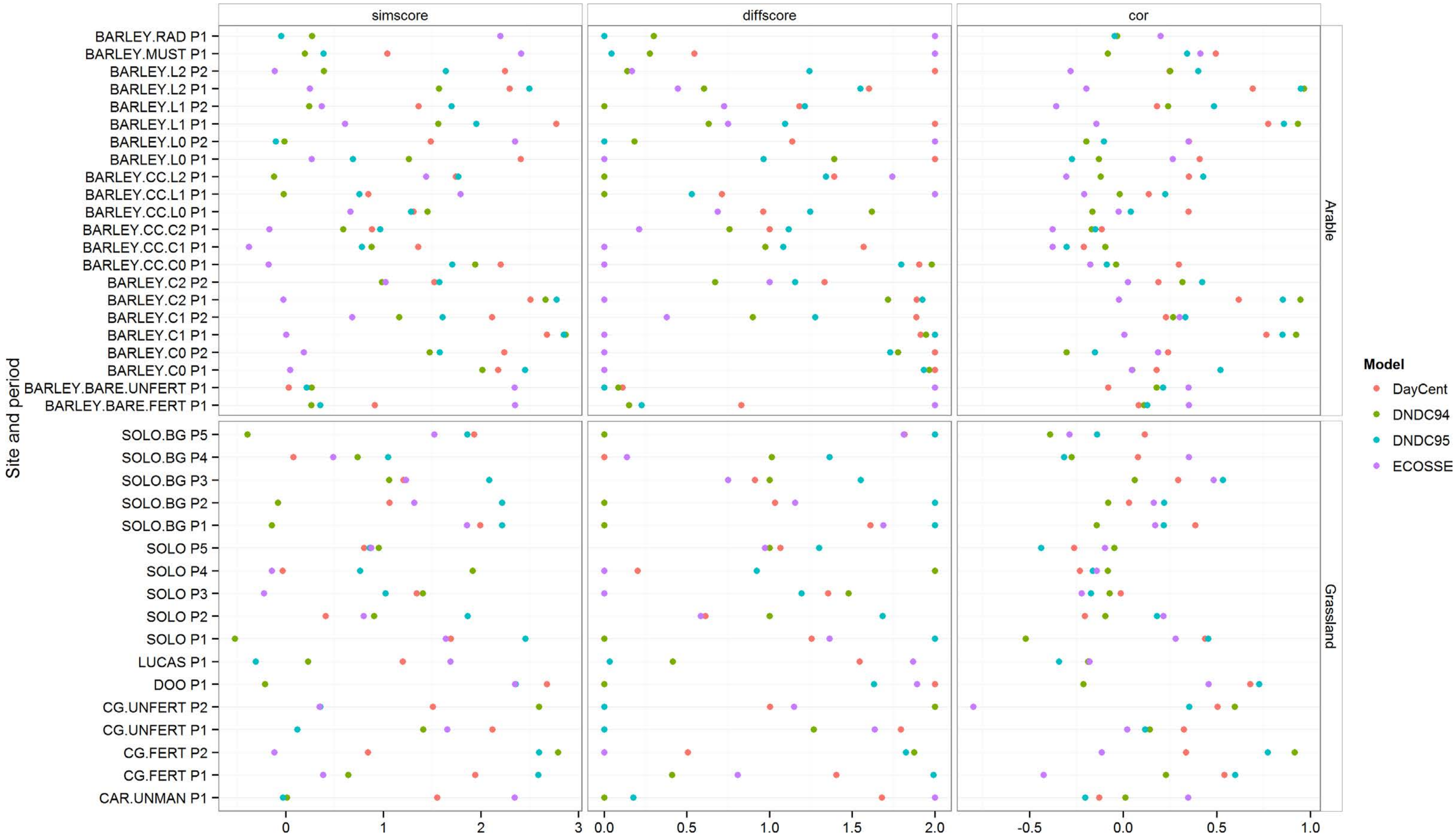


Figure 3.5. Standardised simulation scores for each site and simulation. Each dot represents a simulation. The far left panel, the "simscore", shows the overall simulation scores, which can be used to rank the models in terms of their capability for simulating N_2O emissions on a daily timestep. The "simscore" panel is a combination of the "diffscore" and "cor" panels, the data in which rank the model simulations based on their coincidence and association with the measured data, respectively.

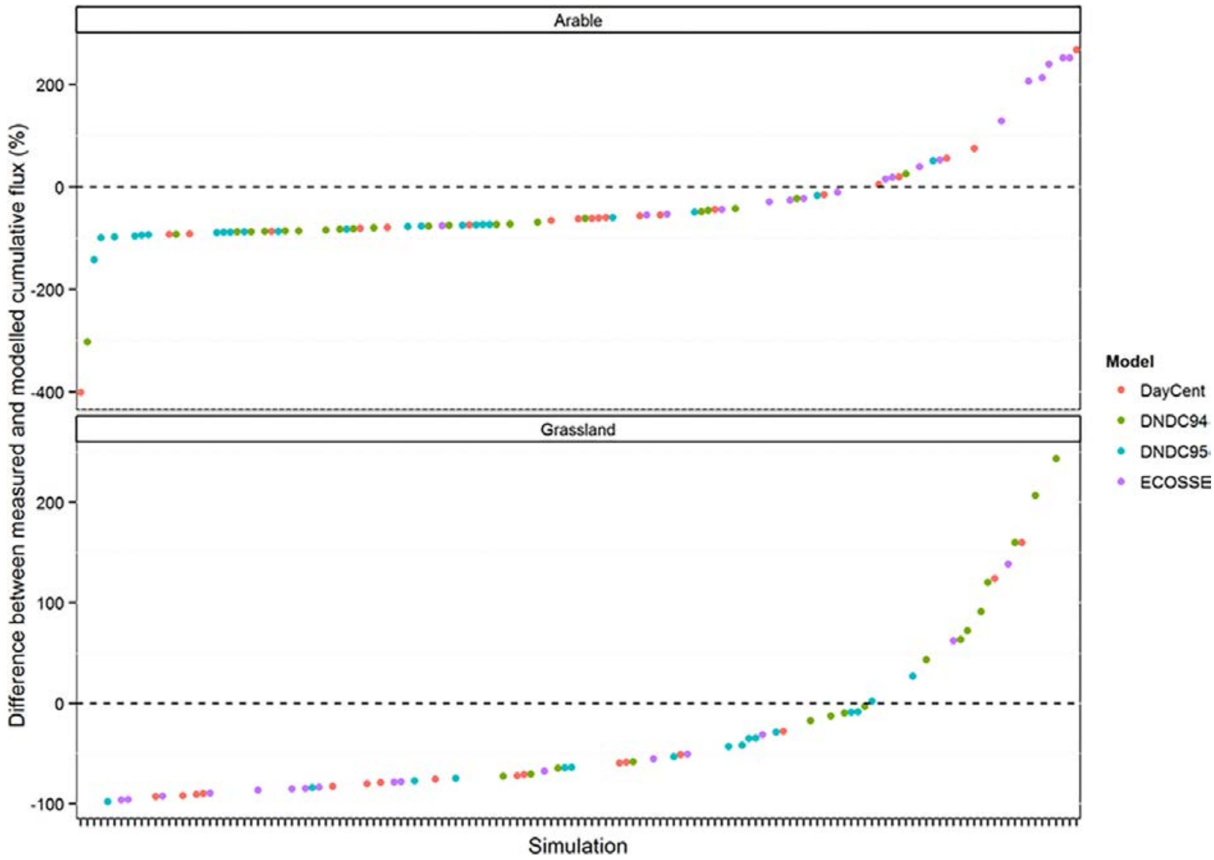


Figure 3.6. Percentage differences between modelled and measured cumulative N_2O fluxes. Each point represents a simulation and points are arranged in increasing order of difference. Negative values indicate that the modelled cumulative fluxes underestimated the measured values.

compare with simulated cumulative fluxes. All of the measured N_2O emissions in this study were derived from chamber-based field campaigns, sampled at varying temporal resolutions. In order to derive an estimate of cumulative emissions at a daily timestep, it is necessary to interpolate between measured data. The methods used for interpolating N_2O fluxes between irregular time series in existing studies are seldom given. In this study we used a fixed interpolation method, in which the interpolated data are extrapolated forward at the value of the last known measurement, until making a step change at the next measurement. Assessing the accuracy of this method of interpolation is difficult without data collected at temporal frequencies typically higher than those employed during conventional static chamber sampling, but it is probable that the fixed interpolation method does not fully represent the highly dynamic nature of N_2O fluxes (Butterbach-Bahl *et al*., 2013). Comparison of estimated and modelled cumulative fluxes is likely to become less reliable when measured flux data exist at a weekly (or less frequent) frequency.

3.2 Simulation of R_{ecos}

R_{ecos} data were superior in number and frequency of measurement than the static chamber data used for simulation of N_2O emissions. As such, a far better correlation between modelled and measured data was obtained. Unlike the various simulations of N_2O fluxes, it was possible to use a single overall model to simulate R_{ecos} fluxes of CO_2 from the arable and grassland sites. Although fewer sites had eddy covariance towers and automated soil respiration chambers fitted than those used for N_2O flux measurement (see Table 2.1), the overall fit of modelled to measured data was high. Individual site analysis data are presented in Appendix 2, with the overall analysis statistics presented here.

3.2.1 Daily R_{ecos}

The greater number and frequency of R_{ecos} measurements available for each site reveals a far better fit of modelled to measured values.

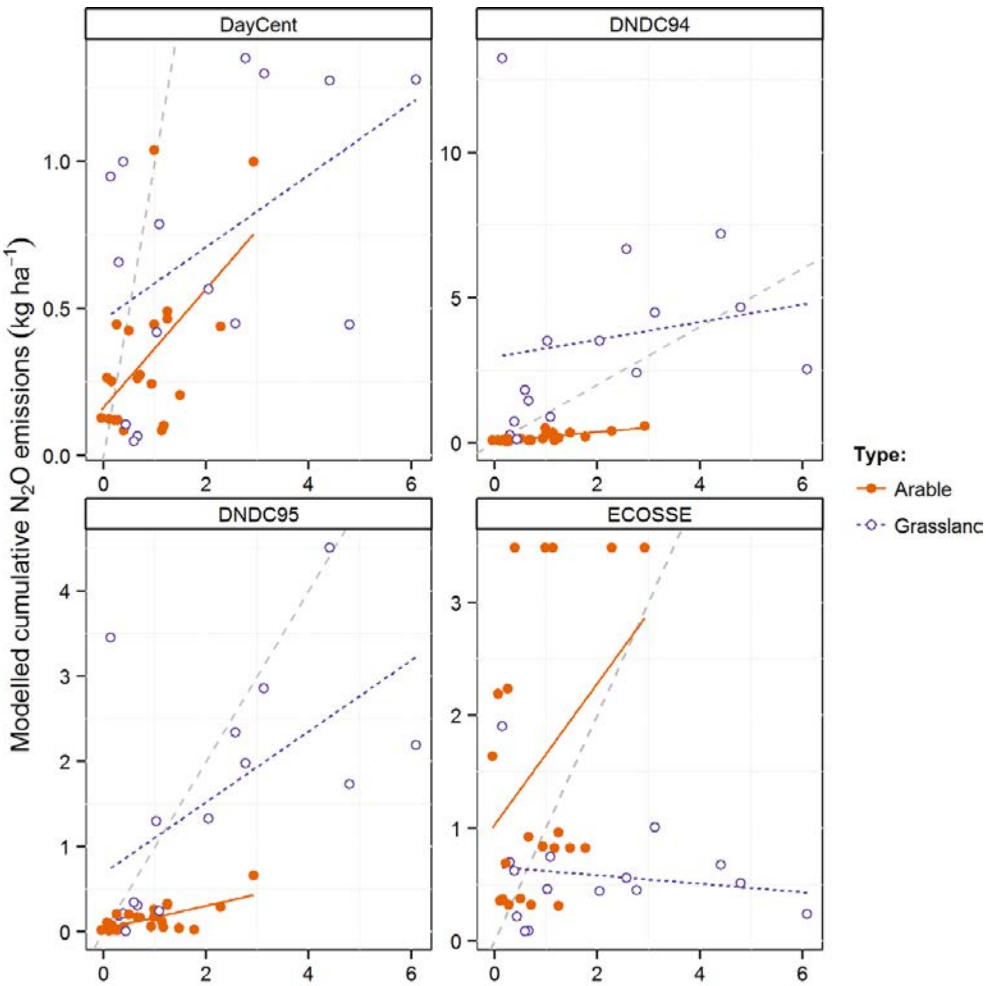


Figure 3.7. Modelled versus measured cumulative N_2O emissions for the arable (closed orange dots) and grassland (open purple dots) sites. The dashed line indicates the 1:1 relationship and the shaded lines represent the linear fits between measured and modelled cumulative fluxes for the arable (orange) and grassland (purple) sites. Two sites have been excluded from this plot for ease of interpretation because they had estimated cumulative emissions far in excess of the majority of the data. These are Solohead grazed and fertilised grassland, measurement periods 3 and 4, for which the estimated cumulative emissions were 12.8 and 29.9 kg N ha^{-1}, respectively.

This is illustrated in Figure 3.8 for the two arable and grassland sites used for CO_2 data. Unlike the simulation of N_2O fluxes, two process-based models, DNDC 9.4 and DNDC 9.5, appear to be highly suited for both arable and grassland systems.

Calculations of *RMSE* and Pearson's correlation coefficients underline the improved fit of modelled to measured data in the case of R_{ecos}. These values are illustrated in Table 3.1 and highlight both the lower *RMSE* values and the significantly higher correlation coefficients for the R_{ecos} simulations than for the majority of the N_2O modelled outputs (see Appendix 1).

In contrast to the overall N_2O data analyses, the correlation of both DailyDayCent and ECOSSE R_{ecos} values with measured data for the two grassland sites was extremely poor and would not support the use of either of these models for simulating R_{ecos} from these grassland systems.

Clearly, both versions of the DNDC model produced a better correlation between simulated and measured R_{ecos} values for the arable and grassland datasets and, with the proviso that only a limited number of sites was used (n = 3), the DNDC model would appear to be best suited overall. This is a far better scenario than for N_2O simulations, where even accepting the high *RMSE* and *E* values, no one simulation model was found to best represent both grassland and arable measured values.

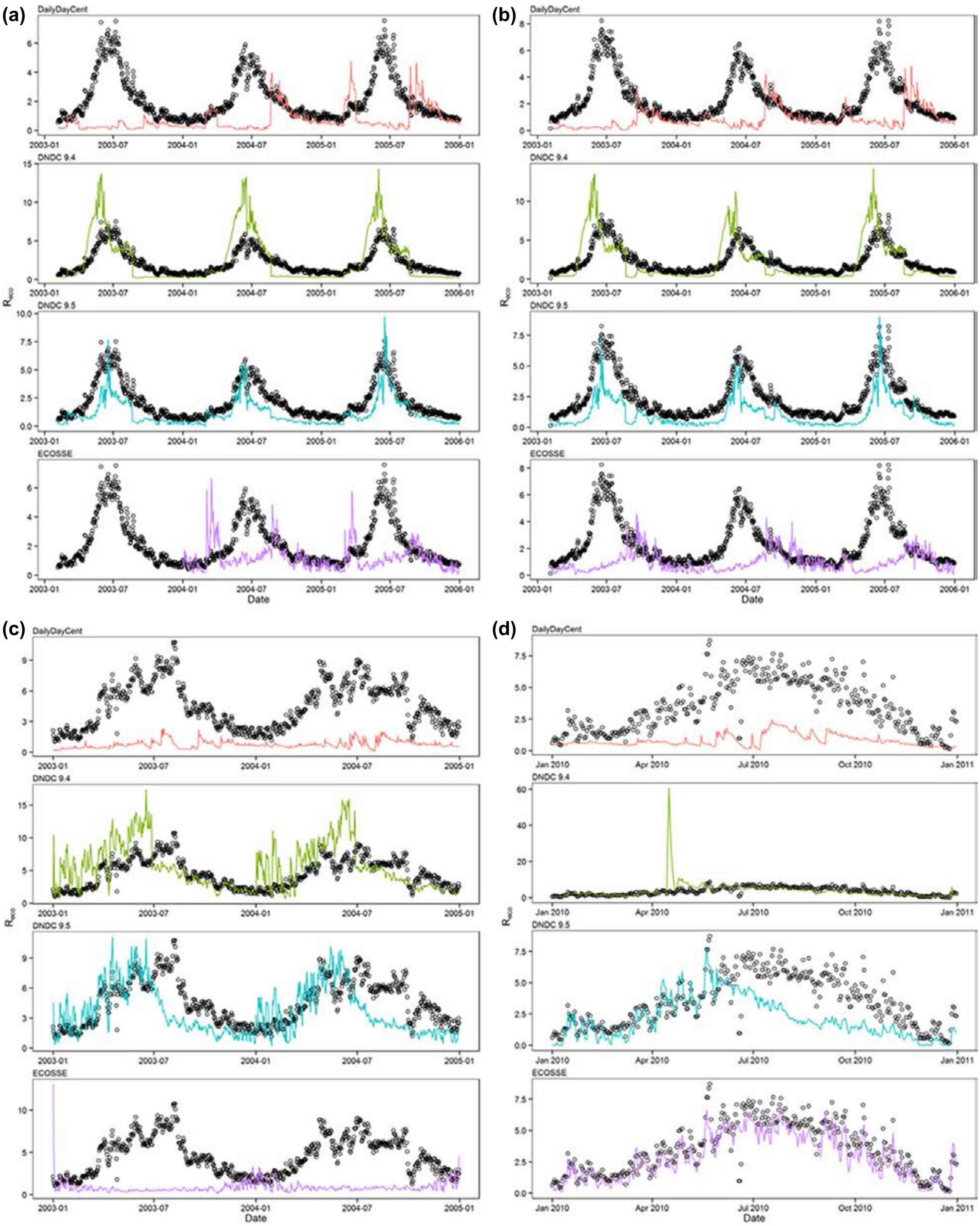


Figure 3.8. Simulation of daily R_{ecos} fluxes by DailyDayCent, DNDC 9.4 and 9.5 and ECOSSE for arable and grassland sites. (a) Barley – conventional tillage, (b) barley – non-inversion tillage, (c) grassland – unmanaged and (d) grassland – cut and fertilised. Black circles indicate measured values; the orange line indicates the DailyDayCent output, the green line indicates the DNDC 9.4 output; the blue line indicates the DNDC 9.5 output; and the purple line indicates the ECOSSE output.

Table 3.1. *RMSE* and R^2 values calculated for simulated daily R_{ecos} values provided by the DailyDayCent, DNDC 9.4 and 9.5 and ECOSSE process-based models

Land use	Simulation model							
	DailyDayCent		DNDC 9.4		DNDC 9.5		ECOSSE	
	RMSE (%)	R^2	*RMSE* (%)	R^2	*RMSE* (%)	R^2	*RMSE* (%)	R^2
Arable (Carlow – barley, conventional tillage)	111.9	–0.2	96.0	0.8	60.5	0.9	89.1	0.1
Arable (Carlow – barley, non-inversion tillage)	107.0	–0.2	82.7	0.7	81.2	0.6	98.2	0
Grassland (Carlow – unmanaged)	95.2	0.4	68.0	0.5	53.0	0.6	98.0	–0.3
Grassland (Mount Lucas – cut grassland)	93.1	0.6	130.0	0.3	58.8	0.7	27.2	0.9

3.2.1 Cumulative R_{ecos}

The significantly higher correlation of simulated daily values of R_{ecos} with measured data is also reflected in the cumulative values illustrated in Figure 3.9. One model, DNDC 9.4, produced the closest fit between the measured and modelled data.

3.3 Sensitivity Analysis

In terms of upscaling regional site data to the national scale, we explored the sensitivity of the four models under evaluation to variations in five key input variables (temperature, precipitation, soil bulk density, pH and clay content) that would be important in constructing our GIS maps. Figures 3.10 and 3.11 illustrate heatmaps displaying the contribution of variation in model input variables to the overall model uncertainty (σ) for each combination of model (y-axis) and input variable (x-axis).

The contribution of input variable uncertainty to overall simulation uncertainty varied between sites and models. The climatic variables (temperature and precipitation) typically eclipsed the soil input variables in terms of their importance for arable site simulations. This is in contrast to the work of Fitton *et al.* (2014b), who found that variation in soil pH made the greatest contribution to overall simulation uncertainty in UK croplands using the DailyDayCent model. Our results agree more closely with those of Fitton *et al.* (2014a), who demonstrated that sensitivity was more evenly distributed between climatic and edaphic input parameters for DailyDayCent simulations at grassland sites, similar to our results for DNDC 9.4.

Abdalla *et al*. (2014) demonstrated that the capability of ECOSSE to simulate CO_2 emissions from a range of natural and semi-natural UK peatland sites was also governed by variation in climatic inputs. Variation in the contribution of model inputs to simulation uncertainty between agricultural management practices and land uses and models emphasises the importance of considering uncertainty in model inputs when moving from site-scale to regional-scale simulations, because it is probable that input variable uncertainty will propagate differently depending on the model being used and the land use being simulated.

3.4 Proof of Concept for GIS Maps of Soil N_2O and Soil CO_2 Efflux

The GIS maps created for this project are preliminary in that no links to management and fertiliser application were considered and only grassland and arable land-use categories were included in the final N_2O and R_{ecos} model runs. This was a proof-of-concept study only, but has succeeded in producing a workable framework onto which management links can be added. Whether existing process models are suited for simulating N_2O flux is questionable (see section 3.1); a far simpler approach would be empirical, relating N_2O flux to temperature, fertiliser application and rainfall. However, accepting the significant weaknesses in N_2O simulation, eight GIS maps have been produced, illustrating the variance in background annual cumulative fluxes of both N_2O and R_{ecos}, using soil and climate parameters to drive the modelled outputs. Three models were chosen, DailyDayCent, DNDC 9.5 and ECOSSE, with the DNDC runs using minimum and maximum scenarios with regard to temperature and precipitation. These maps are presented in Figures 3.12 and 3.13.

The total area of grassland and cropland calculated from the GIS maps was 3 and 0.3 million hectares, respectively, which is in close agreement with the

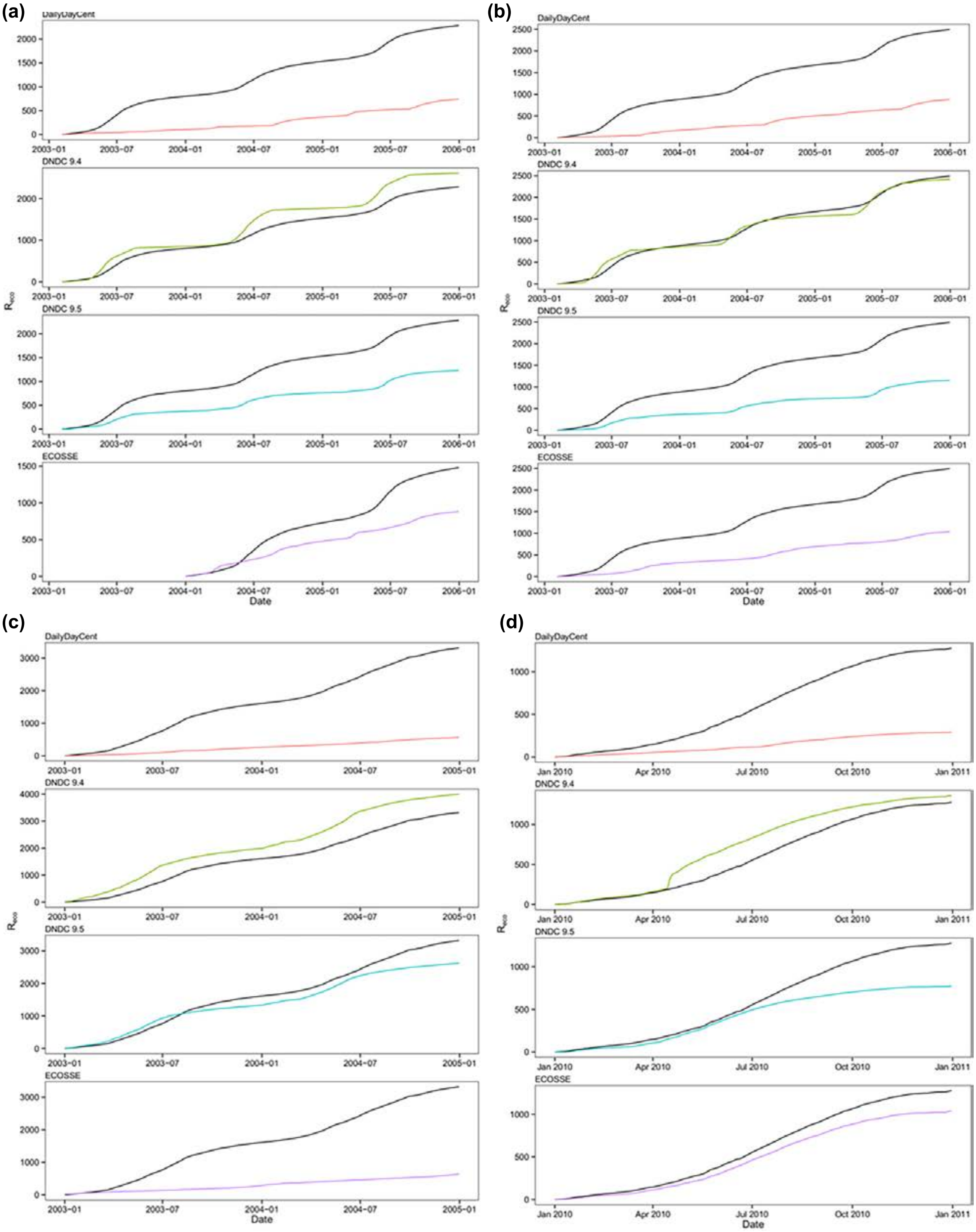


Figure 3.9. Simulation of daily R_{ecos} fluxes by DailyDayCent, DNDC 9.4 and 9.5 and ECOSSE for arable and grassland sites. (a) Barley – conventional tillage, (b) barley – non-inversion tillage, (c) grassland – unmanaged and (d) grassland – cut and fertilised. Black circles indicate measured values; the orange line indicates the DailyDayCent output, the green line indicates the DNDC 9.4 output; the blue line indicates the DNDC 9.5 output; and the purple line indicates the ECOSSE output.

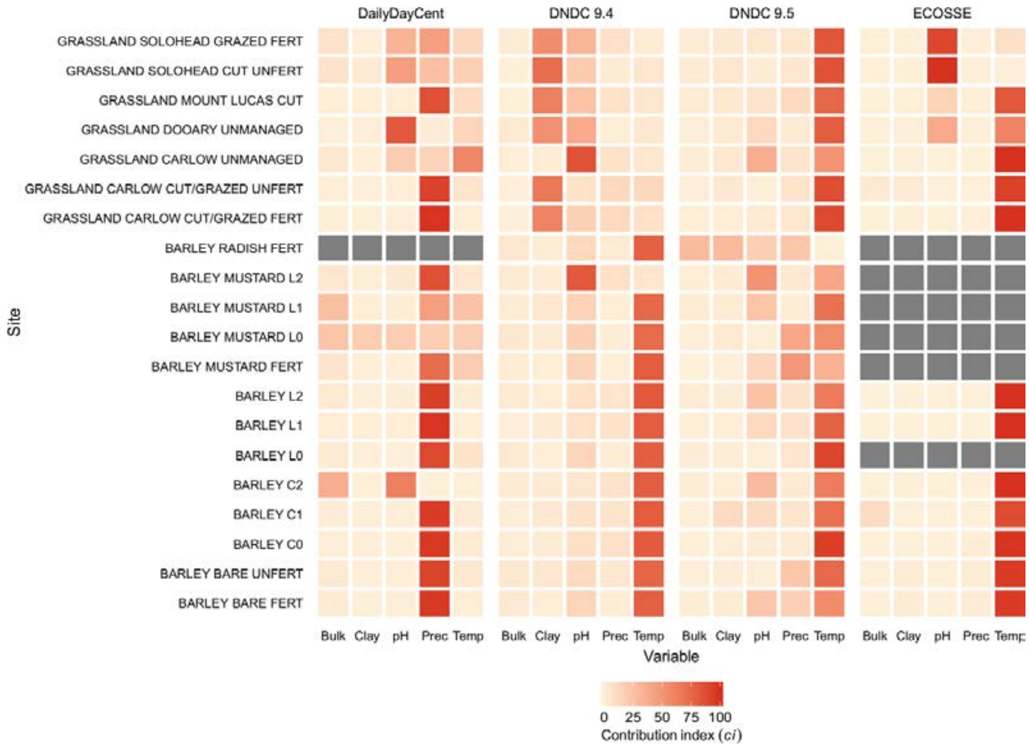


Figure 3.10. Heatmap for N_2O simulations displaying the contribution of variation in model input variables to the overall model uncertainty (σ) for each combination of model (*y*-axis) and input variable (*x*-axis). Grey boxes indicate no data, because of either missing crop parameterisations (radish for DailyDayCent; radish and mustard for ECOSSE) or unsuccessful simulations (Barley L_0 for ECOSSE).

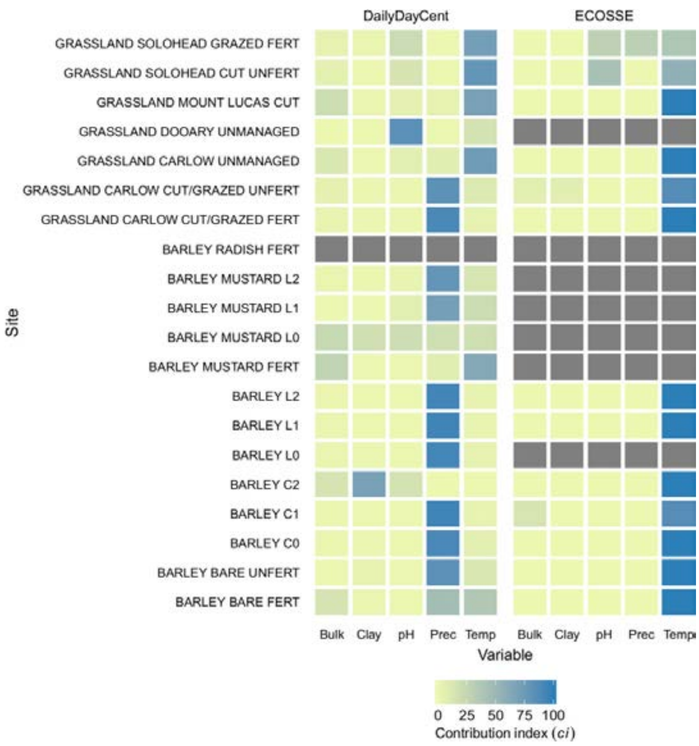


Figure 3.11. Heatmap for R_{ecos} simulations displaying the contribution of variation in model input variables to the overall model uncertainty (σ) for each combination of model (*y*-axis) and input variable (*x*-axis). Grey boxes indicate no data, because of either missing crop parameterisations (radish for DailyDayCent; radish and mustard for ECOSSE) or unsuccessful simulations (Barley L_0 for ECOSSE).

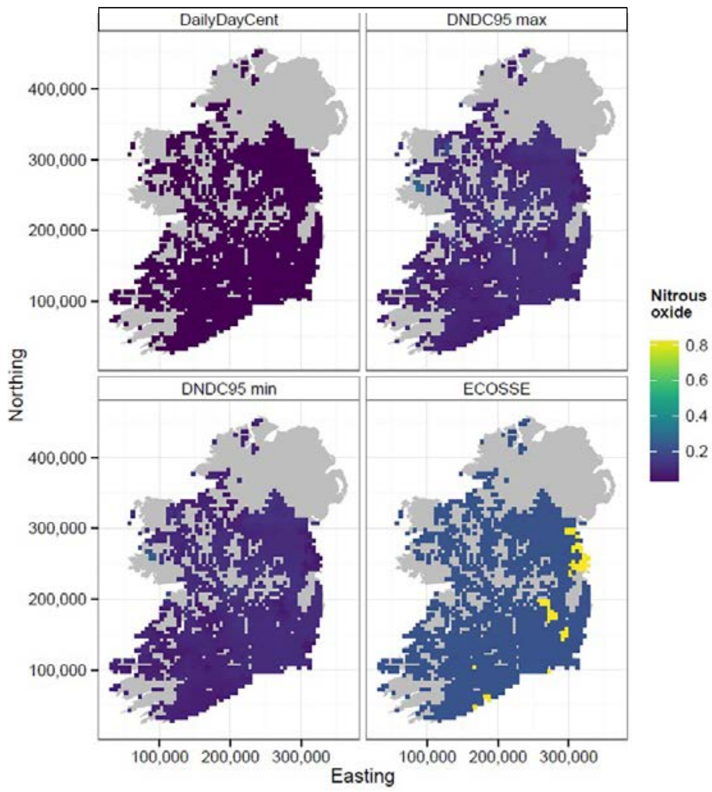


Figure 3.12. GIS maps (5 x 5 km) of Ireland showing background cumulative fluxes of N_2O from grassland and arable areas, as simulated by DailyDayCent, DNDC 9.5 and ECOSSE using soil and climate parameters as the driving variables. Coloured pixels relate to annual flux values (kg N_2O ha^{-1} $year^{-1}$).

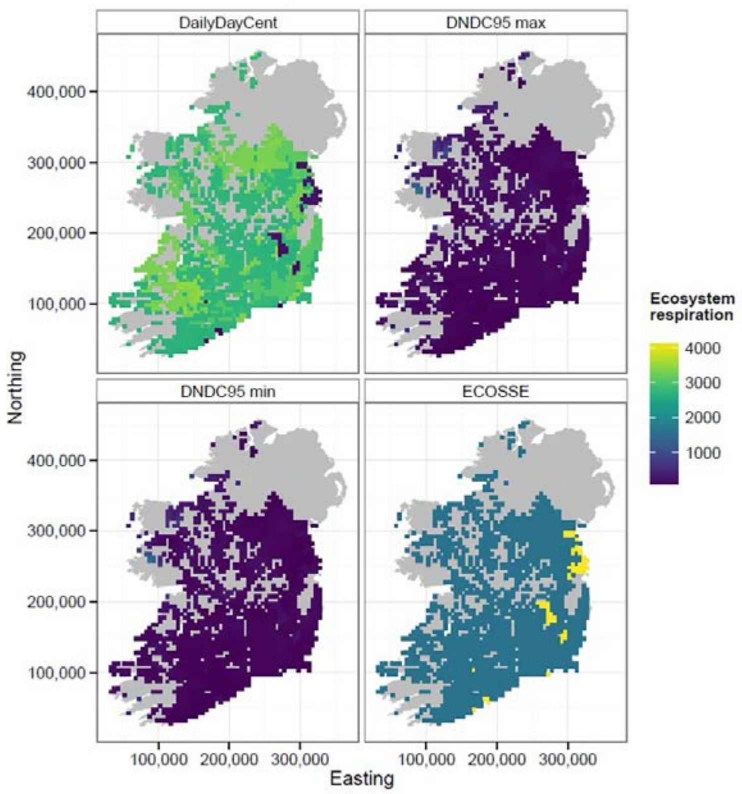


Figure 3.13. GIS maps (5 x 5 km) of Ireland showing background R_{ecos} fluxes from grassland and arable areas, as simulated by DailyDayCent, DNDC 9.5 and ECOSSE using soil and climate parameters as the driving variables. Coloured pixels relate to annual flux values (kg CO_2 ha^{-1} $year^{-1}$).

total area of cropland and pasture land recorded in the 2016 census (3.9 million hectares; CSO, 2018). Upscaling DNDC 9.5 outputs using the GIS map gave combined R_{ecos} and N_2O background emissions of between 0.45 and 0.5 Mt CO_2e for grassland and between 0.074 and 0.08 Mt CO_2e for arable land. These are in broad agreement with inventory values, considering that the effects of fertiliser additions and management were not considered (Duffy *et al*., 2018). However, there was a greater variability between models than across the climate gradient of Ireland. This highlights the major weakness in attempting to simulate N_2O emissions and R_{ecos} across Ireland – that only one process-based model may be used to simulate all GHG emissions for arable and grassland systems and that only in the case of R_{ecos} simulation is this possible. Addition of the forestry sector to the GIS map may further complicate outputs in that different models and model requirements may be needed. Given the poor fit of modelled to measured N_2O data, we suggest, in the absence of improved model and data availability, an empirical approach to upscaling GHG emissions, such as the approaches adopted by Vinther and Hansen (2004), Flynn *et al*. (2005), Flechard *et al*. (2007) and Zhang *et al*. (2015), in which emission factors could be linked to climate data, given that, apart from fertiliser application, in all of our sensitivity analyses (see section 3.3), temperature and precipitation were found to be the major influencing variables.

4 Concluding Remarks

4.1 N_2O and R_{ecos}

We set out to evaluate the capabilities of four commonly used process-based biogeochemical models for simulating N_2O and CO_2 emissions (R_{ecos}) from agricultural soils in Ireland for a range of arable and grassland management scenarios. Model performance varied widely within and between sites, highlighting the fact that, for the production of emissions inventories, care is needed in selecting the appropriate model. Model performance for N_2O emissions was generally poor in terms of simulating dynamics at the daily timestep and estimating cumulative fluxes. This is likely to be a reflection of several factors. First, our process-based understanding of the drivers of N_2O fluxes remains limited, with the lag between experimental work and model implementation resulting in approximate representations of the processes involved in soil N cycling existing in models. Second, accurate measurement of N_2O fluxes across wide spatial scales and at sufficient temporal resolution to reliably test model performance is challenging, with the resulting uncertainties in measured emissions making a clear assessment of the source of deviations between simulated and measured data difficult. Third, it is highly likely that the crop and soil parameterisations used in this study – the model developers' default values – are not representative of agricultural systems in Ireland. However, this is the first study to test four models at many sites under a broad range of management practices in Ireland and it is therefore important to establish a baseline evaluation of model performance using the developers' default values in order to assess the initial transferability of the models and default parameterisations to other environments. Only from this initial, objective evaluation can the need for model improvements be identified.

Our results suggest that, although model performance is highly site specific, there are some general trends in model performance that can be used to inform the future application of models in the development of regional-scale simulations and the generation of emissions inventories. A combination of the DailyDayCent and ECOSSE models is likely to provide the most reliable estimates of future N_2O emissions for arable sites, particularly those with greater use of fertiliser applications. A combination of two versions of the DNDC model, versions 9.4 and 9.5, is likely to produce the most reliable estimates of N_2O emissions for grasslands, particularly fertilised sites. It is important to acknowledge both that all four of the models evaluated in this study tended to underestimate cumulative N_2O emissions estimated from measured data and that the estimation of cumulative emissions itself is not technically trivial and is also prone to error. These caveats aside, this study makes a valuable contribution to the ongoing evaluation of process-based biogeochemical models for the estimation of N_2O emissions from agricultural sites, by providing a baseline from which to target the need for further model development.

Model performance was significantly better for R_{ecos} than for N_2O, producing low *RMSE* values, correlation coefficients approaching 90% and final simulated cumulative fluxes that followed measured values closely. In this case we suggest a combination of DNDC 9.4 and DNDC 9.5 as suitable for providing the most reliable estimates of R_{ecos} flux.

4.2 Proof of Concept of GIS Maps for Ireland for N_2O and R_{ecos} Fluxes

We have developed a GIS map framework for Ireland using a 5 km^2 grid linked to land use and soil type. At present, only arable and grassland agriculture have been considered. Although management data were not linked to the map framework, climate drivers were used to produce GIS maps of Ireland illustrating background cumulative fluxes of N_2O and CO_2 (R_{ecos}) using the DailyDayCent, DNDC 9.5 and ECOSSE process-based models to run each map simulation. Background annual fluxes using DNDC 9.5 are in rough agreement with literature values, but differences in pixel values between the three models are significantly higher than differences in climate and soil type. This highlights the major problem in upscaling N_2O and CO_2 fluxes to the national scale using simulation models – only for R_{ecos} simulations is there one model that is suitable for both grassland and arable systems: DNDC.

Considering the very poor fit of modelled to measured data for N_2O emissions, and a further increase in error as fluxes are calculated on a larger area scale and over an annual basis, we suggest the adoption of a far simpler empirical approach for GIS maps of N_2O fluxes. Here, emission factor calculations of increased background N_2O fluxes can be linked to a simpler empirical equation for temperature and rainfall, as proposed by Vinther and Hansen (2004), Flynn *et al*. (2005), Flechard *et al*. (2007) and Zhang *et al*. (2015).

References

Abdalla, M., Wattenbach, M., Smith, P., Ambus, P., Jones, M. and Williams, M., 2009. Application of the DNDC model to predict emissions of N_2O from Irish agriculture. *Geoderma* 151: 327–337.

Abdalla, M., Jones, M., Yeluripati, J., Smith, P., Burke, J. and Williams, M., 2010. Testing DayCent and DNDC model simulations of N_2O fluxes and assessing the impacts of climate change on the gas flux and biomass production from a humid pasture. *Atmospheric Environment* 44: 2961–2970.

Abdalla, M., Kumar, S., Jones, M., Burke J. and Williams, M., 2011.Testing DNDC model for simulating soil respiration and assessing the effects of climate change on the CO_2 gas flux from Irish agriculture. *Global and Planetary Change* 78: 106–115.

Abdalla, M., Hastings, A., Bell, M.J., Smith, J.U., Richards, M., Nilsson, M.B., Peichl. M., Löfvenius, M.O., Lund, M., Helfter, C., Nemitz, E., Sutton, M.A., Aurela, M., Lohila, A., Laurila, T., Dolman, A.J., Belelli-Marchesini, L., Pogson, M., Jones, E., Drewer, J., Drosler, M. and Smith, P., 2014. Simulation of CO_2 and attribution analysis at six European peatland sites using the ECOSSE model. *Water, Air and Soil Pollution* 225: 2182–2188.

Bahn M., Janssens I.A., Reichstein M., Smith P. and Trumbore S.E., 2010. Soil respiration across scales: towards an integration of patterns and processes. *New Phytologist* 186: 292–296.

Butterbach-Bahl, K., Baggs, E.M., Dannenmann, M., Kiese, R. and Zechmeister-Boltenstern, S., 2013. Nitrous oxide emissions from soils: how well do we understand the processes and their controls? *Philosophical Transactions of the Royal Society B* 368: 20130122. https://doi.org/10.1098/rstb.2013.0122

Cai, Z., Sawamoto, T., Li,C., Kang, G., Boonjawat, J., Mosier, A., Wassman, R. and Tsurata, H., 2003. Field validation of DNDC model for greenhouse gas emissions in East Asian cropping systems. *Global Biogeochemical Cycles* 17(4). https://doi.org/10.1029/2003GB002046

Chadwick, D.R., Sneath, R.W., Phillips, V.R. and Pain, B.F., 1999. A UK inventory of nitrous oxide emissions from farmed livestock. *Atmospheric Environment* 33: 3345–3354.

Cowie, A., Eckard, R. and Eady, S., 2012. Greenhouse gas accounting for inventory, emissions trading and life cycle assessment in the land-based sector: a review. *Crop and Pasture Science* 63: 284–296.

CSO (Central Statistics Office), 2018. Environmental Indicators Ireland 2016. Available online: www.cso.ie/en/releasesandpublications/ep/p-eii/eii2016/lu/ (accessed 31 May 2019).

DAFM (Department of Agriculture, Food and the Marine), 2015. *Food Wise 2025: A 10-Year Vision for the Irish Agri-food Industry*. DAFM, Dublin.

Del Grosso, S., Ojima, D., Parton, W., Mosier, A., Peterson, G. and Schimel, D., 2002. Simulated effects of dryland cropping intensification on soil organic matter and greenhouse gas exchanges using the DAYCENT ecosystem model. *Environmental Pollution* 116: S75–S83. https://doi.org/10.1016/S0269-7491(01)00260-3

Del Grosso, S.J., Ojima, D.S., Parton, W.J., Stehfest, E., Heistermann, M., DeAngelo, B. and Rose, S., 2009. Global DAYCENT model analysis of greenhouse gas emissions and mitigation strategies for cropped soils. *Global and Planetary Change* 67: 44–50.

Dietiker, D., Buchmann, N. and Eugster, W., 2010. Testing the ability of DNDC model to predict CO_2 and water fluxes of a Swiss cropland site. *Agriculture, Ecosystems and Environment* 139: 396–401.

Duffy, P., Black, K., Hyde, B., Ryan, A.M., Ponzi, J. and Alam, S., 2018. *Ireland's National Inventory Report 2018: Greenhouse Gas Emissions 1990–2016*. Environmental Protection Agency, Johnstown Castle, Ireland.

EC (European Commission), 2011. Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions "A Roadmap for moving to a competitive low carbon economy in 2050". COM(2011) 0112 final, 8.3.2011, Brussels.

Environmental Protection Agency Review Group, 2011. *A Review of the Environmental Protection Agency*. Available online: https://www.epa.ie/pubs/reports/other/corporate/EPA%20Review%20Report.pdf (accessed 28 August 2019).

EPA (Environmental Protection Agency), 2012. *Ireland's Greenhouse Gas Emissions*, 2011–2020. EPA, Johnstown Castle, Ireland.

EPA (Environmental Protection Agency), 2018. *Ireland's Greenhouse Gas Emissions*, *2017–2035*. EPA, Johnstown Castle, Ireland.

EPA (Environmental Protection Agency), 2019. *Ireland's Final Greenhouse Gas Emissions 1990–2017*. EPA, Johnstown Castle, Ireland.

Fitton, N., Datta, A., Hastings, A., Kuhnert, M., Topp, C.F.E., Cloy, J.M., Rees, R.M., Cardenas, L.M., Williams, J.R., Smith, K., Chadwick, D. and Smith, P., 2014a. The challenge of modelling nitrogen management at the field scale: simulation and sensitivity analysis of N_2O fluxes across nine experimental sites using DailyDayCent. *Environmental Research Letters* 9: 095003. https://doi.org/10.1088/1748-9326/9/9/095003

Fitton, N., Datta, A., Smith, K., Williams, J.R., Hastings, A., Kuhnert, M., Topp, C.F.E. and Smith, P., 2014b. Assessing the sensitivity of modelled estimates of N_2O emissions and yield to input uncertainty at a UK cropland experimental site using the DailyDayCent model. *Nutrient Cycling in Agroecosystems* 99: 119–133.

Flechard, C.R., Ambus, P., Skiba, U., Rees, R.M., Hensen, A., van den Pol, A., Soussana, J.-F., Jones, M., Clifton-Brown, J., Raschi, A., Horvath, L., van Amstel, A., Neftel, A., Jocher, M., Ammann, C., Fuhrer, J., Calanca, P., Thalman, E., Pilegaard, K., Di Marco, C., Campbell, C., Nemitz, E., Hargreaves, K.J., Levy, P., Ball, B., Jones, S., van de Bulk, W.C.M., Groot, T., Blom, M., Gunnink, H., Kasper, G., Allard, V., Cellier, P., Laville, P., Henault, C., Bizouard, F., Jolivot, D., Abdalla, M., Williams, M., Baronti, S., Berretti, F., Grosz, B. and Domingues, R., 2007. Effect of climate and management intensity on nitrous oxide emissions in grassland systems across Europe. *Agriculture, Ecosystems and Environment* 121: 135–152.

Flynn, H.C., Smith, J., Smith, K.A., Wright, J., Smith, P. and Masshender, J., 2005. Climate and crop-responsive emission factors significantly alter estimates of current and future nitrous oxide emissions from fertiliser use. *Global Change Biology* 11: 1522–1536.

Giltrap, D.L., Li, C. and Saggar, S., 2010. DNDC: a process-based model of greenhouse gas fluxes from agricultural soils. *Agriculture, Ecosystems and Environment* 136: 292–300.

Gottschalk, P., Wattenburg, M., Neftel, A., Fuhrer, J., Jones, M., Lanigan, G., Davis, P., Campbell, C., Soussana, J.F. and Smith, P., 2007. The role of measurement uncertainties for the simulation of grassland net ecosystem exchange (NEE) in Europe. *Agriculture, Ecosystems and Environment* 121: 175–185.

Hastings, A.F., Wattenbach, M., Eugster, W., Li, C., Buchmann, N. and Smith, P. 2010. Uncertainty propagation in soil greenhouse gas emission models: an experiment using the DNDC model and at the Oensingen cropland site. *Agriculture, Ecosystems and Environment* 139: 97–110.

Hiraishi, T., Krug, T., Tanabe, K., Srivastava, N., Baasansuren, J., Fukuda, M. and Troxler, T.G., 2014. *2013 Revised Supplementary Methods and Good Practice Guidance Arising from the Kyoto Protocol*. IPCC Methodology Report. Switzerland.

Kurbatova, J., Li, C., Tatarinov, F., Varlagin, A., Shalukhina, N. and Olchev, A., 2009. Modelling of the carbon dioxide fluxes in European Russian peat bogs. *Environmental Research Letters* 4: 045022. https://doi.org/10.1088/1748-9326/4/4/045022

Levy, P.E., Mobbs, D.C., Jones, S.K., Milne, R., Campbell, C. and Sutton, M., 2007. Simulation of fluxes of greenhouse gases from European grasslands using the DNDC model. *Agriculture, Ecosystems and Environment* 121: 186–192.

Li, C., Narayanan, V. and Harriss, R.C., 1996. Model estimates of nitrous oxide emissions from agricultural lands in the United States. *Global Biogeochemical Cycles* 10: 297–306.

Li, C., Zhuang, Y., Cao, M., Crill, P., Dai, Z., Frolking, S., Moore III, B., Salas, W. and Wang, X., 2001. Comparing a process-based agro-ecosystem model to the IPCC methodology for developing a national inventory of N_2O emissions from arable lands in China. *Nutrient Cycling in Agroecosystems* 60: 159–175.

Lu, X., Cheng, G., Xiao, F. and Huo, C., 2008. Simulating carbon sequestration and GHG emissions in *Abies fabric* forest on the Gongga Mountains using a biogeochemical process model Forest DNDC. *Journal of Mountain Science* 5: 249–256.

Mosier, A.R., Kroeze, C., Nevison, C., Oenema, O., Seitzinger, S. and Van Cleemput, O., 1998. Closing the global N_2O budget: nitrous oxide emissions through the agricultural nitrogen cycle. *Nutrient Cycling in Agroecosystems* 52: 225–248.

Myrgiotis, Y., Williams, M., Rees, R.M. and Topp, C.F.E., 2019. Estimating the soil N_2O emission intensity of croplands in northwest Europe. *Biogeosciences* 16: 1641–1655.

O'Brien, P., 2007. *Data Analysis and Estimation of Greenhouse Gas Emissions and Removal for the IPCC Sector Land Use, Land-Use Change and Forestry Sectors in Ireland*. Environmental Protection Agency, Johnstown Castle, Ireland.

Oertel, C., Matschullat, J., Zurba, K., Zimmermann, F. and Erasmi, S., 2016. Greenhouse gas emissions from soils – a review. *Geochemistry* 76: 327–352.

Parton, W.J., Ojima, D.S., Cole, C.V. and Schimel, D.S.A., 1994. A general model for soil organic matter dynamics: sensitivity to litter chemistry, texture and management. In Bryant, R.B. and Arnold, R.W. (eds), *Quantitative Modelling of Soil Forming Processes*. SSSA Special Publication, vol. 39. Soil Science Society of America, Madison, WI, p. 147.

Poore, J. and Nemecek, T., 2018. Reducing food's environmental impact through producers and consumers. *Science* 360: 987–992.

Skiba, U.M., McTaggert, I.P., Smith, K.A., Hargreaves, K.J. and Fowler, D., 1996. Estimates of nitrous oxide emissions from soil in the UK. *Energy Conversion and Management* 37: 1303–1308.

Smith, P. and Smith, J., 2007. *Introduction to Environmental Modelling*. Oxford University Press, Oxford.

Smith, P., Smith, J., Flynn, H., Kilham, K., Rangel-Castro, J.I., Foereid, B., Aitkenhead, M., Chapman, S., Towers, W., Bell, J., Lumsden, D.G., Milne, R., Thomson, A., Simmons, I., Skiba, U.M., Reynolds, B., Evans, C., Frogbrook, Z., Bradley, R.I., Whitmore, A. and Falloon, P., 2007. *ECOSSE: Estimating Carbon in Organic Soils – Sequestration and Emission*: Final Report. Scottish Executive, Edinburgh.

Smith, W.N., Grant, B.B., Desjardins, R.L., Rochette, P., Drury, C.F. and Li, C., 2008. Evaluation of two process-based models to estimate soil N_2O emissions in Eastern Canada. *Canadian Journal of Soil Science* 88: 251–260.

Tang, X-L., Zhou, G.Y., Liu, S.G., Zhang, D.Q., Liu, S.Z., Li, J. and Zhou, C.Y., 2006. Dependence of soil respiration on soil temperature and soil moisture in successional forests in southern China. *Journal of Integrative Plant Biology* 48: 654–663.

Vinther, F.P. and Hansen, S., 2004. SimDen – a simple empirical model for quantification of N_2O emission and denitrification. *DIAS Report* 104: 1–47.

Vose, D., 2000. *Risk Analysis: A Quantitative Guide*. Wiley, New York, NY.

Willett, W., Rockström, J., Loken, B., Springmann, M., Lang, T., Vermeulen, S., Garnett, T., Tilman, D., DeClerck, F., Wood, A., Jonell, M., Clark, M., Gordon, L.J., Fanzo, J., Hawkes, C., Zurayk, R., Rivera, J.A., De Vries, W., Majele Sibanda, L., Afshin, A., Chaudhary, A., Herrero, M., Agustina, R., Branca, F., Lartey, A., Fan, S., Crona, B., Fox, E., Bignet, V., Troell, M., Lindahl, T., Singh, S., Cornell, S.E., Srinath Reddy, K., Narain, S., Nishtar, S. and Murray, C.J.L., 2019. Food in the Anthropocene: the EAT–*Lancet* Commission on healthy diets from sustainable food systems. *Lancet* 393: 447–492. https://doi.org/10.1016/S0140-6736(18)31788-4

Zhang, W., Gu, J-X. and Zheng, X-H., 2015. Direct nitrous oxide emissions related to fertiliser nitrogen, precipitation, and soil clay fraction: empirical models. *Atmospheric and Oceanic Science Letters* 8: 277–282.

Abbreviations

CO_2e	CO_2 equivalent
COFORD	Council for Forest Research and Development
DNDC	DeNitrification-DeComposition
ECOSSE	Estimating Carbon in Organic Soils – Sequestration and Emission
EPA	Environmental Protection Agency
ETS	Emissions Trading Scheme
EU	European Union
GHG	Greenhouse gas
GIS	Geographic information system
GME	Geospatial Modelling Environment
IPCC	Intergovernmental Panel on Climate Change
LULUCF	Land use, land-use change and forestry
R_{ecos}	Ecosystem respiration
RMSE	Root mean square error
s.e.	Standard error
SIS	Soil Information System
SOC	Soil organic carbon

Appendix 1 Simulation of Daily Flux Values of N_2O

A1.1 Arable Sites

A1.1.1 Fertilised barley with bare fallow period

Rank (daily difference): ECOSSE > DailyDayCent > DNDC 9.5 > DNDC 9.4.

Rank (cumulative difference): ECOSSE > DailyDayCent > DNDC 9.4 > DNDC 9.5.

ECOSSE was the best model at this site on a daily basis, producing the smallest errors (*RMSE* = 83.3%; *E* = −6.8) and highest correlation coefficient (*r* = 0.35) of the four models. DailyDayCent produced the lowest correlation coefficient (*r* = 0.08) and DNDC 9.4 produced the largest errors (*RMSE* = 133.6%; *E* = 80.2). On a cumulative basis, ECOSSE also performed well, slightly underestimating cumulative N_2O emissions (10.6%), whereas the other models performed poorly. DNDC 9.5 produced the poorest fit on a cumulative basis, underestimating emissions by 93.7%.

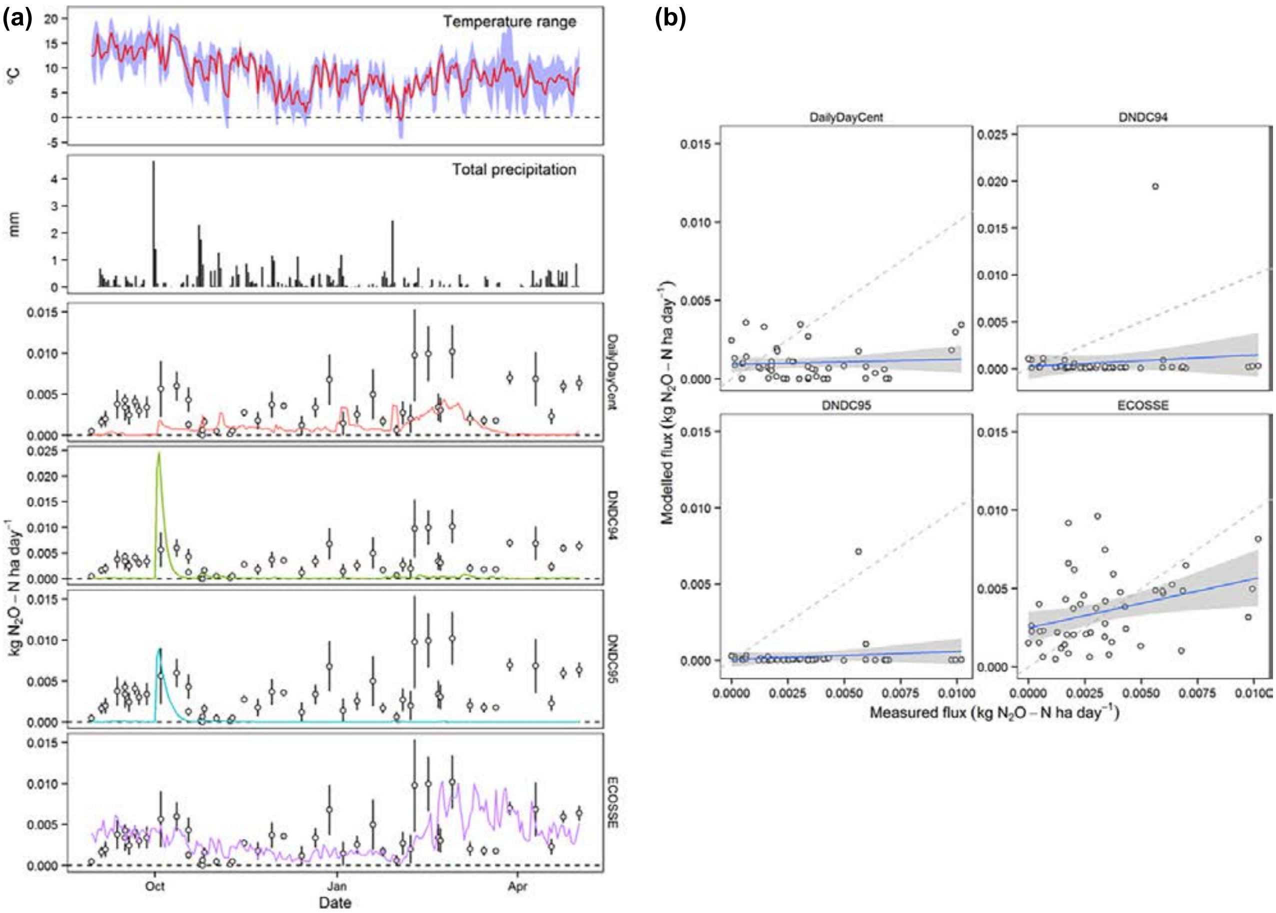


Figure A1.1. (a) Model simulations and weather conditions for the site Barley-bare-fert on a daily timestep over the simulation period. Measured data (open circles) are shown as means ± 1 standard error (s.e.) (b) Measured versus modelled N_2O fluxes on a daily timestep for the site Barley-bare-fert. The dashed grey line represents the 1:1 relationship between measured and modelled fluxes. The solid blue line and shaded grey region represent the linear fit between measured and modelled fluxes and associated 95% confidence interval, respectively.

A1.1.2 Unfertilised barley with bare fallow period

Rank (daily difference): ECOSSE > DailyDayCent > DNDC 9.4 > DNDC 9.5.

Rank (cumulative difference): ECOSSE > DailyDayCent > DNDC 9.4 > DNDC 9.5.

The model simulations for the unfertilised control treatment at this site produced similar results to those for the fertilised site. ECOSSE was again the best model in coincidence (*RMSE* = 98.5%; *E* = 12.3) and association (*r* = 0.35) terms. DailyDayCent produced the lowest correlation coefficient (*r* = −0.08), whereas DNDC 9.5 produced the largest errors (*RMSE* = 137.9%; *E* = 95.9). On a cumulative basis, the pattern was the same as for the fertilised treatment: ECOSSE underestimated cumulative emissions by 29.3%, whereas DNDC 9.5 underestimated cumulative emissions by 95.2%.

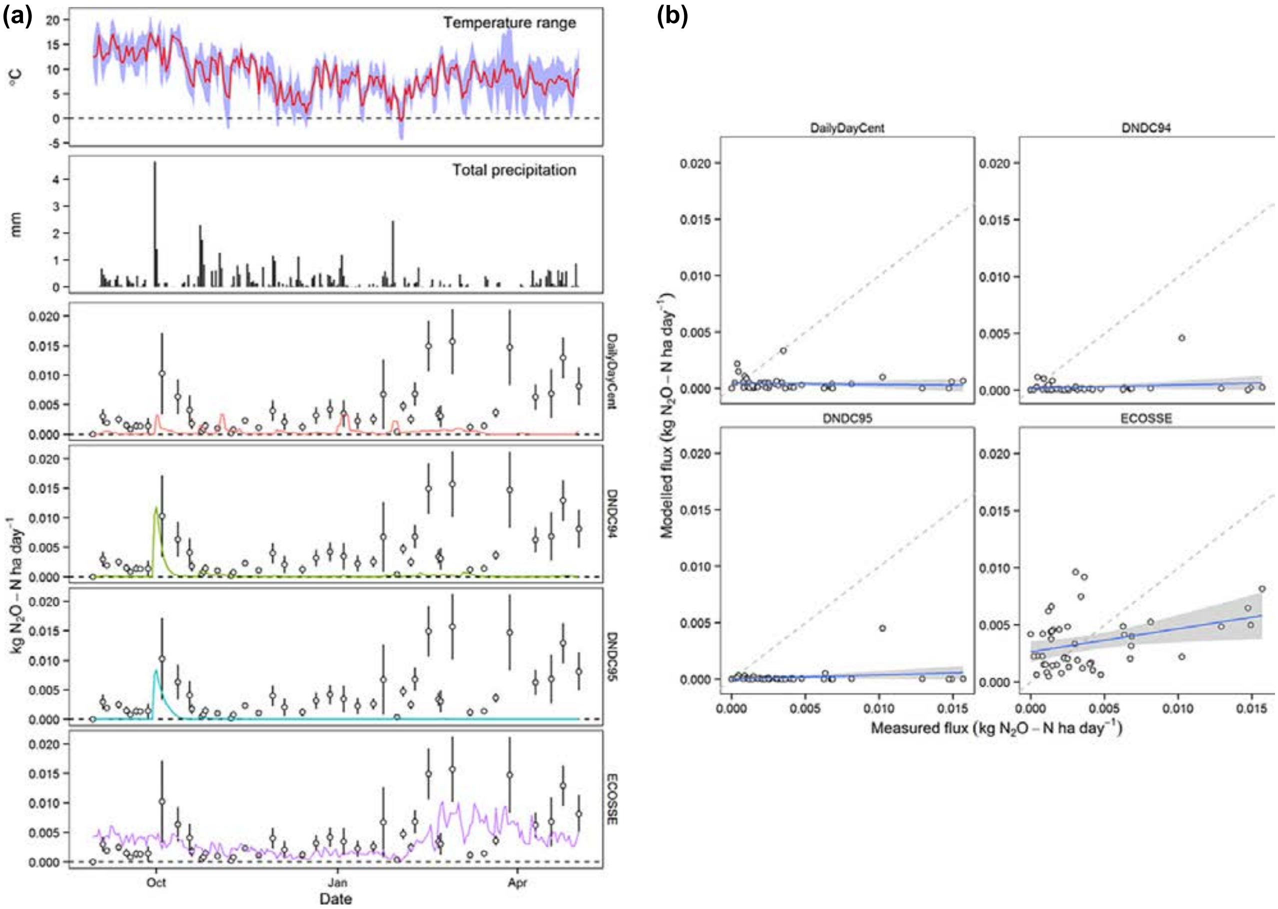


Figure A1.2. (a) Model simulations and weather conditions for the site Barley-bare-unfert on a daily timestep over the simulation period. Measured data (open circles) are shown as means ± 1 s.e. (b) Measured versus modelled N_2O fluxes on a daily timestep for the site Barley-bare-unfert. The dashed grey line represents the 1:1 relationship between measured and modelled fluxes. The solid blue line and shaded grey region represent the linear fit between measured and modelled fluxes and associated 95% confidence interval, respectively.

A1.1.3 Fertilised barley with mustard cover crop

Rank (daily difference): ECOSSE > DailyDayCent > DNDC 9.4 > DNDC 9.5.

Rank (cumulative difference): ECOSSE > DNDC 9.4 > DailyDayCent > DNDC 9.5.

On a daily basis, ECOSSE was the best model at this site, producing the smallest errors (*RMSE* = 97.95%; *E* = 36.3%). DailyDayCent produced the best correlation (*r* = 0.5). The DNDC 9.4 simulation produced the largest difference from the measured values (*RMSE* = 140.14%) and the lowest correlation (*r* = −0.08), whereas DNDC 9.5 was subject to the largest bias (*E* = 96.75%). On a cumulative basis, all models underestimated the measured cumulative flux, with ECOSSE performing the least poorly (44%) and DNDC 9.5 producing the largest underestimate (97.1%).

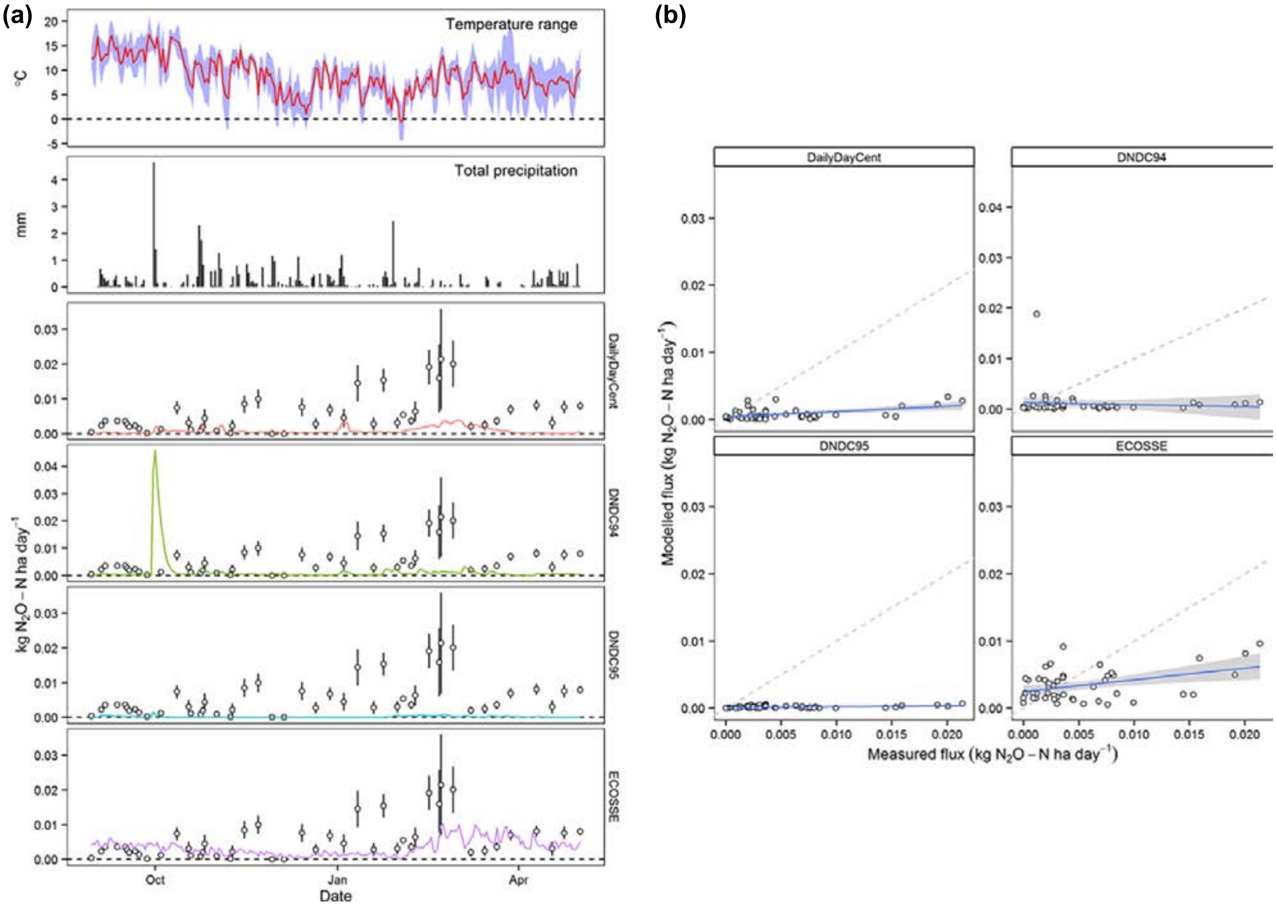


Figure A1.3. (a) Model simulations and weather conditions for the site Barley-mustard-fert on a daily timestep over the simulation period. Measured data (open circles) are shown as means ± 1 s.e. (b) Measured versus modelled N_2O fluxes on a daily timestep for the site Barley-mustard-fert. The dashed grey line represents the 1:1 relationship between measured and modelled fluxes. The solid blue line and shaded grey region represent the linear fit between measured and modelled fluxes and associated 95% confidence interval, respectively.

A1.1.4 Fertilised barley with radish cover crop

Rank (daily difference): ECOSSE > DNDC 9.4 > DNDC 9.5.

Rank (cumulative difference): ECOSSE > DNDC 9.4 > DNDC 9.5.

Simulation of this site and treatment combination with DailyDayCent was not possible because the radish crop was not parameterised. The ECOSSE simulation produced the smallest differences (*RMSE* = 110.81%; *E* = 45.44%) and the only positive correlation (*r* = 0.2) using measured data on a daily basis. ECOSSE was again the best model on a cumulative basis, producing the smallest underestimate of the three models under comparison (53.4%).

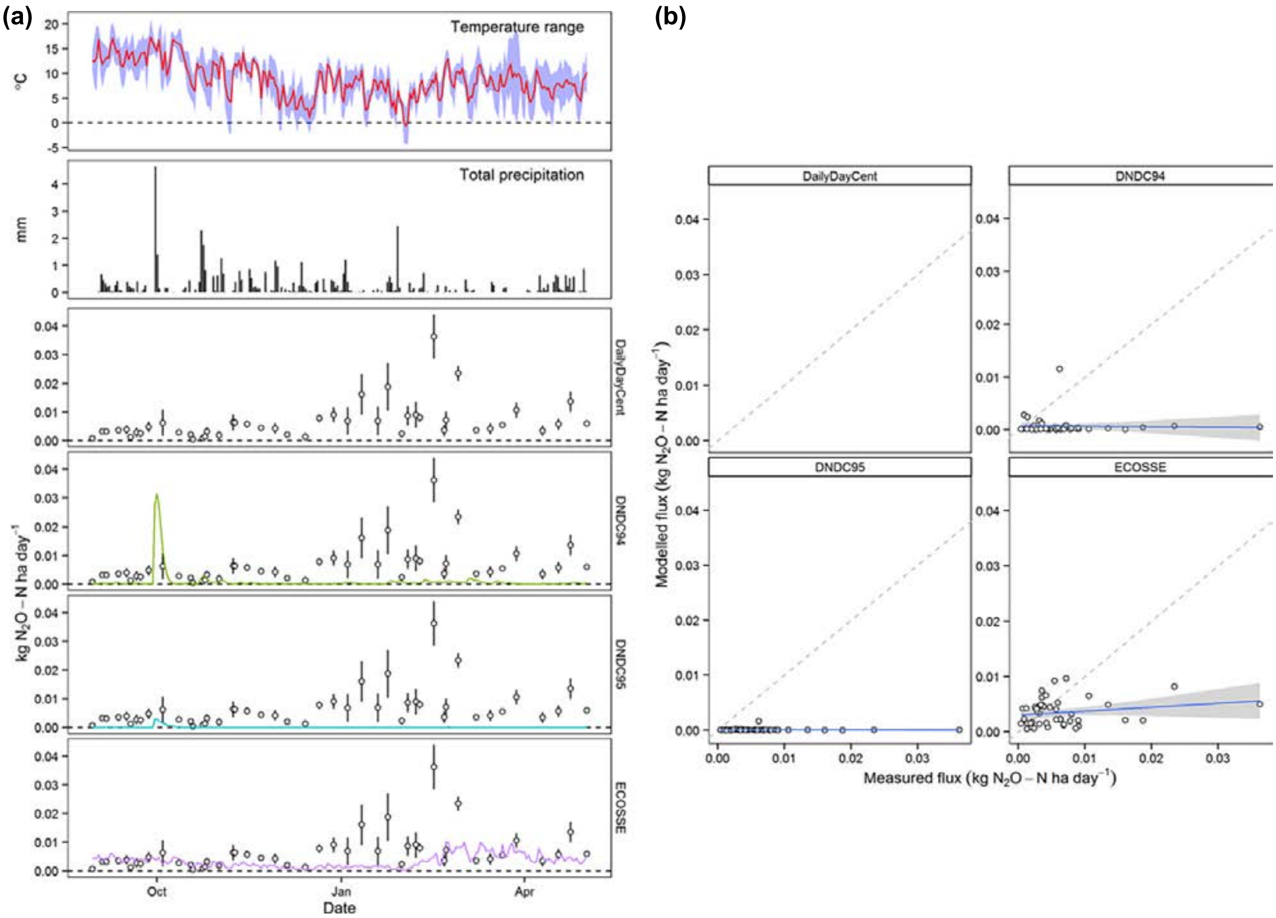


Figure A1.4. (a) Model simulations and weather conditions for the site Barley-radish-fert on a daily timestep over the simulation period. Measured data (open circles) are shown as means ± 1 s.e. (b) Measured versus modelled N_2O fluxes on a daily timestep for the site Barley-radish-fert. The dashed grey line represents the 1:1 relationship between measured and modelled fluxes. The solid blue line and shaded grey region represent the linear fit between measured and modelled fluxes and associated 95% confidence interval, respectively.

A1.1.5 Unfertilised barley with no cover crop and conventional tillage (C_0)

Rank (daily difference) P_1: DailyDayCent > DNDC 9.4 > DNDC 9.5 > ECOSSE.

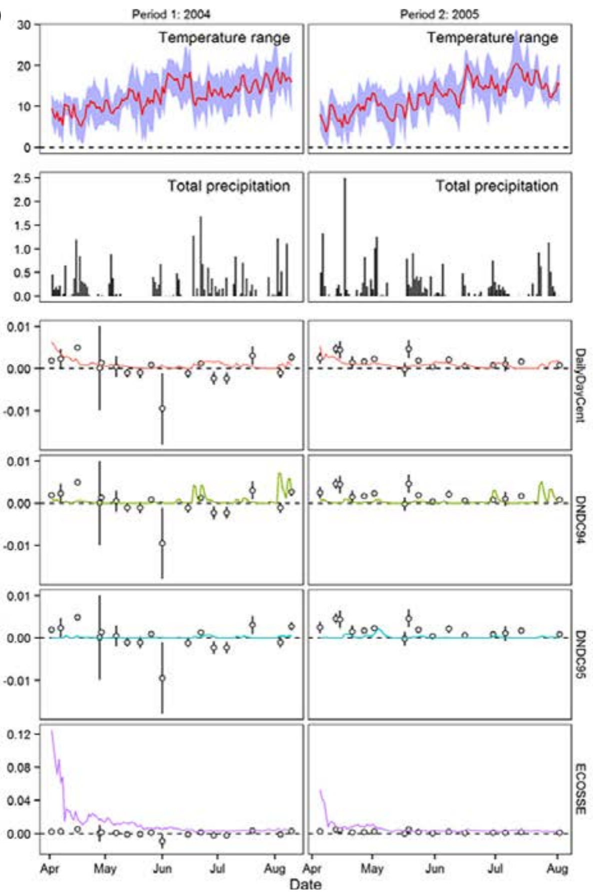
Rank (daily difference) P_2: DailyDayCent > DNDC 9.4 > DNDC 9.5 > ECOSSE.

Rank (cumulative difference) P_1: DNDC 9.5 > DNDC 9.4 > DailyDayCent > ECOSSE.

Rank (cumulative difference) P_2: DailyDayCent > DNDC 9.4 > DNDC 9.5 > ECOSSE.

This site was split into two measurement periods. The DailyDayCent simulation for the first period (P_1) produced the smallest differences from the measured data (*RMSE* = 107.26%; *E* = 11.32%) and the DNDC 9.5 simulation produced the best correlation (*r* = 0.52). ECOSSE produced a very poor simulation, with an *RMSE* of 2316.62%, greater than the 95% confidence limit of 776.67% for this site. The results for the second period (P_2) were similar, except that DailyDayCent produced the best correlation (*r* = 0.24) as well as the smallest differences from the measured fluxes (*RMSE* = 81%; *E* = 29.93%). This treatment was characterised by very low N_2O fluxes, some of which were negative. In the second period, ECOSSE was the only model to overestimate cumulative emissions (213.4%), with the other models underestimating cumulative emissions.

(a)



(b)

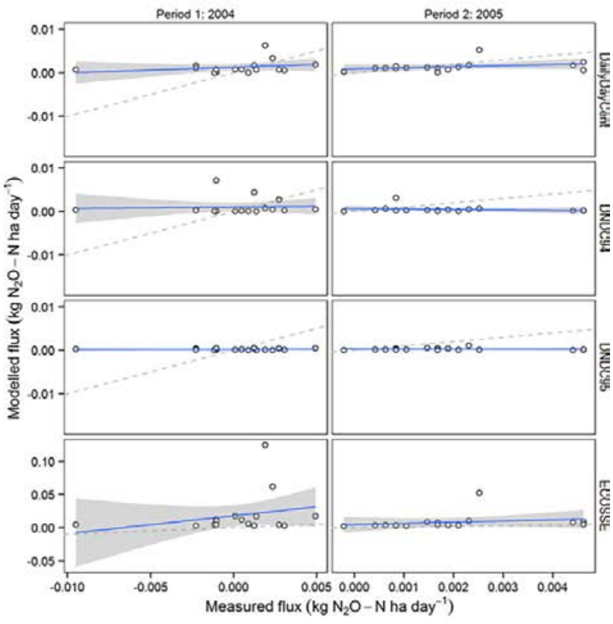


Figure A1.5. (a) Model simulations and weather conditions for the site Barley-C_0 on a daily timestep over the simulation period. Measured data (open circles) are shown as means ± 1 s.e. (b) Measured versus modelled N_2O fluxes on a daily timestep for the site Barley-C_0. The dashed grey line represents the 1:1 relationship between measured and modelled fluxes. The solid blue line and shaded grey region represent the linear fit between measured and modelled fluxes and associated 95% confidence interval, respectively.

A1.1.6 Fertilised barley with no cover crop and conventional tillage (C_1)

Rank (daily difference) P_1: DNDC 9.5 > DNDC 9.4 > DailyDayCent > ECOSSE.

Rank (daily difference) P_2: DailyDayCent > DNDC 9.5 > DNDC 9.4 > ECOSSE.

Rank (cumulative difference) P_1: DNDC 9.4 > DNDC 9.5 > DailyDayCent > ECOSSE.

Rank (cumulative difference) P_2: ECOSSE > DailyDayCent > DNDC 9.5 > DNDC 9.4.

For both measurement periods under the fertilised treatment C_1, DNDC 9.5 produced the simulations with the smallest differences from the measured values (*RMSE* = 82.66% and 98.29% for P_1 and P_2, respectively). The DNDC 9.4 simulation produced the best correlation coefficient for the first period (r = 0.92) and DNDC 9.5 produced the best correlation for the second period (r = 0.33). In the first period all models overestimated the cumulative emissions: DNDC 9.4 overestimated emissions by the smallest amount (25%), whereas ECOSSE overestimated emissions by 2950.9%. In the second period, ECOSSE was the only model to overestimate cumulative emissions but this overestimation also represented the smallest difference from the measured cumulative emissions, at 39.6%.

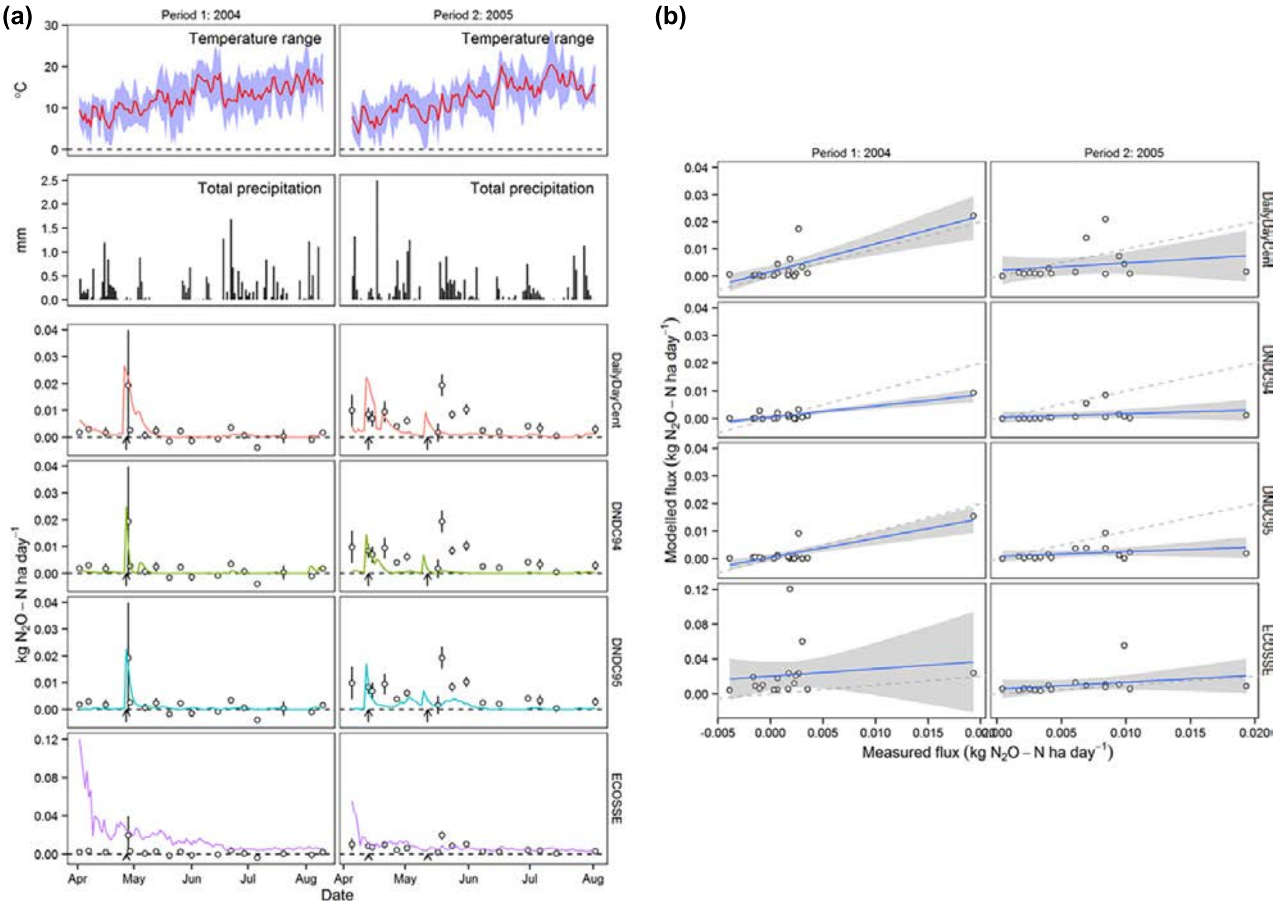


Figure A1.6. (a) Model simulations and weather conditions for the site Barley-C_1 on a daily timestep over the simulation period. Measured data (open circles) are shown as means ± 1 s.e. (b) Measured versus modelled N_2O fluxes on a daily timestep for the site Barley-C_1. The dashed grey line represents the 1:1 relationship between measured and modelled fluxes. The solid blue line and shaded grey region represent the linear fit between measured and modelled fluxes and associated 95% confidence interval, respectively.

A1.1.7 Fertilised barley with no cover crop and conventional tillage (C_2)

Rank (daily difference) P_1: DNDC 9.5 > DailyDayCent > DNDC 9.4 > ECOSSE.

Rank (daily difference) P_2: DailyDayCent > DNDC 9.5 > ECOSSE > DNDC 9.4.

Rank (cumulative difference) P_1: DNDC 9.5 > DNDC 9.4 > DailyDayCent > ECOSSE.

Rank (cumulative difference) P_2: ECOSSE > DailyDayCent > DNDC 9.5 > DNDC 9.4.

For both measurement periods under the high N application treatment C_2, DNDC 9.5 produced the smallest overall differences from the measured vales (*RMSE* = 115.06% for P_1 and 92.89% for P_2). The simulations with the lowest bias were produced by DailyDayCent in the first period ($E = -0.72$) and ECOSSE in the second period ($E = 4.03$). The simulations with the highest correlations with measured fluxes were produced by DNDC 9.4 in the first period ($r = 0.95$) and DNDC 9.5 in the second period ($r = 0.42$), although the latter was not significant. The only significant correlation between simulated and measured fluxes in the second period was produced by DailyDayCent ($r = 0.19$). The model producing the smallest simulation difference in cumulative emissions was DNDC 9.5 (16.6%) during the first period, with both DNDC versions underestimating the cumulative emissions, and DailyDayCent and ECOSSE overestimating the cumulative emissions. In the second period all model simulations underestimated cumulative emissions, with ECOSSE producing the smallest difference (23%).

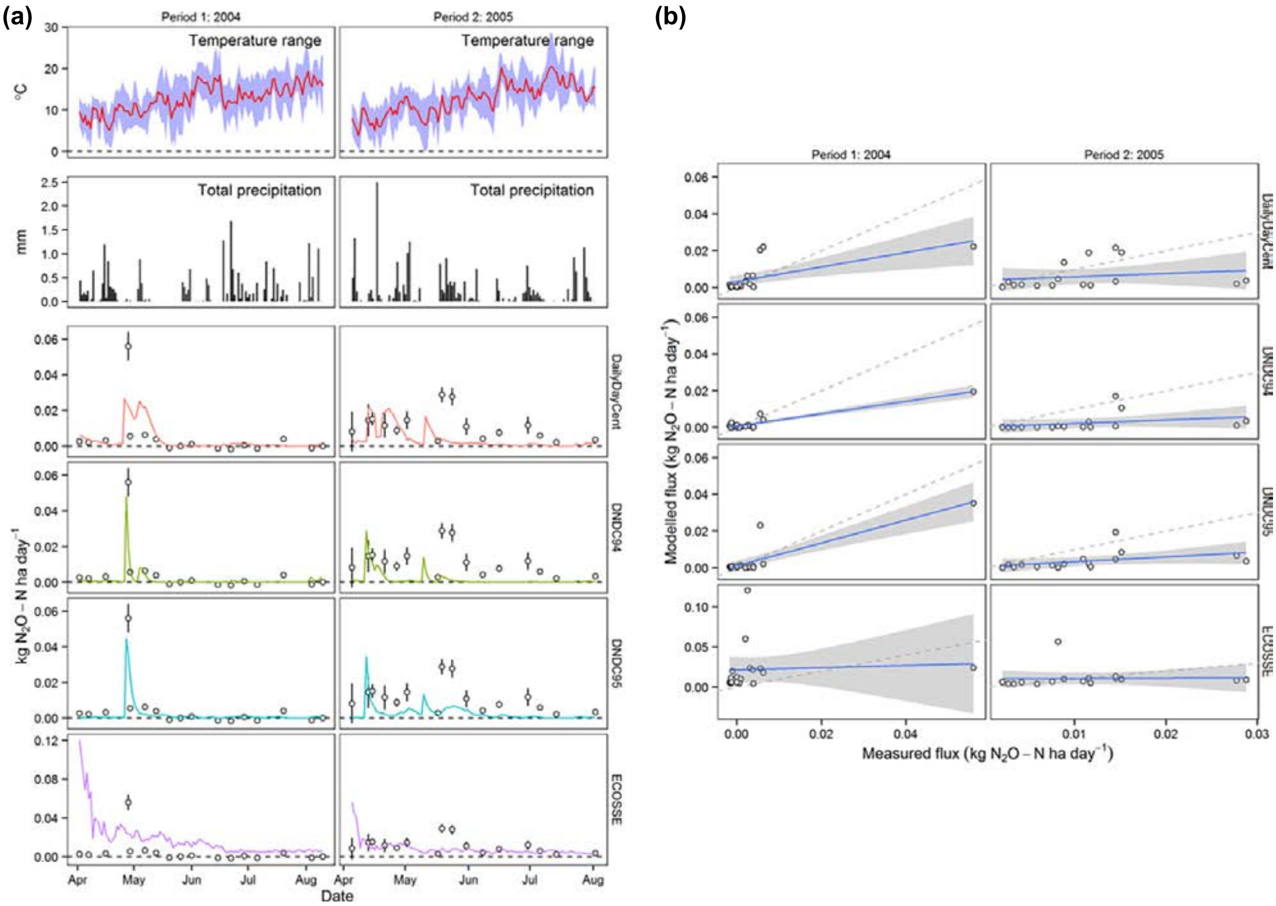


Figure A1.7. (a) Model simulations and weather conditions for the site Barley-C_2 on a daily timestep over the simulation period. Measured data (open circles) are shown as means ± 1 s.e. (b) Measured versus modelled N_2O fluxes on a daily timestep for the site Barley-C_2. The dashed grey line represents the 1:1 relationship between measured and modelled fluxes. The solid blue line and shaded grey region represent the linear fit between measured and modelled fluxes and associated 95% confidence interval, respectively.

A1.1.8 Unfertilised barley with no cover crop and non-inversion tillage (L_0)

Rank (daily difference) P_1: DailyDayCent > DNDC 9.4 > DNDC 9.5 > ECOSSE.

Rank (daily difference) P_2: ECOSSE > DailyDayCent > DNDC 9.4 > DNDC 9.5.

Rank (cumulative difference) P_1: DailyDayCent > DNDC 9.4 > DNDC 9.5 > ECOSSE.

Rank (cumulative difference) P_2: ECOSSE > DailyDayCent > DNDC 9.4 > DNDC 9.5.

For the first measurement period, the DailyDayCent simulation produced the lowest overall error and bias when compared with measured data (*RMSE* = 76.89%; *E* = 20.9%), and the best correlation (r = 0.41), although this was not significant. For the second measurement period, the ECOSSE simulation produced the lowest overall error and bias (*RMSE* = 92.83%; *E* = −2.69%). The correlations produced by the DailyDayCent and ECOSSE simulations were similar ($r_{DailyDayCent}$ = 0.35; r_{ECOSSE} = 0.34) and neither was significant. In cumulative terms, the model providing the best fit with the measured data in the first period was DailyDayCent, which overestimated cumulative emissions by 19.3%. In the second period, ECOSSE produced the best cumulative fit, overestimating emissions by 15.1%, despite producing the worst cumulative fit in the first period, with an overestimation of 239.5%.

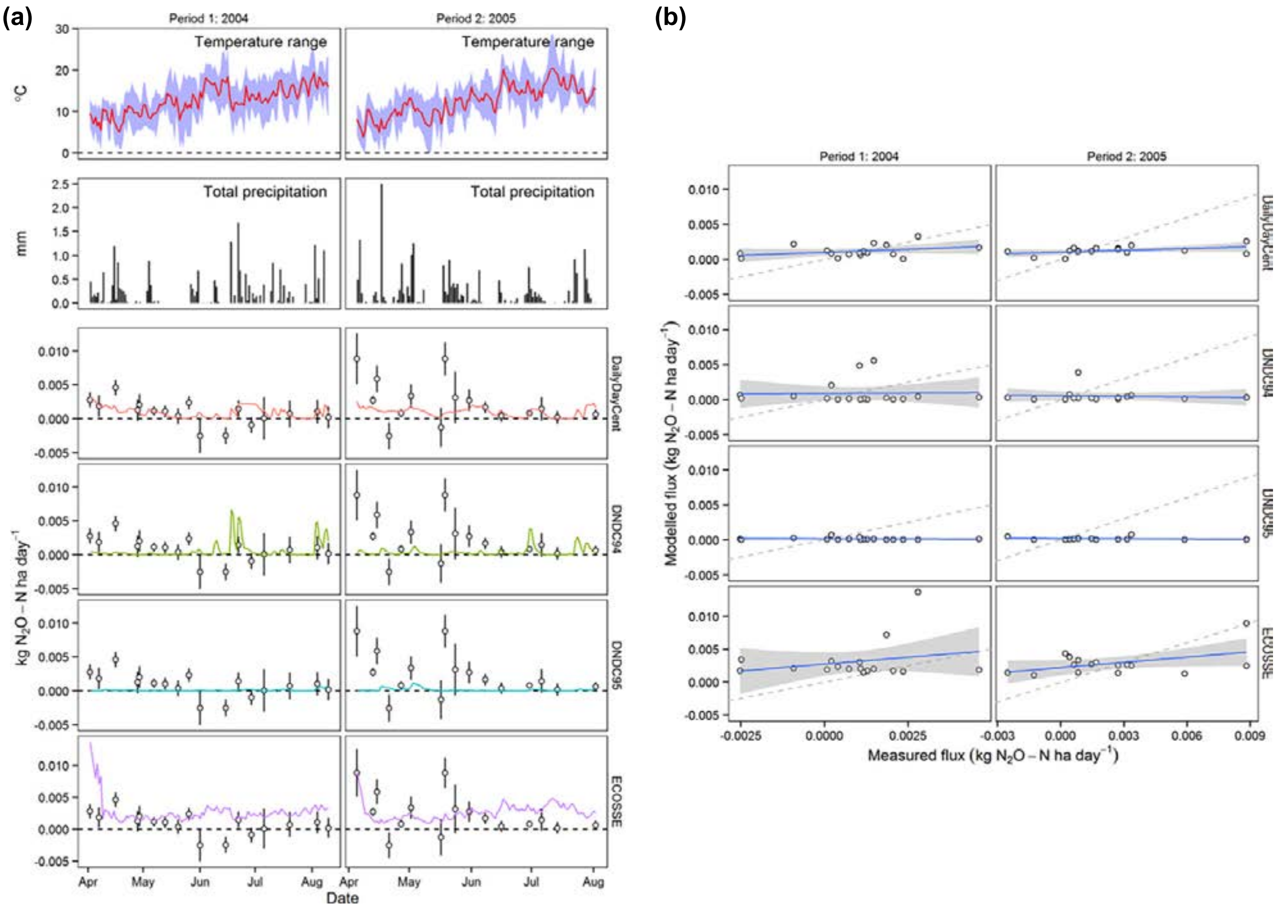


Figure A1.8. (a) Model simulations and weather conditions for the site Barley-L_0 on a daily timestep over the simulation period. Measured data (open circles) are shown as means ± 1 s.e. (b) Measured versus modelled N_2O fluxes on a daily timestep for the site Barley-L_0. The dashed grey line represents the 1:1 relationship between measured and modelled fluxes. The solid blue line and shaded grey region represent the linear fit between measured and modelled fluxes and associated 95% confidence interval, respectively.

A1.1.9 Fertilised barley with no cover crop and non-inversion tillage (L_1)

Rank (daily difference) P_1: DailyDayCent > DNDC 9.5 > ECOSSE > DNDC 9.4.

Rank (daily difference) P_2: DNDC 9.5 > DailyDayCent > ECOSSE > DNDC 9.4.

Rank (cumulative difference) P_1: DNDC 9.4 > DNDC 9.5 > DailyDayCent > ECOSSE.

Rank (cumulative difference) P_2: ECOSSE > DailyDayCent > DNDC 9.5 > DNDC 9.4.

For the first measurement period, the DailyDayCent simulation produced the lowest overall error and bias when compared with measured data (*RMSE* = 118.18%; *E* = 9.89%). The DNDC 9.4 simulation produced the best correlation with measured data (r = 0.93) in the first period. In the second measurement period, the DailyDayCent simulation again produced the smallest bias (*E* = 40.49%) whereas the DNDC 9.5 simulation produced the lowest overall error (*RMSE* = 104.85%). The DNDC 9.5 simulation had the best correlation with measured data (r = 0.48) but it was not significant; the only significant correlation occurred between the DailyDayCent simulation and measured data (r = 0.18). In the first period, both versions of DNDC underestimated cumulative emissions, with DNDC 9.4 producing the smallest underestimate (46.2%). In the second period, all models underestimated the measured cumulative emissions, with ECOSSE producing the smallest underestimate.

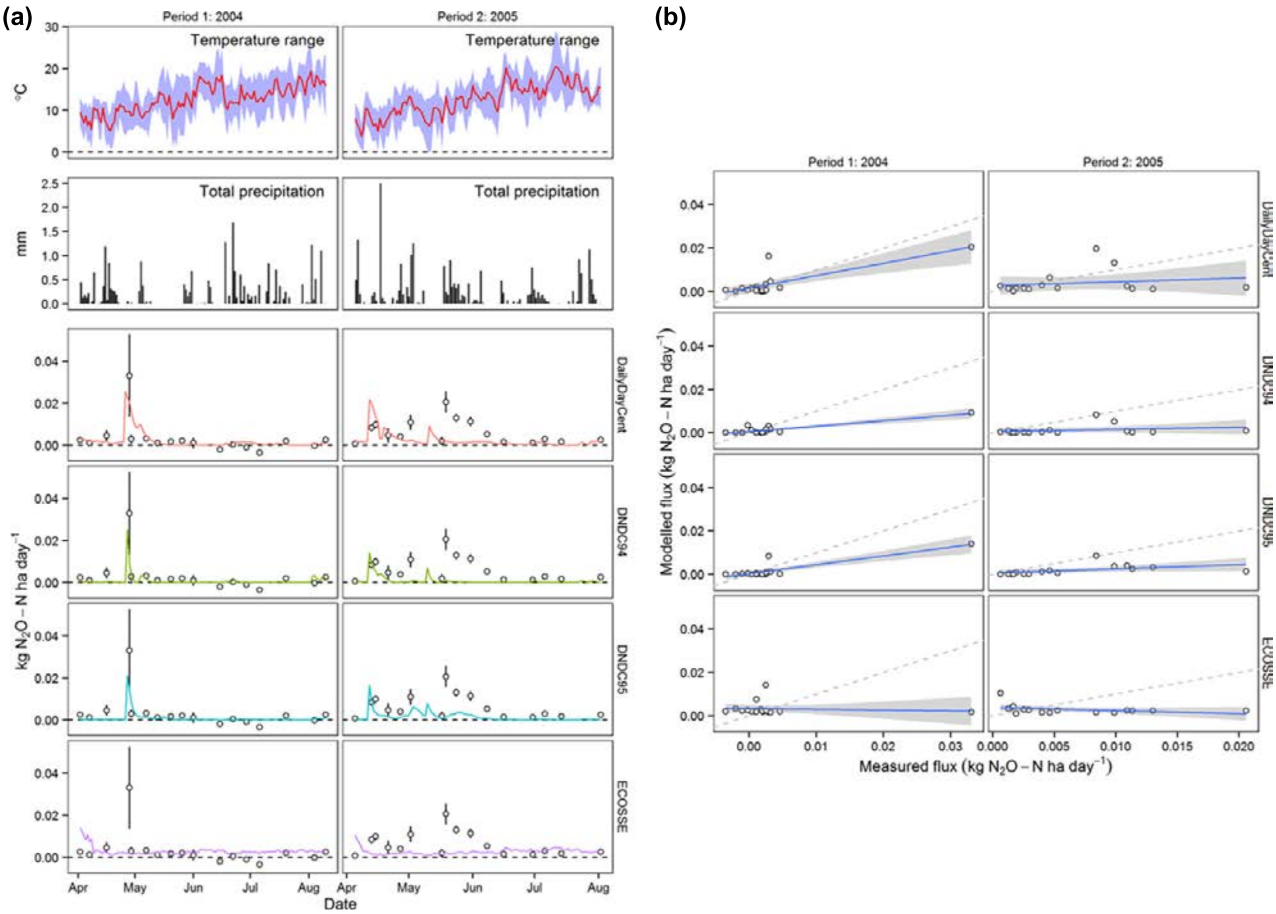


Figure A1.9. (a) Model simulations and weather conditions for the site Barley-L_1 on a daily timestep over the simulation period. Measured data (open circles) are shown as means ± 1 s.e. (b) Measured versus modelled N_2O fluxes on a daily timestep for the site Barley-L_1. The dashed grey line represents the 1:1 relationship between measured and modelled fluxes. The solid blue line and shaded grey region represent the linear fit between measured and modelled fluxes and associated 95% confidence interval, respectively.

A1.1.10 Fertilised barley with no cover crop and non-inversion tillage (L_2)

Rank (daily difference) P_1: DailyDayCent > DNDC 9.5 > DNDC 9.4 > ECOSSE.

Rank (daily difference) P_2: DailyDayCent > DNDC 9.5 > ECOSSE > DNDC 9.4.

Rank (cumulative difference) P_1: DailyDayCent > ECOSSE > DNDC 9.5 > DNDC 9.4.

Rank (cumulative difference) P_2: DailyDayCent > DNDC 9.5 > ECOSSE > DNDC 9.4.

In the first measurement period, the DNDC 9.5 simulation of this treatment produced the lowest overall error when compared with the measured data (*RMSE* = 104.45%). The DailyDayCent simulation had the smallest bias (*E* = 31.85%), and the DNDC 9.4 simulation had the best correlation with the measured data (r = 0.96). In the second measurement period, the DailyDayCent simulation produced the lowest overall error and smallest bias compared with the measured data (*RMSE* = 102.28%; *E* = 48.82%). The correlations between the DNDC 9.4 and DailyDayCent simulations and measured data were similar ($r_{DNDC9.4}$ = 0.25; $r_{DailyDayCent}$ = 0.25), but neither was significant. All models underestimated the measured cumulative emissions in both measurement periods. In both periods, DailyDayCent underestimated cumulative emissions by the smallest amount (15.1% and 60.7% for P_1 and P_2, respectively).

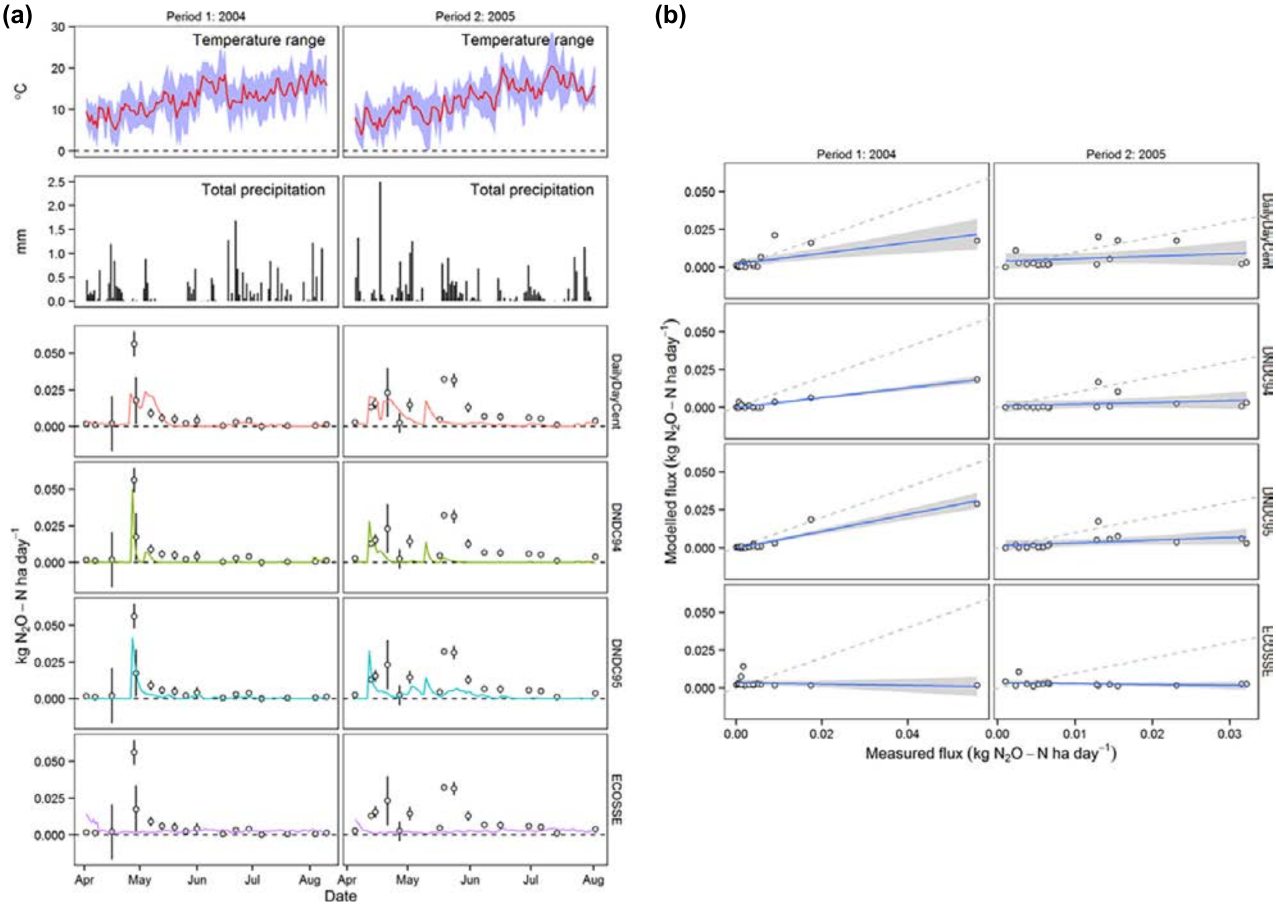


Figure A1.10. (a) Model simulations and weather conditions for the site Barley-L_2 on a daily timestep over the simulation period. Measured data (open circles) are shown as means ± 1 s.e. (b) Measured versus modelled N_2O fluxes on a daily timestep for the site Barley-L_2. The dashed grey line represents the 1:1 relationship between measured and modelled fluxes. The solid blue line and shaded grey region represent the linear fit between measured and modelled fluxes and associated 95% confidence interval, respectively.

A1.1.11 Unfertilised barley with mustard cover crop and non-inversion tillage (cc-L_0)

Rank (daily difference): DNDC 9.4 > DNDC 9.5 > DailyDayCent > ECOSSE.

Rank (cumulative difference): DNDC 9.4 > DNDC 9.5 > DailyDayCent > ECOSSE.

The DNDC 9.5 and DailyDayCent simulations at this site produced similar overall errors compared with measured data ($RMSE_{DNDC9.5}$ = 127.76%; $RMSE_{DailyDayCent}$ = 128.88%). The simulation with the smallest bias was produced by DNDC 9.4 (E = 83.33%). The DailyDayCent simulation had the best correlation with measured data (r = 0.35). DailyDayCent and both versions of the DNDC underestimated cumulative emissions, with DNDC 9.4 underestimating the least (69%). ECOSSE overestimated cumulative emissions by 206.3%.

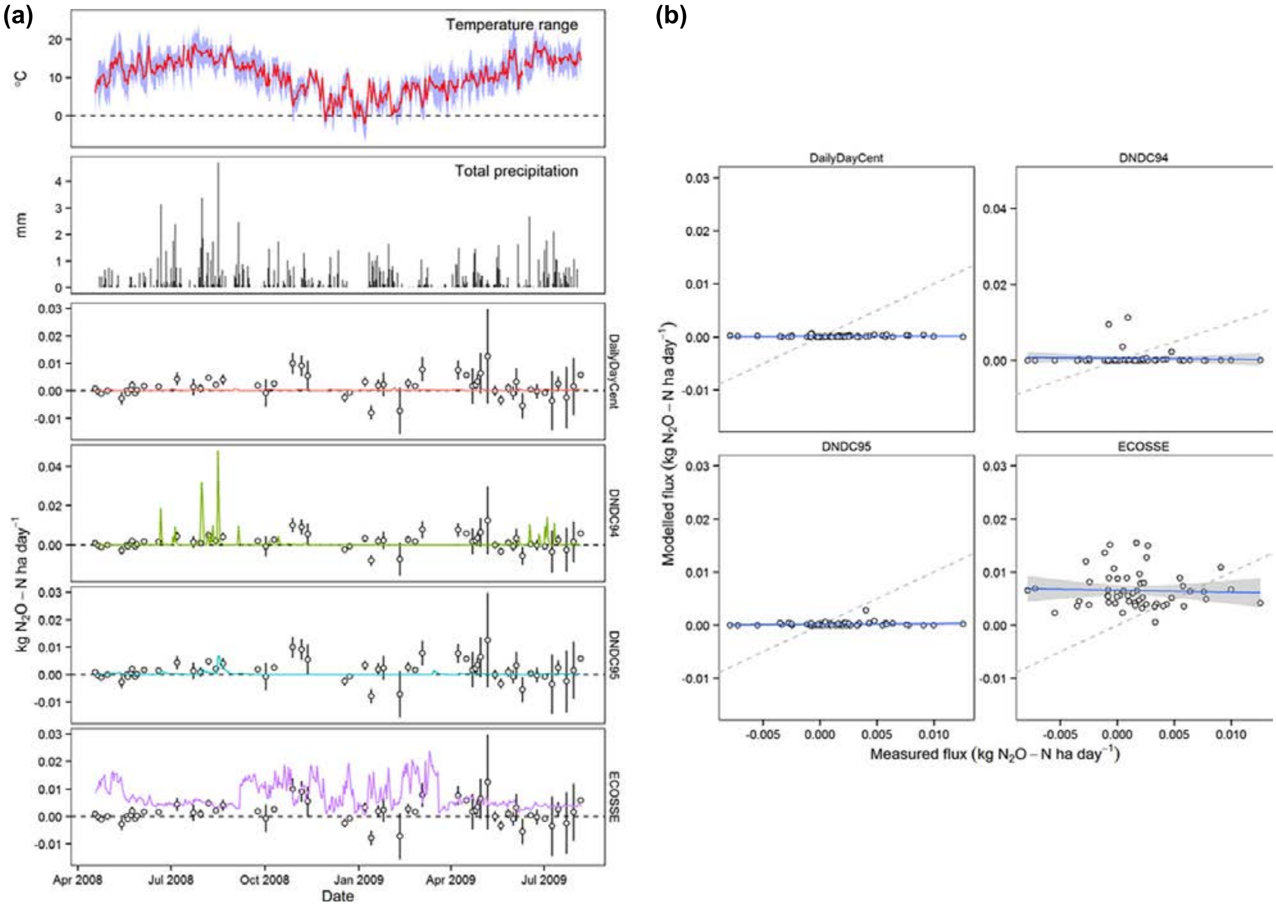


Figure A1.11. (a) Model simulations and weather conditions for the site Barley-cc-L_0 on a daily timestep over the simulation period. Measured data (open circles) are shown as means ± 1 s.e. (b) Measured versus modelled N_2O fluxes on a daily timestep for the site Barley-cc-L_0. The dashed grey line represents the 1:1 relationship between measured and modelled fluxes. The solid blue line and shaded grey region represent the linear fit between measured and modelled fluxes and associated 95% confidence interval, respectively.

A1.1.12 Fertilised barley with mustard cover crop and non-inversion tillage (cc-L_1)

Rank (daily difference): ECOSSE > DailyDayCent > DNDC 9.5 > DNDC 9.4.

Rank (cumulative difference): ECOSSE > DailyDayCent > DNDC 9.4 > DNDC 9.5.

The ECOSSE simulation for this treatment had the lowest overall error and smallest bias when compared with measured data (*RMSE* = 116.65%; *E* = 2.56%). None of the simulations produced significant correlations with measured data, but the strongest correlation was produced by DNDC 9.5 (*r* = 0.22). ECOSSE overestimated cumulative emissions by 52.4% and produced the smallest difference between measured and modelled cumulative emissions.

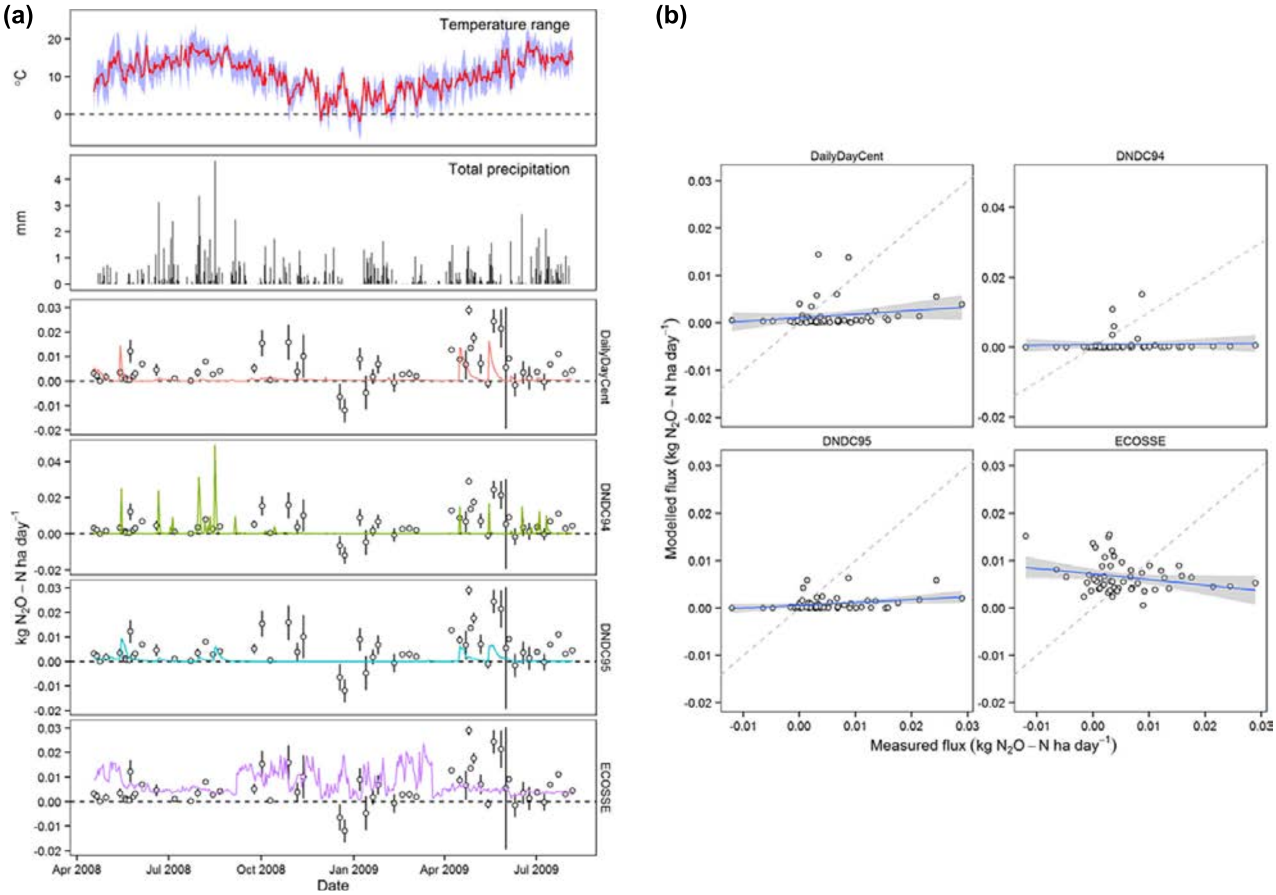


Figure A1.12. (a) Model simulations and weather conditions for the site Barley-cc-L_1 on a daily timestep over the simulation period. Measured data (open circles) are shown as means ± 1 s.e. (b) Measured versus modelled N_2O fluxes on a daily timestep for the site Barley-cc-L_1. The dashed grey line represents the 1:1 relationship between measured and modelled fluxes. The solid blue line and shaded grey region represent the linear fit between measured and modelled fluxes and associated 95% confidence interval, respectively.

A1.1.13 Fertilised barley with mustard cover crop and non-inversion tillage (cc-L_2)

Rank (daily difference): ECOSSE > DailyDayCent > DNDC 9.5 > DNDC 9.4.

Rank (cumulative difference): ECOSSE > DailyDayCent > DNDC 9.5 > DNDC 9.4.

The simulation with the lowest overall error compared with measured data was produced by DNDC 9.5 (*RMSE* = 120.71%). ECOSSE produced the simulation with the smallest bias and had a similar overall error to that of the DNDC 9.5 simulation (*RMSE* = 129.14%; *E* = 27.26%). The DNDC 9.5 simulation had the strongest correlation with measured data ($r = 0.43$). The weakest significant correlation was produced by the ECOSSE simulation ($r = -0.30$). ECOSSE produced the smallest difference between measured and modelled cumulative emissions (18.9%) and was the only model to overestimate emissions.

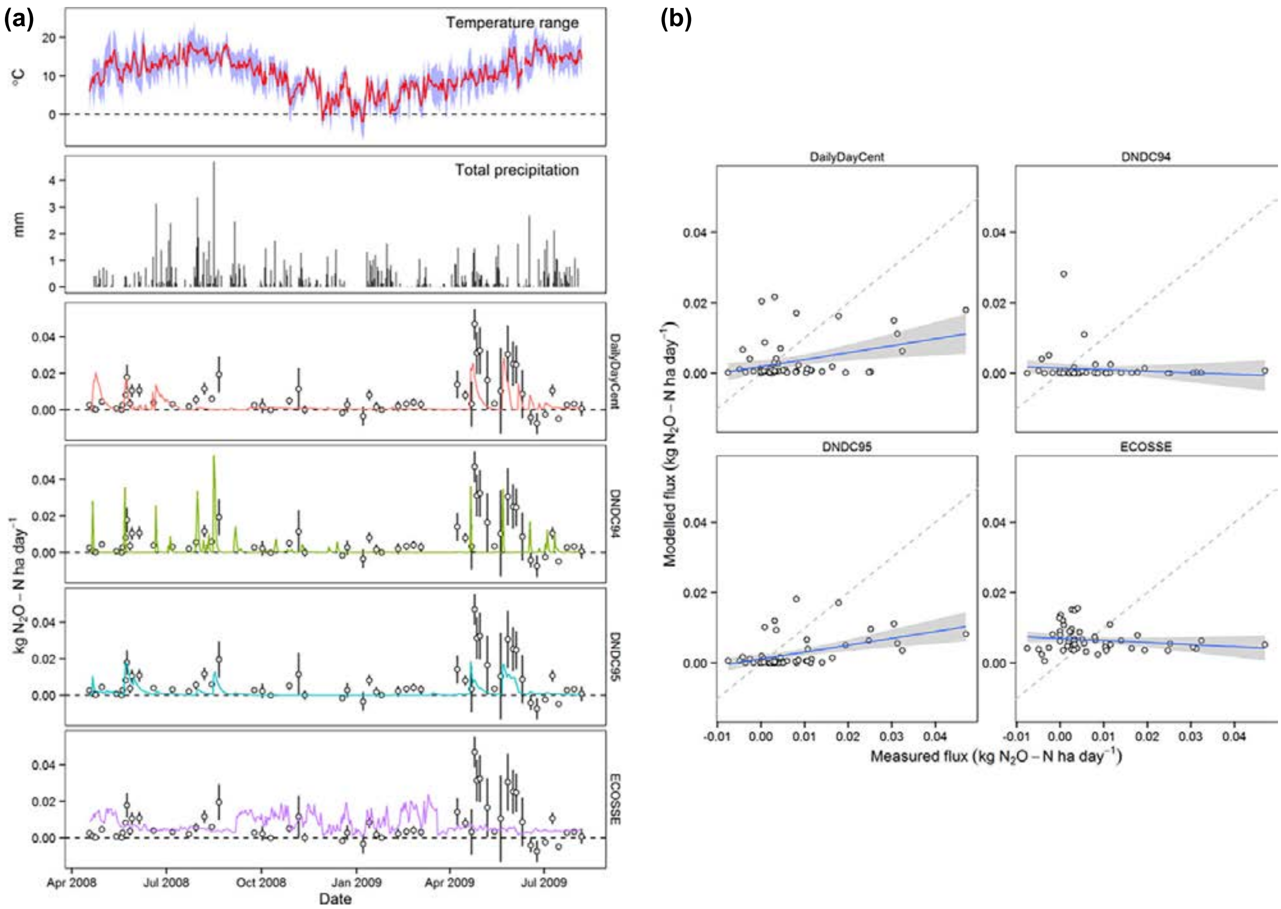


Figure A1.13. (a) Model simulations and weather conditions for the site Barley-cc-L_2 on a daily timestep over the simulation period. Measured data (open circles) are shown as means ± 1 s.e. (b) Measured versus modelled N_2O fluxes on a daily timestep for the site Barley-cc-L_2. The dashed grey line represents the 1:1 relationship between measured and modelled fluxes. The solid blue line and shaded grey region represent the linear fit between measured and modelled fluxes and associated 95% confidence interval, respectively.

A1.2 Grassland Sites

A1.2.1 Fertilised grazed pasture

Rank (daily difference) P_1: DNDC 9.5 > DailyDayCent > ECOSSE > DNDC 9.4.

Rank (daily difference) P_2: DNDC 9.4 > DNDC 9.5 > DailyDayCent > ECOSSE.

Rank (cumulative difference) P_1: DNDC 9.4 > DNDC 9.5 > DailyDayCent > ECOSSE.

Rank (cumulative difference) P_2: DNDC 9.4 > DNDC 9.5 > DailyDayCent > ECOSSE.

During the first period, DailyDayCent produced the simulation with the lowest overall error at this site (*RMSE* = 111.68%). The DNDC 9.5 simulation produced the smallest bias compared with measured data and had an overall error similar to that of DailyDayCent (*RMSE* = 113.18%; *E* = 3.78%). The DNDC 9.5 simulation also had the strongest correlation with measured data (*r* = 0.6). In the second period, the DNDC 9.4 simulation produced the lowest overall error (*RMSE* = 104.69%) and strongest correlation with the measured data (*r* = 0.92), whereas DNDC 9.5 produced the smallest bias (*E* = 43.24%). The overall error and bias associated with the ECOSSE simulation were both outside the 95% confidence limits determined by the measured data. DNDC 9.4 simulations produced the smallest differences from cumulative measured emissions in both measurement periods, underestimating the measured emissions by 12.8% and 58.4% in P_1 and P_2, respectively. All models underestimated cumulative emissions.

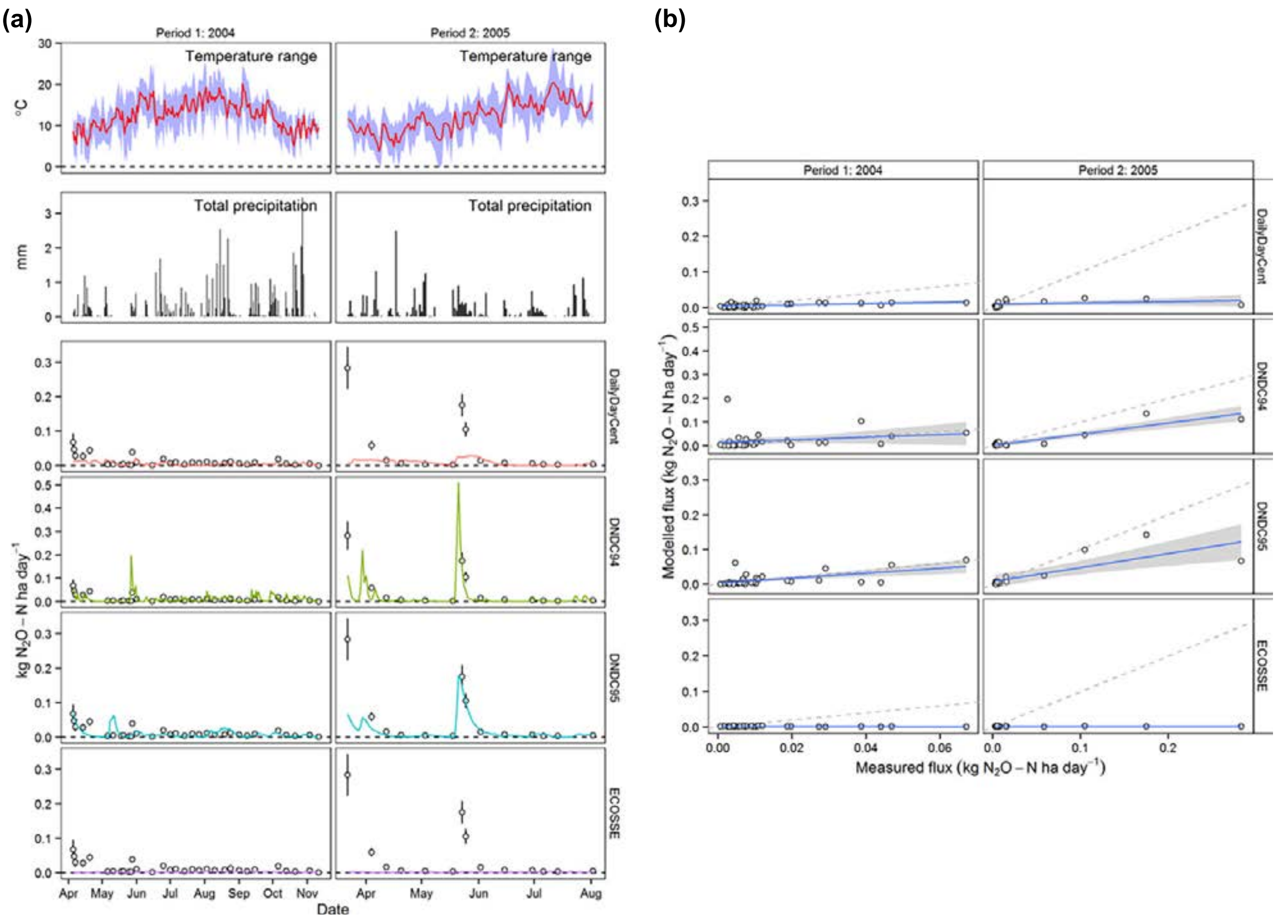


Figure A1.14. (a) Model simulations and weather conditions for the site Carlow cut/grazed fert on a daily timestep over the simulation period. Measured data (open circles) are shown as means ± 1 s.e. (b) Measured versus modelled N_2O fluxes on a daily timestep for the site Carlow cut/grazed fert. The dashed grey line represents the 1:1 relationship between measured and modelled fluxes. The solid blue line and shaded grey region represent the linear fit between measured and modelled fluxes and associated 95% confidence interval, respectively.

A1.2.2 Unfertilised cut pasture

Rank (daily difference) P_1: DailyDayCent > ECOSSE > DNDC 9.4 > DNDC 9.5.

Rank (daily difference) P_2: DNDC 9.4 > ECOSSE > DailyDayCent > DNDC 9.5.

Rank (cumulative difference) P_1: DNDC 9.4 > ECOSSE > DailyDayCent > DNDC 9.5.

Rank (cumulative difference) P_2: ECOSSE > DNDC 9.4 > DailyDayCent > DNDC 9.5.

The simulation that produced the lowest overall error in the first measurement period was DailyDayCent (*RMSE* = 102.04%), which also had the strongest – and only significant – correlation with measured data ($r = 0.32$). The DNDC 9.4 simulation produced the smallest bias during this period ($E = 38.57\%$). In the second measurement period, DNDC 9.4 produced simulations with the lowest overall error and bias (*RMSE* = 119.54; $E = 61.85\%$) and the strongest correlation with the measured data ($r = 0.6$), although the correlation was not significant at $p = 0.05$. All models underestimated cumulative emissions, with DNDC 9.4 producing the smallest difference in the first period (17.4%) and ECOSSE producing the smallest difference in the second period (50.6%). DNDC 9.5 produced the largest underestimates in both periods (77.3% and 97.8% respectively).

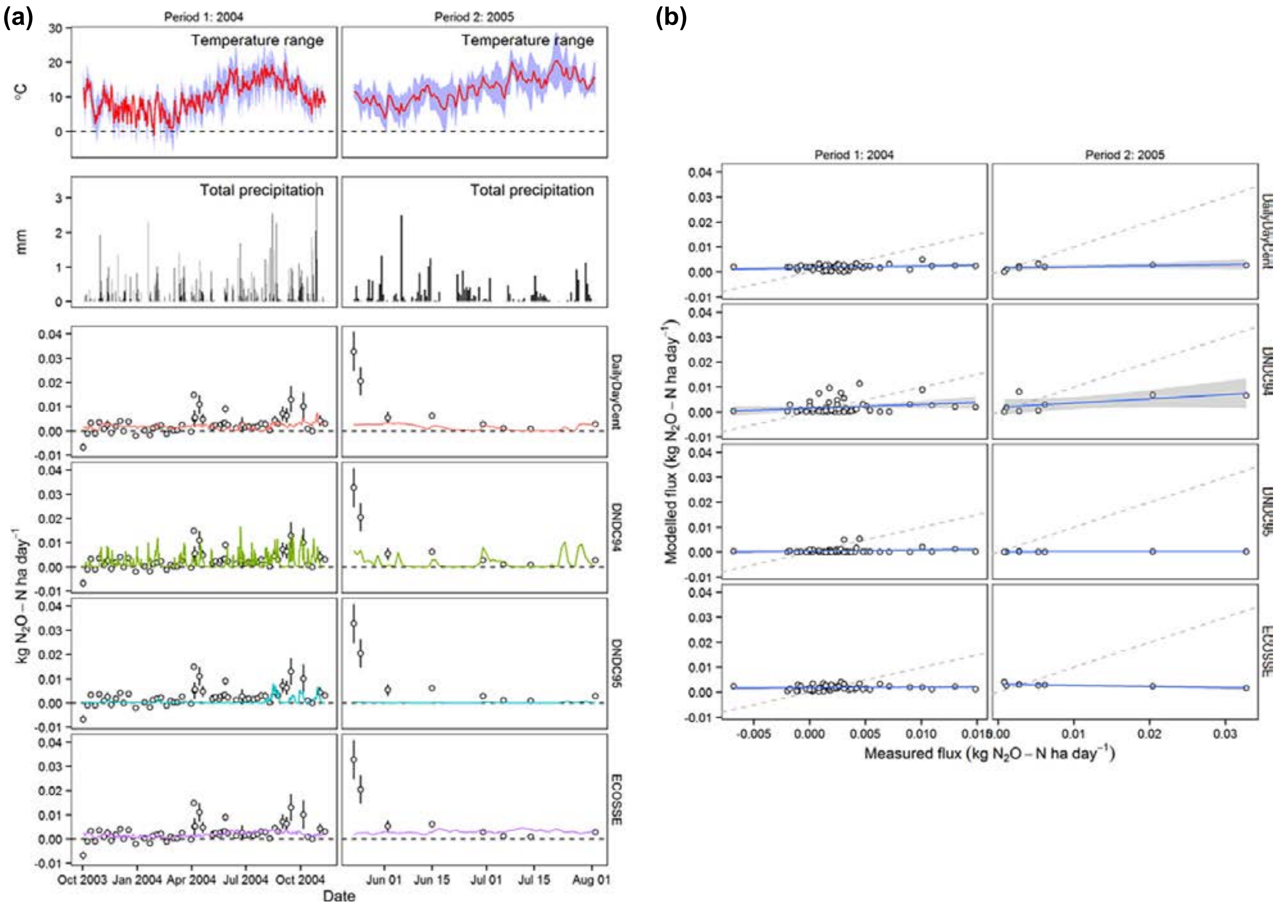


Figure A1.15. (a) Model simulations and weather conditions for the site Carlow cut/grazed unfert on a daily timestep over the simulation period. Measured data (open circles) are shown as means ± 1 s.e. (b) Measured versus modelled N_2O fluxes on a daily timestep for the site Carlow cut/grazed unfert. The dashed grey line represents the 1:1 relationship between measured and modelled fluxes. The solid blue line and shaded grey region represent the linear fit between measured and modelled fluxes and associated 95% confidence interval, respectively.

A1.2.3 Unmanaged grassland, Carlow

Rank (daily difference): ECOSSE > DailyDayCent > DNDC 9.5 > DNDC 9.4.

Rank (cumulative difference): DNDC 9.4 > DNDC 9.5 > DailyDayCent > ECOSSE.

The ECOSSE simulation produced the lowest overall error and bias (*RMSE* = 74.14%; *E* = 36.51%) and the strongest correlation with the measured data ($r = 0.35$) of all of the models, although the correlation was not significant at $p = 0.05$. None of the correlations between simulations and measured data was significant. DNDC 9.4 and DNDC 9.5 underestimated the cumulative emissions by 9.5% and 34.6%, respectively, whereas DailyDayCent and ECOSSE overestimated the cumulative emissions by 124.3% and 138.5%, respectively.

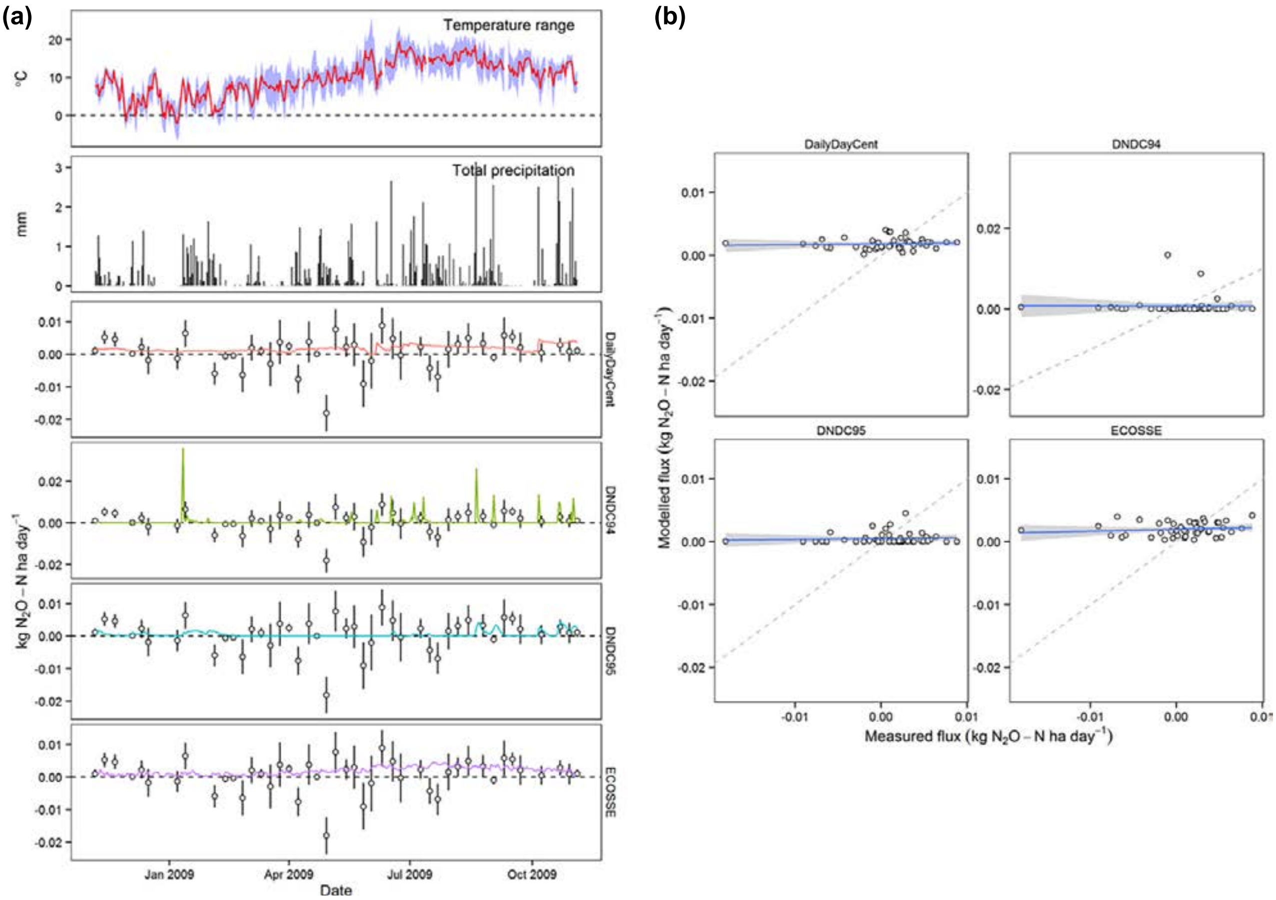


Figure A1.16. (a) Model simulations and weather conditions for the site Carlow unman on a daily timestep over the simulation period. Measured data (open circles) are shown as means ± 1 s.e. (b) Measured versus modelled N_2O fluxes on a daily timestep for the site Carlow unman. The dashed grey line represents the 1:1 relationship between measured and modelled fluxes. The solid blue line and shaded grey region represent the linear fit between measured and modelled fluxes and associated 95% confidence interval, respectively.

A1.2.4 Unmanaged grassland, Dooary

Rank (daily difference): DailyDayCent > ECOSSE > DNDC 9.5 > DNDC 9.4.

Rank (cumulative difference): DailyDayCent > ECOSSE > DNDC 9.5 > DNDC 9.4.

All four models performed poorly when simulating this site. The only simulation to produce an overall error and bias within the 95% confidence interval was DailyDayCent (*RMSE* = 193.76%; *E* = −148.5%). The DNDC 9.5 simulation had the strongest correlation with the measured data (*r* = 0.73), with DailyDayCent having the second strongest correlation (*r* = 0.68). All models overestimated cumulative emissions at this site, with DailyDayCent producing the smallest difference between measured and modelled emissions (565.2%).

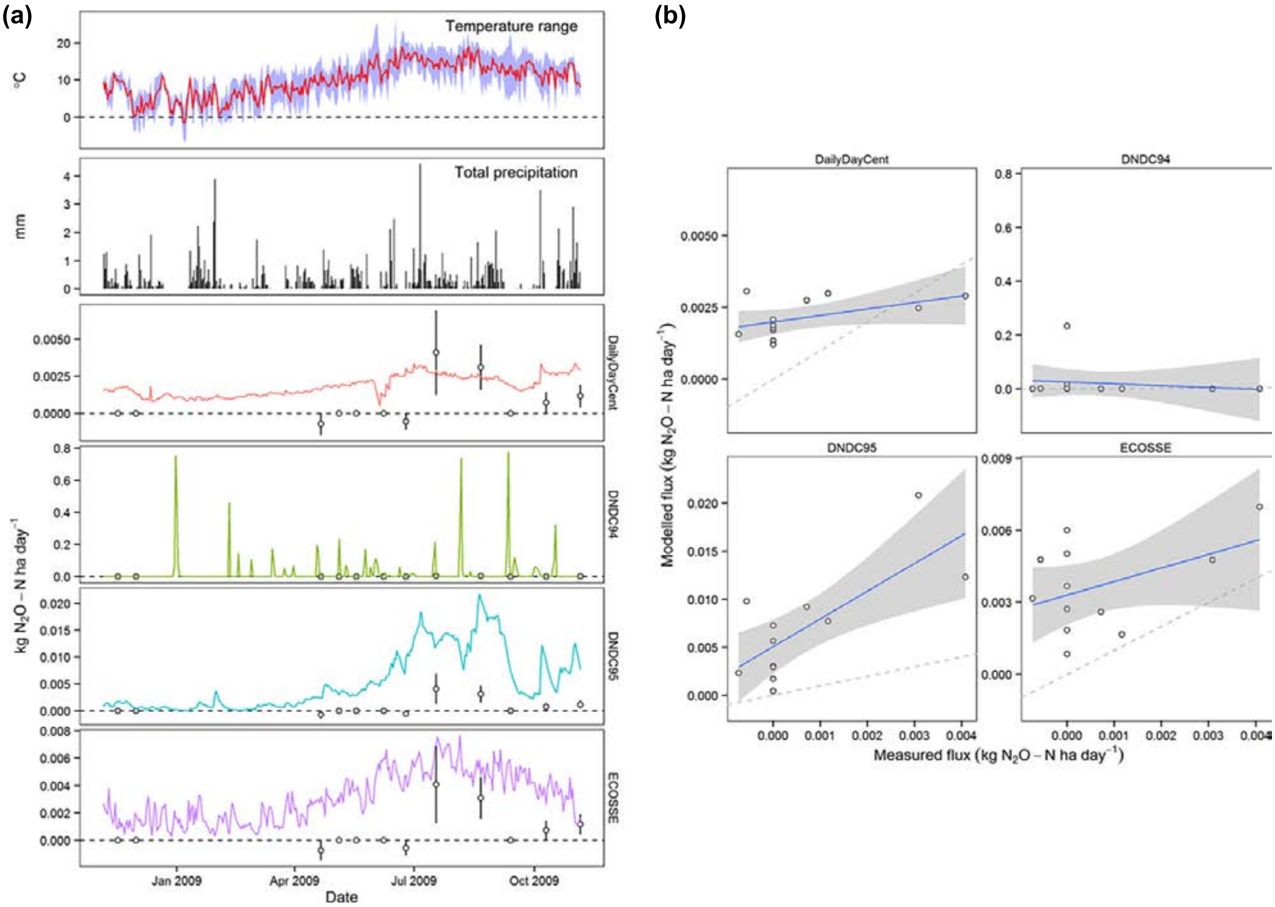


Figure A1.17. (a) Model simulations and weather conditions for the site Dooary unman on a daily timestep over the simulation period. Measured data (open circles) are shown as means ± 1 s.e.
(b) Measured versus modelled N_2O fluxes on a daily timestep for the site Dooary unman. The dashed grey line represents the 1:1 relationship between measured and modelled fluxes. The solid blue line and shaded grey region represent the linear fit between measured and modelled fluxes and associated 95% confidence interval, respectively.

A1.2.5 Unfertilised, cut grassland, Mount Lucas

Rank (daily difference): ECOSSE > DailyDayCent > DNDC 9.4 > DNDC 9.5.

Rank (cumulative difference): DNDC 9.5 > ECOSSE > DNDC 9.4 > DailyDayCent.

ECOSSE produced simulations with the lowest overall errors and bias of all of the models when compared with measured data (*RMSE* = 162.31%; *E* = 48.92%). None of the simulations correlated significantly with the measured data and all produced weak negative correlations. Models overestimated emissions at this site, with the exception of DNDC 9.5, which underestimated emissions and also produced the smallest difference between simulated and measured data (43.1%).

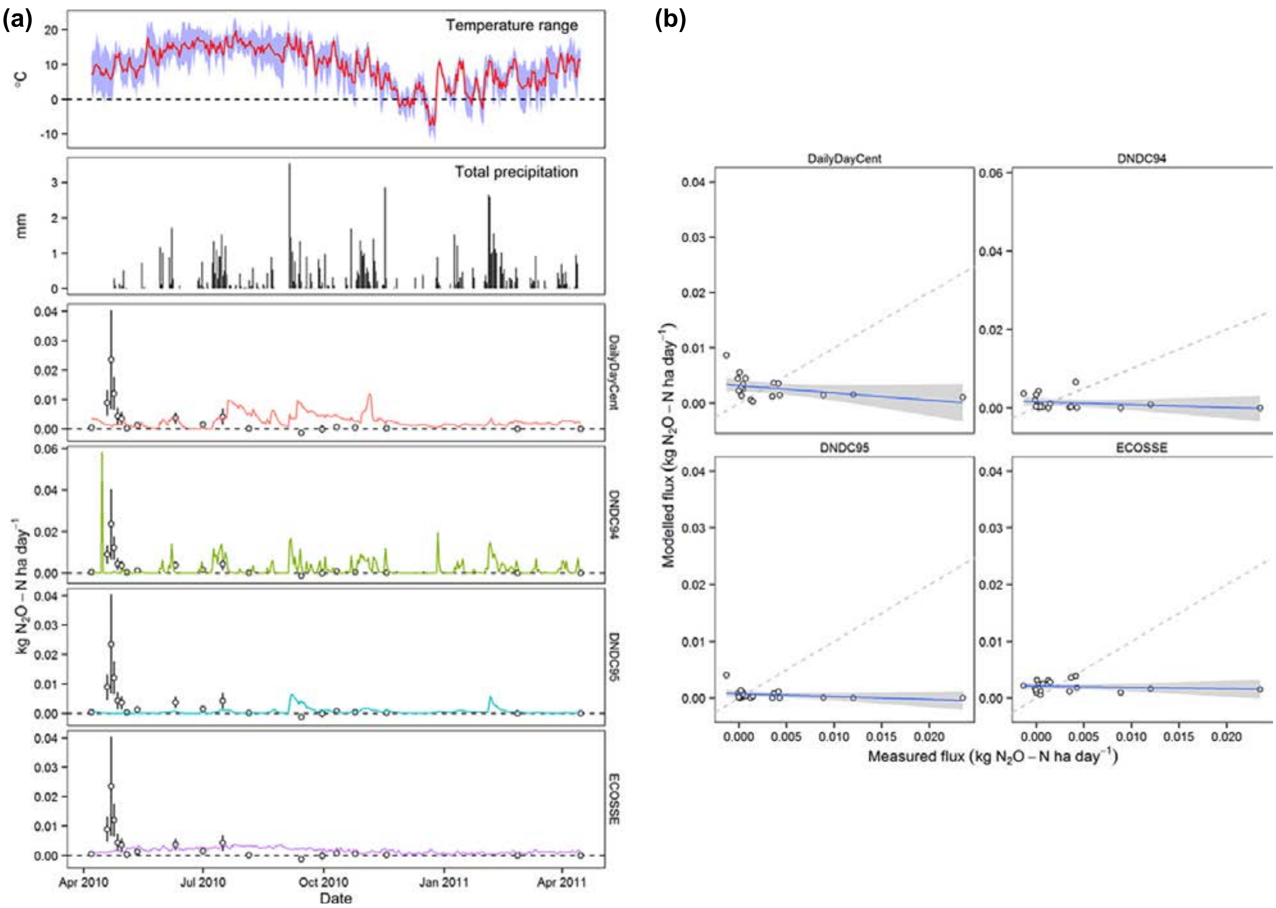


Figure A1.18. (a) Model simulations and weather conditions for the site Lucas on a daily timestep over the simulation period. Measured data (open circles) are shown as means ± 1 s.e. (b) Measured versus modelled N_2O fluxes on a daily timestep for the site Lucas. The dashed grey line represents the 1:1 relationship between measured and modelled fluxes. The solid blue line and shaded grey region represent the linear fit between measured and modelled fluxes and associated 95% confidence interval, respectively.

A1.2.6 Fertilised, grazed pasture

P_1 – *RMSE*: DNDC 9.5: 65.98%; *E*: DNDC 9.5: 51.44%; *r*: DNDC 9.5: 0.46 (not significant).

P_2 – *RMSE*: DNDC 9.5: 108%; *E*: DNDC 9.4: −10.5%; *r*: ECOSSE 0.21 (not significant).

P_3 – *RMSE*: DailyDayCent: 145.4%; *E*: DNDC 9.4: 58.17%; *r*: all weak, negative and non-significant.

P_4 – *RMSE*: DNDC 9.4: 146.4%; *E*: DNDC 9.4: 70.58%; *r*: all weak, negative and non-significant.

P_5 – *RMSE*: DailyDayCent: 107.42%; *E*: DNDC 9.4: −23.17%; *r*: DNDC 9.5: −0.44 (significant, negative).

Rank (daily difference) P_1: DNDC 9.5 > ECOSSE > DailyDayCent > DNDC 9.4.

Rank (daily difference) P_2: DNDC 9.5 > DNDC 9.4 > DailyDayCent > ECOSSE.

Rank (daily difference) P_3: DNDC 9.4 > DailyDayCent > DNDC 9.5 > ECOSSE.

Rank (daily difference) P_4: DNDC 9.4 > DNDC 9.5 > DailyDayCent > ECOSSE.

Rank (daily difference) P_5: DNDC 9.5 > DailyDayCent > DNDC 9.4 > ECOSSE.

Rank (cumulative difference) P_1: DNDC 9.5 > ECOSSE > DailyDayCent > DNDC 9.4.

Rank (cumulative difference) P_2: DNDC 9.5 > DNDC 9.4 > DailyDayCent > ECOSSE.

Rank (cumulative difference) P_3: DNDC 9.4 > DNDC 9.5 > DailyDayCent > ECOSSE.

Rank (cumulative difference) P_4: DNDC 9.4 > DNDC 9.5 > DailyDayCent > ECOSSE.

Rank (cumulative difference) P_5: DNDC 9.5 > DNDC 9.4 > DailyDayCent > ECOSSE.

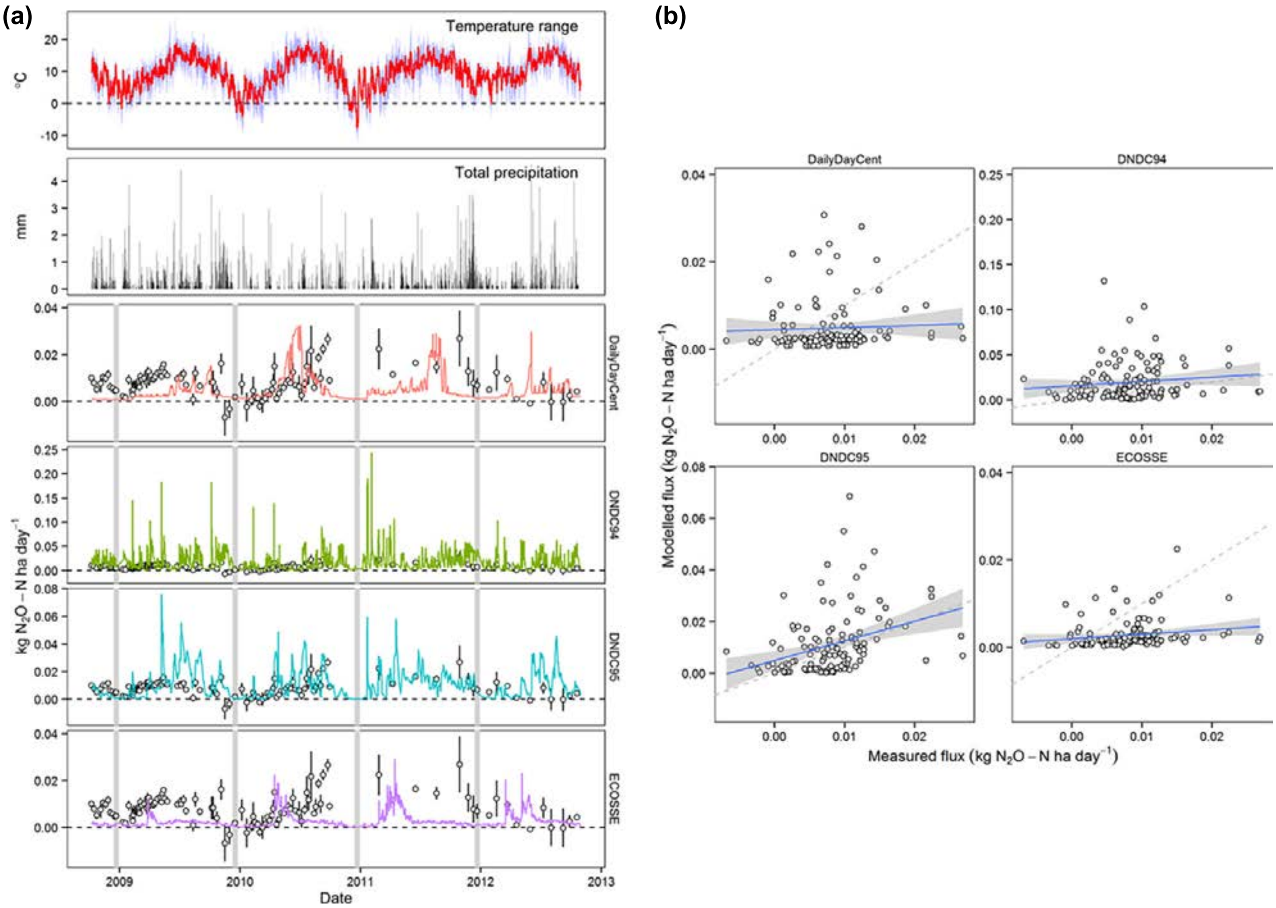


Figure A1.19. (a) Model simulations and weather conditions for the site Solohead on a daily timestep over the simulation period. Measured data (open circles) are shown as means ± 1 s.e. (b) Measured versus modelled N_2O fluxes on a daily timestep for the site Solohead. The dashed grey line represents the 1:1 relationship between measured and modelled fluxes. The solid blue line and shaded grey region represent the linear fit between measured and modelled fluxes and associated 95% confidence interval, respectively.

The measured data from this site were split into five consecutive periods. In two of the five periods, DNDC 9.5 simulations had the lowest errors compared with measured data (*RMSE* = 65.98% in P_1, 108% in P_2). DailyDayCent simulations also had the lowest errors in two of the measurement periods (*RMSE* = 145.4% in P_3, 107.42% in P_5). DNDC 9.4 produced the lowest errors in the fourth period (*RMSE* = 146.4%). DNDC 9.4 simulations had the smallest bias in four out of five measurement periods. None of the simulations correlated significantly with the measured data, apart from that produced by DNDC 9.5 in the fifth measurement period, which had a significant negative correlation ($r = -0.44$).

A1.2.7 Unfertilised, cut pasture

P_1 – *RMSE*: DNDC 9.5: 68.83%; *E*: DNDC 9.5: 42.38%; *r*: none significant.

P_2 – *RMSE*: DNDC 9.5: 83.61%; *E*: DNDC 9.5: 44.8%; *r*: none significant.

P_3 – *RMSE*: DNDC 9.5: 82.77%; *E*: DNDC 9.4: −13.02%; *r*: DNDC 9.5: 0.53.

P_4 – *RMSE*: DNDC 9.5: 81.01%; *E*: DNDC 9.4: −18.43%; *r*: none significant.

P_5 – *RMSE*: DNDC 9.5: 95.76%; *E*: DNDC 9.5: 40.93%; *r*: none significant.

Rank (daily difference) P_1: DNDC 9.5 > ECOSSE > DailyDayCent > DNDC 9.4.

Rank (daily difference) P_2: DNDC 9.5 > ECOSSE > DailyDayCent > DNDC 9.4.

Rank (daily difference) P_3: DNDC 9.5 > DNDC 9.4 > DailyDayCent > ECOSSE.

Rank (daily difference) P_4: DNDC 9.5 > DNDC 9.4 > ECOSSE > DailyDayCent.

Rank (daily difference) P_5: DNDC 9.5 > DailyDayCent > ECOSSE > DNDC 9.4.

Rank (cumulative difference) P_1: DNDC 9.5 > ECOSSE > DailyDayCent > DNDC 9.4.

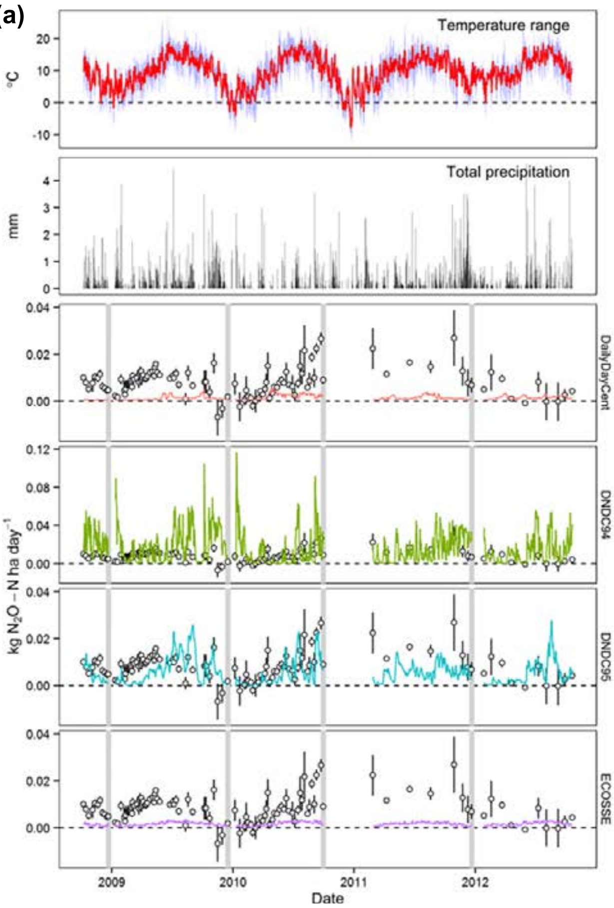
Rank (cumulative difference) P_2: DNDC 9.5 > ECOSSE > DailyDayCent > DNDC 9.4.

Rank (cumulative difference) P_3: DNDC 9.5 > DNDC 9.4 > DailyDayCent > ECOSSE.

Rank (cumulative difference) P_4: DNDC 9.4 > DNDC 9.5 > DailyDayCent > ECOSSE.

Rank (cumulative difference) P_5: DNDC 9.5 > ECOSSE > DailyDayCent > DNDC 9.4.

(a)



(b)

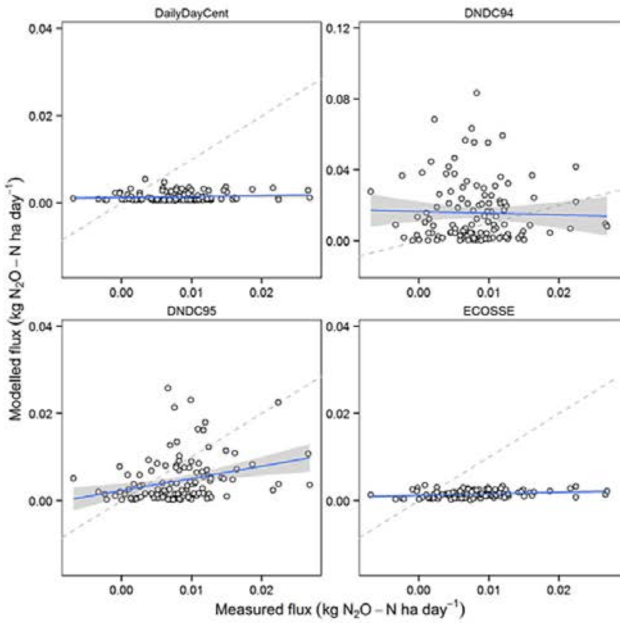


Figure A1.20. (a) Model simulations and weather conditions for the site Solohead-background on a daily timestep over the simulation period. Measured data (open circles) are shown as means ± 1 s.e. (b) Measured versus modelled N_2O fluxes on a daily timestep for the site Solohead-background. The dashed grey line represents the 1:1 relationship between measured and modelled fluxes. The solid blue line and shaded grey region represent the linear fit between measured and modelled fluxes and associated 95% confidence interval, respectively.

The measured data from this site were split into five consecutive periods. The DNDC 9.5 simulations consistently produced the lowest overall errors when compared with the measured data (*RMSE* ranging from 68.83% to 95.76%). DNDC 9.5 simulations also had the lowest bias in three out of five measurement periods (*E* ranging from 40.93% to 44.8%); in the remaining two measurement periods, DNDC 9.4 simulations had the lowest bias (E = −13.02% in P_3, −18.43% in P_4). The only significant correlation between simulated and measured data occurred in the third measurement period, for a DNDC 9.5 simulation (r = 0.53).

Appendix 2 Measured and Modelled R_{ecos}

A2.1 Arable Sites

A2.1.1 Fertilised barley, conventional tillage

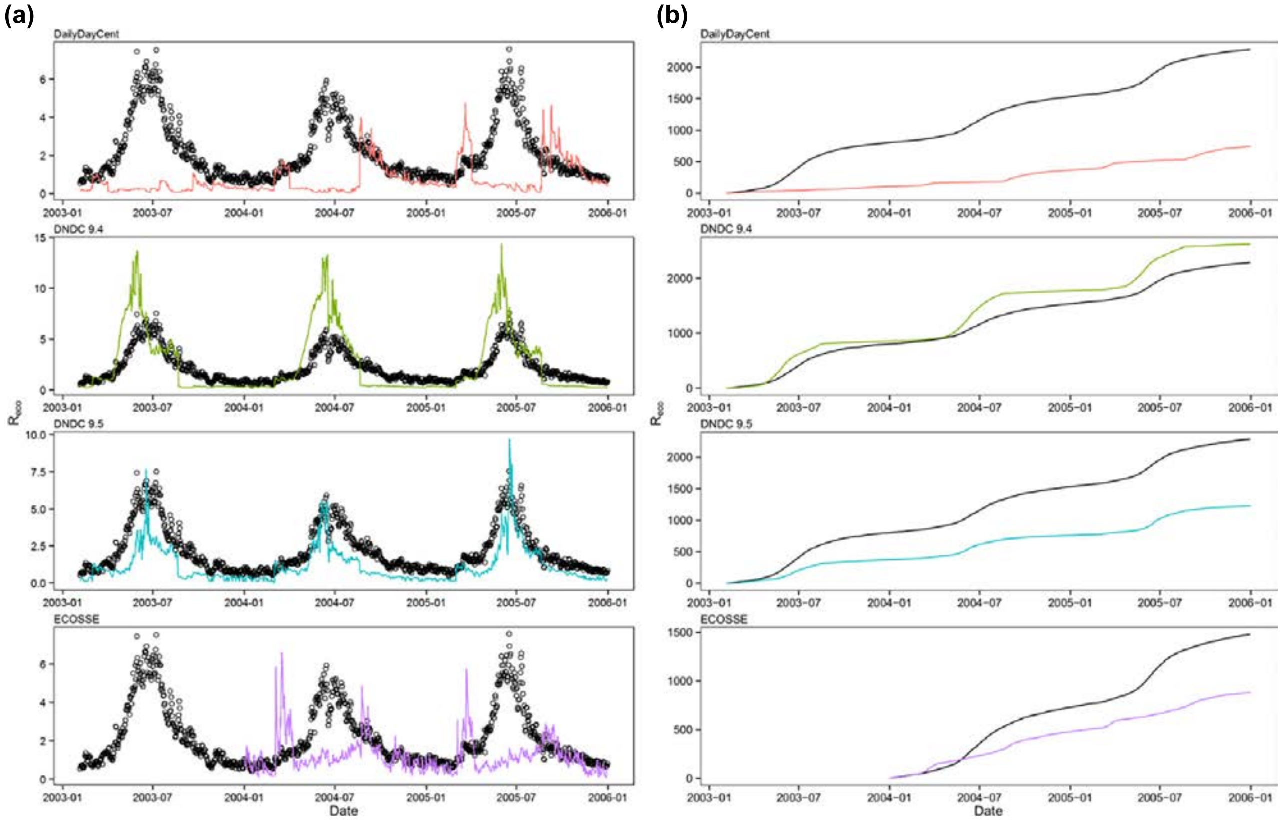


Figure A2.1. Simulation of daily and cumulative R_{ecos} fluxes for a conventional tillage crop of barley receiving full field rate N fertiliser. (a) Daily R_{ecos} values. Black circles indicate measured values calculated from eddy covariance data. (b) Cumulative R_{ecos} data. Black line indicates measured values.

A2.1.2 Fertilised barley, non-inversion tillage

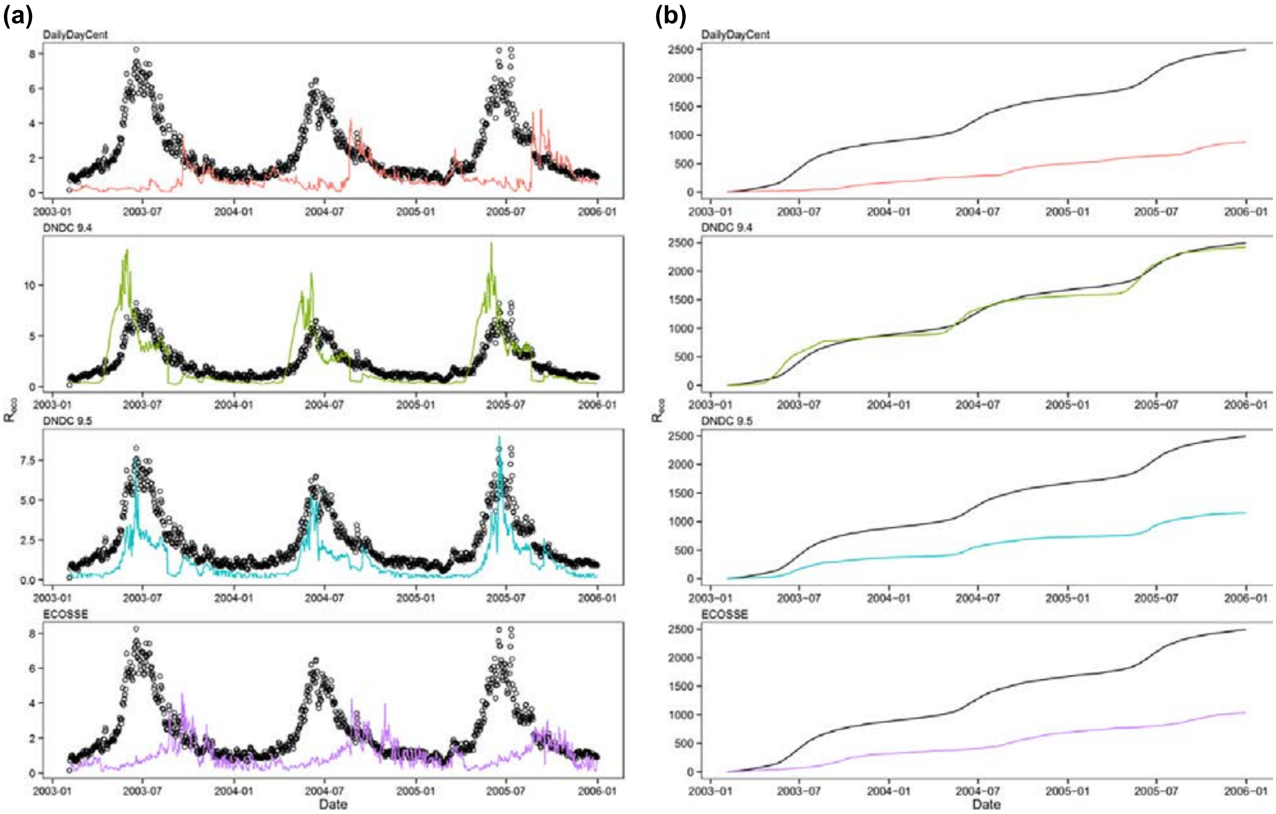


Figure A2.2. Simulation of daily and cumulative R_{ecos} fluxes for a non-inversion tillage crop of barley receiving full field rate N fertiliser. (a) Daily R_{ecos} values. Black circles indicate measured values calculated from eddy covariance data. (b) Cumulative R_{ecos} data. Black line indicates measured values.

A2.2 Grassland Sites

A2.2.1 Unmanaged grassland

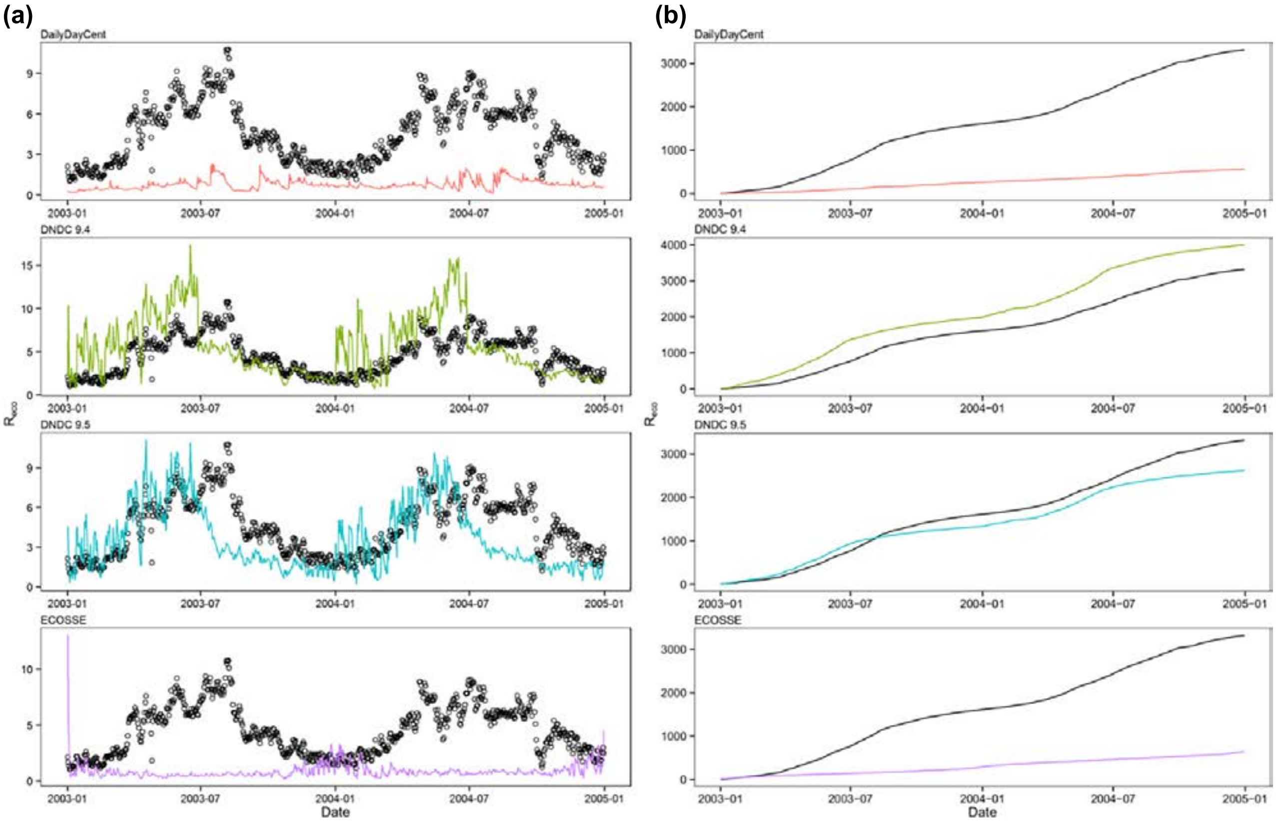


Figure A2.3. Simulation of daily and cumulative R_{ecos} fluxes for an unmanaged grassland at Carlow. (a) Daily R_{ecos} values. Black circles indicate measured values calculated from eddy covariance data. (b) Cumulative R_{ecos} data. Black line indicates measured values.

A2.2.2 Cut, fertilised grassland

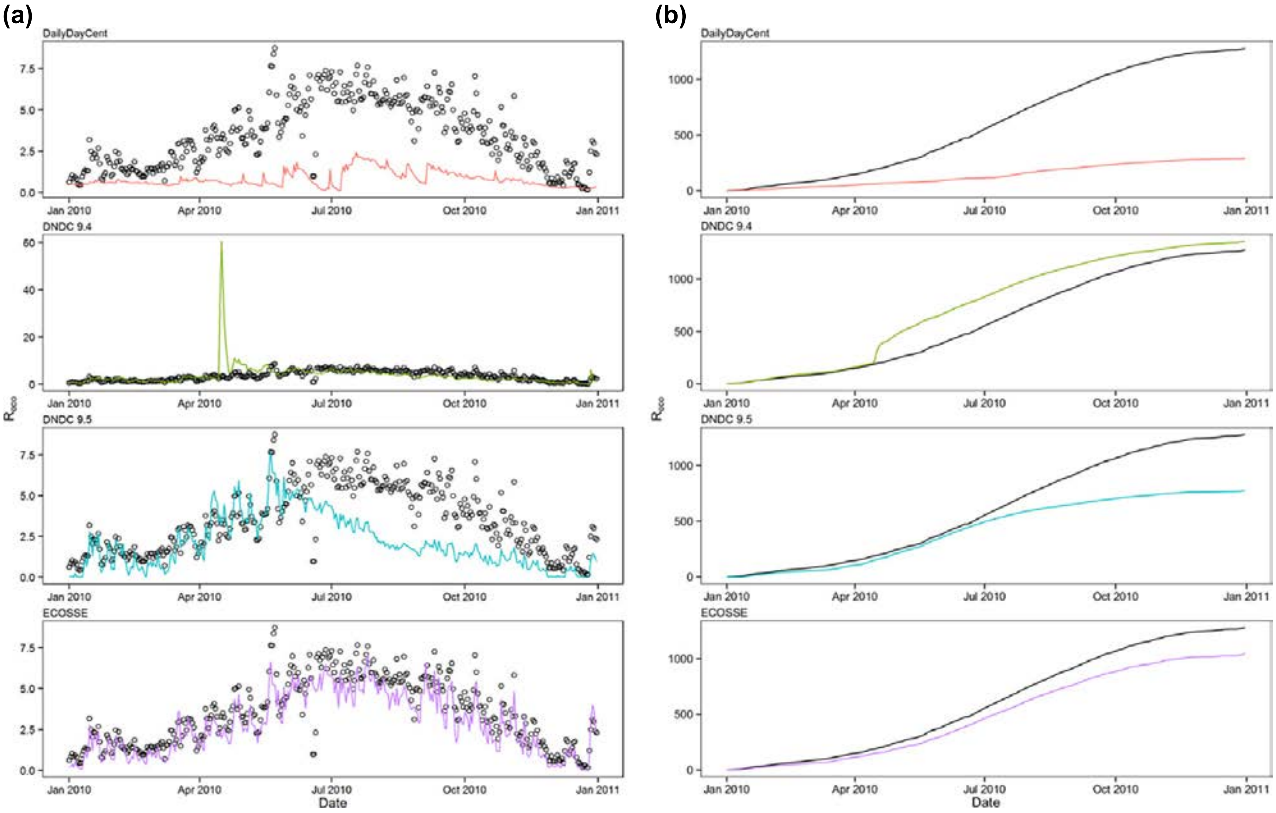


Figure A2.4. Simulation of daily and cumulative R_{ecos} fluxes for a cut grassland at Mount Lucas. (a) Daily R_{ecos} values. Black circles indicate measured values calculated from eddy covariance data. (b) Cumulative R_{ecos} data. Black line indicates measured values.

AN GHNÍOMHAIREACHT UM CHAOMHNÚ COMHSHAOIL
Tá an Ghníomhaireacht um Chaomhnú Comhshaoil (GCC) freagrach as an gcomhshaol a chaomhnú agus a fheabhsú mar shócmhainn luachmhar do mhuintir na hÉireann. Táimid tiomanta do dhaoine agus don chomhshaol a chosaint ó éifeachtaí díobhálacha na radaíochta agus an truaillithe.

Is féidir obair na Gníomhaireachta a roinnt ina trí phríomhréimse:

Rialú: *Déanaimid córais éifeachtacha rialaithe agus comhlíonta comhshaoil a chur i bhfeidhm chun torthaí maithe comhshaoil a sholáthar agus chun díriú orthu siúd nach gcloíonn leis na córais sin.*

Eolas: *Soláthraímid sonraí, faisnéis agus measúnú comhshaoil atá ar ardchaighdeán, spriocdhírithe agus tráthúil chun bonn eolais a chur faoin gcinnteoireacht ar gach leibhéal.*

Tacaíocht: *Bímid ag saothrú i gcomhar le grúpaí eile chun tacú le comhshaol atá glan, táirgiúil agus cosanta go maith, agus le hiompar a chuirfidh le comhshaol inbhuanaithe.*

Ár bhFreagrachtaí

Ceadúnú
Déanaimid na gníomhaíochtaí seo a leanas a rialú ionas nach ndéanann siad dochar do shláinte an phobail ná don chomhshaol:
- saoráidí dramhaíola *(m.sh. láithreáin líonta talún, loisceoirí, stáisiúin aistrithe dramhaíola)*;
- gníomhaíochtaí tionsclaíocha ar scála mór *(m.sh. déantúsaíocht cógaisíochta, déantúsaíocht stroighne, stáisiúin chumhachta)*;
- an diantalmhaíocht *(m.sh. muca, éanlaith)*;
- úsáid shrianta agus scaoileadh rialaithe Orgánach Géinmhodhnaithe *(OGM)*;
- foinsí radaíochta ianúcháin *(m.sh. trealamh x-gha agus radaiteiripe, foinsí tionsclaíocha)*;
- áiseanna móra stórála peitril;
- scardadh dramhuisce;
- gníomhaíochtaí dumpála ar farraige.

Forfheidhmiú Náisiúnta i leith Cúrsaí Comhshaoil
- Clár náisiúnta iniúchtaí agus cigireachtaí a dhéanamh gach bliain ar shaoráidí a bhfuil ceadúnas ón nGníomhaireacht acu.
- Maoirseacht a dhéanamh ar fhreagrachtaí cosanta comhshaoil na n-údarás áitiúil.
- Caighdeán an uisce óil, arna sholáthar ag soláthraithe uisce phoiblí, a mhaoirsiú.
- Obair le húdaráis áitiúla agus le gníomhaireachtaí eile chun dul i ngleic le coireanna comhshaoil trí chomhordú a dhéanamh ar líonra forfheidhmiúcháin náisiúnta, trí dhíriú ar chiontóirí, agus trí mhaoirsiú a dhéanamh ar leasúchán.
- Cur i bhfeidhm rialachán ar nós na Rialachán um Dhramhthrealamh Leictreach agus Leictreonach (DTLL), um Shrian ar Shubstaintí Guaiseacha agus na Rialachán um rialú ar shubstaintí a ídíonn an ciseal ózóin.
- An dlí a chur orthu siúd a bhriseann dlí an chomhshaoil agus a dhéanann dochar don chomhshaol.

Bainistíocht Uisce
- Monatóireacht agus tuairisciú a dhéanamh ar cháilíocht aibhneacha, lochanna, uiscí idirchriosacha agus cósta na hÉireann, agus screamhuiscí; leibhéil uisce agus sruthanna aibhneacha a thomhas.
- Comhordú náisiúnta agus maoirsiú a dhéanamh ar an gCreat-Treoir Uisce.
- Monatóireacht agus tuairisciú a dhéanamh ar Cháilíocht an Uisce Snámha.

Monatóireacht, Anailís agus Tuairisciú ar an gComhshaol
- Monatóireacht a dhéanamh ar cháilíocht an aeir agus Treoir an AE maidir le hAer Glan don Eoraip (CAFÉ) a chur chun feidhme.
- Tuairisciú neamhspleách le cabhrú le cinnteoireacht an rialtais náisiúnta agus na n-údarás áitiúil *(m.sh. tuairisciú tréimhsiúil ar staid Chomhshaol na hÉireann agus Tuarascálacha ar Tháscairí)*.

Rialú Astaíochtaí na nGás Ceaptha Teasa in Éirinn
- Fardail agus réamh-mheastacháin na hÉireann maidir le gáis cheaptha teasa a ullmhú.
- An Treoir maidir le Trádáil Astaíochtaí a chur chun feidhme i gcomhair breis agus 100 de na táirgeoirí dé-ocsaíde carbóin is mó in Éirinn.

Taighde agus Forbairt Comhshaoil
- Taighde comhshaoil a chistiú chun brúnna a shainaithint, bonn eolais a chur faoi bheartais, agus réitigh a sholáthar i réimsí na haeráide, an uisce agus na hinbhuanaitheachta.

Measúnacht Straitéiseach Timpeallachta
- Measúnacht a dhéanamh ar thionchar pleananna agus clár beartaithe ar an gcomhshaol in Éirinn *(m.sh. mórphleananna forbartha)*.

Cosaint Raideolaíoch
- Monatóireacht a dhéanamh ar leibhéil radaíochta, measúnacht a dhéanamh ar nochtadh mhuintir na hÉireann don radaíocht ianúcháin.
- Cabhrú le pleananna náisiúnta a fhorbairt le haghaidh éigeandálaí ag eascairt as taismí núicléacha.
- Monatóireacht a dhéanamh ar fhorbairtí thar lear a bhaineann le saoráidí núicléacha agus leis an tsábháilteacht raideolaíochta.
- Sainseirbhísí cosanta ar an radaíocht a sholáthar, nó maoirsiú a dhéanamh ar sholáthar na seirbhísí sin.

Treoir, Faisnéis Inrochtana agus Oideachas
- Comhairle agus treoir a chur ar fáil d'earnáil na tionsclaíochta agus don phobal maidir le hábhair a bhaineann le caomhnú an chomhshaoil agus leis an gcosaint raideolaíoch.
- Faisnéis thráthúil ar an gcomhshaol ar a bhfuil fáil éasca a chur ar fáil chun rannpháirtíocht an phobail a spreagadh sa chinnteoireacht i ndáil leis an gcomhshaol *(m.sh. Timpeall an Tí, léarscáileanna radóin)*.
- Comhairle a chur ar fáil don Rialtas maidir le hábhair a bhaineann leis an tsábháilteacht raideolaíoch agus le cúrsaí práinnfhreagartha.
- Plean Náisiúnta Bainistíochta Dramhaíola Guaisí a fhorbairt chun dramhaíl ghuaiseach a chosc agus a bhainistiú.

Múscailt Feasachta agus Athrú Iompraíochta
- Feasacht chomhshaoil níos fearr a ghiniúint agus dul i bhfeidhm ar athrú iompraíochta dearfach trí thacú le gnóthais, le pobail agus le teaghlaigh a bheith níos éifeachtúla ar acmhainní.
- Tástáil le haghaidh radóin a chur chun cinn i dtithe agus in ionaid oibre, agus gníomhartha leasúcháin a spreagadh nuair is gá.

Bainistíocht agus struchtúr na Gníomhaireachta um Chaomhnú Comhshaoil
Tá an ghníomhaíocht á bainistiú ag Bord lánaimseartha, ar a bhfuil Ard-Stiúrthóir agus cúigear Stiúrthóirí. Déantar an obair ar fud cúig cinn d'Oifigí:
- An Oifig um Inmharthanacht Comhshaoil
- An Oifig Forfheidhmithe i leith cúrsaí Comhshaoil
- An Oifig um Fianaise is Measúnú
- Oifig um Chosaint Radaíochta agus Monatóireachta Comhshaoil
- An Oifig Cumarsáide agus Seirbhísí Corparáideacha

Tá Coiste Comhairleach ag an nGníomhaireacht le cabhrú léi. Tá dáréag comhaltaí air agus tagann siad le chéile go rialta le plé a dhéanamh ar ábhair imní agus le comhairle a chur ar an mBord.

EPA Research Report 304

Scaling Soil Greenhouse Gas Emissions to the National Level

epaResearch
Climate - Water - Sustainability
Identifying pressures • Informing policy • Developing solutions

Authors - Mike G. Whitfield, Mohamed Abdalla, Giuseppe Benanti, William Burchill, Dru Marsh, Bruce Osborne, Brendan Roth, Matthew Saunders, Pete Smith and Mike Williams

Agricultural soils are a major source of greenhouse gas (GHG) emissions globally, but also a potential sink of carbon through appropriate land management. In Ireland, 81% of the land is devoted to agriculture, which means that there is potential for significant mitigation of agricultural GHG emissions through land-use management and land-use change. However, current tools for assessing GHG emission savings through land-use change – Intergovernmental Panel on Climate Change (IPCC) Tier 1 and Tier 2 – are limited; Tier 3 approaches, in which process-based models are used to estimate GHG emissions for given land-use and climatic scenarios, are more flexible.

Identifying Pressures

The Scaling Soil Process Modelling to National Level project was concerned with improving the national inventory of GHG emissions from Irish soils by the use of Tier 2 and 3 methodologies, effectively upscaling regional data on soil N_2O and CO_2 fluxes to the national level through a combined process-based model and GIS approach.

Developing Solutions

A 5km x 5km GIS map framework for Ireland has been successfully developed that will allow calculation of nationwide annual emissions of N_2O and CO_2 from grasslands and arable soils. This has been linked to climate, land use and soil type using the Soil Information System (SIS).

Upscaling process-based model outputs using the GIS map gave combined CO_2 and N_2O background emissions of between 0.45 and 0.5 Mt CO_2eq for grassland and 0.074 and 0.08 Mt CO_2eq for arable land. These are in broad agreement with inventory values considering that the effects of fertiliser additions and management were not considered.

This GIS/process-based model framework provides the first stage for a workable solution for the calculation of nationwide fluxes of N_2O and CO_2 from grassland and arable systems. Management/activity data linked to this framework will improve the accuracy of outputs, although we recommend a simpler empirical approach for N_2O determination. A similar approach for the forestry sector would allow more inclusive simulations of GHG emissions to help inform policy and identify pressures.

EPA Research: McCumiskey House, Richiew, Clonskeagh, Dublin 14.

Phone: 01 268 0100
Twitter: @EPAResearchNews
Email: research@epa.ie

www.epa.ie

EPA Research Webpages
www.epa.ie/researchandeducation/research/