Report No. 136

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

Development of Methodologies and Modelling for Accounting Greenhouse Gases and Organic Carbon Stocks in Agricultural Soils

Mohammad I. Khalil, UCD

Comhshaol, Pobal agus Rialtas Áitiúil
Environment, Community and Local Government

www.epa.ie

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 Climate, Licensing and Resource Use
- Office of Environmental Enforcement
- Office of Environmental Assessment
- Office of Radiological Protection
- 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 STRIVE Programme 2007-2013

Development of Methodologies and Modelling for Accounting Greenhouse Gases and Organic Carbon Stocks in Agricultural Soils of Ireland

(CCRP-09-FS-1-3)

Final Report

Prepared for the Environmental Protection Agency

By

School of Biology and Environmental Science, University College Dublin, Ireland

Author:

Mohammad I. Khalil

ENVIRONMENTAL PROTECTION AGENCY
An Ghníomhaireacht um Chaomhnú Comhshaoil
PO Box 3000, Johnstown Castle, Co. Wexford, Ireland
Telephone: +353 53 9160600 Fax: +353 53 9160699
Email: info@epa.ie Website: www.epa.ie

ACKNOWLEDGEMENTS

This report is published as part of the Science, Technology, Research and Innovation for the Environment (STRIVE) Programme 2007-2013. The programme (Research Fellowship) is financed by the Irish Government under the National Development Plan 2007–2013. It is administered on behalf of the Department of the Environment, Heritage and Local Government by the Environmental Protection Agency which has the statutory function of co-ordinating and promoting environmental research.

The author would like to thank Christoph Müller (University College Dublin [UCD]) for hosting this fellowship and providing academic support; Phillip O'Brien (Environmental Protection Agency [EPA]) for extending technical support and collaboration; Ger Kiely (UCC), Bruce Osborne (UCD), Gary Lanigan (Teagasc), Mark Richards and M. Abdalla (University of Aberdeen, Scotland) for providing data and modelling supports; Mike Jones (TCD), Mike Williams (TCD), Mohamed Helmy (UCD) and Matt Saunders (UCD) for supplying experimental data for modelling works; Jo Smith and Pete Smith (University of Aberdeen, Scotland) for allowing access to the ECOSSE model; Tom Bolger and Tommy Gallagher (UCD) and Frank McGovern and Mary Turner (EPA) for extending administrative and relevant supports.

EPA STRIVE PROGRAMME 2007–2013

Published by the Environmental Protection Agency, Ireland

ISBN: 978-1-84095-558-3 **Online version**

Price: Free

Details of Project Partners

Mohammad I. Khalil (Sr. Research Fellow)

School of Biology and Environmental Science
University College Dublin
Belfield, Dublin 4, Ireland
Emails: ibrahim.khalil@ucd.ie /khalil_ibrahim@yahoo.com

Christoph Müller (Academic Supervisor)
School of Biology and Environmental Science
University College Dublin
Belfield, Dublin 4
Ireland
Email: christoph.mueller@ucd.ie

Table of Contents

Executive Summary

Agriculture and associated land-use changes contribute a significant portion to global greenhouse gas (GHG) emissions (N_2O, CO_2 and CH_4), whereas soil organic carbon (SOC) has enormous sequestration potential. As an Annex-I country, the Republic of Ireland (ROI) submits annual national inventories of GHGs under the United Nations Framework Convention on Climate Change (UNFCCC), mainly following the Intergovernmental Panel on Climate Change (IPCC) default emission factors (EFs). The development of methodologies and modelling of soil processes will profoundly enhance the value of national inventories, both in terms of more accurate reporting and in identifying mitigation policy options. The current priority research focus is to substitute the IPCC default EFs by using country-specific ones, either through measurements and/or modelling, and to advance previous studies by reducing uncertainty in their estimates. This research fellowship progressed in three areas: (i) estimation of SOC stocks within major agricultural land uses; (ii) detailed model simulation of GHGs and SOC stock changes using the ECOSSE model; and (iii) the intercomparison of the ECOSSE, DNDC, and DailyDayCent process-based models calibrated to Irish conditions.

To develop methodologies and estimations of SOC, an analysis of high spatial resolution databases (Irish NSDB – National Soil Database) and other spatial database was performed. This included collation for major land covers, soil types and land-use areas. Empirical models were developed using measured data following a depth-distribution function and the bulk density (ρ_d) using a pedotransfer function to estimate the NSDB-derived SOC concentrations up to 100 cm depth. The models were validated using separate independent datasets. The SOC densities for grasslands on mineral and organo-mineral soils at depths of 0–10, 0–30, 0–50 and 0–100 cm were estimated at 52, 127, 170 and 214 t C ha^{-1}, respectively. For arable lands, the corresponding SOC densities were 30, 81, 118 and 167 t C ha^{-1}.

From this work, the estimated total national SOC stocks were 888 Tg for a reference depth of 0–30 cm, and 1832 Tg for 0–100 cm reference depth. For the complete soil profile, including peats >100 cm depth, the national estimate was 2824 Tg.

The selection of an appropriate process-based model to represent Irish agricultural and environmental conditions is vital for GHG balance studies and inventory purposes. A multi-pool dynamic model 'ECOSSE' (Estimating Carbon in Organic Soils – Sequestration and Emissions, v5 modified) was tested and calibrated with further improvement, including parameterizations. The model run simulated the 8-year (2003–2011) observations of a research site, and used site-specific inputs such as soil properties to a depth of 0–25 cm and available management information. The sensitivity of GHGs and SOC stock changes to soil properties and management practices was also tested. The simulated values were validated with the available measured (either seasonal and/or annual) data.

The integrated measured seasonal (crop growth period) N_2O losses were 0.39–0.60% of the N applied, and the modelled estimate was 0.23–0.41%. This suggests a model underestimation, perhaps due to the mismatching of peak fluxes between the measured and simulated values during the growing season. However, the measured annual N_2O loss (integrated) was 0.35%, and the corresponding simulated value 0.45%. On an 8-year average the modelled N_2O EF was 0.53±0.03%, indicating the importance of intensive samplings for precise estimation of N_2O EFs. This is less than the IPCC default EF and both model and field observations are consistent.

Sensitivity tests showed a clear response of GHG emissions and SOC stock changes to SOC content, available water, soil pH and management practices (type and amount of N fertilizers), bulk density and clay content. Preliminary results suggest that the model can be used to estimate the GHG balance in arable fields, subject to further refinement and analyses to fully determine the uncertainty in their estimates.

Comparative performances of three dynamic models (ECOSSE, DeNitrification DeComposition (DNDC, v9.4) and Daily Day Century (DailyDayCent) were evaluated against the same measurement data. All the models, the simulated daily or seasonal trends of GHG fluxes matched the measured values but differed significantly in terms of cumulative estimates, particularly for N_2O emissions and SOC stock changes. All models had some difficulties in simulating soil mineral nitrogen and water content, especially for the DNDC and DailyDayCent. Only the ECOSSE simulated values showed a significant correlation (R^2=0.33*) with measured values, and the overall performance of all models was not robust for unfertilized plots. The DNDC and DailyDayCent significantly underestimated total (seasonal/annual) N_2O fluxes compared to the ECOSSE.

Both DAYCENT and DNDC showed good agreement with the ecosystem respiration measured by Eddy Covariance (EC). The SOC stock changes between the DNDC and ECOSSE models were highly variable, with either sinks (9.4–13.1; DNDC) or sources (302–410 kg C ha^{-1} yr^{-1}; ECOSSE). Overall, the ECOSSE model performed better under Irish conditions than the other models in simulating GHGs and SOC stock changes.

However, refinement and validation of all models are recommended based on measured data to improve the prediction and coupling of C and N emissions, including full determination of the uncertainty in their estimates across land-use and soil types.

1 Introduction

Globally, agricultural activity is estimated to be responsible for approximately 14% of anthropogenic greenhouse gas (GHG) emissions (Intergovernmental Panel on Climate Change [IPCC], 2007). In the European Union (EU), it was estimated that about 10% of these are due to CH_4 and N_2O, of which 49 and 63% have been attributed to agriculture, respectively (Weiske and Petersen, 2006). In the Republic of Ireland (ROI), this estimate is more than double the EU average (30%; Duffy et al., 2011) and remains a key component of the national emissions profile despite a recent decrease in Irish national GHG emissions (which are linked mainly to factors associated with the recent economic downturn; EPA, 2010). The Cancun Agreements[1] emphasize that significant reductions in anthropogenic GHG emissions are needed to keep global temperature below 2^{o}C relative to pre-industrial times. It is recognized within the United Nations Framework Convention on Climate Change[2] (UNFCCC) that significant efforts are required to place global agriculture and food production on an environmentally sustainable, climate-resilient low-carbon pathway.

The soil organic carbon (SOC) pool – one of the most important reservoirs of the global-C cycle – could have the potential to act as a main source or sink of GHGs due to its large extent and active interaction with the atmosphere (Lal, 2004; Gal et al., 2007). Agricultural land is one of important pools in the global C cycle, and management practices associated with arable lands in particular determine C source or sink categories. Annual respiration rates correspond to short-term net exchange and do not give an indication of long-term soil C sequestration (Johnson et al., 2007). The potential for C sequestration, particularly in arable lands, is found to be high when related to conservation tillage, mulching, introduction of cover crops, increasing crop rotation and management practices, leading to increased crop and biomass productivity (West and Post, 2002; Six et al., 2004; Khalil et al., 2004; Franzluebbers and Follett, 2005; Johnson et al., 2007; Lal, 2007). Increases in SOC from reduced tillage now appear to be much smaller than previously claimed, at least in temperate regions, and in some situations increased N_2O emission may negate any increase in stored C (Powlson et al., 2011). However, detailed information from European studies on the

[1] http://cancun.unfccc.int/
[2] http://newsroom.unfccc.int/

environmental benefits is sparse and disparate (Holland, 2004). To achieve the targets set under the Kyoto Protocol,[3] overall GHG balance under variable inputs, soils and climatic conditions should be estimated, including elucidation of factors that regulate the processes that lead to the emission or removal of GHGs (Baggs et al., 2003; Six et al., 2004; Helgason et al., 2005; Venterea et al., 2005) and identification of the management-induced trade-off relations (Khalil and Inubushi, 2007).

Agriculture and associated disturbances regulate the distribution of carbon (C) and nitrogen (N) pools. Among the GHGs, nitrous oxide (N_2O) is a potent GHG with a global warming potential (GWP) of 298 compared to methane (CH_4) (GWP-25) and carbon dioxide (CO_2) (GWP-1). Frequent soil disturbances such as tillage practices, fertilizer application and harvesting regulate the turnover of C and N in agricultural soils, and contribute substantially to GHG emissions (e.g. Richter and Roelcke, 2000). Nitrous oxide is produced mainly by two microbial processes in the soil: (i) nitrification and (ii) denitrification, sometimes simultaneously, and the main regulating factors are pH, temperature, oxygen status, soil water, substrate supply, and so on (Conrad, 1996; Smith et al., 1998; Khalil et al., 2002; Khalil and Baggs, 2005; Stehfest and Bouwman, 2006). Important C substrates that provide an energy source for heterotrophic organisms (denitrifier), and produce N_2O, are animal manure and plant litter (Drury et al., 1998; Khalil et al., 2002; Rochette et al., 2008).

The end product of oxidation of C in organic materials is CO_2, which is released primarily from microbial decay, the burning of plant litter and soil organic matter (SOM) or lime application, and is associated with soil disturbance and land-use changes (Janzen, 2004). Methane is produced during organic matter turnover under oxygen-limiting conditions, notably from histosols and rice grown under flooded conditions (Mosier et al., 1998). Under aerobic conditions, both methanogenesis to form CH_4 in anaerobic microsites and methanotrophy to oxidize CH_4 in the interface to aerobic zones occur simultaneously, and are associated with other driving forces (Chan and Parkin, 2001; Khalil and Baggs, 2005; McLain and Martens, 2006). Soils can either be a net sink or source of CH_4, depending on moisture, N level and ecosystem (Chan and Parkin, 2001; Gregorich et al., 2005; Liebig et al., 2005). In agricultural systems, particularly under upland conditions, CH_4 oxidation prevails (Chan and Parkin, 2001; Abdalla et al., 2011; Khalil et al., 2012a) but may vary

[3] http://unfccc.int/kyoto_protocol/items/2830.php

dependent on management-induced spatial variability of GHG emissions. Thus, understanding the association of controlling factors across the landscape, their interactive relationships and site-specific soil conditions is vital (Oenema et al., 2001).

The IPCC Tier 1 approach is used to establish trends in GHG emissions (IPCC, 1996; 2006). Tier 2 emphasizes the development of country and regional-specific emission factors (EFs) for key activities. Tier 3 requires additional resources to develop more sophisticated methodologies include modelling, which can lead to improvements in estimates of GHG budgets. The higher tiers reflect more robust emission accounting, and are required to identify specific mitigation options across land use management (LUM) and land-use change. In transition to a Tier 2 approach, robust country-specific research and activity data are needed to reflect the diversity of management practices. Further refinement should include regional variations. This is also relevant to the Land Use, Land Use Change and Forestry (LULUCF) sector. The quantification of baseline SOC stocks with soil depth associated with the variety of land uses and practices is essential for assessing changes in SOC associated with land-use change. This is highly pertinent for the sustainable management of soil and thereby the identification of source and sink categories for offsetting GHG emissions. Tier 3 estimates of the GHG balance are based on an improved understanding of the relative importance of country-specific different sink and source categories and their spatial distribution. The current research exploresthe use of dynamic models to develop methodologies for SOC accounting and simulation of GHG emissions and removals. This was to reflect the soil and environmental conditions correctly and provide more accurate estimation of C and N emissions for inventory reporting.

2 Estimation of Organic Carbon Stocks in Agricultural Soils in Ireland

2.1 Introduction

With reference to the Kyoto Protocol and accounting rules set out within the Marrakech Accords,[4] it is important that revisions to inventory methodology are compatible with the net–net accounting rules. This includes the comparison of emissions and removals during the first (2008–2012) and second (2013–2020) commitment periods of the Kyoto Protocol from cropland, grazing land management, and re-vegetation with the base year. This is highly relevant to national SOC stock estimates where enormous uncertainty prevails, and where a description of the vertical distribution of SOC with depth and its spatial variation is often absent. The SOC distribution with depth has been examined by either: (i) grouping the measurements into fixed depth increments or by (ii) fitting continuous functions to the data (e.g. Omonode and Vyn, 2006). Pedotransfer functions and regression modelling, taking into account soil, land use, drainage, climate, and so on, have been used to obtain a more complete and detailed spatial distribution of SOC stocks (e.g. Meersmans et al., 2008; 2009). Exponential functions have been used widely (e.g. Meersmans et al., 2009) while logarithmic, power or polynomial functions have also been employed (e.g. Jobbagy and Jackson, 2000).

In line with commitments under the UNFCCC, the Republic of Ireland (ROI) publishes annual estimates of changes in SOC stock (McGettigan et al., 2011) using the IPCC Good Practice Guidelines (GPG) Tier 1 methodology (due to limited country-specific data, except forestry) but is committed to achieving Tier 2 or better methodology. In the ROI, previous studies predominantly focused on grassland and interpolations of SOC values to map the spatial distribution of SOC at a finer resolution using geostatistics and GIS techniques, but were limited to characterisation of the near surface soil. Previous estimates of SOC stocks in the ROI were derived mainly from: national data, including Co-ordination of Information on the Environment (CORINE) land cover map; the General Soil Map (GSM); and UK datasets

[4] http://unfccc.int/cop7/documents/accords_draft.pdf

(e.g. SOC concentrations and bulk densities for a particular soil type) with limited spatial resolution (Tomlinson, 2005; Eaton et al., 2008).

To reconcile the above discrepancies and the lack of information on SOC stocks for disaggregated agricultural land covers and soil types, a more detailed spatial assessment of baseline SOC stocks is required. Data on measured SOC concentrations and bulk densities that would reflect the SOC stocks are essential. A combination of modelling and GIS techniques provide a suitable technique for estimating soil C stocks of disaggregated agricultural land covers (Cruickshank et al., 2000; Tomlinson, 2005; Eaton et al., 2008; Xu and Kiely, 2009; Xu et al., 2011a; Zhang et al., 2011). The objectives of this study were to:

1. Collate spatially explicit pedon data and land areas for disaggregated agricultural land covers available in the ROI;
2. Develop empirical models from measured data to estimate SOC concentrations and bulk densities;
3. Estimate SOC densities (i.e. the product of SOC concentration and bulk density) for selected grid-points of the NSDB using the models (from (ii) above), relating to the various soil types; and
4. Calculate the national SOC stocks, disaggregated into grassland and arable lands using the highest- resolution spatial data available.

2.2 Materials and Methods

2.2.1 Data Acquisition

Data for land cover, land use, soil type and SOC concentration and related properties were collated to estimate the SOC densities and thereby stock (the product of SOC density and land cover area) for disaggregated agricultural land covers in the ROI. Empirical models were developed using available pedon data so as to estimate SOC densities at increments of 10 cm down to 100 cm soil depth. To achieve this, currently available relevant higher spatial resolution maps and databases were collected and the steps followed are shown in Fig. 2.1.

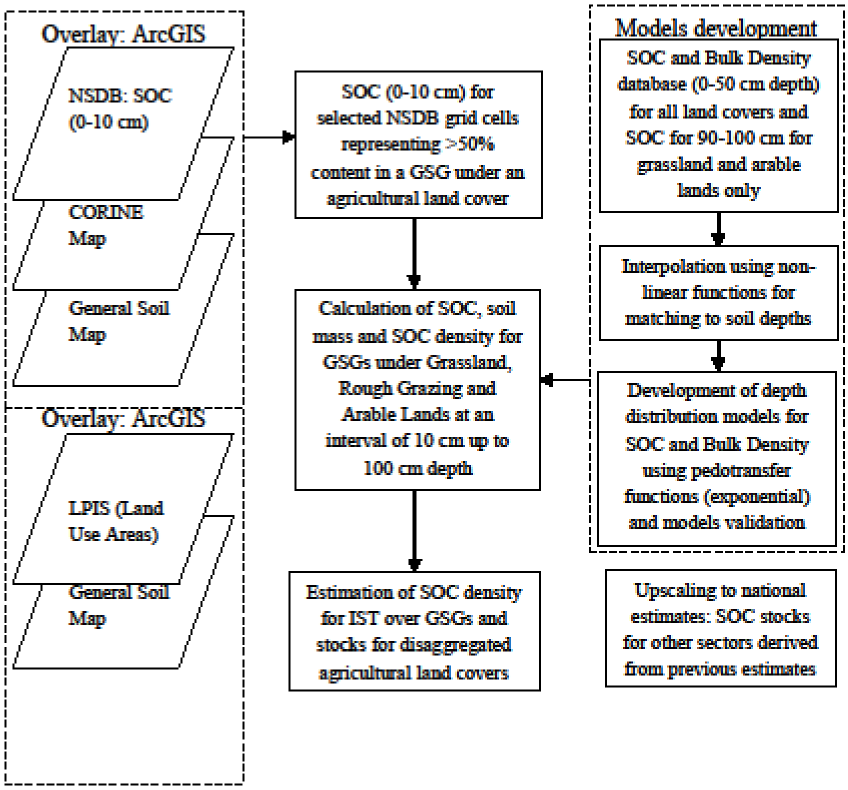

Figure 2.1. Flow paths of methodologies to estimate organic C stocks in soils under disaggregated agricultural land covers and to develop empirical models using measured pedon data (NSDB=National Soil Database, SOC=Soil Organic Carbon, GSG=Great Soil Group, LPIS=Land Parcel Information System, IST=Indicative Soil Type).

Measured SOC concentration data to a depth of 10 cm were acquired from the National Soil Database (NSDB; Fay et al., 2007). Land cover at the sampling sites comprised of grassland, arable, forestry and peat land types. In a later study, measurements of SOC concentration and bulk density (ρ_d) data to a depth of 50 cm were made at 69 selected sites of the NSDB (Kiely et al., 2009). For validation of models, independent but limited datasets on SOC concentrations and bulk densities, measured recently across soil depths (>100 cm) in Teagasc (Irish Agriculture and Food Development Authority) projects were collated and interpolated to match with soil depths (Richards et al., 2009; Diamond and Sills, 2011).

To integrate the measurement data (Kiely et al., 2009), the CORINE map was initially used to identify land cover classes based on the year 2000.[5] Out of 44 land cover classes, a subset of land cover classes as devised by Eaton et al. (2008) representing agricultural sectors (grassland, rough grazing, arable and heterogeneous agricultural areas/other) was used. The selected agricultural land covers in combination with ArcGIS (version 10, ESRI, Ireland) were used to elucidate SOC contents derived from the NSDB within a land cover and also between the land covers.

The NSDB was overlaid on the combined General Soil Map (GSM; Gardiner and Radford, 1980) and CORINE 2000 maps to estimate the SOC for a specific Great Soil Group (GSG) under each given land cover. Ten GSGs (Brown Podzolics, Grey Brown Podzolics, Brown Earth, Gleys, Podzols, Rendzinas, Lithosols, Regosols, Basin peats and Blanket peats) predominantly fall within the agricultural land covers. Basin and Blanket peats were merged into one as 'peats' while Regosols were omitted as they hold no agricultural land covers. Based on the similarity/difference in soil properties, the first four and the next three were classified as mineral and organo-mineral soils, respectively. The EPA Indicative Forestry Soils map (the 'Indicative Soil Map' [ISM]), was used to derive a set of Indicative Soil Types (IST) for each combination of land cover/land use and GSGs. In this updated system, the mineral soils are classified on the nature of their parent rock, deep or shallow, and wet or dry. Peats are classified by location, elevation and evidence of human modification.

2.2.2 Data Compilation

To better represent the diversity of soil type and vegetation, the CORINE land cover, the GSM and the NSDB spatial data were imported into ArcGIS. Buffer zones were defined with a 1 km radius centred on the NSDB sample grid-points. To ensure that the SOC data from the NSDB were representative of the local landscape, only those sample sites where the GSG and the land cover identified by the NSDB soil survey team were consistent with >50% of the GSG and land cover within the larger buffer zone were selected for further analysis. This resulted in a subset of 1028 from the total 1310 NSDB sample points. These included 350 for grassland, 51 for rough grazing, 46 for arable lands and 581 sites for other land cover type. The SOC content (10 cm depth) in the NSDB was used as the only source of accounting its densities/stocks for across land covers and soil types.

[5] http://www.epa.ie/soilandbiodiversity/soils/land/corine/#.VFi4onYuL0M

The data for both the SOC concentration and the bulk density (ρ_{d}), measured by Kiely et al. (2009) were sorted according to land cover and thereafter GSGs within a land cover, and the data were interpolated with soil depth using non-linear relationships. To estimate SOC_{ref} (baseline) stocks for the disaggregated land cover and soil type, the Land Parcel Information System (LPIS) database (2004) maintained by Department of Agriculture, Food and the Marine (DAFM) was sorted into two categories: (i) grassland and (ii) non-grassland, using ArcGIS. A total of 703,181 grassland and 180,584 non-grassland polygons were identified. These polygons were then integrated with the GSM and ISM, from which an estimate of land areas for all soil types under a land use was derived. Areas for disaggregated agricultural land covers were devised as: grassland (Pasture, Rough, Hay, and Silage) and arable crops (Cereals, Roots + Tubers, Oilseed + Forage + Fodder + Silage, and Horticulture + Fruits + others). The total area for grassland acquired from the LPIS was higher (4,333,008 ha) than the area estimated by the Central Statistics Office (CSO, 3,881,000 ha). The proportions of the CSO areas were considered to be more relevant for calculating the disaggregated areas for grassland activities. The total area of agricultural grassland is best represented by the LPIS analysis.

2.2.3 Development of Empirical Models

Empirical models were developed using the extended soil database of Kiely et al. (2009). The SOC concentration and ρ_d with depth up to 50 cm measured were fitted with an exponential function and extrapolated to 100 cm. Data for SOC and ρ_d were arranged according to the GSGs available under the agricultural land covers. Three approaches to develop empirical models were:

1 Soil type specific (STS) based either on the mean value of several measurement points or the measured single dataset available, and Land Cover Specific (LCS);
2 The mean value of GSGs under a land cover (LCS-Mean); and
3 All data points for GSGs under a land cover with removal of some outliers (LCS-All).

The rough grazing showed bidirectional profile of SOC content with depths, and an LCS-mean was taken.

Soil organic carbon content at depths more than 10 cm were calculated using the empirical models developed from distribution ratios of the measured/interpolated SOC with depth as:

$$z > 10\ cm:\ SOC_z = a\,e^{(-k \times z)} \times SOC_{z10} \qquad \text{(Eq. 2.1)}$$

Where SOC_z=Soil organic carbon content (%) at z depth (from 10–100 cm); a and k=Constants derived from the shape of the exponential part of the curve where 'a' is the initial state and 'k' the scale/depth constant of proportionality; SOC_{z10}=soil organic carbon concentration (%) at 10-cm depth from NSDB.

Owing to the unavailability of bulk density (ρ_d; g cm^{-3}) in the NSDB, empirical models were developed to calculate ρ_d from the pedotransfer function (herein SOC), as:

$$z = 10 - 100\ cm\text{: } \rho_d = a\ e^{(-k \times SOCz)} \qquad \text{(Eq. 2.2)}$$

2.2.4 Soil Mass and SOC Density

The depth distribution models were used to estimate SOC content at the NSDB sample points to 100 cm depth, but tightly constrained by the original 0–10 cm measurement data in each case. Where not available, the SOC contents across soil depths for the ISTs were derived from the values of the respective GSGs. Following the estimation of SOC content across soil depths for each soil type under the agricultural land covers derived from the NSDB, the soil depth (z=cm) was multiplied by Equation 2.2 to get soil mass (SM_z, t ha^{-1}) as:

$$SM_z = z \times \rho_d \times 100 \qquad \text{(Eq. 2.3)}$$

Then, SOC content (%) for the respective incremental soil depth (0–100 cm) was multiplied by Eq. 2.3 to calculate SOC density (t C ha^{-1}), referring to SOCD (soil organic carbon density), for each soil type (GSG versus IST) under the agricultural land covers chosen.

$$SOCD_z = SM_z \times \frac{SOC_z}{100} \qquad \text{(Eq. 2.4)}$$

2.2.5 Total SOC Stocks in Disaggregated Agricultural Soils and National Estimates

Total organic carbon stocks (TOCS) for the respective soil type under a land cover were pooled to represent specific reference soil depth (0–10, 0–30, 0–50 and 0–100 cm, except for Rendzinas, which is assumed to be 50 cm due to the presence of rocks/gravels), as:

$$TOCS_{0-100} = \sum_{0}^{100} SOCD(z)dz \qquad \text{(Eq. 2.5)}$$

The TOCS were calculated by multiplying the respective areas derived from the LPIS with SOC stocks under a land use for grassland or a group of land use for arable lands using the stocks for soil types under the land cover. For national estimates, the TOCS for other land cover classes were adopted from Eaton et al. (2008).

2.2.6 *Statistical Analysis and Evaluation*

The data and model outputs were subjected to statistical analysis to establish the potential relationships between SOC content, bulk density, carbon stocks (where applicable) , soil type, land cover and land cover classes, including for model validation. In addition to analysis of the coefficient of variations (CV) comparing the degree of uncertainty for variables within soil groups, two validation indices from the measured and predicted SOC content and bulk density across soil depths i.e. relative mean errors (RME) and the root mean square error (RMSE) were considered (Smith et al., 1997). In addition, the degree of closeness analysis comparing the output from the empirical models of SOC content and ρ_d to the measured datasets and a validation of the empirical models developed using independent datasets were performed. To test the significance of non-linear functional relationships, the ln-transformed linear bivariate fit (centred polynomial) model was followed.

2.3 Results

2.3.1 *Initial Interpolation and Quality Evaluation*

The initial interpolation of data showed a good fit of SOC to an exponential function (Range of R^2=0.90–0.99), whilst ρ_d to a natural logarithmic function (ln, R^2=0.76–0.99, majority >0.85) and both were significantly correlated (Table 2.1). Overall, the 50 cm average standard errors of means across land covers and soil groups were very small. The non-linear functional relationships provided good estimates of SOC up to 50 cm depth (R^2=0.93–0.99) and ρ_d ($R^{2=}$0.76–0.99), with lowest ρ_d for the Peats. The RME demonstrated slight under- and over-estimations for SOC and ρ_d (<1.2%) and especially a huge variation for SOC under rough gazing (0.01– -13.04%). The RMSE was small for both variables under the most soils under grassland and arable land covers (0.18–15.11%), with the exception of the Brown Podzolics and Grey Brown Podzolics under grassland. The range of RMSE was also quite high for all soil groups present under rough grazing (22.94–39.18%).

Table 2.1. Initial verifications of the simulated values for soil organic carbon (SOC) and bulk density (ρ_d) with measured data (50 cm) used to develop models by relative mean error (RME, %), root mean square error (RMSE, %) and coefficients of determination (R^2).

Soil depth (cm)	Gleys		Podzols		Brown Podzolics		Grey Brown Podzolics		Brown Earth		Lithosols		Peats	
	SOC	ρ_d	SOC	ρ_d	SOC	ρ_d	SOC	ρ_d	SOC	ρ_d	SOC	ρ_d	SOC	ρ_d
Grassland														
SE	0.06	0.06	0.09	0.04	0.10	0.04	0.05	0.02	0.04	0.05			0.03	0.13
RME	0.93	<-0.01	0.68	<-0.01	-0.62	-0.60	-0.38	<0.01	-0.15	0.31			<-0.01	-0.67
RMSE	15.02	3.61	9.49	1.64	27.51	3.24	22.94	2.24	11.20	2.15			0.18	6.67
R^2*	0.97	0.96	0.99	0.99	0.90	0.97	0.95	0.99	0.98	0.97			0.99	0.97
Rough grazing														
SE	0.11	0.06	0.13	0.14							0.06	0.07	0.04	0.19
RME	-0.41	<-0.01	-2.07	-6.07							-5.75	<-0.01	0.29	-13.04
RMSE	39.18	10.49	26.87	14.96							26.05	6.88	8.00	38.72
R^2*	0.94	0.98	0.95	0.93							0.99	0.98	0.99	0.76
Arable lands														
SE	0.13	0.09		-	0.07	0.03	0.10	0.08	0.07	0.06				-
RME	0.45	0.187			-0.75	<0.01	0.44	<-0.01	0.12	1.11				
RMSE	9.41	1.20			11.26	1.10	15.11	3.36	10.68	3.76				
R^2*	0.93	0.97			0.97	0.99	0.94	0.95	0.96	0.96				

SE=Standard error (50 cm average); * Significant at ≤0.05 level of probability

2.3.2 Development of Empirical Models

2.3.2.1 Soil organic carbon estimates and validation of models

The exponential depth-distribution models, developed using soil-depth ratio functions, fitted well for all GSGs under the agricultural land covers (Table 2.2). The R^2 of a STS approach, explaining 87 to 99% of the variance at ≤0.05–0.001 levels of significance, confirmed these. The k values (scale constant, cm^{-1}; negative) differed between the GSGs within or between land covers. The models were validated with independent datasets separately for both up to 50 and 100 cm, covering major soil types, and found to have equal statistical agreements. The models of mineral and organo-mineral soil types yield RME of ≤44% and RMSE of ≤61%. with the exception of the model for Gleys soils under rough grazing, which showed larger bias and low accuracy of the predictions. However, the R^2 was high, explaining 87% of the variance, and was significantly correlated (p<0.05).

Table 2.2. Parameters of depth distribution models derived from measured soil organic carbon (SOC) ratio function to estimate SOC content (%) at lower depths based on its amount at the 0-10 cm in the NSDB (SOC ($z \leq 10$ cm)=SOC_{z10}) and their statistical evaluations.

Great Soil Group	Soil type specific (STS)		Statistical evaluation for STS			Land Cover Specific (LCS)	
	Equation (x SOC_{z10})	R^2	RME	RMSE	R^2	Mean	All data points
Grassland§							
Gleys	$1.2653 \cdot e^{(-0.031z)}$	0.99***	-14	53	0.88*	$1.4556 \cdot e^{(-0.037z)}$ x SOC_{z10}	$1.499 \cdot e^{(-0.040z)}$ x SOC_{z10}
Podzols	$1.0769 \cdot e^{(-0.029z)}$	0.87*	32	36	0.99*	R^2=0.99***	R^2=0.76***
Brown Podzolics	$1.5477 \cdot e^{(-0.039z)}$	0.99***	6	26	0.97*		
Grey Brown Podzolics	$1.6339 \cdot e^{(-0.045z)}$	0.99***	7	31	0.96*		
Brown Earth	$1.4895 \cdot e^{(-0.035z)}$	0.99***	4	26	0.96*		
Lithosols	$1.9668 \cdot e^{(-0.080z)}$ [a]	0.99***					
Rendzinas	$1.2359 \cdot e^{(-0.023z)}$ [b]	0.97***					
Peats	$1.4211 \cdot e^{(-0.038z)}$ [c]	0.99*					
Sand	$1.3456 \cdot e^{(-0.051z)}$	0.95**					
Rough grazing§§							
Gleys	$1.6975 \cdot e^{(-0.042z)}$	0.98**	-78	128	0.87*	$1.1531 \cdot e^{(-0.020z)}$ x SOC_{z10}	$1.1531 \cdot e^{(-0.020z)}$ x SOC_{z10}[c]
Podzols	$1.5357 \cdot e^{(-0.046z)}$	0.99***	-12	28	0.97*	R^2=0.98**	R^2=0.98**
Brown Podzolics	$1.1054 \cdot e^{(-0.016z)}$ [a]	0.96***					
Grey Brown Podzolics	$1.1054 \cdot e^{(-0.016z)}$ [a]	0.96***					
Brown Earth	NA						
Lithosols	$1.9668 \cdot e^{(-0.080z)}$	0.99***					
Rendzinas	$1.2359 \cdot e^{(-0.023z)}$ [b]	0.97**					
Peats	$1.1457 \cdot e^{(-0.003z)}$	0.95***					
Sand	NA						
Arable lands							
Gleys	$1.2909 \cdot e^{(-0.016z)}$	0.91*				$1.3518 \cdot e^{(-0.021z)}$ x SOC_{z10}	$1.3535 \cdot e^{(-0.021z)}$ x SOC_{z10}
Podzols	NA					R^2=0.95***	R^2=0.83***
Brown Podzolics	$1.3993 \cdot e^{(-0.023z)}$	0.93**					
Grey Brown Podzolics	$1.4355 \cdot e^{(-0.025z)}$	0.96**	-44	61	0.94*		
Brown Earth	$1.3217 \cdot e^{(-0.021z)}$	0.98**					
Lithosols	NA						
Rendzinas	NA						
Peats	NA						
Sand	NA						

z=soil depth (0-100cm); NA=not available; RME=relative mean error (%); RMSE=Root Mean Square Error (%); R^2=Coefficient of determination; *, **, *** Significant at ≤0.05, 0.01 and 0.001 levels of probability. § For grassland: a=derived from rough; b=derived from IFS 12, 22 and 31, representing Brown Earth & peat mineral; c=derived from both grass and peat, §§ For rough grazing: a=derived from Gleys (IFS 41); b=derived from grassland; c= mean taken due to huge variations

The LCS models also showed very high prediction power for SOC with depth (R^2=0.83–0.99; $p \leq 0.01$–0.001). A comparative study between the STS and LCS models demonstrated little variations in SOC within a land cover, but some over- or under-estimations for a specific GSG under a land cover were observed (data not shown). Thus, STS models were finally adopted to estimate the SOC concentration (%) to 100 cm using the 10-cm depth values available in the NSDB. Based on the SOC concentration of 0–10 cm depth available in the NSDB, the estimated concentrations (mean) using the depth-distribution models (STS) for the acquired GSGs under a land cover varied significantly ($p \leq 0.05$–0.001) with depths between soil types within a land cover as well as between land covers (Fig. 2.2a,b,c).

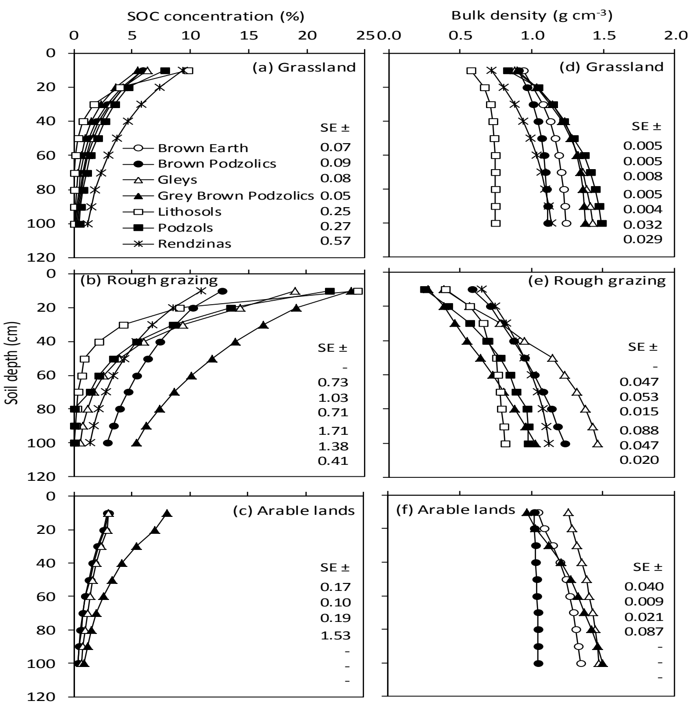

Figure 2.2. Estimated (mean) soil organic carbon (SOC) concentration (%) and bulk density (g cm^{-3}) of the Great Soil Groups (GSG) except peats with soil depth under major agricultural land cover/use: (a, d) grassland, (b, e) rough grazing, and (c, f) arable lands. Within GSGs under a land cover/use, the standard error (SE) for SOC content and bulk density is the averaged SE of 0–100 cm profile.

2.3.2.2 Bulk density estimates and validation of models

Table 2.3 shows the STS and LCS empirical equations to estimate ρ_d from pedotransfer function (SOC) for individual GSGs within land-cover data. Regardless of land covers, the k values varied between the GSGs and the R^2 were greater than 90% of the variance except for the Peats and Rendzinas under grassland/rough grazing ($p \leq 0.05$–0.001). Statistical evaluation of the models showed an RME of ≤21% (±) and an RMSE of ≤22% except for Podzols under rough grazing (45%). The R^2 (except for Brown Podzolics and Brown Earth under grassland) were also high and significantly correlated ($p \leq 0.05$), explaining ≥84% of the variance.

Table 2.3. Estimate parameters for soil bulk density (ρ_d) derived from measured pedotransfer function [soil organic carbon (SOC), %] across soil depths and their statistical evaluations.

Great Soil Group	Soil type specific (STS)		Statistical evaluation for STS			Land Cover Specific (LCS)	
	Equation (x SOC_{z10})	R^2	RME	RMSE	R^2	Mean	All data points
Grassland§							
Gleys	$1.466\cdot e^{(-0.083\cdot SOCz)}$	0.99**	10	14	0.87*	$1.3342\cdot e^{(-0.071\cdot SOCz)}$	$1.3699\cdot e^{(-0.076\cdot SOCz)}$
Podzols	$1.5091\cdot e^{(-0.81\cdot SOCz)}$	0.95*	4	6	0.98*	R^2=0.99***	R^2=0.70***
Brown Podzolics	$1.1272\cdot e^{(-0.038\cdot SOCz)}$	0.93**	4	9	0.68*		
Grey Brown Podzolics	$1.3828\cdot e^{(-0.082\cdot SOCz)}$	0.99***	12	14	0.81*		
Brown Earth	$1.2542\cdot e^{(-0.050\cdot SOCz)}$	0.99**	18	22	0.74*		
Lithosols	$0.7437\cdot e^{(-0.027\cdot SOCz)\ a}$	0.91*					
Rendzinas	$1.2177\cdot e^{(-0.057\cdot SOCz)\ b}$	0.85*					
Peats	$1.4045\cdot e^{(-0.048\cdot SOCz)\ c}$	0.86**					
Sand	$1.1701\cdot e^{(-0.313\cdot SOCz)}$	0.90**					
Rough grazing§§							
Gleys	$1.5232\cdot e^{(-0.075\cdot SOCz)}$	0.95**	3	18	0.85*	$1.624\cdot e^{(-0.064\cdot SOCz)}$	$1.624\cdot e^{(-0.064\cdot SOCz)\ d}$
Podzols	$0.9749\cdot e^{(-0.067\cdot SOCz)}$	0.97*	21	45	0.93*	R^2=0.98**	R^2=0.98**
Brown Podzolics	$1.5232\cdot e^{(-0.075\cdot SOCz)\ a}$	0.97**					
Grey Brown Podzolics	$1.5232\cdot e^{(-0.075\cdot SOCz)\ a}$	0.97**					
Brown Earth	NA						
Lithosols	$0.7437\cdot e^{(-0.027\cdot SOCz)}$	0.95*					
Rendzinas	$1.2177\cdot e^{(-0.057\cdot SOCz)\ b}$	0.85*					
Peats	$1.4045\cdot e^{(-0.048\cdot SOCz)\ c}$	0.86*					
Sand	NA						
Arable lands							
Gleys	$1.5257\cdot e^{(-0.062\cdot SOCz)}$	0.98*				$1.4018\cdot e^{(-0.082\cdot SOCz)}$	$1.6296\cdot e^{(-0.157\cdot SOCz)}$
Podzols	NA					R^2=0.98**	R^2=0.73***
Brown Podzolics	$1.0454\cdot e^{(-0.016\cdot SOCz)}$	0.93*					
Grey Brown Podzolics	$1.6925\cdot e^{(-0.152\cdot SOCz)}$	0.97**	-7	10	0.84*		
Brown Earth	$1.4289\cdot e^{(-0.105\cdot SOCz)}$	0.99***					
Lithosols	NA						
Rendzinas	NA						
Peats	NA						
Sand	NA						

z=soil depth (0-100cm); NA=not available; RME=relative mean error (%); RMSE=root mean square error (%); R^2=Coefficient of determination; *, **, *** Significant at ≤0.05, 0.01 and 0.001 levels of probability. §For grassland: a=derived from rough grazing; b=derived from IFS 12, 22 and 31, representing Brown Earth & peat mineral; c=derived from both grass and peats. §§For rough grazing: a=derived from Gleys (IFS 41); b=derived from grassland; c=derived from both grass and peat; d=mean taken due to large variations.

The model based on mean values of all GSGs, labelled LCS (Mean) in Table 2.3, under the land covers, explained >98% of the variance (p≤0.01–0.001), whereas when the individual data points under each land cover, labelled LCS (All), resulted in a lower predictive power for ρ_d from SOC, particularly for grassland and arable land (R^2=0.70 versus 0.73; p≤0.001) than with LCS (Mean). The estimated ρ_d (mean) using the STS pedotransfer function for the corresponding soil depths of GSGs under a land cover/use varied significantly (p≤0.05–0.001) between soil types within a land cover as well as between land covers (Fig. 2.3d,e,f).

Finally, the STS empirical models were adopted to estimate soil mass for individual soil types and thereby SOC density for disaggregated agricultural land covers.

2.3.3 Soil Organic Carbon Density Variations

Under grassland, large differences in SOC density up to 60 cm soil depth between the GSGs were detected, being significantly ($p \leq 0.001$) greater in the Peats across soil depths and in the surface and bottom layers of the Rendzinas (data not shown). The Lithosols had higher SOC density but decreased substantially at the deeper layers. There were mostly insignificant variations among the Gleys, Brown Podzolics, Grey Brown Podzolics and Brown Earth. Under rough grazing, the SOC density for the Peats was significantly ($p<0.001$) higher than other soil types (except Lithosols) in the surface layer. For the Lithosols it was higher in the surface soil only though it did not differ significantly with other soil groups. The Brown Podzolics and Rendzinas demonstrated higher SOC density in the surface only but varied insignificantly from the Grey Brown Podzolics and Gleys. The Podzols had SOC values significantly lower from 30 cm downwards than in the other soil types with the exception of Lithosols. Under arable lands, the overall SOC densities were smaller than those under rough grazing and grassland – except for the Peats, which were significantly ($p \leq 0.001$) different from other soil groups. Soil organic carbon densities across soil depths were estimated to be higher for the Gleys but similar to the Grey Brown Podzolics, Brown Earth and Brown Podzolics.

When the SOC values for the Peats were combined with the other soil groups, huge differences between the land covers were found, with CV ranging between 58 and 163% (data not shown). Rough grazing had the highest SOC density up to 100 cm depth over grassland and arable lands, and they varied significantly ($p<0.001$). When the Peat data were removed, the CVs reduced to 46 and 67%. Under rough grazing, the SOC density was again significantly ($p<0.001$) higher throughout the profile than for the other two land covers, with significant ($p<0.001$) variations only at the surface soil. For arable lands, significant ($p<0.001$) increase in SOC density from 70 cm depth downwards over grassland was found. For the Peats, the average of land covers reduced the huge variations to 65%, but the SOC density mostly differed significantly ($p<0.001$) across soil depths between land covers.

The model-based estimates of SOC density varied significantly (p<0.001) and for grassland (on average including rough grazing and without Peats), it was 52.2, 127.1, 170.9 and 213.8 t ha^{-1} at the 0–10, 0–30, 0–50 and 0–100 cm reference depths, respectively (Table 2.4). The corresponding amount for arable lands was significantly lower (29.9, 81.3, 117.6 and 167.5 t ha^{-1}). Relative to grassland (land use factor of 1), the SOC references at the 0–30 cm depth of mineral soils under arable are 0.67, corresponding to 40 t C ha^{-1} lower than grassland soils; and under rough grazing is 1.51, corresponding to 62 t C ha^{-1} higher than grassland soils.

Table 2.4. Estimates of soil organic carbon (SOC) density (tonne per hectare) derived from the respective GSGs under grassland, rough grazing and arable lands with and without Peats, with standard error (SE) of mean and coefficient of variation (%) in the parenthesis.

Reference soil depth (cm)	SOC density ± SE (t C ha^{-1})			
	Grassland	Rough grazing	Grassland + Rough grazing (average)	Arable lands
With peat				
0–10	52.3 ± 0.9c (26)	78.6 ± 2.3a (29)	56.0 ± 0.9b (32)	39.1 ± 2.3d (78)
0–30	124.7 ± 2.7c (29)	228.3 ± 6.7a (28)	139.1 ± 2.5b (39)	109.2 ± 6.7c (84)
0–50	164.5 ± 4.7c (32)	363.4 ± 11.6a (35)	192.5 ± 4.3b (50)	165.6 ± 11.7bc (94)
0–100	204.1 ± 10.9c (60)	641.3 ± 27.0a (52)	265.0 ± 10.1b (85)	268.6 ± 27.3bc (120)
Without peat				
0–10	50.9 ± 0.6b (22)	95.1 ± 2.0a (18)	52.2 ± 0.6b (24)	29.9 ± 1.6c (33)
0–30	121.5 ± 1.7b (25)	183.2 ± 5.5a (17)	127.1 ± 1.7b (28)	81.3 ± 4.5c (34)
0–50	160.6 ± 2.8c (28)	274.0 ± 8.8a (37)	170.9 ± 2.7b (34)	117.6 ± 7.2d (33)
0–100	194.9 ± 4.7c (47)	404.1 ± 15.0a (44)	213.8 ± 4.5b (47)	167.5 ± 12.2c (33)

The mean values followed by the same letter are not significantly different between the land uses

2.3.4 Total SOC Stocks in Disaggregated Agricultural Land Cover and National Estimates

Being the dominant land use under grassland, pasture had a higher SOC stock of 139.4, 332.1, 441.3 and 537.1 Tg at 0–10, 0–30, 0–50 and 0–100 cm soil depths, respectively (Table 2.5). The nation total in the ROI (the sum of disaggregated grassland) SOC stocks (TOCS) for grassland was estimated to be 246.9, 608.1, 829.5 and 1079.3 Tg at the corresponding soil depth. Cereals, which were the dominant land use under arable lands, had a SOC stock of 10.6 for the 0–10 cm, 28.7 for the 0–30 cm, 40.2 for the 0–50 cm and 52.2 Tg for the 0–100 cm soil depths, which was several times higher than the estimate for other crops. The TOCS for arable lands was 13.5 for the 0–10 cm, 36.7 for the 0–30 cm, 50.2 for the 0–50 cm and 67.0 Tg for the 0–100 cm soil depth.

Table 2.5. Areas (ha, hectare) and soil organic carbon (SOC) stocks (Terragram, Tg) for disaggregated land-use classes under grassland and arable lands derived from Land Parcel Information System (LPIS, 2004) and their total estimates at four reference depths.

Land cover	Disaggregated, grouped land cover/use	Area (ha)		SOC stocks (Tg) at a reference depth (cm)			
		LPIS (2004)	CSO (2004)	0–10	0–30	0–50	0–100
Grassland							
	Pasture	2,476,435	2,218,100	139.4	332.1	441.3	537.1
	Rough	506,318	453,500	33.6	97.9	150.5	240.4
	Hay	211,012	189,000	11.2	27.5	37.4	47.1
	Silage	1,139,243	1,020,400	62.7	150.6	200.3	254.6
Total*		4,333,008	3,881,000	246.9	608.1	829.5	1079.3
Arable lands	Cereals	319,955	310,100	10.6	28.7	40.2	52.2
	Roots + Tubers	41,054	49,700	1.3	3.6	4.3	6.6
	Oilseed + Foliage + Fodder	30,103	36,900	1.0	2.7	3.6	5.1
	Horticulture + Fruit + Other	18,496	26,100	0.6	1.7	2.1	3.2
Total		409,608	422,800	13.5	36.7	50.2	67.0
Grand total		4,742,616	4,303,800	260.5	644.8	879.8	1146.2

National estimates	SOC stocks (Tg) at a reference depth (cm)		
	0–30	0–100	0–100+ (>100 for peats)
This study**	888	1832	2824
Eaton et al. (2008)	728	1469	2437
Tomlinson (2005)	–	–	2021

* The proportions of CSO are taken for best estimation of land-use classes in the LPIS (2004). For disaggregated CSO under arable, fodder beet is included under Roots and Tubers. ** For comparison, land-use areas under CORINE 2000 used by Eaton et al. (2008) and Tomlinson (2005) were taken.

The TOCS for grassland and arable lands were summed with the other land cover classes from Eaton et al. (2008) to calculate national stocks. A TOCS of 888 for the 0–30 cm and 1832 Tg for the 0–100 cm soil depth were found (Table 2.5). For the complete soil profile that includes peats >100 cm depth (0–100+) using the values from Tomlinson (2005) and Eaton et al. (2008), our estimated TOCS is 2824 Tg. Grassland accounted for 68.5% for the 0–30 cm, 58.9% for the 0–100 cm and 38.2% for the 0–100+ cm soil depth of the total national stocks. For arable lands, this amount was 4.1% for the 0–30 cm, 3.7% for the 0–100 and 2.4% for the 0–100+ cm soil depth, and the remaining accounted for other land cover classes.

2.4 Discussion

The depth distribution models based on exponential functions developed using the data of Kiely et al. (2009) perform well, explaining 87 to 99% of the variance. The total error and bias differences between measured and simulated values were mostly <61% and correlated highly significantly. This indicates that these empirical models can estimate SOC across soil depths reliably, particularly for mineral and organo-mineral soils. Despite the high R^2 (>87%), the large SOC variability for the Gleys under rough grazing specifies that the amount of independent datasets should be land use specific and large enough to validate a model. The LCS models show a little variation for SOC within a land cover type compared to the STS models. Use of a single empirical equation to describe SOC might not capture the importance of land cover and soil type, which is in line with Xu and Kiely (2009). The empirical models developed to estimate ρ_d from the pedotransfer function (SOC) are applicable for each GSG within a land cover, which is in accordance with the statistical evaluation of the model's predictability with total error and bias of <45%. Exponential functions provided the best fit to the measurement data, in agreement with others (e.g. Meersmans et al., 2009; Xu and Kiely, 2009). To minimise uncertainty within a soil type and to better represent a soil type under a land cover/use, the soil-type specific models explaining more than 86% of the variance were adopted to estimate SOC below the surface layers and ρ_s from SOC across soil depths.

Analysis based on the GSGs shows that SOC densities in mineral soils (Gleys, Brown Podzolics, Grey Brown Podzolics, Brown Earth and somewhat Podzols) – particularly under grassland and arable lands – are similar but vary with the amount across soil depths. In a few instances, there is evidence of organo-mineral soil layers, particularly within Lithosols and Rendzinas. However, influences of particle-size distribution, bulk density, elevation and climatic conditions, including rainfall distribution, which regulate the degree of decomposition and thereby organic C accumulation in soils, are thought to be important factors for long-term SOC stocks (Meersmans et al., 2009). Unlike under grassland, the SOC density for the Peats under rough grazing and arable lands provide a reasonable estimate. Arable crops are generally not grown on peat soils, and errors associated with GSM should be corrected through reinvestigation. Despite some variations within the organo-mineral soils under all land covers near the surface layers, the models provide a good estimate of the SOC concentration and thereby density across the soil depths.

A high spatial variability (CV of 50%) for SOC density in grassland compared to arable lands has been reported by Cannell et al. (1999) where soil samplings with depths had a large contribution (Chevallier et al., 2000). In our study, Peats played a key role in uncertainty and the separate analysis of Peats reduced the CV in the analysis of the other soil groups to 28%. The average estimate of three land covers for the Peats, with CV of 65%, may be used for a realistic estimate under the agricultural land covers. The large SOC variability for the Peats suggested that it is useful to separate analysis of Peats from other soil types, including the requirement of a large number of sampling sites. Our estimate is consistent with the IPCC default values (IPCC, 1996; 2007) for the SOC references at 0–30 cm depth of the mineral soils under arable lands relative to grassland (considering land-use factor of 1). The factor for rough grazing is higher (1.51) than the 'IPCC natural reference=1' but this probably reflects the poor-quality high peat content of these low-productivity soils.

On average, the SOC density for all soils (excluding peats) under grassland (including rough grazing) is greater for the 0–10 cm and 0–30 cm (11 versus 4%) but lower for the 0–50 cm (-4%) than the estimates of Xu and Kiely (2009). Considering the 0–30 cm versus 0–100 cm depths, it is 27 and 7% greater than estimates of others (Bradley et al., 2005; Eaton et al., 2008). In this study, the estimated amount of arable lands is 34 and 24% lower compared to reference depths estimated by Xu and Kiely (2009) but higher by 8 and 25% compared to the amounts estimated by Bradley et al. (2005). The main reasons for the SOC density differences with ours are most likely the use of a common equation, variable data sources, absence of land cover/use as variables and inclusion of peats/peaty soils in their calculations.

Considering the 0–100 cm depth values, our estimate for SOC density for grassland (without Peats) is 16% greater than for arable lands, which is similar to the estimates (16%) in Great Britain by Cruickshank et al. (1998). The inclusion of values for rough grazing raises the estimate to 28%, which is lower (except for the latter conditions) than the estimates (24–43%) made by others (e.g. Meersmans et al., 2009; 2011). When Peats are included, the estimate for grassland SOC density either increased or decreased at deeper depths over arable lands, again implying separate accounting of Peats for reliable estimates of SOC density. Grassland is the dominant land cover in the ROI and pasture SOC stocks account for 50% of the total grassland stocks, silage (24%), rough grazing (22%) and hay (4%). In comparison with Eaton et al. (2008), our estimates for the 0–30 cm and 0–100 cm depth are 61 and 79% higher. Moreover, our estimates are 38% at the 0–10 cm, 32% at the 0–30 cm and 24% at the 0–50 cm higher than the estimates of Xu and Kiely (2009). Although cattle-grazing and silage under grassland is the dominant land use, the high amount of SOC in soils under rough grazing prompted us to estimate the carbon stocks under rough grazing separately in this study, in contrast to the approach taken in other studies (Eaton et al., 2008; Xu and Kiely, 2009).

In this study, for the first time for the ROI, the higher-spatial resolution data were used to estimate the total SOC stocks for the selected soil depths under disaggregated agricultural land covers. The estimated national SOC stocks of 888 and 1832 Tg at the 0–30 and 0–100 cm soil depth are considerably higher (22 versus 25%) than previous estimates (Eaton et al., 2008). For the 0–30 cm soil depth, our estimate is slightly lower (2%) than that of Xu and Kiely (2009). Considering the complete soil profile by taking values for other sectors from Eaton et al. (2008), the total SOC stock 2824 Tg is 16 and 40% higher than the estimates of Eaton et al. (2008) and Tomlinson (2005), respectively. The advantages of the findings of Xu and Kiely (2009) over the previous studies are mainly in terms of the use of measured data. Compared to the current research, they have reported similar estimates of national SOC stocks, but lack information for the 0–100 cm depth. However, the SOC density differences found by Xu and Kiely (2009) between the land cover classes seem unrealistic and may constrain their future use in carbon accountings for agricultural soils. In this study, the methodological approaches used take into account the SOC variations across soil depths, and the estimates of its stocks are consistent with – but larger than – previous estimates. Compared to the previous approaches, the empirical models developed here represent disaggregated land-use classes and soil types. Thus, these models can potentially be used to estimate SOC stocks, particularly the changes occurring in the LULUCF.

2.5 Conclusions

The exponential relationships derived from the measured SOC concentration and bulk density data provide the best estimates of SOC and ρ_d for mineral and organo-mineral soils. The large variability of SOC content for the peats across land covers makes it necessary to analyse peat separately from other soil types to minimise this uncertainty. Soil type specific models can estimate SOC at depths below the surface layers. Bulk densities can then be estimated from the estimated SOC across soil depths with less ambiguity within a soil type and also under a land use. The higher spatial resolution data for land-use areas, providing disaggregated agricultural land covers, offer advantages over the CORINE map. Soil disturbances associated with arable lands lead to lower total SOC stocks than for grassland, having enormous potential to offset GHGs from other sectors and/or opportunities to claim carbon credits. The estimated baseline SOC stocks for disaggregated agricultural land covers could be useful for the LULUCF accounting, including the supply of stratified input data for use in any ecosystem model and their verification. Results imply that the methodological approaches of the present study can provide robust estimates of SOC stocks for the development of Tier 2, and thereby for associated land-use changes.

3 Simulation and Sensitivity Analyses of Greenhouse Gases using the ECOSSE Model

3.1 Introduction

In the ROI, agricultural activity is estimated to be responsible for approximately 30% of anthropogenic GHG emissions (Duffy et al., 2011). Despite a recent decrease in national GHG emissions (Duffy et al., 2011), agricultural emissions remain a key component of Ireland's emissions profile. In line with the commitments under the UNFCCC, the ROI publishes annual estimates of agricultural GHGs mainly using IPCC GPG Tier 1 methodology, but is committed to developing Tiers 2 and 3 using the activity data currently available. Many factors are linked to a model's capability of reproducing exchange processes in an ecosystem with particular reference to the simulation of N_2O emissions. Evaluation of a model's performance is a challenging task, and its reliability depends mainly on validation against measured high-quality activity data and the addressing of relevant issues. Data collection across land use, soil type and management is time consuming and expensive. A process-based model which takes into consideration the most vital processes for producing GHGs and represents the influence of field and management conditions is an alternative approach for overcoming the these problems.

There are fundamental functional relations between organic C and N derived from either inorganic or organic sources towards GHG emissions (Khalil and Inubushi, 2007). Inputs (above- and below-ground C and N), short-term management history and detailed measurement data for N_2O, CO_2, and CH_4 as well as ancillary information such as soil water content, soil temperature, changes in mineral N and C content are keys for evaluating models (Del Grosso et al., 2009). The application of inorganic and organic fertilizers, tillage intensity and type, crop rotation and cover crop are major management practices that regulate the degree of GHG emissions from arable fields. However, linkages between the sources and sinks processes influenced by different management approaches might offset the benefits, particularly of storing soil C, through enhanced emission of one or other of the non-CO_2 GHGs (Johnson et al., 2005; Khalil and Inubushi, 2007). A process-based model could take into account the functional relations and would provide a flexible and structured way for assessing how different scenarios and measures for land-use management and change can affect GHG emissions and soil C dynamics. From the viewpoint of climate change, the pivotal component is to enable the integrated assessment of net GHG fluxes to elucidate overall management impacts and thereby find mitigation options. To enable a realistic simulation of C and N emissions, all important agricultural activities, having either a major or minor impact, should be considered. Sensitivity analysis for land-use types, site characteristics (soil properties) and major N fertilizers are indispensable criteria for improving the value of a model's performance.

In the ROI, the current research focus is on the simulation of GHG emissions and balance estimates for Agriculture and LULUCF, including the reduction of uncertainty in their estimates. Several process-based models are used to simulate GHGs where complex processes and interactions in the ecosystems are well thought out (DNDC, DayCent, PASIM, etc.). The recently developed ECOSSE model (Smith, 2010) has several advantages compared to many other process models – including a requirement for limited metrological and soil data to run, (Smith et al., 2010). It can simulate the impacts of land-use and climate change on C and N emissions/stores for both mineral and organic soils at the field through national scales. In the ROI, spring barley is the principal cereal crop, occupying 84% and 56% of the total spring cereals (barley, wheat and oats) and total cereals, respectively grown in 2009 (CSO, 2011). The ECOSSE model was initially adapted to predict coupled C and N emissions from spring barley field. The main focuses of this work were to:

1. Simulate N_2O, CO_2 and CH_4 emissions from spring barley field and validate the ECOSSE model outputs with measured data;
2. Evaluate the performance of the model in simulating SOC stock changes in comparison to literature data available across temperate regions; and
3. Test the sensitivity of the model for coupled GHG emissions and SOC stock changes to site characteristics and land-use managements.

3.2 Materials and Methods

3.2.1 Study Sites

Data on inputs and management practices were collected from field experiments (small and large plots) conducted at the Teagasc Oak Park Research Centre, Carlow, Ireland. The soil (0–10 cm depth) at Oak Park site is classified as a sandy loam (overlying loam) in texture, free draining, and Euteric Cambisol (Grey Brown Podzolics). Detailed site characteristics (and some managements), which may differ with others (Abdalla et al., 2009; 2012) due to averaged out of samples taken from both small and large plots/fields are given in Table 3.1. Thirty years (1982–2011) annual mean rainfall, air temperature and potential evapotranspiration measured from the nearby weather stations (Kilkenny and Oak Park Carlow) by Met Éireann were also used as inputs to run the ECOSSE model.

Table 3.1. Site characteristics of experimental field.

Location	**Oak Park, Carlow**
Latitude–Longitude	52°86' N – 6°54' W
Mean annual air temperature (^{o}C)	9.8
Mean annual precipitation (mm)	870.5
land-use history	Cereals (15 years), croplands (50 years), received 140–160 kg N ha^{-1} in 2003 and the year before. Spring barley since 2000.
Soil type (FAO/Irish GSG)	Euteric Cambisol/Grey Brown Podzolics
Soil texture: 0–10/0–25 cm	Sandy loam
Clay (%): 0–10/0–25 cm	15.13/14.73
Silt (%): 0–10/0–25 cm	25.63/33.73
Sand (%): 0–10/0–25 cm	59.24/51.55
Bulk density (g cm^{-3}): 0–10/0–25 cm	1.42/1.46)
Total soil organic carbon (kg ha^{-1}): 0–10/0–25 cm	19,912/42888
Total inert soil organic carbon (kg ha^{-1}): 0–10/0–25 cm	3,863/8163
Soil pH: 0–10/0–25 cm	7.24/7.35
Available water (AW) at field capacity (mm): 0–10/0–25 cm	22.69/55.13
Water content at saturation (%): 0–10/0–25 cm	47.21 (AW=29.51mm)/45.56=113.87 mm (AW=71.17)
Water content at field capacity (%): 0–10/0–25 cm	40.39 (AW=22.69 mm)/38.97=97.43 mm (AW= 54.73mm)
Water content at wilting point (%): 0–10/0–25 cm	17.70 (=17.70 mm)/17.08=42.7 mm
Initial NH_4 and NO_3 (kg N ha^{-1}): 0–10/0–25 cm	2.8/6.92 and 9.5/ 23.17
Annual atmospheric N deposition (kg ha^{-1})	11
Slope (%) and water table depth (cm)	0.004% from vertical and 240
Depth of impermeable layer (cm) and drainage class	>150 and High

3.2.2 Description of Field Experiments

An experiment was carried out in small plots to determine the impact of N fertilizer application rates on N_2O and CH_4 fluxes and ancillary properties (e.g. mineral N, soil water content). Eddy Covariance (EC) for the measurement of soil/ecosystem respiration (R_{eco}) was installed in a large plot (~2.5 ha), receiving the highest rate of N fertilizer (135–159 kg N ha^{-1}), next to the small plots. The depth of conventional tillage (CT) was 22–25 cm (mouldboard ploughing), which was done prior to planting. The crop residues were chopped and left on the field following harvest of each crop (July or August) over the autumn and winter period (Table 3.2). A light tilling was considered for the CT treatment required to sow seeds (spring barley, var. Tavern or Quench) using cultivator drill followed by rolling. N fertilizer was applied in the form of calcium ammonium nitrate (CAN). The experiment was arranged in a complete randomized block design with four replicates (details can be found elsewhere: Abdalla et al., 2009, 2010a, b, 2012). The amount of N applied varied somewhat from year to year (2004–2006) and splits into two from 2005 onwards. The unfertilized control started in 2003 and, prior to that, the whole field received 140–160 kg N ha^{-1}.

3.2.2.1 Measurements of N_2O, CO_2 and CH_4

During the 2004–2005 experimental periods, seasonal (crop growth period; April to August) measurements of N_2O concentrations were carried out using a closed chamber method. Gas

Table 3.2. Inputs and management practices (EC=Eddy Covariance/large plot received highest N rate).

Land use	Spring barley (var. Tavern or Quench)
Date of previous crop harvested	17/08/03
Type and depth of tillage practices	Conventional (22–25 cm)
Date of tillage practices (Ploughed and light till)	19/02/04 and 25/03/04; 09/03/05 and 14/03/05; 10/03/06 and 19/03/06; 24/02/07 and 18/03/07; 22/02/08 and 19/03/08; 18/02/09 and 18/03/09; 02/03/10 and 08/03/10; 02/03/11 and 08/03/11
Date of sowing	26/03/04; 16/03/05; 20/03/06; 21/03/07; 20/03/08; 19/03/09; 09/03/10; 09/03/11
Residue incorporation	3.0 t DM ha^{-1}(1.32 t C ha^{-1}), chopped and left on the field; incorporated during tillage operation only
Type of N fertilizer	Calcium Ammonium Nitrate (CAN)
Number of fertilizer application	2003–04: 1; 2005–11: 2
Fertilizer N rates (kg N ha^{-1})	2003: 140; 2004: 0 and 140; 2005: 0 and 159 (106 + 53); 2006: 0 and 140 (90 + 50); 2007–2011: 0 and 135 (67.5+ 67.5)
Date of fertilizer application	27/04/04; 12/04/05 and 10/05/05; 12/04/06 and 11/05/06; 20/04/07 and 10/05/07; 16/04/08 and 15/05/08; 21/04/09 and 22/05/09; 13/04/10 and 07/05/10; 04/04/11 and 10/05/11
Date of harvest	17/08/03; 17/08/04; 09/08/05; 09/08/06; 17/07/07; 22/08/08; 12/08/09; 06/08/10; 14/08/11

was sampled at 0, 30 and 60 minute intervals between 9 and 11 a.m. every week and more intensively (twice a week) following fertilizer application and measured using a gas chromatography (Abdalla et al., 2009). Following the two-year gap, gas samples for the measurement of both N_2O and CH_4 were collected from September 2008 to September 2010 and from April 2009 to September 2010 respectively, where small cylinder steel chambers, with 18 replicates were used (Abdalla et al., 2012). Gas was sampled weekly during the crop growth period and less frequently (2–3 weeks) during the fallow period. Soil respiration (CO_2 effluxes: R_{eco}) was measured daily using EC from 2003 onwards, but processed data were available until 2007. The ECOSSE model can predict soil heterotrophic respiration (R_H, CO_2 emissions) only. For comparison and validation with measured data, R_{eco} measured by EC from the large fertilized field was transformed to R_H using DailyDayCent fractions. Gas samples were also collected from the large plot for the measurement of N_2O and CH_4, but only the latter was included owing to flux trends found to be similar to the small plots.

3.2.2.2 Ancillary measurements

Gravimetric soil water content (% dry weight) was measured at locations adjacent to each chamber placement at the 0–10 cm depth using a WET-2 Sensor connected to a HH2 moisture meter (both Delta-T devices, United Kingdom). The measured values were transformed to water-filled pore space (WFPS) using the following equation:

$$WFPS\ (\%) = \frac{\theta * \delta_b}{(1 - \frac{\delta_b}{\delta_p})} * 100 \qquad \text{(Eq. 3.1)}$$

Where, δ_b is the measured bulk density (g cm^{-3}), δ_p is soil particle density (2.65 g cm^{-3}) and θ is the measured gravimetric water content (%). Soil up to 20 cm depth was also sampled during gas samplings and on other occasions to determine soil mineral N using standard laboratory methods. A ratio function was used to achieve values for the 0–10 cm depth.

3.2.3 ECOSSE Model Descriptions

The ECOSSE (Estimating Carbon in Organic Soils – Sequestration and Emissions) model (Smith, 2010) was developed to simulate SOC in highly organic soils from concepts originally derived for mineral soils in the RothC and SUNDIAL models. The ECOSSE contains additional descriptions of a number of biogeochemical processes in mineral soils, including simulation of anaerobic processes in organic soils (Smith et al., 2007, 2010). It uses a pool type approach, and all of the major processes of C and N turnover in the soil are included using simple equations driven by readily available input variables. It is a tool for site-specific simulation without high loss of accuracy and makes full use of the limited information that is available to run models at a national scale. Any data available describing SOC, soil water, plant inputs, nutrient applications and timing of management operations are used to drive the model. In the case of missing information, it can still provide accurate simulations of GHGs (N_2O derives from nitrification and denitrification, CO_2 corresponds to

R_H and CH_4 through a balance between methanogenesis and methanotrophy) and changes in SOC stocks. It can deal with both organic and mineral soils, providing more accurate values of net change to soil C and N in response to changes in land use and climate. This model considers variations for outputs by calculating them on each soil layer for each time step. Thus, it may be used to inform GHG inventories at the field and national scales, assess mitigation options and make policy decisions. The ECOSSE version v5.0 updated in 2012 was used for this study.

3.2.4 Sensitivity Analysis

For sensitivity analyses, key driving variables such as site characteristics (SOC, bulk density, clay, pH, available water) and management (tillage practices, major N fertilizer types and rates) were selected. As it can commonly be seen and based on the database of Khalil et al. (2012a), the sensitivity of the model ouput to a specific parameter was assessed based on an extreme but realistic value of the parameter while other parameters were kept constant. Tillage practices included as inputs were conventional (22–25 cm depth), non-inversion (reduced=15 and minimum=7.5 cm depth) and zero tillage. In addition to CAN (main N fertilizer followed by urea used in Ireland), others like ammonium sulphate and potassium nitrate were also taken to estimate the response of GHG emissions to both ammonium and nitrated-based fertilizers.

3.2.5 Statistical Analyses and Evaluation of the Model

The ECOSSE model was run under the initialization of soil C pool at steady state equilibrium values with crop residue input and of N as NO_3 content measured immediately before the start of experiments. In order to match IPCC methodology, all inputs for soil properties up to 25 cm depth with an initiation depth of 0–30 cm were included, and the model was run for 8 years (harvest of previous crop in 2003 until the harvest of the crop in 2011). For the measured and simulated data, cumulative seasonal or annual fluxes (N_2O, CO_2 and CH_4) were calculated by numerical integration. Seasonal and annual cumulative fluxes for the simulated values were also calculated as the sum of simulated daily fluxes. For the measured data, N_2O EFs were calculated by subtracting cumulative (seasonal/annual) flux data for unfertilized fields from that of the fertilized fields and dividing by the amount of N fertilizer applied. Further evaluation for EFs was made by integrating the daily fluxes measured (seasonal/annual), and the corresponding simulated ones to determine the integration discrepancies over measurements taken at longer intervals. Similarly, changes in SOC stocks derived from the slope of the linear-fit regression equation of daily changes in total organic carbon stock over the simulation period (8 years) were compared with the amounts derived from the differential approach.

The simulated values were evaluated in terms of accuracy of model runs with the measured data available either from two years seasonal or annual (day after harvest to harvest, where applicable) studies. The outputs were converted into standard units to match with measured datasets and collated. An analysis of variance for significant test at 0.05 level of probability was performed and the exact 95% confidence intervals were calculated using both SAS v. 9.3 (SAS Inc.) and MODEVAL v 2.0 (Smith and Smith, 1995). Evaluation of the consistency of seasonal (crop growing period)/annual measured data for N and C emissions with simulated values was carried out. A simple mean and standard error of the values for each dataset was taken, and statistical approaches that describe model fits for all data points simulated by placing equal weight on all values was followed.

3.3 Results

3.3.1 N_2O Emissions

The minimum peaks for N_2O emissions measured were -8 g N ha^{-1} d^{-1} from the fertilized and -10.4 from the unfertilized fields, and the corresponding simulated values were 0.7 and 0.0 g N ha^{-1} d^{-1} (Fig. 3.1a, b). The maximum peaks for N_2O emissions varied from year to year and the measured fluxes (56 and 16.6 g N ha^{-1} d^{-1}) were smaller than the simulated ones (80.7 and 22.4 g N ha^{-1} d^{-1}). The impact of tillage and fertilization on N_2O emissions was clear for the simulated values more than the measured ones.

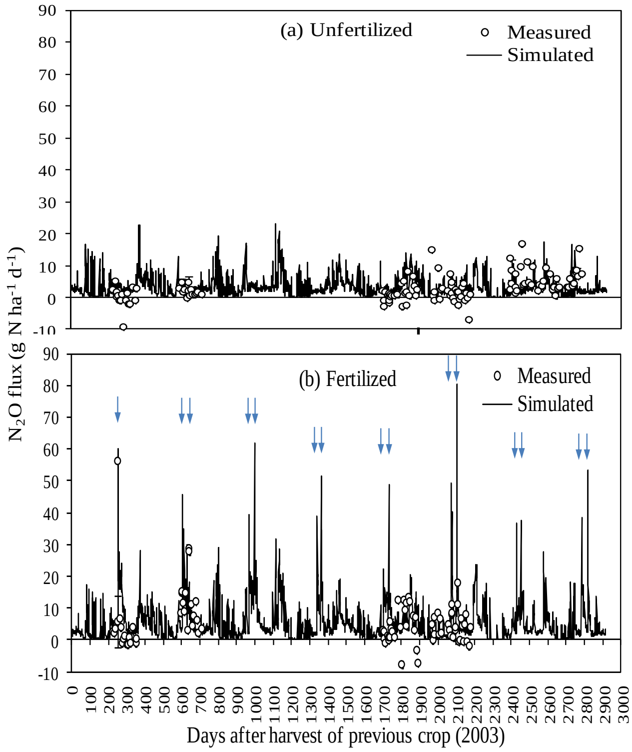

Figure 3.1. Daily measured and simulated N_2O emissions from the unfertilized (a) and fertilized (b) fields cropped to spring barley. The arrows indicate the day of fertilization as CAN, and the day of previous crop harvested is 17/08/2003.

The simulated daily N_2O fluxes were consistent with measured values over years (Table 3.3). The bias in the total difference between the measured and modelled N_2O fluxes was large but in good agreement. For the unfertilized control, the R^2 was poor (-0.06), but the RMSE and RE were within the 95% confidence level. For the fertilized fields, significant correlation between the simulated and measured N_2O fluxes was observed, with an R^2 of 0.33, and the total error and bias differences did not vary significantly. The model somewhat overestimated the seasonal and annual total N_2O fluxes (integrated) compared to the measured values (Table 3.3). Based on the seasonal and annual integration, the measured seasonal N_2O EFs were higher than the simulated values. The corresponding annual (2008–2009) and 8 years average simulated N_2O EFs obtained by summing the modelled daily fluxes was 0.59 and 0.53%.

Table 3.3. Statistical evaluation of the simulated with measured with the daily N_2O fluxes and their seasonal and annual total fluxes as well as the emission factors.

	Unfertilized control		Fertilized		Emission factor (%)	
	n=130		n=89			
R^2	-0.06		0.33*			
$RMSE/RMSE_{95\%}$ (%)	193	485	151	372		
$RE/RE_{95\%}$ (%)	-27	305	-51	367		
MD (%)	-1		-3			
Total flux (g N ha^{-1})	Measured	Simulated	Measured	Simulated	Measured	Simulated
Seasonal: 2004	-19.9	704.3	522.4	1020.3	0.39	0.23
2005	193.5	311.5	1144.5	960.1	0.60	0.41
Annual: 2008–2009	689.3	1296.4	1168.1	1933.4	0.35	0.47 (0.59!)
Average: 8 years		1174.0±57		1914.7±81		0.53±0.03

n=number of population; *=Significant association at <0.05% level; $RMSE/RMSE_{95\%}$=Root Mean Square Error and its 95% confidence level; $RE/RE_{95\%}$=Relative Error and its 95% confidence level; MD=Mean difference; !=Calculated from the sum of daily simulated values.

3.3.2 Soil Respiration/CO_2 Effluxes

A small difference was found between the measured and simulated R_H (Fig. 3.2a,b). For the unfertilized field, the simulated minimum and maximum peaks ranged from 0.07 to 0.59.43 kg C ha^{-1} d^{-1} and for the fertilized fields from 0.02 to 56.49. For the latter, the measured (estimated) minimum value was 0.49 kg C ha^{-1} d^{-1} and the maximum 59.17. A clear influence of tillage on R_H was seen, but the emissions following harvest of each crop.

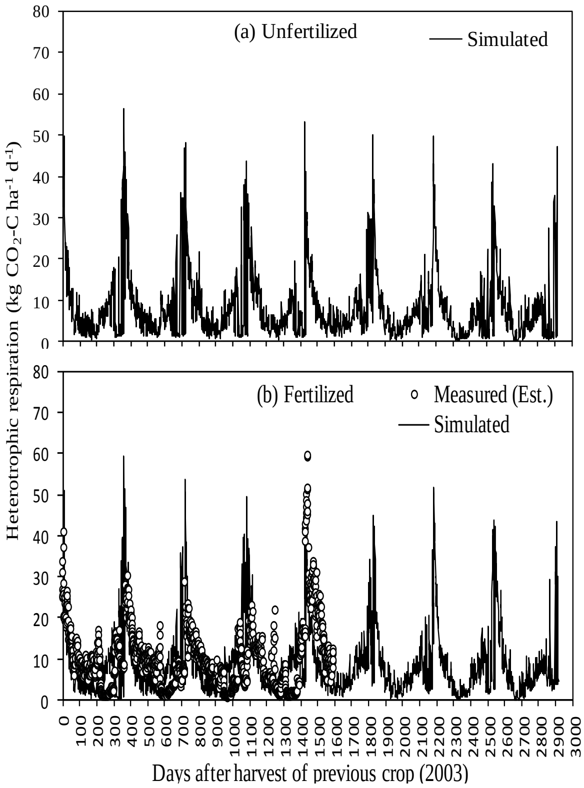

Figure 3.2. Comparison between the daily measured and estimated using the Eddy Covariance data and the modelled heterotrophic respiration (R_H) of the unfertilized (a) and fertilized (b) fields cropped to spring barley. The day of previous crop harvested is 17/08/2003.

There was a significant association between the measured and simulated daily CO_2 fluxes (R^2 =0.45) (Table 3.4). The total bias and error differences were small and within the 95% confidence levels. The model predicted the annual R_H well, showing small variation over a 4-year period with the measured values (3249 versus 3072 kg C ha^{-1}). The annual R_H on an 8-year average was 2962 for the unfertilized and 3191 kg C ha^{-1} for the fertilized fields.

Table 3.4. Statistical evaluation of the measured (estimated using the Eddy Covariance data) with the simulated daily CO_2 (heterotrophic respiration) and the annual total fluxes.

Validation	Fertilized only	Total emissions (kg C ha^{-1})	Unfertilized control		Fertilized	
			Measured	Simulated	Measured	Simulated
	n=1596					
R^2	0.45*	Annual (4 years)			3072±157	3249±56
RMSE (%)	88	Annual (8 years)		2962±112		3191±89
RE (%)	6.8					
MD (%)	0.8					

n=number of population; *=Significant association at <0.05% level; RMSE=Root mean square error; RE=Relative error; MD=Mean difference. Standard errors (±) correspond to variations within years.

3.3.3 CH_4 Emission/Oxidation

The simulated pattern of CH_4 emissions for both unfertilized and fertilized fields was somewhat inconsistent but within the peak ranges compared to the measured data (Fig. 3.3). The measured data showed both emissions and oxidation regardless of seasons, and the simulated data demonstrated emissions following harvest of the crop (autumn–winter period).

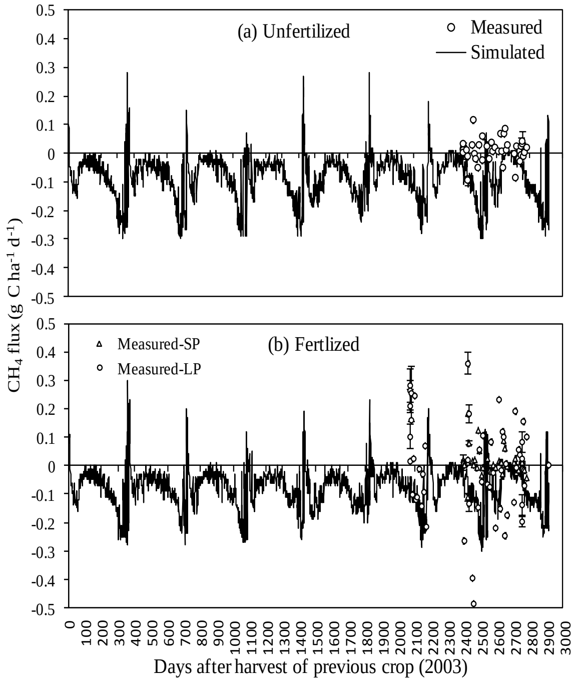

Figure 3.3. Comparison between the daily measured emissions over two years in fertilized field only and the modelled CH_4 fluxes of the unfertilized (a) and fertilized (b) fields cropped to spring barley. The day of previous crop harvested is 17/08/2003.

Statistical evaluations for the daily CH_4 fluxes derived over a year of measurement depicted poor R^2 (0.06 versus 0.13) (Table 3.5). In contrast to the fertilized field, the overall bias and error differences were significantly large for the unfertilized field. Though small, integration of CH_4 fluxes over a year resulted in oxidation for both measured and modelled values for the fertilized field only. Integration of fluxes measured over a year in the unfertilized field showed small CH_4 emissions, and its uptake decreased from -31.37 to -26.61 g C ha^{-1} in the fertilized field. The model predicted a consistent decrease in CH_4 oxidation due to N fertilization over the 8-year period, and went down from -30.51 to -28.43 g C ha^{-1} yr^{-1}.

Table 3.5. Evaluation of the simulated with measured daily CH_4 fluxes and their annual total.

	Unfertilized control		Fertilized	
	n=41		n=60	
R^2	0.06		0.13	
$RMSE/RMSE_{95\%}$ (%)	2309*	2071*	1430	1768
$RE/RE_{95\%}$ (%)	1704*	1318*	919	1487
MD (%)	0*		0*	
Total flux (g C ha^{-1})	Measured	Simulated	Measured	Simulated
Annual: 2009–2010	2.29	-31.37	-3.64	-26.61
Average: 8 years		-30.51±0.97		-28.43±1.18

n=number of population; *=Significant association at <0.05% level; $RMSE/RMSE_{95\%}$=Root Mean Square Error & its 95% confidence level; $RE/RE_{95\%}$=Relative Error & its 95% confidence level; MD=Mean difference.

3.3.4 Soil Properties

Compared to measured soil NO_3 content, the ECOSSE model was unable to predict <5 kg N ha^{-1} regardless of fertilization practices. This is evidence of some disagreements but matched the peak amounts with the timing of N fertilization (Fig. 3.4a,b). Nitrogen fertilizer was applied in two (mainly) equal splits where the second application raised the soil NO_3 level more than the first application. The relationship between simulated and measured soil NO_3 values was poor for the unfertilized and a good significant association was observed for the fertilized (R^2=0.54) fields (Table 3.6). Unlike the bias, the total error difference between the measured and simulated values was significant and large for the latter.

The trends and/or the amounts of soil water content measured in 2004 and 2005 were not similar to the measured values obtained from the later years (Fig. 3.4c,d). The model showed a limitation in predicting soil water content in that it was unable to predict <41 and >65% WFPS. The statistical evaluation yielded poor R^2 and significantly large total error differences between the measured and simulated WFPS (Table 3.4). The bias in total difference between them was relatively small and within the 95% confidence level.

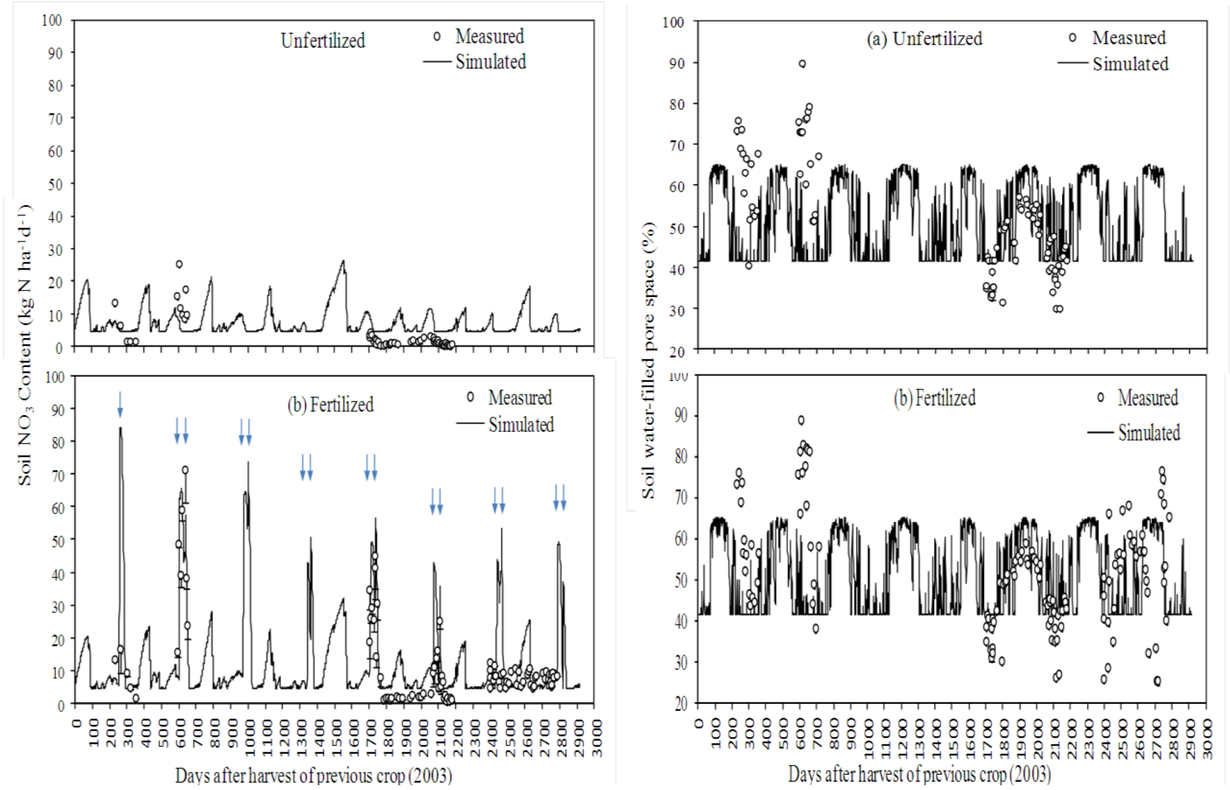

Figure 3.4. Comparison between the daily measured and modelled soil nitrate and water content of the unfertilized (a) and fertilized (b) fields cropped to spring barley. The day of previous crop harvested is 17/08/2003.

Table 3.6. Statistical evaluation of the measured with the simulated daily soil nitrate content (kg N ha^{-1}) and soil water content (water-filled pore space, WFPS %).

	Unfertilized control		Fertilized	
Soil NO_3	n==53		n=94	
R^2	0.07		0.54*	
RMSE/RMSE$_{95\%}$ (%)	163*	157*	111*	105*
RE/RE$_{95\%}$ (%)	-70*	65*	-40	70
MD (%)	-2		-4	
WFPS	n=88		n=129	
R^2	0.00		0.01	
RMSE/RMSE$_{95\%}$ (%)	32*	24*	32*	23*
RE/RE$_{95\%}$ (%)	9	17	6	17
MD (%)	5*		3*	

n=number of population; *=Significant association at <0.05% level; RMSE/RMSE$_{95\%}$=Root mean square error & its 95% confidence level; RE/RE$_{95\%}$=Relative Error & its 95% confidence level; MD==Mean difference.

3.3.5 SOC Stock Changes

The simulated initial SOC stock matched well with the amount of SOC used as an input for the 0–25 cm (42,888) and thereby 0–30 cm (49,561 kg C ha^{-1}) soil depth (Fig. 3.5). The initial SOC density used as an input for model initialization was 19,912 kg C ha^{-1} for the 0–10 cm. The predicted SOC density was smaller than the measured amount for the 0–10 cm but similar for the 0–30 cm depth, and the changes in SOC stocks over years differed markedly between the two depths. Both linear (showing significant R^2 at <0.05 level of probability) and differential estimates of SOC losses were adopted, but the former overestimated the SOC stocks irrespective of fertilization practices. For the 0–10 cm depth, the linear and differential estimates of SOC losses were 193 and 165 kg C ha^{-1} from the unfertilized, and 174 and 143 kg C ha^{-1} from the fertilized fields, respectively. Allowing the 0–30 cm, these losses were higher, and the corresponding amounts were 601 and 559 kg C ha^{-1} from the unfertilized, and 564 and 513 kg C ha^{-1} from the fertilized fields.

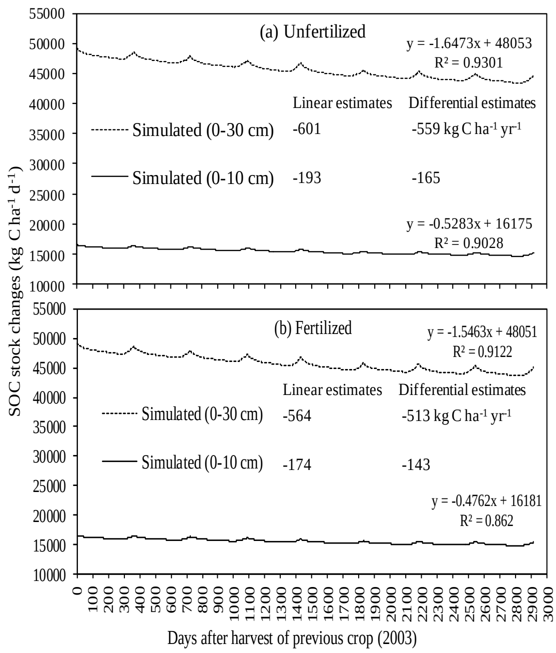

Figure 3.5. Daily simulated soil organic carbon (SOC) stock changes in unfertilized (a) and fertilized (b) spring barley fields. The day of previous crop harvested is 17/08/2003.

3.3.6 Sensitivity to Soil Properties and Management Practices

The model responded well for total N_2O fluxes, and thereby EFs to various indigenous SOC contents, showing a higher scale constant (k) for the former (fertilized 5E-06 and unfertilized 6E-06) than the latter (4E-06) (Table 3.7). It was exponential for the R_H (k=7E-06), and the CH_4 went from a sink to a source. Though linearly correlated, the loss of SOC was notably larger (2.3–6.7 times) at the two highest SOC levels (2.2–2.7%) than the measured SOC content, and the lowest SOC content demonstrated a small sequestration. Unlike other properties, the model did not respond to variable soil bulk densities, excepting a marked influence on CH_4 oxidation that increased with decreasing bulk density, and particle size distribution (%clay). The total N_2O response to drier conditions (≤80% available water) was unrealistically large and the rate of increase between soil water content at saturation and field capacity was small, including for N_2O EFs (Table 3.7). The model showed little impacts on R_H and therefore little relationship between the loss of SOC and water levels. However, the CH_4 oxidation/sink at drier conditions turned to emissions with the increase in water levels. The predictions for total N_2O flux, increased with increasing soil pH and the N_2O EFs decreased, particularly at very acidic and alkaline conditions. The response of the model to soil pH was the opposite for CH_4 oxidation, with no influence of management at pH neutral or above and overall the influence is very low.

Table 3.7. Response of C and N emissions to soil properties.

Soil properties (0–25 cm soil depth)		Total N_2O flux (kg N ha^{-1} yr^{-1})		N_2O EF	Total CO_2 flux (g C ha^{-1} yr^{-1})		Total CH_4 flux (g C ha^{-1} yr^{-1})		SOC stock changes (30 cm; kg C ha^{-1} yr^{-1})	
		UF	F	(%)	UF	F	UF	F	UF	F
SOC (100% =42888 kg C ha^{-1})	50%	1.06	1.68	0.45	2307	2525	-0.037	-0.035	62	79
	100%	1.17	1.91	0.53	2962	3191	-0.031	-0.028	-601	-564
	+200%	1.49	2.30	0.58	4323	4476	-0.018	-0.016	-1957	-1899
	+400%	2.52	3.69	0.84	6944	7061	0.006	0.008	-4609	-4526
Bulk density (g cm^{-3})	1.00	1.17	1.84	0.48	2965	3162	-1.05	-1.05	-601	-564
	1.46	As of 100% SOC								
	1.80	1.17	1.84	0.48	2965	3162	-0.031	-0.029	-601	-564
Clay (100% =14.73%)	100%	As of 100% SOC								
	200%	1.17	1.84	0.48	2965	3162	-0.031	-0.029	-601	-564
	400%	1.17	1.84	0.48	2965	3162	-0.031	-0.029	-601	-564
Available water (100% =55.13 mm)	80%	13.79	15.15	0.97	3018	3225	-0.056	-0.053	-640	-613
	100%	As of 100% SOC								
	120%	1.17	1.88	0.51	2977	3181	0.405	0.406	-608	-582
	140%	1.20	1.93	0.53	3178	3389	0.021	0.023	-608	-574
	180%	1.91	2.73	0.59	3100	3292	0.067	0.069	-613	-583
Soil pH	4.35	0.74	1.13	0.29	2567	2751	-0.073	-0.071	-214	-180
	5.35	1.02	1.63	0.44	2925	3123	-0.070	-0.068	-557	-519
	6.35	1.13	1.79	0.47	2961	3165	-0.068	-0.068	-594	-562
	7.35	As of 100% SOC								
	8.35	1.19	1.84	0.47	2965	3162	0.016	-0.029	-600	-564

UF=Unfertilized control; F=fertilized on average 139.25 kg N ha^{-1} yr^{-1}; 100% corresponds to respective initial measured variable used as input to run the model.

The model responded well to fertilizer N containing NH_4 (including urea), demonstrating a considerable increase in total N_2O flux and EFs. Its sensitivity to 100% nitrate-based N fertilizer was small, and that provided an EF of 0.17%, which was lower than the other N fertilizers-derived EFs (0.53–0.71%) (Table 3.8). The model sensitivity for C emissions to fertilizer N types was slight. The simulated total N_2O fluxes and thereby EFs increased exponentially from 0.51 to 0.73% with increasing rates of N fertilizer application. Unlike CH_4 oxidation, the model response for R_H and thereby SOC losses to N rates were positively linear. The model was relatively insensitive for N_2O EFs to tillage practices, and slightly for R_H and CH_4 emissions, demonstrating increased SOC losses with increasing intensity of soil disturbances.

Table 3.8. Response of C and N emissions to key management practices.

Soil managements		Total N_2O flux (kg N ha^{-1} yr^{-1}) UF	F	N_2O EF (%)	Total CO_2 flux (g C ha^{-1} yr^{-1}) UF	F	Total CH_4 flux (g C ha^{-1} yr^{-1}) UF	F	SOC stock changes (30 cm; kg C ha^{-1} yr^{-1}) UF	F
Fertilizer N type	CAN*	1.17	1.91	0.53	2962	3191	-0.031	-0.028	-601	-564
	AS		2.16	0.71		3166		-0.029		-570
	PN		1.42	0.17		3171		-0.029		-576
	Urea		2.05	0.63		3191		-0.028		-556
Fertilizer N rate as CAN	0	As of CAN								
	70		1.53	0.51		3092		-0.029		-533
	140*	As of CAN								
	210		2.43	0.60		3284		-0.028		-656
	280		3.23	0.73		3308		-0.027		-671
Tillage practices	CT*	As of CAN								
	RT	1.18	1.85	0.48	2911	3107	-0.031	-0.029	-548	-500
	MT	1.17	1.84	0.48	2871	3068	-0.032	-0.030	-511	-473
	ZT	1.12	1.78	0.48	2791	3002	-0.032	-0.030	-431	-398

UF=Unfertilized control; F=fertilized on average 139.25 kg N ha^{-1} yr^{-1}; 100% corresponds to respective initial, measured variable used as input to run the model.* On average 139.25 kg N ha^{-1} yr^{-1} applied. CAN=Calcium Ammonium Nitrate, AS=Ammonium Sulphate, PN=Potassium Nitrate, CT=Conventional tillage, RT=Reduced tillage, MT=Minimum tillage and ZT=Zero tillage.

Regardless of soil properties and management, the simulated total N_2O flux and EFs were within the ranges of 1.13–15.14 (2.55±0.52) kg N ha^{-1} yr^{-1} and 0.17–0.97 (0.54±0.03)%, respectively. Omission of the unusual estimate at very low available water resulted in the corresponding values of 1.13–3.69 (2.05±0.12) kg N ha^{-1} yr^{-1} and 0.17–0.84 (0.52±0.03)%. The application of 100% nitrate resulted in the lowest N_2O EF. Removal of this value for both provided the total N_2O fluxes of 1.13–3.69 (2.07±0.12) and EFs of 0.29–0.84 (0.54±0.02)%. The simulated SOC loss from a field having large SOC content was enormous, and on average 233±38 kg C ha^{-1} yr^{-1} for the 0–10 cm and 726±107 for the 0–30 cm soil depth. By omitting the massive losses, this loss on average went down to 164±8 kg C ha^{-1} yr^{-1} for the 0–10 cm and 532±21 for the 0–30 cm soil depth.

3.4 Discussion

3.4.1 Simulation and Validation of N_2O Emissions

The ECOSSE simulated peaks for N_2O emissions from the fertilized field were higher than the measured values. This can be attributed to the possibility of missing peak fluxes because of the sporadic timing of gas samplings, in agreement with others (Abdalla et al, 2009; 2012), and because N_2O emissions are commonly released as a pulse from soils to the atmosphere under the influence of tillage, rainfall events, and other management practices. On some occasions negative values were measured from the field, similar to the finding of Khalil et al.

(2002) whereas the model cannot simuate negative emissions. This means that any soil and climatic conditions favourable to causing a sink for N_2O could remain unaccounted. However, the simulated daily N_2O fluxes were equitably consistent with the measured values. This conforms with the statistical evaluations, demonstrating the total bias and error differences within the 95% confidence level and also a significant correlation, particularly for the fertilized field. This indicates that the ECOSSE model could predict N_2O emissions better than the DNDC (version 8.9 and 9.2), dealing commonly with the same fertilized and unfertilized arable sites (Abdalla et al., 2009; 2012). In this study, the degree of association for the daily time-step improved from 0.25 to 0.33 although a monthly (4 weeks) time-step was reported to be more successful in predicting N_2O emissions (Bell et al., 2012) but this was site specific. This study also showed a very poor R^2 for the unfertilized field, in line with the DNDC model estimates (Abdalla et al., 2009).

The ECOSSE-simulated seasonal and annual total (integrated) N_2O flux estimates were higher than the measured values but were within the European cropland average of generally below 3 kg N ha^{-1} (Freibauer and Kaltschmitt, 2003). A different integration approach was used from that used for the measured data reported by Abdalla et al. (2009; 2012), demonstrating that an underestimation by the DNDC (v8.9 or 9.2) may somewhat vary with the analysis presented here. Concerning annual estimates including 2008–2009, the simulated total N_2O fluxes for the unfertilized and fertilized fields increased by 88 and 66% over the measured ones, respectively. Taking into account the seasonal and annual total, the ECOSSE provided R^2 of 0.55 regardless of fertilization practices. The data did not permit weekly or monthly estimation of aggregated N_2O emissions for comparison with the findings of Bell et al. (2012). It is inconclusive whether errors are associated with the measurements or the model simulation. However, validation of models using seasonal data and their estimates might always be questionable in calculating N_2O EFs, and linked to errors associated with possible missing and mismatching of peaks during integration. This discrepancy is in line with this study where the simulated seasonal N_2O EF on average (0.32%) decreased by 65% and the simulated annual (0.47 and 0.59%, which is the sum of daily values) increased by 34% (and 69%) over the measured ones (0.50 versus 0.35%). Based on the seasonal measured data (Abdalla et al., 2010a,b), the EF at the highest fertilizer N rate should on average be 0.50%, which is similar to that found in the current research, instead of 0.62% as reported. The previous ECOSSE version provided a seasonal EF of 1.11% (Khalil et al., 2012b). The simulated N_2O EF on the 8-year average was 0.53%, which is 47% lower than the IPCC default (1%), and even further below if we consider the range 0.3–3% (IPCC, 2006).

The simulated WFPS values were higher than the lower limits and vice-versa, leading to less contribution of fertilizer-induced N_2O emissions via denitrification to overall estimations. However, the ECOSSE-derived EFs are within the lower uncertainty ranges (0.2 to 8%) for cereals crops (e.g. Eichner, 1990; Kaiser et al., 1998; Smith et al., 1998, Dobbie et al., 1999; Crutzen et al., 2008). The availability of good measured datasets could help not only to reduce the biases and errors while improving the degree of association but also to refine the performance and accuracy of the model.

3.4.2 Simulation and Validation of Soil Respiration

The minimum and maximum peaks for daily R_H estimated from the R_{eco} measured using EC were lower but reasonably closer to the findings of Moyano et al. (2007). This may be attributed to the possible errors associated with chamber techniques (daylight measurement) for separation among the respiration components. Compared to our estimates, Abdalla et al. (2011) also found larger daily and cumulative CO_2 fluxes, with the lowest during winter and the maximum during summer (crop growth period). There was a clear influence of tillage operations on R_H, which was nonethelss lower than as observed mainly following the harvest of each crop because of the addition of crop residues following harvest; the trends were similar to the estimated measured values. In addition to possible diffusion out following soil disturbances, the stimulating effects of ploughing on soil respiration have been affirmed (e.g. Müller et al., 2009; Morell et al., 2010; Abdalla et al., 2012). Considering the uppermost 30 cm soil depth, this land-use type has significant influence on annual R_H. In this study, the modelled (3249 kg C ha^{-1}) and the measured values (3072 kg C ha^{-1}) for total annual R_H (4 years average) matched well and are within the reported range of 2000–8000 kg C ha^{-1} for arable soils (Kutsch and Kappen, 1997; Rees et al., 2005), and of 7500±4300 kg C ha^{-1} yr^{-1} for average annual RH from croplands in temperate region. The simulated amount from the previous version was on average 4000 kg C ha^{-1} yr^{-1} (Khalil et al., 2012). Our 8-year average estimate (3191 kg C ha^{-1}) is closely harmonized to the total weighted R_H mean (3065 kg C ha^{-1}) for croplands across bio-climatic zones of Russia (Kurganova, 2003).

The influence of N fertilization on both daily and annual CO_2 fluxes (R_H) was clear. On the 8-year average, the simulated annual R_H increased by 7.7%. Similar fertilizer-induced soil C losses (R_H) up to a maximum of 10.6% regardless of N fertilizers and soil types were cognizant where high soil pH and/or indigenous soil C displayed the highest CO_2 flux, in contrast to relative C losses (Khalil et al., 2007). Likewise, N fertilizer-induced SOC losses have also been reported (Khan et al., 2007; Mulvaney et al., 2009; Poirier et al., 2009). The large variations between studies may be ascribed to differences in soils, seasonal microbial activities, cropland types, N fertilizer types and application rates (e.g. Osborne et al., 2010). The significant association between measured (estimated) and simulated daily CO_2 fluxes (R^2=0.45) and the insignificant small total bias and error differences observed imply that the ECOSSE model could predict daily R_H efficiently, and uncertainty may be related to the variable WFPS predictions when compared to the measured data and added C inputs, warranting further refinement of the model.

3.4.3 Simulation and Validation of CH_4 Fluxes

The ECOSSE simulated peaks for CH_4 fluxes demonstrated predominant uptake during the spring-summer period but were closer to the measured ones, displaying both emissions and oxidation with little seasonal variations from either field. Similar seasonal variations, depicting either consumers or producers or neutral for CH_4 fluxes from agricultural systems have been reported earlier (Chan and Parkin, 2001). The daily CH_4 oxidation and emissions measured may be attributed to simultaneous processes occurring in aerobic–anaerobic microsites (Khalil and Baggs, 2005) during the spring-summer period where soil water content and the availability of substrate are presumably the major driving factors. However, the daily CH_4 oxidation rates (measured or simulated) were several times lower than as estimated for EU-15 arable lands of 2.63 g C ha^{-1} d^{-1} (Boeckx and Van Cleemput, 2001). These concurrent processes were probably not formulated properly in the model, especially with regard to the minimization of bulk density effects and the mismatching of simulated soil water content with the measured values, and thereby variable influences over time and space. Despite attaining closer values, this deviation presumably resulted in poor R^2 with large significant bias and error differences between simulated and measured values.

The cumulative value of simulated fluxes over a year resulted in CH_4 oxidation, with 7% reduction over the unfertilized field. The previous version of the ECOSSE predicted a similar but relatively higher oxidation (Khalil et al., 2012b). Application of N fertilizer usually results in a reduction of CH_4 uptake by on average 40% for arable soils (Mosquera et al., 2007). The lower reduction of CH_4 uptake may be explained by the N fertilizer type (CAN), containing equal amounts of ammonium and nitrate. The amount of ammonium in particular is probably below the threshold level to develop severe toxicity for CH_4 oxidizers to limit oxidation, including through osmosis (Bodelier and Laanbroek, 2004). The fertilized field showed a 59% increase in oxidation over the unfertilized field, showing a rather small source of CH_4 and the reason cannot be explained from this study.

On average, the simulated annual CH_4 oxidation was 29.5 g C ha^{-1}, which is closer to the amount observed in Belgian arable soils receiving different fertilizer treatments (Boeckx et al., 1998). In contrast, our estimate is markedly lower than as estimated for arable land under EU-15 of 1125 g C ha^{-1} yr^{-1} (Boeckx and Van Cleemput, 2001). The crop fields used test herbicides, which may have had an inhibitory effect on methanotrophs activity, and this may also have contributed to lower CH_4 oxidation (Arif et al., 1996). There was a clear impact from fertilization in the reduction of simulated CH_4 oxidation, and this effect was consistent over the 8-year period. This inhibition may even result in a net increase in CH_4 emissions from soil and N_2O production during nitrification caused by methylotrophs through interactions with other driving forces (Khalil and Baggs, 2005), which should be considered in the formulation of a process-based models to estimate a reliable ecosystem carbon budget.

3.4.4 Simulation of SOC Stock Changes

Like most biogeochemical models, the ECOSSE considers homogeneous distribution of soil properties across depths; initialization of the model with the 0–30 cm depth resulted in a very good estimate of initial SOC density compared to the 0–10 cm depth. Our simulated findings suggest that a linear functional relation can also be used to estimate SOC stock changes over multiple years. Compared to the differential approach (the day after harvest), an overestimation by 19% for the 0–10 cm and by 9% for the 0–30 cm would be possible. The differential estimate of SOC loss was on average 154±11 from the 0–10 cm and 536±23 kg C ha^{-1} from the 0–30 cm depth regardless of fertilization practices. In addition to the low amount of left-over crop residues and the conventional tillage-induced massive soil disturbance, the higher sand-fraction of the experimental soil presumably enhanced decomposition and thereby became a source of carbon in comparison to soils having greater silt- or clay-size fractions (Dalal and Mayer, 1986). The previous version simulated higher carbon loss (on average 1060 kg C ha^{-1} yr^{-1}) with a very small difference between the fertilizer practices (Khalil et. al., 2012a). Similar to ours, Dawson and Smith (2007) estimated 140±100 kg C ha^{-1} yr^{-1} for UK croplands and other researchers in Europe (e.g. Sleutel et al., 2006; Lugato et al., 2010). Contrasting results have also been reported from studies performed in temperate regions where arable lands acted as a sink for atmospheric CO_2 (West and Marland, 2003), even with or without straw (Uhlen et al., 1991; Paustian et al., 1992), and with a high fertilizer rate (Nieder and Richter 2000; Van Meirvenne et al., 1996).

The modelled SOC loss was 13% (0–10 cm soil depth) and 8% (0–30 cm soil depth) less from the fertilized over the unfertilized field, indicating the influence of N fertilization to enhance carbon sequestration in the soil. This may be ascribed to the increased net primary productivity resulted in an increased return of residual crop biomass into the soil (Snyder et al., 2009). Since temporal fluctuations of soil moisture and temperature decrease with soil depth, a deeper distribution of organic matter causes reduced variability of R_H by showing less sensitivity to short timescale climatic fluctuations than a soil with a shallow distribution (Braakhekke et al., 2011). The soil system is the main source of large uncertainty and these relations need to be characterized properly. This is to achieve better estimates at various scales through validation of a model with good datasets and a wider range of repeated soil C inventories to constrain modelled soil C losses, which are lacking under Irish conditions.

3.4.5 Sensitivity Analyses

The ability of the ECOSSE model to simulate C and N emissions using limited inputs has been reported (Smith et al., 2010; Bell et al., 2012). Sensitivity analyses using site characteristics and land-use managements were performed to provide representations of the model's uncertainty estimates. The simulated values are compared with literature data that has been generated mainly in temperate regions, bearing in mind that the high spatial variability of soil characteristics can have significant impacts on N_2O emissions.

3.4.5.1 Soil characteristics

Responses of GHGs and SOC stock changes to major soil properties were tested. An exception was soil temperature because of the lack of an option to include this as an input variable in the ECOSSE model. However, the model sensitivity for all soil biological and physicochemical processes including GHG emissions and the SOM turnover to temperature was shown to be strong (Smith et al., 2010; Bell et al., 2012). Given the large uncertainty in the temperature response – particularly to SOM dynamics – the ECOSSE model has a built-in conversion of air to soil temperature for a reliable prediction of agricultural soils as a carbon sink or source.

Soil organic carbon

The model responded well to variations in SOC inputs and found that simulated values for total N_2O fluxes and EFs increased exponentially with increasing SOC content. This means that the model could provide good estimates at varying indigenous SOC contents. This is by taking into consideration microbial-mediated N transformation processes that produce and release N_2O from arable soils (e.g. Stehfest and Bouwman, 2006). Based on the scale constant differences, the model response to SOC inputs was more on the unfertilized than on the fertilized fields, resulting in a small increase in the N_2O EFs compared to the annual total. This implies that the model underestimates – if not overall denitrification for producing N_2O – complete denitrification in the presence of lower NO_3 levels and that further refinement of the model associated with the denitrification process is needed.

With regard to N_2O emissions, the model simulates showed an exponential increase in soil CO_2 effluxes (R_H) with increasing indigenous SOC levels. This suggests a dominant effect of the latter, ascribing to the simultaneous availability of mineralized N through increasing soil biological activity and thereby the availability of mineral N as substrates for N_2O emissions, to the former. The predicted relative R_H was higher (12%) at the lowest SOC and then decreased from 7 to 4% with increasing SOC levels. Similarly, an increase in CO_2 effluxes (R_H), rather than relative C loss with increasing indigenous soil C, was reported (Khalil et al., 2007). The model's sensitivity for R_H to native SOC levels is reasonably effective provided that other influencing factors are functioning well.

Considerable responses for the annual CH_4 flux, showing a linear decrease, to various SOC contents were observed, and the highest SOC level caused an emission, indicating functional relations with the R_H. The model predicted an increase in SOC losses and the relative losses increase in proportion to the initial SOC levels present in the soil (1.4–2.7% of the total SOC in the 0–30 cm for the unfertilized and 1.3–2.6% for the fertilized fields). This suggests that the model can simulate SOC losses reliably and that the differences in relative losses between

R_H and SOC arise. Presumably, exposure of large carbon pools is necessary for decomposition to occur under the same management. Similar enormous losses of SOC caused by the conversion of grassland to arable lands were reported (e.g. Arrouays et al., 2002; Guo and Gifford, 2002). In contrast, the values though small at the lowest SOC content were predicted to be a sink of atmospheric CO_2 (62–79 kg C ha^{-1} yr^{-1}).

Bulk density

In the modified model, N_2O emissions were insensitive to variation in soil bulk densities although Bell et al. (2012) found increased emissions with increasing bulk densities. This is ascribed to reduced aeration, particularly under moist soil conditions, leading to either ebhanced N_2O emissions or its further reduction to N_2, which is severe – particularly in clay soils. The model was unable to show responses of R_H and SOC stock changes to bulk density variations. Given the sensitivity of heterotrophic activity to soil temperature and moisture, this function is linked to the interaction effects of soil texture, organic carbon content and bulk density for the best estimate of soil-dependent SOC dynamics (Moyano et al., 2012).

Interestingly, the model exhibited a marked response of CH_4 fluxes to the lowest bulk density of 1.0 g cm^{-3} compared to >1.46 g cm^{-3}, showing 3.5 times higher annual oxidation overall. This indicates that the CH_4 sub-model responded independently to bulk density, but was more functional at relatively high aerobic conditions caused by the reduction in bulk density, leading to enhanced oxygen diffusion and thereafter more oxidation. At high bulk densities, the negligible CH_4 oxidation differences might be caused by the reduced aeration. However, the extent of reduction of aeration status with increasing bulk densities on CH_4 oxidation is negligible and unexpected. Smith et al. (2000) reported a steady decrease in oxidation rate with increasing bulk density and with an increasing proportion of WFPS as both factors reduce gas diffusivity. Concerning interactive relations with other soil variables, a lack of model sensitivity to soil bulk densities could have implications for C and N emissions, justifying further improvement of the model in order to minimize biases and errors.

Clay content

The model response for GHG emissions to particle size distribution (here in %clay) was very poor. Variations in clay content affect the pore size structures and thereby oxygen diffusivity which increases with decreasing clay content. Hénault et al. (1998) proved clearly that N_2O

EFs, ranging from 0.16%–2.5% of the applied N, could largely be affected by clay content, organic matter content and alkaline pH. In contrast, Lohila et al. (2003) reported a slightly higher – or similar to – soil respiration in sandy soil than that in clay soil. Given huge conflicts in the literature on the effects of soil texture, the CH_4 oxidising capacity of fine textured soils can be lower than that of coarse textured soils and depends on diffusion and permeability. Moreover, soil texture controls the stabilization of humified SOC both by adsorption onto negatively charged clay minerals and by entrapment from microbial mineralization through the formation of soil aggregates (e.g. McLauchlan, 2006). The decrease in SOC decomposition rate with increasing clay contents and thereby the increase in SOC sequestration is sufficiently strong and originally included in the model. Hence, the dynamic role of clay should be reactivated to make the model appropriately functional.

Available water

The model response for N_2O emissions to soil water content (herein 'available water') was clear. All tests showed that the model considers nitrification as the dominant process for producing N_2O. Thus, its emissions were remarkably large at drier conditions, but small at soil water content between saturation and field capacity. Like the total fluxes, the model sensitivity for N_2O EFs to soil water content was relatively high, in agreement with Bell et al. (2012), including denitrification-induced emissions. In our findings, the model predicted relatively less soil water content compared to upper limits of the measured values, showing a small contribution of denitrification for producing N_2O fluxes. This was inconsistently higher at the drier conditions, and the above saturation limit, indicating the limitation of the model for considering soil water content variations. Large N_2O emissions could occur at WFPS between 60 and 90% and low emissions at >90% or <40% values (Linn and Doran, 1984, Granli and Bøckman, 1994; Kaiser et al., 1998; Khalil and Baggs, 2005). Moreover, denitrification is controlled primarily by soil O_2 supply, WFPS and C availability. The N_2O:($N_2O + N_2$) ratio could be high at abundant moisture, that is <90% WFPS, and low at >90% WFPS, but may vary with water-retention characteristics of a soil (Gillam et al., 2008; Ruser et al., 2006).

Except fertilizer-induced acceleration, the model depicted small and inconsistent responses for R_H to various available water levels. The highest and the lowest available water levels demonstrated minor reductions of R_H. Similar to the model estimates, a poor relationship between soil water content and CO_2 production was reported (Ruser et al., 2006). In contrast, soil CO_2 production is enhanced with increasing soil moisture up to 60% WFPS, and differences in soil water content accounts for 90% of the variation (Granli and Bøckman, 1994; Linn and Doran, 1984). The negligible impact could be associated with the model's lower sensitivity for R_H to soil bulk density and texture, including the averaging-out of microbial respiration to soil moisture content, indicating that soil physical factors need to be taken into account.

The model predicted CH_4 oxidation in dry conditions, and some CH_4 emissions at mid-moisture levels and lower emissions at higher soil water levels. This is in contrast the expectation of anaerobic conditions developing with increasing soil water content, leading to higher CH_4 emissions. It is generally considered that aerated soil is a sink for atmospheric CH_4 through microbial oxidation, and the consumption rate is usually found to be negative in arable ecosystems (Koga et al., 2004). Given large uncertainties, higher correlation coefficients between CH_4 and soil water content were observed (Del Grosso et al., 2000), including steady decreases in oxidation rate with increasing WFPS through a reduction in gas diffusivity (Smith et al., 2000). In our study, the model predicted higher SOC losses at the lowest soil water (dry conditions), and thereafter an increase in SOC stock at 100% available water followed by a slow decrease with further increase in soil water levels. Indeed, high soil water content tends to conserve SOM, through reduced oxygen availability, resulting in slow decomposition of SOM by soil microbes (Batjes, 2011). On the other hand, drier and well-aerated soils accelerate rapid decomposition and accumulate less SOM, somewhat in line with model outputs, but showing inconsistency. This suggests the need for modification requirement of the functional relationship between C emissions and main controlling variables in the model.

Soil pH

The model was highly sensitive to total N_2O flux to soil pH. Given nitrification as the predominant process, the predicted lower N_2O emissions may be attributed to acid sensitivity of nitrifiers as its production may stop at pH 4 (e.g. Paavolainen and Smolander, 1998). Stehfest and Bouwman (2006) reported a significant decrease in N_2O emissions at pH values higher than 7.3 compared to at lower pH values. They found an increase in $N_2O/(N_2O+N_2)$ ratio due to changes in denitrifier activity with decreasing pH. This means that the decrease in N_2O EFs can be achieved particularly at extremely acidic and alkaline conditions. The model response for R_H to soil pH was linear and positive. An exception was the highest pH (8.3) that decreased R_H, particularly under fertilized conditions. Neutral or slightly alkaline conditions favour bacterial growth and an acid pH favours fungal growth, resulting in a drastic shift in basal respiration. Several studies showed significant effects of soil pH on soil respiration (Anderson and Nilsson, 2001) and a biological activity of soil microorganisms is permitted between a soil pH of a minimum of 3 and a maximum of 7 to 8 (Schaeffer and Schachtschabel, 2002).

In contrast to the pronounced effect of soil pH on the CH_4 uptake capacity of soils (e.g. Goulding et al., 1996), the simulated CH_4 oxidation increased with decreasing soil pH even though a rather narrow pH range (5.9–7.7) appeared to allow CH_4 oxidation (Arif et al., 1996). Only the high NH_4 application rate (240 mg N kg^{-1}) could have the persistent inhibitory effect, attributing partly to a pH decrease during nitrification (Hütsch, 1998). Generally, CH_4 oxidation in agricultural soils is of minor importance, but the model's ability to predict the emissions and oxidation process cannot be ignored. The model responded linearly with SOC losses to soil pH, which is functionally linked to decomposition rates that increase with increasing soil pH. However, microbial activity, particularly bacterial, at very acid or alkaline pH levels is poor, leading to a stop in, or a slow down in, organic matter mineralization (Primavesi, 1984). The highest pH level (8.35) did inhibit R_H to a small extent, contrasting to SOC loss, though again small compared to a pH of 7.35.

3.4.5.2 Land-use managements

Addition of organic materials and cover crops

Application of organic matter in the form of plant/crop residues, compost and manure stimulates microbial biomass growth, increases enzyme activity and soil N mineralization, and also influences soil physical properties, resulting in variable GHG emissions and SOC storage. In the modified ECOSSE, organic matter as an input can be included but was found to be non-functional. The inclusion of cover/catch crops over the autumn–winter growing period clearly increased the total N_2O, R_H and SOC losses, relating to discrepancies in relevant submodels included in the model. This is in line partly with Bell et al. (2012) although cover crop should commonly decrease N_2O fluxes by exploiting residual nitrogen

Fertilizer N type

The model responded well for total N_2O flux and the EFs to fertilizer N containing NH_4 (including urea), contrasting to 100% nitrate-based N fertilizer, leading to an EF of 0.17% compared to the estimates from other fertilizer N types (0.53–0.71%). The findings are similar to the previous version (Bell et al., 2012), indicating dominance of nitrification for producing N_2O in arable soils, and in agreement with the results of Abdalla et al. (2009) and Clayton et al. (1997). It seems that the model under-predicted the influence of high soil water content for enhancing denitrification-induced N_2O emissions. Bouwman et al. (2002) reported lower N_2O emissions for NO_3-based fertilizers compared to NH_4-based fertilizers, but differences between N fertilizer types disappeared on an identical site-specific management (Stehfest and Bouwman, 2006). The model was also highly sensitive to fertilizer type and a switch from the principal form of N fertilizer being applied in Ireland (CAN) to urea or ammonium sulphate fertilizers increased N_2O fluxes, presumably through nitrification.

The model response to fertilizer N types was small for C emissions, demonstrating a negative correlation for total R_H with CH_4 oxidation and SOC stock changes. Compared to the other two N types, the model probably takes into account higher contribution of CAN and urea to produce biomass, leading to greater total R_H but lower SOC losses and with little influence to CH_4 flux. Nitrogen fertilization may cause slight increases in soil CO_2 flux (Khalil et al., 2007). However, improved N use efficiency of crops can enhance C sequestration and reduce CO_2 emissions (Paustian et al., 1992). Nevertheless, higher reductions in CH_4 uptake can be expected from ammonium-based fertilizers (Schnell and King, 1994), meriting the need for the model to consider the impact of various fertilizer types, particularly on C emissions.

Fertilizer N rates

The model responded well to fertilizer N rates and the simulated total N_2O fluxes and thereby EFs increased exponentially from 0.51 to 0.73%. Bouwman et al. (2002) showed relatively static N_2O emissions across a broad range of rates, relating to the amount required to satisfy crop N demands, but an increase thereafter at higher rates. This is in contrast to the linear EF approach adopted by the IPCC. The model response for R_H and thereby SOC losses (in contrast to CH_4 oxidation), to N rates was linear. Fertilization increases soil N and organic matter content, resulting in enhanced N_2O emissions and reduced CH_4 consumption rates.

The model response for CH_4 flux to N fertilizer rates was small, which can be attributed to the adaptation of oxidizing microbial function. The model predicted an increase in SOC losses with increasing N fertilizer rates. In contrast to the reports of others (Khan et al., 2007; Mulvaney et al., 2009; Powlson et al., 2010), adequate levels of fertilization are found to be beneficial for SOC sequestration through increased residue production (Alvarez, 2005; Follett, 2001; Halvorson et al., 1999) and this needs to be included in model development.

Tillage practices

Regardless of fertilization practices, the model sensitivity for total N_2O to tillage practices was consistent, showing an increase with increasing soil disturbance. Nitrous oxide fluxes are commonly greater under no tillage than under conventional tillage (Freibauer et al., 2004), suggesting site-specific evaluation of the interaction of soil, climate and management systems should be conducted. Reduced tillage promotes N_2O emissions in some areas but, depending on soil and climatic conditions, either reduces or have no measurable influence elsewhere (Marland et al., 2001). The model response for R_H to tillage practices was linear, linking to increased decomposition rates by disrupting soil structure and changing porosity. Many studies showed a decrease in CO_2 emissions under no-tillage compared to conventional tillage (e.g. Sainju et al., 2008), with huge differences during the high fluxes appearing to follow tillage operations (e.g. Reicosky and Archer, 2007). A slight negative response for CH_4 emissions to tillage practices was detected. Indeed, tillage-induced disturbance has a clear negative effect on CH_4 oxidation in arable soils (e.g. Hütsch, 2001). However, conservation tillage may not increase its uptake in all cases (Robertson et al., 2000).

The model was highly sensitive to SOC stock changes to tillage practices and the estimated SOC losses for 0–30 cm depth were 11.3 (reduced tillage), 16.1 (minimum tillage) and 29.4% (zero tillage) less over conventional tillage. The model demonstrated an increase in SOC losses with increasing intensity of soil disturbances, but no sequestration despite 8 years of simulation, contrasting to other reports –for example, by Franzluebbers (2005). However, Powlson and Jenkinson (1981) found no difference in SOC between long-term ploughing and no-tillage cereal plots when sampled to 40 cm. Since soil disturbance tends to enhance soil C losses through increasing decomposition, reduced or no-till agriculture often results in soil C gain, but not always (e.g. Alvarez, 2005) or unusually small at least in temperate climates (Angers and Eriksen-Hamel, 2008).

3.5 Conclusions

The ECOSSE simulated trends for N_2O fluxes were consistent with the measured values, with acceptable biases and errors, particularly for fertilized fields. The sum of the measured N_2O emissions taken over the crop growth period could vary with predicted values due to integration and sporadic timing of measurements. This implies the requirement of intensive sampling for precise estimations as evidenced by the peak differences accounted for in total N_2O emissions and the EFs. The model simulates R_H exceptionally well and also CH_4 fluxes, simulating in cropland an uptake of $CH_{4,}$ though values measured in the nearby field caused either uptake or small emissions. The model also indicated an average loss of SOC: however, this cannot be verified due to the unavailability of measured data in Ireland. The modified version is unable to predict soil water content and to some extent NO_3 content well. The model is sensitive to site characteristics except to soil bulk density and clay content, which are vital if a model is to provide reliable estimates for the prediction of GHGs and SOC stock changes. Its response to management practices is also strong except to the addition of organic materials and inclusion of cover crop, which are pertinent for finding mitigation strategies. Sensitivity analyses imply that the ECOSSE is able to provide a good estimate of N_2O EFs (0.54±0.02%) and SOC stock changes (164±8 for the 0–10 cm and 532±21 kg C ha^{-1} yr^{-1} for the 0–30 cm soil depth) in arable lands. There are inconsistencies in the estimation of N_2O EFs and the processes interactively form and release GHG fluxes, leading to limited widespread application of this tool. Similar concluding remarks are also made by Bell et al. (2012), relating to the lack of incorporation of all of the processes necessary for describing daily soil N turnover and N gas emissions although priority is given to the model's ability to simulate monthly and annual fluxes. Thus, further refinement and validation using site-specific good datasets are imperative so as to enhance the applicability of this model for predicting coupled C and N emissions from agricultural soils, and the inclusion of sub-models for other land uses and land managements, and the development of robust estimates of EFs associated with management and deployment of mitigation options.

4 Comparative Simulation of Greenhouse Gases using Three Process-based Models

4.1 Introduction

Most Annex-I countries use IPCC methodologies, that is both IPCC methodologies and default EFs (Tier 1) because of a lack of detailed, spatially explicit activity data; some countries have moved to Tier 2, that is IPCC methodologies but with country-specific EFs, with very few countries adopting Tier 3 approaches in their national inventories. However, many are still at the development stage. The Tier 1 approach has several limitations for a country/region in terms of addressing planning and policy issues with regard particularly to implementing GHG mitigation relevant to Agriculture, Forestry and Other Land Use (AFOLU)/LULUCF (IPCC, 2007). The development of higher tiers deserves reasonable country/regional-specific good activity data. Compared to Tier 2, more additional resources are required for the development of Tier 3, that is, a biogeochemical model is needed. It is impractical to directly measure GHGs covering all soil types, land use/cover types and associated managements over large areas and over a long period of time. To overcome this, the development of a process-based model is highly desirable. This type of modelling approach provides improved estimates of GHG and SOC budgets and reflects more robust emission (sink or source) accounting by reducing uncertainty based on sensitivity analysis and the potential impact of changes in land use and management practices, climate and soil type. The advantages in using this type of model include: the ability to predict agricultural GHG emissions from the site-specific to the global level the elucidation of potential mitigation strategies and the relationship between each GHG gas and another, and improved understanding how agricultural soils can act as a sink or source of GHGs.

In line with commitments under the UNFCCC, the ROI is committed to improving the estimation of GHGs and changes in SOC stocks by developing Tier 3 approaches. There are several process-based models available globally that are able to predict a variety of variables related to different ecosystems. In the ROI, only some models (DNDC, DayCent, RothC, PASIM, etc.) have been tested/validated using limited activity data measured from grassland and arable systems (Abdalla et al., 2009; 2012; Rafiq et al., 2011; Xu et al., 2011a; Byrne and Kiely, 2012). The simulation of GHGs, mainly N_2O, using these models had major operational shortcomings with respect to options for inclusion in the inventory process, for example, a lack of activity data and complex coding and data management requirements. Moreover, the outputs obtained are inadequate for adopting any of the models for use in the inventory process. Importantly, the ability of models to predict coupled emissions of GHGs and SOC stock changes in agricultural soils is meagre. For up-scaling of GHG emissions from site to regional/national scales, continuous progress toward improving model accuracy and precision is essential.

Based on the performances, three process-based models (updated ECOSSE v5, DNDC v 9.4 and DailyDayCent) were chosen to achieve precise reporting primarily for agricultural GHGs and C balance. This work was designed to establish an emission inventory system that reflects the site-specific diversity of practices influencing GHG emissions and changes in SOC, with a future objective of including national/regional variations for refining their analysis. Reasonable flux data for spring barley (a major cereal in the ROI) were available to initiate model-comparison exercises. The main objectives were to:

1 Simulate daily GHG emissions and SOC stock changes in conventionally tilled spring barley fields using the three models;
2 Assess the extents of qualitative and quantitative statistical agreements between model outputs and measured datasets; and
3 Evaluate the differences between the measured and modelled seasonal/annual GHG emissions and their emission factors.

4.2 Materials and Methods

4.2.1 Experimental Sites and Datasets

Details on experimental sites and datasets are given in Sections 3.2.1–4. Soil physical and chemical properties for the 0–10 cm depth (Table 3.1) were taken to initiate the models due to depth limitation for the above inputs.

4.2.2 Description of Models

As noted above, three dynamic models – DNDC, DailyDayCent and ECOSSE (latest versions) – were selected for this comparison study. The inputs requirement for the models are similar except with regard to weather data where daily maximum/minimum air temperature and precipitation for DNDC and DailyDayCent are needed, and mean daily air temperature, precipitation and potential evapotranspiration are required for ECOSSE. All models provide outputs for daily N and C fluxes. A brief description of each model is given below.

4.2.2.1 ECOSSE

Details of the ECOSSE model are given in Section 3.2.3 above.

4.2.2.2 DeNitrification and DeComposition (DNDC)

The DNDC is a widely used process-based model (e.g. Li et al., 2000, 2007), but several modified versions that have been adapted to various production systems exist. This model couples denitrification and decomposition processes in order to predict emissions of C, with CH_4 oxidation, and of N from agricultural soils that are governed by various soil and environmental factors. It contains four interacting submodels: (i) soil climate, (ii) decomposition, (iii) denitrification, and (iv) plant growth, and includes subroutines for cropping practices (fertilization, irrigation, tillage, crop rotation and manure addition) to simulate SOM turnover. Organic matter formed during decomposition is a dependent variable considering soil specificity associated with clay adsorption of humads. Decomposition follows first order kinetics. Ecosse treats soil as a series of discrete horizontal layers with uniform soil properties within each layer. However, some soil physical properties are treated as constant across all layers. Variations and changes (soil moisture, temperature, pH, C and N pools) over time are considered necessary in order to provide a reliable estimate of C and N fluxes by calculating them on each soil layer for each time-step.

4.2.2.3 DailyDayCent

DailyDayCent is a biogeochemical model built from the monthly version of Century and for the most part the parameter files used are identical to those used by Century 4.5 and DayCent 4.5 (e.g. Parton et al., 1998; Del Grosso et al., 2002). This model simulates C and N fluxes between the atmosphere, vegetation, and soil. Major factors (e.g. nutrient availability, water, temperature) controlling plant growth are included to simulate GHGs and SOC changes over time. This model considers nutrient supply as a function of SOM decomposition and external nutrient additions. Other model inputs include timing and description of management events (e.g. fertilization, tillage, harvest), and soil texture data. Submodels – mainly plant production, SOM decomposition, soil water and temperature by layer, nitrification and denitrification, and CH_4 oxidation – are also included. Improvement of this model is ongoing, and a comparison of model results and plot data have shown that DailyDayCent reliably simulates crop yield, SOM levels, and trace gas fluxes for various native and managed systems (Del Grosso et al., 2012).

4.2.3 Statistical Evaluation and Calculation

The models were run using the common inputs and weather data (Tables 3.1 and 3.2). The outputs were converted into standard units to match with measured datasets and then collated. The simulated values were compared and validated quantitatively with measured and/or literature data; calculations and statistical evaluation are discussed in Section 3.2.7 above.

4.3 Results

4.3.1 Simulated and Measured Soil Nitrate-N and Water Content

The N fertilizer (CAN) was applied as a single dose in 2004 only and in two splits in later years. The measured soil NO_3 content was found to be a maximum of 71.3 following fertilization and went down to 0.82 kg N ha^{-1} at later periods (data not shown). In the unfertilized field, the minimum and maximum NO_3 levels (seasonal/annual) measured were 0.20 and 25.2 kg N ha^{-1}, respectively. The DailyDayCent and DNDC predicted NO_3 contents were markedly higher for the fertilized field than the measured and those simulated by ECOSSE. Only the ECOSSE predicted values were closer to the amount of NO_3 applied, and consistent over the 8 years. No models simulated the soil NO_3 contents well, showing poor R^2 (Table 4.1). For the fertilized field, the ECOSSE (R^2=0.55) and the DNDC (R^2=0.31) models estimates correlated significantly (p<0.05) with the measured ones. The total error and bias differences were large and significantly (p<0.05) greater than their 95% confidence intervals for both fields.

Table 4.1. Comparison of daily NO_3 concentration (kg N ha^{-1}) simulated by the three models with values measured on a conventionally tilled field cropped to spring barley.

Statistical parameters	Fertilized			Unfertilized (Control)		
	DNDC	DailyDayCent	ECOSSE	DNDC	DailyDayCent	ECOSSE
R	0.31*	0.14	0.55*	-0.07	0.00	0.13
RMSE (%)	925*	2847*	115*	837*	684*	169*
$RMSE_{95\%}$ (%)	103	103	103	157	157	157
RE (%)	-610*	-1807*	-46*	-419*	-497*	-86*
$RE_{95\%}$ (%)	66	66	66	65	65	65
MD (%)	-68	-203	-5	-14	-16	-3

* Significant at 5% level of probability. R=Coefficient of Determination; RMSE=Root mean square error; RE=Relative error (Mean); MD=Mean difference; n=53

Field measured soil water content (water-filled pore space, WFPS) showed an upper limit of 88.8% and a lower limit of 25.0% (data not shown). The DNDC simulated lower WFPS, with a maximum of 40% and a minimum of 3% WFPS – a level, below the wilting point. The DailyDayCent predicted similar trends except for the upper limit but not closer to the measured values and these were highly variable. The ECOSSE simulated trends for WFPS, with a minimum of 41.4% and a maximum of 65.1%, and was similar to the measured data (except 2004 and 2005). Irrespective of the models, there was no significant correlation between the simulated and measured WFPS values (Table 4.2). The total bias and error differences were relatively small but significantly higher than their 95% confidence intervals.

Table 4.2. Comparison of simulated daily WFPS (%) with values measured on a conventionally tilled field cropped to spring barley.

Statistical parameters	Fertilized			Unfertilized (Control)		
	DNDC	DailyDayCent	ECOSSE	DNDC	DailyDayCent	ECOSSE
R	0.01	0.02	0.01	-0.18		0.00
RMSE (%)	70*	54*	32*	52*		32*
$RMSE_{95\%}$ (%)	23	23	23	24		24
RE (%)	57*	26*	6	36*		9
$RE_{95\%}$ (%)	18	18	18	17		17
MD (%)	29*	14*	-3	19*		5*

* Significant at 5% level of probability. R=Coefficient of Determination; RMSE=Root Mean Square Error; RE=Relative Error (Mean); MD=Mean Difference; n=129 (DNDC), 85 (DailyDayCent), 88 (unfertilized).

4.3.2 Performance of Models to Simulate GHG Emissions

4.3.2.1 N_2O emissions

The only maximum peak for N_2O flux measured from the fertilized field in 2004 (56.0 g N ha^{-1} d^{-1}) and the other years showed the maximum 17.6 and the minimum -8.0, demonstrating small differences with the unfertilized field (16.6 versus -10.4 g N ha^{-1} d^{-1}). Regardless of the models, the simulated N_2O fluxes were consistent over years but differed with the measured values, and none of the models predicted fluxes less than zero. The N_2O fluxes varied largely between the fertilized (80.0–100.9 g N ha^{-1} d^{-1}) and unfertilized (24.5–56.5) fields, with DailyDayCent yielding the highest estimate and including an unusual and unexpected peak for the unfertilized field (110.1). The ECOSSE simulated values correlated well with the measured values ($R^{2=}$0.33, p<0.05) under fertilized conditions only (Table 4.3). Overall, the total bias and error differences did not vary significantly with their 95% confidence levels.

Table 4.3. Comparison of simulated daily N_2O fluxes (g N ha^{-1}) with values measured on a conventionally tilled field cropped to spring barley.

Statistical parameters	Fertilized			Unfertilized (Control)		
	DNDC	DailyDayCent	ECOSSE	DNDC	DailyDayCent	ECOSSE
R	-0.02	0.19	0.33*	-0.02	-0.03	-0.04
RMSE (%)	189	367	154	186	183	197
$RMSE_{95\%}$ (%)	372	372	372	305	305	305
RE (%)	87	74	-59	94	87	-43
$RE_{95\%}$ (%)	267	267	267	305	305	305
MD (%)	5*	4*	-3	2*	2*	-1

* Significant at 5% level of probability. R=Coefficient of Determination; RMSE=Root mean square error; RE=Relative error (Mean); MD=Mean difference; n=130

For the fertilized fields, both DNDC (87%) and DailyDayCent (81%) underestimated total N_2O fluxes (seasonal/annual), and the ECOSSE overestimated it by 59% (Table 4.4). On an 8-year average, the DNDC simulated total N_2O fluxes for the fertilized (207 kg N ha^{-1}) and unfertilized (81 kg N ha^{-1}) fields were 2 to 15 times lower than the estimates of other two. Both DNDC and DailyDayCent provided an underestimation of N_2O EFs while ECOSSE estimates were closer to the measured values. Compared to the measured annual, the DNDC decreased EF by 94% and the DailyDayCent by 44%, and the ECOSSE increased it by 35%. An estimation discrepancy for total fluxes and thereby EFs between integrated values and the sum of daily fluxes was observed. On an 8-year average, the simulated EF was 0.09% with the DNDC, 0.31% with the DailyDayCent and 0.52% with the ECOSSE.

Table 4.4. Comparison of simulated seasonal and annual N_2O fluxes (g N ha^{-1}) and emission factors (EFs) with values measured on a conventionally tilled spring barley field.

Total N_2O fluxes	Fertilized				Unfertilized (Control)			
	Measured	DNDC	DailyDayCent	ECOSSE	Measured	DNDC	DailyDayCent	ECOSSE
Seasonal (04)	522	137	94	1091	-20	18	83	816
Seasonal (05)	1145	33	74	1066	194	2	64	342
Annual (08–09)	1168	88	380	2049	689	61	119	1423
Annual (8 yrs Av)	–	207	644	2037	–	81	218	1319
N_2O EFs								
Seasonal (04)	0.39	0.09	0.01	0.20				
Seasonal (05)	0.60	0.02	0.01	0.46				
Annual (08–09)*	0.34	0.02	0.19	0.46				
Annual (08–09)**	–	0.06	0.34	0.48				
Annual (8 yrs Av)	–	0.09	0.31	0.52				

* Integrated (harvest to harvest); ** Sum of daily simulated values (harvest to harvest); EF=Emission factor

4.3.2.2 Soil/Ecosystem respiration

The R_{eco} measured using EC from the large fertilized field demonstrated only a maximum flux of 75.6 kg C ha^{-1} d^{-1} during the crop growth and went down to 0.59 during the non-crop period, corresponding to R_H. The DNDC simulated values for R_{eco} showed trends similar to the measured values, with a R^2 of 0.34 (p<0.05), and the total bias and error differences were ≤34% and ≤ 91%, respectively (Table 4.5). The estimated R_{eco} for the DailyDayCent also showed trends similar to the measured values, with higher fluxes from 2007 onwards, an R^2

of 0.41 (p<0.05) and relatively small biases (≤50%) and errors (≤85%). The DNDC fractions did not match well to estimate R_{eco} from the ECOSSE or simulated values of R_H. Considering the statistical significance, the DailyDayCent fractions were used to estimate measured R_H. Given possible uncertainties, all models were found to simulate R_H efficiently, with an R^2 range from 0.44–0.62 (p<0.05) and with small biases (≤50%) and errors (≤87%).

The annual total R_{eco} measured using the EC was on average 6771 kg C ha^{-1}, which is closer to the DailyDayCent value (6736) but higher than the DNDC estimate (4455; Table 4.5). The ECOSSE estimate is omitted due to large mismatching. On a 4-year average, the measured R_H (estimated) was 3624 kg C ha^{-1}, which is closer to the ECOSSE and the DailyDayCent simulated values but higher than the DNDC estimate (1794). On an 8-year average, the R_H somewhat differed with the above although the simulated amount was similar.

Table 4.5. Validation of daily soil (R_{eco}) and heterotrophic respiration (R_H) simulated by three process-based models with values measured from spring barley fields.

Statistical parameters	R_{eco}				R_H			
	Measured	DNDC	DailyDayCent	ECOSSE	Measured!	DNDC	DailyDayCent	ECOSSEϕ
R		0.34*	0.41*			0.58*	0.62*	0.44*
RMSE (%)		85	91			85	68	87
RE (%)		34	1			50	24	7
MD (%)		6*	0			5*	2*	1*
Total CO_2 fluxes kg C ha^{-1}								
Annual total R_{eco}	6771	4455	6736					
Annual total R_H						1826	2668	3218
Annual total R_H (4 yrs average)					3624	1794	2744	3387

* Significant at 5% level of probability. !=estimated using DailyDayCent derived ratio; ϕ=R_{eco} estimated using a conversion ratio derived from DNDC outputs for ECOSSE and DailyDayCent. R=Coefficient of determination; RMSE=Root mean square error; RE=Relative error (Mean); MD=Mean difference

4.3.2.3 CH_4 fluxes

The measured CH_4 fluxes (emission and oxidation) were small and varied significantly between the fertilized (-040 to 0.36 g C ha^{-1} d^{-1}) and unfertilized (-0.09–0.12) fields. The highest simulated oxidation and emission respectively were 2.92 and 0 g C ha^{-1} d^{-1} with the DNDC, 4.02 and 0 with the DailyDayCent, and 0.24 and 0.31 with the ECOSSE, which provides values closer to the measured ones for the fertilized field only. The DNDC and the DailyDayCent simulated values correlated poorly with the measured values, demonstrating large biases and errors (Table 4.6). The ECOSSE simulated values correlated well ($R^{2=}$0.34, p<0.05), with the total bias and error differences less than their 95% confidence intervals. For the unfertilized fields, either model estimates showed poor R^2, large biases and errors.

Table 4.6. Validation of daily CH_4 effluxes (g C ha^{-1} d^{-1}) simulated by three process-based models with values measured from spring barley fields and their total fluxes.

Statistical parameters	Fertilized			Unfertilized (Control)		
	DNDC	DailyDayCent	ECOSSE	DNDC	DailyDayCent	ECOSSE
R	0.02	0.02	0.34	0.02		0.07
RMSE (%)	18926*	183761*	401	38037*		2286*
$RMSE_{95\%}$ (%)	14821	14821	14821	2071		2071
RE (%)	17564*	16786*	-65	35238*		1670*
$RE_{95\%}$ (%)	101499	101499	101499	1318		1318
MD (%)	2*	2*	4*	2*		0*

Total annual fluxes (g C ha^{-1})	Measured	DNDC	DailyDayCent	ECOSSE	Measured	DNDC	DailyDayCent	ECOSSE
Integrated	3.50	-646	-612	-25	2.35	-729		-31.1
Sum of daily flux		-682	-657	-28		-712		-31.4
8 years average		-666	-704	-28		-667		-30.3

* Significant at 5% level of probability. R=Coefficient of determination; RMSE=Root mean square error; RE=Relative error (Mean); MD=Mean difference

Annual estimations of the measured data showed the arable land an unusually small CH_4 source, with the emission of 2.35 g C ha^{-1} under the unfertilized field increased to 3.50 g C ha^{-1} under the fertilized field (Table 4.6). On an 8-year average, the model estimates the Spring Barley land use is a sink for CH_4, with the annual oxidation of 666 g C ha^{-1} from the DNDC, 704 from the DailyDayCent and 28 from the ECOSSE. There were no clear and large differences between the integrated and sum of the daily flux for the calculation of total CH_4 fluxes.

4.3.3 Predictability of the Models for SOC Stock Changes

The DNDC predicted 22% (using soil depth ratio function) or 38% (based on homogenous distribution) lower SOC than the amount included as an input (0–10 cm soil depth) to run the model and the ECOSSE model simulated 40% more (Table 4.7). The DailyDayCent simulated values for SOC changes were not available for comparison. The ECOSSE model simulated consistently well the changes in SOC stock over years (linear function showed R^2 of 0.96–0.97) compared to the DNDC estimates ($R^{2=}$0.06).

There was a negligible difference between linear and differential approaches for the estimation of annual SOC stock changes. The DNDC predicted small sinks (9.4–13.1 kg C ha^{-1}) and the ECOSSE losses (302–410) of SOC from the arable land receiving 1.32 t C ha^{-1} as crop residues. Both models were able to predict the influence of N fertilization on SOC stocks and that increased with increasing rates of N application. Statistical evaluation of the model's performance was performed using the literature data due to the unavailability of measured data (Table 4.7).

Table 4.7. Comparison of annual SOC stock changes (kg C ha^{-1}) in the arable land simulated by three process-based models with values measured elsewhere in temperate crops.

	Simulated			Measured	References
	DNDC*	DailyDayCent	ECOSSE**		
Fertilized					
Linear model	13.1		-386	30–570	West and Marland, 2003
Annual balance (7 yrs)	10.1		-302		
				0.05–0.20%	Uhlen, 1991
Unfertilized control				160	Triberti et al., 2008
Linear model	9.7		-410	-5%	Stockfisch et al., 1999
Annual balance (7 yrs)	9.4		-332	0.47–0.73%	Janson, 1975

‘where a minus sign indicates a loss of carbon * Soil depth 0–50 cm; ** Soil depth 0–10 cm;: literature review, arable crops, N fertilized ± crop residues and NOT corresponds to simulations. Considering SOC stock for 0–10 cm of 19,912 kg ha^{-1}, the estimates for Uhlen, 1991=10–40; Stockfisch et al., 1999: -996, and Janson, 1975: 94–145 kg C ha^{-1} yr^{-1}).

4.4 Discussion

4.4.1 Performance of the Models for the Simulation of Soil Nitrate-N and Water Content

Compared to the unfertilized field, the measured soil NO_3 content following CAN fertilizer application, containing half the NO_3 level, was mostly in order of magnitude. The peak for soil N mineralization during the later years of measurements might be missed and/or denitrified rapidly. The decrease of soil NO_3 concentration over time is pre-assumed to be through plant uptake and other N loss processes. The DailyDayCent and DNDC predicted soil NO_3 levels were noisy, attributing to a mismatch with plant N uptake and other N loss processes. Moreover, the simulated peak for NO_3 levels was not within the measurement ranges. Similar large overestimations were reported by others (Abdalla et al., 2009; 2012; Del Grosso et al., 2002; 2005) using the previous versions of DNDC and DailyDayCent. This may be ascribed to their limitations in the treatment of soil depth increments to consider for inputs/outputs and/or assumptions of high availability of mineralized N and high nitrification rates. As discussed below, the low predictions of soil water content and R_H – particularly by the DNDC – might limit the contribution of the relevant process to that effect. The ECOSSE simulated values were closer to the amount of NO_3-N applied, in line with Bell et al. (2012), and consistent over 8 years in contrast to the other two models. Except fertilizer-induced peaks for NO_3 levels, there were small differences between fertilized and unfertilized fields. Statistical evaluations confirm that the ECOSSE simulated soil NO_3 well ($R^{2=}$0.50, p <0.05) for the fertilized field, and that it performed better than the DNDC ($R^{2=}$0.31, p <0.05) and the DailyDayCent (R^2=0.14). The models were unable to predict lower limits of NO_3 levels compared to the measured data and the DNDC v9.2 predicted maximum peaks for NO_3, showing underestimations (Abdalla et al., 2012). However, the total bias and error differences are within their 95% confidence intervals. Among the models, the ECOSSE had a greater predictive power for soil NO_3 than the other two models, except with regard to the unfertilized fields.

The measured WFPS were consistent over time, but in some instances the values were below the wilting point. Compared to the measured data, the DNDC underestimated the upper and lower limits of WFPS. A similar discrepancy in soil water dynamics with the previous version of the DNDC was observed (Roland et al., 2010). This is in contrast to the DNDC v9.2 (R^2=0.58) where most of the dataset included was similar to this study (Abdalla et al., 2012). Among the models, the ECOSSE predicted values were closer to the measured values, but the upper limits of WFPS were not favourable for denitrification to occur, within the range set in the model, and therefore underestimation of N emissions would be possible (Bell et al., 2012). The poor R^2 and the large total bias and error differences indicate the inability of models to simulate well soil NO_3 and WFPS, and thereby take into account the processes involved in C and N emissions.

4.4.2 *Simulation Capacity of the Models for GHG Emissions*

4.4.2.1 N_2O emissions

The measurement intervals of N_2O emissions were sporadic and the maximum peak that appeared in 2004 may be missed in the sampling campaign (Abdalla et al., 2012), as the rainfall pattern and thereby soil water content did not vary largely. Simulation of N_2O emissions using the three models was reasonably consistent over years. However, none of the models was able to predict N_2O fluxes less than zero. This is in contrast to the measured values where a sink of N_2O under conditions of low oxygen and mineral N was observed, in line with others (Khalil et al., 2002; Chapuis-Lardy et al., 2007). The DailyDayCent simulated N_2O fluxes well except for an unusual peak derived from the unfertilized field. The total bias and error differences were somewhat large but within their 95% confidence levels. This indicates quite high predictive potentials of the models, although only the ECOSSE simulated values showed a significant correlation with the measured ones under fertilized conditions. Similar R^2 for daily N_2O fluxes was observed for all models, including DailyDayCent (Del Grosso et al., 2002; Bell et al., 2012). Higher R^2 was reported with the DNDC by Abdalla et al. (2012) but this did not correspond to to the daily fluxes. Similar strong relations for total N_2O fluxes might be achieved from the other two models, but overall performance seems to depend mainly on daily fluxes. Given the simulated values within 95%

confidence intervals, none of the models simulated well daily N_2O fluxes for the unfertilized field, showing poor R^2.

For the fertilized fields, both DNDC and DailyDayCent underestimated (81–87%), and the ECOSSE overestimated (59%) the total N_2O fluxes (seasonal/annual). On an 8-year average, the DNDC simulated total fluxes were 2 to 15 times lower than the DailyDayCent and the ECOSSE estimates. The variations between the model estimates and their relationship with key driving forces such as soil water and NO_3 levels are assumed to be functionally limited to the production and release of N_2O. This conforms with the DNDC-simulated low soil water content, in line with Beheydt et al. (2007) when default values were used, and creates a noisy simulated output with the DailyDayCent, including high NO_3 content. This indicates that both models consider denitrification as the major contributor to N_2O production, but the simulated low soil water content is thought to limit the process. In contrast, nitrification might be the major pathway formulated in the ECOSSE and the N_2O emissions, though overestimated, were somewhat consistent with the simulated soil water and NO_3 levels. This means that the ECOSSE could further enhance the emissions with increasing soil water contents, provided that the substrates and thereby denitrification process are not limiting. These are in agreement with the literature values for total N_2O emissions measured from crop fields, ranging from 0.7 to 3.5 kg N ha^{-1} yr^{-1} (Kaiser and Heinemeyer, 1996; Flessa et al., 1998; Kaiser et al., 1998; De Gryze et al., 2010). The inconsistencies in modelled predictions emphasize the requirement of accurate simulation of soil moisture for a reliable prediction of N_2O emissions (Frolking et al., 1998).

Similarly, huge underestimations of N_2O EFs (either seasonal or annual or simulated 8 years average) by the DNDC followed by the DailyDayCent models compared to the measured data were observed. Estimation of EFs using simulated values was constrained by total flux differences between fertilized and unfertilized fields. However, replacement of unfertilized value by background annual N_2O emissions of 1 kg N ha^{-1} (Del Grosso et al., 2005) could also be erroneous. Similar overall underestimations – particularly using the earlier versions of DNDC – have been reported (Beheydt et al., 2007; Abdalla et al., 2009; 2012). The DailyDayCent also underestimated the N_2O EF by 44%, a similar finding using the DayCent (~25%), when compared with the default annual, was reported by Del Grosso et al. (2005). In contrast, the ECOSSE on average increased EF by 35% but within closer ranges (0.52%) to the measured estimates. This is in line with the previous version (Khalil et al., 2012b) although lower than the IPCC default value (1%). There was a discrepancy in calculating total/cumulative N_2O fluxes and therefore EFs, which may lead to an under- or over-estimate of the EF, depending on the corresponding peak sizes, and the sum of daily fluxes. Nitrous oxide emissions vary largely, either temporal and/or spatial (Khalil et al., 2009), resulting in EF uncertainty of >50% (Mosier et al., 1999; Lim et al., 1999). This uncertainty may improve based on several years of measurements and calibration of the model against more management-induced variations (Clayton et al., 1997; Kaiser et al., 1998). However, the measured lower total N_2O fluxes and thereby EFs may be explained by the application of CAN during relatively dry periods, leading to less denitrification, and high SOC density, which is favourable for complete denitrification at high soil water levels. The above statement remains uncertain due to sporadic gas samplings for better estimates, suggesting the need for intensive samplings following tillage, fertilization, rainfall and other environmental factors that regulate the degree of N_2O emissions. Moreover, further improvement of the models by identifying errors associated with the processes that interactively produce N_2O and also by using robust measurement data to validate and thereby calculate N_2O EFs across disaggregated arable lands and managements is imperative.

4.4.2.2 Soil respiration

We assumed that there are small differences between R_{eco} measured, showing consistent estimations from the EC technique, and soil respiration (R_s, autotrophic plus heterotrophic). This conforms to both DailyDayCent and DNDC simulated values, demonstrating good correlation with the measured values ($R^{2=}$0.41 versus 0.34, p<0.05) and relatively small total bias and error differences. Similarly, the DNDC simulated cumulative CO_2 fluxes of cropland site in Europe well except for some over-estimation of net CO_2 uptake (Dietiker et al., 2010). Frolking et al. (1998) found that the ability of DayCent to simulate CO_2 emissions for various management systems. Our study indicates that a further improvement of both models is required to remove the discrepancy with regard to the early appearance of the simulated CO_2 peaks compared to the measured values. Irrespective of the models, this shift cannot be seen for the R_H either modelled or measured, and these correlated well *(*R^2=0.44–0.62; p<0.05), with small biases and errors. The DailyDayCent and DNDC simulated R_H better than the ECOSSE. The relatively poor performance of the ECOSSE is probably caused by the estimation errors associated with the conversion of the measured R_{eco} data to R_H.

Accordingly, the annual estimates for the total R_{eco} measured using the EC (6771 kg C ha^{-1}) is closer to global croplands average (5440±800, Raich and Schlesinger, 1992). The measured value was almost similar to the DailyDayCent predictions. The DNDC underestimated it by 34%, attributable to the poor simulation of soil water. Despite having lower R^2, the ECOSSE simulated total R_H was 7% less but closer to the measured values, and the DailyDayCent and DNDC underestimated it by 24 and 51%, respectively. Similar consistent simulated values on an 8-year average were also observed, implying that the ECOSSE was better for R_H prediction than the other two models.

4.4.2.3 CH_4 emission/oxidation

The measured data demonstrated both CH_4 emission and oxidation although their extents were relatively small. This might be linked to the fractional contribution of R_H with the simultaneous influence of mainly soil water contents/precipitation events through creating aerobic and anaerobic conditions (Khalil and Baggs, 2005). The measured peaks for CH_4 showed stimulating effects of N fertilization on both emissions and oxidation. The three models were unable to predict similar trends, possibly because of constraints from several regulating factors, and consideration of the flux variations between fertilized and unfertilized fields may not be appropriate for judging the model's performance. Both DNDC and DailyDayCent predicted CH_4 oxidation, in line with former versions (Del Grosso et al., 2002; Li et al., 2005) and the ECOSSE, providing values mainly for the fertilized field closer to the measured ones. The simulated and measured values were poorly correlated, including remarkably high total bias and error differences, particularly with the DNDC and DailyDayCent. The ECOSSE modified version performed better ($R^{2=}$0.34) than the previous one (Khalil et al., 2012b). The CH_4 fluxes from arable lands might have less impact for overall GHG accounting. However, evaluation of a process-based model would be necessary to determine whether any functional relationship between C and N in association with regulating factors is characterised properly.

The measured data showed the land use as a CH_4 source, increasing with the application of N fertilizer. This indicates fertilizer-induced diminution unlike that observed for field-measured CH_4 peaks. Methane can be produced from anaerobic microsites, having further potential to metabolize methanotrophs, and arable soils may mainly cause a sink rather than source, if small (Bodelier and Laanbroek, 2004; Khalil and Baggs 2005) due to high water-holding capacity of the sandy loam soil. Indeed, tillage and N fertilization have a tendency to reduce oxidation potentials (Bronson and Mosier, 1994). In contrast, increased CH_4 oxidation in arable soils (De Gryze et al., 2010) may be linked to well-aerated conditions with a positive redox potential to limit methanogenic activities through draining coupled with ploughing (Borken et al., 2003). The three models also demonstrated annual reduction of CH_4 oxidation from the N fertilizer-treated compared to the unfertilized fields. Results suggest functional constraints for CH_4 emissions from arable fields are better predicted by the DailyDayCent and DNDC than by the ECOSSE model.

4.4.3 Prediction Power of the Models for Changes in SOC Stocks

The validation of DNDC and ECOSSE simulated values for SOC stock changes were constrained by the unavailability of measurement data. Previous studies reported that the DayCent explained between 69% and 87% of the variance (De Gryze et al., 2010), and the annual net ecosystem carbon balance estimated for 3 years (2004–2007) from the same R_{eco} data used in this study was 549±102 kg C ha^{-1} (Ceschia et al., 2010). However, the input used to run the models and the model outputs could have enormous implications in evaluating the performance of a model. This emphasises the importance of baseline information derived from field data, and their representativeness in comparison to data derived from similar arable fields of temperate regions. The main constraint in the DNDC model is that it uses input for 0–10 cm soil depth whereas it provides output for 0–50 cm. On the other hand, the ECOSSE does not perform well with the input depth, particularly for SOC stocks. In both cases, homogenous distribution of SOC and the relevant soil properties are considered in both models, including a series of default algorithms to distribute SOC among different pools (Li et al., 1994; Smith et al., 2010). There appeared to be large uncertainties in the output generations, linked to methods used to initialise SOC within the models. This leads to an underestimation by the DNDC (22–38%) and overestimation (40%) by the ECOSSE model for SOC density compared to the input value.

The ECOSSE model simulated consistently well the changes in SOC stocks over years where both linear model and differential approaches were equally effective, compared to the DNDC estimates. The DNDC predicted small sinks (9.4–13.1 kg C ha^{-1}), in line with the findings of Uhlen (1991) but a bit lower than as reported by others (Jansson, 1975; West and Marland, 2003; Triberti et al., 2008). In contrast, the ECOSSE model showed losses, ranging from 302 to 410 kg C ha^{-1}, of SOC from the arable land, which is comparable to those estimated by Ceschia et al. (2010). However, the ECOSSE model estimates were close to an average estimate of 380 kg C ha^{-1} per cropping period in Europe where spring barley showed a small sink, and where excluding rice sites increased the loss to 810 kg C ha^{-1} (Moors et al., 2010), the latter is similar to model annual estimate on average 700 kg C ha^{-1} (Janssens et al., 2005) and the CESAR model estimate of 830 kg C ha^{-1} (Freibauer et al., 2004). Changes in SOC are highly variable, and similar but higher losses and/or both sinks and sources have been reported elsewhere (e.g. Stockfish et al., 1999; Smith et al, 2005; Ciais et al., 2009; De Gryze et al., 2010; Smith et al., 2012). In a test with the ECOSSE model, we could not find any functional relationship between the amount of crop residues remaining in the field and the changes in SOC stocks. The model probably considers the fractional contribution of above- and below-ground biomass. Based on the large variable estimates stated above and a bit higher prediction by the previous version of the ECOSSE (Khalil et al., 2012b), it is not appropriate to conclude from this study that the updated model performed better. Both models simulated the influence of N fertilization in increasing SOC stocks, attributing this to the increase in biomass production (Paustian et al., 1992). The predicted values differed largely between the two models but within uncertainty ranges. This warrants further refinement and validation of the models using the land use- or country-specific measured data by taking into consideration the inherent variability of SOC and the possible imperfections in the model estimates.

4.5 Conclusions

Compared to the measured values, the ECOSSE simulates the amount of nitrate concentration better than the DNDC and DailyDayCent. None of the models predict soil water content well – either under- and over-estimating – and the DNDC and DailyDayCent estimates are not reasonable. The DNDC and DailyDayCent simulate daily and total N_2O fluxes less than the ECOSSE, predicting fertilizer-induced N_2O fluxes and EFs better. All models simulate soil and/or heterotrophic respiration well except for an underestimation with the DNDC, relating more to soil water content variations compared to other model predictions. Only the ECOSSE can predict field CH_4 emission/oxidation closer to measured ones than other two, demonstrating overall oxidation. Though inclusive, the DNDC and ECOSSE simulated SOC stocks are within the uncertainty ranges for arable lands. There are constraints with the processes formulated to predict coupled C and N emissions, with special reference to soil water contents that lead to the underestimation of GHGs. Thus, refinement and further validation of the models using country-specific activity data are required to better predict coupled GHG emissions and SOC stock changes. In addition, it is important to avoid reliance on the default values of model inputs. Country-specific input parameters shold be developed, based on comprehensive measured programmes. This would improve model performance in the simulation of the impact of Irish agricultural systems, including land use and land management practices, and climate, thus enabling upscaling to national GHG estimates and representation of the impact of deployment of mitigation options.

References

Abdalla, M., M. Wattenbach, P. Smith, P. Ambus, P., M. Jones and M. Williams, M. 2009. Application of the DNDC model to predict emissions of N_2O from Irish agriculture. Geoderma. 151: 327–37.

Abdalla, M., M. Jones, P. Ambus and M. Williams. 2010a. Emissions of nitrous oxide from Irish arable soils: effects of tillage and reduced N input. Nutr Cycl Agroecosys. 86: 53–65.

Abdalla, M., M. Jones, and M. Williams. 2010b. Simulation of N_2O fluxes from Irish arable soils: effect of climate change and management. Biol Fertil Soils. 46: 247–60.

Abdalla, M., S. Kumar, M. Jones, J. Burke, and M. Williams. 2011. Testing DNDC model for simulating soil respiration and assessing the effects of climate change on the CO_2 gas flux from Irish agriculture. Glob Pl Chang. 78: 106–15.

Abdalla, M., K. Rueangritsarakul, M. Jones, B. Osborne, M. Helmy, B. Roth, J. Burke, P. Nolan, P. Smith and M. Williams. 2012. How effective is reduced tillage-cover crop management in reducing N_2O fluxes from arable crop soils? Water Air Soil Pollut. DOI 10.1007/s11270-012-1268-4.

Alvarez, R. 2005. A review of nitrogen fertilizer and conservation tillage effects on soil organic storage. Soil Use Manage. 21: 38–52.

Anderson, S. and S.I. Nilsson, 2001. Influence of pH and temperature on microbial activity, substrate availability of soil-solution bacteria and leaching of dissolved organic carbon in a mor humus. Soil Biol Biochem. 33: 1181–91.

Angers, D.A. and N.S. Eriksen-Hamel. 2008. Full inversion tillage and organic carbon distribution in soil profiles: a meta-analysis. Soil Sic Soc Am J. 72: 1370–4.

Arif, M.A.S., F. Houwen and W. Verstraete. 1996. Agricultural factors affecting methane oxidation in arable soil. Biol. Fertil. Soils. 21: 95–102.

Arrouays D., J. Balesdent, G.C. Germon, P.A. Jayet, J.F. Soussana and P. Stengel. 2002. Contribution a` la lutte contre l’effet de serre. Stocker du carbone dans les sols agricoles de France? Expertise Scientifique Collective, Synthe`se du rapport. INRA, Paris.

Baggs E.M., M. Stevenson, M. Pihlatie, A. Regar, H. Cook and G. Cadisch. 2003. Nitrous oxide emissions following application of residues and fertiliser under zero and conventional tillage. Plant Soil. 254: 361–70.

Batjes, N.H. 2011. Soil organic carbon stocks under native vegetation – revised estimates for use with the simple assessment option of the Carbon Benefits Project system. Agric Ecosyst Environ. 142: 365–73.

Beheydt, D., P. Boeckx, S. Sleutel, C. Li, and O. Van Cleemput. 2007. Validation of DNDC for 22 long-term N_2O field emission measurements. Atmos Environ. 41: 6196–211.

Bell, M.J., E. Jones, J. Smith, P. Smith, J. Yeluripati, J. Augustin, R. Juszczak, J. Olejnik and M. Sommer. 2012. Simulation of soil nitrogen, nitrous oxide emissions and mitigation scenarios at 3 European cropland sites using the ECOSSE model. Nutr Cycl Agroecosyst. 92: 161–81.

Bodelier, P.L.E. and H.J. Laanbroek. 2004. Nitrogen as a regulatory factor of methane oxidation in soils and sediments. FEMS Microbiol Ecol. 47: 265–77.

Boeckx, P. and O. Van Cleemput. 2001. Estimates of N_2O and CH_4 fluxes from agricultural lands in various regions in Europe. Nutr Cycl Agroecosyst 60: 35–47.

Boeckx, P, O. Van Cleemput and T. Meyer. 1998. The influence of land use and pesticides on methane oxidation in some Belgian soils. Biol Fertil Soils. 27: 293–8.

Bond-Lamberty, B. and A. Thomson. 2010. A global database of soil respiration data. Biogeosci Discuss. 7: 1321–44.

Borken, W., Y.-J. Xu, and F. Beese. 2003. Conversion of hardwood forests to spruce and pine plantations strongly reduced soil methane sink in Germany. Glob Change Biol 9: 956–66.

Bouwman, A.F., L.J.M. Boumans and N.H. Batjes. 2002. Modelling Global annual N_2O and NO emission from fertilized fields: summary of available measurement data. Glob Biogeochem Cycl. 16:28.1–28.9.

Braakhekke, M.C., C. Beera, M.R. Hoosbeek, M. Reichstein, B. Kruijt, M. Schrumpf, and P. Kabat. 2011. SOMPROF: A vertically explicit soil organic matter model. Ecol Model 222: 1712–30.

Bradley, R.I., R. Milne, J. Bell, A. Lily, C. Jordan and A. Higgins. 2005. A soil carbon and land use database for the United Kingdom. Soil Use Manage. 21: 363–9.

Bronson, K.F. and A.R. Mosier. 1994. Nitrous oxide emission and methane consumption in wheat and corn cropped systems in Northeastern Colorado. In: Harper, L.A., Mosier, A.R., Duxbury, J.M., Rolston, D.E. (Eds.), Agricultural Ecosystem Effects on Trace Gases and Global Climate Change. ASA Special Publication, No. 55. American Society of Agronomy, Crop Science Society of America and Soil Science Society of America, Madison, WI, pp. 133–44.

Byrne, K. and G. Kiely**.** 2012. Evaluation of Models (PaSim, RothC, CENTURY and DNDC) for Simulation of Grassland Carbon Cycling at Plot, Field and Regional Scale. http: //erc.epa.ie/safer/resource?id=b58963e1-42aa-102c-b381-901ddd016b14

Cannell, M.G.R., R. Milne, K.J. Hargreaves, T.A.W. Brown, M.M. Cruickshank, R.I. Bradley, T. Spencer, D. Hope, M.F. Billett, W.N. Adger, and S. Subak. 1999. National inventories of terrestrial carbon sources and sinks, the UK experience. Clim Chang. 42: 505–30.

Ceschia, E, P. Béziat, J.F. Dejoux, M. Aubinet, Ch. Bernhofer, B. Bodson, N. Buchmann, A. Carrara, P. Cellier, P. Di Tommasi, J.A. Elbers, W. Eugster, T. Grünwald, C.M.J. Jacobs, W.W.P. Jans, M. Jones, W. Kutsch, G. Lanigan, E. Magliulo, O. Marloie, E.J. Moors, C. Moureaux, A. Olioso, B. Osborne, M.J. Sanz, M. Saunders, P. Smith, H. Soegaard and M. Wattenbach. 2010. Management effects on net ecosystem carbon and GHG budgets at European crop sites. Agric Ecosyst Environ. 139: 363–83.

Chan, A.S.K. and T.B. Parkin. 2001. Effect of land use on methane flux from soil. J Environ Qual. 30: 786–97.

Chapuis-Lardy, L., N. Wrange, A. Metay, J.L. Chotte and M. Bernoux. 2007. Soils, a sink for N_2O? A review. Glob Chang Biol. 13: 1–17.

Chevallier, T., M. Voltz, E. Blanchart, J.L. Chotte, V. Eschenbrenner, M. Mahieu, and A. Albrecht. 2000. Spatial and temporal changes of soil C after establishment of a pasture on a long-term cultivated vertisol (Martinique). Geoderma. 94: 43–58.

Ciais, P., M. Wattenbach, N. Vuichard, P. Smith, S.L. Piao, A. Don, S. Luyssaert, I.A. Janssens, A. Bondeau, R. Dechow, A. Leip, P.C. Smith, C. Beer, G.R. van der Werf, S. Gervois, K. van Oost, E. Tomelleri, A. Freibauer and E.D. Schulze. 2009. CarboEurope Synthesis Team. The European carbon balance: Part 2: croplands. Glob Chang Biol. doi: 10.1111/j.1365-2486.2009.02055.x.

Clayton H., I.P. McTaggart, J. Parker, L. Swan and K.A. Smith. 1997. Nitrous oxide emission from fertilised grassland: A 2-year study of the effects of N fertiliser form and environmental conditions. Biol Fertil Soils. 25: 252–60.

Conrad, R. 1996. Soil microorganisms as controllers of atmospheric trace gases (H_2, CO, CH_4, OCS, N_2O, and NO). Microbiol Rev. 60: 609–40.

Cruickshank, M.M., R.W. Tomlinson, P.M. Devine, and R.M. Milne. 1998. Carbon in the vegetation and soils of Northern Ireland. Report April 1998. Department of the Environment, Transport and the Regions, Global Atmosphere Division.

Cruickshank, M.M., R.W. Tomlinson, and S. Trew. 2000. Application of CORINE land-cover mapping to estimate carbon stored in the vegetation of Ireland. J Environ Manage. 58: 269–87.

Crutzen, P.J., A.R. Mosier, K.A. Smith and W. Winiwarter. 2008. N_2O release from agrobiofuel production negates global warming reduction by replacing fossil fuels. Atmos Chem Phys. 8: 389–95.

Central Statistics Office (CSO). 2011. Irish Central Statistics Office. Access at: www.cso.ie.

Dalal, R.C. and R.J. Mayer. 1986. Long-term trends in fertility of soils under continuous cultivation and cereal cropping in southern Queensland: III. Distribution and kinetics of soil organic carbon in particle-size fractions. Aust J Soil Res. 24: 293–300.

Dawson, J.J.C. and P. Smith. 2007. Carbon losses from soil and its consequences for land-use management. Sci Total Environ. 382: 165–90.

De Gryze, S., A. Wolf, S.R. Kaffka, J. Mitchell, D.E. Rolston, S.R. Temple, J. Lee, and J. Six. 2010. Simulating greenhouse gas budgets of four California cropping systems under conventional and alternative management. Ecol Appl. 20: 1805–19.

Del Grosso, S.J., D.S. Ojima, W.J. Parton, A.R. Mosier, G.A. Petereson and D.S. Schimel. 2002. Simulated effects of dryland cropping intensification on soil organic matter and greenhouse gas exchanges using the DAYCENT ecosystem model. Environ Pollut. 116 (Suppl. 1): S75–S83.

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

Del Grosso, S.J., A.R. Mosier, W.J. Parton and D.S. Ojima. 2005. DAYCENT model analysis of past and contemporary soil N_2O and net greenhouse gas flux for major crops in the USA. Soil Till Res. 83: 9–24.

Del Grosso, S.J., W.J. Parton, A.R. Mosier, D.S. Ojima, C.S. Potter, W. Borken, R. Brumme, K. Butterbach-Bahl, P.M. Crill, K. Dobbie and K.A. Smith. 2000. General CH_4 oxidation model and comparisons of CH4 oxidation in natural and managed systems. Glob Biogeochem Cycles. 14: 999–1019.

Del Grosso, S.J., W.J. Parton, P.R. Adler, S. Davis, C. Keogh and E. Marx. 2012. DayCent model simulations for estimating soil carbon dynamics and greenhouse gas fluxes from agricultural production systems. In: Managing Agricultural Greenhouse Gases New York, NY: Elsevier Inc. p. 241–50.

Diamond, J. and P. Sills. 2011. Soils of Co. Waterford. National Soil Survey of Ireland. Soil Survey Bulletin No. 44. Teagasc, Oak Park, Carlow, Co. Carlow. Grehan Printers, Dubin. 314 pp.

Dietiker, D., N. Buchmann and W. Eugster. 2010. Testing the ability of the DNDC model to predict CO_2 and water vapour fluxes of a Swiss cropland site. Agric Ecosyst Environ. 139: 396–401.

Dobbie, K.E. and K.A. Smith. 1996. Comparison of CH_4 oxidation rates in woodland, arable and set aside soils. Soil Biol Biochem. 28: 1357–65.

Dobbie, K.E., I.P. McTaggart and K.A. Smith. 1999. Nitrous oxide emissions from intensive agricultural systems: variations between crops and seasons; key driving variables; and mean emission factors. J Geophys Res. 104: 26891–9.

Drury, C.F., T.O. Oloya, D.J. McKenney, E.G. Gregorich, C.S. Tan and C.L. van Luyk. 1998. Long-term effects of fertilization and rotation on denitrification and soil carbon. Soil Sci Soc Am J. 62: 1572–9.

Eaton, J.M., N.M. McGoff, K.A. Byrne, P. Leahy and G. Kiely. 2008. Land cover change and soil organic carbon stocks in the Republic of Ireland 1851–2000. Clim Chang. 91: 317–34.

Eichner, M.J. 1990. Nitrous oxide emissions from fertilized soils: summary of available data. J Environ Qual. 19: 272–80.

Fay, D., D. McGrath, C. Zhang, C. Carrigg, V. O'Flaherty, O.T. Carton and E. Grennan. 2007. Towards a national soil database. Final Report (2001–CD/S2–M2). Environmental Protection Agency, Johnstown Castle, Co. Wexford, Ireland. 363 pp.

Flessa, H., U. Wild, M. Klemisch, and J. Pfadenhauer. 1998. Nitrous oxide and methane fluxes from organic soils under agriculture. Europ J Soil Sci. 49: 327–35.

Follett, R.F. 2001. Soil management concepts and carbon sequestration in cropland soils. Soil Till Res. 61: 77–92.

Franzluebbers, A.J. 2005. Soil organic carbon sequestration and agricultural greenhouse gas emissions in the southeastern USA. Soil Till Res. 83: 120–47.

Franzluebbers, A.J. and R.F. Follett. 2005. Greenhouse gas contributions and mitigation potential in agricultural regions of North America: introduction. Soil Till Res. 83: 1–8.

Freibauer, A. and M. Kaltschmitt. 2003. Controls and models for estimating direct nitrous oxide emissions from temperate and sub-boreal agricultural mineral soils in Europe. Biogeochem. 63: 93–115.

Freibauer, A., M. Rounsevell, P. Smith and A. Verhagen. 2004. Carbon sequestration in the agricultural soils of Europe. Geoderma. 122: 1–23.

Frolking, S. E., A.R. Mosier, D.S. Ojima, C. Li, W.J. Parton, C.S. Potter, E. Priesack, R. Stenger, C. Haberbosch, P. Dörsch, H. Flessa and K.A. Smith. 1998. Comparison of N_2O emissions from soils at three temperate agricultural sites: simulations of year-round measurements by four models. Nutr Cycl Agroecosyst. 52: 77–105.

Gal, A., T.J. Vyn, E. Micheli, E.J. Kladivko and W.W. McFee. 2007. Soil carbon and nitrogen accumulation with long-term no-till versus mouldboard plowing overestimated with tilled zone sampling depths. Soil Till Res. 96: 42–51.

Gardiner, M., Radford, J. 1980. Ireland: General Soil Map. Second Edition. An Foras Talúntais (now Teagasc), Dublin, Ireland.

Gervois, S., P. Ciais, N. de Noblet-Ducoudre, N. Brisson, N. Vuichard and N. Viovy. 2008. Carbon and water balance of European croplands throughout the 20th century. Glob Biogeochem Cycl. 22: doi: 10.1029/2007GB003018.

Gillam, K.M., B.J. Zebarth and D.L. Burton. 2008. Nitrous oxide emissions from denitrification and the partitioning of gaseous losses as affected by nitrate and carbon addition and soil aeration. Can J Soil Sci. 88: 133–43.

Goulding, K.W.T., T. Willison, C.P. Webster and D.S. Powlson. 1996. Methane fluxes in aerobic soils. Environ Monitor Assess. 42: 175–87.

Granli, T. and O.C. Bøckman. 1994. Nitrous oxide from agriculture. Norwegian J Agric Sci. (Suppl. 12): 128 pp.

Gregorich, E.G., P. Rochette, A.J. VandenBygaart and D.A. Angers. 2005. Greenhouse gas contributions of agricultural soils and potential mitigation practices in Eastern Canada. Soil Till Res. 83: 53–72.

Guo, L.B. and R.M. Gifford. 2002. Soil carbon stocks and land use change: a meta-analysis. Glob Chang Biol. 8: 345–60.

Halvorson, A.D., C.A. Reule, and R.F. Follett. 1999. Nitrogen fertilization effects on soil carbon and nitrogen in a dryland cropping system. Soil Sci Soc Am J. 63: 912–17.

Helgason, B.I., H.H. Janzen, M.H. Chantigny, C.F. Drury, B.H. Ellert, E.G. Gregorich, R.L. Lemke, E. Pattey, P. Rochette and C. Wagner-Riddle. 2005. Toward improved coefficients for predicting direct N_2O emissions from soil in Canadian agroecosystems. Nutr Cycl Agroecosyst. 71: 87–99.

Hénault, C., X. Devis, S. Page, E. Justes, R. Reau and J.C. Germon. 1998. Nitrous oxide emissions under different soil and land management conditions. Biol Fertil Soils. 26: 199–207.

Holland, J.M. 2004. The environmental consequences of adopting conservation tillage in Europe: reviewing the evidence. Agric Ecosyst Environ. 103: 1–25.

Hütsch, B.W. 1998. Tillage and land use effects on methane oxidation rates and their vertical profiles in soil. Biol Fertil Soils. 27: 284–92.

Hütsch, B.W. 2001. Methane oxidation in non-flooded soils as affected by crop production-invited paper. Eur J Agron. 14: 237–60.

Intergovernmental Panel on Climate Change (IPCC). 1996. Chapter 5, Land-use change and forestry. Revised 1996 Guidelines for National Greenhouse Gas Inventories: Reference Manual. pp. 5.6–5.75. The Intergovernmental Panel on Climate Change, Blackwell, UK.

IPCC. 2006. Agriculture, forestry and other land use. IPCC Guidelines for National Greenhouse Gas Inventories. H.S. Eggleston, L. Buendia, K. Miwa, T. Ngara and K. Tanabe (Eds.). Hayama: Institute for Global Environmental Strategies. Prepared by the National Greenhouse Gas Inventories Programme.

IPCC. 2007. Climate Change 2007: the Physical Science Basis 'Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change'. S. Solomon, D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L. Miller (Eds.). Cambridge University Press, Cambridge. 996 pp.

Janssens I.A., A.Freibauer, B. Schlamadinger, R. Ceulemans, P. Ciais, A.J. Dolman, M. Heimann, G.J. Nabuurs, P. Smith, R. Valentini and E.D. Schulze. 2005. The carbon budget of terrestrial ecosystems at country-scale – a European case study. Biogeosci. 2: 15–26.

Jansson, S.L. 1975. Bordighetsstudier for Markvird. Forsok i Malmohus Ian 1957–74. (Long-term soil fertility studies. Experiments in Malmohus County 1957–74). J Royal Swedish Acad Agric Fores. Suppl. 10, Stockholm, 60 pp.

Janzen H.H. 2004. Carbon cycling in earth systems – a soil science perspective. Agric Ecosyst Environ. 104: 399–417.

Jobbagy, E.G. and R.B. Jackson. 2000. The vertical distribution of soil organic carbon and its relation to climate and vegetation. Ecol Appl. 19: 423–36.

Johnson, J.M.-F., N.W. Barbour and S.L. Weyers. 2007. Chemical composition of crop biomass impacts its decomposition. Soil Sci Soc Am J. 71: 155–62.

Kaiser, E.A., K. Kohrs, M. Kucke, E. Schnug, O. Heinemeyer and J.C. Munch. 1998. Nitrous oxide release from arable soil: importance of fertilization, crops and temporal variation. Soil Biol Biochem. 30: 1553–63.

Kaiser, E. A. J. C. Munch, O. Heinemeyer, 1996. Importance of soil cover box area for the determination of N_2O emissions from arable soils. Plant and Soil. 181, 2: 185–92.

Khalil, M.I. and E.M. Baggs 2005. Soil water-filled pore space affects the interaction between CH_4 oxidation, nitrification and N_2O emissions. Soil Biol Biochem. 37: 1785–94.

Khalil, M.I. and K. Inubushi K. 2007. Possibilities to reduce rice straw-induced global warming potential of a sandy paddy soil by combining hydrological manipulations and urea-N fertilizations. Soil Biol Biochem. 39: 2675–81.

Khalil, M.I., A.B. Rosenani, O. Van Cleemput, C.I. Fauziah, and J. Shamshuddin. 2002. Nitrous oxide emission from a maize-groundnut crop rotation supplied with different nitrogen sources in the humid tropics. J Environ Qual. 31: 1071–8.

Khalil, M.I., M.A. Haque, M.A. Sattar and U. Schmidhalter. 2004. Relative contribution of crop residue bound-N to irrigated rice and carbon storage in a subtropical soil. In: *Proceedings of the 11th International Conference of the FAO ESCORENA Network on Recycling of Agricultural, Municipal and Industrial Residues in Agriculture* held from 6–9 October 2004 in Murcia, Spain. Bernal et al. (eds). pp. 169–72.

Khalil, M.I., O. Van Cleemput, A.B. Rosenani, J. Shamshuddin and C.I. Fauziah. 2003. Nitrous oxide formation potential of various humid tropic soils of Malaysia: A laboratory study. Nutr Cycl Agroecosyst. 65: 191–200.

Khalil, M.I., M.S. Rahman and U. Schmidhalter. 2007. Nitrogen-fertilizer induced mineralization of soil organic C and N in six contrasting soils of Bangladesh. J Pl Nutr Soil Sci.170: 210–18.

Khalil, M.I., G. Kiely, P. O'Brien and C. Müller. 2012a. Organic carbon stocks in agricultural soils in Ireland using combined empirical and GIS approaches. Geoderma (In press).

Khalil, M.I., J.U. Smith, M. Abdalla, P. O'Brien, P. Smith and C. Müller. 2012b. Simulation of greenhouse gases and organic carbon in an Irish arable land using the ECOSSE model. Proceedings of the Agricultural Research Forum Meeting held from 12–13 March, 2012 in Tullamore, Ireland. p 110.

Khan, S.A., R.L. Mulvaney, T.R. Ellsworth and C.W. Boast. 2007. The myth of nitrogen fertilization for soil carbon sequestration. J Environ Qual. 36: 1821–32.

Kiely, G., N.M. McGoff, J.M. Eaton, X. Xu, P. Leahy and O.T. Carton. 2009. Soil C – measurement and modelling of soil carbon stocks and stock changes in Irish soils. STRIVE Report Series No. 35. Environmental Protection Agency, Johnstown Castle, Co. Wexford, Ireland. 30 pp.

Koga, N., H. Tsuruta, T. Sawamoto, S. Nishimura and K. Yagi. 2004. N_2O emission and CH4 uptake in arable fields managed under conventional and reduced tillage cropping systems in northern Japan. Global Biogeochemical Cycles: 18(4).

Kurganova, I. 2003. Carbon dioxide emission from soils of Russian terrestrial ecosystems. Interim Report (IR–02–070). International Institute for Applied Systems Analysis, Austria. 69p.

Kutsch, W.L. and L. Kappen. 1997. Aspects of carbon and nitrogen cycling in soils of the Bornhöved Lake district. II. Modelling the influence of temperature increase on soil respiration and organic carbon content in arable soils under different managements. Biogeochem. 39: 207–24.

Lal, R. 2004. Soil carbon sequestration impacts on global change and food security. Sci. 304 (5677): 1623–7.

Lal, R., 2007. Carbon management in agricultural soils. Mitig Adapt Strat Glob Chang. 12: 303–22.

Li, C.S. 2000. Modeling trace gas emissions from agricultural ecosystems. Nutr Cycl Agroecosyst. 58: 259–76.

Li, C.S. 2007. Quantifying greenhouse gas emissions from soils: Scientific basis and modeling approach. Soil Sci Pl Nutr. 53: 344–52.

Li, C.S., V. Narayanan and R. Harriss. 1996. Model estimate of N_2O emissions from agricultural lands in the United States. Glob Biogeochem Cycl. 10: 297–306.

Li, C.S., S. Frolking and K. Butterbach-Bahl. 2005. Carbon sequestration in arable soils is likely to increase nitrous oxide emissions, offsetting reductions in climate radiative forcing. Clim Chang. 72: 321–38.

Liebig, M.A, J.A. Morgan, J.D. Reeder, B.H. Ellert.2005. Greenhouse gas contributions and mitigation potential of agricultural practices in northwestern USA and western Canada. Soil & Tillage Research. 83 (1): 25–52.

Lim, B., P. Boileau, Y. Bonduki, A.R. van Amstel, L.J.M. Janssen, J.G.J. Olivier and C. Kroeze. 1999. Improving the quality of national greenhouse gas inventories. Environ Sci Policy. 2: 335–46.

Linn, D.M. and J.W. Doran. 1984. Effect of water-filled pores space on carbon dioxide and nitrous oxide production in tilled and nontilled soils. Soil Sci Soc Am J. 48: 1267–72.

Lohila, A., M. Aurela, K. Regina and T. Laurila. 2003. Soil and total ecosystem respiration in agricultural fields: effect of soil and crop type. Pl Soil. 251: 303–17.

Lugato, E., M. Zuliani, G. Alberti, G. Delle Vedove, B. Gioli, F. Miglietta and A. Peressotti. 2010. Application of DNDC biogeochemistry model to estimate greenhouse gas emission from Italian agricultural areas at high spatial resolution. Agric Ecosyst Environ. 139: 546–56.

Marland, G., B.A. McCarl and U.A. Schneider. 2001. Soil carbon: policy and economics. Clim Chang. 51: 101–17.

McLain, J.E.T. and D.A. Martens. 2006. N_2O production by heterotrophic N transformations in a semiarid soil. Appl Soil Ecol. 32: 253–63.

McLauchlan, K.K. 2006. Effects of soil texture on soil carbon and nitrogen dynamics after cessation of agriculture. Geoderma. 136: 289–99.

Meersmans, J., F. De Ridder, F. Canters, S. De Baets and M. Van Molle. 2008. A multiple regression approach to assess the spatial distribution of soil organic carbon (SOC) at the regional scale (Flanders, Belgium). Geoderma. 143: 1–13.

Meersmans, J., B. van Wesemael, F. De Ridder and M. Van Molle. 2009. Modelling the three-dimensional spatial distribution of soil organic carbon (SOC) at the regional scale (Flanders, Belgium). Geoderma. 152: 43–52.

Meersmans, J., B. van Wesemael, E. Goidts, M. Van Molle, S. De Baets and F. De Ridder. 2011. Spatial analysis of soil organic carbon evolution in Belgian croplands and grasslands, 1960–2006. Glob Chang Biol. 17: 466–79.

Moors, E.J., C. Jacobs, W. Jans, I. Supit, W.L. Kutsch, C. Bernhofer, P. Beziate, N. Buchmannc, A. Carrara, E. Ceschia, J. Elbers, W. Eugster, B. Kruijt, B. Loubet, E. Magliulo, C. Moureaux, A. Olioso, M. Saunders and H. Soegaard. 2010. Variability in carbon exchange of European croplands. Agric Ecosyst Environ. 139: 325–35.

Morell, F.J., J. Alvaro-Fuentes, J. Lampurlanes and C. Cantero-Martinez. 2010. Soil CO_2 fluxes following tillage and rainfall events in a semiarid Mediterranean ago-ecosystem: Effects of tillage systems and nitrogen fertilization. Agric Ecosyst Environ. 139: 167–73.

Mosier, A.R., A.D. Halvorson, C.A. Reule and X.J. Liu. 2006. Net global warming potential and greenhouse gas intensity in irrigated cropping systems in northeastern Colorado. J Environ Qual. 35: 1584–98.

Mosier, A.R., J.M. Duxbury, J.R. Freney, O. Heinemeyer and K. Minami. 1998. Assessing and mitigating N_2O emissions from agricultural soils. Cl Chang. 40: 7–38.

Mosier, A., C. Kroeze, C. Nevison, O. Oenema, S. Seitzinger and O. van Cleemput. 1999. An overview of the revised 1996 IPCC guidelines for national greenhouse gas inventory methodology for nitrous oxide from agriculture. Environ Sci Policy. 2: 325–333.

Mosquera, J., J.M.G. Hol, C. Rappoldt and J. Dolfing. 2007. Precise soil management as a tool to reduce CH4 and N2O emissions from agricultural soils. Report 28. Animal Sciences Group, AB Lelystad, The Netherlands. 42 p.

Moyano, F., W. Kutsch and E-D. Schulze. 2007. Response of Mycorrhizal, Rhizosphere and Soil Basal Respiration to Temperature and Photosynthesis in a Barley Field. Soil Biol Biochem. 39: 843–53.

Moyano, F.E., N. Vasilyeva, L. Bouckaert, F. Cook, J. Craine, J. Curiel Yuste, A. Don, D. Epron, P. Formanek,A. Franzluebbers, U. Ilsted, T. Katterer V. Orchard, M. Reichstein, A. Rey, L. Ruamps, J.-A. Subke, I. K. Thomsen and C. Chenu. 2012. The moisture response of soil heterotrophic respiration interaction with soil properties. Biogeosciences. 9: 1173–82.

Müller, E., H. Wildhagen, M. Quintern, J. Heß, F. Wichern and R.G. Joergensen. 2009. CO_2 evolution from a ridge tilled and a mouldboard ploughed Luvisol in the field. Appl Soil Ecol. 43: 89–94.

Mulvaney, R.L., S.A. Khan, and T.R. Ellsworth. 2009. Synthetic nitrogen fertilizers deplete soil nitrogen: A global dilemma for sustainable cereal production. J Environ Qual. 38: 2295–314.

Nieder, R. and J. Richter. 2000. C and N accumulation in arable soils of West Germany and its influence on the environment—developments 1970 to 1998. J Plant Nutr Soil Sci. 163: 65–72

Oenema, O., A. Bannink, S.G. Sommer and G.L. Velthof. 2001. Gaseous nitrogen emissions form livestock farming systems. In: Follett, R.F., Hatfield, J.L. (Eds.), Nitrogen in the Environment: Sources, Problems, and Management. Elsevier, Amsterdam, The Netherlands (Ch. 10), pp. 255–89.

Omonode, R.A. and T.J. Vyn. 2006. Vertical distribution of soil organic carbon and nitrogen under warm-season native grasses relative to croplands in west-central Indiana, USA. Agric Ecosyst Environ. 117: 159–70.

Osborne, B., M. Saunders, D. Walmsley, M. Jones and P. Smith. 2010. Key Questions and Uncertainties Associated with the Assessment of the Cropland Greenhouse Gas Balance. Agric Ecosyst Environ.139: 293–301.

Paavolainen, L. and A. Smolander. 1998. Nitrification and denitrification in soil from a clear-cut Norway spruce (*Picea abies*) stand. Soil Biol Biochem. 30: 775–81.

Parton, W.J., M.D. Hartman, D.S. Ojima and D.S. Schimel. 1998. DAYCENT: Its land surface submodel: description and testing. Glob. Planet. Chang. 19: 35–48.

Paustian, K., W.J. Parton and J. Persson. 1992. Modeling soil organic matter in organic-amended and N-fertilized long-term plots. Soil Sci Soc Am J. 56: 476–88.

Poirier, V., D.A. Angers, P. Rochette, M.H. Chantigny, N. Ziadi, G. Tremblay and J. Fortin. 2009. Interactive effects of tillage and mineral fertilization on soil carbon profiles. Soil Sci Soc Am J. 73: 255–61.

Powlson, D.S. and D.S. Jenkinson. 1981. A comparison of the organic-matter, biomass, adenosine-triphosphate and mineralizable nitrogen contents of ploughed and direct-drilled soils. J Agric Sci. 97: 713–21.

Powlson, D.S., A.P. Whitmore and K.W.T. Goulding. 2010. Soil carbon sequestration for mitigating climate change: distinguishing the genuine from the imaginary. In: Hillel, D., Rosenweig, C. (Eds.), Handbook of Climate Change and Agroecosystems, ICP Series on Climate Change Impacts, Adaptation, vol. 1. Imperial College Press., London, pp. 393–402.

Powlson, D.S., M.J. Glendining, K. Coleman, K. and A.P. Whitmore. 2011. Implications for soil properties of removing cereal straw – results from long-term studies. Agron J. 103: 279–87.

Primavesi, A. 1984. Manejo ecológico del suelo. La agricultura en regiones tropicales. 5ta Edición. El Ateneo. Rio de Janeiro, Brazil. 499 pp.

Rafique, R. M. Peichl, Deirdre Hennessy and G. Kiely. 2011. Evaluating management effects on nitrous oxide emissions from grasslands using the process-based DeNitrificationeDeComposition (DNDC) model. Atmos Environ. 45: 6029–39.

Raich, J.W. and W.H. Schlesinger. 1992. The global carbon dioxide flux in soil respiration and its relationship to vegetation and climate. Tellus. 44B: 81–99.

Rees, R.M., I.J. Bingham, J.A. Baddeley and C.A. Watson. 2005. The role of plants and land management in sequestering soil carbon in temperate arable and grassland ecosystems. Geoderma. 128: 130–54.

Reicosky, D.C. and D.W. Archer. 2007. Moldboard plow tillage depth and short-term carbon dioxide release. Soil Till Res. 94: 109–21.

Richards, K.G., M.I. Khalil, P. Johnston and V. O'Flaherty. 2009. Subsoil and groundwater denitrification. Six-monthly progress report of a project (RSF 06-383) submitted to the Department of Agriculture Food and Fisheries (DAFF), Ireland. Annexure-III. 54 pp.

Richter, J. and M. Roelcke. 2000. The N-cycle as determined by intensive agriculture: examples from Central Europe and China. Nutr Cycl Agroecosyst. 57: 33–46.

Robertson, G.P., E.A. Paul and R.R. Harwood. 2000. Greenhouse gases in intensive agriculture: Contributions of individual gases to the radiative forcing of the atmosphere. Sci (Washington, DC). 289: 1922–5.

Rochette, P., D.A. Angers, M.H. Chantigny, B. Gagnon, and N. Bertrand. 2008. N_2O fluxes in soils of contrasting textures fertilized with liquid and solid dairy cattle manures. Canadian J Soil Sci. 88: 175–87.

Roland K., Q. Sun, J. Ingwersen, X. Chen, F. Zhang, T. Müller and V. Römheld. 2010. Modelling water dynamics with DNDC and DAISY in a soil of the North China Plain: a comparative study. Environ Modell Softw. 25: 583–601.

Ruser, R., H. Flessa, R. Russow, G. Schmidt, F. Buegger and J.C. Munch. 2006. Emission of N_2O, N_2 and CO_2 from soil fertilized with nitrate: effect of compaction, soil moisture and rewetting. Soil Biol Biochem. 38: 263–74.

Sainju U.M., J.D. Jabro and W.B. Stevens. 2008. Soil carbon dioxide emissions and carbon content as affected by irrigation, tillage, cropping system and nitrogen fertilization. J Environ Qual. 37: 98–106.

Schaeffer, F. and P. Schachtschabel. 2002. Lehrbuch der Bodenkunde, Ed. Spectrum Publ., Heidelberg, Germany. 593 p.

Schnell, S. and G.M. King. 1994. Mechanistic analysis of ammonium inhibition of atmospheric methane consumption in forest soils. Appl Environ Microbiol. 60: 3541–21.

Six, J., S.M. Ogle, F.J. Breidt, R.T. Conant, A.R. Mosier and K. Paustian. 2004. The potential to mitigate global warming with no-tillage management is only realized when practised in the long term. Glob Chang Biol. 10: 155–60.

Sleutel, S., S. De Neve, B. Singier and G. Hofman. 2006. Organic C levels in intensively managed arable soils—long term regional trends and characterization of fractions. Soil Use Manage. 22: 188–96.

Smith, K.A., I.P McTaggart, K.E. Dobbie and F. Conen. 1998. Emissions of N_2O from Scottish agricultural soils, as a function of fertilizer N. Nutr Cycl Agroecosyst. 52: 123–30.

Smith J.U., P. Gottschalk P, J. Bellarby, S. Chapman, A. Lilly, W. Towers, J. Bell, K. Coleman, D.R. Nayak, M.I. Richards, J. Hillier, H.C. Flynn, M. Wattenbach, M. Aitkenhead, J.B. Yeluripurti, J. Farmer, R. Milne, A. Thomson, C. Evans, A.P. Whitmore, P. Falloon and P. Smith. 2010. Estimating changes in national soil carbon stocks using ECOSSE—a new model that includes upland organic soils. Part I. Model description and uncertainty in national scale simulations of Scotland. Clim Res. 45: 179–92.

Smith, P., R. Milne, D.S. Powlson, J.U. Smith, P. Falloon and K. Coleman. 2000. Revised estimates of the carbon migration potential of UK agricultural land. Soil Use Manage. 16: 293–5.

Smith, P., D. Martino, Z. Cai, D. Gwary, H. Janzen, P. Kumar, B. McCarl, S. Ogle, F. O'Mara, C. Rice, B. Scholes and O. Sirotenko. 2007. Agriculture. In: B. Metz, O.R. Davidson, P.R. Bosch, R. Dave and L.A. Meyer (eds) *Climate Change 2007: Mitigation. Contribution of working group III to the fourth assessment report of the Intergovernmental Panel on Climate Change*. Cambridge University Press. Cambridge, United Kingdom and New York, NY, USA.

Smith, P., D.S. Powlson, M.J. Glendining and J.U. Smith. 1998. Preliminary estimates of the potential for carbon mitigation in European soils through no-till farming. Glob Chang Biol. 4: 679–85.

Smith, P., O. Andren, T. Karlsson, P. Perala, K. Regina, M. Rounsevell and B. van Wesemael. 2005. Carbon sequestration potential in European croplands has been overestimated. Glob Chang Biol. 11: 2153–63.

Smith, W.N., B.B. Grant, C.A. Campbell, B.G. McConkey, R.L. Desjardins, R. Kröbel and S.S. Malhi. 2012. Crop residue removal effects on soil carbon: Measured and inter-model comparisons. Agric Ecosyst Environ. 161: 27–38.

Smith, J.U. and P. Smith. 1995. *'MODEVAL': Quantitative methods to evaluate and compare SOM models*, Software.

Snyder, C.S., T.W. Bruulsema, T.L. Jensen and P.E. Fixen. 2009. Review of greenhouse gas emissions from crop production systems and fertilizer management effects. Agric Ecosyst Environ. 133: 247–66.

Stehfest, E. and L. Bouwman. 2006. N_2O and NO emission from agricultural fields and soils under natural vegetation: summarizing available measurement data and modeling of global annual emissions. Nutr Cycl Agroecosyst. 74: 207–28.

Stockfisch, N., T. Forstreuter and W. Ehlers. 1999. Ploughing effects on soil organic matter after twenty years of conservation tillage in Lower Saxony, Germany. Soil Till Res. 52: 91–101.

Tomlinson, R.W. 2005. Soil carbon stocks and changes in the Republic of Ireland. J Environ Manage. 76: 77–93.

Triberti, L., A. Nastri, G. Giordani, F. Comellini, G. Baldoni and G. Toderi. 2008. Can mineral and organic fertilization help sequestrate carbon dioxide in cropland? Europ. J. Agron. 29: 13–20.

Uhlen, G. 1991. Long-term effects of fertilizers, manure, straw and crop rotation on total- N and total-C in soil. Acra Agncultsrne SwAnavica. 41: llP-127.

Van Meirvenne, M., J. Pannier, G. Hofman and G. Louwagie. 1996. Regional characterization of the long-term change in soil organic carbon under intensive agriculture. Soil Use Manage. 12: 86–94.

Venterea, R.T., M. Burger and K.A. Spokas. 2005. Nitrogen oxide and methane emissions under varying tillage and fertilizer management. J Environ Qual. 34: 1467–77.

Weiske, A. and S.O. Petersen. 2006. Mitigation of greenhouse gas emissions from livestock production. Agric Ecosyst Environ. 112: 105–06.

West, T.O. and G. Marland. 2003. Net carbon flux from agriculture: carbon emissions, carbon sequestration, crop yield and land-use change. Biogeochem. 63: 73–83.

West, T.O. and W.M. Post. 2002. Soil organic carbon sequestration rates by tillage and crop rotation: a global data analysis. Soil Sci Soc Am J. 66: 1930–46.

Xu, X. and G. Kiely. 2009. SOC stock and its distribution in the Republic of Ireland: Estimate based on geostatistics and GIS techniques. http://www.ucc.ie/en/hydromet/publications/#A4

Xu, X., W. Liu, C. Zhang and G. Kiely. 2011a. Estimation of soil organic carbon stock and its spatial distribution in the Republic of Ireland. Soil Use Manage. 27: 156–62.

Xu, X., W. Liu, C. Zhang and G. Kiely. 2011b. Modeling the change in soil organic carbon of grassland in response to climate change: Effects of measured versus modeled carbon pools for initializing the Rothamsted Carbon model. Agric Ecosyst Environ. doi: 10.1016 /j.agee.2010.12.018.

Zhang, C., Y. Tang, X. Xu and G. Kiely. 2011. Towards spatial geochemical modelling: use of geographically weighted regression for mapping soil organic carbon contents in Ireland. Appl Geochem. 26: 1239–48.

Acronyms

AFOLU	Agriculture, Forestry and other Land Use
CAN	Calcium Ammonium Nitrate
CH_4	Methane
CO_2	Carbon Dioxide
CORINE	Co-ordination of Information on the Environment
CSO	Central Statistics Office
DAFM	Department of Agriculture, Food and the Marine
DNDC	DeNitrification DeComposition
EC	Eddy covariance
ECOSSE	Estimating Carbon in Organic Soils - Sequestration and Emissions
EF	Emission factor
EPA	Environmental Protection Agency
GHG	Greenhouse gas
GIS	Geographical Information System
GSG	Great Soil Group
GSM	General Soil Map
IPCC	Intergovernmental Panel on Climate Change
ISM	Indicative Soil Map
IST	Indicative Soil Type
LCS	Land Cover Specific
LPIS	Land Parcel Information System
LULUCF	Land Use, Land Use Change and Forestry
NIR	National Inventory Report
NIT	Non-inversion Tillage
N_2O	Nitrous oxide
NO_3	Nitrate
NSDB	National Soil Data Base
PASIM	Pasture Simulation Model

R_{eco}	Ecosystem respiration
R_H	Heterotrophic respiration
RME	Relative mean errors
RMSE	Root mean square errors
ROI	Republic of Ireland
RothC	Rothamsted Carbon Model
Rs	Soil respiration
SOC	Soil organic carbon
SOM	Soil organic matter
STS	Soil Type Specific
Teagasc	Irish Agriculture and Food Development Authority
TCD	Trinity College Dublin
UCC	University College Cork
UCD	University College Dublin
UNFCCC	United Nations Framework Convention on Climate Change
WFPS	Water-filled pore space

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 Aeráide, Ceadúnaithe agus Úsáide Acmhainní
- An Oifig Forfheidhmithe i leith cúrsaí Comhshaoil
- An Oifig um Measúnú Comhshaoil
- An Oifig um Cosaint Raideolaíoch
- 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 136

Development of Methodologies and Modelling for Accounting Greenhouse Gases and Organic Carbon Stocks in Agricultural Soils

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

Report Author: Mohammad I. Khalil, UCD

Background

Agriculture and land management are major sources of emissions and removals of greenhouse gases in Ireland, and globally, Local conditions and practices can profoundly influence the emissions of nitrous oxide, methane and the emission or removal carbon dioxide.

Identifying Pressures

Agriculture, particularly grassland based livestock farming, is the dominant land use in Ireland, and is recognised as the principle primary industry in the State. As a consequence, Agriculture is responsible for largest share of GHG emissions compared to other sectors of the economy. Nevertheless, there is also the potential for removal of carbon dioxide from the atmosphere through good practice in the management of agricultural and other lands. Both the emissions and removal potential needs to quantified at a national level in order to better inform decision making on future land management.

Informing Policy

- Findings from this study indicate that the carbon stored in Ireland's agricultural soils is of the order of 1,146 Tg (1m depth). The amount of carbon stored depends on a variety of factors, including climate and soil type. However, management (pasture, rough grazing, tillage etc.) is also seen to be a major factor.
- Advance models of soil processes, which simulate the interaction between soils, climate, and management, have greatly improved. Coupled with observations from nearly a decade of field research, it is now possible to provide insight into the impact of farming practices on N_2O emissions and soil carbon dynamics.

Developing Solutions

- This research investigates existing data gathered from a range of agricultural land use systems to begin to develop a structure modelling approach to the estimation of greenhouse gas emissions and removals, and the specific impact of changes in practices to manage these, and provide robust options for mitigation of climate change in the agricultural land use sector.

Comhshaol, Pobal agus Rialtas Áitiúil
Environment, Community and Local Government

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

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

Cover photo: John Doheny

www.epa.ie

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