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Modelling greenhouse gas emissions for the UK and overseas food production

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Modelling Greenhouse Gas Emissions for the UK and Overseas Food Production

A thesis submitted to the University of Wales by Elizabeth York in candidature
for the degree of Philosophiae Doctor

School of the Environment, Natural Resources and Geography

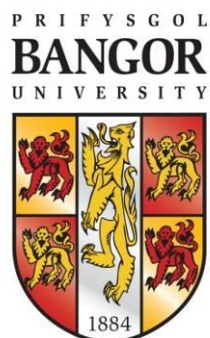
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Summary

Despite the large quantity of research undertaken into the sustainability of food production and transportation systems, there is currently little consensus on the total contribution that greenhouse gas (GHG) emissions make to the overall GHG budget of food production systems. To date, most research has focused on the miles that food has travelled and the energy put into the production of pesticides and fertilisers associated with crop production. Understanding whether food imported from distant countries has a higher GHG footprint than locally produced food remains a very topical issue. Our fundamental lack of knowledge of this issue is limiting policy development in this area. Due to difficulties in field measurements mathematical models such as DNDC (DeNitrification DeCompositon) are being used to predict GHG emissions from different ecosystems. In this thesis, a combination of field measurements and model simulations were used to evaluate GHG emissions from different agricultural production systems undertaken in different countries (UK, Spain and Kenya). This thesis also considered the accuracy of the model by undertaking a sensitivity analysis and evaluating the outputs from different model versions. In addition, the accuracy of using a Q_{10} value approach to predict organic matter degradation was also evaluated.

Overall, the results suggested that different model versions gave varying outputs, suggesting that predictions of GHG emissions obtained with models such as DNDC should be treated with caution. However, the model did predict similar results to those obtained in the field, although the model outputs tended to be higher. For comparison of GHG emissions from vegetable types grown in different geographical regions, no specific region produced lower GHG results when averaged across all crops. However, when individual crops were considered, Spain had the highest GHG emissions. The models showed different degrees of sensitivity to different inputs, with some not showing any variation at all. In the Q_{10} evaluation experiments the Q_{10} values varied greatly, though all gave results above the standard Q_{10} of 2. Further research is needed into the accuracy of climate and farm management models, and whether or not it is necessary to compare large data sets when considering different vegetable types and areas.

Acknowledgements

I would like to acknowledge the following people -

My supervisors Professor Davey Jones and Professor Gareth Edward Jones for their continual support and guidance throughout my research. Without their help and time I would not have been able to complete this thesis, and all their input is gratefully acknowledged and appreciated. I would also like to thank ESRC for funding the Ph.D. project.

I am grateful for all the encouragement, support and advice that Dr Paul Hill and Dr Georgia Koerber has given me over the Ph.D. They have always been on hand for technical advice and reassurance.

I am exceedingly grateful for all the help, support and encouragement that my family has given me over the Ph.D. They have always there to support me when I needed some extra encouragement.

My friends and colleagues for their interest, support and encouragement over the years and the providing of wise words and hot beverages when needed.

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Abbreviations

% – Percentage

µg – Micrograms

C – Carbon

CH₄ – Methane

cm – Centimetre

CO₂ – Carbon dioxide

DNDC – DeNitrification DeComposition,

DOC – Dissolved organic carbon

Eh – Redox potential

Fe³⁺ – Iron ion

g – Gram

GHG – Greenhouse gas

GWP – Global warming potential

h – Hour

ha – Hectare

HCO₃⁻ – Bicarbonate

HNO₃ – Nitric acid

IPCC – Intergovernmental panel on climate change

IRGA – Infra-red gas analyser

K – Kelvin

KCl – Potassium Chloride

kg – Kilogram

l – Litre

m – Metre

M – Molar

mg – milligrams

min – minute

ml – millilitres

mm – millimetres

Mn⁴⁺ – Manganese ion

N – Nitrogen

N₂ – Dinitrogen

N_2O – Nitrous oxide
 NaOH – Sodium hydroxide
 NH_3 – Ammonia
 NH_4^+ – Ammonium
 NH_4NO_3 – Ammonium nitrate
 NO – Nitric oxide
 N_2O – Nitrous oxide
 NO_3^- – Nitrate
 NO_x – Nitrogen oxide
 O_2 – Oxygen
P – Phosphorous
PnET – Photosynthesis-Evapotranspiration
ppbv – Parts per billion by volume
ppm – Parts per million
S – Sulphur
SEM – Standard error of the mean
 SO_4^{2-} – Sulphate
SOC – Soil organic carbon
SOM – Soil organic matter
Tg – Teragram
v – Volume
w – Weight
WFPS – Water-filled pore space
yr – Year

Chapter 1. Introduction and Literature Review

Elizabeth York

School of the Environment, Natural Resource and Geography

Bangor University, Bangor

Gwynedd LL57 2UW, UK

1.1. Introduction

1.1.1. General introduction and need for research

Food security and the origin of foodstuffs are currently high on the political agenda due to the UK's commitment to meet the Kyoto agreement for reducing greenhouse gas (GHG) emissions from agroecosystems and the realisation that some critical natural resources are becoming rapidly depleted (e.g. rock P needed for fertilizer production). Degradation of cropland soils is a serious issue (Oldeman, 1994), which has and will continue to result in drastic adverse impacts on global food security and environmental quality (Lal et al., 1999). Food mileage was originally the only criterion used when assessing where food was produced and its potential harm to the environment. Scientists have now realised, however, that how far food travels from its point of origin does not provide a holistic view, as it neglects to include all that goes into growing and producing vegetables. For example, energy goes into food production through fertilisers, pesticides, tractors, transport, cleaning and packaging. People also fail to consider how much carbon (C) gets emitted into the atmosphere as a result of land use conversion for vegetable production. Current evidence suggests that there is a fine balance in soils as to whether they represent sinks or sources of GHG, and how the land is managed can have a great effect on the type and quantity of GHG emitted.

Accurately quantifying GHG from vegetable production systems represents a major problem, as all agroecosystems are inherently complex with net GHG emissions being dependent upon a range of factors. These include parent material, climate, changes in organism community and changes in soil properties. Some of these factors can be reproduced, to some extent, under laboratory conditions. However, this rarely captures the complexity of GHG from a field environment. Measuring GHG constantly under field conditions is often deemed impractical in terms of the time and funding it would require. To address this issue, mathematical models have been developed which allow the user to predict GHG emissions over whole cropping cycles. While many models have focused on one specific aspect (e.g. soil C), the model used here (DNDC; DeNitrification DeComposition; Leip et al., 2008), combines three models -

namely soil, climate and farm management - to allow for a more holistic assessment of GHG emissions. DNDC has been calibrated and validated for some land uses around the world, with long term data sets demonstrating its power for GHG scenario testing. While the model has progressively evolved and refined over time, it is uncertain whether the overall performance of the model has significantly improved with these revisions. To some extent this is due to the poor documentation of the changes between different versions of the model. Furthermore, modellers do not always use the most recent versions of the DNDC, which makes comparison of model outputs difficult. This has direct implications if the outputs of DNDC are used for policy formulation.

The aims of the project are (1) to validate DNDC under vegetable cropping systems; (2) to use the model to assess the importance of key environmental and management variables on GHG emissions from these systems; and (3) to evaluate the impact of different model versions on GHG predictions from vegetable cropping systems. This will be done, firstly, through a series of model comparisons using collected farm data. Once the model has been validated a series of datasets collected from farms within 3 different UK counties will be modelled and the results compared.

1.1.2. The main chapters

The point of this study is to predict GHG emissions from agricultural soils. This will be conducted through a series of chapters. The first few chapters will look at the reliability of the model leading on to the last chapter where field data will be modelled. The four chapters that form the core of this thesis can be summarised as follows:

Chapter 3: Model Comparison Between Different Versions of the DNDC Model

Most published papers do not state which version of the DNDC model was used to predict GHG emissions. Consequently, it is uncertain whether the outputs from different studies can be reliably compared. To address this, 5 different versions of DNDC were used to predict GHG emissions from 6 different vegetable types using the same input data.

Chapter 4: Sensitivity of Soil Respiration to Variation in Temperature

Temperature and moisture have a profound effect on soil GHG emissions and are key drivers regulating modelled soil GHG emissions. The mathematical description of the change in soil respiration over a 10°C change in temperature (i.e. Q_{10} value) is critical for predicting the effects of weather on CO₂ emissions from soil. For biological systems, the Q_{10} value is generally between 1 and 3, and for soils it is considered to be around 2. Most models use a Q_{10} factor of 2 in the system, though it has been found that soils may deviate significantly from this value. The aim of this chapter was to collect soils from different global geographical areas and to evaluate their Q_{10} relationship over a rising and falling temperature cycle.

Chapter 5: Sensitivity of the DNDC Model to Variations to Weather and Model Inputs

Models can have different sensitivities to inputs, and how sensitive the models are can have a great impact upon the accuracy of the outputs. The 3 latest versions of the DNDC model were used for this comparison; real data from a UK lettuce field was used as the baseline, and a sensitivity analysis was undertaken with the input data. Variation in model output in response to annual weather data was compared using different regional weather datasets. All three models were compared and the results graphed to consider which inputs are the most important and which have the greatest effect on the results.

Chapter 6: A Comparison of GHG Emissions from Vegetables in Different Countries and Model Validation

There is currently a significant, ongoing debate on food miles and whether foods travelling from abroad have higher GHG emissions than those produced locally. To address this, three countries were considered: Kenya, Spain and the UK. Within the UK three counties were used: Anglesey, Lincolnshire and Worcester. The outputs from the model were compared to nitrate and ammonium laboratory

data to validate the model. GHG emissions were converted for each vegetable type and area to consider their global warming potential as a whole.

1.2. Greenhouse gas emissions in agroecosystems

Balancing food production and environmental protection, and predicting the impacts of climate change or alternative management in agroecosystems, is attracting great attention from scientists (Zhang et al., 2002). Increasing population and the intensification of agriculture to meet urban food demand could further enhance the importance of these agricultural sources - the most significant factors being fertiliser use, irrigation, and land use change in the next century (Li et al., 1994). Agriculture profoundly influences the global environment, affecting atmospheric chemistry, water quality and quantity, and nutrient cycles. For example, due to increased human activity N fertiliser production and application and crop biological fixation have doubled the transfer of N from the atmosphere to biologically available pools (Zhang et al., 2002). Agriculture also represents a significant opportunity for GHG mitigation projects through soil carbon sequestration and lowering of CH₄ and N₂O emissions. Projects such as reduced tillage, timing of fertiliser/manure application and the use of different types of irrigation can result in soil carbon sequestration and reductions in CH₄ and N₂O emissions. These often result in compound environmental benefits through improved soil structure which, in turn, can improve air and water quality and sustainability of agroecosystems (Salas and Li, 2003).

Cropping systems are human-modified terrestrial ecosystems that act as either sources or sinks of GHG (Cai et al., 2003). Modern technology has greatly promoted agricultural productivity by means of genetic improvement, irrigation, fertilization and pesticide applications (Zhang et al., 2002). It is estimated that 80% of nitric oxide (NO), nearly 70% of ammonia (NH₃) and more than 40% of nitrous oxide (N₂O) emitted globally are human-activity induced (Vitousek et al., 1997). Since the late 1950s, global synthetic N fertilizer consumption has increased from ~10 to ~100 Tg N in 2008, with the global N input into agricultural systems from synthetic fertilizer increasing more than 40 fold since 1930 (Millar et al., 2010). Food production contributes approximately 70% of

global atmospheric input of nitrous oxide (N_2O) and 40% of global atmospheric input of methane (CH_4) (Li et al., 2005). It is estimated that agriculture accounts for 26%, 92% and 65% of the total anthropogenic emissions of CO_2 , N_2O and CH_4 , respectively (Zhang et al., 2002). Of the three gases, CO_2 , CH_4 and N_2O , influenced by agricultural activities, current estimates indicate that N_2O emissions from agricultural soils represent the largest source of GHG from the sector (Smith et al., 2004; Neufeldt et al., 2006). Normal crop production practices, such as fertiliser use and tillage, generate N_2O and decrease the soil sink for atmospheric CH_4 (Li et al., 2004). Figure 1-1 shows the increases in atmospheric CO_2 , CH_4 and N_2O from ice cores.

Agricultural activity can increase carbon dioxide (CO_2) emissions by increasing soil decomposition rates and burning plant biomass (Zhang et al., 2002). Clearing, tilling, and draining native soils for agricultural production have released large amounts of CO_2 from soils' organic matter pool (Li et al., 2004).

Since each GHG has its own radiative potential, a net global warming potential (GWP) of a crop production system can be estimated, accounting for all of the three gases (Li et al., 2005). Most published research focuses on soil C dynamics, with less attention paid to the other GHGs, nitrous oxide (N_2O) and methane (CH_4), each of which may offset gains in GHG emissions if not managed properly (Salas and Li, 2003). This is compounded by the inherent relationships between soil organic carbon (SOC) storage and N_2O or CH_4 emissions in agricultural soils (Salas and Li, 2003).

When assessing the impact of food production and distribution, the entire suite of GHGs needs to be considered (Li et al., 2005). Different GHGs can be compared on a common basis by converting the fluxes of the non- CO_2 GHGs into the CO_2 equivalents via their radiative forcing, called GWP (Global Warming Potential) which gives a uniform measurement. The IPCC values of GWP for N_2O and CH_4 , equate to 1 kg of these gases to 310 and 23 kg of CO_2 equivalents, respectively, over 100 years (Levy et al., 2007; Li et al., 2004; Pluimers et al., 2000; Qui et al., 2009).

Recently, significant investments have been made in assessing carbon sequestration projects in agricultural soils, due to the potential for trading carbon credits coupled with significant environmental benefits through improved soil quality, soil fertility and reduced erosion potential (Li et al., 2004). Changes in

farming management practices are being evaluated for their potential in mitigating GHGs emitted by the agricultural sector (Salas and Li, 2003). Agricultural soils generally have capacity to store carbon, as their pre-cultivation SOC reserves were depleted in the first few decades after conversion to agriculture in the 17th, 18th and 19th centuries, a process that caused a dramatic loss of soil organic matter to microbial mineralization and progressive wind and water erosion (Li et al., 2004; Qui et al., 2009). The maximum soil C sink capacity is thought to approximately equal the historic C loss, which was 50 to 75% of the original, estimated at 1550 Pg SOC pool (Lal, 2008).

Agricultural systems account for approximately one quarter of global NO_x emissions; of this, about 20-70% of the N₂O emitted, is derived from soil (Mosier et al., 1998). Nitrous oxide is important in the chemistry of the stratosphere as NO oxidation is involved in the ozone equilibrium (Jambert et al., 1997). On a per molecule basis, N₂O is 200-320 times more potent than CO₂ (Verma et al., 2006) and it has been calculated that an increase of 0.2-0.3% in atmospheric concentrations would contribute about 5% to the greenhouse warming (Mosier et al., 1998). Current atmospheric concentrations of N₂O are around 320 ppbv, but its atmospheric abundance is increasing at a rate of 0.3% per year due to human activities (Verma et al., 2006; Millar et al., 2010). Thirty eight industrialized countries currently contribute more than half of global emissions, and over the next 20 years global emissions are expected to rapidly rise as intensification increases in developing economies of Latin America and Asia (Lal and Bruce., 1999). As N₂O has an atmospheric life of 150 years, this is not a short term problem (Verma et al., 2006).

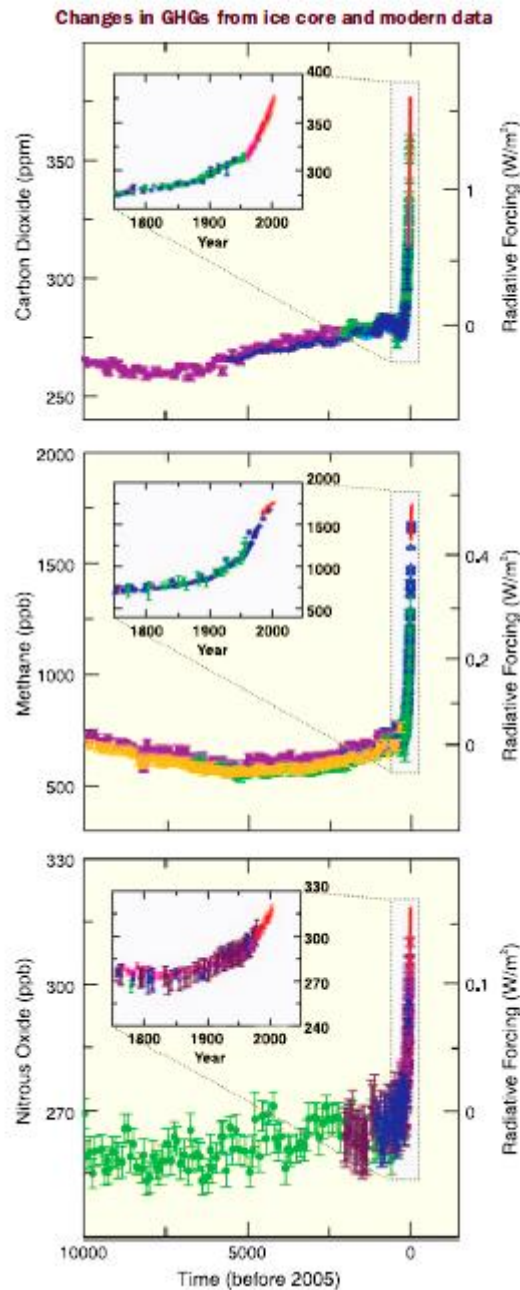


Figure 1-1: Atmospheric concentrations of CO₂, CH₄ and N₂O over the last 10,000 years (large panels) and since 1750 (inset panels). Measurements are shown from ice cores (symbols with different colours for different studies) and atmospheric samples (red lines) (IPCC, 2007).

Nitrous oxide is produced primarily by microbial processes, nitrification and denitrification in soil (Verma et al., 2006) (See Figure 1-2). Soil structure and water content can affect the balance of N₂O and N₂ production by the reduction of N₂O escape and further reduction to N₂ (Mosier et al., 1998). Soil pH, and soil temperatures above 25 °C favour denitrification (Johnson et al., 1994). Further, N₂O fluxes can also differ markedly with landscape position (Mosier et al., 1991).

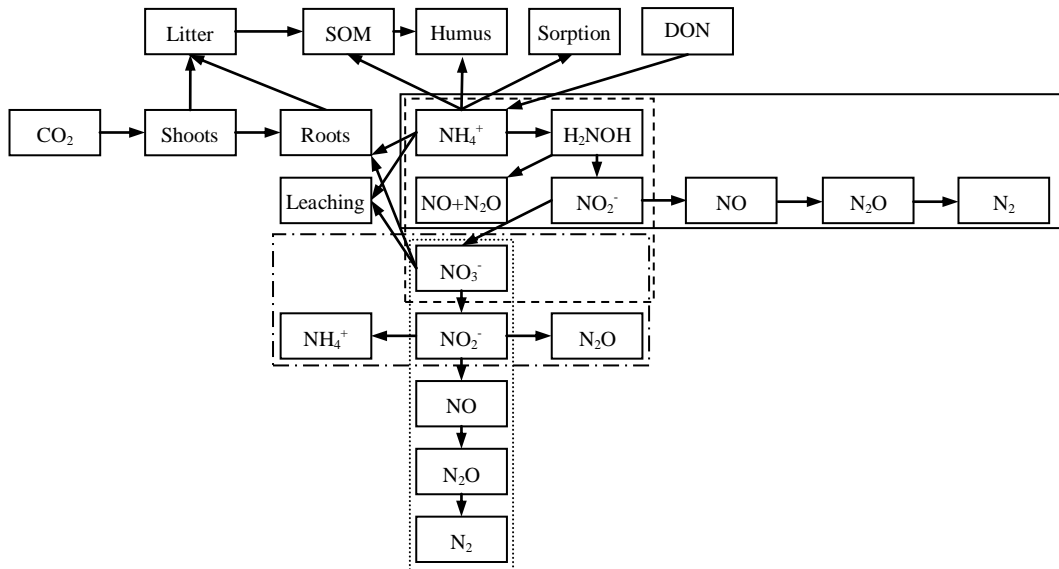


Figure 1-2: Diagram of the soil nitrogen cycle. The diagram considers both the biological and non-biological pathways and presently known processes — Nitrifier Denitrification, Denitrification, - - - - Nitrate and Ammonification and - . - . Nitrification. This was adapted from Johnson et al., 1994 and Smith, 2010).

Soils have been recognized as an important source of tropospheric NO_x since 1978, when Galbally et al. (1978) reported the first field measurements (Davidson et al., 1997). These results were used by Logan (1983) to make a global NO budget which demonstrated that soil emissions of NO contribute significantly to tropospheric ozone precursors, and act as a source of N in atmospheric deposition, though this was found later to be to a low estimate (Davidson et al., 1997). The NO_x emitted from the soils or from fossil fuel combustion reacts rapidly in the atmosphere with light, ozone and hydrocarbons to produce HNO_3 and NO_3^- . Figure 1-2 depicts the portion of the N cycle that occurs in soils. Nitrogen is a unique nutrient, in that there are few mineral sources of N in soils, and yet soils contain a large N pool. This N originated primarily via N -fixing organisms, though in some systems N is easily leached (as NO_3^-) from the soil or volatilized as N_2O or N_2 following denitrification (Johnson et al., 1994). This graph is a simplified view of what happens in the soil in relation to nitrification and denitrification as NO_2^- and other intermediate steps are not mentioned.

After NO is emitted from the soil, it is often rapidly oxidized in the atmosphere to NO_2 , which is then readily absorbed onto leaf surfaces if a canopy is present (Bakwin et al., 1990). This process reduces the amount of NO and NO_2

that escapes the soil-plant system and enters the atmosphere (Davidson et al., 1997). If N_2O exists long enough to reach the stratosphere it is converted into NO , contributing to the destruction of the ozone layer in the process. The initial estimates made by Galbally and Roy made in 1978 ($10 \text{ Tg NO-N yr}^{-1}$) was later found, with greater accuracy, more accurately to be $21 \pm 4 \text{ Tg NO-N yr}^{-1}$ (Davidson et al., 1997).

The greatest input of N into agricultural systems is via fertilisers (Webb et al., 2004). Outputs of N from agriculture are mainly as crop offtake, NO_3^- leaching and as gases. Crop N offtake typically ranges from 54-98% of total N output; usually less ($< 100 \text{ kg ha}^{-1}$) for crops where residues remain in the field, e.g. sugar beet (Webb et al., 2004). The atmospheric concentration of N_2O is a result of biotic and anthropogenic activities with $1.5 \text{ Tg of N yr}^{-1}$ directly released into the atmosphere as N_2O from fertiliser applications to agricultural ecosystems (Mosier et al., 1998). Nitrous oxide emissions follow a seasonal pattern, being high in the summer and autumn when the soils are usually warm and moist (Webb et al., 2004), though this is a heavily simplified view of the emissions, which are typically greatest in spring when N fertilisers are applied. N fertiliser use and biological N_2 fixation are projected to continue to increase over the next 100 years due to increases in global food production (Mosier et al., 1998). N applied to agricultural soils may be lost from the fields through surface erosion or leaching, and continues recycling in the soil–water–air system until it is eventually denitrified and converted to N_2O and N_2 and released back to the atmosphere or buried in sediments (Mosier et al., 1998a). It has been estimated that doubling the concentration of N_2O in the atmosphere would result in a 10% decrease in the stratospheric ozone layer, which would increase the ultraviolet radiation reaching the earth by 20% (Jambert et al., 1997; Mosier et al., 1998). Further increases in N_2O could result in an increased incidence of skin cancer and other human health problems (Lijinsky, 1977; Mosier et al., 1998).

The conversion of forests and grasslands to croplands has accelerated C and N cycling and increased N_2O emissions from soil (Mosier et al., 1998). Mosier et al. (1998) found that after a forest had been cleared and turned to pasture, emissions increased threefold, though they returned to background levels after 10-20 years. Willison et al. (1995) also found that changing soils from pastoral to intensive agriculture decreased CH_4 uptake, though since

industrialization, diffusion has increased due to the increase in CH₄ mixing ratios. Flessa et al. (1998) reported that drainage of peatland soils for use as cultivated agricultural land, caused loss of N through leaching. At the same time methane emissions were reduced through drainage.

1.3. Methane emissions in agroecosystems

Methane is important in the chemistry of the stratosphere, as CH₄ oxidation partially controls the water vapour balance (Jambert et al., 1997). The current CH₄ concentration in the atmosphere is 1.8 ppmv (Dobbie et al., 1996). It has a residence time of 8-12 years and a radiative absorption increase of 32 ppm (Bouwman 1990). Methane is 15 times more effective than CO₂ (on a mass basis) at absorbing infrared radiation (Chen et al., 1997). Agriculture contributes approximately 20-40% of global atmospheric input of methane (Van der Weerden et al., 1999; Willison et al., 1995).

The atmospheric concentrations of CH₄ and NO_x have increased over the past few decades by a rate of 1.1 and 0.25% per year respectively (Mosier et al., 1991). Increased biospheric CH₄ production is generally suggested as a reason for the increase, but a decrease in global sinks may also be important (Mosier et al., 1991; Willison et al., 1995). This indicates that perhaps 54% of the current CH₄ uptake by UK soils is a result of the increased concentration of CH₄ in the atmosphere (Willison et al., 1995).

Sources of CH₄ from ruminants, rice paddies and human exploitation of naturally occurring CH₄ sources such as coal, oil, natural gas and biomass (Dobbie et al., 1996) have increased (Willison et al., 1995). These increases in atmospheric concentration may be partly due to decreasing rates of oxidation in soils (Jambert et al., 1997). The main biological sink for CH₄ is the microbial oxidation of methane by methanotrophic bacteria in terrestrial ecosystems (Robertson et al., 2004; Van der Weerden et al., 1999; Willison et al., 1995) and the main sink is the atmosphere from the reaction with hydroxyl radicals, •OH in the troposphere (Dobbie et al., 1996). Methane is produced in soils through biogeochemical cycles of C and N in the agroecosystems, decomposition, nitrification/denitrification, and methanogenesis respectively; any change in either management or climate/soil conditions will alter the biochemical or

geochemical processes, which will finally lead to changes in the gas fluxes (Li et al., 2004). It has long been recognized that nitrogen limitations often constrain carbon accumulations in mid- and high-latitude ecosystems. Recent research on plant responses to elevated CO₂ concentrations is also consistent with the idea that low nitrogen availability can constrain carbon sequestration in terrestrial ecosystems (Sokolov et al., 2007).

Current estimates vary, but indicate that microbes in soils may oxidise up to 50 Tg yr⁻¹ of CH₄ globally, accounting for 10% of total CH₄ destruction (Willison et al., 1995). Flooded rice fields are an important source of CH₄ emissions on a global scale (Figure 1-3). Diffusion of atmospheric CH₄ into the soil is considered to be one of the most important controls of CH₄ consumption in dry conditions. Soils with high porosity are expected to have elevated CH₄ uptake. Production of CH₄ is primarily controlled by the availability of biodegradable organic C. This production is also regulated by the degree of anoxia, by soil water content and O₂ diffusion limitation (Jambert et al., 1997).

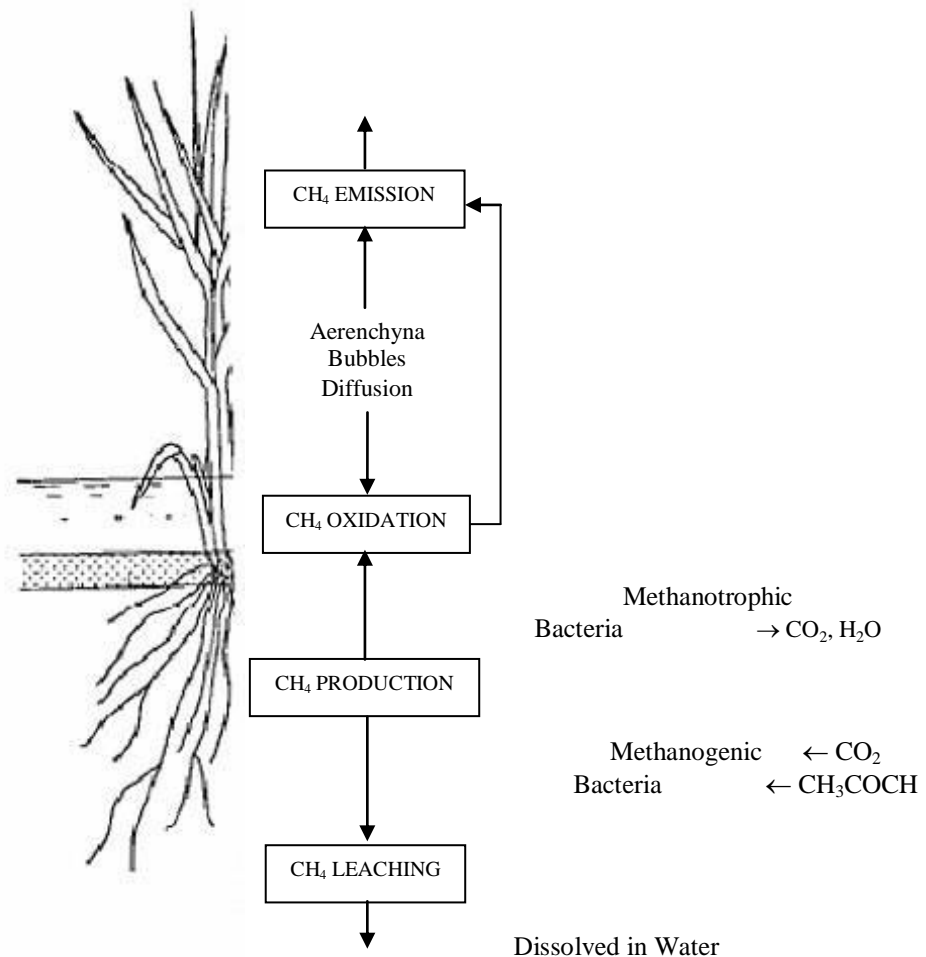


Figure 1-3: Amended diagram of CH₄ production, oxidation, leaching and emissions in soil for paddy rice fields (Mosier et al., 2004).

Mosier et al., (1991) found that cultivation of the soil by either ploughing or rotovating did not result in decreased CH₄ oxidation states, which contrasts with observations made by Willison et al. (1995) of the IACR-Rothamsted long-term arable systems. It is likely that any short-term effect of cultivation on oxidation rates are too small to be observed, as was found by Van der Weerden et al. (1999). Cultivation may reduce the rate of CH₄ consumption in two ways. Firstly, NH₄⁺ released via mineralization of organic N may inhibit CH₄ monooxygenase enzyme activity. Secondly, increased aeration following soil disturbance may lead to lower soil moisture content. Methanotrophic bacteria are sensitive to water stress and oxygen availability, thus affecting their ability to consume CH₄ as methanotrophs are therefore traditionally considered obligate aerobic respiratory bacteria (Roslev and King, 1994; Van der Weerden et al., 1999).

Recent extensive changes in land management and cultivation could be contributing to the observed increase in both atmospheric CH₄ and N₂O (Figure 1-1). Nitrogen fertilization and cultivation can decrease CH₄ uptake on cultivated grasslands and in temperate forest soils and increase N₂O production (Mosier et al., 1991). This has been shown in laboratory and field studies: the optimum soil pH for CH₄ oxidation is 7.0-7.5 (Willison et al., 1995). Hütsch et al. (1994) also observed decreasing CH₄ oxidation of grassland soil with decreasing pH ranging from 6.3-5.6, though this decrease was presumed to be due to an increase in water-filled pore space as it followed cultivation and thus reduced the soil's aeration status (Van der Weerden et al., 1999). It has been estimated that combined land conversion to agriculture, disturbance of ecosystems, changes in agricultural practice and increased atmospheric deposition may have decreased the soil CH₄ sink by 37 kt CH₄ yr⁻¹ (Willison et al., 1995). Land use change from forest/woodland to agricultural land can cause up to a 60% reduction of CH₄ uptake: this was shown in a range of soils from Scotland and Denmark (Dobbie et al., 1996). Ojima et al. (1993) concluded that the mechanisms responsible for the reduction of CH₄ are not clear, though factors such as water availability, fertiliser applications, atmospheric N deposition, soil structural changes, and cropping management contribute to modifications of the soil uptake.

Figure 1-4 is a retrospective estimate of global CH₄ soil sink, relative to changes in atmospheric methane, derived from estimates of historic CH₄ mixing ratios, temperate forest and grassland cover patterns, area impacted by chronic N deposition and consequent CH₄ uptake rates (Ojima et al., 1993).

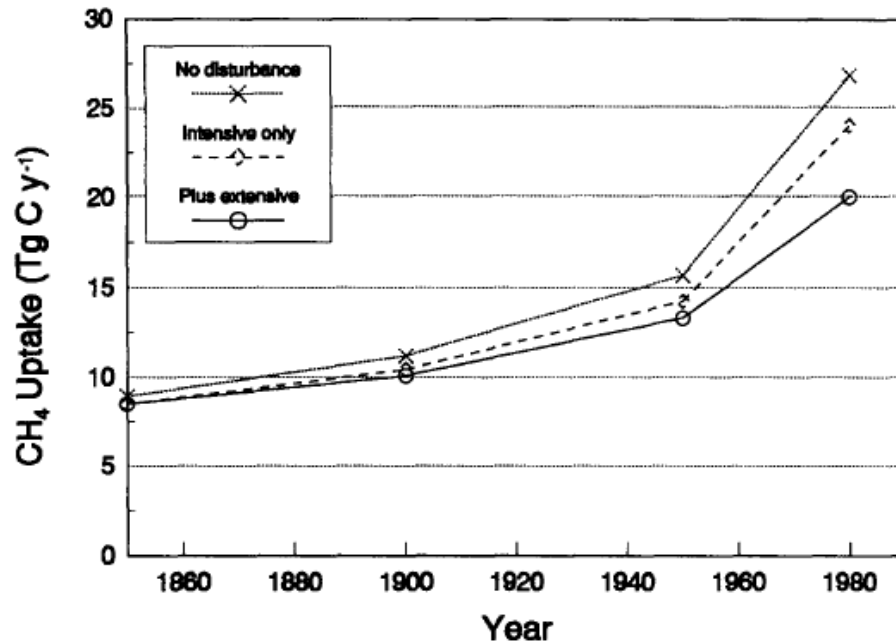


Figure 1-4: A retrospective estimate of the global CH₄ soil sink relative to changes in atmospheric methane from 1850 to 1980. The 'No disturbance' line indicates estimated soil CH₄ uptake assuming that no major land cover changes have taken place and that uptake rates were near maximal. The 'Intensive' line represents estimated soil CH₄ uptake assuming that soil CH₄ uptake was altered by land cover changes resulting from forest or grassland conversion to cropland or pasture. The 'plus extensive' line represents the added change in CH₄ uptake due to increased atmospheric inputs of N over large areas of the world (Ojima et al., 1993).

1.4. GHG measurement

Methods for measuring different GHGs include flux chambers, gradient analyses, eddy correlation, and aircraft measurements (Davidson et al., 1997). The methods for extrapolation varies greatly; they include averaging over seasons, calculating temperature-dependent algorithms, adjusting for daily variations and applying ratios of NO and N₂O emissions to more complete datasets on N₂O emissions (Davidson et al., 1997). Few studies have been designed to estimate annual emissions of NO from soils, and most have been carried out in temperate climates (though NO may not be a GHG in the air it is converted to nitric acid which is implicated in acid rain) (Davidson et al., 1997). Furthermore, both NO and NO₂ participate in ozone layer depletion. Extrapolating experimental data obtained for a given region and cultivation practice to a larger geographical scale is very difficult, owing to large variations in potential emissions from natural soils. In addition, the potential combination of soil types and agricultural systems

at the regional scale - and the response of these systems to fertiliser application, climate, and cultivation practices - can be substantial (Jambert et al., 1997). There are likely to be important regional differences in climate change responses, with the effects of increased CO₂ concentration dominating in warmer regions, and the effects of increased temperature dominating in cooler regions. The latter may lead to losses in soil carbon in boreal and tundra regions (Kirschbaum, 2000).

To reliably predict CO₂, N₂O and CH₄ emissions, soil chemical and physical characterisation are required. Soils sampled from a depth of 15 cm can be analysed for pH, NH₄HCO₃-soluble P and NH₄HCO₃-soluble K, while total soil organic C (SOC) is multiplied by 1.7 to give soil organic matter SOM (Webb et al., 2004). To determine soil mineral N, samples can be taken at 30 cm increments down to 90 cm (Webb et al., 2004). NH₄⁺ and NO₃⁻ can be extracted by shaking 40 g of soil with 200 ml 2 M KCl for 2 h before filtering and analyzing (Webb et al., 2004). Together, these methods can be used to estimate net N outputs via leaching of mineral-N, NH₃ fluxes, N₂O and N₂ emissions, and crop N offtake (Webb et al., 2004). To estimate N₂ emissions from denitrification activity, the acetylene inhibition technique can be used; however, Bollman and Conrad (1997) found that the observed discrepancies between denitrified NO rates and actual denitrification rates were created by the acetylene used in the denitrification assay. The acetylene probably caused scavenging of part of the NO that was produced as intermediate in the denitrification sequence, and thus could not be further reduced to N₂O. Consequently, the denitrification rates were underestimated. Ammonia emissions can be measured using the aerodynamic gradient method as modified by Schjørring (1995). Wind speed and NH₃ concentration profiles are made linear with respect to the logarithm of height using the relationship between zero plane displacement and crop height (Webb et al., 2004).

Methane and N₂O fluxes can be measured by inserting static perspex/steel chambers into the ground (Van der Weerden et al., 1999). These are airtight, and gas samples can be drawn from the headspace using a syringe at different time intervals (e.g. 0, 10, 30, 60 min). The gas in the air-tight syringes is typically analysed using a gas chromatograph equipped with electron capture detector and packed porapak Q column (Verma et al., 2006). Soil temperature is typically

taken inside and outside the chamber (e.g. at 2.5 cm depth) to account for variations due to radiation causing large temperature increases in the chamber (Jambert et al., 1997; Van der Weerden et al., 1999).

A complete budget of fertiliser N, biologically fixed N₂ and N mineralized from the soil organic matter is difficult to produce, but is needed if we are to accurately assess the impact of increased use of N in agricultural ecosystems on terrestrial N₂O emissions (Mosier et al., 1998). Studies of N₂O emissions from similar agricultural systems show highly variable results in both time and space, with the main factors influencing turnover are soil temperature, moisture, fertility, availability of organic substrate and drainage (Bowman, 1990; Mosier et al., 1998). Biome stratification of each stratum can be carried out to account for variations in NO emissions for various types of ecosystems (Davidson et al., 1997). For Davidson et al. (1997) it succeeded in revealing that three strata (savannahs/woodland, chaparral and cultivated lands) have some very high NO emissions.

The temperature dependence of biochemical processes such as respiration has been described mathematically since the late 19th century by Van't Hoff (1898) and Arrhenius (Davidson et al., 2006; Janssens et al. 2003). Soil temperature is typically a reliable predictor of soil respiration when no severe drought stress occurs. Exponential relationships, especially the Q_{10} relationship, have been commonly used to estimate soil respiration rates from temperature (Eqn. 1; Curiel Yuste et al., 2004).

$$Q_{10} = \text{Respiration rate at } (T + 10) / \text{respiration rate at } T \quad (\text{Eqn. 1})$$

Q_{10} is the increase in reaction rate per 10°C increase in temperature, with the average Q_{10} of 2 being calculated by Wiant (1967) for CO₂ evolution in soil (Winkler et al., 1996) and by Blackmer et al. (1982), Crill et al. (1994), Müller (1995) and Roslev et al. (1997) for N₂O and CH₄ evolution for temperatures between 0 and 30°C (Van der Weerden et al., 1999). However, this is true only over a limited temperature range, owing to physiological restrictions on metabolic functioning at higher temperatures >35°C (Huang et al., 2005). Q_{10} has been found to be also higher and lower than 2.0; for example Davidson et al.

(1998) measured soil temperatures at 2, 5 and 10 cm depth, respectively, and found corresponding diurnal Q_{10} s for CO₂ flux of 2.2, 2.7 and 4.2. The temperature response is usually expressed as a Q_{10} value, where T is the temperature in K (Smith et al., 2003). The Q_{10} function is most widely used to simulate the temperature response of soil respiration (Janssens et al., 2003).

It was noted that Q_{10} values tend to be higher at low temperatures, so the relationship is not linear; this is consistent with observations and a large number of other studies (Palmer Winkler et al., 1996). With an increase in temperature, respiration increases and is generally modelled as increasing exponentially with temperature, with a Q_{10} (the proportional increase in respiration for every 10°C rise in temperature) near 2.0. However, this is true only over a limited temperature range, as more often Q_{10} itself is temperature dependent, decreasing with an increase in measured temperature (Huang et al., 2005). The Arrhenius equation predicts that the Q_{10} of chemical reactions decreases with increasing temperature, as is also commonly observed in many chemical and biological reactions in nature. The theoretical explanation for the decrease in Q_{10} with increasing temperature is that as temperature increases, there is a decline in the fraction of molecules with sufficient energy to react (Davidson et al., 2006). There is increasing evidence to suggest that the Q_{10} of soil respiration is not constant during the year, but tends to decrease with increasing temperature and decreasing soil moisture - though some argue that these seasonal changes are ecologically insignificant because the total annual flux is not altered (Janssens et al., 2003). Q_{10} discrepancies may stem from simple differences in experimental procedure, e.g. making temperature measurements at different depths. It has been argued that the substantial differences between observed Q_{10} in various publications might be partly explained by the decrease in diurnal variation in temperature with depth. Others have found an increase in Q_{10} with increasing depth in the soil (Smith et al., 2003). Experimental results demonstrated that Q_{10} values vary with temperature, quantity and quality of soil organic matter, soil moisture and land cover type (Zhou et al., 2009). All the environmental and biological factors such as soil temperature, moisture, and soil organic matter are spatially heterogeneous. Accordingly, estimated Q_{10} from measured soil respiration likely varies spatially at different geographic locations (Zhou et al., 2009).

Most empirical models rely on the correlation between the seasonal patterns of soil respiration and temperature, and thus have a constant parameter value for Q_{10} . Consequently, they may over- or underestimate soil respiration over at smaller time scales. The response of soil respiration is not well known below that of the seasonal pattern (Janssens et al., 2003). Given the recognized uncertainties associated with assigning the appropriate Q_{10} value to the appropriate place and season, a better understanding is still needed (Davidson et al., 1998).

1.5. Modelling GHG emissions

If C sequestration in conventional agricultural soils is to become a tradable commodity in the emerging C markets, then methods are needed to predict, monitor and validate not only changes in soil C stocks over time, but also their impacts on non-CO₂ GHG, like CH₄ and N₂O (Salas and Li, 2003). Given the considerable expense of establishing and maintaining flux measurement sites, the use of simulation models to estimate fluxes from agricultural soils has obvious benefits. Modelling also allows the complex links between soils' physical, chemical and microbial processes to be examined (Adballa et al., 2009). On a global scale, models allow the comparison between countries to be established, which is especially useful in light of the ongoing debate around 'local food'. Therefore, approaches that rely on spatially explicit, process based models coupled with direct measurements to validate and constrain uncertainties in model estimates are probably the most cost-effective and efficient (Salas and Li, 2003). If nations wish to explore the consequences of various mitigation strategies, both in terms of GHG production as well as crop yield, process-oriented models will be necessary tools (Li et al., 2001). There have been a number of different models developed in recent years. Good examples include:

1. CANDY (CARbon-Nitrogen-DYnamics). This simulates dynamics of soil N, temperature and water in order to provide information about N uptake by crops, leaching and water quality (www.ufz.de/index.php?de=14007) (Franko, 1996).
2. CENTURY was developed to simulate long-term (decades to centuries) SOM dynamics, plant growth and cycling of N, P and S. It was originally

developed for grasslands but has since been extended to agricultural crops, forests and savannah systems

(www.nrel.colostate.edu/projects/century) (Parton et al., 1995).

3. DAISY simulates crop production and dynamics of soil water and nitrogen under diverse agricultural management systems. It was developed as a tool for field management and regional administrative purposes. It has been applied to catchment areas, farmland areas and specific sites (code.google.com/p/daisy-model) (Hansen et al., 1991).
4. DNDC (DeNitrification and DeComposition) couples denitrification and decomposition processes as influenced by the soil environment to predict emissions of CO₂, N₂O and N₂ from agricultural soils (www.dndc.sr.unh.edu) (Li et al., 1992).
5. ITE (Institute of Terrestrial Ecology - Edinburgh) Forest Model. The pasture model aims to simulate N cycling in a grazed soil-plant system (Thornley and Verberne, 1990, 1992).
6. NCSOIL simulates N and C flow through soil microbes and organic components. It comprises four organic components: plant residues, microbial biomass, humads and stable organic matter (Molina et al., 1983).
7. ROTHC is the Rothamsted C model in which the turnover of C in aerobic soil is sensitive to soil type, temperature, moisture and plant cover (www.rothamsted.ac.uk/aen/carbon/rothc.htm) (Jenkinson et al., 1987).
8. SOMM is described as the raw humus sub-model of a single plant ecosystem model (SPECOM) developed for forested ecosystems (Chertov, 1990).
9. The Verberne/Van Veen model aims to simulate N and water balance in a grassland soil-plant system in order to predict yield, N uptake, N leaching, N mineralization and accumulation of soil organic N (Verberne et al., 1990; Smith et al., 1997).

These models are well used; however, there are still inherent problems with them, as the mathematical recreation of nature will never be completely accurate, owing to the number of variables and feedback loops involved. There is little evidence that either the ITE Forest Model, NCSOIL, SOMM or Verberne/Van

Vein model are still being used. However, process-based models clearly have an important role in designing, evaluating and implementing C sequestration and CH₄ and N₂O mitigation projects. In particular, models can

- Provide opportunities for assessing potential soil C sequestration rates in the project evaluation phase
- Be used for scenario analyses to examine risks (e.g. climate variability)
- Simulate secondary impacts of agricultural C sequestration projects on net GWP for long term projects
- Provide guidance on monitoring phase of C, by verifying changes in soil C stocks over time at the contract target levels
- Be used to adjust predicted (or potential) values, that are based on predicted climate, soil, and management conditions, to simulated actual conditions (critical for monitoring)
- Be augmented with direct observations to assess reliability of model predictions, adjust model inputs and provide updates to overall uncertainties (Salas and Li, 2003).

In the modelling domain, uncertainty is commonly understood as an attribute that must be acknowledged and associated with the quality of the information used to build and run a model (Zimmermann, 2000). However, when modelling a complex system the quality of information is not the only thing that matters; the modeller's beliefs and experience also play an important role (Brugnach et al., 2008). Even though a model can be based on sound process understanding, when there are many unknowns about the system to be modelled, the modeller is forced to make assumptions and take (necessarily subjective) decisions about why and how a problem should be modelled, and to incorporate uncertainty into the model through various stages of development (Brugnach et al., 2008).

A number of 'process-oriented' simulation models have been developed over the last few years with the objective of simulating terrestrial ecosystem C and N biogeochemistry and N trace gas emissions (Li et al., 2001). Different models, ranging from simple regressions to completely process-based models have been developed. As these regression models neglect several variables, they cannot always be used to test different management or mitigation scenarios, in

contrast to the more complicated process-based models (Beheydt et al., 2007). A process-based model can include more factors that influence regional and inter-annual variability in CH₄ flux than an empirical method that multiplies crop area by mean flux rates (Babu et al., 2006). The IPCC methodology is also a strictly empirical model. Process-oriented ecosystem models attempt to simulate many or all of the components of the N cycle. As a result, process-oriented models require many more details about the ecosystem being simulated than strict empirical models. A process-oriented model can, therefore, be driven by temperature, moisture, pH, redox potential and other basic environmental factors that are not usually applied to strictly empirical models (Li et al., 2001).

Crop growth models such as DSSAT and RCSOD focus on high crop production and efficient management, especially for water and fertiliser management. Crop growth, development and soil water dynamics are usually simulated well, but soil biogeochemistry is usually not considered, or simulation is simplified in terms of nutrient effects on crops in the models. Biogeochemical models such as RothC, CENTURY and DNDC pay more attention to soil processes, such as decomposition, nitrification and denitrification.

The difficulties of modelling NO and N₂O emissions have three causes:

1. There are at least three sources of NO and N₂O: nitrification, denitrification and chemodenitrification. The three reactions are so different in their thermodynamics and kinetics that, when they are mixed together, the pattern of NO to N₂O fluxes is unavoidably complex.
2. Each of the reactions is driven by a number of forces, including soil environmental factors, (e.g. temperature, moisture, pH, Eh, and substrate concentration) and ecological drivers (e.g., climate, soil physical properties, vegetation, and anthropogenic activity). Any change in the combination will alter the magnitude/pattern of fluxes.
3. NO and N₂O are intermediates or by-products of nitrification and denitrification. This means fluxes are determined by the kinetics of the production, consumption and diffusion of gases in the sequential biochemical reactions (Li et al., 2000).

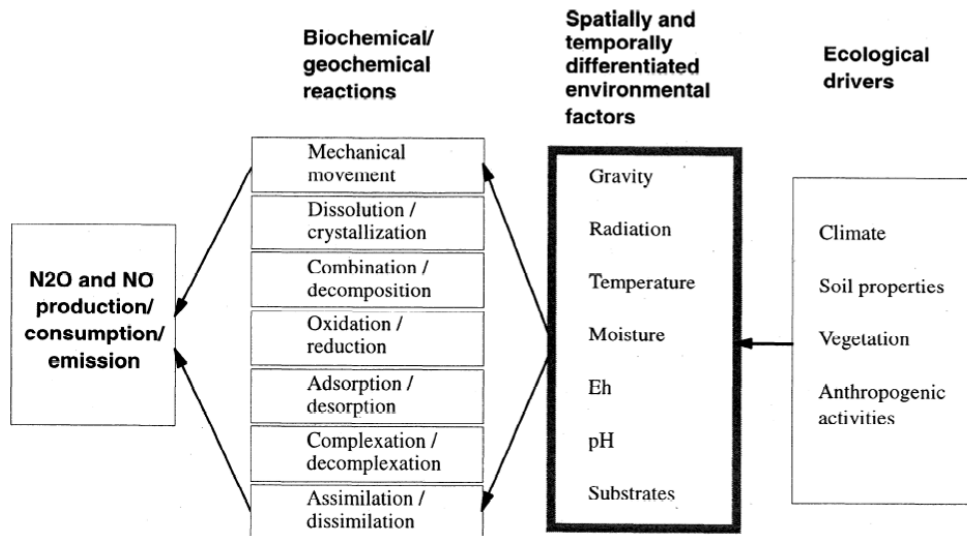


Figure 1-5: A biogeochemical field is an assembly of forces controlling concerned biochemical or geochemical reactions in a specific ecosystem. The ecological drivers control spatial and temporal variations of the environmental factors, and the latter regulate all of the relevant geochemical and/or biochemical reactions. A biochemical model is to integrate the links among the ecological drivers, the environmental factors, and the biogeochemical reactions. The DNDC model was developed based on the biogeochemical concept (Li et al., 2000).

A biochemical system is an assembly of forces regulating biochemical (e.g. combination/decomposition, oxidation/reduction, assimilation/dissimilation) and geochemical (e.g. mechanical movement, dissolution/crystallization, oxidation/reduction, absorption/desorption, complexation/decomplexation) reactions in a specific ecosystem. The soil emissions from an ecosystem must be controlled by a series of reactions driven by the forces (Figure 1-5) (Li et al., 2000).

Soil-crop models such as SiB and BATs pay more attention to physical processes such as radiation, water, heat and momentum fluxes. Therefore gaps exist among the modelling efforts of agronomists, environmentalists and climatologists due to their different focuses. The DNDC model integrates crop growth processes with soil biogeochemistry (Zhang et al., 2002).

1.6. DNDC model

According to the functions of the Crop-DNDC model, the following factors have been quantified for the consideration of sustainable agriculture:

- Productivity: grain yield, crop total biomass and economic benefit.

- Efficiency: Water use efficiency and nitrogen use efficiency.
- Longevity: long-term soil organic carbon accumulation.
- Environmental implications: emissions of GHG, other atmospherically active gases and nitrate leaching (Zhang et al., 2002).

The DeNitrification-DeComposition (DNDC) model developed by C. Li and his colleagues is a process-based biogeochemical model constructed for predicting C sequestration, N dynamics and trace gas emissions from agroecosystems in the USA, China, India and Europe. Originally, it was a rain-event driven model of soil N and C biogeochemistry that has been adapted to predict N₂O emissions from agricultural soils over the year. The Crop Decomposition-Denitrification model can be used to determine C and N biogeochemistry in agro-ecosystems; the model can also yield daily data on emissions with the input parameters based upon 4 major ecological drivers: (1) climate, (2) soil properties, (3) vegetation, and (4) anthropogenic activities. It consists of six sub-models: soil climate (including water flow and leaching), crop growth, decomposition, nitrification, denitrification, and fermentation. The six interacting sub-models include fundamental factors and reactions, which integrate C and N cycles into a computing system. Crop growth is estimated using a generalized crop growth curve for both upland and wetland agroecosystems. The original DNDC model was designed for non-flooded agricultural lands, simulating the fundamental processes controlling the interactions among various ecological drivers, soil environmental factors and relevant biochemical or geochemical reactions, which collectively determine the rates of trace gas production and consumption in agricultural ecosystems (Babu et al., 2006). The newly developed Crop-DNDC model has a linking between crop growth and soil biogeochemical processes and has been validated for a number of ecosystems, including grasslands, forests, agricultural lands; pastures, crop fields and rice paddies (Abdalla et al., 2009, Cai et al., 2003, DNDC, 2003, Leip et al., 2008; Li et al., 1992; Li et al., 2004; Qui et al., 2009; Tonitto et al., 2007; Zhang et al., 2002).

The model has been applied to agricultural fields (Li et al., 1996, 2001; Gou et al., 1999), dairy farms (Brown et al., 2001), rice fields (Li et al., 2005)

and soil organic carbon dynamics (Li et al., 1997). A forest version of DNDC, PnET-N-DNDC, was developed for forest soils. It integrated three models: the Photosynthesis-Evapotranspiration (PnET) model, the DNDC model, and the nitrification model. PnET is a forest physiology model for predicting forest photosynthesis, respiration, organic carbon production and allocation and litter production (Cai et al., 2003; Li et al., 2000). Some alterations – such as the inclusion of specific data on soil characteristics and crop information - have been made to the database structure and content since the model's inception to improve suitability for use in the UK. Information on the changes that have been made, and their rationale, is unavailable (Brown et al., 2002).

The major considerations for the model development include: (1) the dynamics of crop growth and its responses to climatic conditions and farming practices; (2) interactions of crop growth with soil biogeochemical processes, and (3) the overall behaviour of the model in simulating crop yield and trace gas emissions responding to climate conditions and management practices (Zhang et al., 2002). In the version of DNDC modified for prediction in rice paddies, any change in the farming management will simultaneously alter several soil environmental factors including temperature, moisture, Eh, pH and substrate concentration gradients. These altered environmental factors will simultaneously and collectively affect a series of biochemical or geochemical reactions such as elemental mechanical movement, oxidation / reduction, dissolution / crystallization, adsorption / desorption, complexation / decomplexation, assimilation / dissimilation, etc., which finally determine CO₂, CH₄ and N₂O emissions from the modelled ecosystems (Li et al., 2004).

The model can predict climate (soil temperature and moisture profiles based on soil physical properties, daily weather, and plant water use); crop growth and soil biogeochemistry and their interactions; soil C dynamics; N leaching and trace gas emissions (e.g. NO, N₂O, N₂, CH₄ and NH₃). The model can also yield daily data on emissions with the input parameters based upon the four major ecological drivers. These parameters can be used to simulate as many years' data as is required. The model can be used for individual point locations (e.g. a single field) or, by means of coupling with GIS data, can be used at the regional scale (DNDC, 2003; Leip et al., 2008).

A number of versions of DNDC exist for individual land uses (e.g. forestry). Crop-DNDC model has two major advantages over other such models as CERES (Crop Environment Resource Synthesis), GePSi (Generic Plant Simulator), RothC, CENTURY and ECOSYS, as it integrates crop growth and soil biogeochemistry and can be used for predicting impacts of climate change or alternative management on both agricultural production and the environment (Zhang et al., 2002).

DNDC can simultaneously simulate at a sub-daily time step. That means it can provide more comprehensive simulations of the responses of agroecosystems to climate warming and atmospheric CO₂ enrichment (Levy et al., 2007; Zhang et al., 2002). Among the advantages of DNDC are that it has been extensively tested and has shown reasonable agreement between measured and modelled results for many different ecosystems such as grassland, cropland and forest (Figure 1-6, 1-7, 1-8). DNDC uses databases with spatially and temporally differentiated information on climate, soil, vegetation and farming practices as parameters for supporting local, regional and national scale analyses (Salas and Li, 2003). Apart from Li and some others, there has been little systematic comparison of the different model versions.

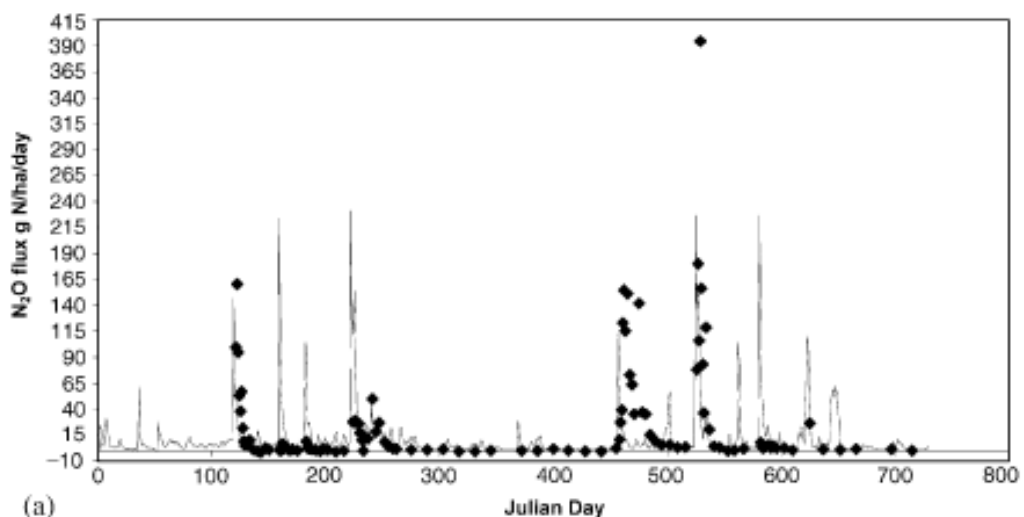


Figure 1-6: A comparison of a modelled (—) versus measured (◆) emissions of N₂O-N at a grassland site near Edinburgh (Brown et al., 2002).

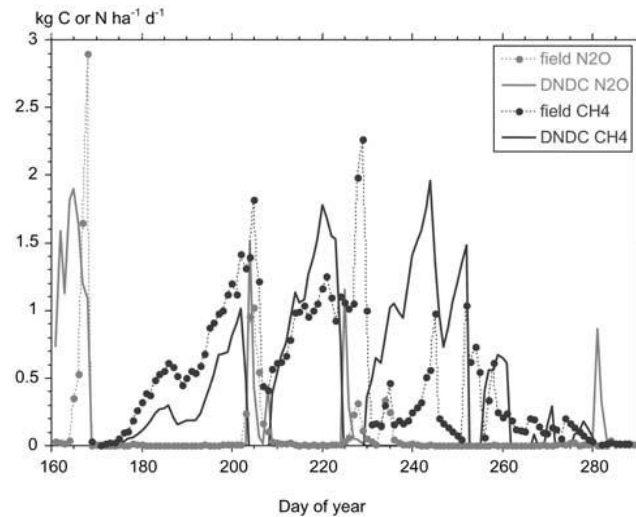


Figure 1-7: Comparison between observed and modelled CH₄ and N₂O fluxes from a rice paddy field (Li et al., 2005).

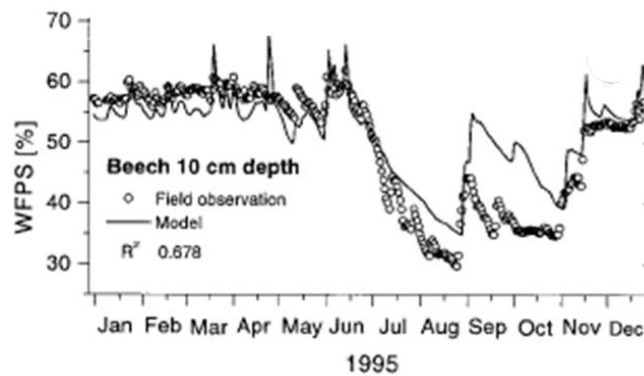


Figure 1-8: Comparison of measured and simulated values of percent water-filled pore space (WFPS) for a beech forest site (Stange et al., 2000).

In the Crop-DNDC model, crop growth is simulated not only by tracking crop physiological processes and decomposition rates, but also by calculating water stress and N stress. Biogeochemical processes that control CH₄ and N₂O emissions are non-linearly coupled with anthropogenic and ecological drivers that are highly variable in space and time (Salas and Li, 2003). DNDC predicts N₂O emissions by tracking the reaction kinetics of nitrification and denitrification driven by climatic conditions, soil properties, and management practices (Li et al., 2004).

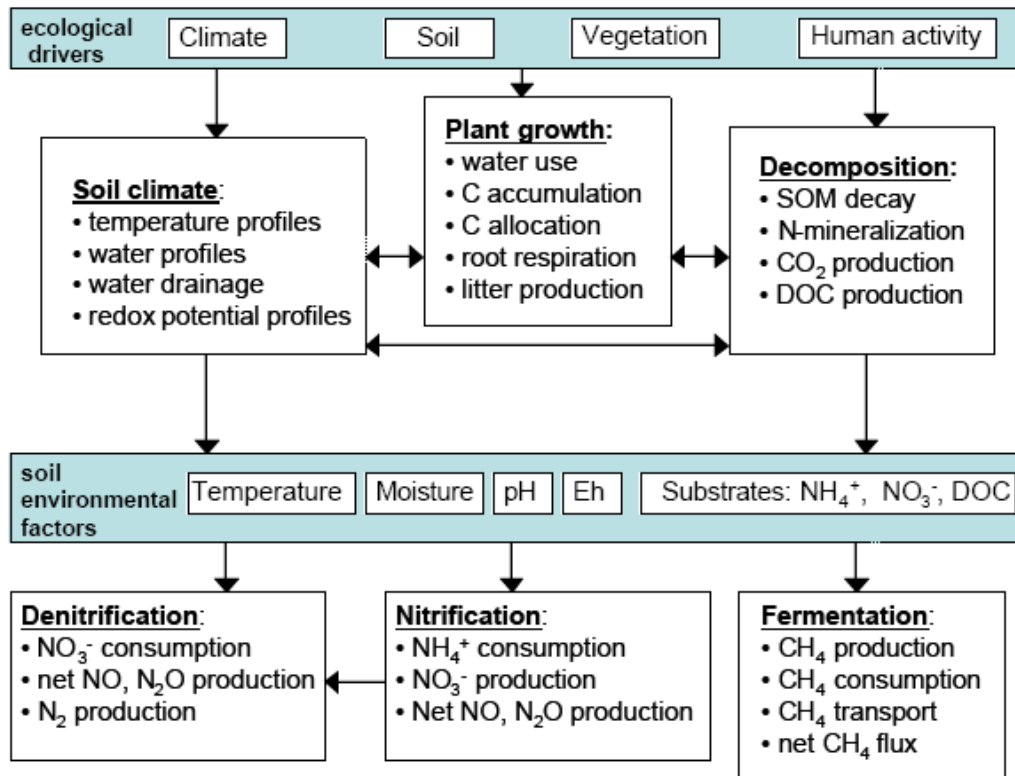


Figure 1-9: Crop DNDC model structure (Li et al., 2006).

The DNDC model is constructed on two components that reflect the two-level driving forces that control geochemical and/or biochemical processes related to C and N fluxes (Figure 1-9). The first consists of soil climate, crop growth and decomposition sub-models and predicts soil temperature, moisture, pH, redox potential (Eh) and substrate concentration profiles (ammonium, nitrate, dissolved organic carbon) based on ecological drivers. These include daily precipitation, maximum and minimum air temperature, soil organic matter, soil texture, soil clay content, soil bulk density, vegetation and anthropogenic activity. The second component consists of nitrification, denitrification and fermentation sub-models and predicts NO, N₂O, CH₄ and ammonia (NH₃) fluxes based on soil environmental variables derived from the first component (Xu-Ri et al., 2006; Kiese et al., 2005; Salas and Li, 2003).

During changes in soil water content, the soil redox potential (Eh) is also subject to substantial changes. Consequently, CH₄ and N₂O are produced and consumed under certain conditions at different stages of the varying soil redox potential (Li et al., 2005). It is known that the redox potentials in soil in which N₂O and CH₄ are produced differ. The critical redox potential of a flooded rice

soil in which N_2O is produced is +250 to +300 mV over a range of soil pH conditions. For CH_4 it was found to be approximately -140 to -160 mV (Chen et al., 1997). To quantify Eh dynamics, DNDC combines the Nernst equation with the Michaelis-Menten equation. The two equations can be linked by a common factor: oxidant concentration (Li et al., 2005).

The premise of the DNDC model is that by modelling the processes that lead to N_2O fluxes, a model can make reasonable estimates of emissions from a range of agro-ecosystems (Li et al., 2001). DNDC simulates a full C and N balance, including different C and N pools and the emissions of all relevant trace gases from soils (Neufeldt et al., 2006).

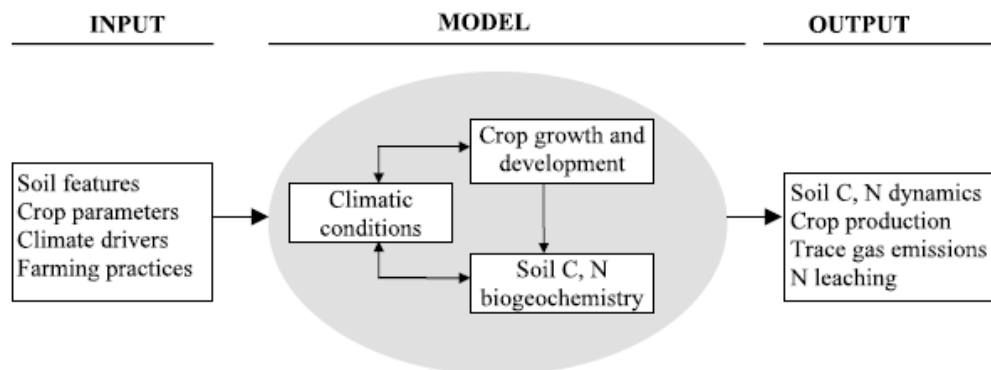


Figure 1-10: The overall structure of the Crop-DNDC model (Zhang et al., 2002).

The soil climate sub-model calculates hourly and daily soil temperature and moisture fluxes. Water fluxes and heat flows through the soil which is divided into horizontal layers which are determined by soil texture and the gradients of soil moisture potential and soil temperature (Brown et al., 2002).

The crop growth sub-model simulates crop biomass accumulation and partitioning based on thermal degree days and daily N and water uptake (Brown et al., 2002). The plant growth sub-model includes subroutines for cropping practices such as fertilization, irrigation, tillage, crop rotation and manure addition to simulate SOM turnover in arable lands. Clay adsorption of humads (moderately stable fractions of carbon in the form of living organisms and living humus) allows some soil-specificity; decomposition is a first order kinetic process, such that biomass formed during decomposition is a dependent variable (Smith et al., 1997; Borzecka-Walker et al., 2011) (Figure 1-10).

The decomposition sub-model calculates decomposition, nitrification, NH_3 volatilisation and CO_2 production on a daily time step. Decomposition can occur in three organic matter pools: decomposable residues, microbial biomass and humads, each of which has a labile and resistant component. The effect of soil properties; soil temperature, clay fraction and water content is modelled using factors that constrain decomposition rate from the maximum in non-optimum conditions (Brown et al., 2002). During decomposition and assimilation, organic C, ammonium, and nitrate are produced and may accumulate. The levels of these substrates depend on the balance between the rates of mineralization, assimilation and loss (Li et al., 1992).

By tracking crop biomass production and soil organic carbon (SOC) decomposition rates, DNDC captures short- and long-term SOC dynamics. It predicts N_2O emissions by tracking the reaction kinetics of nitrification and denitrification across climatic zones, soil types, and management regimes (Li et al., 2004). Classical laws of physics, chemistry and biology, and empirical equations generated from laboratory observations, were used in the model to parameterize each specific reaction. The entire model forms a bridge between basic ecological drivers including management of agro-ecological systems, and water, C and N cycles (Salas and Li, 2003). The process algorithms in the DNDC model have been developed and parameterized using data collected in field and laboratory studies performed by a number of research groups in a number of locations, including two sites in China. The goal of process modelling is to include robust parameterizations of key processes so that the effects of process interactions and feedbacks can be simulated in a range of settings and conditions (Li et al., 2001).

Since C sequestration, CH_4 and N_2O emission are affected by many environmental factors, albeit in different ways, shifting from one location to another will alter the effects of any management alternatives on the net global warming potential (Li et al., 2004). During decomposition and assimilation, organic C, ammonium, and nitrate are produced and may accumulate. The levels of these substrates depend on the balance between the rates of mineralization, assimilation and loss (Li et al., 1992)

DNDC models the growth of over 40 types of crop plants based on such factors as their optimum yield, partitioning of assimilated C to root, leaf, stem

and grain, C/N ratios of root, leaf, stem and grain and water requirement. Harvest terminates root growth and turns 100% of the root biomass into root litter, which is automatically incorporated in the soil profile. Tillage following harvest will incorporate this part of the aboveground litter into the soil profile. As soon as the litter is incorporated in the soil, the litter is partitioned into three soil litter pools: (1) very labile, (2) labile and (3) resistant pools. The labile pool is carbon, which turns over relatively rapidly (< 5 years) (Hoyle et al., 2008). The partitioning fractions are calculated based on the C/N ratio of the fresh litter (Li et al., 2004). The crop/vegetation growth sub-model simulates the growth of various crops from planting to harvest, predicting biomass and N-content of grain, stalk and root. Crop growth is limited by N and water availability in the root zone in the crop growth sub-model. Transpiration water losses are calculated from crop growth and a crop-specific water-use-efficiency parameter. A decomposition sub-model has four soil C pools: litter, labile humus, passive humus and microbial biomass (Li et al., 2001).

When crop respiration is simulated growth and maintenance respiration are considered separately (Zhang et al., 2002). Root respiration is a result of three processes: (1) root growth, (2) root maintenance and (3) ion uptake and transport. Osman (1971) observed that root respiration of wheat was an exponential function of the temperature from 10-30°C, with a Q_{10} value of 2.5 (Li et al., 1994a). However, there are large differences in carbon dynamics across crop types and geographical area. In general, pastures are the largest sinks of carbon. Cotton, corn, rice with winter flooding, tomatoes, citrus and deciduous fruit cropping systems are additional sinks of C, as a result of farming practices. On the other hand, lettuces, beans, oats and winter wheat cropping systems appear to be a net source of carbon, and thus cause a decrease in soil carbon. Areas of rice paddies (without winter flooding), beets, sorghum, sunflowers, and viticulture do not appear to be significant sources or sinks of C (Li et al., 2004). The cropping systems of cotton, corn, alfalfa, non-legume hay (or pasture), citrus and deciduous fruit orchards made positive contributions to carbon sequestration. This sequestration is likely due to the high litter production of these cropping systems. SOC was reduced for lettuce, dry beans and sunflower cropping systems by 0.003–0.8 Tg C over the modelling period, most likely due to their low amounts of litter entering the soil. The cropping systems of cotton, corn and

grapes are the highest contributors to total nitrous oxide emissions. By tracking crop biomass production and decomposition rates, DNDC tracks short- and long-term SOC dynamics (Li et al., 2004).

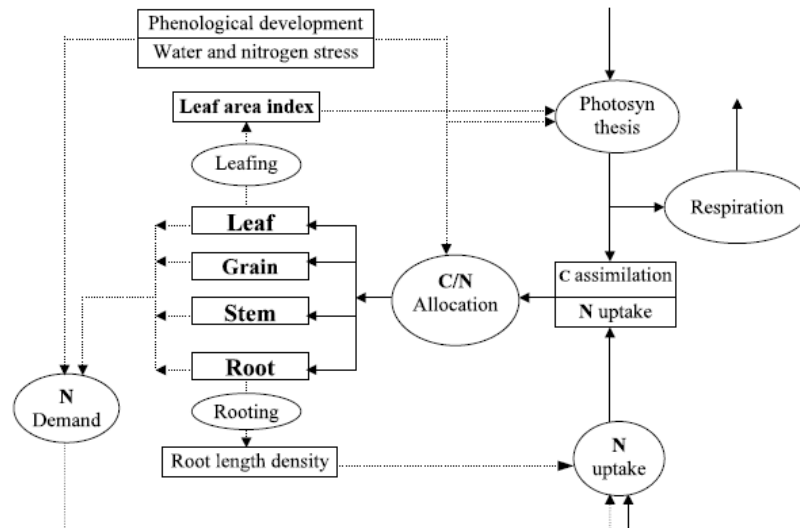


Figure 1-11: Crop sub-model for DNDC. Where rectangles are steady state, circles/ellipses are processes, whilst solid lines and dash lines are for matter flow (Zhang et al., 2002).

In the Crop-DNDC model, crop growth is simulated not only by tracking crop physiological processes but also by calculating water stress and nitrogen stress, which are closely related to soil biogeochemical processes and hydraulic dynamics. Biogeochemical processes that control CH_4 and N_2O emissions from agroecosystems are non-linearly coupled with anthropogenic and ecological drivers that are highly variable in space and time (Salas and Li, 2003). Figure 1-11 shows the structure of the crop sub-model. The major state processes and variables include phenological development; LAI; photosynthesis and respiration; assimilate allocation; rooting processes; water and nitrogen uptake; and biomass and nitrogen content of crop organs. Crops assimilate atmospheric carbon through photosynthesis, and carbon assimilation produces nitrogen demand. The actual nitrogen uptake also depends on the availability of mineral nitrogen in soil. Phenological stages and stress factors (water and nitrogen) influence carbon allocation and nitrogen demand (Zhang et al., 2002). Crop-DNDC also quantifies crop residue incorporated in the soil at the end of each growing season. Thus the model has coupled crop growth algorithms with soil

biogeochemical components, and simulates the carbon, nitrogen and water cycles in agroecosystems with a relatively complete scope. The model was validated against field measurements, including soil moisture, leaf area index, crop biomass and nitrogen content and the modelled results were in agreement with observations on soil carbon dynamics and trace gas emissions as well. Sensitivity tests, demonstrating the accuracy of the model to field measurements, demonstrated that the modelled results in crop yield, soil carbon dynamics and trace gas emissions were sensitive to climate conditions, atmospheric CO₂ concentration and various farming practices. There remains the potential for applying the model for simultaneously predicting effects of changes in climate or management on crop yield, soil carbon sequestration and trace gas emissions (Zhang et al., 2002).

DNDC is able to track the turnover of crop litter in the soils in terms of its quantity and quality as well as by the soil's temperature, moisture level, and aeration. In DNDC, tillage affects SOC decomposition rates through two mechanisms (Li et al., 2004). Phenological information for mapping cropping practices was obtained with multi-temporal EVI (Enhanced Vegetation Index). Figure 1-12 shows Multitemporal EVI development curves which are plotted against time; thresholds will be established for each cover type to indicate the onset (B), growth rate (A), maximum potential growth (D), time corresponding to the maximum, and harvest (Salas and Li, 2003).

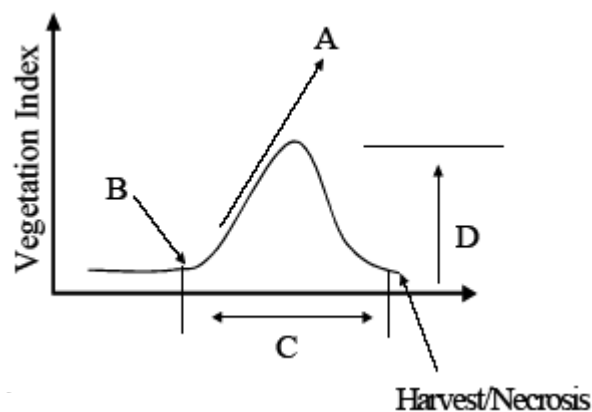


Figure 1-12: Multitemporal EVI development curve where (B) is growth rate, (A) is maximum potential growth and (D) is time corresponding to the maximum (senescence) and harvest. (Salas and Li, 2003)

DNDC characterizes soil physical properties by soil texture (Li et al., 1992). DNDC uses four soil properties: (1) soil bulk density, (2) clay fraction, (3) pH and (4) organic carbon content (Li et al., 2004). The soil thermal conductivity depends on soil water content, N_2O and CO_2 from decomposition and on the type of soil. Soil water tension and unsaturated hydraulic conductivity are strong functions of the soil water content (Li et al., 1992). Day length is estimated based on latitude and Julian date. Photosynthetically active radiation at a certain time of the day is estimated based on daily solar radiation and solar elevation. Canopy and soil temperatures are estimated based on daily air maximum and minimum temperatures (Zhang et al., 2002).

For an overview of decomposition of organic matter in soils; nitrogen behaviour is simulated in the following ways. (1) When organic C is oxidised to CO_2 , the associated N is transformed to the NH_4^+ . (2) NH_4^+ can be nitrified to nitrate or transferred to ammonia and volatilised to the air. (3) When organic C transfers from one pool to another, surpluses or deficits of available N can occur because of the differences in C:N ratios among different pools (Li et al., 1992). Plant nitrogen comes from NO_3^- and NH_4^+ pools, based on their relative concentrations (Li et al., 1992). Because each of the soil litter pools possesses its own specific decomposition rate, the partitioning algorithms will determine the difference in the bulk decomposition rate for each of the simulated specific crop residues. Through these mechanisms, DNDC is able to precisely track the turnover of crop litter in the soils driven by its quantity and quality (i.e., C/N ratio) as well as by the soil temperature, moisture, and aeration. In DNDC, tillage affects SOC decomposition rates through two mechanisms. At first, tillage increases soil aeration, which elevates decomposition rates. Second, tillage redistributes SOC in the soil profile through physical disturbance. Overall decomposition rates would decrease as more SOC is redistributed into the deep soil layers where the oxygen partial pressure is relatively low. DNDC tracks both effects and determines the net impacts of the system. Especially, when the crop is harvested, all of the roots will be incorporated in the soil (Li et al., 2004).

The Priestly–Taylor approach (1972) is employed to measure potential evapotranspiration using solar radiation and temperature. Based on Dhakhwa et al. (1997), it was assumed that potential transpiration decreases 30% when atmospheric CO_2 concentration doubles. Actual plant transpiration is jointly

determined by potential transpiration (demand) and crop uptake capacity (provision), which depend on soil moisture and root conditions (amount and distribution) (Zhang et al., 2002). At harvest, all of the grain is removed from the soil/plant system and all of the roots stay in the soil. The proportion of straw/stalks left in the fields after harvest is assumed to stand inert until the next tillage moves them in the soil (Li et al., 1994a). Actual yield simulated by the model will generally be suboptimal due to limitations by climate, water and/or N availability (Levy et al., 2007).

Major farming management measures have been parameterized in DNDC, including tillage, fertilization, manure amendment, flooding and crop rotation. Tillage is defined based on its timing and depth (Li et al., 2004). The sensitivity of DNDC to farm management practices such as timing and type of fertiliser application makes it ideal for investigation of the effect of many management practices that are suggested as options for mitigation of N₂O emissions (Brown et al., 2002).

a: Carbon processes

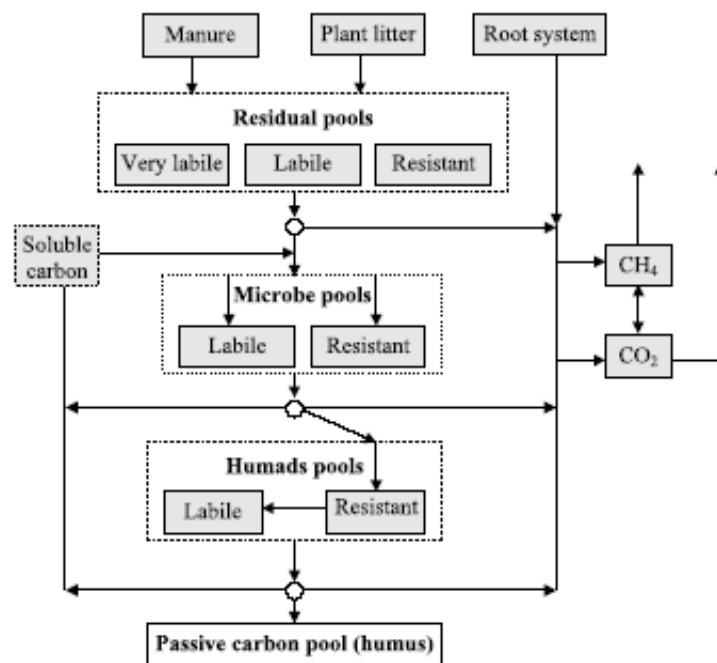


Figure 1-13: The different C pools and their transformation processes as in the DNDC Model (Zhang et al., 2002).

DNDC predicts SOC dynamics mainly by quantifying the SOC input from crop litter incorporation and manure amendment, as well as the SOC output through decomposition (Qui et al., 2009). Tillage following harvest will incorporate this part of the aboveground litter into the soil profile. A considerable uncertainty in our analysis comes from crop residue incorporation estimates (Li et al., 2004). The decomposition sub-model has three active C pools and one passive pool for the decomposition sequence, and each active pool is further divided into two or three sub-pools (Figure 1-13). The soil profile is divided into horizontal layers with a typical thickness of 2 cm. Each layer is assumed to have uniform properties (Li et al., 1992). The actual decomposition rate also depends on environmental factors, including temperature, moisture, nitrogen availability, soil texture (clay adsorption) and farming practices (soil disturbance). During decomposition of residual pools, the carbon decomposed will be partitioned into microbial pools and CO₂. Under anaerobic conditions, CO₂ and some small molecular carbon substrates may be converted to CH₄. Soil redox potential is estimated based on flooding conditions. CH₄ emission is the difference between production and oxidation. The production and oxidation rates are simulated based on Cao et al. (1995) (Zhang et al., 2002). The C pools decompose via first-order kinetics. This formulation has been widely used to estimate mineralization potentials of soils and yield results consistent with data from incubation studies (Li et al., 1992). The carbon released is either respired as CO₂ or incorporated into microbial biomass. DNDC calculates the amount of carbon incorporated into microbial biomass, with 90% going into labile biomass and 10% going into resistant biomass (Li et al., 1992).

There are considerable uncertainties in the magnitude of SOC dynamics, owing to uncertainties in initial soil conditions and crop residue management. The patterns of N₂O emissions based on geographical area or crop type are very different from that of SOC dynamics (Li et al., 2004). The SOC balance is hence determined by the total decomposition rates, which leads to SOC loss, and the total litter incorporation, which leads to SOC gain. The decomposition rates are well modelled by DNDC, based on the SOC contents in all of the SOC pools and soil temperature/moisture conditions. Soil organic carbon gain must rely on a user-determined fraction of aboveground crop residue. Because crop residue incorporation is the most important source for SOC, any deviation in the fraction

of crop residue incorporation will affect the model's accuracy. Unfortunately, this information (i.e., the fraction of aboveground crop residue incorporation) is usually missing or not precisely reported in most publications or reports. The inaccuracy in the amount of crop residue incorporated in soil is actually the most important factor that introduces uncertainties in the modelled SOC sequestration (Li et al. 1994; Li et al. 2003; Li et al., 2004).

1.7. N Production and Reduction in DNDC

DNDC predicts N_2O emissions by tracking the reaction kinetics of nitrification and denitrification driven by climatic conditions, soil properties and management practices (Figure 1-14). Based on experimental observations and biogeochemical analysis, SOC and nitrate or nitrite have been recognised to be dominant factors affecting soil N_2O emissions. Soil temperature, moisture, pH, redox potential and other substrate concentrations (e.g., DOC, NO_3^- , NH_4^+) can also affect N_2O production (Li et al., 2004).

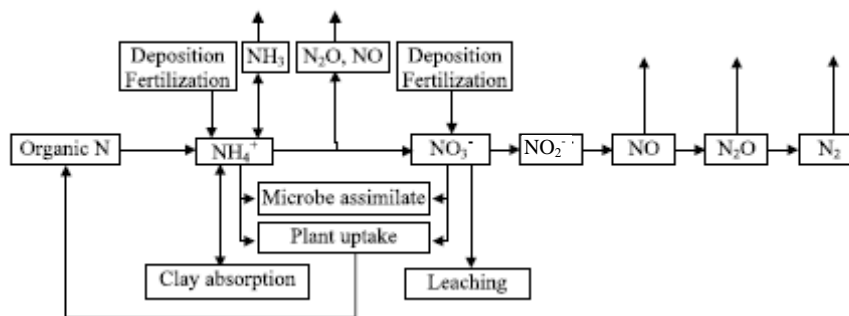


Figure 1-14: The different N pools and their transformation processes as in the DNDC Model (Zhang et al., 2002).

In the DNDC model, inorganic N availability for N_2O production was derived only from the decomposition process of soil organic matter and without considering the effect of high initial NH_4^+ concentration. A simple equation was added to the nitrification sub-model of DNDC to calculate the N_2O gas flux from the excess soil NH_4^+ concentration (Xu-Ri et al., 2003). The daily decomposition rate for each sub-pool is regulated by pool size, its specific decomposition rate (SDR) or fraction lost per day, soil clay content, N availability, soil temperature and moisture and effective depth of the soil profile (Tang et al., 2006). The

reactions of nitrification, denitrification and chemodenitrification are separately simulated in the model due to their inherently different mechanisms. Nitrifiers require aerobic conditions, as they use the enzymes ammonia monooxygenase, which needs molecular oxygen to oxidize NH_3 to N_2O . In contrast, anaerobic conditions favour denitrifiers as they can use nitrogen oxides as electron acceptors when oxygen is depleted in the soil (Li et al., 2000). In DNDC it is assumed that only free NH_4^+ and NO_3^- are available for microbial biomass and the plants (Li et al., 1994a). Transformation of the ammonium to ammonia is influenced by the soil pH, temperature and buffer capacity (Li et al., 1992). The denitrification sub-model tracks the sequential biochemical reductions from NO_3^- to NO_2^- , NO , N_2O and N_2 based on soil redox potential and dissolved organic carbon (DOC) concentration. Soil factors such as pH and temperature are taken into account. The growth and death of denitrifier populations are simulated, which enables consumption of C, NO_3^- , NO_2^- , NO and N_2O (Brown et al., 2002).

The Nernst equation and the Michaelis-Menten equation were adopted in DNDC to integrate the ecological drivers, soil environmental factors and the biogeochemical reactions into a modelling framework. DNDC tracks the soil redox potential evolution and calculates productions and consumptions of CO_2 , N_2O and CH_4 sequentially for both upland and wetland ecosystems (Qui et al., 2009). The Michaelis-Menten equation is a widely applied formula describing the kinetics of microbial growth with dual nutrients, which are DOC and electron acceptors (i.e., nitrogen oxidants) in the denitrification reactions (Tonitto and Li, 2006). The Nernst equation is a basic thermodynamic formula defining soil Eh based on concentrations of the oxidants and reductants existing in the soil's liquid phase (Tonitto and Li, 2006).

The Nernst and the Michaelis-Menten equations can be coupled, as they share a common factor: the oxidant concentration. This coupling has been realized in DNDC through a simple kinetic scheme called the 'anaerobic balloon'. The nitrification/denitrification scheme was improved using the simple kinetic scheme of an 'anaerobic balloon' that swells or shrinks according to the redox potential of the soil. The balloon represents the volumetric fraction of anaerobic microsites in a soil layer. Substrates (such as DOC, NH_4^+ and NO_3^-) were allocated to the anaerobic or aerobic compartments of each layer based on

oxygen availability and consumption in the soil profile (Cai et al., 2003; Li et al., 2004; Giltrap et al., 2009; Shirato, 2005).

The Nernst equation calculates the soil bulk Eh. As soon as the Eh value for a soil layer is estimated (based on the dominant oxidant species) the size of the anaerobic balloon can be determined, and hence the soil substrates will be allocated inside and outside of the balloon proportionally. Relatively anaerobic microsites will be allocated within the anaerobic balloon and relatively aerobic microsites outside the balloon) (Li et al., 2004, Tonitto and Li, 2006). It is defined that only the substrates allocated within the balloon will be involved in the anaerobic reactions (e.g., denitrification etc.) and the substrates allocated outside of the balloon will be involved in the aerobic reactions (e.g., nitrification etc.) (Tonitto and Li, 2006). On the proportional size, DNDC allocates the substrates (e.g., DOC, NO_3^- , NH_3 or NH_4^+) into the aerobic and anaerobic microsites in the soil. Those within the anaerobic microsites can only be involved in reduction reactions and those outside can only participate in the oxidation reactions. The Michaelis-Menten equation is used to determine the rates of the reactions occurring within and outside of the balloon (Li et al., 2004). By tracking the formation and deflation of a series of anaerobic balloons - driven by depletions of, respectively, oxygen, NO_3^- , Mn^{4+} , Fe^{3+} and SO_4^{2-} - DNDC estimates soil Eh dynamics as well as production and consumptions of the products from the reductive/oxidative reactions, including CO_2 , N_2O and CH_4 . With the anaerobic balloons, DNDC links soil Eh to trace gas emissions for wetland soils (Li et al., 2004). If O_2 is depleted in the soil, certain groups of microbes (e.g., denitrifiers) can use other oxidants as electron acceptors. After oxygen, the most readily reduced oxidant is nitrate. As soon as the microbes transfer the electrons from organic C to NO_3^- , N_2O and N_2 will be produced (Firestone, 1982; Li et al., 2004).

When the anaerobic balloon is inflated - by events such as irrigation or flooding causing the oxygen content to decrease - several processes will take place. These include: (1) more substrates (e.g., DOC, NH_3 , NO_2^- , NO, or N_2O) being allocated within the balloon; (2) the rate of the reductive reactions (e.g., sequential denitrification reactions) increasing within the constraints imposed by Michaelis-Menten mediated microbial growth; and (3) the intermediate product gases (e.g., N_2O , NO etc.) taking longer to diffuse from the anaerobic to the

aerobic fraction, increasing the rate at which N gases are further reduced to N_2 and stimulating denitrification (Tonitto and Li, 2006). As soon as the oxygen is depleted, the anaerobic balloon will reach its maximum and burst. At this moment, a new oxidant (i.e., NO_3^-) will become the dominant species in the soil, and a new anaerobic balloon will be born and swell, driven by the NO_3^- depletion. When the anaerobic balloon is deflated, nitrification will be enhanced. NO and N_2O are produced during both nitrification and denitrification processes, and are subject to further transformation during their diffusion among the aerobic and anaerobic microsites (Li et al., 2004; Shirato, 2005). Denitrification induced NO and N_2O emissions are the result of competition among the processes of production, consumption, and diffusion of the two gases within the anaerobic balloon (Li et al., 2000). This enables the nitrification and denitrification to occur in the same soil, simultaneously in anaerobic and aerobic microsites as quantified by the Nernst and Michaelis-Menten equations (Li et al., 2004; Li et al., 2006; Giltrap et al., 2009; Shirato, 2005).

The factors directly controlling denitrification rates are soil Eh, denitrifier activity, and concentration of substrates. The indirect factors include soil temperature, moisture, pH and any C or N-related processes. The production of N_2 and N_2O is regulated by microbial population dynamics. The flux of N gas from the soil to the atmosphere is regulated by soil clay, soil moisture (WFPS), and soil temperature (Tonitto and Li, 2006).

Denitrifiers' activity is driven by soil Eh, temperature, moisture and substrates including DOC and N oxides. As intermediates of the process, NO and N_2O are tightly controlled by the kinetics of each step in the sequential reactions. Classical calculations for biochemical reactions kinetics were employed in the model (Li et al., 2000). The same is true for CH_4 production, although the process occurs under more reductive conditions related to hydrogen production. These processes demonstrate how SOC content and N_2O are related through the coupling and decoupling of C and N in the plant soil systems. In summary, an increase in SOC storage elevates soil DOC and available N content through decomposition, which in turn stimulates the activity of a wide scope of soil microbes, including nitrifiers, autotrophic nitrifiers and denitrifiers, which are responsible for N_2O production in the soils (Li et al., 2004).

The rate of denitrification is very temperature dependent in the 10-35°C range, with a Q_{10} of 2.0. The rate continues to increase at higher temperatures, reaching a maximum at 60-75°C and then falling to zero. At lower temperatures the denitrification rate decreases but remains measurable down to temperatures between 0°C and 5°C (most parameters adopted in this study are based on a standard temperature of 22.5°C (Li et al., 1992)).

The developers of the DNDC model took rainfall into account and considered precipitation to be a dominant force driving N₂O emissions from upland agriculture (Cai et al., 2003). The model assumed that all rain events start at midnight, are of constant intensity and of variable duration (Li et al., 1992). Nitrate, nitrous oxide and ammonium rapidly accumulate in soils between rainfall events and this can stimulate high peaks of N₂O emission through denitrification, owing to high DOC and nitrate in the soil (Li et al., 2001). The decomposition sub-model runs in a daily time step for every day of the simulation. When a rain event occurs, the decomposition sub-model pauses, and the denitrification sub-model continues to run either until the top 20 cm of the soil has an average water content of less than 40% of porosity, or for a maximum of 10 days - after which time little denitrification occurs in the model owing to the depletion of substrates (Li et al., 1992). Water movement is simulated with consideration for the processes of surface runoff, infiltration, gravitational and matric redistribution, evaporation and transpiration. Water available for infiltration includes rainfall, irrigation, snow melt and ponds existing on the surface. Precipitation is considered as snowfall when daily mean air temperature is below zero and precipitation may be intercepted by the crop canopy (Zhang et al., 2002).

DNDC simulates only a few of the dominant controlling factors (temperature, soil redox potential, and substrate availability – DOC for CH₄, and DOC and nitrate for N₂O) in process-based detailed dynamics. It does not simulate in detail factors that control gas transport, which will have a significant effect on the temporal dynamics of gas fluxes (Babu et al., 2006). Neither does DNDC take into account all factors that could influence crop biomass yield (e.g., pest, weed competition, micro-nutrients, severe winds or hail), nor does it account for weed growth during fallow periods (Li et al., 1997). Model requirements for data and significant variability in climatic conditions, soils and

N₂O emissions can result in high levels of uncertainty in predictions. The DNDC model simulates N₂O emissions under a wide variety of management scenarios using readily available input data. The model is, however, less rigorous in predicting soil–water dynamics than some other N models, such as ECOSYS or Expert-N (Smith et al., 2004). Though the DNDC model, in contrast, made both under- and over-estimations for specific fields, it tends to give a better agreement between measured and calculated N₂O losses compared with the regression models methods Bouwman (1996), Freibauer and Kaltschmitt (2003) and Roelandt et al. (2005) for the area under consideration (Beheydt et al., 2007). Future applications of DNDC and other similar models will reduce uncertainties and provide policy-relevant data for cost-benefit analysis of specific mitigation strategies in the agricultural sector (Li et al., 1994). With ongoing modification and calibration, DNDC can become a powerful tool for estimating GHG emissions and yield trends, and for studying the impact of climate change – which in turn will have an effect on the formation of policy (Babu et al., 2006). DNDC has had validation and sensitivity tests that have been published by Cai et al. (2003), Brown et al. (2002), Li et al. (2001), Smith et al. (2004), Strange et al. (2000). These found varying results:

The variability between measured and predicted emissions was, however, high, indicating that the model often over- or underestimated on a site-to-site basis, but did well on the average. (Smith et al., 2004)

Most of the validation tests indicate that DNDC is capable of producing reasonable predictions for SOC dynamics and trace gas emissions from croplands (Li et al., 2004). Validation analysis showed that the model is able to capture the patterns of soil moisture, crop growth and soil carbon and nitrogen dynamics. Application analysis demonstrates the sensitivity of the model to climate conditions, atmospheric CO₂ concentration and various farming practices. This shows the potential application of the model in climate change research and policy-making, GHG mitigation and sustainable agriculture (Zhang et al., 2002). To date, however, there are only a limited number of data sets with which daily models such as DNDC have actually been validated. This is a reflection of the paucity of datasets of appropriate length, variety and frequency rather than of the

input requirements of DNDC (Brown et al., 2002). Other authors have also found contrasting results between measured and simulated temporal patterns of N₂O emissions (Brown et al., 2002; Smith et al., 2003; Cai et al., 2003). Li et al. (2001) argued that DNDC is able to capture general patterns and magnitudes of N₂O emissions observed in the field, although discrepancies do exist. Sensitivity tests were run (Strange et al. 2000) by varying one factor and keeping all others constant. The sensitivity of the model output to variation in the input values was investigated by looking at alternative scenarios commonly observed in the local farmland and changing the value of the single input variable while holding all others at baseline values (Brown et al., 2002). Smith et al. (2004) is one of the few to consider the weather, looking at variations in rainfall and temperature from year to year and finding they are responsible for the high interannual variation in N₂O emissions. These sensitivity analyses demonstrate the basic behaviour of the model (Strange et al., 2000), though not all inputs have been considered. In general, the number of inputs considered has been small with few studies looking at all possibilities.

Throughout this review of the literature there is evidence that models are being used to simulate field reaction to certain conditions and are being validated against large data sets. There is, however, limited evidence comparing different model versions and examining why such differences occur. There is also limited evidence that there is a full understanding of the magnitude of the effect that inputs will have on the resultant outputs.

In this study, therefore, I wish to examine these problems further to consider the reliability of the outputs given, and how well this approach will work when comparing areas with differing environmental conditions, prevailing climate and land management. The areas considered will comprise 3 different countries to see if we can compare field outputs of GHG emissions to give realistic results for use in GHG budgeting and policy making. Therefore I hypothesise that the UK will have lower modelled greenhouse gas emissions for horticultural production than equivalent production systems overseas and that the model will give realistic and robust results in comparison to experimentally derived greenhouse gas estimates.

**Chapter 2. Model Comparison between Different Versions of the DNDC
Model**

Elizabeth York, Georgia Koerber, David L. Jones, Gareth Edward-Jones

School of Agricultural, Natural Resource and Geography, Bangor University,

Gwynedd LL57 2UW, UK

2.1. Abstract

Twenty percent of the worldwide annual increase in greenhouse gas (GHG) emissions originates from agriculture. Consequently, practical ways are being sought to actively reduce GHG emissions within agro-ecosystems. To aid the decision making process, a range of mathematical models have been used to predict the future of land use change on GHG emissions from agriculture. DeNitrification DeComposition (DNDC) is a commonly used process-based simulation model that models carbon and nitrogen biogeochemistry in agro-ecosystems. Since its first use, numerous versions of the model have been released in response to increased knowledge of the behaviour of GHG emissions over a wider range of cropping systems. One of the major problems with using models, however, is the potential variation in output between different versions of a single model. This variation can reduce the potential for comparing the results obtained from modelling studies that may have used different versions. The aim of this chapter was to compare the 6 model outputs of five different releases of the DNDC model, namely versions 82, 86, 90, 91 and 92 using 7 different cropping regimes (beans, brassicas, lettuces, potatoes, sugar beet, vining peas and wheat). The crop parameterisation data was obtained for the same geographical region; model runs were based on real farm agronomic and climate data and included a number of field replicates.

It was found that some models gave similar results: DNDC82 and 86 being one set, and DNDC91 and 92 being the other. DNDC90 produced prediction results intermediate between those of DNDC86 and DNDC91. Each version of the model predicted different vegetables to be the highest GHG emitter, and few crop type trends were apparent between the model versions. For example, N₂O emissions from a bean cropping system gave the lowest results: 0.13 ± 0.05 kg N ha⁻¹ y⁻¹ for DNDC92 and a result of 5.24 ± 1.95 kg N ha⁻¹ y⁻¹ for DNDC82, though sugar beet was the lowest for DNDC82 with 2.25 ± 0.23 kg N ha⁻¹ y⁻¹. The output of the model run over ten consecutive years was also considered and DNDC82, 86 and 90 gave larger output values for GHG emissions than DNDC91 and DNDC92. In conclusion, different versions of the DNDC model produced predictions that significantly varied in both the amount and pattern of

GHG release. This brings into question the use of models as a management tool for designing agronomic mitigation strategies for GHG reduction.

2.2. Introduction

Radiative forcing of the Earth's atmosphere is increasing at unprecedented rates, largely because of increases in atmospheric concentrations of three greenhouse gases (GHG): CO₂, CH₄, and N₂O (Chen et al., 1997). The release of GHG from agriculture accounts for approximately one fifth of the annual global increase in radiative forcing (Cole et al., 1997). Unfortunately, most of the published research has tended to focus on soil C dynamics with less attention paid to N₂O and CH₄ (Salas et al., 2003). Consequently, the fundamental regulation of GHG emissions from agricultural systems needs to be better understood, and this information translated into mathematical models to help predict future GHG emission scenarios and inform policies related to climate change.

Within a single agricultural system it is possible to calculate the net global warming potential (GWP) value for a specific crop production system which accounts for all GHGs. Such analyses allow for direct comparisons between management systems (Li et al., 2005). Agricultural soils have the potential to greatly reduce GHG emissions by changing management to increase soil organic matter content and decrease N₂O emissions (Mosier et al., 2005). The greatest input of N into an agricultural system is from fertilisers (Webb et al., 2004) and their application is projected to continue to increase over the next 100 years (Mosier et al., 1998). Outputs of N from agriculture mainly occur as crop off take (ca. 54-98% of the total) and NO₃⁻ leaching, with the amount lost via each pathway dependent on crop type and plant residue management (Webb et al., 2004). These outputs can be mitigated, without decreasing production, by sound agricultural management (Mosier et al. 2005).

Crop growth models have been developed to simulate crop yield and other agronomic factors under different conditions (Leip et al., 2008). Agronomists pay most attention to crop growth and yield formation rather than GHG emissions. Examples of such models include DSSAT, RCSODS, and models produced by deWit and his colleagues in Wageningen (Zhang et al., 2002). Crop growth, development and soil water dynamics are usually simulated in detail, but soil biogeochemistry is rarely considered, and when it is it tends to

be simulated in terms of nutrient effects. Soil-crop models pay more attention to physical processes; gaps therefore exist among the modelling efforts of scientists, environmentalists and climatologists due to their different focuses. One exception to this is the Denitrification-decomposition (DNDC) model, which attempts to integrate crop growth processes with soil biogeochemistry (Zhang et al., 2002).

The DNDC model can be used to determine C and N biogeochemistry in agro-ecosystems. The model can also yield daily data on GHG emissions with the input variables based upon 4 major ecological drivers (Cai et al., 2003): climate, soil physical properties, vegetation, and anthropogenic activities. It consists of the six sub-models for soil climate, crop growth, decomposition, nitrification, denitrification, and fermentation. The six interacting sub-models have included the fundamental factors and reactions, which integrate C and N cycles into a simulation system (Li, 2004). The DNDC model is constructed of two components: the first consists of soil climate, crop growth and decomposition sub-models, which predict soil and environmental variables based on ecological drivers. The second component consists of nitrification and denitrification sub-models, which predict N₂O and NO fluxes based on soil environmental variables derived from the first component (Xu-Ri et al., 2006; Kiese et al., 2005). DNDC uses databases with spatially and temporally differentiated information on climate, soil, vegetation and farming practices as parameters for supporting local, regional and national scale analyses (Salas et al., 2003). In the DNDC model, crop growth is simulated not only by tracking crop physiological processes and decomposition rates, but also by calculating water stress and nitrogen stress. Biogeochemical processes that control CH₄ and N₂O emissions are non-linearly coupled with anthropogenic and ecological drivers that are highly variable in space and time (Salas et al., 2003). DNDC predicts N₂O emissions by tracking the reaction kinetics of nitrification and denitrification driven by climatic conditions, soil properties and management practices (Li, 2004).

DNDC models can simulate the growth of over 40 types of crops based on such factors as: their optimum yield; partitioning of assimilated C; C/N ratios; and water requirement. The model considers a variety of crop types owing to the significant differences in C dynamics across crops and countries (Li, 2004).

DNDC simulates the crop growth at a daily time step, using a pre-defined logistic function (S-curve) representing a trajectory to maximum obtainable nitrogen uptake and biomass carbon (Leip et al., 2008). There are considerable uncertainties in the magnitude of soil organic C dynamics, due to uncertainties in initial soil conditions and crop residue management (Li, 2004).

The DNDC model is used predicatively in a policymaking context (for Integrated Sink Enhancement Assessment) by the European Commission and the Institute for Environment and Sustainability, an EC subgroup working on the Kyoto Protocol (Raes et al., 2009). It has also been used at the UK level by the Institute of Grassland and Environmental Research as a Nutrient and Greenhouse Gas Evaluation Tool. They also use DNDC in conjunction with other models (e.g. the Economic Farm Emission Model) and calibrate DNDC from UK-based measurements (Brown et al., 2001; Neufeldt et al., 2006)

In this chapter I hypothesise that the latest release version of the model gives the most realistic results, but that these may differ significantly with previous versions of the model. Therefore I will, (1) compare different versions of the DNDC model to see if there are any significant variations in outputs between them, and (2) test if the most recent version gives the most realistic predictions. DNDC represents a primary tool used by researchers to inform regional, national, and continental policy, and is used in the formulation of emission reduction targets in the UK and USA. Five versions of the model from different time periods will be compared using real data over a 10-year period. Since its inception, numerous versions of the DNDC model have been released and used by different organizations. Its evolution through time would suggest that policymakers may not always be using the most accurate versions of the model, and that outputs from older versions may not be reliable. It is important to estimate the error and uncertainty associated with model prediction so that policymakers understand scientists' predictions of GHGs. To date, some field-based validation of DNDC has been undertaken but its ability to correctly predict the output varies greatly; according to some accounts, modifications by users have been made to rectify this problem. According to Giltrap et al. (2009), these modifications are mostly adjustment to soil or crop parameters. However, there has been no obvious consideration of variation between different versions of the model to date. Consequently this will be the focus of this chapter.

2.3. Method

2.3.1. Versions of the DNDC model

Between 1989 and the present day, many versions of the DNDC model have been released. Five model versions were used in this comparative analysis, these being DNDC versions 82, 86A, 90, 91, and 92. These were officially released between 2003 and 2008. These versions were collected from the official DNDC release site (www.dndc.sr.unh.edu) and from Dr. Declan Mulligan (EU JRC, Ispra, Italy). DNDC90 was the original model download for this project; through time DNDC90 was modified to create DNDC91 and DNDC92. As it was decided to compare the differences between these models, older versions were needed to see if problems with DNDC90 had occurred previously. Dr Declan Mulligan supplied two older versions for testing. The required input data varied between versions 90, 91, 92 and version 82 and 86A as extra or different inputs became available in the later versions. In addition, as the DNDC versions evolve there is a corresponding increase in the amount of output data (e.g. between DNDC82 and DNDC92). The most important differences in the output data relates to greater information on the hydrological system and on the cropping section. Unfortunately, changes to the program code from model version to version are not open access and so it is difficult to see how each version of the model differs mathematically.

2.3.2. Farm management input data

The inputs for the model were agricultural management data collected for a range of crop types from 7 farms in Worcestershire, UK. The different vegetable types used in this comparison were; sugar beet (*Beta vulgaris*), vining peas (*Pisum sativum*), lettuce (*Lactuca sativa*), beans (*Phaseolus vulgaris*), wheat (*Triticum aestivum*), potatoes (*Solanum tuberosum*), and brassicas (*Brassica oleracea*) (Table 3-3).

The same data were subsequently used when running all five versions of the model. The data collected from the farmers included agronomic management information for individual fields for specific vegetable crops. If key data was not available this was obtained from The Farm Management Handbook 2006/2007 (SAC, 2006). The potato and lettuce fields had irrigation. Lettuce, vining peas,

some brassicas and some beans had one or more crops grown per rotational year. DNDC82 also has a difference in model-based input data of Litter SOC, Humads SOC, Humus SOC, Soil NO₃⁻, Soil NH₄⁺ and moisture.

Table 2-1: Summary of the different inputs added or removed between versions 82 (older version) and 92 (newer version) of the DNDC model.

Factors	Model versions (DNDC)				
	82	87	90	91	92
Initial soil moisture	Yes	No	No	No	No
Initial soil temperature	Yes	No	No	No	No
Increase rate of atmospheric CO ₂ concentration	No	Yes	Yes	Yes	Yes
Depth of water retention layer	No	Yes	Yes	Yes	Yes
High groundwater table	No	No	No	Yes	Yes
Ability to redefine the SOC portioning and profile	No	Yes	Yes	Yes	Yes
Crop/land use types					
Papaya	Yes	No	No	No	No
Steppe	Yes	No	No	No	No
Savannah	Yes	No	No	No	No
Silage beet	Yes	No	No	No	No
Celery	No	Yes	Yes	Yes	Yes
Hops	No	Yes	Yes	Yes	Yes
Rain fed rice	No	No	Yes	Yes	Yes
Mixed cover crop	No	Yes	Yes	Yes	Yes
Safflower	No	Yes	Yes	Yes	Yes
Flax	No	Yes	Yes	Yes	Yes
Is it a cover crop?	No	No	Yes	Yes	Yes
Ability to modify crops	No	Yes	Yes	Yes	Yes
Ability to add new crops	No	No	Yes	Yes	Yes
Controlled-release fertiliser	No	Yes	Yes	Yes	Yes
Nitrification inhibitor application	No	Yes	Yes	Yes	Yes
A choice of flooding options	Yes	No	No	No	No
Conventional flooding (5-10 cm)	No	Yes	Yes	Yes	Yes
Marginal flooding (-5-5 cm)	No	Yes	Yes	Yes	Yes
Grass cutting (How often, when and amount?)	No	Yes	Yes	Yes	Yes

Table 2-2: The input ranges for each crop during initial model parameterisation (the units are those used by the model).

Crop	Units	Lettuce	Vining Peas	Brassicas	Beans	Wheat	Potatoes	Sugar Beet	
	N conc. in rainfall	mg N l ⁻¹	0.286	0.286	0.286	0.286	0.286	0.286	
	NH ₃ background	µg N m ⁻³	0.060	0.060	0.060	0.060	0.06	0.060	
	CO ₂ background	ppm	350	350	350	350	350	350	
Soil	Soil texture		Clay	Clay, Silty	Clay	Loam	Silty Clay	Silty Clay	Silty Clay
			Loam	Clay	Loam	Loamy Sand	Loam	Loam	loam
			Loamy Sand	Loam				Loamy Sand	Loamy Sand
				Loamy Sand					
	Bulk density	g cm ⁻³	1.75	1.68	1.80		1.68	1.68	1.48
	Soil pH		4.98-7.45	5.52-7.07	5.88-7.35	6.15-6.80	4.63-6.25	4.72-6.30	6.07-7.10
	SOC at surface	kg C kg ⁻¹	0.013-0.026	0.010-0.037	0.010-0.031	0.008-0.027	0.010-0.027	0.012-0.025	0.011-0.023
	Slope	%	3-15	4-25	5-15	5-15	5-10	5-10	5-30
Farming	No. crops		2-3	2	1-2	1-2	1	1	1
	Crop type		lettuce	vining peas	brassicas	beans	wheat	potatoes	sugar beet
	Harvest mode		1	1	1	1	1	1	1
	Fraction left		0.3-0.5	0.3	0.5	0.3-0.4	0.1	0.2	0.2
Tillage	No. tillage		5	3	3	2	2	5	3.000
	Tillage method		2,3,3,4,5	2,4,5	3,3,4,	3,4	3,5	2,2,4,4,5	2,2,5
Fertilization	No. applications		2-3	None	1	None	1	1	1
	Type		Urea	None	NH ₄ NO ₃	None	NH ₄ NO ₃	NH ₄ NO ₃	Urea
	Amount	kg N ha ⁻¹	67.9-102	None	500	None	119	454	100

	Application type		Surface	None	Surface	None	Surface	Surface	Surface
	Depth	cm	0.2	None	0.2	None	0.2	0.2	0.2
Manure amendment	No. applications		None	None	None	None	None	1	None
	Type		None	None	None	None	None	farmyard	None
	Amount	kg C ha ⁻¹	None	None	None	None	None	208.53	None
Weeding	Weed problem		None	None	Yes	None	None	None	None
	No. sessions		0	None	Moderate	None	None	None	None
Irrigation	No. applications		3	None	None	None	None	6	None
	Amount used	cm	1	None	None	None	None	1	None
	Water pH		7	None	None	None	None	7	None

Four replicates were taken for each experimental field, with each location sampled monthly from July 2005 until September 2006. CO₂ emissions were measured using an EGM-4 equipped with an SRC-1 soil chamber (PP Systems Ltd, Hitchin, UK). Soil and air temperature were measured *in situ*. Air temperature was measured 30 cm above ground level. For the sites in Worcestershire, 3 pits were dug to a depth of 1 m and samples collected every 15 cm down the soil profile using 50 cm³ cores to determine bulk density.

Soils collected monthly at 0–10 cm depths from each plot were dried at 105 °C for 24 h to determine moisture content while loss on ignition at 450 °C was undertaken to determine soil organic matter (SOM) content. In addition, soils collected at the start of the growing season from all locations were analysed for SOC with a Leco CHN 2000 analyser by Georgia Koerber. 1 M KCl extracts (1:% w/v) were taken to determine NO₃⁻ and NH₄⁺ levels in soil. The extracts were frozen prior to analysis. Nitrate concentrations in the extracts were measured using the vanadium chloride method of Miranda et al. (2001), while ammonium concentrations were determined according to Mulvaney (1996) with a Skalar segmented-flow autoanalyser. Soil pH was measured in a 1:5 (w/v) ratio of soil-to-distilled water using a Hanna 209 pH meter.

Table 2-3: Summary of the Worcestershire fields sampled and used in the DNDC model simulations.

Vegetable	No of fields
Beans (<i>Phaseolus vulgaris</i>)	5
Brassicas (<i>Brassica oleracea</i>)	4
Lettuces (<i>Lactuca sativa</i>)	6
Potatoes (<i>Solanum tuberosum</i>)	6
Sugar beet (<i>Beta vulgaris</i>)	6
Vining peas (<i>Pisum sativum</i>)	6
Wheat (<i>Triticum aestivum</i>)	6

2.3.3. Meteorological input data

Weather data (maximum, minimum and average air temperature, rainfall, solar radiation, hours of sun and wind speed) for 10 years (1998 to 2008) for Brize Norton, Worcestershire was purchased from the UK Met Office (Figure 2-1). The 10 year dataset allowed for the possibility of running simulations over longer time periods in order to explore the variability/stability in model output with different annual weather patterns (i.e. inter-annual variation). In all versions of the DNDC model the input variables included maximum and minimum air temperature and rainfall. Wind speed became an additional input variable in DNDC versions 90, 91 and 92.

The weather data used for the results found in the Results section ‘Running averages in DNDC modelling outputs’ was the average of ten years weather data from Brize Norton. This was to remove variation caused through climatic changes.

2.3.4. Model simulation runs

Each DNDC model version was run for each individual field for a 10 year period with the same crop. The crop would start with initially bare soil until the selected vegetable was planted and followed by bare soil once the crop had been harvested. The model was not pre-run to allow it to equilibrate as Li (2003) makes no suggestion of this in the manual. This contrasts with Qiu et al. (2009) who implemented a 20-year pre-simulation, and with Tonitto et al. (2007) who disregarded the first year of simulation to eliminate the possible uncertainties that could arise with the initial settings (e.g. SOC partitioning). However, two sets of results were considered:

- In the first, the average of all 10 years of results was taken (termed average).
- In the second, results from only the 10th year were considered (i.e. the final model simulation year).

The advantage of this latter method is that some level of equilibrium will have been achieved.

2.3.5. Statistical Analysis

All statistical analysis was performed using SPSS version 18 (SPSS Inc, Chicago, IL). A univariate analysis of variance was used for the 10 year average and the 10th year,

with the dependent variable for figure 2-(3 to 7) and figure 2-9 being the different model versions for each response available.

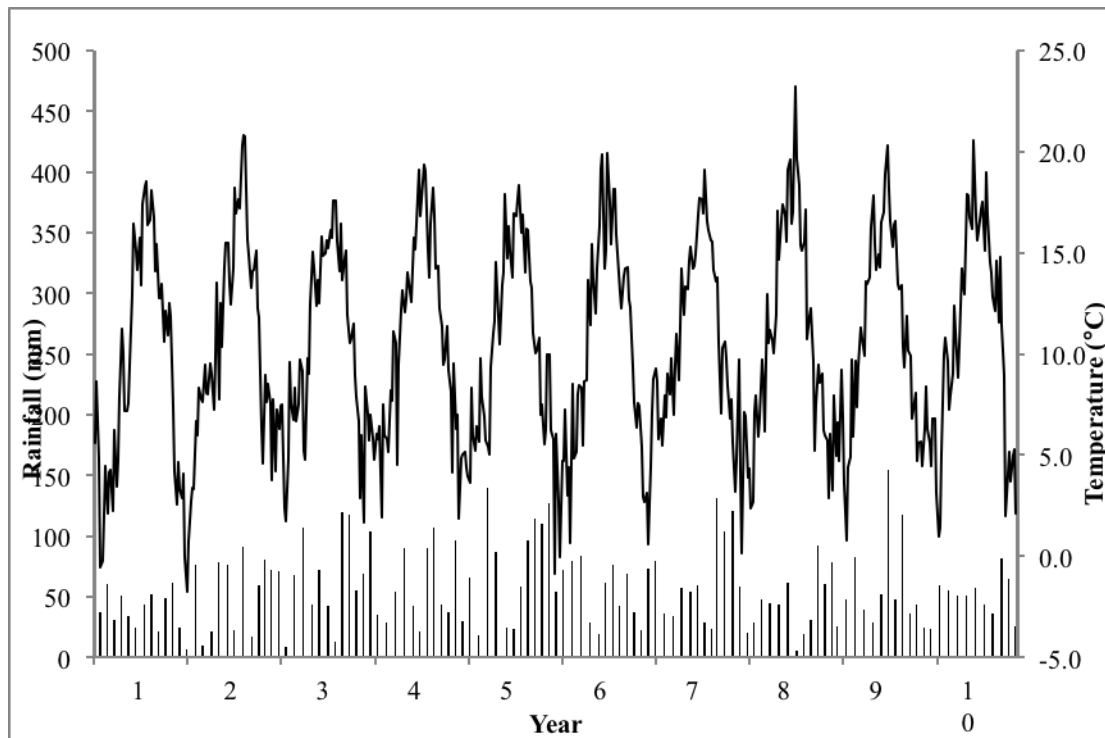


Figure 2-1: Ten years of real weather data for Worcestershire where the experimental fields were located and for which the DNDC model simulations were run. Rainfall (bar chart) measured in mm and graphed monthly. Average temperature (solid line) in degrees Celsius and graphed weekly.

2.4. Results

2.4.1. Influence of model version on crop biomass predictions

Results for crop biomass show that overall DNDC90 and 92 predicted the highest crop biomass for most vegetables, but especially for potatoes with values of 11.1-11.3

t C ha⁻¹ and 13.1-15.0 t C ha⁻¹ respectively. Potatoes had the highest mass of crop biomass for all model types except for version 91, where wheat did. Lettuce had the lowest value in DNDC82, and overall it had the lowest average value for all versions of the models tested. DNDC86 gave the lowest results for beans of 0.28 t C ha⁻¹. DNDC82 gave similar values for vining peas and beans, with values of 0.41 t C ha⁻¹. DNDC92 gave the highest results for all vegetable types except for brassicas, with highest biomass values of 13.13 t C ha⁻¹ from DNDC86.

The predictions of crop yield averaged over the entire ten year period and obtained from the 10th (final) year only were different in all vegetable and model versions, with the newer versions having more variation between the average of the ten years and the 10th year result, although there were no significant differences found between the model types.

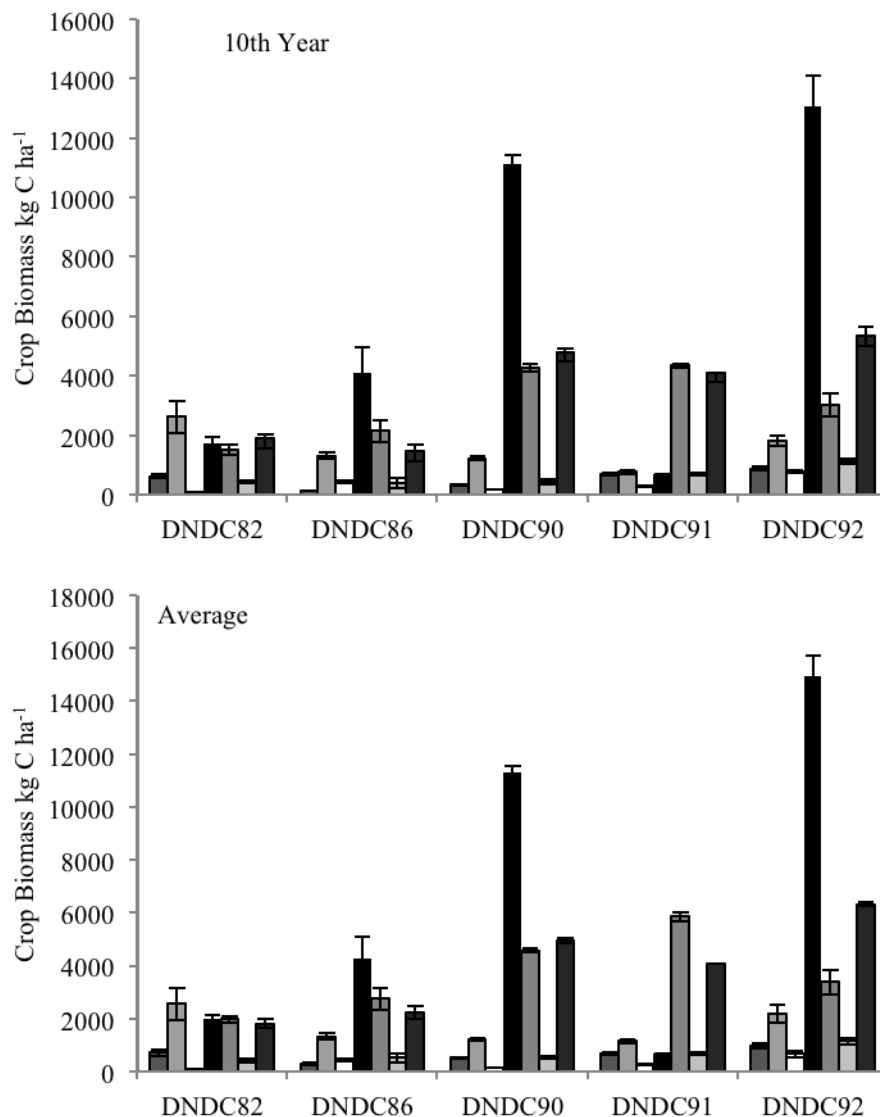


Figure 2-2: Comparison of the crop biomass produced by seven different crop types (■ beans, ■ brassicas, □ lettuce, ■ potatoes, ■ sugar beet, □ vining peas ■ wheat) for five different versions of DNDC for both the final year of the model simulation (10th year; upper panel) and averaged over the entire 10 year simulation period (lower panel) for a series of farms in Worcestershire. Values represent means ± SEM ($n > 4$).

2.4.2. Influence of model version on soil organic carbon (SOC) changes

Though DNDC82 is the oldest model version it was not the one predicting the greatest change in SOC; it had the third lowest set of results and was only significantly different in output from DNDC86 ($P = 0.001$). Lettuce had the highest loss of SOC in this version, with $-1.66 \text{ t C ha}^{-1} \text{ yr}^{-1}$. Wheat had the lowest with $-0.54 \text{ t C ha}^{-1} \text{ yr}^{-1}$. DNDC86 and DNDC90 were the versions with the most dramatic changes in SOC and both proved significantly different in their modelled outputs to DNDC91 ($P = 0.000$ and 0.006 respectively) and DNDC92 ($P = 0.000$ and 0.004 respectively), with the highest loss for DNDC86 being lettuce with $-6.07 \text{ t C ha}^{-1} \text{ yr}^{-1}$, while for DNDC90 it was beans with $-4.65 \text{ t C ha}^{-1} \text{ yr}^{-1}$. DNDC91 and DNDC92 behaved similarly, especially with potatoes, which actually created the most SOC over the 10 year model run cycle (Figure 2-2). Though these two models are similar they do differ in which vegetable type loses the most SOC and by how much. As with crop biomass, the different versions of the model predicted different changes in the SOC pool for each vegetable type, allowing no definitive SOC loss series for different vegetables to be established between the models (see Figure 2-2).

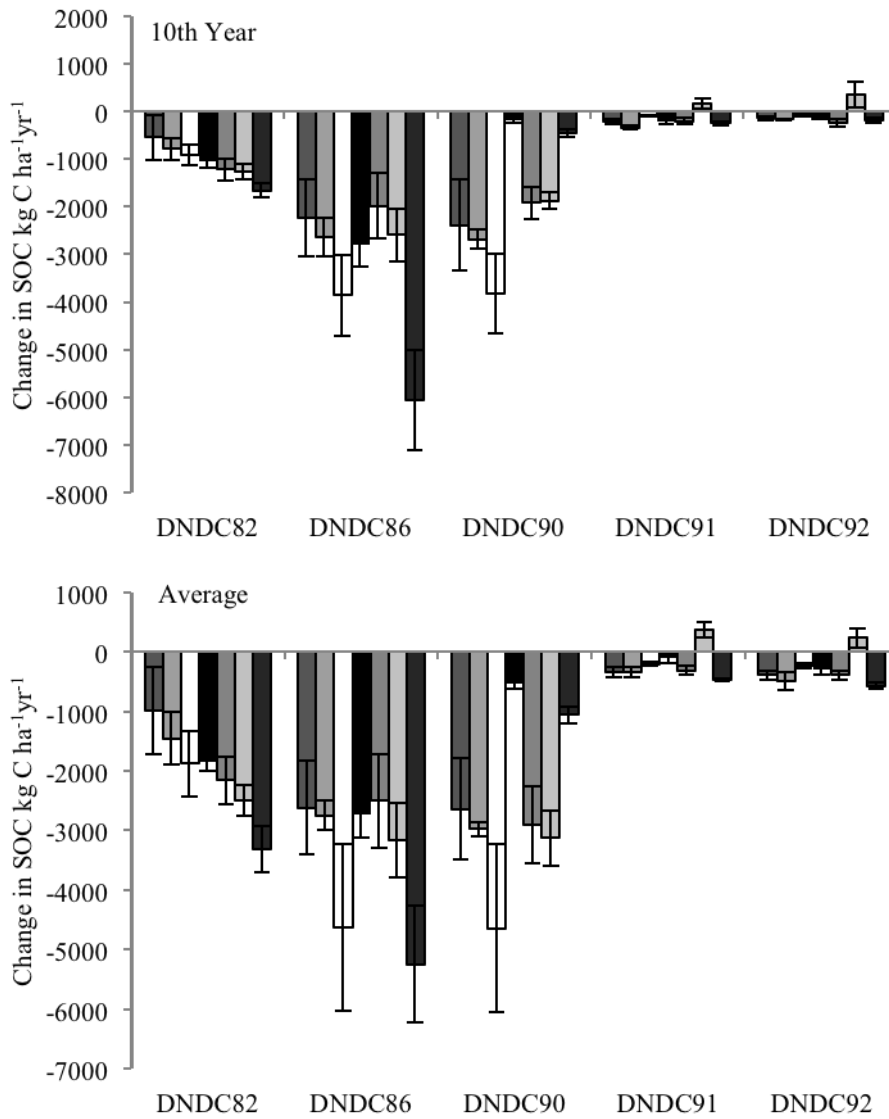


Figure 2-3: Comparison of soil organic carbon (SOC) loss from seven different crop types (wheat, brassicas, beans, sugar beet, vining peas, potatoes, lettuce) for five different versions of DNDC for both the final year of the model simulation (10th year; upper panel) and averaged over the entire 10 year simulation period (lower panel) for a series of farms in Worcestershire. Values represent means \pm SEM ($n > 4$).

2.4.3. Influence of model version on prediction for heterotrophic CO₂ emissions

Overall there were significant differences between the five models in their prediction of soil CO₂ emissions ($p < 0.001$). DNDC91 measurement of the potatoes fields gave the largest losses for soil heterotrophic CO₂ for both the 10th year and 10-year average at 12.3 t C ha⁻¹ yr⁻¹ and 14.1 t C ha⁻¹ yr⁻¹. DNDC82 was significantly different in its predictions of CO₂ efflux in comparison to all the other models tested for all vegetable types for the 10th year ($P < 0.001$). DNDC82, however, was similar to DNDC86 for the running averages over the 10 year period ($P = 0.236$). The smallest predicted loss in CO₂ was seen with DNDC86 at 0.31 t C ha⁻¹ yr⁻¹ from sugar beet. DNDC86 gave statistically similar outputs to DNDC91 and DNDC92 ($P = 0.504$ and 0.476 respectively) for the 10th year, but not for the 10 year running averages. For both the DNDC82 and DNDC86 models, brassica crops were predicted to be the greatest emitters for both in the 10th year (1.62 t C ha⁻¹ yr⁻¹ and 2.33 t C ha⁻¹ yr⁻¹ respectively) and for the 10 year running averages (1.93 t C ha⁻¹ yr⁻¹ and 2.66 t C ha⁻¹ yr⁻¹ respectively). For the DNDC91 and DNDC92 simulations, potatoes were predicted to be the highest emitters for both the 10th year (12.3 t C ha⁻¹ yr⁻¹ and 14.1 t C ha⁻¹ yr⁻¹) and the 10 year averages (9.9 t C ha⁻¹ yr⁻¹ and 10.1 t C ha⁻¹ yr⁻¹), while for DNDC90 it was wheat for both the 10th year and 10-year average (7.8 t C ha⁻¹ yr⁻¹ and 8.5 t C ha⁻¹ yr⁻¹ respectively). The smallest losses of CO₂ predicted to occur were wheat for DNDC82 (0.6 t C ha⁻¹ yr⁻¹) and beans for DNDC86 (0.5 t C ha⁻¹ yr⁻¹; Figure 2-4). In contrast, for DNDC90, 91 and 92 the smallest losses in CO₂ were found for lettuce (0.89 t C ha⁻¹ yr⁻¹, 0.72 t C ha⁻¹ yr⁻¹ and 0.78 t C ha⁻¹ yr⁻¹, respectively). DNDC91 and DNDC92 gave statistically similar results for all vegetable types (Figure 2-4).

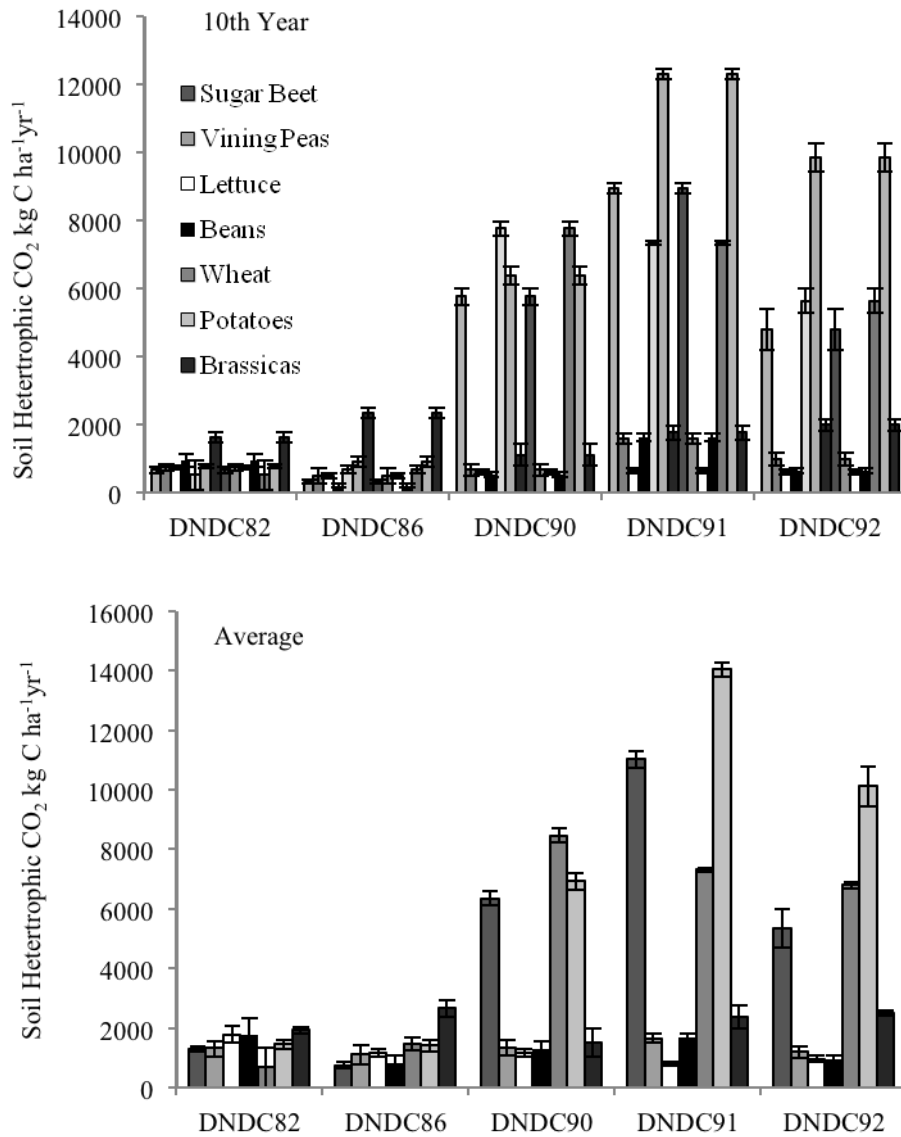


Figure 2-4: Comparison of soil heterotrophic respiration (CO_2) produced from seven different crop types (sugar beet, vining peas, lettuce, beans, wheat, potatoes, brassicas) for five different versions of DNDC for both the final year of the model simulation (10th year) and averaged over the entire 10 year simulation period for a series of farms in Worcestershire. Values represent means \pm SEM ($n > 4$).

2.4.4. Influence of model version on methane consumption by soil

Agricultural soils can both produce and consume CH₄, depending on the prevailing soil and climatic conditions (e.g. waterlogged soils produce large quantities of CH₄ during rice production whilst aerobic/oxic soils such as those investigated here are normally net consumers of methane). In all the scenarios tested here, the soils were predicted to be net consumers of methane. Overall, DNDC82 and DNDC86 had the highest predictions for soils being CH₄ sinks, while DNDC90 gave the lowest and DNDC91 and DNDC92 gave intermediate but similar results. Predictions of the net CH₄ flux from DNDC82 were significantly different from DNDC91 ($P = 0.040$). DNDC86 predicted the second highest levels of methane consumption overall, although the patterns were similar to DNDC82 ($P = 0.321$). Within these, the vegetable crop with the greatest CH₄ sink potential was wheat (2.52 kg C ha⁻¹ yr⁻¹ and 2.12 kg C ha⁻¹ yr⁻¹ for DNDC82 and DNDC86; Figure 2-5) while beans gave the lowest predicted rates of consumption (0.11 kg C ha⁻¹ yr⁻¹). DNDC91 and DNDC92 gave similar results ($P = 0.998$), which were slightly higher than the values produced by DNDC90, but again statistically similar ($P = 0.246$ and 0.401 respectively). In these versions of the model soils containing lettuce were predicted to be the greatest methane sinks (Figure 2-5).

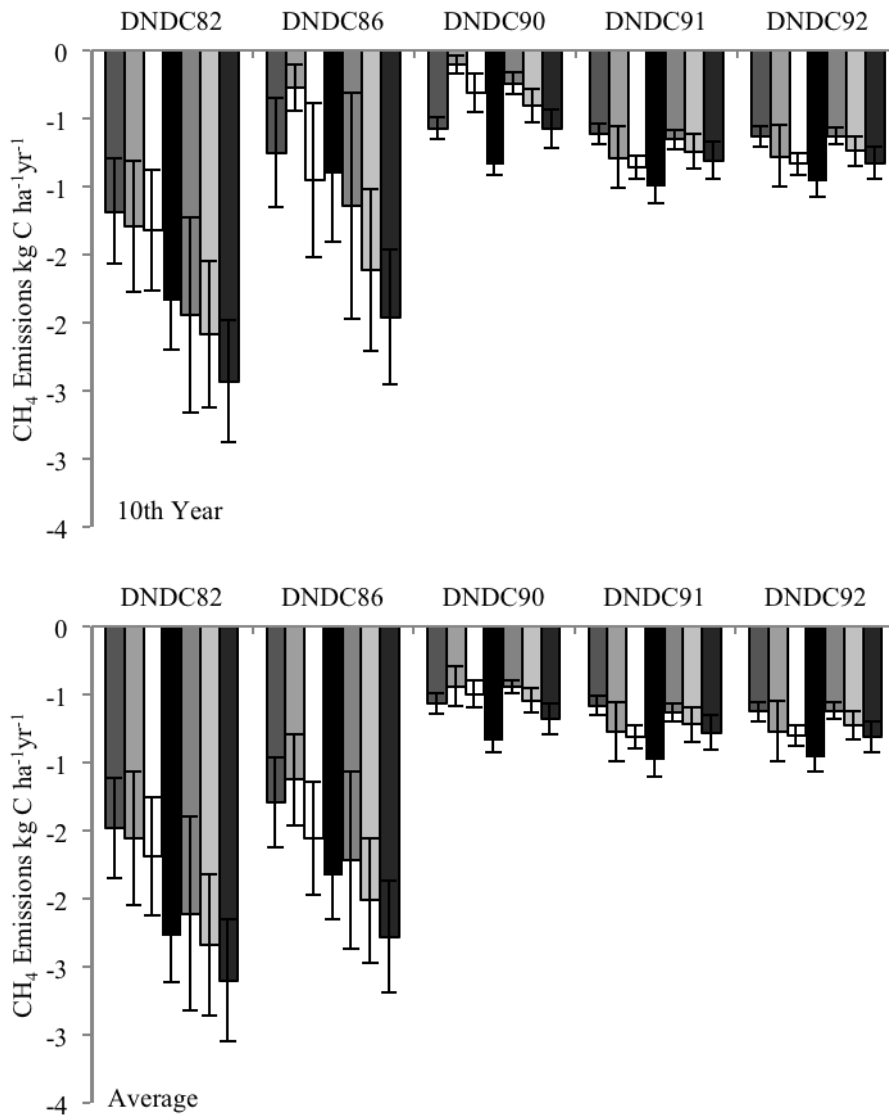


Figure 2-5: Comparison of net methane emissions from seven different crop types (■ sugar beet, ■ beans, □ potatoes, ■ lettuce, ■ brassicas, ■ vining peas, ■ wheat) for five different versions of DNDC for both the final year of the model simulation (10th year) and averaged over the entire 10 year simulation period for a series of farms in Worcestershire. Negative values indicate that the soils are net consumers of methane. Values represent means \pm SEM ($n > 4$).

2.4.5. Influence of model version on nitrate leaching from soil

When considering the amount of nitrate leached through the soil profile, DNDC82 predicted the greatest rates of loss with the highest value obtained for potatoes both in the 10th year and 10-year running average (405 and 454 kg N ha⁻¹ yr⁻¹ respectively) while the lowest values were obtained for vining peas (42 kg N ha⁻¹ yr⁻¹). In contrast to the predictions from DNDC82, DNDC90 gave significantly lower results and differences between crop types (e.g. the lowest predicted rates of N leaching were for beans at 15 kg N ha⁻¹ yr⁻¹ while the highest values were again for potatoes 386 kg N ha⁻¹ yr⁻¹; Figure 2-6). However, DNDC86 gave lower results than both DNDC90 and DNDC82, with an overall range from wheat at 3 kg N ha⁻¹ yr⁻¹ to brassicas at 292 kg N ha⁻¹ yr⁻¹. Just to further highlight the differences between model versions, DNDC91 gave the lowest output for beans (1.9 kg N ha⁻¹ yr⁻¹) whilst in DNDC92, wheat gave the lowest value (8.9 kg N ha⁻¹ yr⁻¹). Overall, the first three versions of the model studied here had greater similarities in predicting which crop type had the highest leaching potential in comparison to the two later versions of the model. Taking all the results together, all five versions were similar in their outputs ($P = 0.099$ for 10th year results, and $P = 0.29$ for the 10 year running average). DNDC82 and DNDC86 did give significant differences ($P = 0.015$).

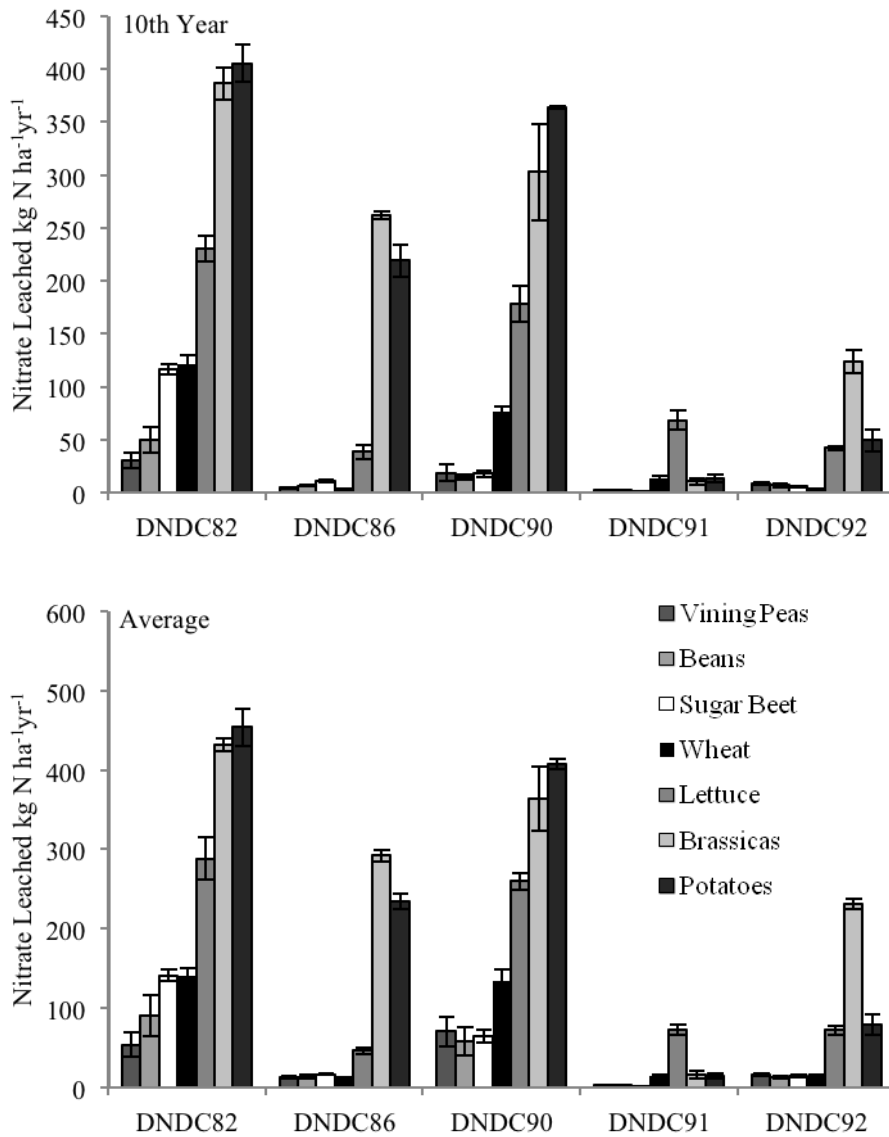


Figure 2-6: Comparison of nitrate leaching from seven different crop types (vining peas, beans, sugar beet, wheat, lettuce, brassicas, potatoes) for five different versions of DNDC for both the final year of the model simulation (10th year) and averaged over the entire 10 year simulation period for a series of farms in Worcestershire. Values represent means \pm SEM ($n > 4$).

2.4.6. Influence of model version on predicted nitrous oxide emissions from soil

When simulating N₂O emission loss rates, the models with the lowest emissions were DNDC86 and DNDC90 which gave statistically similar results ($P = 0.528$). DNDC86 predicted lower N₂O emission rates for vining peas ($0.22 \text{ kg N ha}^{-1} \text{ yr}^{-1}$; 10th year) and lettuce ($1.90 \text{ kg N ha}^{-1} \text{ yr}^{-1}$, 10-year average) in comparison to DNDC90 which predicted higher values for beans ($0.85 \text{ kg N ha}^{-1} \text{ yr}^{-1}$; 10th year) and lettuce ($5.80 \text{ kg N ha}^{-1} \text{ yr}^{-1}$; 10th year) (Figure 2-7). DNDC82 gave the highest value for brassicas ($11.8 \text{ kg N ha}^{-1} \text{ yr}^{-1}$), while sugar beet was the lowest, emitting $2.25 \text{ kg N ha}^{-1} \text{ yr}^{-1}$ (both 10-year averages). DNDC91 and DNDC92 predicted some low and some very high emissions, the highest being for lettuce in DNDC91 ($14.2 \text{ kg N ha}^{-1} \text{ yr}^{-1}$, 10th year), albeit it was similar to DNDC92 ($P = 0.906$). In addition, there were significant similarities between the average and tenth year results (Figure 2-7) for all models ($P < 0.05$).

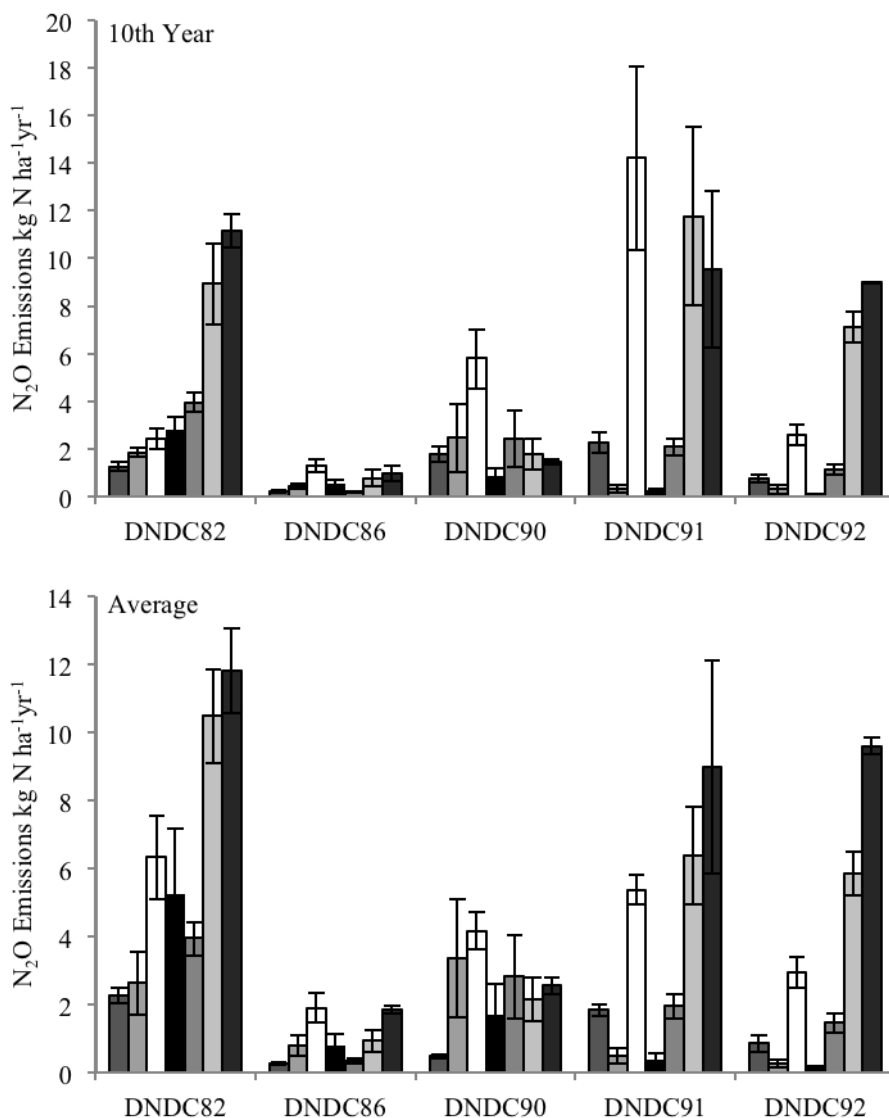


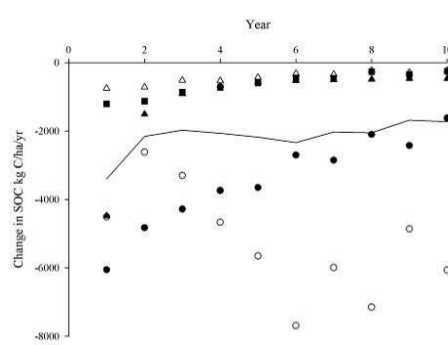
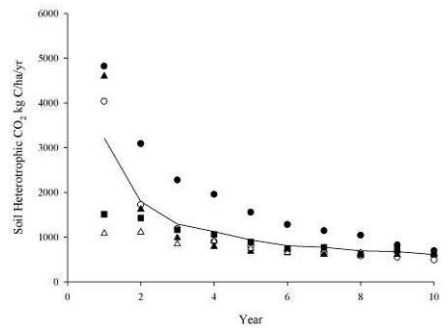
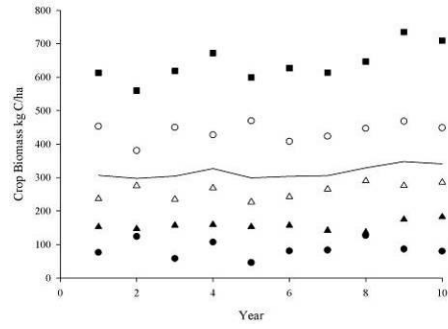
Figure 2-7: Comparison of nitrous oxide (N₂O) emission rates from seven different crop types (■ sugar beet, ■ vining peas, □ lettuce, ■ beans, ■ wheat, ■ potatoes, ■ brassicas) for five different versions of DNDC for both the final year of the model simulation (10th year) and averaged over the entire 10 year simulation period for a series of farms in Worcestershire. Values represent means ± SEM (*n* > 4).

2.4.7. Temporal variation in model outputs over a 10 year simulation period

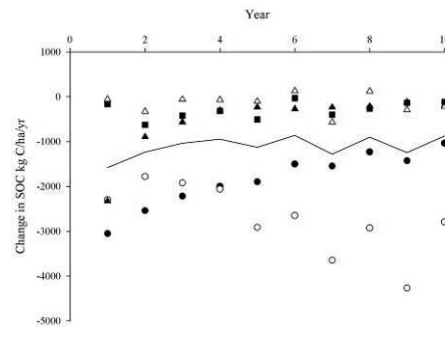
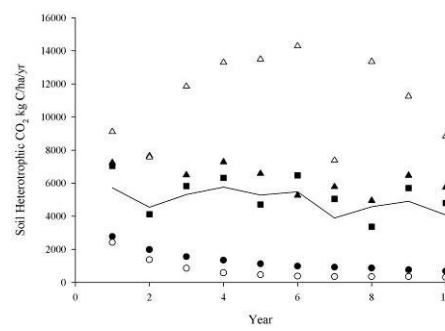
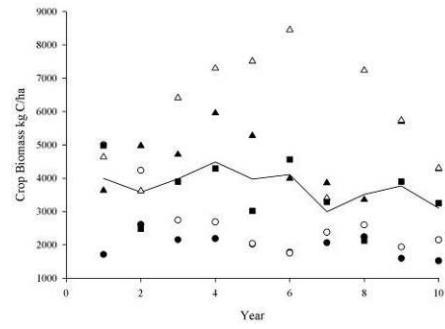
It is clear from examining successive years of model predictions for a range of crops that the outputs from DNDC are critically dependent on the amount of time the model is run for. This is exemplified in the range of plots shown in Figure 2-8. The variation in predictions between the 5 versions of the DNDC model over the 10 year simulation period was found to be very large. In general, the model versions giving the most varied or extreme results were DNDC82 and DNDC86 (Figure 2-8). It should be noted that some of the variation in outputs for each of the years are partly due to variations in the real weather data used to run the models, as well factors associated with the agronomic sub-models. Climate (temperature and moisture) is a primary driver of the plant growth and microbial GHG emission sub-models.

To evaluate the temporal stability of the model, simulation comparisons were undertaken with three contrasting crops: lettuce, sugar beet and wheat (Figure 2-8). With both the lettuce and wheat crops, simulations made using DNDC92 produced the highest values for crop biomass, with an average value across the years of 0.64 t C ha⁻¹ and 4.87 t C ha⁻¹ respectively. DNDC91 gave the highest results for sugar beet with a mean of 5.86 t C ha⁻¹ and generally gave results close to the average line, with lettuce lower than the average line with a mean of 0.26 t C ha⁻¹. Wheat was higher than the average line with a mean of 4.09 t C ha⁻¹. DNDC82 gave the lowest results for all three vegetable types: lettuce, sugar beet and wheat gave 0.46 t C ha⁻¹, 1.51 t C ha⁻¹ and 1.31 t C ha⁻¹ respectively; see Figure 2-8.

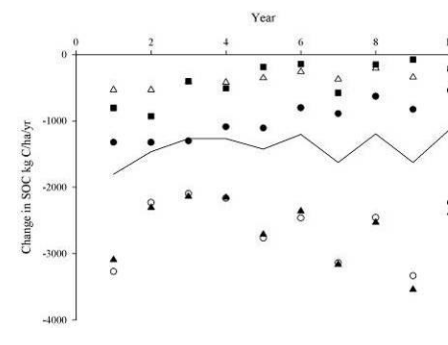
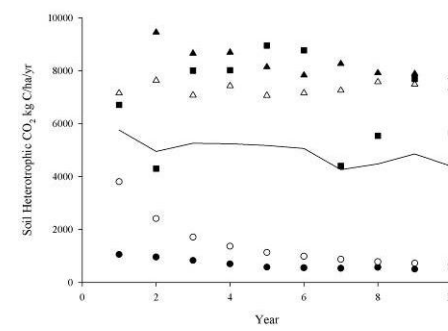
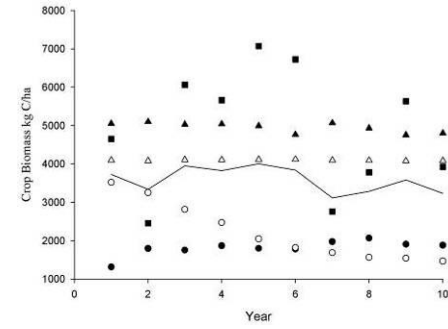
Lettuce



Sugar beet



Wheat



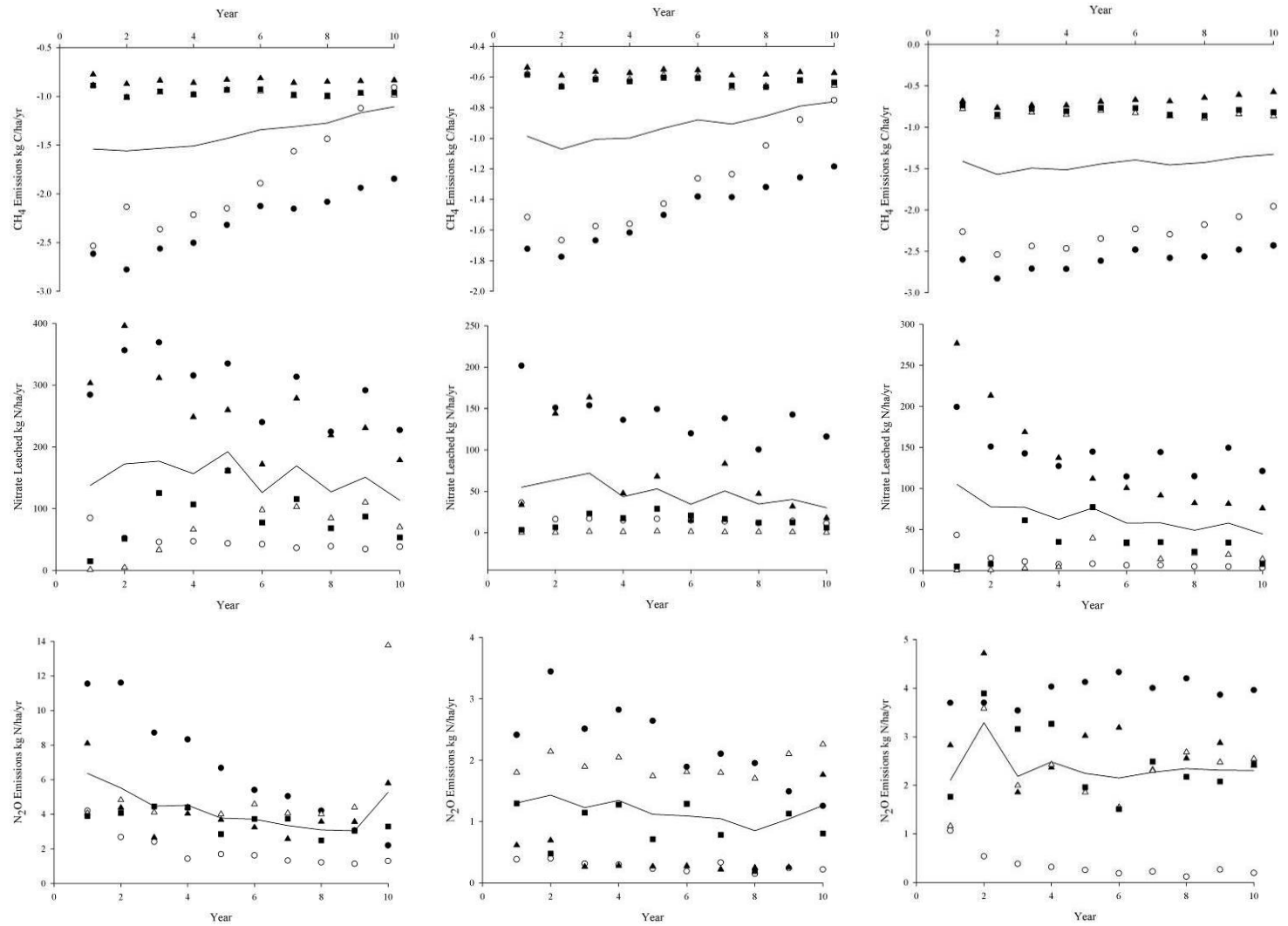


Figure 2-8: Comparison of outputs from different versions of the DNDC model over a 10 year simulation period for three crop types. Three different vegetable types were modelled to compare which outputs were the most affected by the variations in the different models. Each field measured (n=6) is averaged for the same years to produce the model output for that specified year. The models considered are (●) DNDC82 (○) DNDC86 (▲) DNDC90 (△) DNDC91 (■) DNDC92. The solid line represents the average of all 5 model types for a specific year.

Sugar beet had the highest outputs for soil heterotrophic CO₂, while lettuce had the lowest (11.1 t C ha⁻¹ yr⁻¹ and 0.8 t C ha⁻¹ yr⁻¹ respectively; Figure 2-8). DNDC82 and DNDC86 had the lowest predicted CO₂ emissions with an average of 1.29 t C ha⁻¹ yr⁻¹ and 0.74 t C ha⁻¹ yr⁻¹ for sugar beet and 0.68 t C ha⁻¹ yr⁻¹ and 1.45 t C ha⁻¹ yr⁻¹ for wheat respectively. For DNDC82, lettuce gave the highest predicted CO₂ efflux rates, with an average of 1.86 t C ha⁻¹ yr⁻¹. DNDC90 gave the highest values for wheat with an average of 8.47 t C ha⁻¹ yr⁻¹, while DNDC82 gave a lower average of 0.68 t C ha⁻¹ yr⁻¹.

For the change in SOC, DNDC86 predicted that lettuce cultivation induced the greatest loss (5.3 t C ha⁻¹ yr⁻¹) while DNDC82 had a reduced loss of SOC by the tenth year, giving an average value of 3.4 t C ha⁻¹ yr⁻¹ (Figure 2-8). DNDC90, DNDC91 and DNDC92 behaved similarly, with losses of less than 2 t C ha⁻¹ yr⁻¹ for lettuce. DNDC86, DNDC90, DNDC91 and DNDC92 gave results for sugar beet that were similar to lettuce. DNDC86 and DNDC90 gave similar results for wheat of -2.6 t C ha⁻¹ yr⁻¹. DNDC82, DNDC91, and DNDC92 predicted similar results for wheat with averages of -0.98 t C ha⁻¹ yr⁻¹, -0.36 t C ha⁻¹ yr⁻¹ and 0.40 t C ha⁻¹ yr⁻¹ respectively.

Predictions for soil methane consumption had a similar pattern across the three vegetable cropping systems, with DNDC90, DNDC91 and DNDC92 generally predicting similar results (Figure 2-8). DNDC82 predicted a higher CH₄ sink, with a range and average of -2.43 and -2.83 kg C ha⁻¹ yr⁻¹ respectively for wheat, while DNDC86 predictions were marginally different at -2.54 and -1.96 kg C ha⁻¹ yr⁻¹. DNDC86 gave different results for lettuce and wheat, with means of -1.83 and 2.28 kg C ha⁻¹ yr⁻¹ respectively. DNDC82 gave a lower result for sugar beet, with an average of -1.48 kg C ha⁻¹ yr⁻¹. In comparison DNDC86 predicted an average CH₄ consumption of -1.29 kg C ha⁻¹ yr⁻¹ (Figure 2-8).

For the amount of nitrate leached under each cropping system, DNDC90 and DNDC82 gave the highest results for all three vegetable types (Figure 2-8).

DNDC86, DNDC91 and DNDC92 gave low, and similar, predictions for sugar beet and wheat. DNDC86 had the lowest average of 46.4 kg N ha⁻¹ yr⁻¹ for lettuce, whereas DNDC91 and DNDC92 had similar 10-year averages of 73.3 and 86.2 kg N ha⁻¹ yr⁻¹ respectively.

In the case of N₂O emissions, DNDC82 gave a higher average emission for lettuce than for sugar beet and wheat (6.68, 2.25 and 3.94 kg N ha⁻¹ yr⁻¹, respectively); these were the highest results, compared to the other models, for each vegetable type. DNDC86 gave the lowest results of 1.90, 0.28 and 0.35 kg N ha⁻¹ yr⁻¹ for lettuce, sugar beet and wheat respectively. In contrast, DNDC90, DNDC91 and DNDC92 produced similar emission estimates for lettuce (4.16, 5.23 and 3.60 kg N ha⁻¹ yr⁻¹ respectively). DNDC91 gave the second highest results for sugar beet (1.93 kg N ha⁻¹ yr⁻¹) and lettuce and the third for wheat (2.56 kg N ha⁻¹ yr⁻¹) compared to the other models, which closely followed the average line, as seen in Figure 2-8.

2.4.8. Running averages in DNDC modelling outputs

The temporal stability of DNDC was discussed above. However, the variability in model outputs for the same crop in response to repeated agronomic cycles with the same climatic regime is dealt with below. Figure 2-9 shows the cumulative average in output parameters for a range of DNDC versions plotted against the actual average for each year for a series of lettuce fields in Worcestershire. This differs from Figure 2-8 by having a cumulative (running) average for each model rather than the average for all the models. The results show a progressive step as the outputs from one year provide the input variables for the next year (e.g. soil organic carbon).

For soil heterotrophic CO₂ production, all models were found to be statistically similar ($P = 0.650$) for the actual average values. DNDC90 gave a high starting level with a value of 7.1 t C ha⁻¹ yr⁻¹, which decreased to 1.8 t C ha⁻¹ yr⁻¹ for the second year and then followed the pattern of the rest of the models (Figure 2-9). Cumulatively, DNDC90 gave the highest results (7.1 t C ha⁻¹ yr⁻¹) and DNDC91 (1.4 t C ha⁻¹ yr⁻¹) gave the lowest results. DNDC90 was found to be significantly different from DNDC91 and DNDC92 ($P < 0.001$ and $P < 0.003$ respectively).

Changes in soil organic carbon (SOC) show the same pattern as described for soil heterotrophic CO₂, with actual average results for all models being statistically similar ($P = 0.152$). DNDC90 predicted the greatest loss in SOC, with a loss in the first year of 7.1 t C ha⁻¹ yr⁻¹, but only a cumulative average loss over the ten years of 1.6 t C ha⁻¹ yr⁻¹. DNDC82 had an average cumulative loss similar to DNDC90 of 1.60 t C ha⁻¹ yr⁻¹, but without the substantial loss at the beginning. DNDC91 again predicted the lowest loss in SOC, with a range of -1.2 to 0.6 t C ha⁻¹ yr⁻¹ according to the cumulative average and was found to be statistically different from DNDC82 ($P = 0.012$) and DNDC 90 ($P < 0.001$). Lastly, DNDC90 was found to be significantly different from DNDC92 ($P < 0.001$)

For CH₄ emissions, DNDC82 and DNDC86 predicted more net consumption than the other three versions of the models, with DNDC82 showing the greatest sink values (average of 2.7 and 2.4 kg C ha⁻¹ yr⁻¹ for DNDC82 and DNDC86 respectively; Figure 2-9). DNDC90 predicted less methane

consumption than the other models, with an average of $0.83 \text{ kg C ha}^{-1} \text{ yr}^{-1}$ with the predictions remaining fairly constant throughout the ten year simulation period. The only two models that were significantly similar were DNDC91 and DNDC92 (0.92 and $0.91 \text{ kg C ha}^{-1} \text{ yr}^{-1}$ respectively, $P = 0.993$). DNDC90 was significantly different from DNDC82, DNDC87, DNDC91 and DNDC92 ($P = 0.001, 0.001, 0.015$ and 0.047 respectively). DNDC82, DNDC87, DNDC91 and DNDC92 were all significantly different from each other ($P < 0.001$).

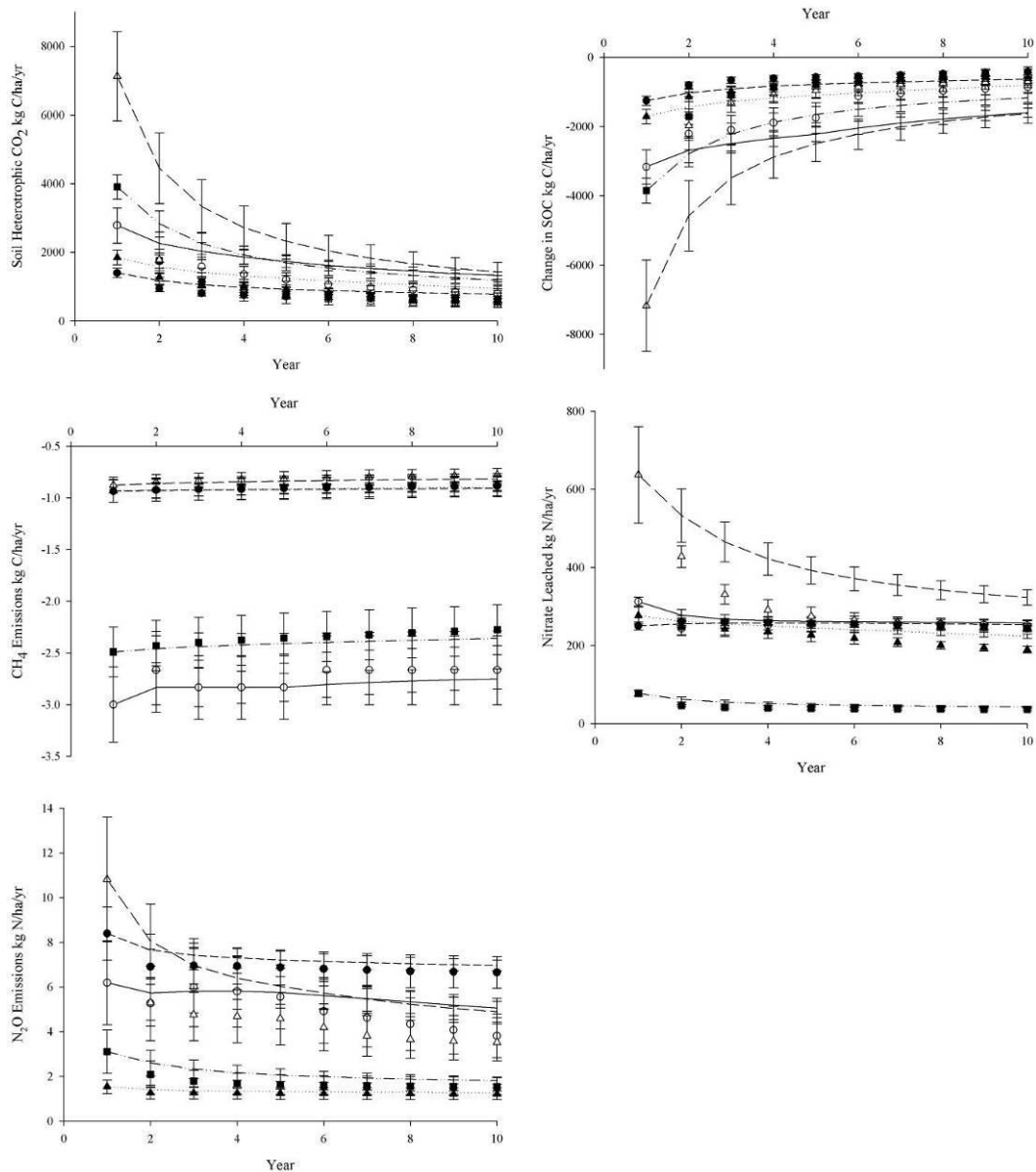


Figure 2-9: Running average over a 10 year period for outputs from different versions of the DNDC model when simulating C and N cycling for a series of 6 individual lettuce fields. The symbols indicate that year's average results for all 6 lettuce fields for each model; (○) DNDC82, (■) DNDC86, (△) DNDC90, (●) DNDC91 and (▲) DNDC92. The lines for each model is the average for that year and all the years preceding it for all 6 lettuce fields for each model; (—) DNDC82, (-·-·-·) DNDC86, (—) DNDC90, (----) DNDC91 and (····) DNDC92. Values represent means for each model \pm SEM ($n = 6$).

The amount of nitrate leached showed a downward trend from the first to the tenth year (Figure 2-9). DNDC90 gave the highest trend, with a cumulative average of 637 kg N ha⁻¹ yr⁻¹ reducing to 322 kg N ha⁻¹ yr⁻¹. DNDC86 gave the lowest trend with an average of 47 kg N ha⁻¹ yr⁻¹. DNDC86 was found to be statistically different from all other models; the only other significant difference was found between DNDC90 and DNDC92 (P = 0.003).

Nitrous oxide emissions fell in the first year and reached a plateau for all models except for DNDC90, which continued to decrease from 10.8 kg N ha⁻¹ yr⁻¹ to a final running average of 4.9 kg N ha⁻¹ yr⁻¹. DNDC90 was found to be statistically different from DNDC86, DNDC91 and DNDC92 (P < 0.001 in all cases). DNDC82 behaved in an intermediate manner, and was found to be significantly different to DNDC86, DNDC91 and DNDC92 (P < 0.000, P = 0.003 and P < 0.001, respectively). Other statistical differences were between DNDC86 to DNDC91 (P < 0.001) and DNDC91 to DNDC92 (P < 0.001) Figure 2-9.

2.4.9. Model variation between fields

When making recommendations on GHG mitigation to farmers and policymakers it is important that proposed GHG reduction strategies are applicable to a wide range of farm types and not highly specific to geographical areas. This is also important when scaling up estimation of GHG emissions from the field level to the regional level. To evaluate the impact of geographical (field scale) location on model performance, a number of simulations for different fields containing the same crop were undertaken with DNDC92. The input parameters were based on actual management regime data collected from farmers. Figure 2-10 shows that DNDC92 produced significant variation in model outputs between different fields growing the same crop within the same geographical region. Furthermore, this level of variability was also seen for other versions of the DNDC model (data not presented).

The predicted crop biomass for lettuce field L4 was very high (average 1.2 t C ha⁻¹ yr⁻¹), while L3 had the lowest predicted biomass yield (0.35 t C ha⁻¹ yr⁻¹) (Figure 2-10). L1 was found to be significantly similar to L2 (P = 0.095), L2 was found to be similar to Lettuce3 (P = 0.092) and L5 was found to be similar to

L6 ($P = 0.99$). All other relationships were found to be significantly different ($P < 0.05$).

For changes in SOC, the six different fields followed the same pattern, starting high and progressively lessening over the 10 year simulation period. L3 had the highest loss rate (average $-0.97 \text{ t C ha}^{-1} \text{ yr}^{-1}$), whereas L1 had the lowest loss rate ($-0.36 \text{ t C ha}^{-1} \text{ yr}^{-1}$) (Figure 2-10). The change in SOC at L3 was found to be statistically different from fields L1 and L6 ($P = 0.015$ and $P = 0.044$ respectively).

Soil heterotrophic CO_2 production had a downward trend for all fields over time. L4 had the highest average value ($1.4 \text{ t C ha}^{-1} \text{ yr}^{-1}$) being significantly different from L1, L2 and L6 (P values of 0.001, 0.026 and 0.012 respectively). Field L1, had the lowest predicted rates of CO_2 emission with an average of $0.60 \text{ t C ha}^{-1} \text{ yr}^{-1}$ and a range of 0.38 to $0.82 \text{ t C ha}^{-1} \text{ yr}^{-1}$.

For CH_4 consumption by soil, the overall result for all fields was characterised by slight fluctuations from year to year (Figure 2-10). Field L3 had the largest sink, with an average of $-1.36 \text{ kg C ha}^{-1} \text{ yr}^{-1}$, whilst L6 had the smallest sink of $-0.67 \text{ kg C ha}^{-1} \text{ yr}^{-1}$. L6 and L4 were the only fields found to be statistically similar ($P = 0.219$).

For nitrate leaching, all fields produced similar results, with the amount leached varying between years (Figure 2-10). The only significant difference was between field L3 and both L4 and L6 ($P = 0.02$ and $P = 0.012$ respectively). L4 had the lowest rate of leaching with an average of $51 \text{ kg N ha}^{-1} \text{ yr}^{-1}$ and L3 had the highest loss with $135 \text{ kg N ha}^{-1} \text{ yr}^{-1}$.

Field L5 initially gave the highest N_2O emissions for the first two years (6.66 and $7.76 \text{ kg N ha}^{-1} \text{ yr}^{-1}$), while L3 gave the highest overall average of $5.48 \text{ kg N ha}^{-1} \text{ yr}^{-1}$. L3 was found to be significantly different to L1, L2, L4 and L6 (all $P < 0.001$). L2 gave the lowest results with an average emission rate of $2.52 \text{ kg N ha}^{-1} \text{ yr}^{-1}$. L1 was very close to the average for the group of fields, with an average of $3.39 \text{ kg N ha}^{-1} \text{ yr}^{-1}$. L5 was found to be significantly different from L2, L4 and L6 ($P = 0.002$, 0.007 and 0.03 respectively).

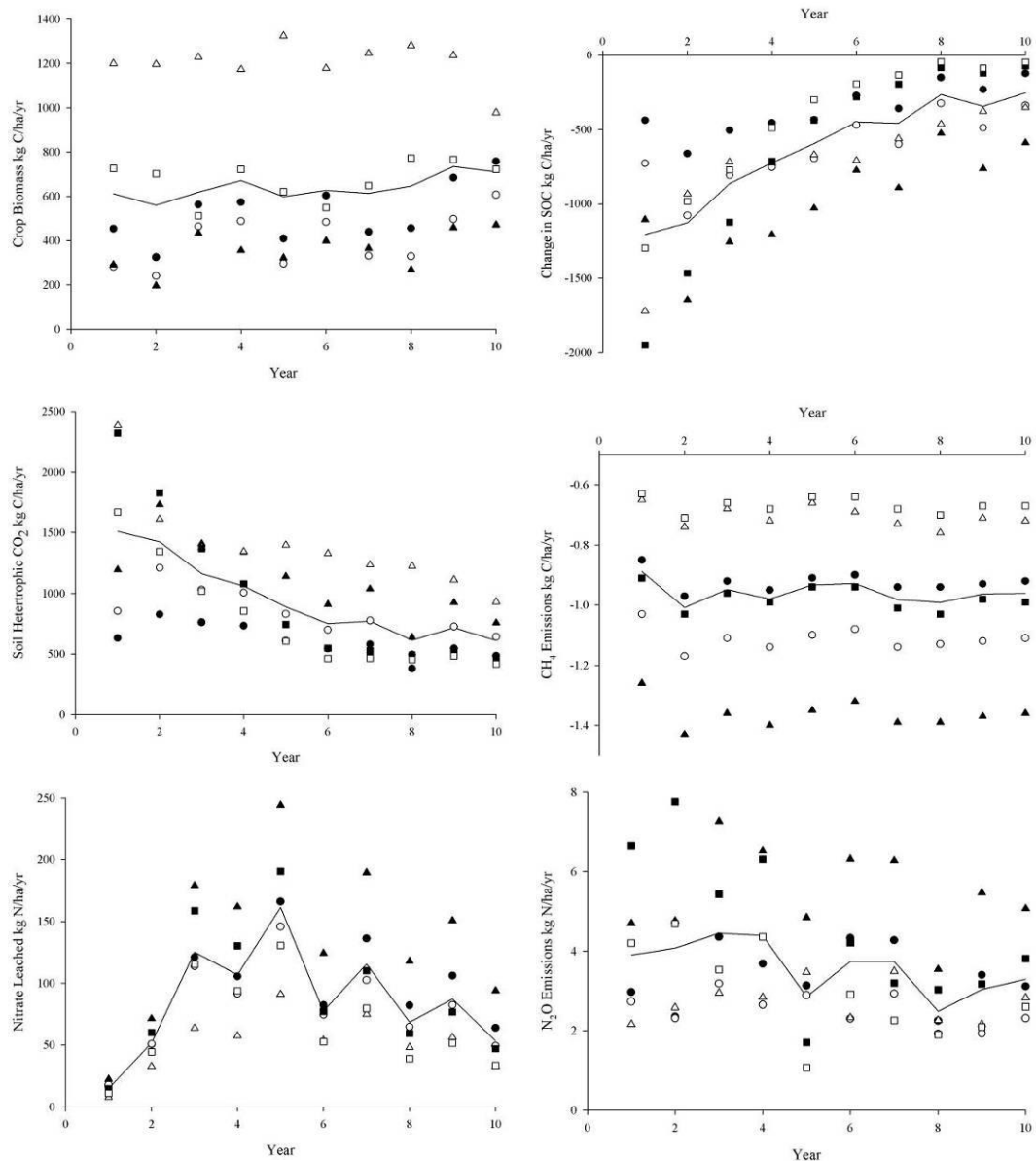


Figure 2-10: Variation in DNDC model outputs for six individual lettuce fields (●L1, ○L2, ▲L3, △L4, ■ L5, □ L6) predicted using DNDC92 over a ten year simulation period. The solid line represents the average of the 6 fields for each year.

2.5. Discussion

An ecosystem model is a simplified representation of real world system functioning. In theory, a model can provide a representation of what the results may be if the system was measured (i.e. at steady state). When a measurement may be unattainable in a field situation, a model can estimate the results; however, if the outputs required are to possess a reasonable degree of accuracy, the inputs need to be accurate and specific. Variations and changes, however small, within the model's matrix can have significant affects upon the results

obtained - as exemplified here. The complexity of environmental models is often a result of the number of variables within an environmental system and their interactions (e.g. feedback loops). DNDC is a complex model comprising four ecological drivers and six sub-models (Cai et al., 2003; Li, 2004). These drivers must interact with the sub-models and with each other to keep the system balanced; if this does not occur then the output given may not be realistic. The model aims to simulate a carbon and nitrogen cycle at a daily level over a given period of years for an agricultural system (Tonitto et al., 2007; Abdalla et al., 2009; Wang et al., 2008). The inputs for this system include various data for the soil system, weather data (either yearly data or a repeated use of one year's data) and the management system for the field (Zhang et al., 2002). Beheydt et al. (2007) used 22 long-term N₂O emissions plots to validate the model, the oldest of these datasets being from 1993. They found that the default DNDC field capacity and wilting point needed to be adjusted to better simulate N₂O emissions. The management system will ultimately run for any number of simulation timescales, from years to centuries, until the model is told to stop by the user. However, the stability of the model over longer timescales remains uncertain.

The work undertaken here considered five versions of the model that have been produced over a period of about 10 years, with each model being more complex than the previous versions (i.e. from DNDC82 through to DNDC92). This should give more realistic results, but can also cause more errors within the models as a result of an increased number of linked calculations. In more complex models, a larger volume of data may make the model more accurate but harder to use. Errors can occur in any model and they need to be constantly assessed. The main developments in the model's evolution have been:

- Weather data - the later model takes into account the wind speeds. In addition, Global Met Data files can be used instead of plain text files.
- Soils – Hydrological conductivity information can be included in addition to data on the presence of macro-pores and water-logging problems. Soil temperature and moisture content are not available inputs in later versions.

- Vegetable types have been added: SJ corn, SJ rice, SY corn, SY wheat, Henlan1, Woju, Ratooned Sugarcane, Shrub- blueoak, Qingcai, Raddish, Pepper, Edible amaranth, Qingcai2. The ability to specify whether or not the crop is a cover crop has been added.
- In the new version there is an additional tillage option for deep ploughing at 45 cm.
- Fertiliser - the option for slow released-controlled fertilisers and for nitrification inhibitors to be applied is now available in the simulation, as well as an option to use one's own fertiliser files.
- Manure - extra types have become available: compost, bean cake and human waste.
- Flooding - flooding duration is defined as rain fed (control 2), observed water table fluctuation (control 3) as well as irrigation (control 1) is noq available and conventional flow (5-10 cm), marginal flow (0.5-5 cm) and water leakage rate instead.
- Grass cutting - the number of times a year with date and amount cut in kg C/ha (DNDC manual 9.1)

All of these variations can either increase or decrease the emissions from the system. With changes to tillage practice there are likely to be greater emissions with deeper tillage, owing to increased disturbance to the microbes in the soils (Al-Kaisi et al., 2005). With flooding and reduced hydrological conductivity in soil there may be an increase in methane emission, owing to increased waterlogging (Li et al., 1992). The ability to consider different crop types allows for greater accuracy, and grass cutting and slow-release fertilisers comes the likelihood of seeing less CO₂ and N₂O emissions.

The results presented here indicate that differences between model versions can have profound effects upon the model predictions, confirming the hypothesis that the models would differ significantly. Unfortunately, relatively few field experiments have measured these outputs on the same temporal scale at which the models operate and therefore the knowledge of how accurate the latest version of the model would be is unknown.

DNDC has been used to measure a variety of situations, from rice paddies in China to European forests. Some of the models have been validated against

data sets by Beheydt et al. (2007), Brown et al. (2002), Cai et al. (2003), Grant et al. (2004), Jagadeesh Babu et al. (2006), Li (2000), Li et al. (1992, 1994, 1997, 2000, 2006 and 2008), Miehle et al. (2006), Neufeldt et al. (2006), Qui et al. (2009), Salas et al. (2003), Smith et al. (1997 and 2004), Stange et al. (2000), Tang et al. (2006), Tonitto et al. (2007a,b) Xu-Ri et al. (2003), and Zhang et al. (2002). Though these results have, in the main, shown some general accordance with measured results, a good proportion have found the need to calibrate the model. Beheydt et al. (2007) was not alone in observing a poor fit between observed and expected data: Abdalla et al. (2009) found DNDC to constantly underestimate field measurements of the N₂O flux due to overestimating water filled pore space and the effect of initial soil organic carbon (SOC) on N₂O flux. The area that had least agreement is N₂O emissions, which are one of the most important outputs. Neufeldt et al. (2006) and Abdalla et al. (2009) found that the model underestimated emissions. In the case of Abdalla et al. (2009), this was mainly associated with low input systems, while Smith et al. (2004) found the model to both over- and under-estimate on a site-to-site basis. Levy et al. (2007) also found the model to both over and under-estimate emissions from highly organic soils. Lamer et al. (2007) found that the model reproduced measured N₂O fluxes poorly, although Pampolino et al. (2006) found the annual N₂O emission predictions to be very close to field observations. The level of agreement depended on the length of data used and what was being measured. Dietiker et al. (2010) found that DNDC, generally, predicted the seasonal trends and the absolute magnitude of the CO₂ fluxes in a realistic way. However, discrepancies were during winter, when a net CO₂ uptake overestimation was observed for several crops, suggesting that DNDC only considered a plant's reaction to temperature and not other climatic issues such as sunlight hours or intensity.

What is not mentioned in many of the papers is which version of the DNDC model is used. This is unfortunate, because – as this chapter suggests – the version used could have a significant influence on model results. Lamers et al. (2007) suggests the routine disclosure of the source code for DNDC and other biogeochemical models. Open source code would not only help in identifying errors but also enable model users to better understand the contents, and hence the limitations, of popular models. Ideally, a version should be validated against

a data set and any new versions validated against the same data set to allow easier comparisons to be made and the difference between versions to be understood.

DNDC72 (the year in which it was developed is not clear), was used by Smith et al. (2004) and Xu-Ri et al. (2003), while Neufeldt et al. (2006) used version 80. Version 82 was both used by Tonitto et al. (2007) and Li et al. (2004). Beheydt et al. (2007) and Levy et al. (2007) used 83 and 86 and 89 was used by Pampolino et al. (2006) and Leip et al. (2008), respectively. Abdalla et al. (2009) used 92. Lamers et al. (2007) notes the date on which the model was downloaded (8 Dec 2006), but do not give a version number. Such a wide range of models are noted in published papers then many of the apparent differences in the success of validation could well be due to the use of different versions.

Much variation is shown between the yearly results for the ten years of simulation. Li et al. (1994a) found that one consequence of a dynamic agricultural operation is that soil properties determined by slower rate processes (e.g. decomposition) will seldom reach equilibrium. SOC sequestration might exhibit quite different short- versus long-term sensitivities to certain variables. Qiu et al. (2009) used a 20-year pre-simulation and Tonitto et al. (2007) disregarded the first year of simulation to eliminate the possible uncertainties that could be induced from the initial settings of some input parameters such as SOC partitioning. Unfortunately, Qiu et al. (2009) did not comment on what differences were found between the pre-simulation results and the final results. Using a 20-year pre-simulation may have a significant effect on the outcome, as the soils' conditions may no longer reflect those being modelled (e.g. due to losses of SOC). Most papers do not state whether they use the pre-simulation option when using the model.

2.6. Conclusions

Overall, the different versions of the DNDC model were found to give very different predictions when directly compared to each other. Although one might expect that newer versions would be superior to previous versions of the model, this does not always seem to be the case - which may suggest that we may not have learnt from past problems (i.e. greater instability may have been

introduced into the model as default parameter values or equations are altered) and unfortunately not confirming the hypothesis. There is, therefore, a need for further investigation into the model's performance (e.g. capacity for spurious predictions with increasing model complexity) to gain a better understanding of its strengths and weaknesses. From this respect, a sensitivity analysis would provide modellers with a better understanding of how the different sub-models interact.

Many scientists use models for predicting the possible gains and losses of C, N and other nutrients from terrestrial ecosystems. They use models either because parts of the system are difficult to measure (intrinsically complex or practically difficult), or because they wish to consider long periods that are impractical to assess empirically. All models are simplified representations of the real world, and our knowledge about the accuracy of model predictions is limited by the data available to validate the model output. Unfortunately, even validation is imperfect, as the test data is location specific, and also sometimes time specific. These issues can reduce the generalisation of the model predictions.

Generally, such limitations are well recognised by scientists, however, when models become central to the policymaking process, their limitations can bring serious risks to society. It is essential that policy makers are also aware of the limitations of the models they use, and that at a most basic level they can be sure that different versions of the same model are comparable. Unfortunately, the results of this work cast doubt on the comparability of versions of DNDC, but as yet there is no evidence that these differences have influenced any legislative or policy decisions. However, this risk remains a real one.

If policy makers take outputs from models that have not been tested or updated, then deciding on the future policies does not become a low risk process. Although models are routinely updated, it is not always known if a particular version is reliable (i.e. which parts of the model have been newly validated) and can only be presumed to provide an approximate answer at best.

Chapter 3. Sensitivity of Soil Respiration to Variation in Temperature

Elizabeth York, Georgia Koerber, Paul W Hill, Paula Roberts, David L. Jones,

Gareth Edward-Jones

School of Agricultural, Natural Resource and Geography, Bangor University,

Gwynedd LL57 2UW, UK

3.1. Abstract

Soil respiration represents a major flux by which biosphere C is returned to the atmosphere. Understanding the factors regulating this flux remains critical to our understanding of ecosystem feedbacks in global climate change. One of the major abiotic regulators of soil respiration is temperature; however, there is uncertainty about how this is mathematically related. In many global warming models soil respiration is one of the most useful outputs, and it is therefore vital that the sub-model which predicts CO₂ emissions is parameterised correctly. For the model DNDC, a single Q_{10} is presumed to be appropriate for all soil types globally. Here we specifically tested whether a Q_{10} model could be applied across a global soil gradient and whether it could successfully describe CO₂ efflux from contrasting soils exposed to a wide range of temperatures. To achieve this, soil was exposed to a sequential temperature ramp from 5 to 30°C and back again over repeated 24 h cycles while soil respiration was simultaneously measured. The results showed that all the soils responded similarly to changes in temperature and that there was no hysteresis in respiration between the rising (5 to 30°C) and falling (30 to 5°C) temperature ramps. Respiration from all the soils conformed well to a Q_{10} mathematical model, with an average value of 2.72 ± 0.15 . Overall, the results suggested that on a large geographical scale, global latitude had some effect on the Q_{10} value. There was also variability in the Q_{10} values obtained over a small geographical scale, possibly relating to differences in land management strategy (e.g. crop type and tillage/fertiliser regime). In conclusion, our results suggest that soil respiration can be adequately described by a Q_{10} model, but that the theoretical value of 2.0 may be an underestimation and that a higher Q_{10} value should be used in terrestrial models describing CO₂ efflux from soils in response to temperature.

3.2. Introduction

The efflux of CO₂ from the terrestrial and marine biosphere represents approximately 25% of the total annual flux of C to and from the atmosphere, and is estimated to be $>68 \times 10^{15}$ g C yr⁻¹ (Palmer Winkler et al., 1996). Due to anthropogenic emissions, however, the land-atmosphere CO₂ concentration

balance has shifted causing a 30% increase in atmospheric CO₂ concentrations. A likely outcome of this change is an alteration in global temperature patterns. Estimated increases of 1.4 to 5.8°C in mean global surface temperature have been predicted to occur between 1990 and 2100, and these changes are likely to vary substantially among regions and exhibit both seasonal and diurnal variation (Wythers et al., 2005). While soils and oceans can potentially act as a large sink for CO₂ they can only achieve this under a limited range of environmental conditions. If climate change were to cause even a small release of organic carbon (SOC) stored in soil, it could constitute a positive feedback effect (Kirschbaum, 2004; Lou et al., 2004).

Respiration is the principal pathway of C loss from the ecosystem to the atmosphere and is the sum of root respiration and microbial respiration (Lou et al., 2004; Byrne and Kiely, 2006). Soil temperature and water content are the two major abiotic factors that regulate the production and consumption of greenhouse gases in soil mediated via changes in microbial and root activity in soil (Smith et al., 2003; Eliasson et al., 2005). Soil temperature has been identified as the most important environmental variable for predicting soil respiration, followed by soil moisture and nutrient availability (Lou et al., 2004; Tingey et al., 2006). Thus seasonal changes and climatic differences generate differences in respiration rates with time (Bernhardt et al., 2006). The strong temperature response of respiration can be seen in laboratory incubations, seasonal field observations, short-term soil-warming experiments and incubation experiments on litter in different climatic zones (Kirschbaum, 2004). Temperature has been shown to account for approximately 85–90% of the seasonal variability in soil CO₂ fluxes (Lou et al., 2004). In Europe, seasonal changes in soil respiration follow the order of summer > autumn > spring > winter. The lower fluxes in winter are connected with depressed root and microbial respiration caused by low soil temperatures (<10°C) (Lou et al., 2004). A recent study has suggested that the temperature sensitivity of soil respiration may be independent of the mean annual temperature of the soil across a wide variety of ecosystems and average temperatures (Smith et al., 2003).

Although the general relationship between temperature and respiration is well established, there has been some uncertainty in describing the microbial response (Winkler et al., 1996; Kätterer et al., 1998; Smith et al., 2003). For

example, some experiments have shown that soil respiration declines under prolonged warming, and eventually returns to rates similar to unwarmed soil. Consequently, extrapolations of the relationship of soil CO₂ efflux to temperature, as measured prior to warming, may overestimate the flux. C budget models that ignore this so-called acclimation of soil respiration may therefore overestimate soil C loss in response to global warming without consideration of substrate availability etc. (Eliasson et al., 2005). An important feature of these temperature–response curves is the higher relative temperature sensitivity at lower temperatures. This implies that C stored in cooler regions is more likely to be lost with global warming than C stored in warmer regions (Kirschbaum, 2004). The notion of a strong effect of temperature on C efflux rate has also been challenged in recent work (Giardina and Ryan, 2000). The question remains as to the true temperature dependence of soil processes, and how soil C stocks may be affected by changes in global temperature (Kirschbaum, 2004).

Due to the intrinsic complexity of the biosphere and the need to develop global climate change models to predict what will happen in the future, scientists are always looking for simple relationships in nature. The temperature dependence of biogeochemical processes such as respiration has been described mathematically since the late 19th century (Davidson et al., 2006). Of these, exponential relationships, especially the Q_{10} relationship, have been commonly used to predict changes in soil respiration rates in response to changes in temperature (Curiel Yuste et al., 2004). The Q_{10} for a reaction rate is defined as the factor by which the rate increases with a 10°C rise in temperature, and is defined by the equation:

$$Q_{10} = \text{Respiration rate at } (T + 10) / \text{Respiration rate at } T \quad (\text{Eqn. 1})$$

(Where T is temperature). A widely accepted view in ecosystem research is that the rate of soil organic matter (SOM) decomposition, like most biological reaction rates, tends to double for every 10°C rise in temperature (i.e. Q_{10} value for decomposition = 2) (Davidson et al., 2006). In many decomposition studies, the Q_{10} relationship is therefore compared to this theoretical value and used to describe the dependence of decomposition on temperature (Kätterer et al., 1998). Examples of possible Q_{10} relationships are shown in Figure 3-1.

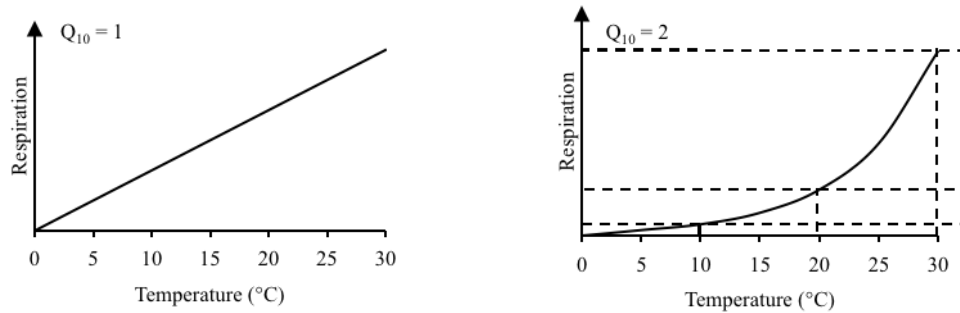


Figure 3-1: Theoretical relationship between soil temperature and soil respiration showing Q_{10} values of 1 (left hand panel) and 2 (right hand panel).

The origin of this rule-of-thumb ($Q_{10} = 2$), however, and the limits to its validity are less well known. Early experiments by Van't Hoff and colleagues indicated that, around 20°C , reaction rates 'roughly double or triple' for every 10°C rise in temperature (i.e. Q_{10} values of 2-3) (Davidson et al., 2006a). This works in accordance with the first law of thermodynamics that when one variable doubles then it proportionally affects an output.

Most Q_{10} values for soil are believed to be 2, but will normally range between 2 and 3 and may go as high as 5 (Janssens et al., 2003). Palmer-Winkler et al. (1996) noted that Q_{10} values tend to be higher at low temperatures, consistent with other observations that root respiration is low at $<10^{\circ}\text{C}$ (Kirschbaum, 1995). With an increase in temperature ($>10^{\circ}\text{C}$), respiration increases and generally conforms to a Q_{10} value close to 2.0. However, this is true only over a limited temperature range due to physiological restrictions on metabolic functioning at temperatures above 35°C (Huang et al., 2005).

There is also increasing evidence to suggest that the Q_{10} of soil respiration is not constant during the year, but tends to decrease with increasing temperature and decreasing soil moisture (Leahy et al., 2004). Because most empirical models rely on the correlation between the seasonal patterns of soil respiration and temperature to produce a single Q_{10} value, such models may over- or under- estimate soil respiration over smaller time scales. Discrepancies in Q_{10} values may stem from simple differences in experimental procedure (e.g. making temperature measurements at different soil depths). For example, Moore et al. (1996) and Davidson et al. (1998) measured soil temperatures at 2, 5 and 10 cm depth, respectively, and found corresponding diurnal Q_{10} s for CO_2 flux of 2.2, 2.7 and 4.2. Davidson et al. (1998) argued that the substantial differences

between observed Q_{10} and those previously published might be partly explained by the decrease in diurnal variation in temperature with depth. Others have found an increase in Q_{10} with increasing soil depth (Smith et al., 2003). The temperature response of soil respiration is also expected to be dependent upon a range of other factors that may cause variation in the Q_{10} response (Kätterer et al., 1998). Examples of these include differences in agricultural management regime (e.g. tillage, fertiliser application, crop type) or abiotic conditions (e.g. salt concentration, O_2 oxygen partial pressure) (Kätterer et al., 1998).

Overall, relatively little is known about the short-term responses of soil respiration to shifts in temperature (Janssens et al., 2003). Further, the relative impact of global latitude, farm management or plant type has on the Q_{10} response remains poorly understood. The biogeochemical model DNDC uses a Q_{10} of 2.0 (Li et al., 1992; Li et al., 2000), although a Q_{10} value of 2.5 has also been used by Li et al. (1994). This Q_{10} value stays constant throughout the model simulation and does not vary with the environment/ecosystem being simulated. This could possibly lead to variations in model output due to the Q_{10} used being larger or smaller than in a real environment. From the previous chapter we saw distinct variation in the outputs and for the GHG and this could be linked to the variation in the Q_{10} value used in the model. However to justify the need for clarification of the Q_{10} used there is a need to consider whether there is a significantly large amount of variation in the soils from different location and regimes for this to possible effect the outputs. If a Q_{10} of 2 or slightly higher is found there is no justification for this, however if there is considerable variation then a further understanding of the Q_{10} used by the DNDC model is needed and an explanation of why 2 is used. I hypothesise that the soil respiration will increase with increasing temperatures giving results which can be described well using a Q_{10} value of 2 and confirming the values use for the DNDC model. Therefore this chapter critically tests the influence of geographical location and management on the applicability of Q_{10} values over short time scales. It is hypothesised that the Q_{10} values will vary with latitude (i.e. Q_{10} s are higher at higher, colder latitudes) and that values significantly greater than 2 will be obtained over extended temperature ranges (5-30°C).

3.3. Materials and methods

3.3.1. Soil samples

Three replicate 50 g samples of soil were taken at a 0-15 cm depth from agricultural fields located in (1) the Murcia region of Spain, (2) Worcestershire in the UK, and (3) the Wakiso, Kampala, Mukono and Luwero districts of Uganda. Samples were randomly selected from within the fields (Koerber et al., 2009). The overseas samples were shipped to the UK in cool boxes and stored at 5°C until needed for the experiments. The fields used for sampling had been selected as part of a larger experiment concerned with greenhouse gas emissions from vegetable production as detailed in Koerber et al. (2009). As a result, each country contained fields of at least one of the target vegetable type (brassicas, leafy salads, peas and beans). Samples of soils from Germany, Australia and Antarctica were obtained from other surveys and experiments being undertaken within the School of the Environment and Natural Resources at Bangor University. These included soils collected by Prof Davey Jones (Australia; as detailed in Jones and Murphy, 2007), Dr Paul Hill (Germany; as detailed in Akagi and Zsolnay, 2008) and Dr Paula Roberts (Antarctica; as detailed in Roberts et al., 2009). Details of the soils used in the experiments are presented in Table 4-1 while the chemical and physical properties of the soils are reported in the individual studies detailed above. Each of the soils had been collected with similar methods to those described for the soils from Spain, the UK and Uganda, above, except that the Antarctica soils were stored frozen at -20°C and defrosted at 5°C for 7 days prior to use. Three replicates were taken from each field with the exception of the Spanish field 'Lettuce 7' where only two replicates were taken, and two of the Australian areas where only one sample could be used, owing to the small amount of soil collected.

Table 3-1: Summary of the geographical location, crop type and climatic regime of the soil samples used in the experiments. nd indicates not determined. Values represent means \pm SEM.

Country	No. of fields sampled	Vegetation status	Annual rainfall (mm)	Maximum temp (°C)	Minimum temp (°C)	Soil type	Soil moisture (g g ⁻¹)	Bulk density (g cm ⁻³)	Soil pH	SOC at surface (kg C kg ⁻¹)
Spain	9	Brassicas	300-350	39	-0.3	Loam	0.21 \pm 0.01	1.21 \pm 0.03	7.85 \pm 0.03	0.053 \pm 0.003
	7	Lettuce	300-350	39	-0.3	Loam	0.17 \pm 0.01	1.22 \pm 0.03	7.88 \pm 0.04	0.054 \pm 0.004
UK	5	Beans	600-650	35	-10	Loam-Sandy Loam	1.05 \pm 0.04	1.68	6.38 \pm 0.09	0.015 \pm 0.003
	4	Brassicas	600-650	35	-10	Clay-Loam	1.10 \pm 0.02	1.80	6.55 \pm 0.32	0.015 \pm 0.004
	1	Lettuce	600-650	35	-10	Clay-Loam-Loamy Sand	1.07 \pm 0.02	1.75	6.32 \pm 0.36	0.025 \pm 0.007
	1	Vining peas	600-650	35	-10	Clay-Loamy Sand	1.12 \pm 0.02	1.67	6.32 \pm 0.36	0.019 \pm 0.004
Uganda	5	Cabbage	750-2000	30	15	Sandy Clay Loam	0.26 \pm 0.01	1.063 \pm 0.121	5.06 \pm 0.25	0.037 \pm 0.004
	3	French beans	750-2000	30	15	Sandy Loam	0.24 \pm 0.04	1.063 \pm 0.121	5.18 \pm 0.21	0.045 \pm 0.019
	3	Lettuce	750-2000	30	15	Silty Clay Loam	0.21 \pm 0.01	1.063 \pm 0.121	4.91 \pm 0.08	0.025 \pm 0.003
	3	Sugar beet	750-2000	30	15	Sandy Clay Loam	0.16 \pm 0.01	1.063 \pm 0.121	5.76 \pm 0.41	0.020 \pm 0.004
Germany	3	No plants	820-920	37	-27	Clay Loam	0.21 \pm 0.01	nd	6.00 \pm 0.03	nd
	3	Grassland	820-920	37	-27	Clay Loam	0.26 \pm 0.01	nd	5.70 \pm 0.09	nd
	3	Rape	820-920	37	-27	Clay Loam	0.22 \pm 0.01	nd	6.80 \pm 0.10	nd
Antarctic	3	Lichen tundra	500-1000	-15	-70	Sandy Silt Loam	0.78	nd	6.82 \pm 0.12	nd
	3	Polar grass	500-1000	-15	-70	Sandy Silt Loam	0.14	nd	6.02 \pm 0.13	nd
	3	No plants	500-1000	-15	-70	Sandy Silt Loam	0.390	nd	5.22 \pm 0.32	nd
Australia	1	Jarrah forest	1000	23	11	Loamy sand	0.22 \pm 0.01	1.04 \pm 0.01	5.84 \pm 0.01	0.38 \pm 0.03
	1	Karri forest	1100	23	11	Loamy sand	0.22 \pm 0.01	1.04 \pm 0.01	5.84 \pm 0.01	0.38 \pm 0.03
	3	Banksia bushland	800	23	11	Loamy sand	0.02 \pm 0.00	1.36 \pm 0.02	6.55 \pm 0.03	0.20 \pm 0.02

3.3.2. Soil respiration measurements

Twenty grams of the 50 g collected of soil was measured into a 50 cm³ polypropylene centrifuge tube. To remove any CO₂ present in the soil samples prior to experimentation, a 1.5 ml reaction vial, containing 1 ml of 1 M NaOH, was placed on the surface of the soil and the tubes capped for 24 h. This procedure was undertaken to ensure that all CO₂ trapped in the soil was removed prior to respiration measurements being taken. The NaOH reaction vials were subsequently removed from the centrifuge tubes prior to placement of the tubes on an automated 12 channel SR-1 Soil Respirometer equipped with an infra-red gas analyser (IRGA) (PP-Systems Ltd, Hitchin, UK). The gas switching unit of the SR-1 ensures that respiration measurements are made from each sample channel every 16.5 mins. During each run, 9 of the channels logged respiration from soil. The three remaining channels contained no soil and were used as controls (blanks).

The SR-1 was placed in a Sanyo climate-control cabinet (Sanyo Biomedical Europe Ltd., Loughborough, UK) and a 24 h temperature ramping programme employed to automatically regulate the temperature of the soil. A progressive upward temperature ramp at 5°C intervals was run between 5 and 30°C for 12 h, followed by a declining ramp from 30 to 5°C over the next 12 h. The temperature in the climate control cabinet was held at a given level for 2 h before moving to the next temperature. The temperatures were chosen to reflect the typical range of those experienced in the field at most sites. The humidity in the cabinet was kept constant at 70% and the system was kept in the dark. During each experimental run a set of 3 Watchdog temperature loggers were placed in the cabinet to monitor whether the set temperatures were achieved.

Each experiment ran for 72 h to allow the soils to settle after being disturbed and the respiration results recorded only for the third day unless otherwise stated.

3.3.3. Calculations of Q_{10} values

The respiration results were plotted against temperature and the Q_{10} values calculated using the equation:

$$Q_{10} = (R_2/R_1)^{(10/T_2-T_1)} \quad (\text{Eqn. 2})$$

where R_1 is the first respiration result at T_1 , R_2 is the second respiration result at T_2 , and where T_1 and T_2 are the temperatures used for the two measurements (Figure 3-2). The Q_{10} value was calculated at two main intervals: during the 10-20°C rise, the 20-30°C rise, the 30-20°C fall and the 20-10°C fall. In addition, the mean Q_{10} for each 10°C temperature difference was calculated for all soils to check for extreme differences.

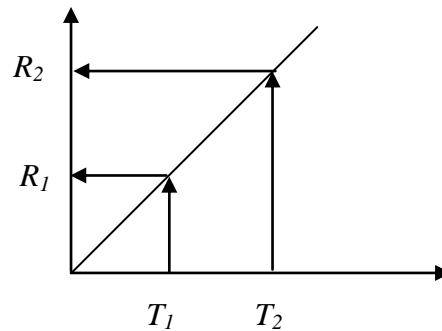


Figure 3-2: The values for the Q_{10} calculation, with respiration results on the y-axis and temperature on the x-axis. T_1 and T_2 have a 10°C difference.

3.3.4. Statistical Analysis

All statistical analysis was performed using SPSS version 18 (SPSS Inc, Chicago, IL). A univariate analysis of variance was used with the dependant variable for figure 3-(5 to 11) being the temperature. For figures 3-12 and figure 3-13 the dependent variable was the countries and for figure 3-16 the dependant variable was the crop type.

3.4. Results

3.4.1. Experimental climate regime

During each experimental run the climate-controlled cabinet was monitored to determine whether the programmed maximum and minimum temperatures were achieved. Figure 3-3 shows the temperature at which the climate cabinet was set and the actual temperature recorded at the level of the soil samples. It is apparent that the temperature inside the cabinet did not increase in a stepwise regime, as expected, but in a more linear pattern ($r^2 > 0.999$ on both upward and downward ramps). The maximum temperature recorded was 29.1°C and the minimum temperature was 4.6°C.

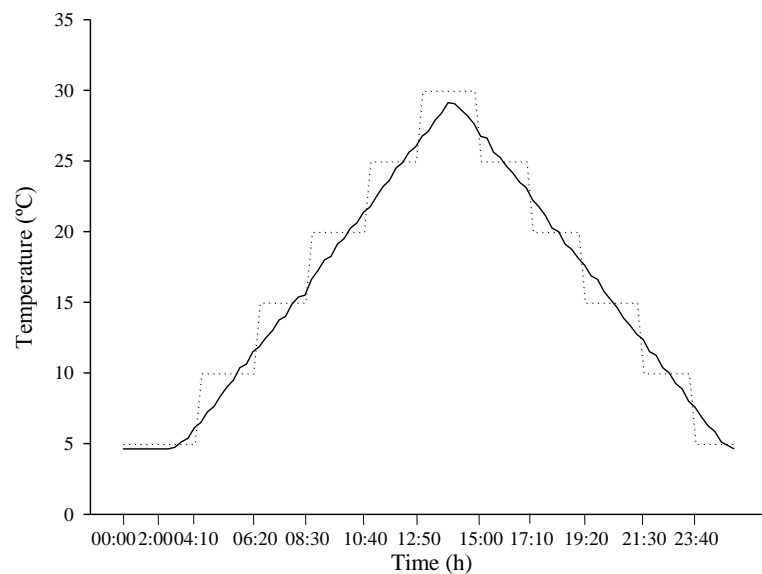


Figure 3-3: Comparison of the actual temperature (solid line) and expected temperature (dashed line) observed over a 24 h period. Experimental values represent the average of three independent temperature cycles.

3.4.2. Long term soil respiration response

In one experimental sample run, soil respiration was measured over 12 successive thermal cycles to determine the long term trends in CO₂ output. Overall, it was found that soil respiration progressively declined over the 12 day period - although the magnitude of the decline reduced with time (Figure 3-4). The decrease in soil respiration was thought to be due to (1) the microbes settling after being physically disturbed by the movement and setting up of the containers in the chambers, and (2) progressive C substrate limitation of the soil microbial community. From the third

thermal cycle onwards the rising and falling limbs were found to possess approximately the same shape, and therefore these results were used for calculating Q_{10} values. Although the peak in respiratory flux declined over time, this pattern was not apparent at 5°C, where a constant flux was observed.

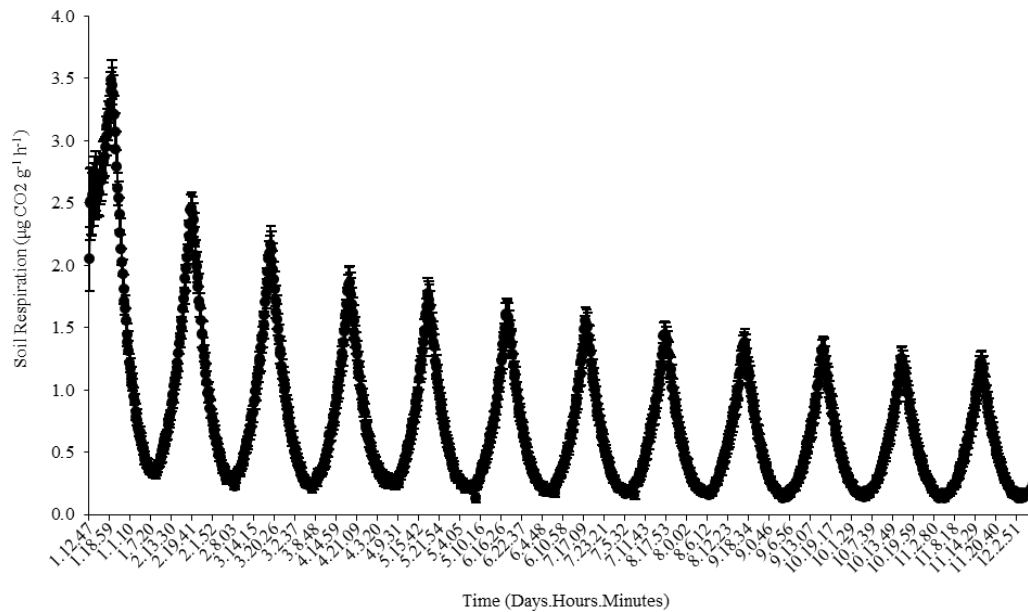


Figure 3-4: Soil respiration measured over a 12 day period in soil collected from a Brassica field in Spain. Each peak represents a 24 h thermal cycle whilst each • represents a 15 min interval. Values represent means \pm SEM ($n = 3$). The results obtained on the third day were used in the Q_{10} calculations.

3.4.3. Responses of soil respiration to daily temperature cycles

The soil respiratory flux measured during either the rising or falling half of the thermal cycle were plotted against temperature for each field in each geographical location. Graphing the fields in this way allowed us to see if there were any lags in the microbial response to the temperature. If such a response was apparent, this would have been representative of hysteresis, which is the dependence of a system not only on its current environment but also on its past conditions (evidenced by the system's failure to respond immediately to the change in its environment). If the system exhibits hysteresis then a flat top in CO_2 efflux during the downward thermal cycle would be expected. From Figure 3-5 it is evident that there was no lag phase in the respiration response found at either the highest or lowest temperature phases, suggesting that there was no hysteresis. The highest and lowest values for soil

respiration of both limbs were $2.57 \text{ mg CO}_2 \text{ kg}^{-1} \text{ h}^{-1}$ and $0.34 \text{ mg CO}_2 \text{ kg}^{-1} \text{ h}^{-1}$, respectively. A paired t-test showed no significant differences in the soil respiration response to temperature between the upward and downward halves of the cycle ($p = 0.917$).

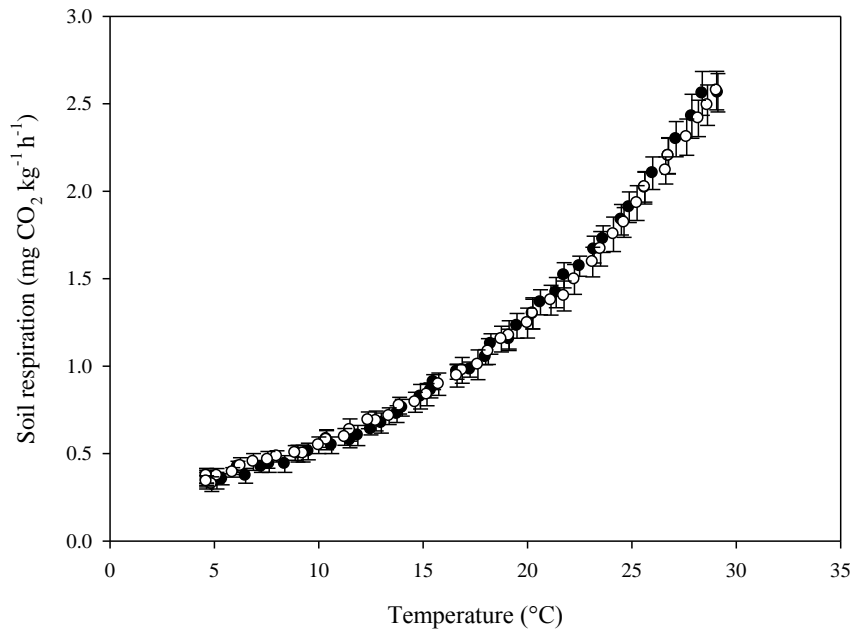


Figure 3-5: Soil respiration during the rising (●) or falling (○) limb of a diurnal thermal temperature cycle for soil collected from a lettuce field in Spain. Values represent means \pm SEM ($n = 3$).

Statistically significant differences in soil respiration were apparent between soils collected from the same location but under different vegetable crops ($p < 0.001$). The highest emissions were seen for soil collected from lettuce fields in Uganda and Spain: $2.67 \text{ mg CO}_2 \text{ kg}^{-1} \text{ h}^{-1}$ and $2.87 \text{ mg CO}_2 \text{ kg}^{-1} \text{ h}^{-1}$ respectively (Figure 3-6A and 3-6B). The respiration patterns in response to temperature were similar to those presented in Figure 3-3.

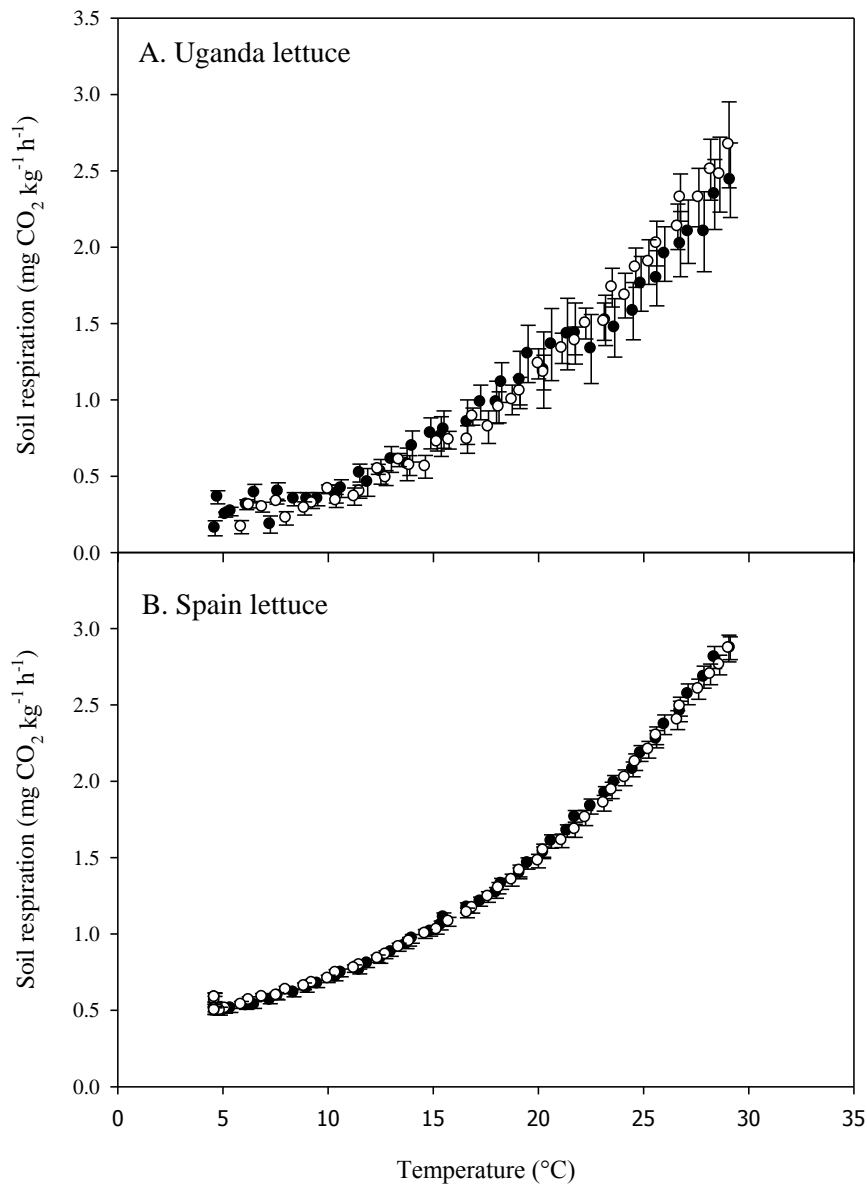


Figure 3-6: Soil respiration during the rising (●) or falling (○) limb of a diurnal thermal temperature cycle in two lettuce field soils from two contrasting geographical locations (Spain and Uganda). Values represent means \pm SEM ($n = 3$).

3.4.4. Influence of geographical region

The results obtained for the different vegetable fields in each country were collated to give an average graph for soil respiration (Figures 3-7). Australia was removed from this study as the soil respiration showed very little reaction to changes in temperature; it did however have a correlation between the rising and falling limb, though not to the same CO₂ emission levels as the other soils. The lack of reaction to temperature

may be due to the small amount of soil used and the length of time the soils were stored before use (i.e. high level of C substrate limitation).

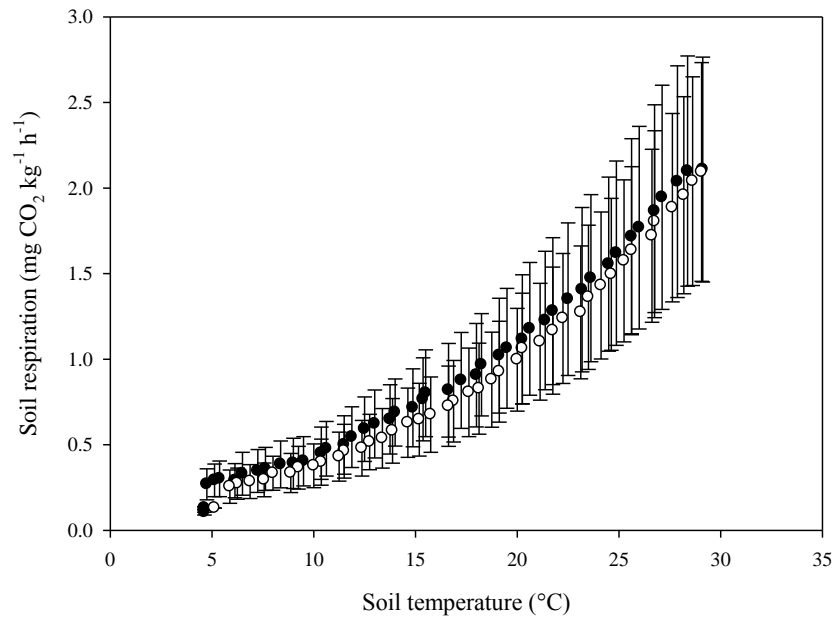


Figure 3-7: Soil respiration during the rising (●) or falling (○) limb of a diurnal thermal temperature cycle for a range of soils obtained from UK vegetable fields. Values represent means \pm SEM ($n = 11$).

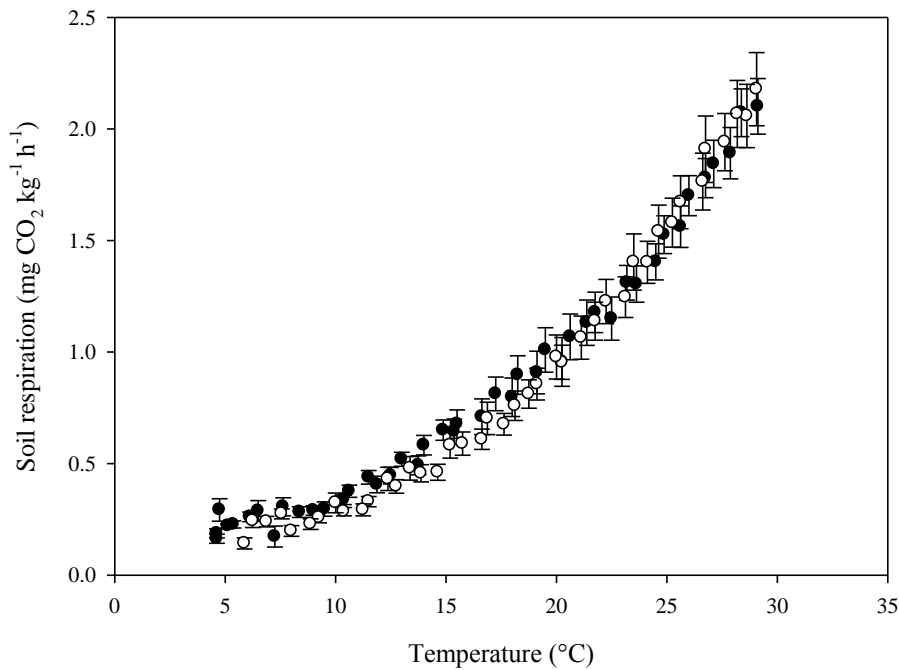


Figure 3-8: Soil respiration during the rising (●) or falling (○) limb of a diurnal thermal temperature cycle for a range of soils obtained from Ugandan vegetable fields. Values represent means \pm SEM ($n = 14$).

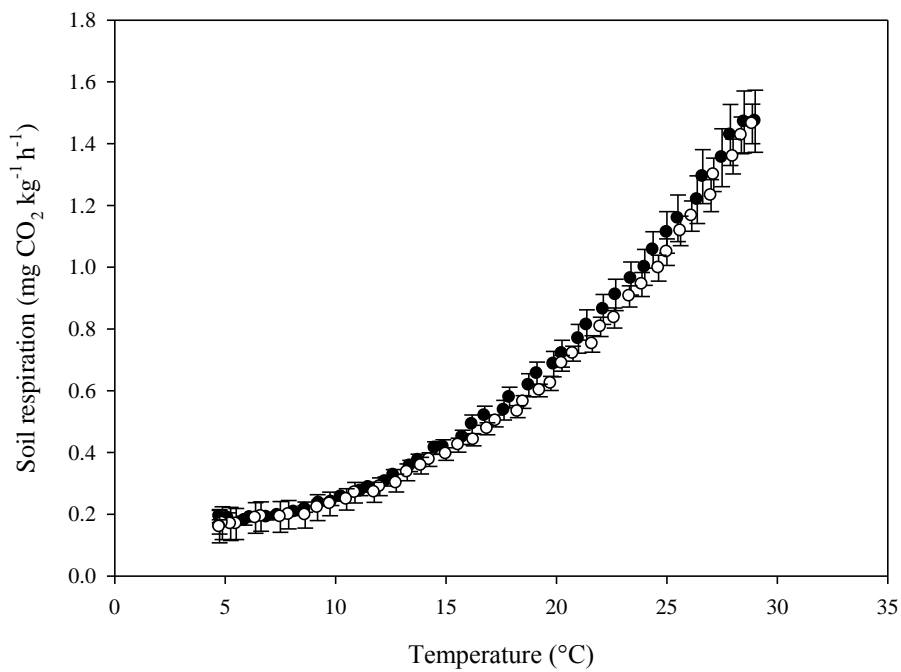


Figure 3-9: Soil respiration during the rising (●) or falling (○) limb of a diurnal thermal temperature cycle for a range of soils obtained from German agricultural fields. Values represent means \pm SEM ($n = 9$).

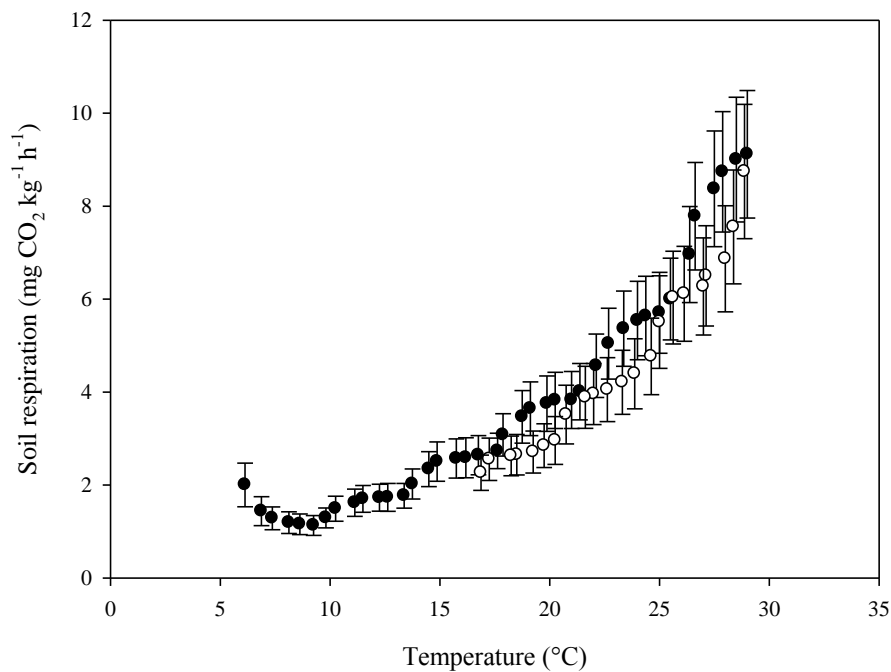


Figure 3-10: Soil respiration during the rising (●) or falling (○) limb of a diurnal thermal temperature cycle for a range of soils obtained from Antarctica. Values represent means \pm SEM ($n = 9$).

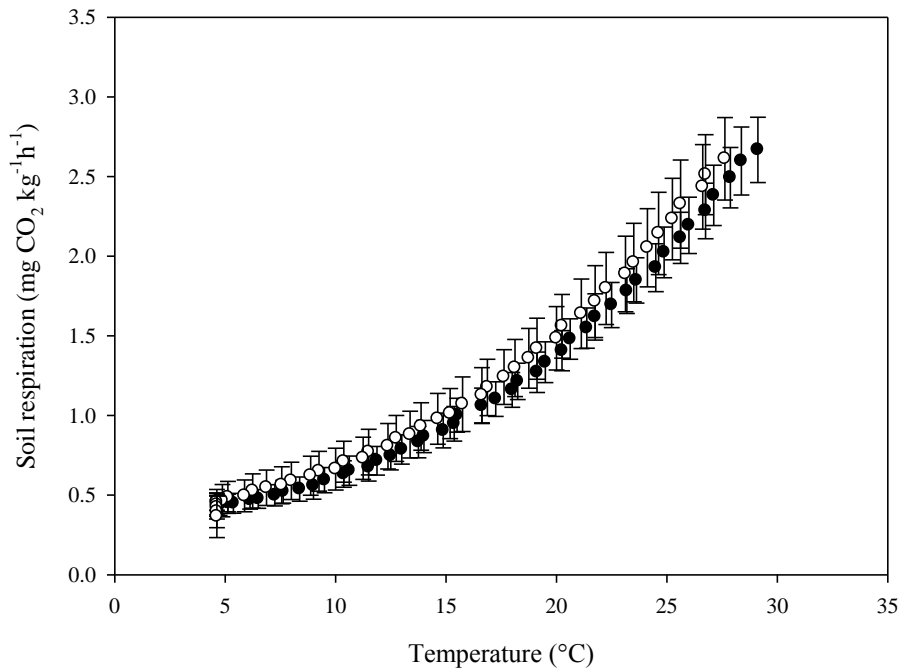


Figure 3-11: Soil respiration during the rising (●) or falling (○) limb of a diurnal thermal temperature cycle for a range of soils obtained from Spanish vegetable fields. Values represent means \pm SEM ($n = 16$).

The soil respiration results for each area varied, with the Antarctic soils (Figure 3-10) having the highest emissions of CO₂ and the soils from Germany (Figure 3-9) the lowest (Table 4-2). It is also apparent that the magnitude of the standard errors increased as the temperature increased. This, however, appeared proportional to the increase in the mean value. Antarctica had reduced measurements taken on the falling temperature limb due to equipment failure.

For the UK soils, soil respiration in the falling temperature limb did not give significantly lower results than with the rising limb ($p < 0.462$). In contrast, Spain was the only country to have a lower result for the rising limb in comparison to the falling limb ($p < 0.05$). For the Antarctic there are greater emissions from the rising than for the falling limb, which stopped at 16°C due to technical problems.

Table 3-2: Average soil respiration for each country measured at either 5°C or 30°C. Values represent means \pm SEM.

Geographical region	Soil respiration (mg CO ₂ kg ⁻¹ h ⁻¹)	
	5°C	30°C
Spain	0.36 \pm 0.13	2.67 \pm 0.21
UK	0.12 \pm 0.02	2.11 \pm 0.66
Uganda	0.14 \pm 0.02	2.18 \pm 0.16
Germany	0.16 \pm 0.02	1.47 \pm 0.10
Antarctic	2.00 \pm 0.47	9.12 \pm 1.37

3.4.5. Dependence of geographical location on the Q_{10} for soil respiration

The respiration results described below were used to calculate the Q_{10} value for the area within each country. The values are not meant to be representative of the whole country. In most of the literature, the Q_{10} value is classified as being equal to 2 for soil respiration; consequently all the experimental values were compared to this theoretical value. In the results presented here all the countries on both the rising and falling limb had an experimentally derived Q_{10} value above 2 and an overall average value of approximately 2.72 (Figure 3-12). The Antarctic was found to give significantly different results from Spain, Worcestershire and Germany ($p = 0.000$, 0.001 and 0.001 respectively) and Spain was found to be significantly different from Uganda ($p = 0.002$).

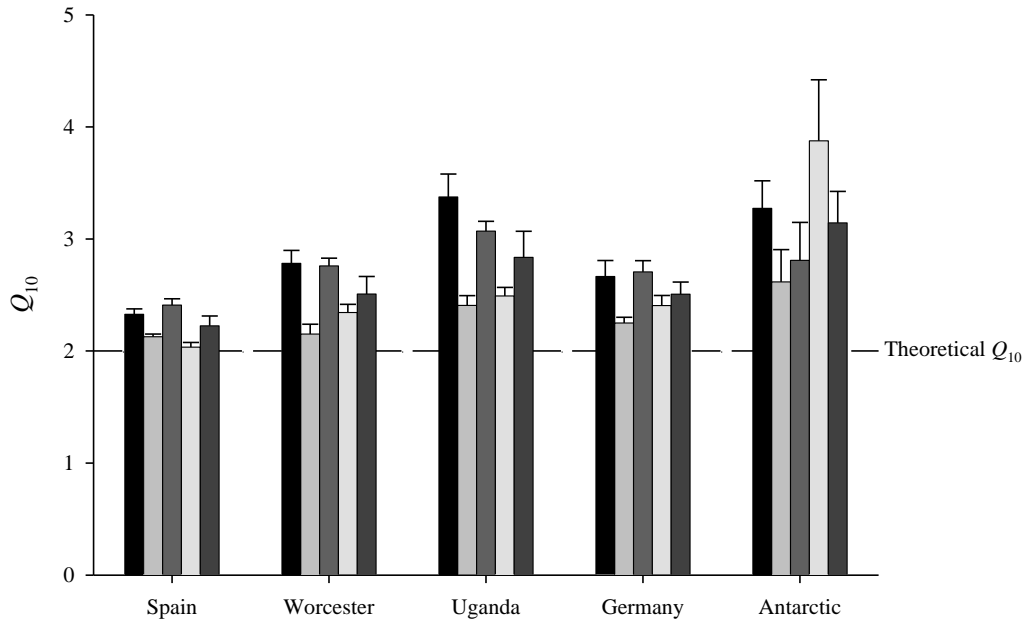


Figure 3-12: Q_{10} value for soil respiration measured for a range of countries across the temperature range 10 to 30°C. Q_{10} values were determined during a rise or fall in temperature from either 10-20 or 20-30°C. Bars are denoted as follows: Rising 10-20°C (black), 20-30°C (light gray) and falling 10-20°C (dark gray), 20-30°C (white) temperature and average Q_{10} (dark gray).

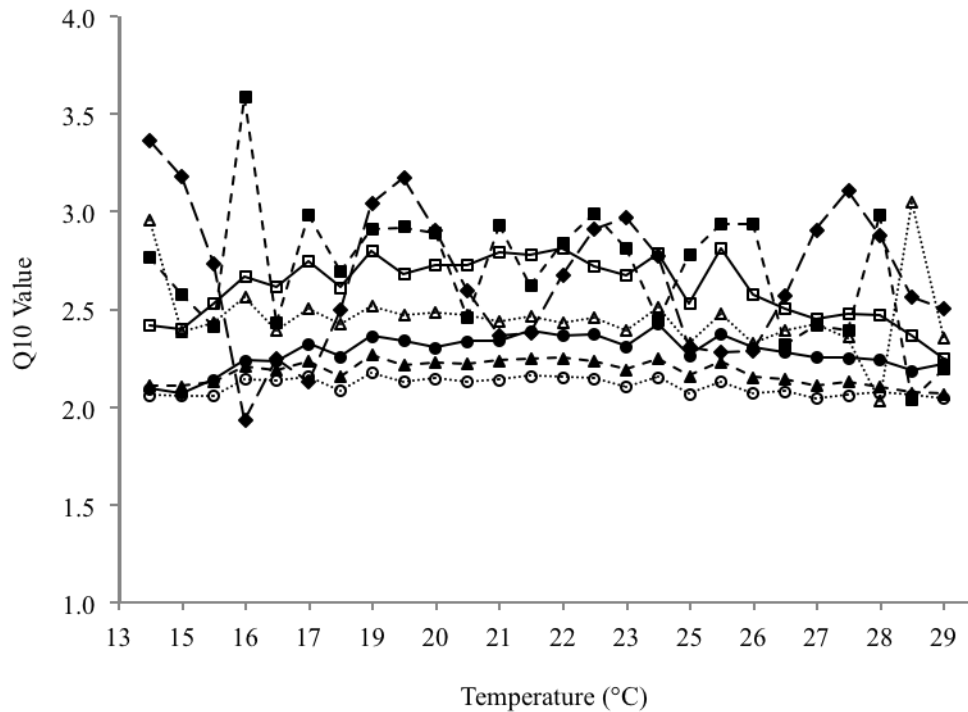


Figure 3-13: Comparison of the Q_{10} value for soil respiration in samples from a range of countries measured across the temperature regime 5 to 30°C. Q_{10} values were determined at 10°C intervals for each temperature difference (i.e. 5 to 15, 6 to 16, 7 to 17°C etc). Values represent means \pm SEM. The legend and mean \pm SEM for each country is as follows: 2.28 ± 0.017 ($n = 9$) for Spain brassicas (\bullet), 2.11 ± 0.008 ($n = 7$) for Spain lettuce (\circ), 2.18 ± 0.012 ($n = 16$) for Spain (\blacktriangledown), 2.43 ± 0.056 ($n = 11$) for the UK (∇), 2.70 ± 0.064 ($n = 14$) for Uganda (\blacksquare), 2.61 ± 0.031 ($n = 9$) for Germany (\square) and 2.66 ± 0.072 ($n = 9$) for Antarctica (\blacklozenge).

The Q_{10} values shown in Figure 3-13 were calculated for each 1°C incremental difference in temperature from 5 to 30°C (rather than just 10-20°C and 20-30°C) except for the soil from Australia. The results were found to be statistically similar ($p = 0.466$). The results shown above all show a consistent result of having a Q_{10} above 2.0 and a generally constant Q_{10} value is seen across the complete temperature range, apart from the Antarctic. Soils collected from under lettuce fields in Spain had the lowest Q_{10} values on average, while soils from Uganda had the highest. The experimental values shown in Figure 3-14 were log transformed to make comparison between countries easier.

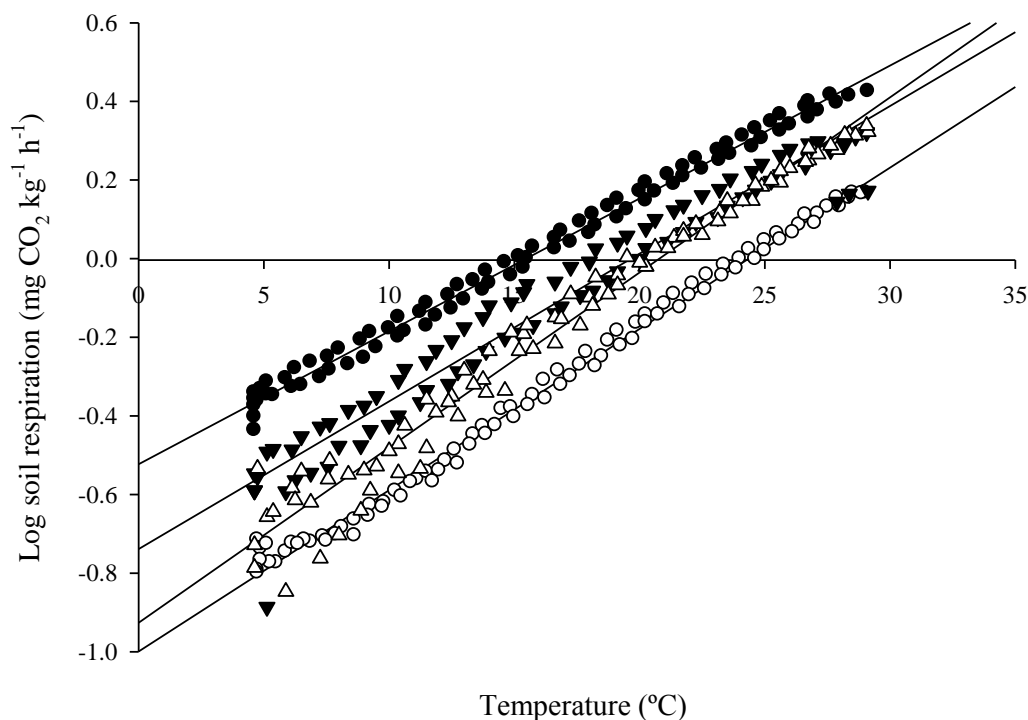


Figure 3-14: Natural Log_{10} transformed soil respiration values for each country across the temperature range 5 to 30°C. The countries are ● Spain, ○ Germany, ▼ UK and ▽ Uganda. Spain had an r^2 of 0.993 and equation of $y=0.0338x-0.5230$, Germany had an r^2 of 0.994 and equation of $y=0.0410x-0.9994$, UK had an r^2 of 0.948 and equation of $y=0.0376x-0.7388$ and Uganda had an r^2 of 0.974 and equation of $y=0.0446x-0.9259$.

The log transformed CO_2 emission values calculated for each country are shown in Figure 3-14 and confirm that the results adhere to a first order rate of reaction. The graph shows a difference between each of the countries. Uganda's results were found to be further away from the trend line when compared to Figure 3-10. The result for each country converges towards the higher end of the temperature range. The results with the highest respiration had also the highest climatic temperatures, and this pattern

continued - the lowest results being for the area with the lowest mean annual temperature. Many of these average results fit well to a trend line and show that the results are of a first degree linear order for Q_{10} .

3.4.6. Differences between vegetable species

The variation in Q_{10} values between soils collected from under different vegetables crops was examined across the range of countries over the 10-20°C and 20-30°C range for the rising and falling limbs of the thermal cycle (Table 4-3, Figure 3-16). Although there were some differences in the Q_{10} values for the rising and falling limbs there was no consistent pattern across all vegetable types. All vegetables gave a Q_{10} value over 2, with sugar beet having the largest overall value, while Beans and Lettuce had the lowest average Q_{10} (Table 4-3). Overall, the differences between the vegetables are minimal and all fit in a range between 2.26-2.97.

Table 3-3: Average Q_{10} values for four different cropping soils for the rising and falling limbs over two temperature steps (10-20 and 20-30°C) and then averaged across the 10-30°C range. The Antarctic and Australian soils have not been included in this.

Vegetable	Rising temperature		Falling temperature		Mean
	10 to 20°C	20 to 30°C	10 to 20°C	20 to 30°C	
Brassicac	2.45	2.20	2.67	2.15	2.37
Lettuce	2.49	2.11	2.34	2.10	2.26
Beans	2.89	2.18	2.94	2.47	2.62
Sugar beet	4.44	2.62	2.65	2.15	2.97

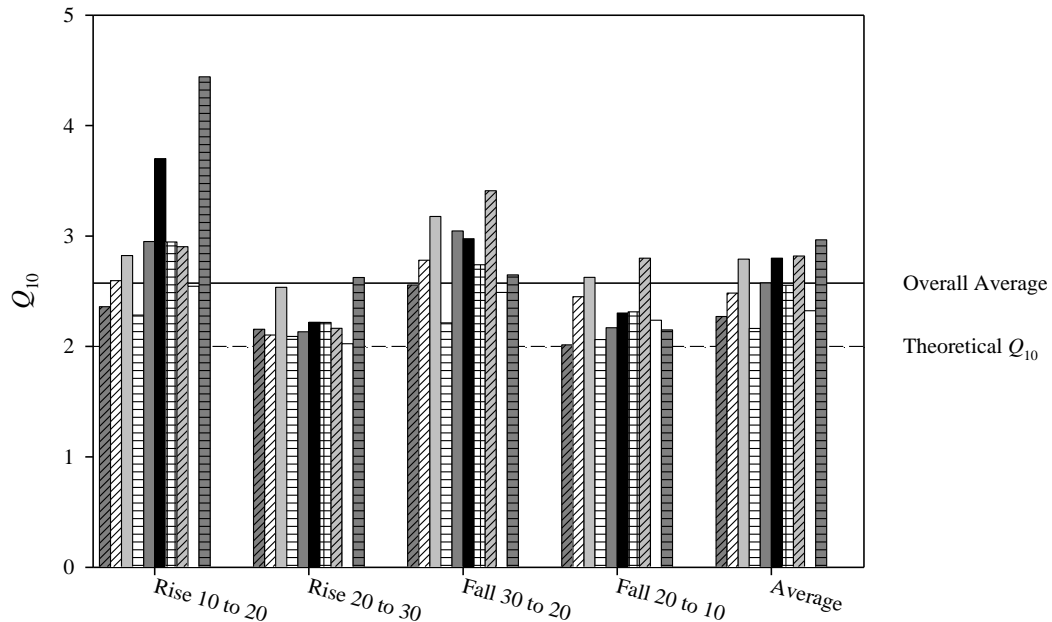


Figure 3-15: Effect of crop type on the Q_{10} value for soil respiration measured across the temperature range 10 to 30°C for different crops in different geographical locations. Q_{10} values were determined during a rise or fall in temperature from 10-20 or 20-30°C. The legend and mean \pm SEM values for each treatment are as follows: 2.27 ± 0.119 ($n = 9$) for Spain brassicas (▨), 2.48 ± 0.143 ($n = 4$) for UK brassicas (▧), 2.79 ± 0.142 ($n = 5$) for Uganda brassicas (▩), 2.16 ± 0.052 ($n = 7$) for Spain lettuce (▪), 2.58 ± 0.245 ($n = 1$) for UK lettuce (▬), 2.80 ± 0.345 ($n = 3$) for Uganda lettuce (▣), 2.55 ± 0.173 ($n = 5$) for UK beans (▩), 2.82 ± 0.256 ($n = 3$) for Uganda French beans (▧), $2.32 \pm 0.12+0$ ($n = 1$) for UK vining peas (▭) and 2.97 ± 0.505 ($n = 3$) for Uganda sugar beet (▨).

Figure 3-17 shows the log transformed soil respiration data using the experimental results shown in Figure 3-(7-11). Overall, this gives a clear picture of which vegetable types will give off more emissions and which will give off the least and at what temperatures, if the soil characteristics for those crops are similar. At higher temperatures the type of vegetable crop has little effect on the amount of CO₂ produced. At a lower temperature there does seem to be some effect, with sugar beet being the lowest producer and the rest being approximately the same, with little variation.

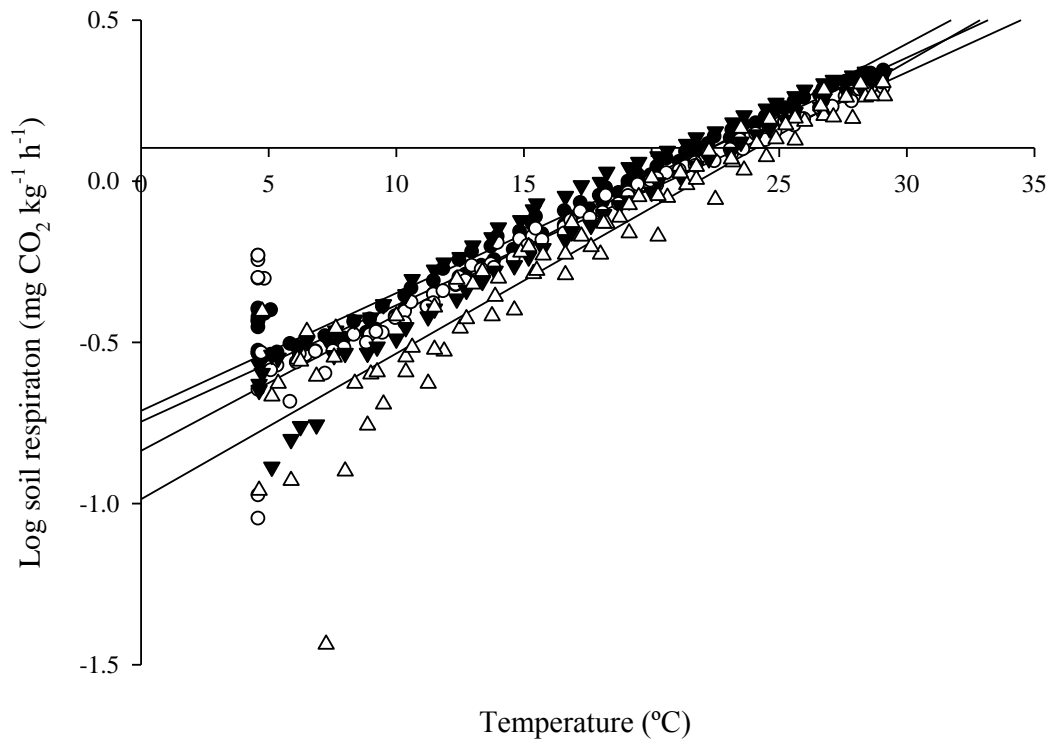


Figure 3-16: The \log_{10} of soil respiration for each vegetable type averaged across a range of countries. Each vegetable has a linear regression line of best fit put through it. The legend and linear regression coefficient for each vegetable are as follows: (●) brassicas had an r^2 of 0.974 and a $y=0.0365x-0.7121$, (○) lettuce had an r^2 of 0.875 and a $y=0.0361x-0.7463$, (▼) Beans had an r^2 of 0.950 and a $y=0.0421x-0.8363$ and (▽) sugar beet had an r^2 of 0.872 and a $y=0.0452x-0.9865$.

3.5. Discussion

The only common theme among these various approaches to modelling respiration is that they all include an empirically derived Q_{10} function, although the range of reported Q_{10} values is large (Davidson et al., 1998). As Pavelka et al. (2007) states, the complex mixture of production and transport processes usually has to be reduced to a simpler equation. One such relationship, which is well established in biology, is the one that exists between enzymatic reactions and temperature (Davidson et al., 2006). The Q_{10} temperature coefficient is a measure of the rate of change of a biological or chemical system as a consequence of raising or lowering the temperature by 10°C.

For individual enzymes the Q_{10} value is typically equal to 2. Many studies have shown that the soil respiration rate, an indicator of soil microbial activity, increases exponentially with an increase in temperature (Huang et al., 2005; Liu et al., 2006). However, describing the relationship in a complex soil environment is more difficult. Regardless of the soil type, texture or history, a diverse and abundant microbial community exists in soil in which many enzymes are operating simultaneously (Nelson, 1997). Thus it is clearly conceivable that soil respiration is actually the summation of the action of maybe 100,000 different enzymes. The biochemical feedback loops between these enzymes is likely to be highly complex. This could mean that the Q_{10} value can deviate from the theoretical value of 2. In this respect, the results presented here support this view that soil-temperature relationships cannot be described by a universal Q_{10} value.

Across a wide range of soils, the experiments described here found Q_{10} values to range between 2.26 to 4.44 with an overall average value of 2.64. These values disprove my hypothesis of 2 being an acceptable value for the Q_{10} used for the DNDC model. The values found agree with the broad soil science literature, which suggests that Q_{10} values can vary greatly between individual experiments, with published values ranging between 1.35 and 2.88 (Kätterer et al., 1998). We therefore suggest modellers should consider values according to the intrinsic soil characteristics, vegetation type or latitude rather than just using the one value for all situations. Typically, Q_{10} values for soil respiration are assumed to range between 2 and 3, but in extreme cases may go as high as 5 (Clark et al., 2009). The premise that the Q_{10} constant is 2 is now being reconsidered by some ecosystem mathematical modellers in light of the increasing evidence that Q_{10} values may approximately double or triple for every 10°C rise in temperature. The reaction of SOM pools to the variations in temperature is considered to be equal ($Q_{10}=2$ at 30–35°C; $Q_{10}=4-6$ at 5–10°C) in most current C turnover models which are based on measurements of the CO₂ efflux from short term laboratory incubations of bulk soils (Kirschbaum, 1995; Von Lützow and Kögel-Knabner, 2009). For example, Li et al. (1992), the developers of the widely used DNDC (DeNitrification-DeComposition) model originally used a Q_{10} value of 2 to describe how soil organic matter breakdown is affected by temperature. However, in an updated version of the model Li et al. (1994a) use a Q_{10} value of 2.5, while in Li et al. (2000) the Q_{10} is once again described as 2.0. This change in value may account for the variable output from different versions of the DNDC model reported in

Chapter 3. In nearly all the published work made using DNDC the authors do not actually report the Q_{10} value used, so it is difficult to assess the validity of the model outputs. The CENTURY and Rothamsted (RothC) soil organic matter turnover models use temperature functions to describe the decomposition of soil organic matter to account for greater temperature sensitivity at lower temperatures rather than a single Q_{10} value (Davidson et al., 1998). This approach has significant merit, especially for soils which experience frequent temperatures below 10°C. As studies have revealed that soil temperature can explain up to 95% of variance in soil respiration rates, it is critical that the right approach to modelling soil temperature responses is taken (Pavelka et al., 2007).

When considering the results presented here in relation to the properties of the soils in each area studied, it was found that the variability in intrinsic soil characteristics appeared to have little impact on the resultant Q_{10} values. For example, no clear pattern was observed between the magnitude of CO₂ efflux, pH, texture, moisture content or organic matter content with Q_{10} . It should be mentioned, however, that to definitively test these relationships would require much better sample stratification than used here (e.g. replicate soils sampled over a sand to clay texture gradient or the sampling of soil held at varying matric potentials from -50 kPa (field capacity) to beyond permanent wilting point (<-1500 kPa)). Despite this limitation, the results may not be that surprising for soil moisture, as Illeris et al. (2004) found that soils with different moisture contents had similar temperature response CO₂ efflux profiles. The pH of the soils used here was found to be very similar, so Q_{10} relationships with this soil factor could not be reliably established in this study. To carry out a more systematic study on the impact of pH, soils could be used which naturally vary in pH (e.g. acid podzols through to calcareous rendzinas at high pH). However, this approach would have many other confounding factors, as the soils will vary significantly in many other parameters other than pH. A better approach would be to sample soils across an established liming gradient as undertaken in Rousk et al. (2011).

We found a very weak correlation between Q_{10} and latitude from which the sample originated. A similar response was also found by Bekka et al. (2003). This may reflect either differences in microbial community structure or differences in C substrate availability (Davidson et al., 1998). This is supported to some extent by Von Lützow and Kögel-Knabner (2009) who suggest that, due to higher C stocks being

found at higher latitudes, more SOM is available for soil respiration by the microbes. Trumbore et al. (1996) reported a latitudinal variation in Q_{10} values with higher values found in colder climates, although the values were also affected by soil moisture conditions (Davidson et al., 1998).

Overall, the Q_{10} values for soils collected from under different vegetable crops showed similar temperature responses, irrespective of geographical latitude. Beier et al. (2008) found that the plots with different vegetation cover showed no differences in temperature sensitivity, since no significant differences were observed across the temperature gradient. It was expected that the different crops would create differences in the structure, activity and biomass of the soil microbial community and that this may have affected both the rates of soil C cycling and, possibly, enzymatic breakdown pathways (Jones et al., 2004). This change in the microbial community can occur directly as a result of: plant-induced changes in rhizodeposition; species differences in root turnover rates; differences in mycorrhizal status and N_2 fixing bacteria; above-ground litter inputs/quality; and, indirectly, in response to different agronomic management regimes (e.g. fertilisers, pesticides). As Liu et al. (2006) point out, it is important to consider changes in Q_{10} with environmental conditions as well as soil types and geographical locations. Although the microbial community was not characterised here, the variation in the areas where the samples were collected could give an indication of different microbial communities as well as soil characteristics. Briones et al. (2004) found that impacts of soil warming on mesofauna (e.g. enchytraeids) is also an important consideration when trying to explain how CO_2 fluxes will respond to changes in temperature. One drawback of this study was that only a limited number of samples were available for some crop types in some countries, creating a potential bias (e.g. one field per vegetable type in the UK, with three replicates). Bernhardt et al. (2006) and Cruiel Yuste et al. (2004) have found variation in Q_{10} depending on seasonality and climatic changes, factors that were not considered here. In their study, seasonal changes in soil temperature follows the order summer > autumn > spring > winter, which corresponded to seasonal variations in soil CO_2 flux which could cause variation in Q_{10} values (Lou et al., 2004). This may also contribute to the variability between crop types, as soil sampling did not occur at the same point in the season, and the stage of plant development was also different.

The Australian results could not be used in the overall analysis. This was because of the very low levels of respiration in these samples, which was thought to

be a consequence of the small quantity of soil used and the air-dry conditions in which the soil was stored for a few months prior to analysis. Even when the three replicates were combined, there was still too little soil to give consistent results. If this experiment were to be repeated, there are parts of the protocol that would need improvement. It would be worth having a bigger set of samples and more replicates for the vegetable crop types, preferably all grown on the same soil type. In addition, soil moisture should be maintained at a constant matric potential (e.g. -50 kPa) for each soil, particularly as Davidson et al. (1998) found altered respiration patterns under dry (drought) soil conditions (< -1.5 MPa). This excessive dryness could affect the soil respiration by reducing microbial movement and limiting substrate and enzyme diffusion rates and ease of CO₂ escaping from the sample. Although we found no evidence for hysteresis in soil respiration, this may be because of the way the small volumes of soil were uniformly warmed. In the field, temperature change is not uniform throughout a soil; typically, it warms from the top down in spring and cools from the top down in autumn – conditions in which hysteresis may be more likely to occur (Davidson et al., 2006).

The results presented here clearly show that Q_{10} values are highly dependent on soil type, and a default Q_{10} value of 2 should not be assumed for all soils. At present, as we have seen, many modelling studies make this assumption. The list of identified problems associated with empirical respiration models is growing. For example, we know that the Arrhenius' and Van't Hoff's assumption of constant temperature sensitivities of respiratory enzymes at all temperatures is incorrect (Davidson et al., 2006). The question of whether these varying values are down to soil type, moisture content or latitudinal origin are beyond the scope of this study, but there are insights into the possibilities to be found throughout the literature. Several examples exist of empirical relationships that have been established between field measurements of soil respiration, soil temperature and water content. Most of these relationships tend to be site specific, and no widely accepted and commonly used model has emerged.

3.6. Conclusions

Modelling the relationship between soil respiration and temperature remains critical for understanding and predicting greenhouse gas emissions from soil, particularly in a climate change context. The results presented here across a broad range of

geographical latitudes and vegetation types clearly shows that temperature has a dominant effect on the amount of CO₂ released, irrespective of the vegetation type, country of origin and other soil properties. In summary, all the soil respiration-temperature response curves displayed approximately the same gradient. Soils were found to have a Q_{10} of greater than 2 with some variation in response to latitude and crop type.

It is possible that soil temperature in hot climates may, in the future, become rate limiting if global warming continues. If the microbes are already at their optimal level of production, CO₂ production may fall as temperatures increase and microbial communities start to shut down or die (e.g. >40°C) unless adaptation by the microbes occurs (i.e. microbial shift towards a mesophilic community or change in physiology).

Most global climate models use a Q_{10} value of 2 to describe how biosphere process rates change with temperature. In light of the results presented here, I conclude that this assumption may not be correct, and that Q_{10} values are slightly greater than 2. This would suggest that the DNDC models should use a larger Q_{10} or that the users may be able to add their own Q_{10} value to the model. The Q_{10} used is important when considering the possibility of soil warming and subsequent greenhouse gas emissions. It would imply that global warming might enhance the loss of soil organic matter to a greater extent than would be currently predicted from current global climate change models. In addition, the results presented here indicate that the Q_{10} value is not a constant but varies with temperature, making the mathematical modelling of the temperature response complex. Further work is required, using the same technique to examine the Q_{10} response in a greater range of ecosystems, especially those not studied here (e.g. arctic tundra, boreal forest, tropical rainforest etc). It would also be useful to determine the Q_{10} value for N₂O and CH₄ efflux from the same soils in response to changing temperature. As moisture is known to be the other major soil property affecting greenhouse gas emissions, it would also be useful to undertake the experiments across a wide range of soil moisture contents. If, when we considered the CO₂ emissions in the previous chapter, we had used a Q_{10} of 2.72 (the average found here, rather the default value of 2), we have seen a great increase (26.5%) in the reported emissions. Potatoes, which had the highest value for net CO₂ efflux in Chapter 3 of 14.1 t C ha⁻¹ yr⁻¹, would have seen an increase to 17.8 t C ha⁻¹ yr⁻¹. Overall, current models such as DNDC could underestimate field emissions by approximately 25%, depending upon the climate at the site.

**Chapter 4. Sensitivity of the DNDC Model to Variations to Weather and
Model Inputs**

Elizabeth York, Georgia Koerber, David L. Jones, Gareth Edward-Jones

*School of Environment, Natural Resource and Geography, Bangor University,
Gwynedd LL57 2UW, UK*

4.1. Abstract

One-fifth of the worldwide annual increase in greenhouse gas (GHG) emissions originates from agriculture. Consequently, practical ways are being sought to actively reduce GHG emissions within agro-ecosystems. To aid the decision making process, a range of mathematical models have been used to predict the future of land use change on GHG emissions from agriculture. DeNitrification DeComposition (DNDC) is a commonly used process-based simulation model that simulates carbon and nitrogen biogeochemistry in agro-ecosystems. Since its inception, there have been numerous versions of the model released in response to increasing knowledge of the behaviour of GHG emissions over a wider range of cropping systems. One of the major problems with using models is the potential variation between different versions and the importance of using the correct and most accurate farm data available to limit the variation create by inaccurate data. The variations between the different models were considered in chapter 3, with the latest version being considered the most reliable.

The aim of this chapter is to run a step-wise sensitivity analysis on three versions of the DNDC model, these versions being DNDC90, 91 and 92 using contrasting cropping regimes (lettuce, sugar beet and wheat) located in the same geographical region. The simulations included input data obtained from a number of field replicates, with model runs based on real farm and climate data. This chapter will critically consider the importance of the input data and what effect this may have on the outputs.

The sensitivity analysis results indicated that the most important variables were soil type, soil density, crop type, fertiliser rate/type and tillage regime. When field values were altered slightly, the percentage difference in GHG emissions from the baseline field values rose to over 2000%. Of all the inputs into the model, the model proved most sensitive to variation in initial soil organic carbon content. With respect to the input weather data, it was found that a data set based on average weather, run repeatedly for 10 years, produced significantly different output from an actual 10 year weather data set. N₂O emissions were predicted to be considerably lower for the average data set (max emission of 1.42 kg N ha⁻¹ yr⁻¹), while for the actual 10 year weather data set the highest predicted emission rate was 4.45 kg N ha⁻¹ yr⁻¹. It was also found that different regional weather data could have a large impact

on the output of the model. In conclusion, the results presented here suggest that the outputs from DNDC can be disproportionately affected by some input variables. It is concluded that input data for key variables should be considered carefully and weighted for accuracy.

4.2. Introduction

It is estimated that 80% of nitric oxide (NO), nearly 70% of ammonia (NH₃) and more than 40% of nitrous oxide (N₂O) emitted globally are anthropogenic in origin. Of this, agriculture accounts for 92% of total N₂O emissions, 26% of CO₂ emissions and 65% of CH₄ emissions (Zhang et al., 2002). Nitrous oxide emissions from animal and crop production account for approximately 70% of annual global N₂O and are expected to increase with increasing use of nitrogen fertilisers, which are needed to feed the rising global human population (Cai et al., 2003, Levy et al., 2007). Of the three gases influenced by agricultural activities (CO₂, CH₄ and N₂O), current estimates indicate that N₂O emissions from agricultural soils represent the largest source of greenhouse gases (GHG) from the sector (Smith et al., 2004, Neufelt et al., 2006). As countries try to assess their production of GHG, and their potential for mitigation of GHG, one major area of focus will be the agricultural sector (Li et al., 1997, Li et al., 2005).

A number of 'process-oriented' simulation models have been developed in recent years with the objective of simulating terrestrial ecosystem carbon and nitrogen biogeochemistry and nitrogen/carbon trace gas emissions (Li et al., 2001). Different models, ranging from the empirical to the completely process-based, have been produced and made available to the user community. As regression models neglect several variables, they cannot always be used to reliably test different management or mitigation scenarios. This is in contrast to the more complicated process-based models (Beheydt et al., 2007), which may have better flexibility for predicting GHG fluxes (Babu et al., 2006).

Crop growth models focus on crop production and efficient management. Crop growth, development and soil water dynamics are usually simulated in detail, but soil biogeochemistry is not considered, or simulated in terms of nutrient effects on crops (Zhang et al., 2002). Biogeochemical models pay more attention to soil processes, such as decomposition, nitrification and denitrification. Soil-crop models pay more attention to physical processes, such as radiation, water, heat and momentum fluxes. Therefore gaps exist between the modelling efforts of agronomists, environmentalists

and climatologists due to their different focuses. The DeNitrification-DeComposition (DNDC) model attempts to bridge this gap by integrating crop growth processes with soil biogeochemistry (Zhang et al., 2002).

The DNDC model is a process-based biogeochemical model originally developed for predicting carbon and nitrogen dynamics and trace gas emissions from agroecosystems (Cai et al., 2003; Qiu et al., 2009). DNDC couples denitrification and decomposition processes as influenced by the soil environment, and has been developed to assess N₂O, NO, N₂, NH₃, CH₄ and CO₂ emissions from agricultural soils. The model contains 4 main sub-models: soil climate, crop growth, decomposition and denitrification (Brown et al., 2002; Smith et al., 1997). The DNDC model was constructed with two components to reflect the two-level driving forces that control geochemical and/or biochemical processes related to C and N fluxes. The first component consists of the soil climate, crop growth and decomposition sub-models, and predicts soil temperature, moisture, pH, redox potential and substrate concentration profiles based on ecological drivers. The second component, consisting of the nitrification, denitrification and fermentation sub-models, predicts NO, N₂O, CH₄ and NH₃ fluxes based on the soil environmental variables (Salas and Li, 2003).

Originally, DNDC was a rain-event driven model of soil nitrogen and carbon biogeochemistry that had been developed to predict N₂O emissions from agricultural soils over a growing season. Crop growth was originally estimated using a generalized crop growth curve for both upland and wetland agroecosystems, but has subsequently been greatly revised for individual vegetation types (Cai et al., 2003; Li et al., 1992; Li et al., 2004; Qiu et al., 2009; Zhang et al., 2002). Some alterations have also been made to the database structure and content of DNDC to improve its suitability for use in the UK (Brown et al., 2002), as well as for the simulation of GHG in regions of the United States and China (Brown et al., 2002). The premise of the DNDC model is that, by modelling the processes that lead to N₂O fluxes, it can make reasonable estimates of emissions from a range of agro-ecosystems (Li et al., 2001). DNDC simulates a full C and N balance of the plant-soil system, including different C and N pools, and the emissions of all relevant trace gases from soils (Neufelt et al., 2006). One limitation is that it does not predict changes in atmospheric GHG concentrations, and therefore contains no climate change feedbacks for long term simulations (e.g. 50-100 y in length).

Model requirements for input data and large variability in climate, soils, and N₂O emissions can result in high levels of uncertainty in predictions, as DNDC simulates the process-based dynamics of only a few of the dominant controlling factors in detail (temperature, soil redox potential, and substrate availability) (Babu et al., 2006). The DNDC model simulates N₂O emissions under a wide variety of management scenarios using readily available input data. It is unable to simulate factors that control gas transport in detail, which will have a significant effect on predictions of the temporal dynamics of gas fluxes or rigorous soil-water dynamics (Babu et al., 2006, Smith et al., 2004). However, future versions of DNDC could reduce the level of uncertainty and provide data for policy-relevant cost-benefit analysis of specific mitigation strategies in the agricultural sector (Li et al., 1994). With ongoing modification and calibration, DNDC can potentially become a powerful tool for estimating GHG emissions and yield trends, for studying the impact of climate change, and thus for formulating policy (Babu et al., 2006).

DNDC has been validated by a number of research groups. Sensitivity tests have been published by Cai et al. (2003), Brown et al. (2002), Li et al. (2001), Smith et al. (2004) and Stange et al. (2000). These analyses report varying results, with Smith et al. (2004) finding the model to often over- or underestimate the emissions on a site-to-site basis whereas Li et al. (2004) found the model to give reasonable predictions. Brown et al. (2002) did suggest that there are a limited number of data sets with which daily models such as DNDC can be validated. Further, the accuracy of the predictions could be a reflection of the paucity of data sets of appropriate length, variety and frequency, rather than of the input requirements of DNDC.

Sensitivity tests can be run by varying one factor and keeping all the others constant and assessing changes in outputs (Stange et al., 2000). Alternatively, one could look at the variability in model outputs in response to alternative scenarios that are commonly observed to occur in agricultural regions (Li et al., 2004). In the UK, sensitivity of the model output to variation in the input values was investigated by changing the value of the single input variable and holding all others at baseline values (Brown et al., 2002). Smith et al. (2004) are among the few to consider the influence of weather on model output and specifically, variations in rainfall and temperature from year to year. They found that these factors are responsible for the high interannual variation in N₂O emissions. These different sensitivity analyses

demonstrate the basic behaviour of the model (Stange et al., 2000), though consideration of all inputs together has not been undertaken.

This chapter will investigate the sensitivity of the DNDC model, since it represents a primary tool used by researchers to inform regional, national, and continental policy and is used in the process of deciding emission reduction targets. Also the hypothesis is that the predicted amount of greenhouse gas emissions from the DNDC model will be most sensitive to variation in the carbon and nitrogen inputs and that weather input data also has a major influence on modeled gas emissions. Three consecutive versions of the model will be compared using collected farm data for a period of ten years. Each input variable will be taken in turn and changed while all other inputs will be kept constant. This allows us to consider the importance of each input in relation to itself and how sensitive each variable may be to the data used, over a set of outputs. The effect that different weather inputs have on the model outputs will also be considered. It is important to estimate the error and uncertainty associated with model prediction so that it identifies gaps in current understanding and helps identify where the most accurate input data are needed and which areas need to be improved to use input data more efficiently.

4.3. Materials and methods

Between 1989 and the present, many versions of the DNDC model have been officially released. For this study I chose the three most modern versions of the model - DNDC90, DNDC91 and DNDC92 - as the results from Chapter 3 showed that they gave the most consistent results. These versions were collected from the official release site (www.dndc.sr.unh.edu) and run on a normal desktop PC.

Actual agricultural management data was collected for a range of crop types from seven farms in Worcestershire, UK (for location details see Koerber et al. 2010). With the model giving the option of 49 different crop types, it was decided to pick three crop types commonly found in large-scale production in the UK and abroad. These were lettuce, sugar beet and wheat. Lettuce was used as the test crop for the main bulk of the sensitivity analysis; however, sugar beet and wheat were also considered when undertaking a sensitivity analysis to different weather data. The soils types used reflected those found on the test farms. The data collected from the farms included agronomic management information for individual fields. If key data were not available then secondary values were obtained from The Farm Management

Handbook 2006/2007 (SAC, 2006). The Farm Management Handbook provides a comprehensive and up-to-date source of information for farmers and those involved in the assessment and planning of farm business, and allowed us to complete the dataset with representative information (Table 5-1).

For soils, actual CO₂ emission measurements and soil surface (0-10 cm) temperatures were sampled monthly between July 2005 and September 2006 for each field in Worcestershire. In three fields, soil pits were also dug to a depth of 1 m and samples taken every 15 cm for soil bulk density and soil organic carbon (SOC) determination. Soils collected monthly at 0-10 cm depth from each plot were dried at 105 °C for 24 h to determine moisture content, while loss on ignition at 450 °C was undertaken to determine soil organic matter (SOM) content. In addition, soils collected at the start of the growing season from all locations were analysed for SOC with a Leco CHN 2000 analyser. 1 M KCl extracts (1:5 w/v) of the soil were also taken monthly and frozen at -20°C to await N analysis. Nitrate and ammonium concentrations in the KCl extracts were determined according to Miranda et al. (2001) and Mulvaney (1996). Soil pH levels were measured in a 1:5 (w/v) ratio of soil-to-distilled water using a Hanna 209 pH meter.

4.3.1. Meteorological input data

Weather data (maximum, minimum and average air temperature, rainfall, solar radiation, hours of sun and wind speed) for a 10 year period (1998 to 2008) were obtained for Brize Norton, Oxfordshire from the UK Met Office (Figure 4-1). The 10 year dataset allowed for the possibility of running simulations over longer time periods to look at the variability/stability in model output in response to changing climate. In all versions of the DNDC model the input variables included maximum and minimum air temperature, rainfall and wind speed.

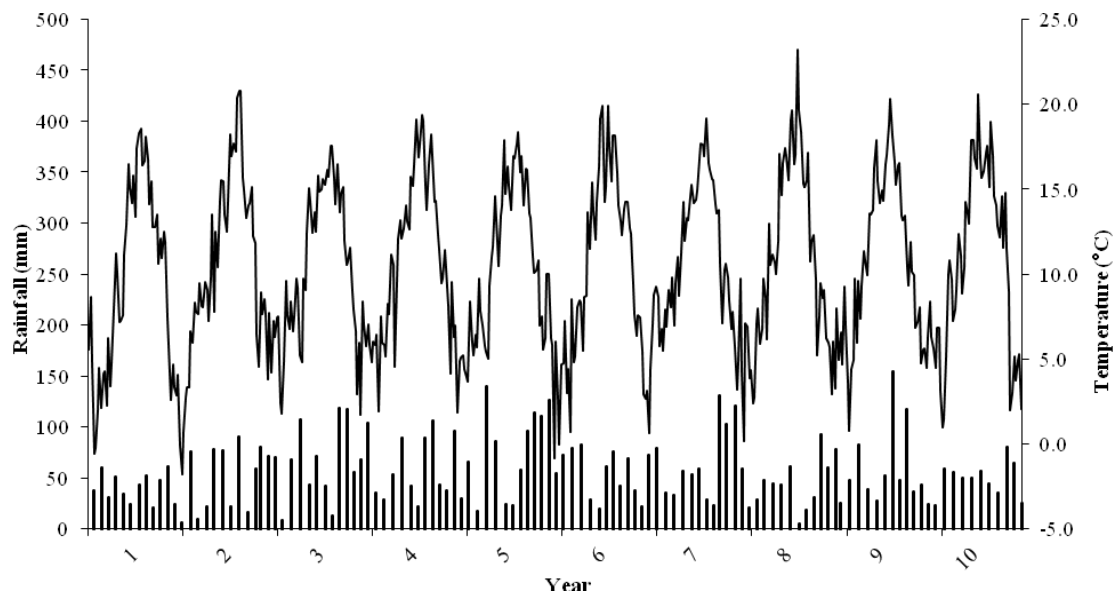


Figure 4-1: Ten years weather data for the geographical area where the fields were located and which was used to parameterise the DNDC model. Rainfall (bar chart) was measured in mm and graphed monthly. Average temperature (solid line) is presented in degrees Celsius and is graphed weekly.

Each variable in the model was measured in a stepwise manner (where possible) and was kept within realistic parameters (where possible), as done in Brown et al. (2002), Stange et al. (2000) and Li et al. (1992a).

Table 4-1: Details of the parameter inputs used for the sensitivity analysis of the DNDC model. Values include the range used in the analysis, the number of variations and the step interval.

Input	Units	Range	No. of variations	Step
Amount of manure	kg C ha ⁻¹	0-29.66	8	0, 3.71, 7.42, 11.12, 14.83, 18.54, 22.25, 29.66
Amount of fertiliser	kg N ha ⁻¹	0-164.71	9	0, 0.25, 0.5, 0.75, 1, 1.25, 1.5, 1.75, 2
Additional in atmospheric CO ₂ conc.	ppm	0-30	2	0, 30
Crop cover			2	yes or no
Crop type			6	fallow, corn, vegetable, bean, lettuce, brussels sprouts
Fertiliser application method			2	surface or injected
Fertiliser type			7	Urea, anhydrous ammonium, ammonium bicarbonate, NH ₄ NO ₃ , (NH ₄) ₂ SO ₄ , nitrate, (NH ₄) ₂ HPO ₄
Flood leaking rate	mm day ⁻¹	0-100	6	0, 1, 10, 20, 50, 100
Flooding depth	cm	0.5-10	2	0.5-5, 5-10
Flooding pH		6-8	5	6, 6.5, 7, 7.5, 8
Fraction of crop left in field		0-1	5	0, 0.25, 0.5, 0.75, 1
High ground water		yes, no	2	Yes, No
Irrigation amount	cm	0-3	5	0, 0.5, 1, 2, 3
Irrigation water pH		6-8	5	6, 6.5, 7, 7.5, 8
Latitude	Decimal unit	0.25-74.78	5	0.25, 15.98, 39.48, 52.15, 74.78
Manure type			8	none, farmyard, green manure, straw, animal slurry, compost, bean cake, human waste

Microbial activity		0.01-1	3	0.01, 0.5, 1
No of crops		1-3	3	1, 2, 3
No of fertiliser applications		0-2	3	0, 1, 2
No of flooding events		0-3	4	0, 1, 2, 3
No of manure events		0-3	4	0, 1, 2, 3
No of tillage events		0-5	6	0, 1, 2, 3, 4, 5
No of weeding events		0-3	4	0, 1, 2, 3
Slope	%	0-20	5	0, 5, 10, 15, 20
Bulk density	g cm ⁻³	0.75-2	6	0.75, 1, 1.25, 1.5, 1.75, 2
Soil organic matter	kg C kg ⁻¹	0.01-0.4	8	0.01, 0.02, 0.03, 0.05, 0.08, 0.1, 0.2, 0.4
Soil pH		6-8	6	6, 6.5, 6.96, 7, 7.5, 8
Soil type		0.03-0.63	7	sandy to clay soil 0.03, 0.06, 0.09, 0.14, 0.19, 0.41, 0.63
Tillage depth	cm	0-45	5	0, 5, 10, 20, 45
Variable N in rainfall	kg N ha ⁻¹ yr ⁻¹	0.52-3.13	6	0.286, 0.52, 1.04, 1.57, 2.8, 3.13
Weeding problem			3	none, moderate, serious

The difference between Baseline (B) and the results produced with a varied input (VI) was found as a percentage difference (PD) as follows (Eqn. 1):

$$PD = \frac{(VI - B)}{B} \times 100 \quad (\text{Eqn. 2})$$

Negative percentages are due to the output values being lower than the baseline values and positive percentages are due to the output values being correspondingly higher. For methane, the positive output values are the result of the field producing more CH₄ than the baseline field, whereas negative values are caused by a greater net CH₄ consumption/oxidation.

4.3.2. Statistical Analysis

All statistical analysis was performed using SPSS version 18 (SPSS Inc, Chicago, IL). A univariate analysis of variance was used for the 10 year average and 10th year with the dependant variable being the weather data for figure 4-8 and figure 4-10.

4.3.3. Weather comparison

Comparisons were run to investigate the effect of input weather data on model outputs. Two comparisons were made, as follows:

1. Average weather data versus variable weather data: The average of 10 years of weather data for Brize Norton was calculated and the model run for 10 consecutive years. This output was compared to that obtained when the 10 years data not averaged. This was run using the 6 lettuce fields described above.
2. Different weather data: A comparison of the outputs from three sets of UK weather data [(1) Brize Norton, Oxfordshire, (2) Holbeach, Lincolnshire and (3) Valley, Anglesey], were used to see what variations different weather patterns had on model outputs. This was measured using six lettuce fields, six sugar beet fields and six wheat fields (Table 5-2). This will give an insight into how weather can affect the outputs rather than the soil and farm management inputs.

Table 4-2: The average input ranges for the lettuce, sugar beet and wheat crops used in the sensitivity analysis runs.

		Units	Lettuce	Sugar Beet	Wheat
Atmosphere	N Concentration in rainfall	mg N/l	0.286	0.286	0.286
Atmosphere	NH ₃ background at atmosphere	µg N/m ³	0.060	0.060	0.060
Atmosphere	CO ₂ background at atmosphere	ppm	350	350	350
Soil	Soil texture		Clay, Loam, Loamy sand	Silty clay, Loam, Loamy sand	Silty clay, Loam
Soil	Bulk density	g/cm ³	1.75	1.48	1.68
Soil	Soil pH		4.98-7.45	6.07-7.10	4.63-6.25
Soil	Soil organic C at surface	kg C/kg	0.013-0.026	0.011-0.023	0.010-0.027
Soil	Slope	%	3-15	5-30	5-10
Farming	No. Crops		2-3	1	1
Farming	Crop type		lettuce	sugar beet	wheat
Farming	Harvest mode		1	1	1
Farming	Fraction left		0.3-0.5	0.2	0.1
Tillage	No. of tillage events		5	3	2
Tillage	Tillage method		2,3,3,4,5	2,2,5	3,5
Fertilization	No. Applications		2-3	1	1
Fertilization	Type		Urea	Urea	NH ₄ NO ₃
Fertilization	Amount	kg N/ha	67.9-102	100	119
Fertilization	Application type		Surface	Surface	Surface
Fertilization	Depth	cm	0.2	0.2	0.2
Manure Amendment	No. Applications		None	None	None
Manure Amendment	Type		None	None	None
Manure Amendment	Amount	kg C/ha	None	None	None
Weeding	Weed problem		None	None	None
Weeding	No. of weeding events		0	None	None
Irrigation	No. Applications		3	None	None
Irrigation	Amount used	cm	1	None	None
Irrigation	Water pH		7	None	None

4.4. Results

As expected, the output of the DNDC model was modified to differing extents depending on which of the key input variables was altered. Overall, there was considerable difference in the effect of different variables to the model outputs. Variables having no significant effect on the model outputs are summarised in Table 5-3.

Table 4-3: Variables for which variation in input value resulted in no major variation on model outputs specifically relating to change in SOC, soil heterotrophic CO₂, crop biomass, CH₄ emissions, nitrate leached and N₂O emissions.

Variables
Atmospheric CO ₂ concentration
Crop cover
Fertiliser application method
Floodwater pH
Irrigation water pH
Latitude
Number of weeding events
Slope
N content in rainfall

4.4.1. Change in SOC

Changing the different input parameter values had a varying influence on predictions of SOC stocks (Figure 4-3). Some variables such as microbial activity had a large effect in DNDC90 (0-2.1 t C ha⁻¹ yr⁻¹), produced a small effect in DNDC91 (0-0.15 t C ha⁻¹ yr⁻¹), but had almost no effect in DNDC92 (<0.03 kg C ha⁻¹ yr⁻¹). This effect is partly attributable to changes in the way the physiochemical process between the models alters in response to soil pH levels which influences soil microbial activity (Stange et al., 2000).

The four main variables that had a major effect on SOC storage were the number of tillage events, tillage depth, soil bulk density and soil type. The range in SOC output values for the two tillage variables was greatest for DNDC92, and least for DNDC91. A different pattern emerged for soil bulk density and soil type where DNDC90 produced the greatest range in outputs and DNDC91 the least. DNDC92 produced the greatest range of values for tillage depth and number of tillage events,

while DNDC90 had the greatest range for soil type. All three models showed a similar range for the variations in soil bulk density.

In DNDC92, crop type and the fraction of the crop left in the field had a moderate effect on changes in SOC stocks and was intermediate between DNDC91 and DNDC90 (Figure 4-3). Overall, DNDC90 had the fewest input variables affecting changes in SOC storage, but it also had the greatest variation in range.

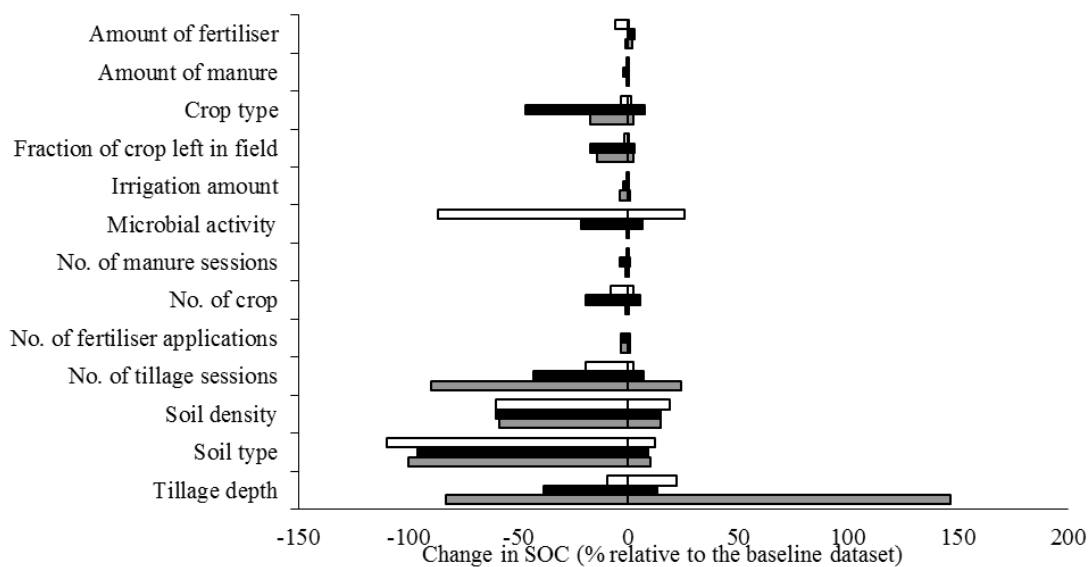


Figure 4-2: Change in soil organic carbon as a percentage difference from the baseline, with versions DNDC90 (□), DNDC91 (■) and DNDC92 (▒). The output named soil organics was not graphed due to the large percentage difference and can be found in figure 4-8.

Table 4-4: The highest and lowest predicted values for change in SOC ($\text{kg C ha}^{-1} \text{ yr}^{-1}$) for three different versions of the DNDC model. The negative numbers are those below the baseline dataset values and the grey shaded areas are where the input values had no significant effect on the output values.

	DNDC90		DNDC91		DNDC92	
	Lower	Higher	Lower	Higher	Lower	Higher
Amount of fertiliser	0	143.86	-22.16	0.02	-32.19	14.78
Amount of manure	0	3.73	0	15.76	0	11.46
Crop type	-39.24	78.35	-9.5	321.23	0	266.81
Fertiliser type			-0.03	0.01	-5.74	2.34
Flood leaking rate			-0.09	0	-4.09	0.637
Flooding depth	-9.7	0	0	0.15	-4.7	2.35
Fraction of crop left in field	0	45.14	0	118.5	0	220.58
High ground water	-22.84	0			-5.58	2.790
Irrigation amount	0	2.67	-0.45	15.76	-6.38	59.18
Manure type	-1.7	0.18	-7.34	0	-2.73	0.44
Microbial activity	0	2078.51	0	145.84	0	0.3
No of crops	0	202.62	0	132.66	0	18.21
No of fertiliser applications			0	22.16	0	13.92
No of flooding events	0	30.17	-9.53	0	0	47.05
No of manure events	0	6.93	0	25.07	-17.64	4.106
No of tillage events	0	490.41	-8.15	294.88	-376.25	1387.48
Soil bulk density	-474.04	1476.19	-103.2	413.11	-226.98	906.97
Soil organic matter	-275275	0	-51206.2	0	-131030	15822.21
Soil pH			-0.01	0	-1.82	0.26
Soil type	-169.49	2797.91	0	660.08	0	1549.54
Tillage depth	-522.21	223.91	-87.04	251.72	-1450.68	820.12
Weeding problem			-0.19	0.15	-13.47	3.936

4.4.2. Soil heterotrophic CO₂ production

In all three version of the DNDC model the same input variables had the most impact on the outputs in terms of soil heterotrophic CO₂, albeit by differing amounts (Figure 4-4). In both DNDC90 and DNDC91 it was apparent that crop type had a major effect on soil heterotrophic CO₂ emissions, with DNDC91 having the largest predicted range (Table 5-4). In contrast, variation in tillage depth had the greatest effect for DNDC92, while both DNDC90 and DNDC91 gave smaller and similar model responses. The other three variables that had a large influence on the net CO₂ emissions were soil type, soil bulk density and number of tillage events, with DNDC91 giving the lowest predicted range in values. DNDC90 showed the greatest value range of all three models for soil type and soil density while DNDC92 produced the greatest range for the number of tillage events (Figure 4-4).

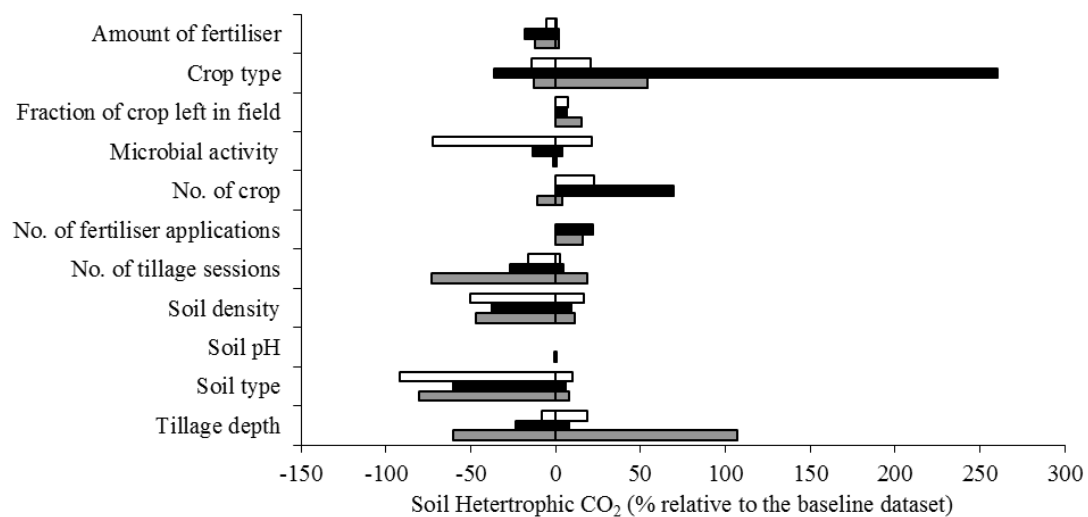


Figure 4-3: Soil heterotrophic CO₂ as a percentage difference from the baseline, with versions DNDC90 (□), DNDC91 (■) and DNDC92 (▒). The output named soil organics was not graphed due to the large percentage difference and can be found in figure 4-8.

Table 4-5: The highest and lowest predicted output for soil heterotrophic CO₂ (kg C/ha/yr) for three different versions of DNDC. The negative numbers are those below the baseline dataset and the grey shaded areas are where the input values had no variation on the output values.

	DNDC90		DNDC91		DNDC92	
	Lower	Higher	Lower	Higher	Lower	Higher
Amount of fertiliser	-156.6	0	-199.5	0.07	-243.0	42.6
Amount of manure	0	25.9	0	13.9	0	19.4
Crop type	-419.7	618.9	-396.5	2846.8	-228.4	972.0
Fertiliser type			-0.46	0	-24.5	4.8
Flood leaking rate			0	0.09	-27.4	4.5
Flooding depth	0	7.7	0	31.6	-10.6	5.3
Fraction left in field	0	221.8	0	75.2	0	308.3
High ground water	0	22.2			-19.6	9.8
Irrigation amount	-22.5	4.6	-15.7	0.4	-60.6	12.6
Manure type	-11.6	0	-6.0	1.5	-0.7	1.0
Microbial activity	-2075.3	0	-145.8	0	-27.3	9.1
No of manure events	0	37.5	0	19.4	0	28.1
No of crop	0	692.4	0	760.0	-225.9	75.2
No of fertiliser applications			0	199.5	0	285.6
No of flooding events	-17.5	0	0	-10.9	-78.7	18.6
No of tillage events	-490.3	0	-294.7	8.1	-1485.9	376.2
Soil bulk density	-1063.0	875.3	-309.7	206.6	-958.2	237.5
Soil organic matter	0	275208	0	51207.4	0	131087.5
Soil pH			0	0.01	-7.3	1.3
Soil type	-2767.6	168.7	-660.1	0	-1646.7	167.5
Tillage depth	-224.0	522.0	-251.7	86.9	-855.6	1520.3
Weeding problem			0	-3.8	0	20.3

4.4.3. CH₄ emissions

CH₄ emission predictions appeared less sensitive to changes in model input parameters in comparison to some of the other model outputs (e.g. SOC storage and CO₂ emissions). Of those that did have an effect, initial SOC level had a small effect which was similar for all versions of the model. In contrast, soil type had a greater impact, especially in DNDC90, which produced an emission range twice that predicted by DNDC91 and DNDC92 (Figure 4-5). Overall, soil bulk density had the greatest effect on CH₄ emissions although the effect was almost identical for all three versions of the model.

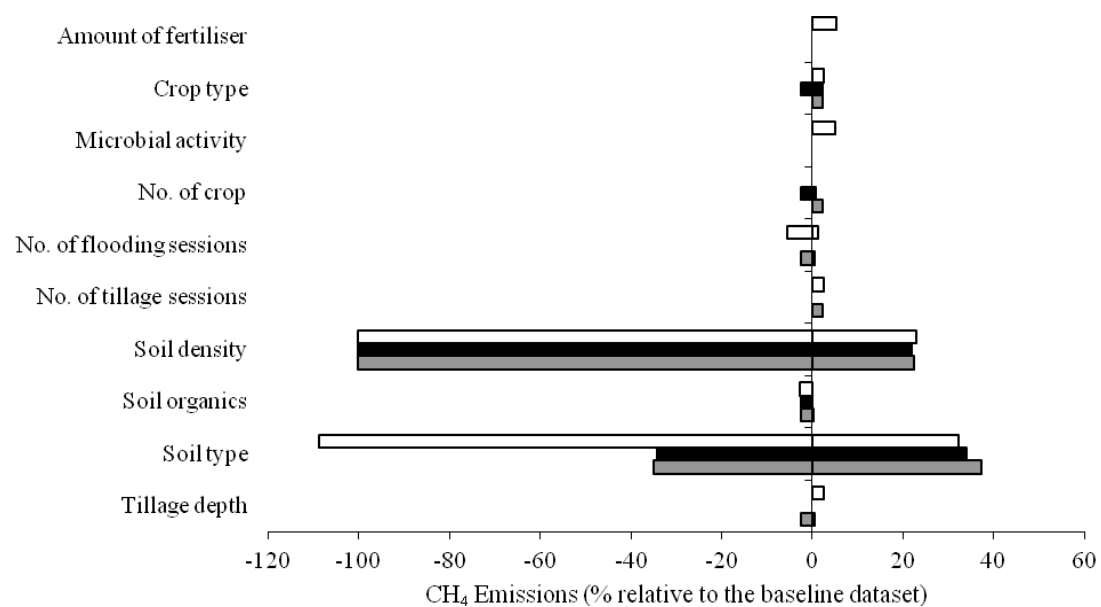


Figure 4-4: CH₄ emissions as a percentage difference from that predicted with the baseline dataset, with versions DNDC90 (□), DNDC91 (■) and DNDC92 (▒).

Table 4-6: The highest and lowest predicted output for CH₄ emissions (kg C/ha/yr) for three different versions of DNDC. The negative numbers are those below the baseline and the grey shaded areas are where the input values had no variation on the output values.

	DNDC90		DNDC91		DNDC92	
	Lower	Higher	Lower	Higher	Lower	Higher
Amount of fertiliser	-0.02	0				
Crop type	-0.01	0	-0.01	0.01	-0.01	0.002
Microbial activity	-0.02	0				
No of crops			0	0.01	-0.01	0.003
No of flooding events	0	0.02			0	0.01
No of tillage events	-0.01	0			-0.01	0.002
Soil bulk density	-0.09	0.39	-0.09	0.41	-0.09	0.4
Soil organic matter	-2.71	0	-2.52	0	-2.47	0.289
Soil type (clay fraction)	-0.12	0.402	-0.14	0.14	-0.15	0.14
Tillage depth	-0.01	0			0	0.01

4.4.4. Nitrate leaching

With respect to predictions of the amount of nitrate leached from the soil profile, DNDC91 showed the biggest effect for number of flooding events (Figure 4-6). However, DNDC90 had the highest range in absolute terms (0 to 27 kg N ha⁻¹ yr⁻¹). All three versions of the model exhibited variation in NO₃⁻ leaching with number of fertiliser applications, following the series DNDC90 > DNDC92 > DNDC91. In addition, and not surprisingly, soil type and the amount of fertiliser applied also had a significant effect with all three versions of the model. For soil type, DNDC90 had the highest predicted range, followed by DNDC92 and finally DNDC91, while for fertiliser application rate the predicted range in NO₃⁻ leaching appeared similar for all three versions of the model.

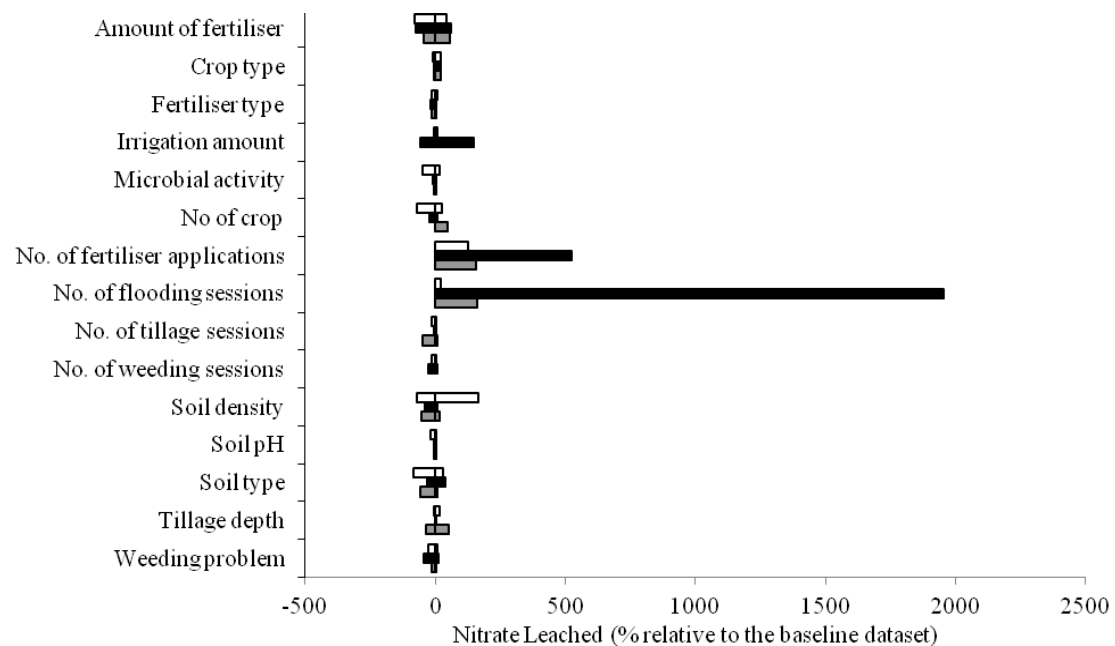


Figure 4-5: Nitrate leached as a percentage difference from the baseline, with versions DNDC90 (□), DNDC91 (■) and DNDC92 (▣). The output named soil organics was not graphed due to the large percentage difference and can be found in figure 4-8.

Table 4-7: The highest and lowest predicted output for nitrate leached (kg N/ha/yr) for three different versions. The negative numbers are those below the baseline and the grey shaded areas are where the input values had no variation on the output values.

	DNDC90		DNDC91		DNDC92	
	Lower	Higher	Lower	Higher	Lower	Higher
Amount of fertiliser	-98.97	51.22	-0.59	0.47	-10.1	11.52
Amount of manure		0.89			-0.02	0.07
Crop type	-10.27	28.32	-0.04	0.33	-0.66	6.06
Fertiliser type	-16.67	9.71	-0.16	0	-3.35	0.451
flood leaking rate	0	4.09			0	13.7
Flooding depth	-5.54	0	-0.01	0	0	7.05
Fraction of crop left in field	0	3.32			0	0.3
High ground water	-14.99	0			0	21.58
Irrigation amount	-9.62	11.6	-0.44	1.13		
Manure type	-0.44	3.09	0	0.04	-0.06	0.72
Microbial activity	-24.43	0.00	-0.07	0	-1.37	0.412
No of crops	-91.53	0	-0.17	0.02	0	0.12
No of fertiliser applications	0	95.44	0	0.94	0	10.08
No of flooding events	0	26.57	0	15.05	0	17.72
No of manure events	0	0.9			0	34.48
No of tillage events	-19.72	0.00	-0.02	0	-10.77	1.855
soil density	-41.61	98.33	-0.3	0.07	-11.71	3.23
Soil Organics	0	10473.79	0	15.66	0	824.52
Soil pH	-10.41	0.21	-0.01	0	-0.93	0.158
Soil type (clay fraction)	-109.29	35.37	-0.24	0.29	-12.41	1.790
Tillage depth	-9.01	21.44	0	0.01	-5.81	8.78
Weeding problem	-36.88	0	-0.35	0	-2.77	0.803

4.4.5. N₂O Emissions

N₂O emissions were highly sensitive to changes in some input parameters (Figure 4-7) in comparison to predictions of CH₄ and CO₂ emissions. In particular, greatest sensitivity was seen in response to changes in initial soil organic matter content and number of fertiliser applications. With respect to fertiliser application events, the range in N₂O outputs followed the series DNDC91 > DNDC90 > DNDC92, while for soil organic matter content the opposite trend was true following the series DNDC92 > DNDC90 > DNDC91. Of the other factors investigated N₂O emissions also appeared to be sensitive to tillage depth although the magnitude of the response appeared to be model version specific. In contrast, variables such as microbial activity, fertiliser type and soil type gave small but similar responses with all three versions of the model.

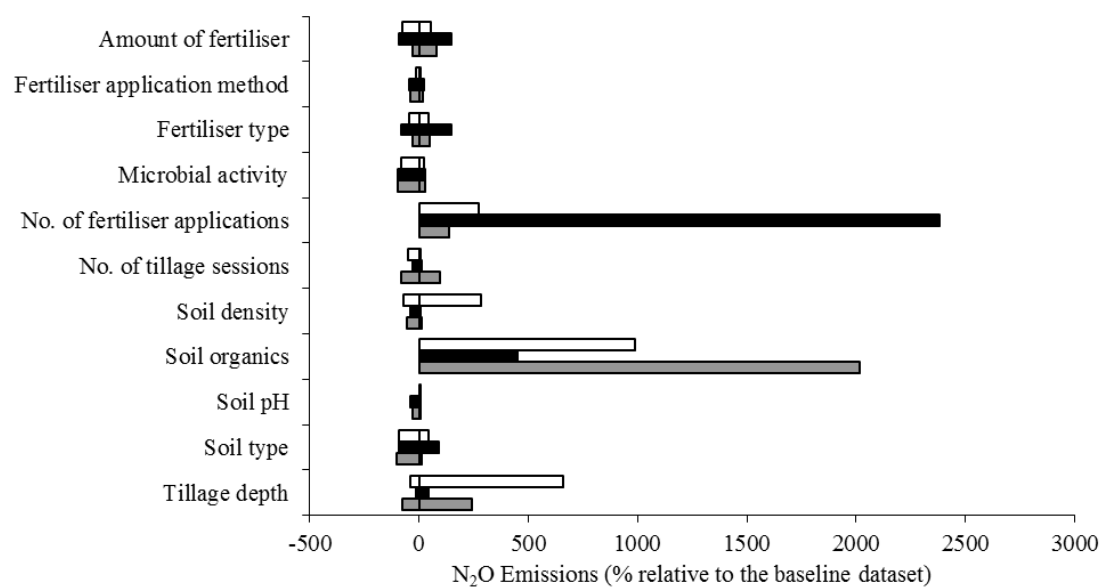


Figure 4-6: N₂O emissions as a percentage difference from the baseline, with versions DNDC90 (□), DNDC91 (■) and DNDC92 (▒).

Table 4-8: The highest and lowest predicted output for N₂O emissions (kg N/ha/yr) for three different versions of DNDC. The negative numbers are those below those predicted by the baseline dataset and the grey shaded areas are where the input values had no variation on the output values.

	DNDC90		DNDC91		DNDC92	
	Lower	Higher	Lower	Higher	Lower	Higher
Amount of fertiliser	-0.75	0.55	-0.84	1.36	-0.43	1.21
Amount of manure	0.00	0.02	0.00	0.01	0.00	0.33
Crop type	0.00	0.11	-0.06	0.00	-0.33	0.47
Fertiliser type	-0.43	0.46	-0.72	1.32	-0.42	0.72
Flood leaking rate	-0.11	0.00	-0.03	0.00	-0.21	0.03
Flooding depth	0.00	0.1	-0.03	0.00	-0.45	0.22
Fraction of crop left in field	0.00	0.07	-0.02	0.00	0.00	0.22
High ground water	-0.06	0.00			-0.14	0.07
Irrigation amount	-0.1	0.08	-0.01	0.15	-0.07	0.02
Manure type	-0.01	0.12	-0.01	0.19	-0.01	0.18
Microbial activity	-0.25	0.00	-0.85	0.00	-1.93	0.56
No of crops	-0.28	0.00	-0.03	0.00	0.00	0.05
No of fertiliser applications	0.00	1.13	0.00	1.43	0.00	1.06
No of flooding events	-0.47	0.00	0.00	0.1	0.00	1.44
No of manure events	0.00	0.55	0.00	0.02	-0.22	0.05
No of tillage events	-0.5	0.00	-0.27	0.13	-1.20	1.45
Soil bulk density	-0.26	1.05	-0.33	0.05	-0.84	0.19
Soil organic matter	0.00	990	0.00	451	0.00	2018
Soil pH	-0.09	0.00	-0.33	0.00	-0.41	0.06
Soil type (clay fraction)	0.00	0.45	-0.81	0.84	-1.48	0.18
Tillage depth	-0.34	5.53	-0.08	0.27	-0.84	2.77
Weeding problem	-0.29	0.00	-0.17	0.14	-0.06	0.01

4.4.6. Initial soil organic matter content

Variation in the initial soil organic matter content gave the largest percentage and value ranges of all the parameters for some key outputs (i.e. changes in soil organic carbon stocks, soil heterotrophic CO₂ emissions and nitrate leaching) – which is why these were graphed together in Figure 4-8. For the percentage change from the baseline values for soil heterotrophic CO₂, DNDC92 gave the largest range, though for the actual value range it was DNDC90, with DNDC91 giving the smallest percentage and value range. A similar pattern was found for nitrate leaching. For changes in net SOC stocks DNDC90 gave the largest percentage and value range with DNDC91 giving the smallest.

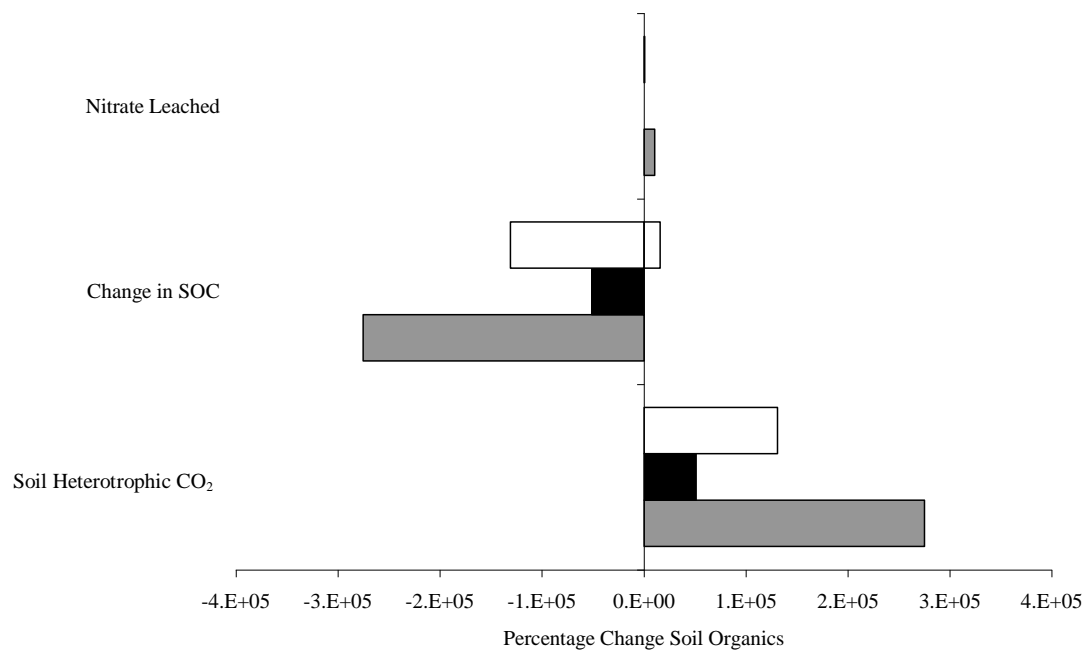


Figure 4-7: Soil organic matter, graphed for change in soil organic carbon, soil heterotrophic CO₂ and nitrate leached as a percentage difference from the baseline, with versions DNDC90 (□), DNDC91 (■) and DNDC92 (▒).

Table 4-9: The highest and lowest predicted output for soil organic carbon, soil heterotrophic CO₂ and nitrate leached for the input soli organics (t N/ha/yr) for three different versions. The negative numbers are those below the baseline.

	DNDC90		DNDC91		DNDC92	
	Lower	Higher	Lower	Higher	Lower	Higher
Nitrate leached	0.00	275.21	0.00	51.21	0.00	131.09
Change in SOC	-275.27	0.00	-51.21	0.00	-131.03	15.82
Soil Heterotrophic CO ₂	0.00	10.47	0.00	0.02	0.00	0.82

4.4.7. Influence of weather data

4.4.7.1. 'Average' versus 'varied' weather data

DNDC allows the use of one year's weather data to be reused each year for the number of simulated years specified. In order to test the importance of weather on the outputs of the model, an average of Brize Norton's 10 year weather data was run alongside the actual 10 year variable weather set. Thus one set of simulations would have a repeating set of weather data ('repeated') while the other had the real weather data, which varied each year ('varied'). To aid in interpretation, a cumulative running average was calculated (e.g. for year 5 the cumulative average would include data from years 1, 2, 3, 4 and 5). The impact of these different weather scenarios on the outputs from the DNDC model is presented in Figure 4-8.

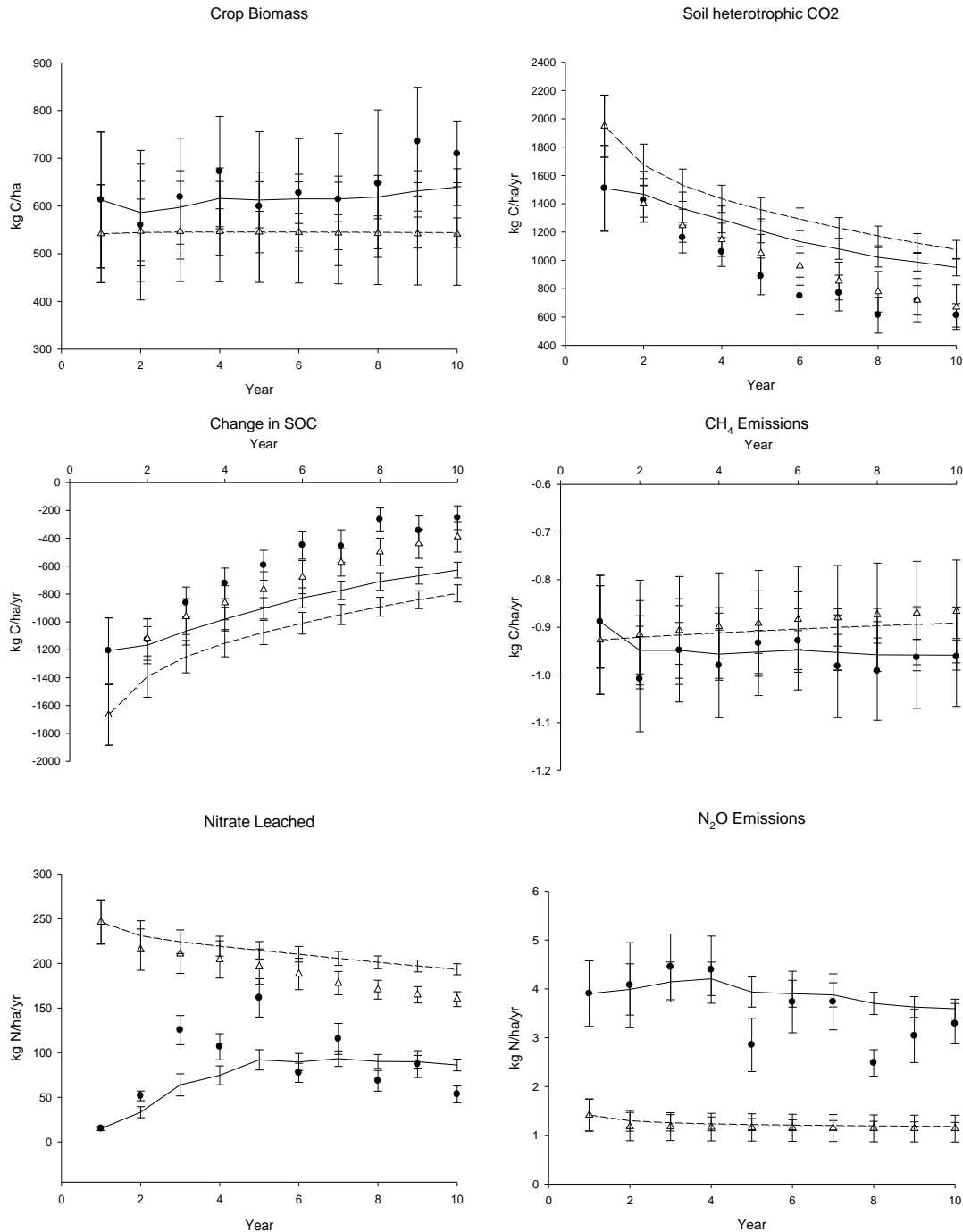


Figure 4-8: Variation between the same ‘repeated’ annual (Δ) weather data and ‘varied’ annual weather (\bullet) data (symbols only). The cumulative running average for the ‘repeated’ (---) and ‘varied’ (—) data is also shown (lines).

Perhaps unsurprisingly, crop biomass production was more or less constant across the 10 years of repeated weather (542 - 545 kg C ha⁻¹; Figure 4-8). However, under the varied weather patterns, crop biomass yield varied from 560 to 735 kg C ha⁻¹. Soil heterotrophic CO₂ decreased over time for both types of weather data, although the outputs for the ‘varied’ weather set tended to be lower than that of the ‘repeated’

weather set though they were significantly similar for the yearly data sets ($p=0.787$). The cumulative average of the ‘repeated’ data had a range of 670 to 1948 kg C ha⁻¹ yr⁻¹, whereas the ‘varied’ data had a range from 611 to 1509 kg C ha⁻¹ yr⁻¹. The cumulative average data was found to not be significantly different between the weather types ($p = 0.541$).

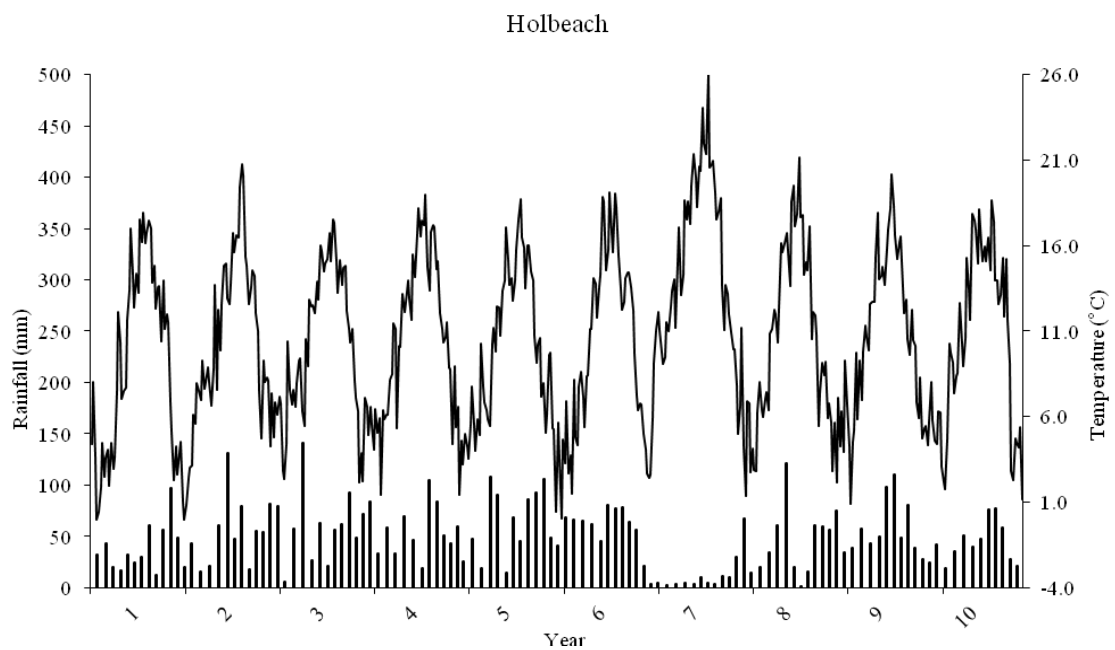
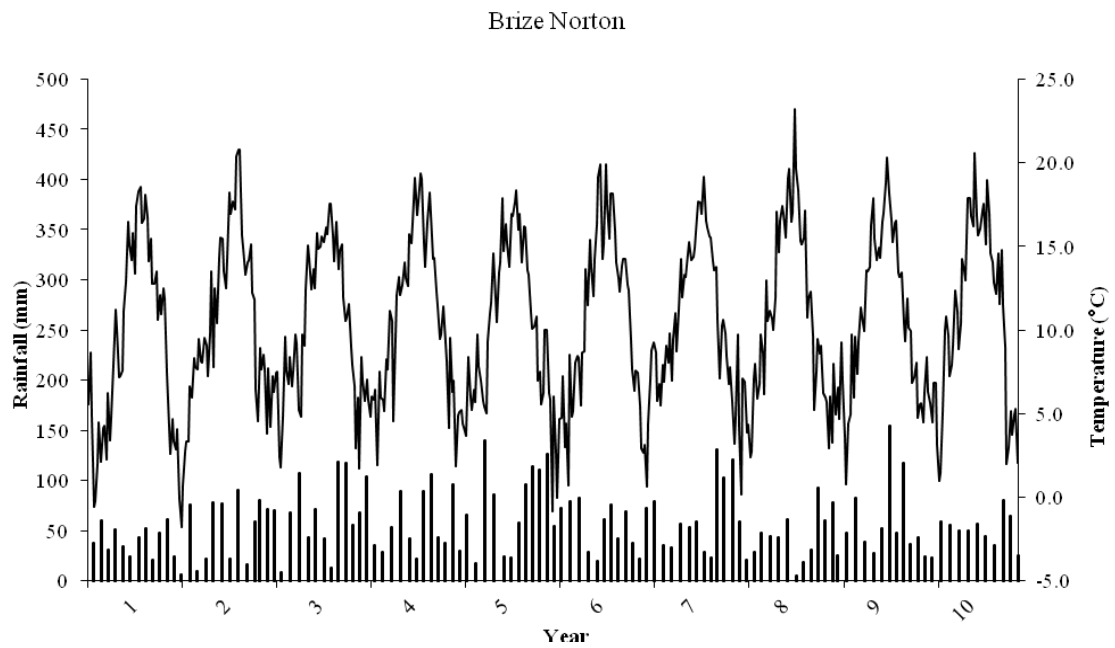
The ‘repeated’ data had a higher cumulative average for changes in SOC stocks than the ‘varied’ dataset (Figure 4-8). There was a greater difference in the values obtained in the initial simulation year than the tenth year of simulation (461 versus 167 kg C ha⁻¹ yr⁻¹, respectively). There was, however, no significant difference between the predictions for the two weather datasets ($p = 0.625$).

In contrast to SOC stocks, net methane emissions showed different patterns for the ‘varied’ and ‘repeated’ weather data. The ‘varied’ data began with a higher 1st year output (-0.89 kg C ha⁻¹ yr⁻¹) than the running average (-0.93 kg C ha⁻¹ yr⁻¹), but then fell below the running average for the remainder of the simulation period ($p<0.001$). The final cumulative averages for the two weather data sets were significantly different from each other ($p = 0.003$).

Predictions of the amount of nitrate leached were significantly different between the ‘repeated’ and ‘varied’ data ($p < 0.001$; Figure 4-8). In year 1 of the simulation period the ‘varied’ data predicted much lower NO₃⁻ leaching than the ‘repeated’ data (15 versus 246 kg N ha⁻¹ yr⁻¹ respectively). The ‘repeated’ data predictions then declined over the subsequent 10 years falling to 193 kg N ha⁻¹ yr⁻¹. The ‘varied’ data gave the highest value for the cumulative running average of 93 kg N ha⁻¹ yr⁻¹ at year 7 falling to 86 kg N ha⁻¹ yr⁻¹ by Year 10.

The predictions for N₂O emissions for the ‘repeated’ and ‘varied’ data sets showed a substantial difference with the ‘repeated’ data predicting consistently higher emissions (Figure 4-8). The predicted emissions for the ‘repeated’ dataset started with a lower value 1.4 kg N ha⁻¹ yr⁻¹, with the output stabilising by Year 7 at 1.1 kg N ha⁻¹ yr⁻¹. The ‘varied’ predictions of N₂O emissions started at 3.9 kg N ha⁻¹ yr⁻¹, and peaked at the 4th year with emissions of 4.2 kg N ha⁻¹ yr⁻¹ falling to 3.6 kg N ha⁻¹ yr⁻¹ by year 10. Predictions of N₂O emissions from the ‘repeated’ and ‘varied’ data were significantly different ($p < 0.001$).

4.4.7.2. Influence of crop type, geographical location and variable weather dataset on the outputs from the DNDC model



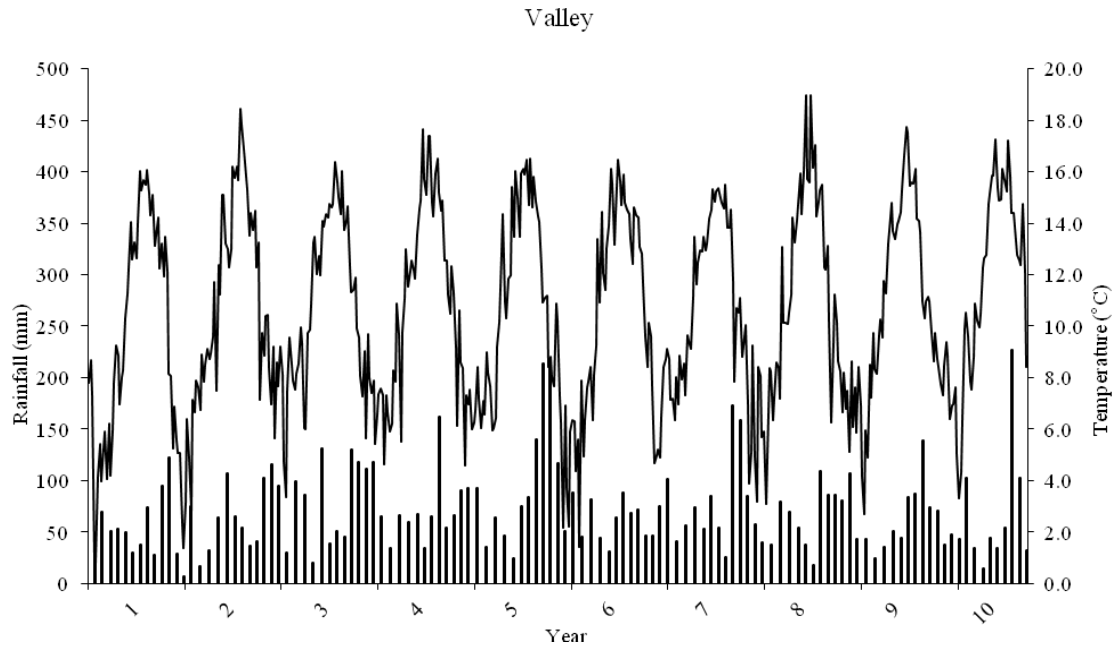
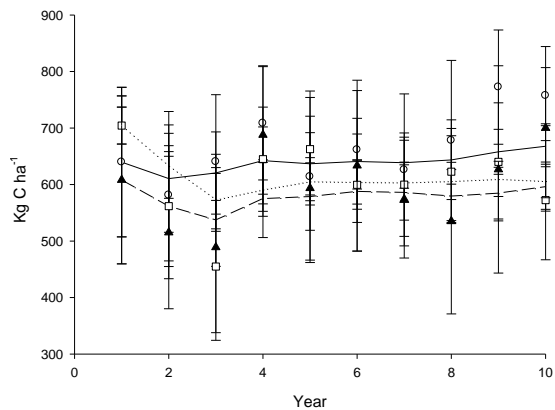


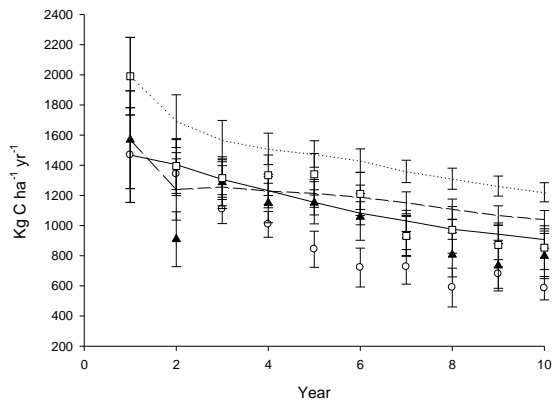
Figure 4-9: weather data used for the weather comparison analysis. Temperature (°C) has been graphed weekly and rainfall (mm) has been graphed monthly (UK Met Office).

Lettuce

Crop Biomass

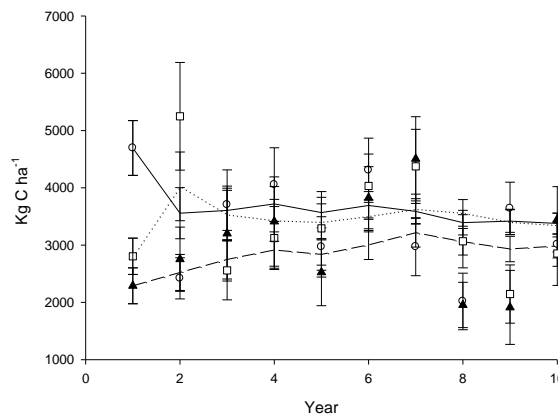


Soil heterotrophic CO₂

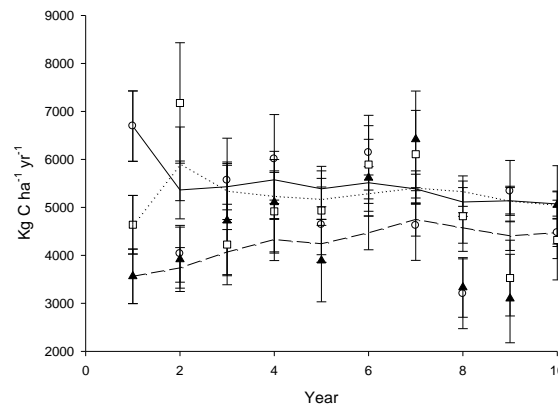


Sugar beet

Crop Biomass

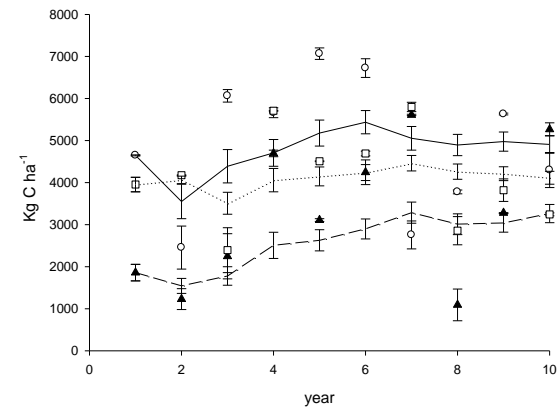


Soil Heterotrophic CO₂

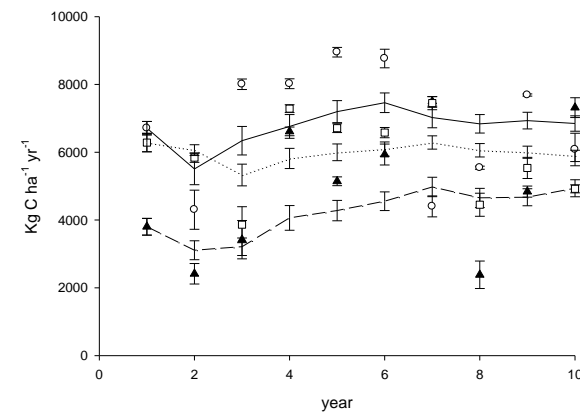


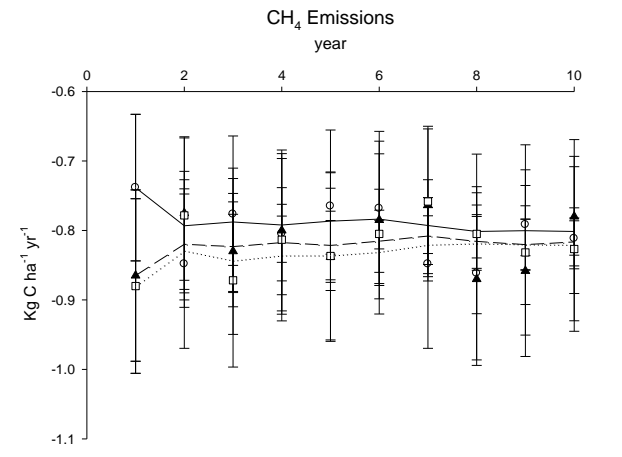
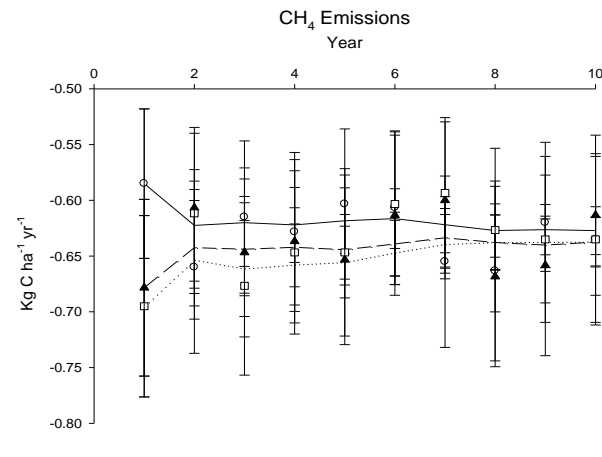
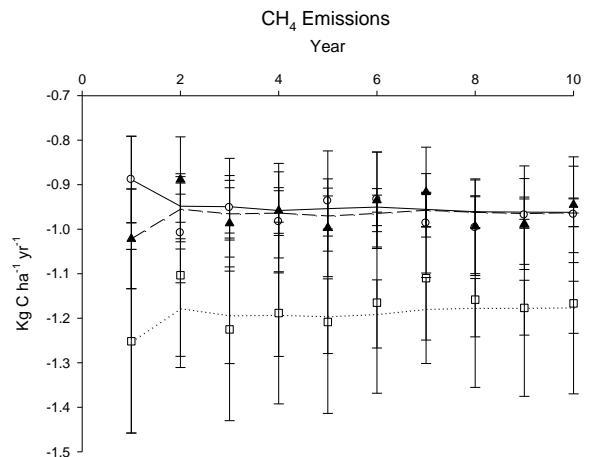
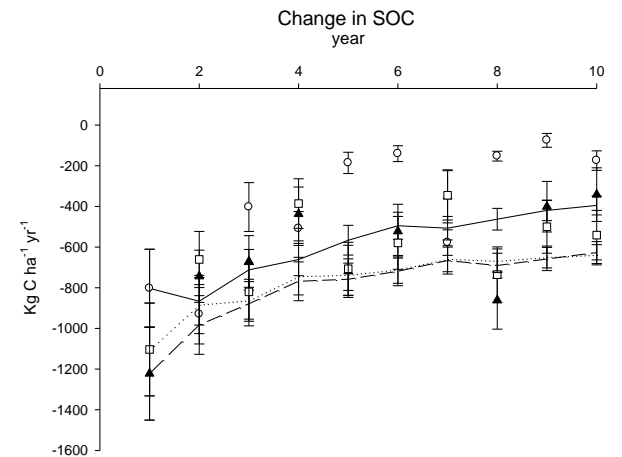
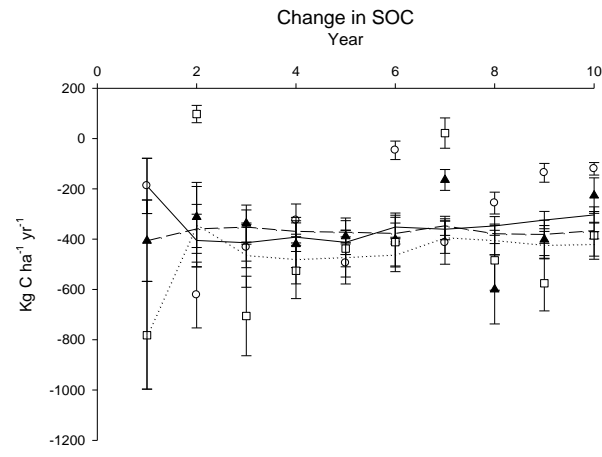
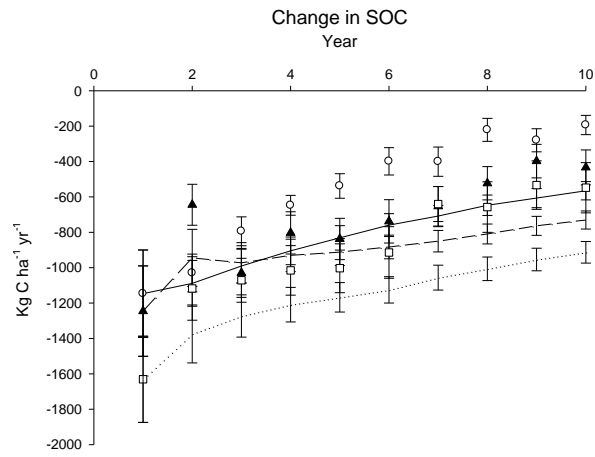
Wheat

Crop Biomass



Soil heterotrophic CO₂





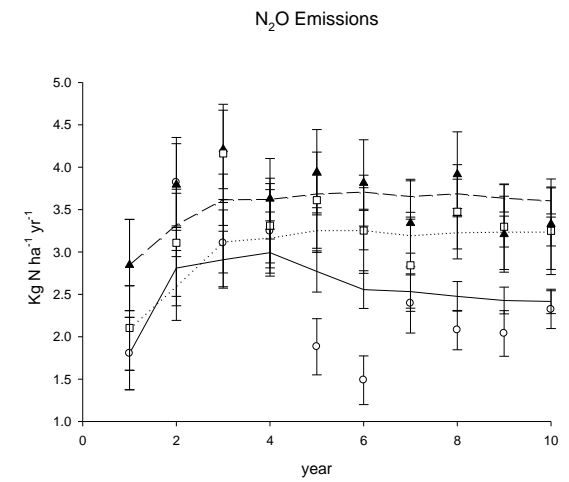
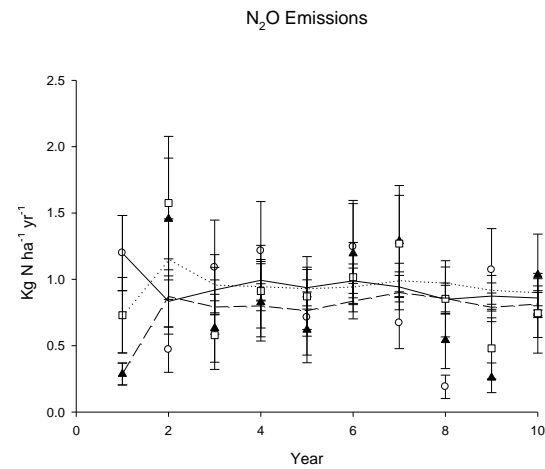
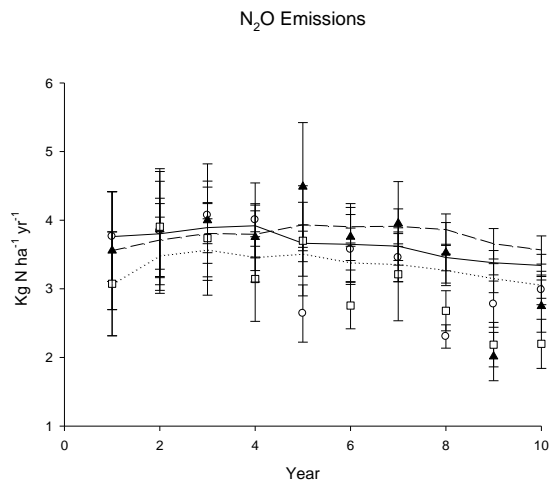
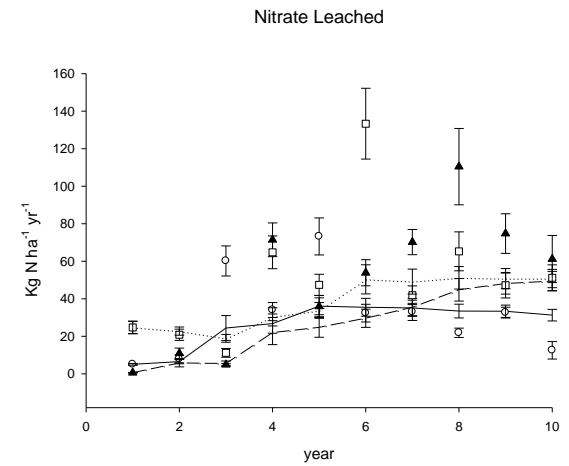
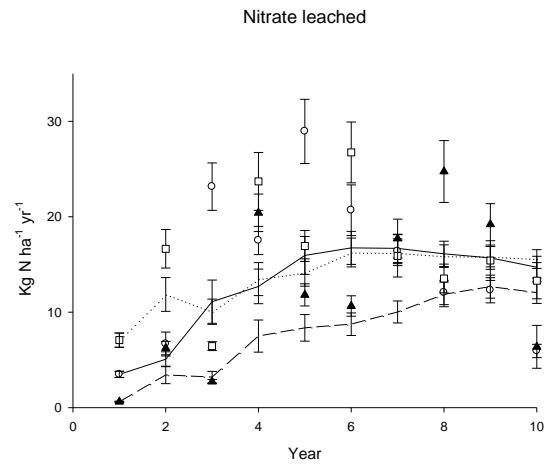
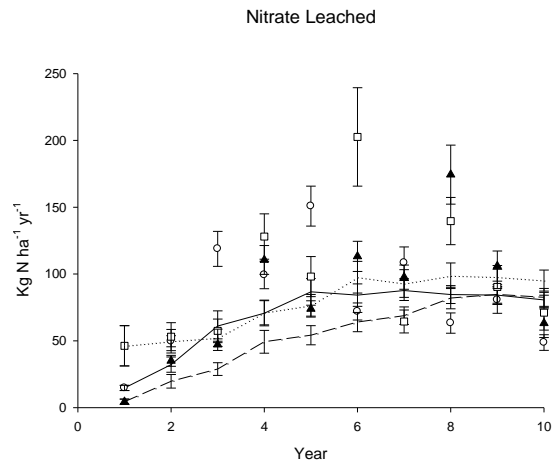


Figure 4-10: Variation of key greenhouse gases, change in SOC and nitrate leached, in three crops for three sets of weather data, crops were lettuce, sugar beet and wheat, and weather data was Brize Norton (○), Holbeach (▲) and Valley (□). Cumulative lines were also added to each of these UK weather areas, Brize Norton (—), Holbeach (---) and Valley (....).

Most of the model outputs for the three crops showed similar patterns over time (Figure 4-10), except for the change in SOC for sugar beet. For sugar beet and wheat the crop biomass and soil heterotrophic CO₂ showed the same graphical pattern for the different geographical locations.

Brize Norton gave higher results for all three vegetable types for crop biomass compared to the other two locations. It was found to be significantly different from Holbeach for both lettuce and wheat (P=0.029 and 0.018 respectively). Holbeach had the lowest productivity for each of the three crops respectively.

Soil heterotrophic CO₂ also varied between areas (Figure 4-10). Valley gave the highest outputs for lettuce. Brize Norton gave the lowest results and was found to be significantly different to Holbeach for wheat (P=0.011). Brize Norton and Valley gave high results for sugar beet and Holbeach gave the lowest. Brize Norton and Valley were statistically similar for all three vegetable types with P values of 0.085, 1.000 and 0.496 respectively. For wheat, Brize Norton gave the highest results and Holbeach gave the lowest. Valley had a larger range for wheat and was statistically similar to Holbeach wheat with a P value of 0.496.

Changes in SOC varied across the three areas. Valley lettuce was significantly different from Brize Norton lettuce, with a P value of 0.045. Holbeach had the smallest loss compared to Brize Norton, though these were statistically similar for all three vegetable types, lettuce (P= 0.711), sugar beet (P=0.948) and wheat (P=0.390). Brize Norton had the smallest loss for wheat. Holbeach started with a greater loss than Valley, but then they converged to give similar results; Valley was significantly different from Brize Norton (P= 0.002) and similar to Holbeach (P= 0.534). At the start of the simulations Valley had the greatest loss for sugar beet and Brize Norton the least. Overall, Valley had the greatest loss compared with Brize Norton and Holbeach; Brize Norton and Holbeach started to converge over time. Valley had the largest variation in yearly data, with two years, - 2 and 7 - acting as sinks.

All weather areas gave statistically similar results for sugar beet and wheat (Figure 4-11). Brize Norton had the lowest uptake of CH₄ for all three crops, though it had very different starting and finishing points for all three. Valley had the greatest levels of emissions lettuce, sugar beet and wheat respectively.

Patterns of nitrate leached were similar over the years between vegetable types, with a large increase to start with, then levelling off towards the 10th year. Holbeach gave the lowest output for lettuce and sugar beet. Holbeach was significantly different from Brize Norton (P=0.000) for wheat, but similar for lettuce and sugar beet (P=0.892 and 0.999, respectively). Holbeach was statistically similar to Valley for all three vegetable types: lettuce (P=0.176), sugar beet (P=0.979) and wheat (P=0.523). At Brize Norton, wheat showed increasing levels of leaching after 5 years; this decreased over time. Valley gave the highest output; Brize Norton and Valley wheat were significantly different with a P value of 0.003. Valley also gave the highest results for lettuce and sugar beet. Brize Norton gave similar values to Valley, for both lettuce and sugar beet with statistically similar values across the weather area (P=0.769 and 0.999 respectively).

Emissions of N₂O were similar across the years for all areas, with no major changes except for wheat. Brize Norton, Holbeach and Valley showed similar results for lettuce, with Brize Norton giving P values of 1.000 and 0.951 compared to Holbeach and Valley, and Holbeach compared to Valley giving a P value of 0.973. The highest emitter was Holbeach, and the lowest emitter was Brize Norton, with Valley lying between the two with a steep increase to year 3, and levelled off by the 10th year.

4.5. Discussion

Sensitivity analyses of DNDC have previously been undertaken by Li et al. (1992, 2004), Adballa et al. (2009) and Robertson et al. (2000), though these studies only considered the sensitivity of the model to a few variables. Only Adballa et al. (2009) have considered more recent versions of the model (v 92), though their study focused only on factors regulating NO_x production. In a UK study, Brown et al. (2002) also found that prediction of N₂O emissions were highly sensitive to aspects of farming practice, particularly the type, rate, timing

and depth of fertiliser application. In this study all variables were considered and compared with three different model versions.

Unlike Li et al. (1992, 1997) the scenarios tested here were run for more than a year, as simulated results showed that SOC decreased rapidly in the early years and gradually approached a quasi-equilibrium. If run for one year the system is unable to equilibrate and may give unrealistic results. This indicates significant initial instability in the model. Qiu et al. (2009) also ran a 20-year simulation to eliminate the possible uncertainties that could be induced from the initial settings of some input parameters such as SOC partitioning.

4.5.1. Carbon dioxide emissions

The results presented here suggest that there are potentially large variations in the sensitivity of the different variables in the different versions of the model tested. In an earlier version of the model, Li et al. (2004) showed that crop rotation and crop residue incorporation had a significant effect on annual CO₂ emissions. In this study we did not find this to be the case; tillage depth and microbial activity had greater effects. Overall, soil type, organic matter content and bulk density represented key variables regulating the model outputs. Some of our findings confirm previous results presented by Li et al. (1992), which show that soil pH, rainfall nitrate concentration, initial soil nitrate and ammonium all had little or no effect on annual CO₂ emissions.

Babu et al. (2006) found the model to be sensitive to SOC content, agreeing with our results. Similarly, Beheydt et al. (2007) found the model output to be 'slightly sensitive to pH' which is also in agreement with my findings. Most aspects of tillage and fertiliser regime had a major effect on the model's greenhouse gas predictions, though surprisingly manure had little effect since it can be a major source of C and N to soil microbial communities (Li et al., 1992). The change in the relative importance of different variables in regulating GHG fluxes is demonstrated by Li et al. (1992) and Li et al. (2004).

Li et al. (1992) reported that as the soil temperature increased from 0° to 30°C, soluble carbon and nitrate increased as was found here. Above 40°C, soluble carbon gradually decreased and nitrate sharply decreased and then increased. At temperatures above 45°C (not normally found in field soils) the

production of CO₂ decreased because of the depression of microbial activity. Nitrification ceases above 45°C, so no nitrate is produced (Li et al., 1992).

4.5.2. Nitrous oxide emissions

Fertilisers represent a large driver of N₂O emissions, particularly when fertilization rates are high ca. 400 kg N/ha (Zhang et al., 2002; Li et al., 1994). Li et al. (1994) predicted that application of fertilisers at lower depths in the soil profile would reduce emissions. When considering tillage depth in this study this did not appear to reduce emissions. Soil type was found to have an effect on the N₂O emissions – a finding supported by Li et al. (1992), who found that when soil clay content was decreased by 20% the annual N₂O emissions increased by more than 40%. Strange et al. (2000) found up to a 1132% difference in N₂O emissions from their study when varying soil types with clay fraction between 0.09 and 0.29.

In this study, irrigation had some effect on nitrate leaching, though not to the same degree as most of the other variables. Li et al. (1994) found that a weekly irrigation regime could increase N₂O emissions by 250%, which is a problem, particularly because irrigation can promote the downward flow and leaching of mineral nitrogen, and increase nitrogen stress (Zhang et al., 2002).

Varying soil pH was found to only have a maximum change of 5.67% whereas Stange et al. (2000) reported that emissions increased by up to 206%. In agreement with Li et al. (1994), we also found soil type, texture and tillage to have a large affect on N₂O emissions. In an early version of the model, Li et al. (1992) reported that changes in soil density, clay content, rainfall nitrate, initial soil nitrate, and initial soil ammonium all had a slight effect, or none at all, on total denitrification.

4.5.3. Methane emissions

In this study methane emissions also proved sensitive to soil texture. This is in general agreement with Li et al. (2004) who predicted that heavier textured soils would emit less CH₄ than lighter textured soils under the same management regime. In contrast to Li et al. (2004) and Babu et al. (2006), however, we did not find CH₄ emissions were sensitive to soil pH and fertiliser regime.

4.5.4. Model response to climate variables

Relatively little work has been undertaken on the sensitivity of DNDC to weather data sets. From the results presented here it is apparent that greater consideration should be given to the influence of weather on model outputs. Work has mainly looked at climate change increases in temperature and rainfall (Brown et al., 2002; Li et al., 1992; Li et al., 2004; Smith et al., 2004). The biggest effect observed in this study was the difference between the outputs obtained with the averaged weather data and the varied 10 year weather data set. As the same weather set was used for the average and varied 10 year weather data set, it was expected that the outputs by both would be very similar, with the possibility of the varied 10 year weather set showing greater fluctuation. This would be owing to the weather extremes not being averaged out. For most long term simulations, one year of weather data is normally used, suggesting that the outputs would give neither exceptionally low or high results due to extremes in weather data. Most sensitivity analysis undertaken with weather data considers the effect of global warming on the system, and therefore compares the output data of base results with those at 4°C higher (Li et al., 2004). Li et al. (1992) found that variations in annual precipitation had the greatest effect on the annual total denitrification; when annual precipitation was increased by 20%, total denitrification increased by more than 50%. In the same vein, Li et al. (1992) found an increase in annual precipitation greatly increased annual N₂ emissions, but slightly reduced N₂O emissions. Where an increase in annual precipitation had a negative impact on annual CO₂ emissions, rates of decomposition are slowed with the increased frequency/duration of anaerobic conditions.

The addition of sunlight hours to the basic weather data - maximum temperature, minimum temperature and rainfall results - unexpectedly gave the same results as the basic weather data. The addition of wind data gave lower results than basic weather data results.

The variation in different regional weather and vegetable types was most interesting, as it could give a significant idea of what vegetables are best grown in which area. From the graphs presented, Brize Norton seems to represent the best area for growing vegetables as it has the lowest GHG emissions. Surprisingly, Holbeach seems to give the highest emissions, making it the least environmentally favourable. Given that most of Lincolnshire is given over to

food production, this may be of concern. Anglesey has relatively low rates of GHG emission, though at the moment it produces very few horticultural crops.

It should be noted, however, that lettuce does produce lower CO₂ emissions than sugar beet. Wheat produces the most crop biomass and lettuce the least. It is not surprising that lettuce comes out worst, given the amount of tillage and fertiliser used for such a short term crop.

4.5.5. Discussion

The hypothesis was not correct for this study as the models were not only more sensitive to the carbon and nitrogen inputs as for soil heterotrophic CO₂ crop type gave a large percentage difference as did flooding type for Nitrate leached which would be expected. Microbial activity, soil type and soil density did however seem to affect the output of most greenhouse gases and are important in the carbon and Nitrogen cycle. The type of weather input did not have a great variation on the output for certain types and therefore disproves my theory that it would have a major influence.

This study does not completely agree with Li et al. (1992) that DNDC provides an extremely accurate predictor of GHG emissions from agricultural systems. Overall the model behaviour (for N₂O and CO₂ emissions etc) is not always what would be representative of what is (or would be) observed in the field. The model provides an idea of the true nature of complex agricultural systems; only by studying the complex interactions among soil climate, decomposition and denitrification processes, and agronomic practices can a complete picture of agroecosystem scale N₂O fluxes begin to emerge. Without a full understanding of a given soil, farming method and model, then no realistic prediction can be contemplated. DNDC was found to be highly sensitive to the type of weather and the accuracy of the inputs used. As stated by Mearns et al. (2007), achieving consistency in - and indeed, even understanding how to assign probabilities to - outcomes or processes that encompass various types of uncertainties is very difficult even in the research realm.

4.6. Conclusion

DNDC has been used and developed for a variety of scenarios around the world. There is no evidence of substantial validation and sensitivity analyses with more

recent versions of the model, as we have seen in this study. My results suggest some similarities with less substantial sensitivity analyses, although there were substantial differences - probably owing to the different versions of the model considered. The different versions showed some large variation between which inputs are the most important, with soil type, soil density, crop types, fertilisers and tillage being the most important variables for all versions. The weather data suggested it was better to use data for each year instead of using a single year's data multiple times to represent a multi-year data set. The three area data sets considered the variation between different growing areas and crop types. We found the model could consider which farming regime and management is most environmental friendly to that area, although as Leip et al. 2008 observed it would also have to consider relevant economic and social criteria. The sensitivity analysis conducted here supports the importance of validating this biogeochemical model for designing specific policies appropriate to the soils, climate, and agricultural conditions of a particular area.

**Chapter 5. A Comparison of GHG Emissions from Vegetables in
Different Countries and Model Validation**

Elizabeth York, Georgia Koerber, Paul Cross, David L. Jones, Gareth Edward-
Jones

*School of Environment, Natural Resource and Geography, Bangor University,
Gwynedd LL57 2UW, UK*

5.1 Abstract

It has previously been widely accepted that food miles provide a good indicator of the environmental sustainability of food production systems. Some recent reports, however, have questioned this viewpoint (Pretty et al., 2005). Consideration of how foods are produced, and – importantly - farm and industrial management regimes, can have a substantial impact on changing the carbon (C) footprint of foods. Many vegetables are imported into the UK (e.g. from Kenya and Spain). The general public perception is that this incurs a larger C footprint than locally sourced food. This chapter considers the quantity of greenhouse gases (GHG) emitted from soil when the same vegetable crops are either grown locally in the UK, or grown overseas in either Spain or Kenya. The UK based work considered crops grown in three different counties: Worcester, Anglesey and Lincolnshire. The model used to calculate the GHG emissions was DNDC (DeNitrification DeComposition model). A validation of the model was performed by direct comparison to field measurements of soil ammonium and nitrate. Patterns of measured soluble N were similar, however, DNDC tended to over-predict soil nitrate concentrations. The greatest modelled emissions of GHG emissions came from crops grown in Spain compared to those produced in either the UK or Africa. The UK had the lowest GHG emissions. The vegetable with the highest GHG modelled emissions were found to be potato. Vining peas and beans were found to cause the lowest emissions and the lowest amounts of GHG. Overall, the study suggests that significantly different losses of GHG occurs between countries, and that site-specific soil emissions should be incorporated into future C footprinting studies – which would necessitate a move away from IPCC Tier 1 default values.

5.2 Introduction

Food is one of the critical areas for the production of greenhouse gas (GHG) emissions, as agriculture contributes approximately 70% of N_2O and 40% of CH_4 to the atmosphere globally while cropped soils also have the potential to sequester atmospheric carbon dioxide (CO_2) (Li et al., 2004). In the European Union, the agricultural sector contributes approximately 10% of total GHG emissions (Schils et al., 2005). When assessing the impact of food, the entire

suite of GHGs needs to be considered (Li et al., 2005). Different GHGs can be compared on a like-for-like basis by converting the fluxes of the non-CO₂ GHG into CO₂ equivalents via their radiative forcing, called global warming potential (GWP). GWP is defined as the cumulative radiative forcing between the present and some defined later time, caused by a unit mass of gas emitted now, expressed relative to the reference gas CO₂ (Levy et al., 2007). The IPCC values for GWP for N₂O and CH₄, equate 1 kg of these gases with 298 and 25 kg of CO₂, respectively, over a 100-year time horizon (IPCC, 2007; Levy et al., 2007; Li et al., 2004; Plumiers et al., 2000; Qiu et al., 2009).

Environmental impacts from agriculture and the food chain have been investigated in many different ways. Agriculture has been the target for studies of emissions and resource use at farm, regional and global levels (Engstrom et al., 2007). Balancing food production and environmental protection, and predicting the impacts of climate change or alternative management on both food production and environmental safety in agroecosystems are drawing great attention in the scientific community (Zhang et al., 2002). Given the considerable expense of establishing and maintaining GHG flux measurement sites, the use of simulation models to estimate GHG fluxes from agricultural soils has obvious benefits (Abdalla et al., 2009). Modelling also allows the complex links between soil physical, chemical and microbial processes that need to be examined (Abdalla et al., 2009). On a global scale, models allow a comparison between countries – which is useful when considering the ‘local food’ debate.

This paper aims to discuss the GWP of differing vegetable types grown in three countries with contrasting climate regimes to establish if soil emissions would have any bearing on the ‘local food’ argument. The model being used is Denitrification-Decomposition (DNDC). This is a process-based biogeochemical model originally developed for predicting C and N biogeochemical cycles, C sequestration and trace gas emissions from upland and wetland agroecosystems in the United States (Abdalla et al., 2009; Li et al., 2004; Tonitto et al., 2007; Qiu et al., 2009), China, India and Europe (Leip et al., 2008). DNDC can simultaneously simulate climate, crop growth and soil biogeochemistry and their interactions; at a sub-daily time step, it can therefore provide comprehensive insights into how agroecosystems will respond to climate warming and atmospheric CO₂ enrichment (Levy et al., 2007; Zhang et al., 2002). DNDC can

be applied both at the field plot-scale and at the regional scale (Leip et al., 2008). It consists of four interacting sub-models: soil and climate (including water flow and leaching), plant growth, decomposition, and denitrification (Levy et al., 2007). Advantages of DNDC are that it has been extensively tested and has shown reasonable agreement between measured and modelled results for many different ecosystems, including as grassland, cropland and forest (Abdalla et al., 2009). Abdalla et al. (2009) believe that the model has reasonable data requirement and is suitable for simulation at appropriate temporal and spatial scales.

The three countries being considered in this analysis are Kenya, Spain and the UK (within the UK the analysis will consider the counties of Anglesey, Lincolnshire and Worcestershire). Vegetables represent an increasingly significant component of the Kenyan agricultural sector, both as a source of food for the rural population and as a foreign exchange earner. Rapid growth has led to a tripling of snap bean production from 1982 to the current average of 18 000 tonnes year⁻¹. Snap beans' high value-to-weight ratio makes them an important component of Kenyan vegetable exports (Kamau and Mills, 1998). Spain, in contrast, exports a large share of vegetables, fruits, wine and olive oil to Europe (Mora and San Juan, 2004), though Spain is widely regarded as a low cost producer of fruit and vegetables (Swinbank and Ritson, 1995).

Changes in dietary habits stemming from increased health awareness, together with demand for convenience foods, have accelerated year-round consumption of fresh fruit and vegetables (Dolan and Humphrey, 2000). Many of these come from abroad with total annual food commodity movements being 19.6 Mt, comprising 12.2 Mt yr⁻¹ for imports and 7.4 Mt yr⁻¹ for exports, of which swapped commodities (the same produce both imported and exported) amount to 5.23 Mt yr⁻¹ (Pretty et al., 2005). Concerns about the environmental impacts of transporting food increasingly long distances prior to its consumption have focussed on the notion of 'food miles'. This idea, popularly understood as the distance that food travels from farm gate to consumer, has generated considerable interest among environmental groups, academics, governments, the media, and the general public (Edwards-Jones et al., 2008). Food miles as a concept is blind to the social and economic benefits associated with trade in food, especially from developing countries. Therefore, the analysis of the sustainability

of food production systems must involve issues as diverse as social justice, pollution, conservation of biodiversity and economic costs (Cowell and Parkinson, 2003). This problem can be considered through Life Cycle Assessment, which can calculate the C footprint of a food item from production to consumption. Gaseous emissions from soil are not considered by consumers when making food choices, and even when they are accounted for in LCAs, the assumptions made are often incorrect (Edwards-Jones et al., 2008). My hypothesis is that the modeled UK results will give lower greenhouse gas emissions than those from abroad for equivalent horticultural production system. As such, the following study aims to assess whether crops grown in different areas emit significantly different quantities of GHGs and whether it is possible to predict if certain areas should be preferentially used for producing certain crops. This will be done through the DNDC modelling system.

5.3 Materials and methods

5.3.1 Geographical regions

Five different regions were considered in this study: three vegetable producing regions in the UK (Lincolnshire, Worcester, Anglesey) –further details in Koerber et al. 2010, - Murcia in Spain located at 37° 45'N, 001° 19'W and Nanyuki in Kenya located at 0° 2'N, 37° 12'E (Table 1). Different vegetable crops were measured in each geographical region, namely: broccoli, purple sprouting broccoli, cabbages and Brussels sprouts *Brassica oleracea* L.; (collectively Brassicas), lettuces *Lactuca sativa* L., vining peas *Pisum sativum* L., French Beans *Phaseolus vulgaris* L., wheat *Triticum aestivum* L., potatoes *Solanum tuberosum* L., and sugar beet *Beta vulgaris* L. Not all vegetable crops were measured in all regions, as this depended on what was grown regionally (Table 2). The fields used for sampling had been selected as part of a larger experiment concerned with GHG emissions from vegetable production as detailed in Koerber et al. (2009). The overlap with this previous study was the collection of soil samples. In summary, each country contained fields of at least one of the target vegetable types (brassicas, leafy salads, peas and beans).

5.3.2 Data collection for DNDC model

To enable accurate parameterization of the model, data was collected from farmers in each region. Most of this information pertained to agronomic management data for individual fields for input into the Denitrification Decomposition (DNDC) model version 92. If key data were not available for UK grown crops they were obtained from The Farm Management Handbook 2006/2007 (SAC, 2006). Each individual field was modelled for a 10 year period, with the same crop rotation. The crop rotation would start with initially bare soil until the selected vegetable is planted and followed by consecutive crops of the same vegetable type or bare soil, once the crop had been harvested. The model was not pre-run to allow it to equilibrate (i.e. the model was run as prescribed in the user manual). Two types of model outputs were considered. In the first, the average results across all 10 years of output were taken (termed average). In the second, results from only the 10th year were considered (i.e. the final model simulation year), as variation through the outputs has been seen in the previous chapters. The advantage of this latter method is that some level of equilibrium will have been achieved. Averages were made across all fields for a particular crop type.

Table 5-1: Visual summary of the three different vegetable producing areas investigated in the study.

Photographs from Spain, demonstrating the different irrigation systems and the size of fields used. In the left photo drip irrigation is being used where the right photo is of flood irrigation. The central photo displays how some of the farms are made with large fields with roads between, where the right picture shows smaller fields with soil reaves splitting them.



Photographs from Kenya looking at bean production. The right picture is of one of the irrigation dams used and refilled during the rainy season. The left picture shows the size of each field, which are separated by earth reaves. These were ready for planting. The centre picture is beans growing on handmade bean poles



Photographs of UK fields. The left photo is a field covered to increase temperature and humidity forcing the plant to grow earlier in the season. The right photo shows the size of the fields we were working with in comparison to the other countries. The central photo is lettuce production.



Table 5-2: Summary of the geographical location, crop type and climatic regime of the soil samples used in the experiments.

Region	No. of fields sampled	Crop	Annual rainfall (mm)	Maximum temperature (°C)	Minimum temperature (°C)
Anglesey	5	Brassicas	827.9	13.1	7.5
	5	Potatoes			
	5	Wheat			
Lincolnshire	5	Brassicas	621.3	13.8	5.7
	5	Lettuce			
	5	Potatoes			
	5	Sugar Beet			
	5	Vining Peas			
	5	Wheat			
	5	Wheat			
Worcester	5	Beans	622.3	14.0	5.2
	4	Brassicas			
	6	Lettuce			
	6	Potatoes			
	6	Sugar Beet			
	6	Vining Peas			
	6	Wheat			
Spain	9	Brassicas	326.0	33.6	3.9
	7	Lettuce			
Kenya	12	Beans	925.0	25.0	10.6

5.3.3 Experimental soil samples

Each field location was sampled monthly from July 2005 until November 2007. On each occasion four soil replicates were taken from each experimental field along with four of the target vegetable plants. On return to the laboratory, plants were dried at 105°C to determine their dry weight for C budgeting.

During each field visit, CO₂ emissions from 4 locations in each field were measured using an EGM-4 equipped with an SRC-1 soil chamber (PP-Systems Ltd, Hitchin, UK). Soil and air temperature were measured *in situ*. Air temperature was measured 30 cm above ground level. This was measured monthly for the UK areas, bimonthly for Spain and for a month in Kenya, though different age plots were used.

Soils were sampled monthly at a depth of 0–10 cm from each plot. The soil and plant samples were shipped to Bangor in cool boxes and stored at 5°C prior to analysis. The soils were subsequently dried at 105 °C for 24 h to determine moisture content while loss-on-ignition at 450 °C was undertaken to determine soil organic matter (SOM) content. In addition, soils collected at the start of the growing season from all locations were analysed for total C using a Leco CHN 2000 analyser (Leco Corp., St Joseph, MI). 1 M KCl extracts (1:5 w/v) of the soil were undertaken to determine NO_3^- and NH_4^+ concentration in soil and the extracts frozen until analysis. Nitrate concentrations in the extracts were measured using the vanadium chloride method of Miranda et al. (2001), while ammonium concentrations were determined with the salicylate-hypochlorite procedure of Mulvaney (1996). Soil pH was measured in a 1:5 (w/v) ratio of soil-to-distilled water using a Hanna 209 pH meter. For all sites except Kenya, 3 pits were dug to a depth of 1 m and samples collected every 15 cm down the soil profile using 50 cm³ cores to determine bulk density. In Kenya, the farms provided the bulk density results directly as they had been measured in a previous study.

5.3.4 Meteorological data

Weather data (maximum, minimum and average air temperature, rainfall, solar radiation, hours of sun and wind speed) for 10 years (1998 to 2008) were purchased from the UK Met Office for Brize Norton (Oxfordshire), Valley (Anglesey) and Holbeach (Lincolnshire). The Spanish weather data were collected from Centro Meteorológico Territorial en Murcia and the Kenyan weather data were collected from an on-site weather station. The 10 year data set allowed us to run simulations over longer time periods to explore the variability/stability in model output with different annual weather patterns (i.e. inter-annual variation). In all versions of the DNDC model the input variables included maximum and minimum air temperature, rainfall and wind speed.

5.3.5 Statistical Analysis

All statistical analysis was performed using SPSS version 18 (SPSS Inc, Chicago, IL). A univariate analysis of variance was used for the 10 year average and 10th year with the dependant variable for figure 5-(2 to 6) being the different counties as was for figure 5-(7 to 13). For figure 5-14 and 5-15 the dependent variable was the vegetable type.

5.3.6 Global warming potential

The global warming potentials (GWP) were calculated by multiplying the yearly emissions value by the compounds GWP value to convert it into CO₂ equivalents. The GWP values are shown in Table 2 and were taken from IPCC (2007).

Table 5-3: Global Warming Potentials for the main three GHG over a 100 year period.

Compound	Global Warming Potential (CO ₂ eq.)
CO ₂	1
CH ₄	25
N ₂ O	298

5.4 Results

5.4.1 Validation of DNDC model

A validation of the DNDC model was undertaken by comparing the ammonium and nitrate concentrations measured from field samples with those predicted to occur from the model on the day the samples were taken (Figure 5-1). Overall, similar patterns for soluble N concentrations in soil were produced by the DNDC model when compared to field results although the model predicted higher results for nitrate than the field results; this was seen across all the regions. This suggests that the model over predicts the nitrate produced as confirmed by Li et al. (2006).

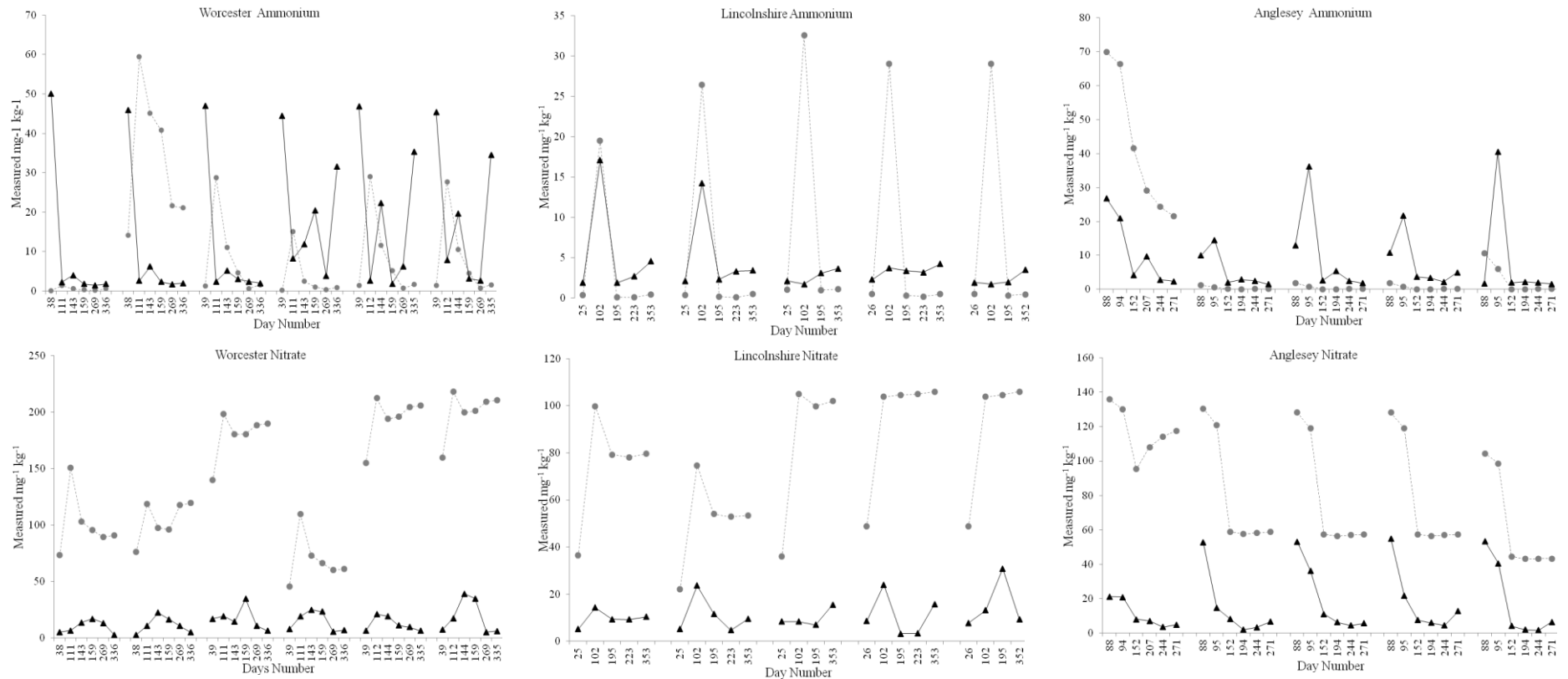


Figure 5-1: Comparison of field (—▲—) and modelled (---●---) Ammonium and Nitrate concentration for wheat fields in Worcester, Lincolnshire and Anglesey. The 10th year has been used for this comparison

When it came to comparing model outputs, the key outputs modelled and graphed were soil organic C (SOC), soil heterotrophic CO₂, crop biomass, CH₄ emissions, nitrate leached and N₂O emissions.

5.4.2 Soil heterotrophic CO₂

When considering soil heterotrophic CO₂ emissions per hectare, the model results suggested that the highest emissions were from potatoes with the lowest from lettuces (Figure 5-2). Generally, soil heterotrophic CO₂ emissions were lowest from Lincolnshire for all vegetable types modelled, except beans (not measured) and potatoes. The greatest level of emissions for both brassicas and lettuce occurred in Spain, with values of 3312 kg C ha⁻¹ yr⁻¹ and 6690 kg C ha⁻¹ yr⁻¹ respectively. Kenya had the highest emissions for beans with emissions of 3432 kg C ha⁻¹ yr⁻¹. Both the 10th year and average results were not significantly different between vegetable types, however between areas they were found to be significant (P = 0.000).

Potatoes were the highest GHG emitting crops in both Worcester and Lincolnshire. Lettuces were the highest emitter for Spain with values of 4698 kg C ha⁻¹ yr⁻¹ (10th year) and 6690 kg C ha⁻¹ yr⁻¹ (average year), while brassicas were the lowest for Spain with values of 2334 kg C ha⁻¹ yr⁻¹. Brassicas were predicted to be the lowest emitting crops for Anglesey, while lettuce was lowest in Lincolnshire. Beans were lowest for Worcester with an average of 935 kg C ha⁻¹ yr⁻¹ and for Worcester 10th year of 611 kg C ha⁻¹ yr⁻¹.

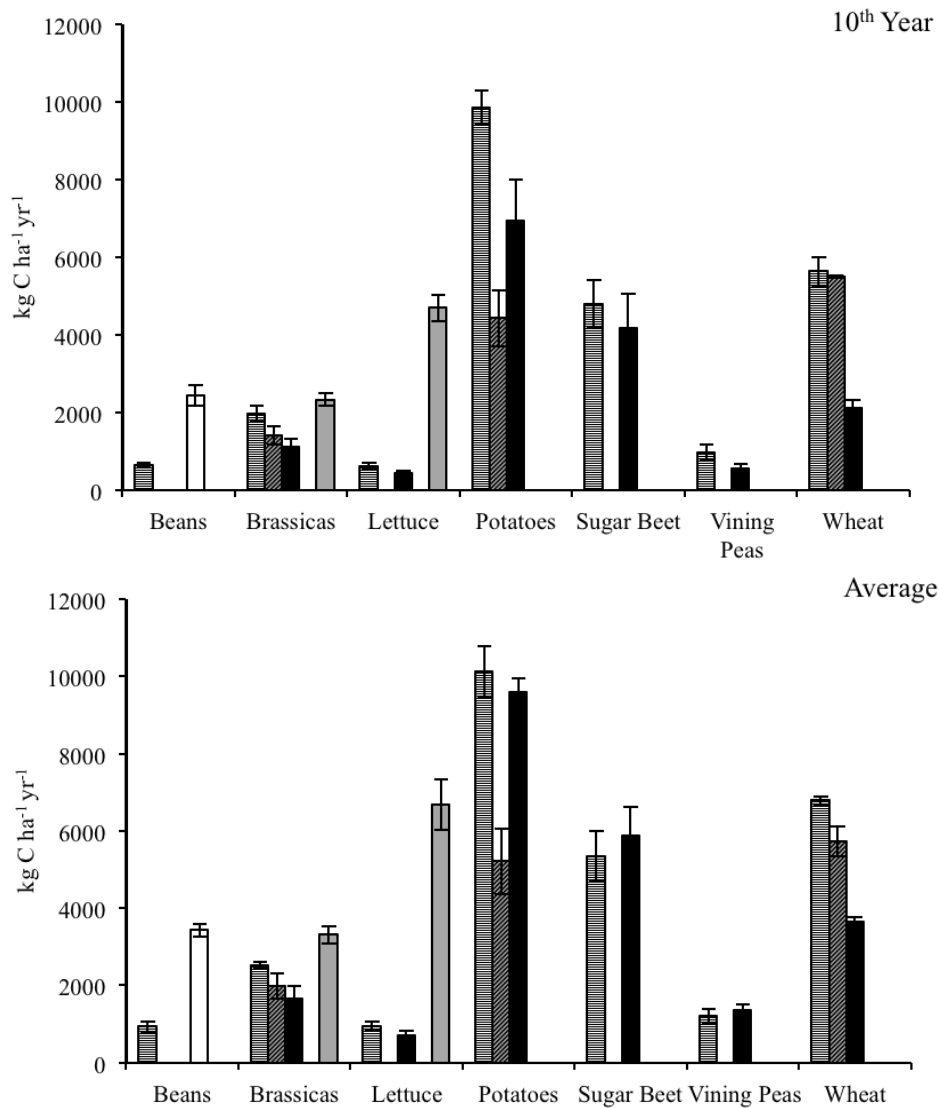


Figure 5-2: Comparison of soil heterotrophic CO₂ emissions produced by five different areas (Worcester Anglesey Lincolnshire Kenya Spain) for seven different crop types for both the final year of the model simulation (10th year) and averaged over the entire 10 year simulation period. Values represent means \pm SEM ($n > 4$).

5.4.3 Change in SOC

For most vegetable types there was a predicted loss of SOC (Figure 5-3). However, the model predicted that in Worcester and Lincolnshire, potato crops were C sinks with sequestration values of 346 kg C ha⁻¹ yr⁻¹ and 48 kg C ha⁻¹ yr⁻¹ respectively. Spain and Kenya gave the highest SOC losses for beans, brassicas and lettuces (1328 kg C ha⁻¹ yr⁻¹, 2685 kg C ha⁻¹ yr⁻¹ and 3856 kg C ha⁻¹ yr⁻¹ respectively). The loss from Spanish lettuces was the highest for all vegetable types. The geographical region with the smallest predicted losses was Lincolnshire. The average results were found to be significantly different

between areas for both average year and 10th year ($P = 0.000$) but not for between vegetable types, with results of 0.671 and 0.129 respectively.

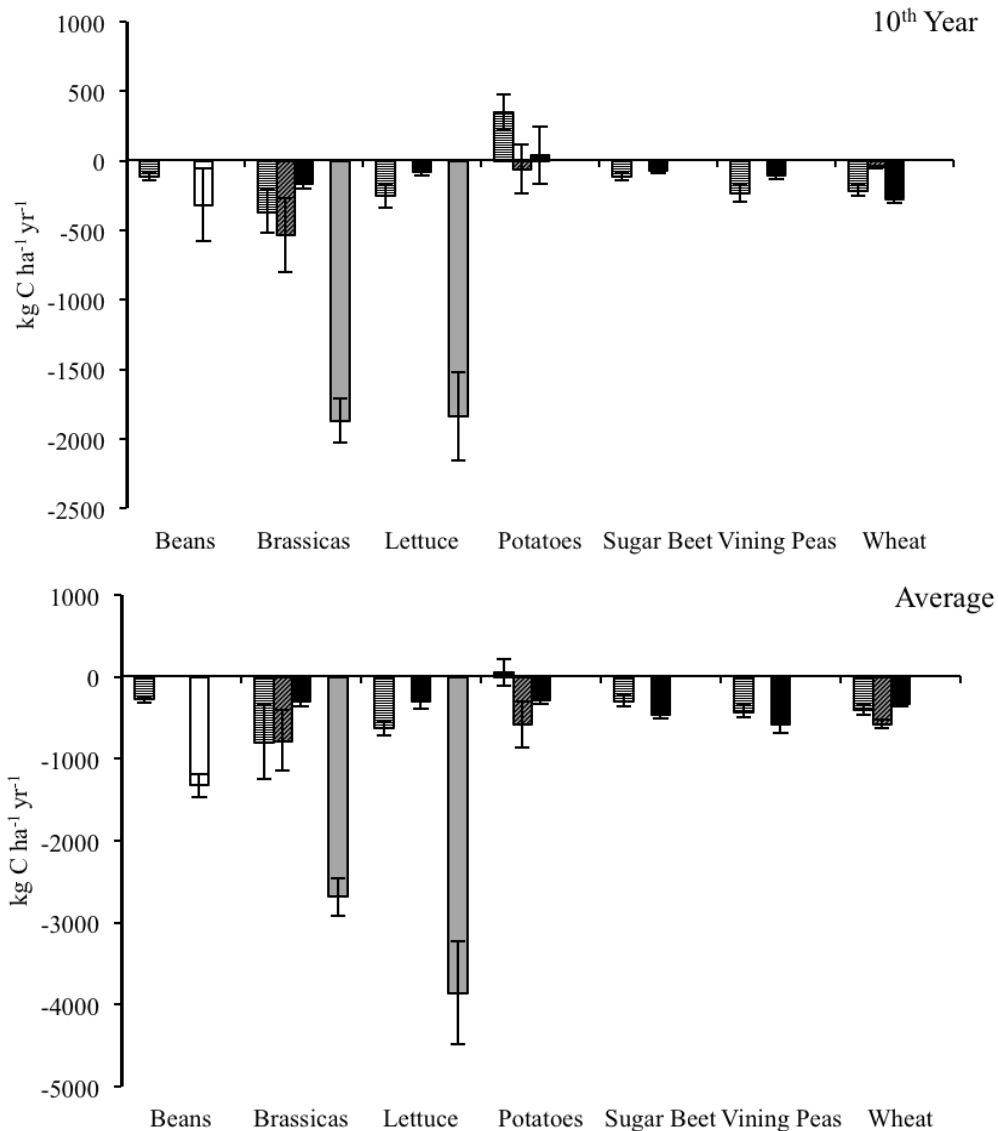


Figure 5-3: Change in SOC produced by five different areas (Worcester Anglesey Lincolnshire Kenya Spain) for seven different crop types for both the final year of the model simulation (10th year) and averaged over the entire 10 year simulation period. Values represent means \pm SEM ($n > 4$).

5.4.4 Nitrate leaching

DNDC predicted Lincolnshire to have the lowest amount of nitrate leached for all vegetable types modelled (range 2.5 to 13 kg N ha⁻¹ yr⁻¹; Figure 5-4). For vegetable types or places there was no significant difference found for either the 10th year or average years' results. Worcester had the lowest predicted N leaching for bean crops (6.5 kg N ha⁻¹ yr⁻¹), while Kenya had the highest predicted level of leaching from beans (58.6 kg N ha⁻¹ yr⁻¹) as seen in Figure 5-4.

Anglesey gave the highest value for brassicas, potatoes and wheat, while Lincolnshire had the highest value for vining peas. Worcester gave the highest value for sugar beet ($14.8 \text{ kg N ha}^{-1} \text{ yr}^{-1}$).

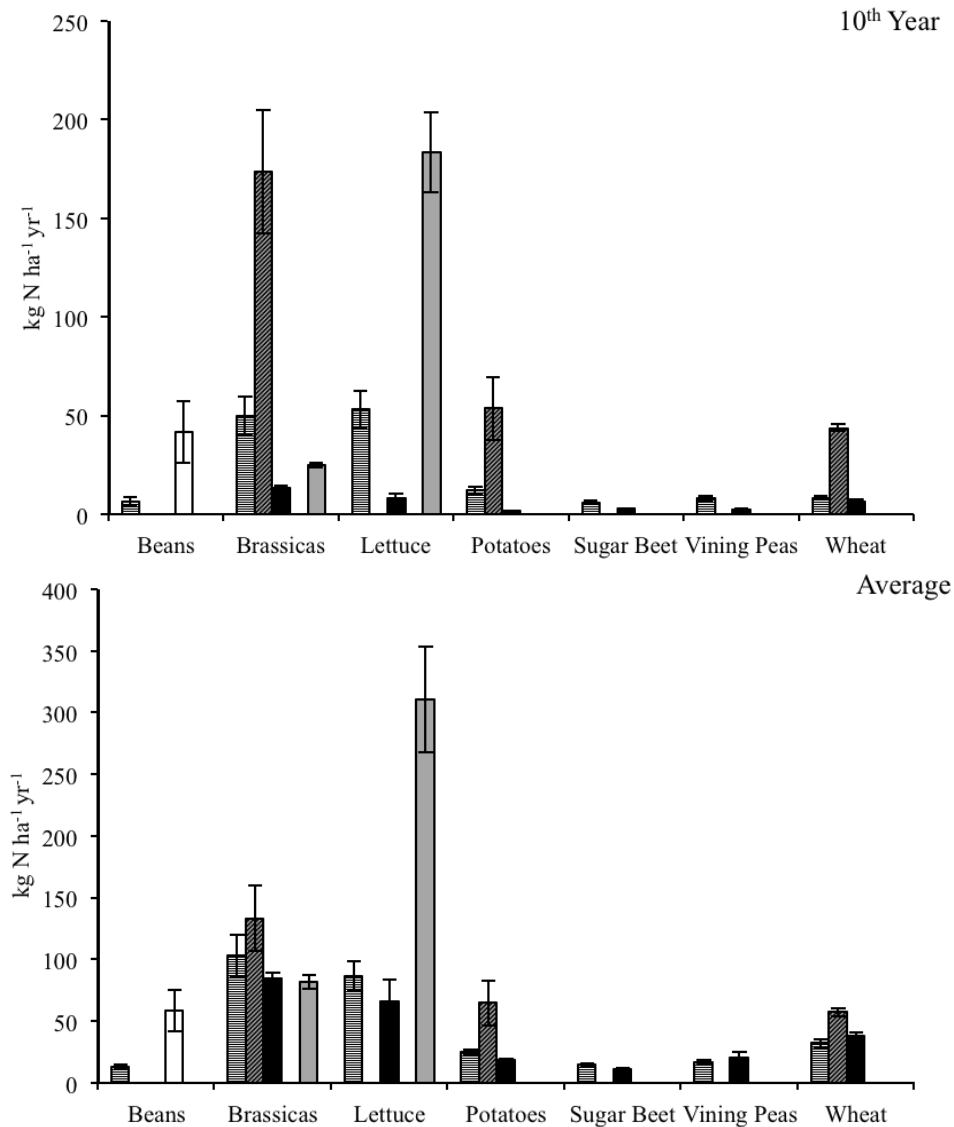


Figure 5-4: Comparison of the amount of nitrate leached by five different areas (Worcester Anglesey Lincolnshire Kenya Spain) for seven different crop types for both the final year of the model simulation (10th year) and averaged over the entire 10 year simulation period. Values represent means \pm SEM ($n > 4$).

5.4.5 CH₄ emissions

Kenya and Spain had the highest predicted methane sink for beans, brassicas and lettuce, at $1.0 \text{ kg C ha}^{-1} \text{ yr}^{-1}$, $3.1 \text{ kg C ha}^{-1} \text{ yr}^{-1}$ and $2.8 \text{ kg C ha}^{-1} \text{ yr}^{-1}$, respectively (Figure 5-5). Lincolnshire had the highest value for sugar beet ($0.8 \text{ kg C ha}^{-1} \text{ yr}^{-1}$), but all sugar beet values were very similar with the lowest being $0.6 \text{ kg C ha}^{-1} \text{ yr}^{-1}$ in Worcestershire. Anglesey had the highest net sink for potatoes and wheat,

while the lowest values for lettuce and wheat were from Lincolnshire. Worcester was the lowest predicted sink of methane for the rest of the vegetable types modelled. The average results and 10th year results were found to give similar results for between vegetable types with P values of 0.941 and 0.991, respectively, however there was found to be a significant difference between areas with P values of both 0.000.

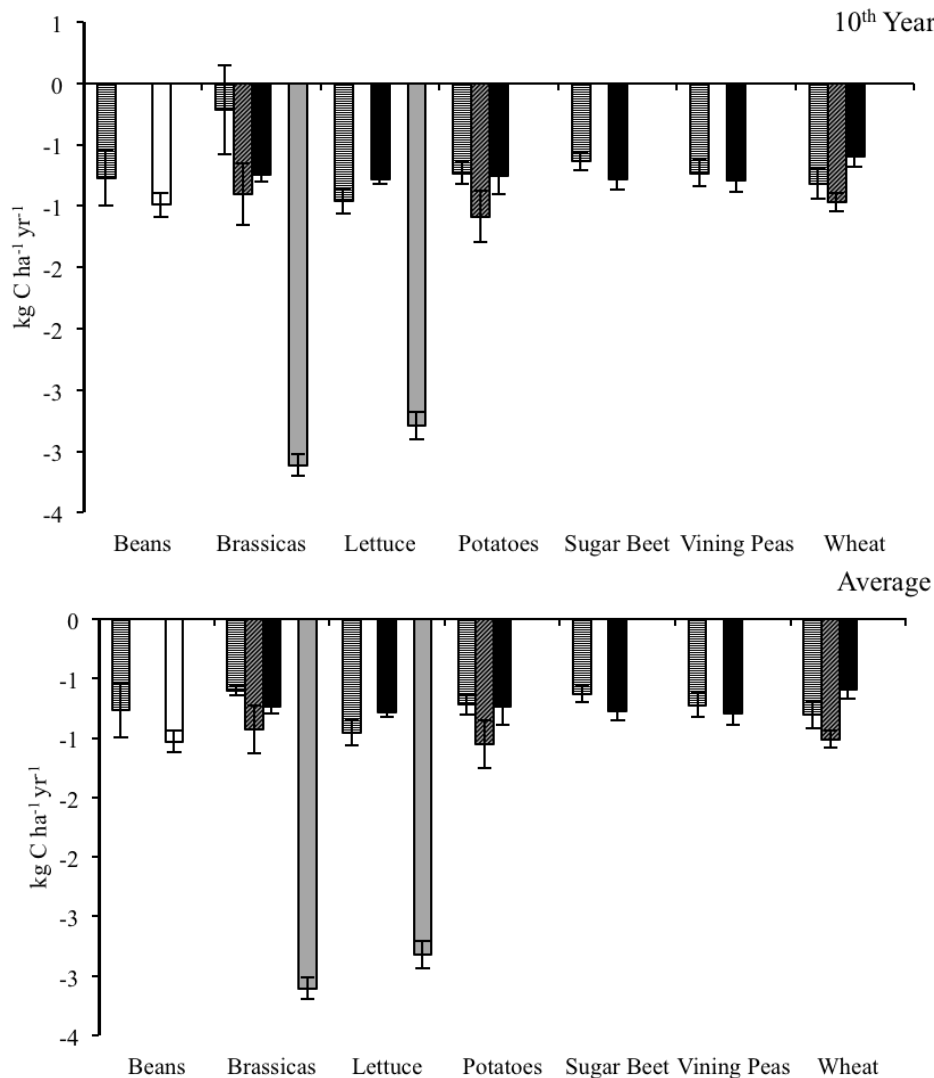


Figure 5-5: Comparison of CH₄ emissions produced by five different areas (Worcester Anglesey Lincolnshire Kenya Spain) for seven different crop types for both the final year of the model simulation (10th year) and averaged over the entire 10 year simulation period. Values represent means ± SEM ($n > 4$).

5.4.6 N₂O Emissions

Worcestershire was the lowest predicted emitter of N₂O for beans, potatoes and sugar beet, with emissions of 0.06 kg N ha⁻¹ yr⁻¹, 1.77 kg N ha⁻¹ yr⁻¹ and 0.81 kg N ha⁻¹ yr⁻¹, respectively. Lincolnshire was the lowest emitter for most other

vegetable types, as seen in Figure 5-6. The exceptions being sugar beet and vining peas, for which it was the highest. Both the 10th year and average results were significantly different from each other for each area measured ($P = 0.046$ and 0.04). Anglesey was the highest predicted emitting region for potatoes and wheat with values of $5.91 \text{ kg N ha}^{-1} \text{ yr}^{-1}$ and $3.50 \text{ kg N ha}^{-1} \text{ yr}^{-1}$. Kenya gave the highest value for beans and Spain gave the highest values for brassicas and lettuce.

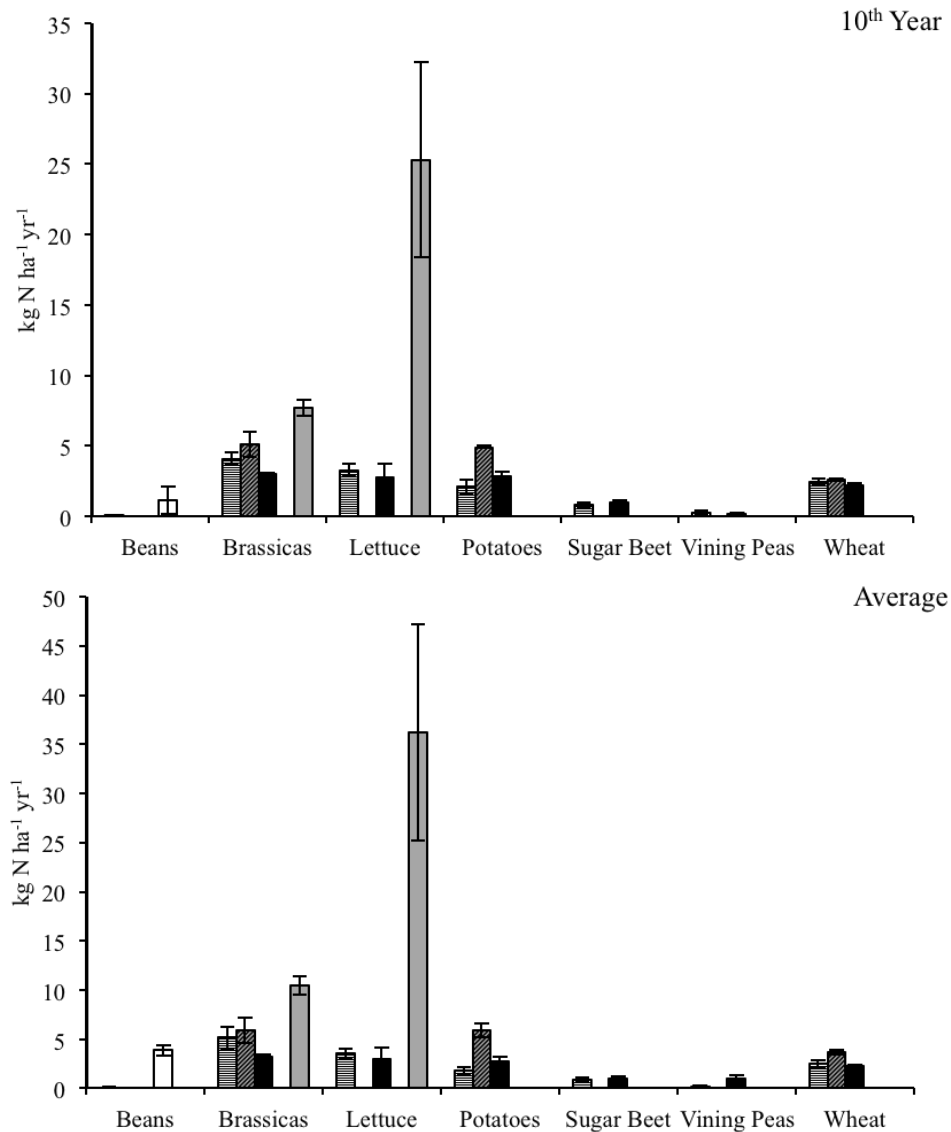


Figure 5-6: Comparison of N₂O emissions produced by five different areas (Worcester Anglesey Lincolnshire Kenya Spain) for seven different crop types for both the final year of the model simulation (10th year) and averaged over the entire 10 year simulation period. Values represent means \pm SEM ($n > 4$).

5.4.7 Carbon Equivalents (Global Warming Potential)

5.4.7.1 Beans

Beans gave higher results for total GWP in Kenya than in Worcester, with the results for Kenya being 4 times greater although the P value suggested no significant difference ($P = 0.102$). Worcester has the lowest values for CO_2 , N_2O emissions and CH_4 sink, with the highest being from Kenya. Though CH_4 has been graphed, it is not visible due to the values being very low (Figure 5-7).

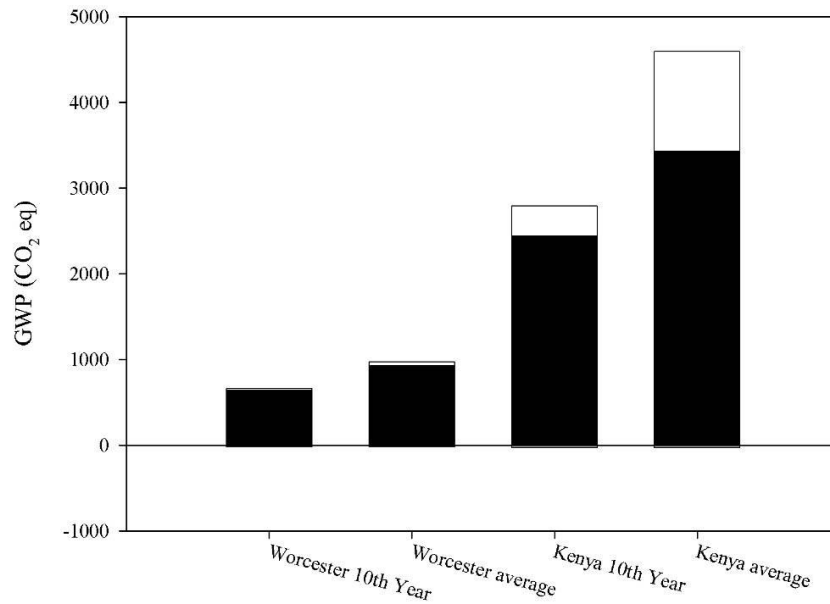


Figure 5-7: Comparison of GWP (■ soil heterotrophic CO_2 □ N_2O emissions ■ CH_4 emissions) of two different areas for beans for both the final year of the model simulation (10th year) and averaged over the entire 10 year simulation period. Values represent means.

5.4.7.2 Brassicas

Spain had the highest results for CO₂, N₂O emissions and CH₄ sink (Figure 5-8). Lincolnshire had the lowest CO₂ and N₂O values, while Worcester had the smallest CH₄ sink. There was no significant difference between the average and 10th year results ($P = 0.275$).

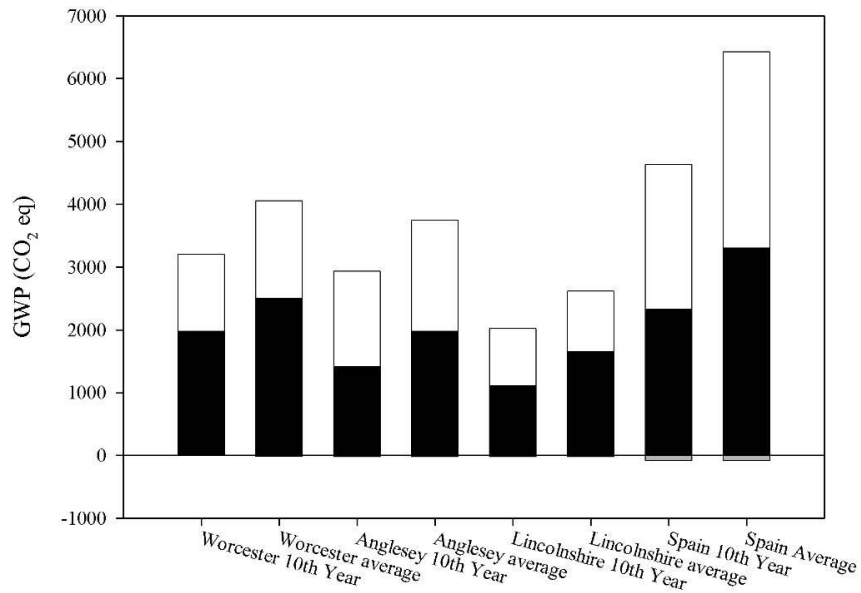


Figure 5-8: Comparison of GWP (■ soil heterotrophic CO₂ □ N₂O emissions ■ CH₄ emissions) of four different areas for brassicas for both the final year of the model simulation (10th year) and averaged over the entire 10 year simulation period. Values represent means.

5.4.7.3 Lettuce

Lettuce emissions were greater in Spain than in other regions, with a magnitude of 9 times due to the N₂O emissions. Spain had the highest CO₂, N₂O emissions and CH₄ consumption. Lincolnshire had the lowest CO₂, N₂O emission and CH₄ consumption. Both the average and 10th year were significantly different (P = 0.02). Spain had the highest N₂O emissions of all vegetable types as seen in Figure 5-9.

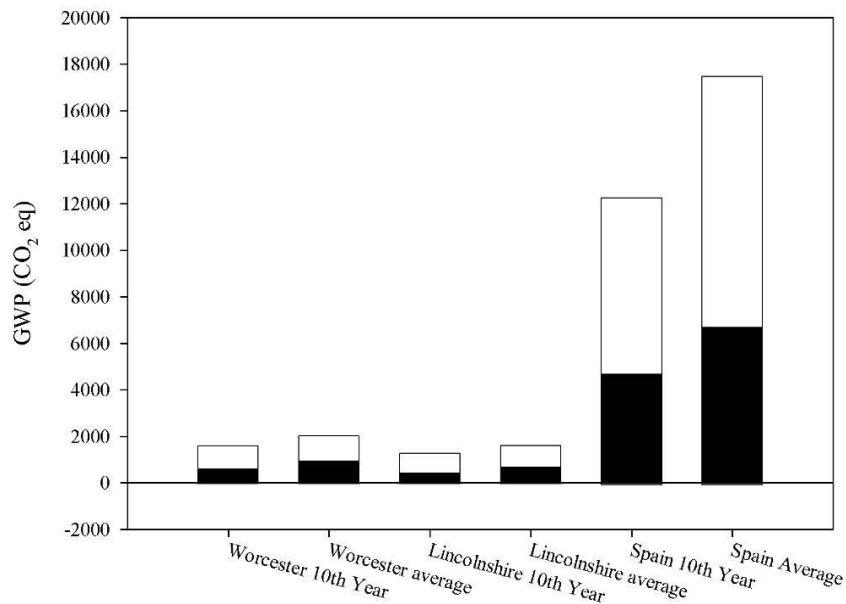


Figure 5-9: Comparison of GWP (■ soil heterotrophic CO₂ □ N₂O emissions ■ CH₄ emissions) of three different areas for lettuce for both the final year of the model simulation (10th year) and averaged over the entire 10 year simulation period. Values represent means.

5.4.7.4 Potatoes

Anglesey had the lowest total GWP results for potatoes with the lowest CO₂ emissions whilst Worcester had the highest. It should be noted, however, that Worcester had the lowest N₂O emissions (Figure 5-10). There was no significant difference between the 10th year and average results ($P = 0.128$). Anglesey had the highest CH₄ sink and the highest N₂O emissions.

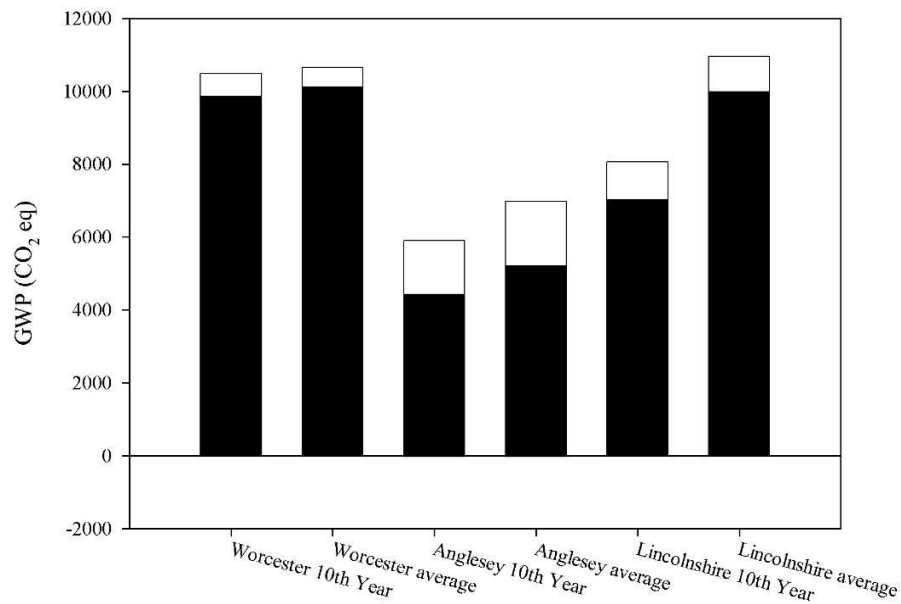


Figure 5-10: Comparison of GWP (■ soil heterotrophic CO₂ □ N₂O emissions ■ CH₄ emissions) of three different areas for potatoes for both the final year of the model simulation (10th year) and averaged over the entire 10 year simulation period. Values represent means.

5.4.7.5 Sugar Beet

Sugar beet gave higher predicted results for Lincolnshire than for Worcester. Lincolnshire, on average, had the highest results for CO₂ and N₂O (Figure 5-11). There was no significant difference between the average and 10th year results ($P = 0.807$). Worcester 10th year values had the highest N₂O result and the Worcester average results were the smallest CH₄ sink.

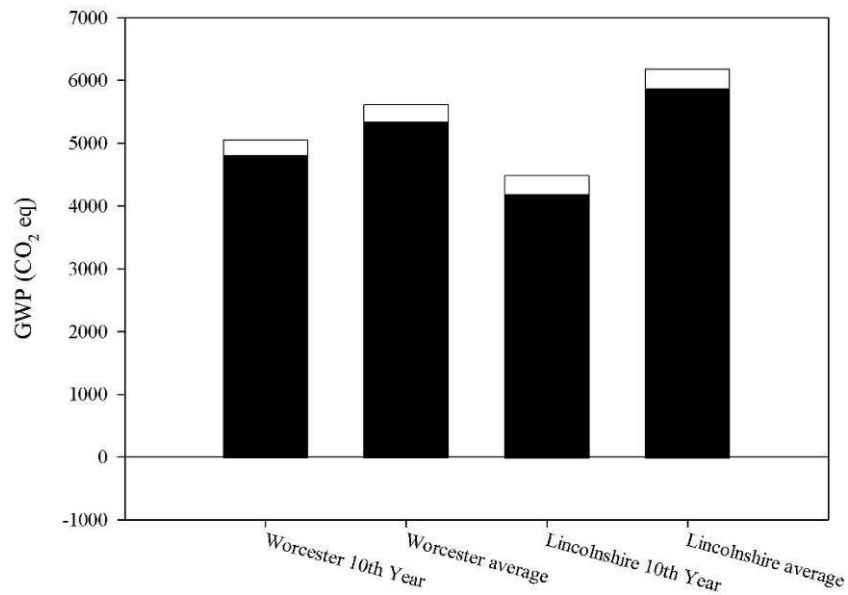


Figure 5-11: Comparison of GWP (■ soil heterotrophic CO₂ emissions □ N₂O emissions ▒ CH₄ sink) of two different areas for sugar beet for both the final year of the model simulation (10th year) and averaged over the entire 10 year simulation period. Values represent means.

5.4.7.6 Vining Peas

Lincolnshire had higher results than Worcester for the average year, but not for the 10th year, giving Lincolnshire both the highest and lowest values for CO₂ and N₂O. Lincolnshire also had the highest sink value for CH₄, but Worcester had the lowest (Figure 5-12). There was no significant difference between the average and 10th year results ($P = 0.365$).

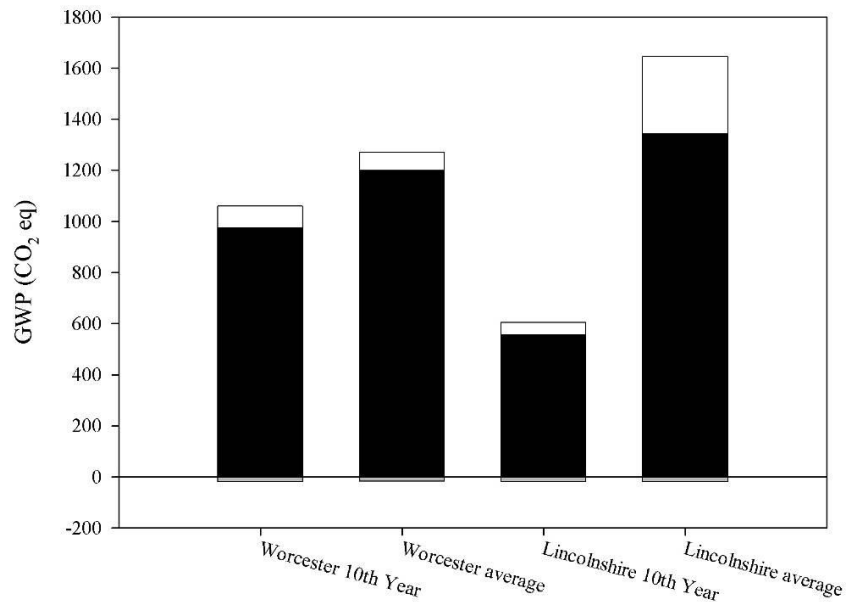


Figure 5-12: Comparison of GWP (■ soil heterotrophic CO₂ □ N₂O emissions ▒ CH₄ emissions) of two different areas for vining peas for both the final year of the model simulation (10th year) and averaged over the entire 10 year simulation period. Values represent means.

5.4.7.7 Wheat

Wheat gave higher results for Worcester and Anglesey than Lincolnshire (as seen in Figure 5-13). There was no significant difference between the average and 10th year results ($P = 0.223$). Lincolnshire had the lowest CO₂, N₂O emissions and CH₄ consumption. Worcester had the highest results for CO₂, and Anglesey had the highest results for N₂O emissions and CH₄ consumption.

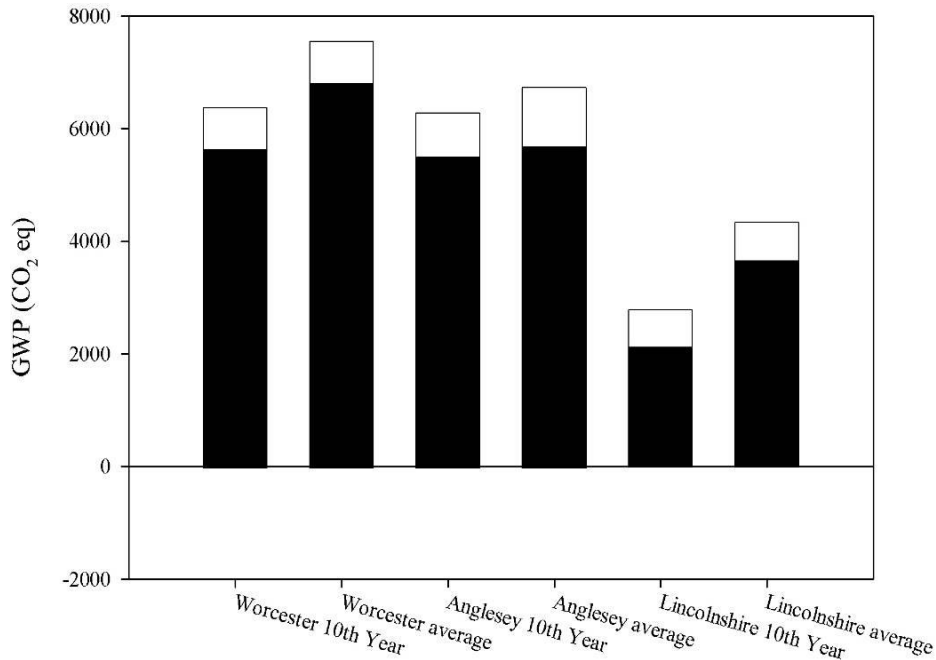


Figure 5-13: Comparison of GWP (■ soil heterotrophic CO₂ □ N₂O emissions ■ CH₄ emissions) of three different areas for wheat for both the final year of the model simulation (10th year) and averaged over the entire 10 year simulation period. Values represent means.

5.4.7.8 All Vegetable Types

Anglesey had the lowest overall GWP equivalent emissions and Worcester had the second lowest GWP equivalent emissions (for beans). Spain had the second highest emissions, owing to high N₂O production from lettuces - even though brassicas were lower than lettuces, the results were still above average, as seen in Figure 5-15. Vining peas also gave very low overall results for Worcester and Lincolnshire.

Beans were the lowest emitters in Worcester, with potatoes being the highest; potatoes were also the highest in Lincolnshire. Lettuces were the highest emitters for Spain and brassicas were the lowest for Spain and Anglesey. The lowest emitter for Lincolnshire 10th year results was vining peas.

Kenya had the highest overall emissions for beans and Spain had the highest for brassicas and lettuces. Lincolnshire's average had the highest results for potatoes, sugar beet and vining peas from all regions modelled; it did however have the lowest result for wheat. Lincolnshire's 10th year results were the lowest results for brassicas, lettuces, sugar beet and vining peas, although Anglesey's 10th year had the lowest results for potatoes, and Worcester's 10th year had the lowest for beans. Worcester, on average, had the highest emissions for wheat. The Average results were found to be significantly different between places ($P = 0.039$) but the 10th year results was found to not be ($P = 0.126$).

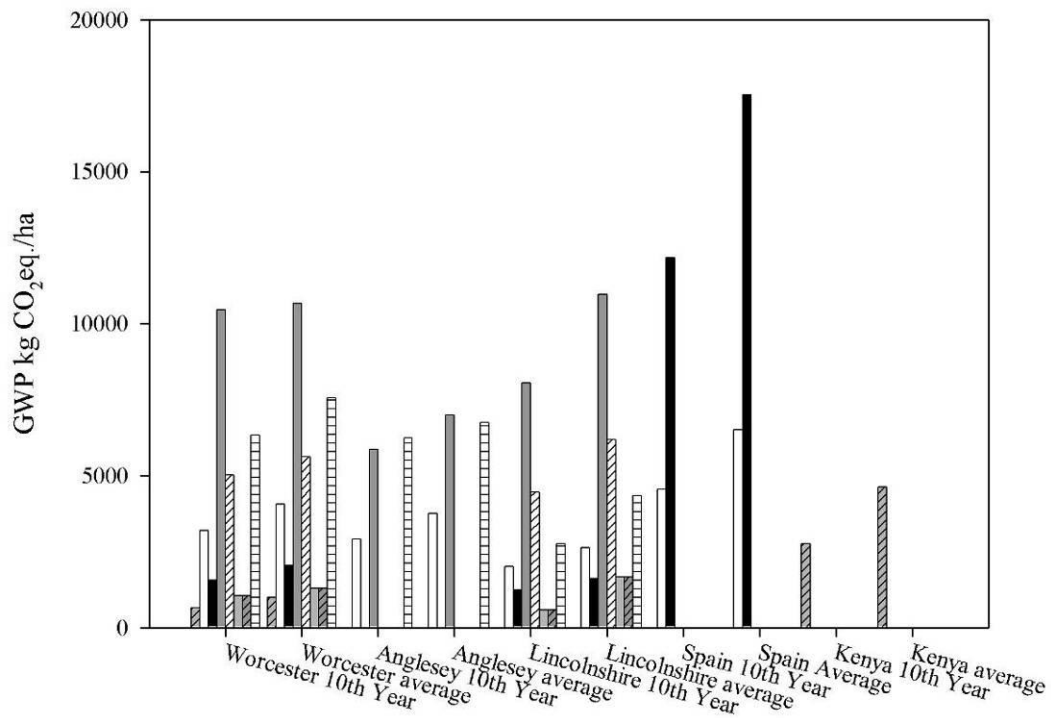


Figure 5-14: Comparison of total GWP of seven different vegetable types (beans, brassicas, lettuce, potatoes, sugar beet, vining peas, wheat) for five different areas, for both the final year of the model simulation (10th year) and averaged over the entire 10 year simulation period. Values represent means.

5.4.8 Carbon equivalent per ton of yield

The carbon equivalents have been divided by the modelled yield output for each vegetable type to produce the greenhouse gas intensity which consider whether the GHG emissions are less per ton of vegetable item produced. Worcestershire emissions are the highest with beans and potatoes producing higher emissions than the other vegetable crops and regions (Figure 5-16). Spain's emissions are much lower when considering the amount of the vegetable produced, though it is the second worst producer after Worcester. Lincolnshire's 10th year results were the lowest, and Anglesey potatoes produced the lowest overall emission per tons of yield. Kenya was intermediate and 10th year and average results were significantly different ($P = 0.001$).

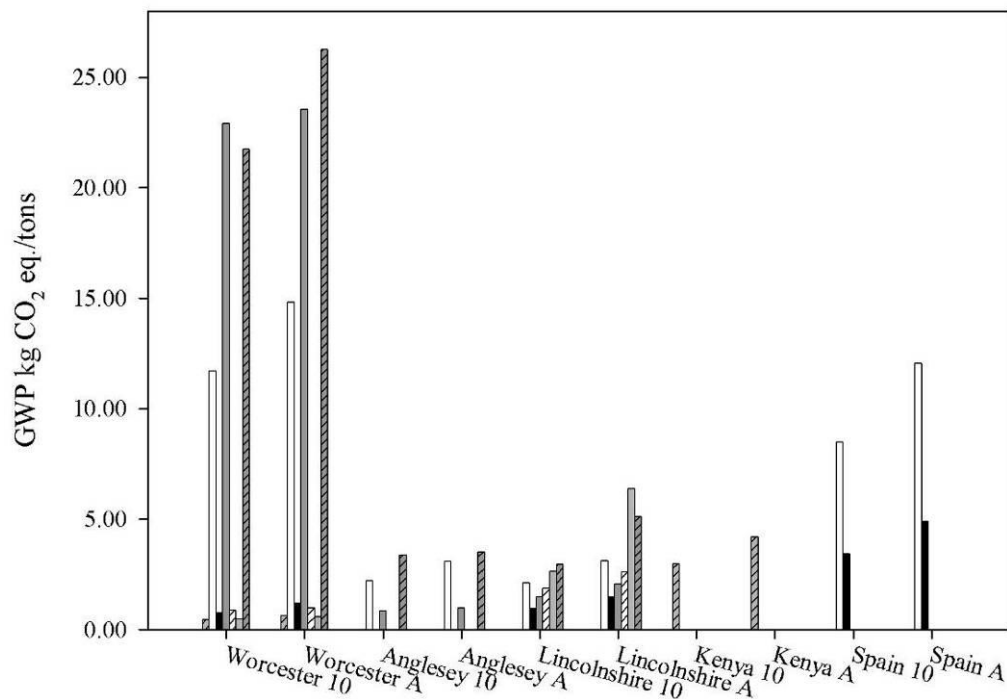


Figure 5-15: Comparison of total GWP divided by the modelled yield of seven different vegetable types (beans, brassicas, lettuce, potatoes, sugar beet, vining peas, wheat) for five different areas, for both the final year of the model simulation (10th year) and averaged over the entire 10 year simulation period. Values represent means.

5.5 Discussion

Within the study described here the DNDC model provided a valuable insight into the influence of geographical location on GHG emissions and other agroecosystem C and N flows. If DNDC is to be used as a decision support model by farmers or regulatory staff, it must be able to accurately predict outcomes on crop production and environmental impacts for a wide range of farming operations and climatic conditions (Li et al., 2006). This necessitates that the model is validated against experimental measurements. While some agreement was seen in the predicted soil N concentrations and the field measurements, it is clear that the model needs further development to better describe a range of climate zones, soil types, and management regimes. It would also be useful to validate the model against more experimentally measured field variables (e.g. crop yield, soil water content etc). This would provide an indication of which sub-model may need optimizing for future studies. One of the major disadvantages of DNDC is also its inability to simulate lateral flow in the soil, which is obviously important on sloping land.

Many aspects of environment and farm management have been shown to significantly affect crop yields and GHG emissions. Farming methods also vary greatly between farms and countries; Kenya and Spain have vastly different farming methods from those in the UK. These differences are largely due to variation in climate, soil and stage of economic development which the model may yet have not been validated for. In temperate climate zones, vegetable crops give high yields, which are attained by optimal agricultural practice, intensive disease and pest control and superior varieties (Wijbrandi and Both, 1993).

Water can be limiting in Spain, and for this reason it uses significant amounts of irrigation, typically either drip irrigation or flood irrigation. The situation is different in Africa, where water can be abundant in some locations at some times. This is evidenced by the facts that in 2001 agricultural uses accounted for about 5% of internal renewable water resources in Africa, while they accounted for 10%, and 17% in the Caribbean, and Asia, respectively (Vlek et al., 2008). Kenya has less trouble with water, as farms there use large storage dams which are filled during the two rainy seasons, and the stored water subsequently used for drip irrigation of vegetables. About 50% of the world's

large dams were built primarily for irrigation, and some 30–40% of the world's irrigated cropland worldwide relies on dams (Vlek et al., 2008). Kenya is also subject to a more constant temperature and number of sunlight hours than the UK or Spain, allowing crops to be grown all year round. Due to the constant number of daylight hours in Kenya it can be necessary to use artificial lights on some crops in the evening; some Kenyan vegetables receiving up to an extra 4 hours of lighting. The Spanish and Kenyan farms we studied also used a lot more manure than their UK counterparts, and, owing to the longer and warmer growing season, planted more consecutive crops, which may be part of the reason why DNDC gave much higher results for Spain and Kenya than for the UK. At the height of summer Spain generally leaves the fields bare and undertakes most of the growing through the cooler winter.

The DNDC model is not programmed to take account of either the extra lighting or the use of drip irrigation with added fertilisers. This may have introduced unforeseen errors into the model predictions, and in the case of the artificial light may have led to an underestimation of the size and rate of growth of the plants. With the use of artificial light also comes an increase in emissions through the extra use of electricity. Also the model does not take into account that in some situations crops are harvested over many weeks (e.g. beans), so again the model outputs may have underestimated the yield. In addition, such a harvesting regime may lead to a longer growing season for some plants, and also a greater level of irrigation, possibly increasing the amount of GHG emissions produced. This may be particularly important in Spain, which has high evapotranspiration and restricted rainfall (Olesen and Bindi, 2002). The irrigation by flood or drip gave overall very high GHG results for Kenya, Spain and all regions using it for potatoes. In the model's manual there was no indication of whether the model uses drip or flood irrigation (neither is there any indication in the published literature). Therefore we cannot be certain about the accuracy of the model on this account. More measurements and alteration to the model may have increased its reliability.

A validation of the model was undertaken by measuring the ammonium and nitrate present in the soil and comparing this to the ammonium and nitrate levels that the model predicted for the day the measurements were taken. It was found that the model and the in-situ results did show a similar pattern over time,

with the modelled results being generally higher. This result raises some doubt about the validity of the nitrogen sub model in DNDC. Li et al. (2006) suggest that to improve the model it would be necessary to introduce a better ability to simulate lateral flow in the soil. DNDC will need the information of horizontal water flow across the simulated grid cells, which can be produced by the spatially distributed hydrological models such as SWAT or MIKE SHE (Li et al., 2006). This is particularly worrying as the nitrogen and carbon elements of the model are closely linked. Smith et al. (2004) found that the variability between measured and predicted emissions was high, indicating the model often over- or underestimated on a site-to-site basis, though they did conclude that it performed well on average. Brown et al. (2002) suggests that in cases where there is poor agreement between measured and model-predicted values it is rarely possible to ascertain whether the model's predicted time of emission, or actual emission magnitude is at fault, as measurements are seldom recorded every day in a measurement period.

There are few data sets with which to validate the large estimates of emissions from vegetables. In southwest Scotland, Dobbie et al. (1999) measured large N₂O losses from brassicas (9.1 kg N₂O-N ha⁻¹) between March and October, following application of 130 kg fertiliser N ha⁻¹ and 12.2 kg N₂O-N ha⁻¹ and from potatoes (4 kg N₂O-N ha⁻¹) following application of 170 kg N ha⁻¹ and 4.7 kg N₂O-N ha⁻¹. Ryden and Lund (1980) recorded losses of 41.8 kg N₂O-N ha⁻¹ yr⁻¹ from celery (fertiliser application of 336 kg N ha⁻¹) and 26.6 kg N ha⁻¹ from cauliflower (fertiliser application of 528 kg N ha⁻¹) in California. These crops, although only grown on small areas, can have a large effect on emission from some geographical areas (Brown et al. 2002).

Potatoes were the only vegetable type measured that gained soil organic carbon, though - surprisingly - they gave the highest GWP UK emissions. This may be owing to the irrigation system implemented by the model (as discussed above), though Olesen and Bindi, (2002) suggested that potatoes, as well as other root and tuber crops, are expected to show a substantial response to rising atmospheric CO₂ due to their large below ground sink for carbon. Overall, lettuce gave very low GHG emission results except for Spain, which had high results for both soil heterotrophic CO₂ and for the N₂O emissions. This suggests that it is not just what vegetable type that is grown that needs to be considered, but also

where it is being grown as some areas maybe more suited to the production of certain vegetable types than other areas and modelling is one way to take into consideration all environmental and management aspects. Wheat showed higher levels of GHG emissions in Anglesey and Worcestershire compared to those grown in Lincolnshire. Brassicas had varied levels of emissions over the four geographical areas considered, with Spain having the highest emission due to the large amount of N₂O emissions produced and Lincolnshire gave the lowest. Beans and vining peas gave the lowest emissions, and this may be to do with the lack of fertilisers used as high levels of fertiliser not only stimulates plant growth but can stimulate microbial activity. Reducing this can therefore reduce emissions as well as less ploughing sessions, as this decreases the amount of soil disturbance.

It appears from the results that Spanish lettuce production is the largest GHG emitter, with Worcester beans being the lowest GHG emitter followed by vining peas in Lincolnshire and Worcestershire. Lettuce production systems also seem reasonably good in the UK but are one of the largest emitters when grown in Spain. In arid and semi-arid environments plant survival and growth is limited by the availability of water, and irrigation is required to increase plant production to the point where crops become economically viable. Irrigation also increases C input to soils via increased litter and root production (Entry et al., 2002). Potatoes were another high greenhouse gas emitter when grown in the UK - as is wheat when the yield produced is not considered. Brassicas in the UK gave lower emissions than wheat and sugar beet. Kenya gives the highest emission for beans but this maybe due to the large amounts of organic matter that is added to the soil. The higher daily temperature in Kenya may increase soil organic matter breakdown and the lack of machinery farming reduces the density of the soil, allowing easier movement of the gases through the soil.

Table 3 summarises the vegetables that tend to have the highest and lowest environmental impact in each region. Spain and Kenya appear to have a greater environmental impact than any of the regions in the UK. Within the UK, Worcestershire was one of the worst growing areas, in terms of environmental impact, with Lincolnshire being the best. Anglesey was only the best environmental option for growing potatoes and gave intermediate results

compared to the rest of the vegetable types. Brassicas were one of the vegetables with the lowest environmental impacts, while potatoes were the worst.

One might conclude that increasing the number inputs might change assessments of which vegetables are best suited to which areas. However, a discussion of that prospect is beyond the scope of this study. However it should be noted that the UK is unable to produce all vegetables at all times of the year; therefore our national eating habits would have to change, or become less healthy, if we were to avoid imports from certain countries. For example, Hospido et al. (2009) point out that open field production of lettuce in the UK provides supply from May to October, while lettuce is imported, primarily from Spain (around 80%), during the rest of the year.

Table 5-4: Comparison of which vegetables and areas are best and worst for growing according to the GWP graphs and modelled results not considering yield produced.

	Best GWP kg CO ₂ eq./ha	Worst GWP kg CO ₂ eq./ha
Region		
Worcester	Beans (799)	Potatoes (10551)
Lincolnshire	Vining Peas (1105)	Potatoes (9486)
Anglesey	Brassicas (3315)	Wheat (6477)
Spain	Brassicas (5452)	Lettuce (14781)
Vegetable		
Beans	Worcester (799)	Kenya (3666)
Brassicas	Lincolnshire (2301)	Spain (5452)
Lettuce	Lincolnshire (1412)	Spain (14781)
Potatoes	Anglesey (6411)	Worcester (10551)
Sugar beet	Neither	
Vining Peas	Neither	
Wheat	Lincolnshire (3542)	Worcester (6931)

When two or more vegetable types were measured in each area the order was not found to be consistent with measurements of which vegetable types were the highest and lowest emitters. There was much variation, as can be seen from Table 6-4. Therefore my hypothesis for this study was correct in that the modelled UK results for the areas studied would be lower than those from

abroad, however the horticultural production system were not strictly the same due to environment and economically variations in the countries studied.

When we consider the tonnage of vegetables produced rather than hectares employed, the graph does suggest that Spain may not be as bad as initially thought, due to the large yield it produces, whereas Worcestershire was the worst and Kenya intermediate. The amount of the food item produced in each field needs to be looked at if we are to take a holistic view of GHG emissions. This is exemplified in the case of Spain. Also if the emission for one chemical is high it does not mean that the results are high for all the rest of the emissions for that specific vegetable type. Small changes to farm management may help reduce one emission, but this does not suggest that any one specific vegetable is worse than another. However, it may be worth considering growing certain vegetable crops in particular regions to minimize GHG emissions and adverse environmental impacts, and also considering the seasonality of these regions.

5.6 Conclusion

Vegetable production can release large amounts of GHGs, however, this can be minimized to some extent by the correct choice of location for their production (in environmental terms). Though many believe local production is better in terms of GHG emissions, this study critically shows that the outcome is highly dependent on where and how the vegetables are grown and not simply how far they travel to market. The results presented here suggest that vegetables produced abroad are not more environmental friendly than those produced within the UK. We ascribe this to warmer temperatures and the use of irrigation overseas in addition to differences in soil type and fertiliser/cropping regime.

Farm management can have a substantial affect on the GHG emissions, as excess fertilisers or excessive tillage may increase emissions and reduce greenhouse gas sinks. These results give an idea of what quantity of emissions may be produced; however, more fields of the same crop need to be measured for a more accurate comparison. The results showed that emissions were excessively large for some vegetable types in some locations suggesting, that their production should be discontinued. This may have negative implications for markets and consumer choice; however, it is clear that changes in food production need to be

made if we are to meet targets for GHG reduction in agriculture. In addition, changes in the location of food production may also have implications for economic development and social wellbeing, particularly in developing economies such as in Kenya.

In summary, it was found that crops grown in different areas do emit significantly different amounts of GHG emissions, and this should be considered when discussing the question of 'food miles' and calculating carbon and ecological footprints. Theoretically, it is possible to predict which geographical area is most suited for each crop's production; however, tests to validate the model outputs would be desirable before the introduction of new agricultural policies designed to combat climate change.

Chapter 6. General Discussion

Elizabeth York

School of the Environment, Natural Resources and Geography, Bangor

University, Gwynedd LL57 2UW, UK

6.1 General Discussion

Vegetable production, both domestically and abroad, makes an important contribution to the impact farming has on the environment, as well as the sustainability of a society. This is exemplified by the supply of fruits, vegetables and potatoes to the UK market, which totals 10.5 million tonnes annually (DEFRA, 2011). Over the past two decades, developing countries have had significant growth in their exports of fruit and vegetable products, with these products now accounting for some 21% of total developing country agro-food exports. The exports of developing countries have expanded beyond traditional tropical fruits and ‘out-of-season’ temperate vegetables to include a wide assortment of items (Jaffee et al., 2005). The environmental concerns of global agro-food systems have led to development of concepts such as ‘local food’ and ‘food miles’ and have become powerful tools in policy discourses built around sustainable agriculture and alternative food systems (Coley et al., 2009). For this reason, ‘food miles’ need to be quantified, to assess the environmental, social and economic factors that may affect both the UK and export countries before a decision on the preferred overseas supplier to the UK can be selected.

This PhD was undertaken to assess whether or not it is more environmentally friendly to grow vegetables within the UK or overseas when simply considering greenhouse gas emissions from soil. This was theoretically assessed using several versions of the DNDC Denitrification Decomposition model with validation of the model output undertaken by comparison to actual soil N measurements in the field. It was decided after a study of the literature and comparison of the five latest model versions that the most recent version of the model would be used for further analyses. This decision was made with the qualification that results should be considered as semi-quantitative, as the model can both over or underestimate GHG emissions by a factor of 5. Through this PhD we have seen that the hypothesis of that the model will give realistic and robust results in comparison to experimentally derived GHG estimates is true for the present knowledge and our ability to measure GHG emissions. It has also been found to true that the UK would give lower modelled GHG emissions than equivalent systems abroad. However there is a chance that if different areas or systems were under consideration then this would not be true.

6.2 Limitations of using the DNDC model

The accuracy of the DNDC model's output was limited when applied to countries to which it had not previously been calibrated. At present, the model has been calibrated for China, India and North America, though it has been partially validated for use within Europe (Babu et al., 2009; Li et al., 1992; Tonitto et al., 2007). Within the 3 countries studied here there were differing farming techniques and conditions that the model's coding does not take into consideration; these included flood irrigation and extended light hours. As such, this calls into question the validity of the model, as it may over or underestimates field N emissions. To what extent differing farm management schemes influence the model results will only be known once the model has been fully calibrated for these areas and the farm management options extended to include those incorporated in this project.

Furthermore, it is noteworthy that the magnitude in variation for some key variables, for example, soil heterotrophic CO₂, between farms within the same area was found to be as dissimilar to that between farms in different areas. This may be due to variation in farming techniques across the areas. For this reason, it would be wrong to say that one country would be better for producing certain vegetables crops than another. Ranatunga et al. (2001) also expressed concern when comparing models over the level of site-specific information required, as some models required less site specific information - although calibration levels are likely to be partly responsible for differences in model performance. This reasoning coincides with findings published by Hospido et al. (2009), who concluded from LCA measurements that no generalisations can be made as to which country has the most environmentally benign production systems. However, both the foreign countries considered in this project did give higher emission values than the three UK counties studied. Whether this is universally true for those entire countries rather than the few fields measured cannot be known without further study.

The variation in model output raises several questions:

1. Why is there so much uncertainty and disagreement?

2. Are there alternatives to the ways these budgets are developed?
3. Why do we need global inventories anyway?

For the last question, there is at least one simple answer: we need global numbers to demonstrate the importance (or lack thereof) of the soil GHG source in contrast to other important sources such as fossil fuel combustion or biomass burning (Matson, 1997).

Models are limited in their ability to fully imitate all factors and processes to the degree that natural systems can, owing to the complexity and number of interactions involved. DNDC is, however, a complicated model in comparison to others, as it combines both nitrogen and carbon modelling with a crop growth model to study the whole system. Due to the nature of modelling, DNDC has been found both here and in the literature to over/underestimate emissions and is more sensitive to certain inputs. However, considering the other models available, the outputs have been found to have low errors and to be more consistent over long data sets (Smith et al., 1997).

There is also the consideration of certainty vs complexity. As models become more complex and require greater numbers of inputs are we in fact removing the certainty that the results are correct? With a system of lower level complexity we can easily identify the interactions in the model and easily collect the data needed in comparison to a more complex system where the interactions are harder to identify and the inputs difficult to collect. However if the more complex system is correct and inputs are realistic this would give a more accurate output than the less complex system. Would it also be scientific to ignore changes in knowledge just because the system would become more complex? The only way to create certainty in a system that is is through the validation of the model to known measurements and to sure that this is accurate as possible.

Pre-simulation was not run for any of the simulations in this PhD, as most published data – with the exception of Qiu et al. (2009) - on the DNDC model did not mention any pre-simulation. It was decided that data from both the tenth year result and the average of the ten years would be considered for analysis; to increase the accuracy of the outputs given. The model is found to have a period of instability that maybe due to the algorithms of the model not being adjusted correctly to the inputs of the parameters. Calibration of the model for Europe

would significantly help this problem, as the algorithms would be able to capture the unique conditions of these environments (Liu et al., 2007)

6.3 DNDC Analysis

The five different versions - DNDC82, 86, 90, 91 and 92 - when compared with the same data, gave varying results. The most modern versions, DNDC 91 and 92 gave the most similar and least extreme results. DNDC90 gave some of the most extreme results, with the nitrate leaching output being far greater than the nitrate input from the fertiliser applied. If this result was accurate, it has been estimated that the true field depletion of N after a number of years would make the field unviable for crop production. From long term studies it has been found that soils do lose N overtime, and that a net reduction in soil-derived N₂O emissions will require mitigation strategies as fertiliser use increases and increased input comes from atmospheric deposition, ranging from 0.5 N m⁻² y⁻¹ in the US to 6 N m⁻² y⁻¹ in Western Europe (Van Der Weerden et al. 1999, Mosier et al., 1998). However the N loss rates were not at the same magnitude as in the DNDC model.

DNDC has been found to give reliable results by some reseachers (Li et al., 1992-2010; Salas et al., 2003; Tonitto et al., 2007). This contrasts with the findings from this exercise where the model did not always yield reliable results, though this may be due to problems with collecting data to validate the model rather than the model itself. The sensitivity analysis run on DNDC90, 91 and 92 found that some of the inputs (atmospheric CO₂ concentration, crop cover, fertiliser application method, floodwater pH, irrigation water pH, latitude, number of weeding events, slope, N content in rainfall) apparently had no effect upon the output of the sensitivity test. For example, for latitude, it was theorised that when the weather data used did not include the number of daylight hours, then latitude would be functional to alter the growth of the plants according to the region. This difference was not found, and therefore day light hours were not included in our simulation. Wind, however was including, owing to the variations in outputs that were found when used. The question is: what variables have the most influence on the model and what variables should be used? There is need for further analysis of why some variables have a larger effect. A

sensitivity analysis on the model looking at the relationship of variables would be useful to assess the full workings of the model. This would be easily calculated by using the same method, but changing the variables each time to calculate the size of the effect each variable has upon another and where each sub model overlaps. It would also help if the DNDC code was made open access to allow validation of the mathematical functions which drive the model, and also to see how the sub-models are connected (i.e. to assess feedbacks).

Some of the outputs were found to be more sensitive to certain inputs than others. Soil organic carbon is a good example, and this was also found by a number of other researchers (Li et al., 1992). The model versions showed significantly different results when modelling the same data, however it is unknown unless the latest version is validated against field measurements whether this would be the most accurate version. It would however be presumed that this version is more accurate than the preceding version due to model having been changed. These changes in model version need to be communicated to the DNDC community as at present any updates are not. There are many users still using older version creating and using inaccurate model results for possible for policy use. The magnitude of variation for the different variables would suggest that the model needs to be modified to allow users to calibrate and validate the model for areas or vegetable/land use that is being measured. This would make the model more flexible and give the user more options for its use. The addition to the model of an added sub-model which would allow users to input collected biophysical data for the model to validate its outputs would also increase the accuracy of the model without the need to calibrate it for each area studied.

6.4 Q₁₀ values and modelling considerations

The Q₁₀ results were assessed to determine whether or not there would be differences in respiration from soils from different geographical areas, as well as if farm management/land use has an effect on respiration. It should be noted that the Q₁₀ for the DNDC model, as well as with most other scientific models – for example, RothC - is assumed to equal 2. Although this has been proven on a small scale under laboratory conditions, this may not always be so when applied at the field scale, as the Q₁₀ for soil measured from the study areas was found to

be greater than 2, with an average of 2.57. This piece of work does suggest that DNDC should reconsider the need for a Q_{10} of a higher value to once more be used or to justify the continuing use of the current Q_{10} value. The DNDC model does not allow for variation in Q_{10} to be added, and this may have a detrimental effect upon the outputs, with the results underestimating the soil and microbial emissions.

DNDC allows users to vary the soil type for the study area. However Q_{10} values change according to the amount of soil moisture, and therefore would give different results compared to a situation in which the same Q_{10} remained constant. Clay soils are known to hold greater quantities of moisture than sandy soils owing to particle size. Therefore soils with a lower moisture content, or which exhibit higher moisture loss, will have a decreasing soil respiration - reducing the Q_{10} value (Liu et al., 2006). Crop types and farm management will also affect the Q_{10} of the soil. One of the factors that will cause the rate of microbial respiration to vary is the quantity and quality of soil organic matter, therefore the greater quantity and better quality of soil organic matter, the greater the respiration potential (Pavelka et al., 2007; Zhou et al., 2009). Farm management will vary between crop types, with some crops needing more or deeper tillage, decreasing soil organic matter levels. Greater use of perennial forage crops can also significantly increase soil C levels, owing to high root C production, lack of tillage disturbance, and protection from erosion (Mosier 1998). The type of crop will not only vary the soil organic matter through dropped leaves, but also through the size of the root system and whether the roots are shallow or deep; root contribution to soil respiration ranges between 10–90% of total in situ soil respiration, depending on vegetation type, season and depth of roots, as respiration potential is located in the upper soil layers most often (Pavelka et al., 2007).

6.5 Comparison of emissions from different vegetable types in different areas

Models are unable to perfectly predict the natural environment and the limitation of a simulated environment will have an effect on the outputs; the magnitude of this effect is not fully known. If substantial variations in results occur between fields; then using model output and scaling these up to compare regions and

countries could produce significant inaccuracies. Freney et al. (1997) suggested that emissions of nitrous oxide from the same site and similar agricultural systems are variable in both time and space. This is due to the heterogeneity of the systems from which nitrous oxide is emitted, and the complex interactions which occur between the chemical, physical and biological variables of the soil. This would be true for all greenhouse gases produced. In the case of nitrous oxide, the regulations that policymakers may place on the agricultural industry to reduce its effects may not be based on data that reflects natural conditions.

By using models, scenarios can be considered for the reduction of N₂O in systems, but these need to be carefully scrutinised. This research project found that the field analysis of soil ammonium and nitrate gave the same pattern as the model but at a smaller magnitude. Other researchers also found a similar pattern with Li et al. (2006) suggesting that the model over-predicts the nitrate produced. Other published data in the literature also found some similarities, but these are mostly based on yearly or seasonal cycles and not day to day measurements, as in this research.

However, when the results for each area and vegetable type were converted to carbon equivalents and compared, only Spanish lettuce N₂O gave greater values than soil heterotrophic CO₂. For Spain, the N₂O results were very large - 36 kg N ha⁻¹ yr⁻¹ - much larger than the highest result for Kenya (4 kg N ha⁻¹ yr⁻¹). For the C equivalents per hectare Spain still gave the largest results with 4553 kg CO₂ eq ha⁻¹ while Kenya gave 2766 kg CO₂ eq ha⁻¹. When calculated on a per ton of yield base, the results were more similar to the rest of the areas measured as yields were greater for Spain and Kenya. This considerable difference with N₂O may be due to the greater use of manure and variation in farming techniques discussed above. However at present from these modelled results the UK would give lower GHG emissions for systems studied.

The results discussed here only consider five versions of the DNDC model. There are potentially numerous outputs from numerous models available - such as Roth C, Century, and Daisy - that can be applied to the DNDC model to improve the output accuracy. Previous studies by Smith et al. (1997) and Ranatunga et al. (2001) have compared models including Roth C and Century and found them to give similar results to those predicted, though it is not known how fertilization and other treatments, as well as plant disease, may affect

outputs. However, all models provided a satisfactory representation of the pattern of soil carbon decline under continuous cultivation. Predicted N₂O emissions varied between the four models (CENTURYNGAS, DNDC, ExpertN and NASA-CASA) from 0.08 to 1.4 kg N₂O-N ha⁻¹ yr⁻¹ in the shortgrass steppe, 0.9 to 4.2 kg N₂O-N ha⁻¹ yr⁻¹ in the Scottish grassland fertilized with urea and 1.9 to 4.8 kg N₂O-N ha⁻¹ yr⁻¹ in the German agricultural cropping sequence (Mosier, 1998). Therefore, the conclusions given here are cautionary, though we generally found emissions of CO₂, N₂O and CH₄ uptake agreed with literature values (Smith et al., 1997) generated from alternative models to DNDC.

6.6 The local vs. overseas scenario

Currently, it is not possible to state with any degree of confidence that one agricultural area within a country, let alone different countries, is more environmentally friendly for vegetable production than another. Even if areas could be designated on environmental grounds, the whole picture needs to be considered, i.e., factoring in social issues.

Coley et al. (2009) discusses that for consumers, purchasing the most geographically local produce per se does not necessarily mean the lowest carbon impact. They are not simply confronted with a choice between ‘local-good’ and ‘global-bad’ as many factors are involved (Coley et al., 2009). Nor is carbon the only way to evaluate the impact of purchasing decisions: other factors will have implications for biodiversity and landscape, for local employment, for fair trade and for international social justice.

The seasonality of the produce grown also needs to be considered by policy makers. Even though on a year round basis it has been shown that growing vegetables in the UK minimises their carbon footprint (Hospido et al., 2009), it is not realistic to meet year round demand, because of the seasonality of vegetation production in this country. For example, lettuce is sourced from abroad during the UK winter as it cannot be grown outdoors. Therefore, would it be better to produce under cover in the UK winter or to accept emissions from bringing vegetables in from abroad when out of season? However, a negative impact of glasshouse production may be that it leads to more greenhouse gas emissions than generated by imports.

In order to provide lettuce to UK consumers all year round, several different supply chains have been developed. Hospido et al. (2009) suggest that to overcome the natural seasonality of supply in northern Europe, four basic strategies have been adopted by industry: protected cultivation to produce out of season; controlled storage to supply out of season; importation of fresh produce from countries where it is in season; and consumption of alternative vegetables that are in season.

However, it must be remembered that carbon sequestration depends on many factors such as variety, sowing date, crop establishments, harvesting date, controls of weeds, disease, pests, soil types, irrigation and fertilizer application rates (Moureaux et al., 2006), and that soil carbon sinks resulting from sequestration activities are not permanent and will continue only as long as a carbon-sequestering management practice is maintained. If a land-management or land-use change is reversed, the carbon accumulated will be lost, usually more rapidly than it was accumulated (Smith, 2004).

An overriding problem in the UK and other European countries is that consumers have become accustomed to the availability of an increased range of produce in shops regardless of the natural seasonality of its production (Hospido et al., 2009). Parts of the food industry will therefore be less reliant in the future on the local supply of produce and demand for products. However, a small part of the European food industry also relies on local food brands (specialities), some of which are registered and protected under EU regulation (Olesen and Bindi, 2002). Such local food specialities, which often have a long local tradition coupled with favourable natural conditions, may be particularly susceptible to climate change, due to the reliance on high quality products (Olesen and Bindi, 2002).

However, the major problem is the expectations and perceptions of the consumer:

For fruit and vegetables, gaps in fresh local supplies due to seasonality of production partially explain high imports, alongside consumer demands for variety (Cowell et al., 2003).

The driving force in agriculture is the global increase in demand for food and fibre by more affluent and expanding world population consuming a higher proportion of meat and exotic food in their diet (Olesen and Bindi, 2002). The current and future demand for biofuels varies significantly between countries and regions and the feedstocks for their production have major implications for crop choices and the associated land demands that arise for biofuel production (Murphy et al., 2011). The result is that global agriculture is exerting increasing pressure on the land and water resources of the earth, often resulting in land degradation, e.g. soil erosion, salinisation and pollution (Olesen and Bindi, 2002).

As alluded to in the previous paragraph, the sustainability of food production and distribution is far wider than just greenhouse gas emissions from fossil fuel use and land use. Maintaining the supply of food also means addressing questions of water pollution, rural economics, landscape amenity and a host of others (Coley et al., 2009). Within the context of this project the main considerations are greenhouse gas emissions from agriculture. These are likely to be significantly affected by greenhouse-gas-induced climatic changes. As many mitigation practices affect more than one GHG, it is important to assess the impact on all GHGs simultaneously (Fitton et al., 2011). Policies influencing changes in land use are also potentially important aspect for policy makers that could be effective in mitigating and delaying global warming (Parry, 1990a).

6.7 Future Work

This research project has contributed to our understanding of greenhouse gas emission and food production. Work that would extend the research carried out so far would be:

- A larger sample size would provide an improved comparison; within this larger sample size would be:
 - A greater number of fields for each vegetable type
 - A greater number of the same vegetable type in each area
 - Additional vegetable types that would be available abroad as well as in the UK

- Addition of another area in each foreign country for greater comparisons
- A larger data set for validation of the model with more data points than collected for this piece of work.
- Calibration of the DNDC model to allow it to measure a greater number of countries and a larger range of farming techniques for the countries it is calibrated for.
- Changes to the model to allow users to input data for parameters that are normally filled by the model.
- Knowledge of the development of the model from the model development team so differences between versions can be assessed. This would allow for greater transparency and accuracy of the results from the DNDC model.
- Further testing of the model and comparison with other models would help validate the DNDC for use in differing scenarios in the future.

6.8 Conclusion

From this study it can be concluded that increased food production within the UK regions measured, would be a better option for minimising greenhouse emissions from soils. This conclusion should, however, be reconsidered when a more robust model has been developed that can accurately represent the farming techniques used in Spain and Kenya. We found the DNDC model gave a similar pattern of results to the validation results of soil nitrogen measured from the fields.

Agriculture and food production will always be interlinked with the social, economical and environmental issues of sustainability. Each of these situations will need to be considered separately according to its own unique problems. It is unethical to make decisions based only on environmental emissions of greenhouse gas emissions. As each situation has many inputs, models will ultimately need to be more complex in their design. Until then, funding needs to be directed to ensuring good field research is able to continue.

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Appendix 1

Correspondence with Changsheng Li discussing DNDC model changes

David L. Jones

Dear Davey,

It's a pity to say we don't have a detailed log to document the changes in DNDC. The reason is we don't have the resources to do so. Sorry for my answer. But if you wish to obtain the latest version of DNDC, I'll be pleased to send it to you.

Sincerely,
Changsheng Li

Dear Changsheng Li,

I hope all is well. I have a quick question. We have used DNDC in the > past and were wondering if there is a detailed log of the changes > between the different versions as they have evolved over time. If you > can point me to the right place I would be really grateful.

Many thanks
Davey

Appendix 2

Testing the assertion that 'local food is best': the challenges of an evidence-based approach

Gareth Edwards-Jones^a, Llorenç Milà i Canals^b, Natalia Hounsome^c, Monica Truninger^d, Georgia Koerber^a, Barry Hounsome^c, Paul Cross^a, Elizabeth H. York^a, Almudena Hospido^b, Katharina Plassmann^a, Ian M. Harris^a, Rhiannon T. Edwards^c, Graham A.S. Day^d, A. Deri Tomos^c, Sarah J. Cowell^b and David L. Jones^a

^a*School of the Environment and Natural Resources, Bangor University, Gwynedd
LL57 2UW, UK*

^b*Centre for Environmental Strategy (D3), University of Surrey, Guildford, Surrey
GU2 7XH, UK*

^c*School of Biological Sciences, Bangor University, Gwynedd LL57 2UW, UK*

^d*School of Social Sciences, Bangor University, Gwynedd LL57 2UW, UK*

^e*Centre for Economics and Policy in Health, Institute of Medical and Social
Care Research, Bangor University, Gwynedd LL57 1UT, UK*

Published in Trends in Food Science & Technology 19, 2008, 265-274

All field and laboratory measurements for Spain and some for the UK was collected by Elizabeth York.

Appendix 3

Geographical variation in carbon dioxide fluxes from soils in agro-ecosystems and its implications for life cycle assessment

Georgia Koerber^a, Gareth Edwards-Jones^a, Paul W. Hill^a, Llorenç Milà i Canals^b,
Philip Nyeko^c, Elizabeth York^a and David L. Jones^a

^a*School of the Environment and Natural Resources, Bangor University, Gwynedd
LL57 2UW, UK*

^b*Centre for Environmental Strategy (D3), University of Surrey, Guildford, Surrey
GU2 7XH, UK*

^c*Department of Forest Biology and Ecosystems Management, Makerere
University, PO Box 7062, Kampala Uganda*

Published in Journal of Applied Ecology 46, 2009, 306-314

All field and laboratory measurements for Spain and some for the UK was collected by Elizabeth York.

Appendix 4

Vulnerability of exporting nations to the development of a carbon label in the United Kingdom

Gareth Edwards-Jones^a, Katharina Plassmann^a, Elizabeth H. York^a, Barry Hounsome^b, David L. Jones^a and Llorenç Milà i Canals^c

^a*School of the Environment and Natural Resources, Bangor University, Gwynedd
LL57 2UW, UK*

^c*Centre for Economics and Policy in Health, Institute of Medical and Social
Care Research, Bangor University, Gwynedd LL57 1UT, UK*

^c*Centre for Environmental Strategy (D3), University of Surrey, Guildford, Surrey
GU2 7XH, UK*

Published in Environmental Science and Policy 12, 2009, 479-490

All field and laboratory measurements for Spain, Kenya and some for the UK was collected by Elizabeth York. Also Elizabeth collected all data needed for the Kenya LCA report.