NUI MAYNOOTH

Ollscoil na hÉireann Má Nuad

A DYNAMIC SPATIAL MICROSIMULATION MODEL FOR IRISH AGRICULTURAL EMISSIONS

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Abstract

This thesis describes the development of a dynamic spatial microsimulation model for Irish agriculture and its use in providing a spatially disaggregated profile of resultant emissions. Following the establishment of a baseline spatial agricultural emissions inventory, a dynamic microsimulation model is developed and is used to simulate agricultural activity forward in time to provide an estimation of future emissions outcomes based on previous historical trends. Finally, in the context of potentially conflicting economic and environmental policies for Irish Agriculture a scenario analysis is undertaken in order to assess the potential emissions impact of achieving the expansionary targets outlined for the dairy sector in the Food Harvest 2020 programme.

An adaptation of the SMILE (Simulated Model of the Irish Local Economy) quota sampling procedure involving the incorporation of a novel stocking rate ranking methodology was found to dramatically improve results for the preservation of spatial heterogeneity of stocking levels and associated agri-emissions. Results from a dynamic spatial microsimulation model based on the Teagasc National Farm Survey project a gradual decline in agricultural activity based on historical trends over a ten year simulation period with a concomitant marginal reduction in associated emissions. Results from a multi-scenario analysis in the post-quota era reveal the potential future spatial locations of new dairy farms required to enter in order to meet target. For three alternative dairy expansion scenarios, total emissions from agriculture are projected to fall by between 2-5% by 2020.

Information on the potential future spatial disaggregation of emissions related activities provides an opportunity for the advanced planning and design of novel mitigation strategies at the sub-national level. This thesis offers a solution to this information deficit for Irish agriculture, the largest contributor to non-Emissions Trading Scheme emissions. It also provides a unique contribution to knowledge by establishing a framework under which economic and environmental policies for the

agricultural sector can be assessed in tandem in terms of their future consequences for national emissions.

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Nomenclature

A.I	Artificial Insemination
BAU	Business as Usual
CARE	Climate Action and Renewable Energy
CCC	Committee on Climate Change
CER	Commission for Energy Regulation
CFCs	Chlorofluorocarbons
CH_4	Methane
CO_2	Carbon Dioxide
CO_2eq	Carbon Dioxide Equivalent
CoA	Census of Agriculture
CPP	Crop Protection Programme
CRF	Common Reporting Format
CSO	Central Statistics Office
DAFF	Department of Agriculture Fisheries and Food
DBERR	Department of Business Enterprise and Regulatory Reform (UK)
DCENR	Department of the Communications, Energy and Natural Resources
DECC	Department for Energy and Climate Change
DEFRA	Department of the Environment Food Rural Affairs (UK)
DEHLG	Department of Environment Heritage and Local Government
EC	European Community
ECCP	European Climate Change Programme
ED	Electoral District
ENF	Enteric Fermentation
EPA	Environmental Protection Agency
ETS	Emissions Trading Scheme
EU	European Union
FAPRI	Food and Agriculture Policy Research Institute of Missouri
FE	Fixed Effects
FH2020	Food Harvest 2020
GHG	Greenhouse Gas
GO	Gross Output
GWP	Global Warming Potential
Ha.	Hectare
HCFCs	Hydro chlorofluorocarbons
HFCs	Hydro fluorocarbons
ICLEI	Local Governments for Sustainability
IPCC	Intergovernmental Panel on Climate Change
l	Litres
LGA	Local Government Association

LII	Living in Ireland
LCA	Life Cycle Analysis
LU	Livestock Unit
MM	Manure Management
MOU	Memorandum of Understanding
N	Nitrogen
N_2O	Nitrous Oxide
NAEI	National Atmospheric Emissions Inventory (UK)
NATACC	National Accounts
NCCS	National Climate Change Strategy
NEBR	National Energy Balance Report
NFS	National Farm Survey
NFS-DSM	National Farm Survey-Dynamic Spatial Microsimulation
NIR	National Inventory Report
NPM	New Public Management
NREAP	National Renewable Energy Action Plan
JCCES	Joint Committee on Climate Change and Energy Security
OLAM	Office for Local Authority Management
PFCs	Perfluorinated Compounds
QS	Quota Sampling
RE	Random Effects
REPS	Rural Environmental Protection Scheme
SA	Simulated Annealing
SAPS	Small Area Population Statistics
SEAI	Sustainable Energy Authority of Ireland
SEM	Single Electricity Markey
SF_6	Sulphur Hexafluoride
SILC	Survey of Income and Living Conditions
SMILE	Simulated Model of the Irish Local Economy
UN	United Nations
UNEP	United Nations Environment Programme
UNFCCC	United Nations Framework Convention on Climate Change
WCC	World Climate Conference
WMO	World Meteorological Organisation
WMS	Waste Management System
WNFS	Weighted National Farm Survey

CHAPTER ONE: INTRODUCTION

1.1 Introduction

The body of evidence to support the conclusion that the emission of greenhouse gases arising from human activity has been the dominant force behind the current period of global warming is compelling. The recent Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report states that it is extremely likely that human influence has been the dominant cause of the observed warming of the world's atmosphere and oceans; reductions in ice and snow, global mean sea level rises and changes in climate extremes particularly since the middle of the last century (IPCC, 2013). The Fifth Assessment Report is the latest in a series of reports considering the influence of human activities on global climate change, the long term implications of which pose a substantial threat to the planet's long-term ability to sustainably support a growing global population in the face of reduced air quality, flooding and inundation, droughts, food security and more extreme weather events (IPCC, 2013).

While the theory of anthropogenic climate change first reached international attention almost 35 years ago at the World Climate Conference in 1979, its presence on the international political agenda is a relatively recent phenomenon. The adoption of the Kyoto Protocol in 1997 represented the first legally binding international agreement on greenhouse gas emissions and involved the setting of individual country specific emissions targets which were to be attained over the 2008-2012 commitment period (UN, 1998). At a supranational level, Member States of the European Union (EU) have subsequently committed to individual emissions targets to achieve a collective 20% reduction in EU emissions by 2020 with even deeper cuts proposed if international agreement is reached between developing countries on comparable emissions reductions (Council Decision, 2009).

However, while the effects of increased emissions concentrations have global consequences, the implementation of international policy on climate change is ultimately the responsibility of individual national governments. This presents many significant challenges. The setting of individual country specific emissions targets raises complex difficulties in relation to the accurate measurement of national emissions. These difficulties have been mitigated to some extent by the provision of a simplified universal accountancy framework (IPCC, 1996; IPCC, 2000) but the suitability of a macro-level national accounting system in the context of a globalised international trade market has been subject to significant criticism (Subak, 1999; Schils et al., 2006; Crosson et al., 2011). While national decisions on production systems and mitigation strategies may be optimal in terms of the individual nation's emissions inventory they may be sub-optimal in terms of achieving a net reduction in global emissions. There is however a significant trade off in measuring emissions from individual unit processes as such methods can be laborious, time-consuming, subject to large uncertainties, and therefore difficult to verify (Schulte & Lanigan, 2011).

In addition to the computational challenges surrounding national governments' commitments to international climate change policy obligations, public acceptance of the implementation of market and/or regulatory climate change policies at the national level is also a cause for concern (Lockwood, 2013). Recent evidence suggests that the level of public concern relating to climate change issues has seen a decline in the face of economic insecurity bought about by the recent global recession (Scruggs & Benegal, 2010). The level of uncertainty surrounding the economic costs of climate change and the emissions footprint of individual consumer products presents significant challenges to attempts to relate the "true" costs of emissions to the individual consumer. Thus the effective implementation of climate change policy in the face of market failure (Bator, 1958) is a key challenge for national governments.

Specifically examining the implementation of climate change policy, there has been an increasing focus in the climate change literature on the role of local governance in delivering policy objectives (Collier & Löfstedt, 1997), with a view that it is at the local level where greenhouse gas emission reductions and mitigation measures will ultimately take place (Kates et al., 1998). Broad national and international policy goals ultimately require the co-operation of local and regional authorities such as county, city and town councils if they are to be successfully implemented (Allman et al., 2004).

There is however, an information deficit that these local authorities suffer from (Allman et al., 2004). The International Council for Local Environmental Initiatives (ICLEI) has identified the establishment of a baseline emissions inventory against which progress on climate change mitigation efforts can be measured as the first of 5 steps towards sustainable cities (ICLEI, 2006). The generation of individual emissions inventories at a local level would however be an impractical and extremely costly process. Moreover, it has been suggested that there is a need for an analytical policy tool to assist local authorities in choosing appropriate mitigation and/or adaptation options (Laukkonen et al., 2009).

Recent developments in the area of spatial microsimulation modelling have provided an opportunity to address this information deficit (Clarke, 1996b; Ballas & Clarke 2001; O'Donoghue et al., 2013) at sub-national scales. The disaggregation of nationally representative micro-level data[1] at various spatial scales provides the opportunity to model baseline emissions from the recorded activities of those micro units (Hynes et al., 2009; Tirumalachetty et al., 2013). Spatial microsimulation models also provide the opportunity to conduct policy analysis enabling decision makers to analyse the potentially differential spatial impacts of climate change policy measures at a disaggregated level (Holm et al., 1996; Hynes et al., 2006). These models have the capacity to facilitate not only the study of the effect of climate change policies on the spatial disaggregation of emissions but also the study of other potentially conflicting policies which may have a significant impact on national emissions.

[1] On micro units such as individuals/households/farms or firms

In Ireland, considerable discussion has centred on the potentially conflicting targets between the achievement of a significant expansion of the agricultural sector via the aims of the Food Harvest 2020 (FH2020) programme and Ireland's national and international commitments to emissions reductions (Donnellan & Hanrahan, 2011b). Agriculture currently accounts for over 40% of total national greenhouse gas emissions[2] (EPA, 2012). Furthermore, the Environmental Protection Agency (EPA) has projected that agriculture will be responsible for 48% of total emissions from the non-Emissions Trading Scheme (ETS) sector by 2020 (EPA, 2013b). While it has been acknowledged that no specific national target for emissions reductions from agriculture has been set (Donnellan & Hanrahan, 2011b), the EPA (2013b) notes the important role that agriculture will play in developing mitigation options for achieving 2020 targets in relation to non-ETS sector emissions. Thus it is likely that considerable emissions reductions will have to be achieved from the agri-sector in order for Ireland to meet its commitment to reduce national emissions by 20% by 2020 (Council Decision, 2009).

The presence of spatial information on agricultural activity has been shown to be able to contribute to the design of policies which can reduce emissions related to the agricultural sector (Quinlan et al., 2006). It may also be asserted that advanced insight into the potential future spatial disaggregation of agricultural activity can contribute to the design of long term policies which may reduce emissions associated with agriculture. This has been previously demonstrated by Quinlan (2013) who examined the optimal location of agricultural processing facilities in order to minimise emissions associated with the transportation of milk.

Thus there is a requirement for a sophisticated spatial analytical tool to effectively assess and inform the implementation of climate change policy. It is in the context of this requirement that this thesis seeks to provide a unique contribution to knowledge in establishing a framework under which economic and environmental policies for

[2] Agriculture accounts for over 40% of Irish emissions from the non-Emissions Trading Scheme (ETS) sector. The emissions reductions targets discussed also refer to the non-ETS sector

the agricultural sector can be assessed in tandem in terms of their future consequences for national emissions.

1.2 Aims and Objectives

The central aim of this thesis is to provide a means for policy makers to make informed decisions when considering the implementation of policies which may affect emissions outcomes for the agricultural sector in Ireland, and to provide for the construction of an analytical tool which can be used to provide feedback to the development of agri-environmental policy in the future. To achieve this aim the following research objectives have been outlined:

1. To comprehensively review Ireland's national and international climate change commitments and to investigate the conditions required for the effective implementation of climate change policy.
2. To develop and validate a baseline spatial emissions inventory of emissions for Irish agriculture, enabling the analysis of policy measures at the micro-level.
3. To construct and validate a dynamic spatial microsimulation model for Irish agriculture in order to provide a framework for the design and implementation of localised measures to mitigate future emissions outcomes for the agricultural sector.
4. To perform a multi-scenario analysis in order to assess the potential emissions impact of achieving the target for the expansion of the dairy sector outlined the Food Harvest 2020 programme
5. To consider the implication of the outputs from this thesis, and the potential development of the model framework for future research.

1.3 Structure of this Thesis

In order to provide a coherent summary of work undertaken, the structure of this thesis is now outlined with a brief summary outline of each chapter, Following an outline of the current climate change policy framework **Chapter 2** investigates the role of local authorities and the role of networked governance in the form of co-operation between authorities, agencies and departments in the facilitation, implementation and adaptation of national and EU climate change policy at the local level. Highlighting the work of Allman et al. (2004) the devolution of Irish climate change policies to local agents is reviewed. The chapter concludes with a discussion outlining the need for an efficient and effective, analytical policy tool for the assessment of climate change policies at the local level.

Chapter 3 conducts a comparative analysis of greenhouse gas emissions modelling and considers the Irish experience reviewing the National GHG inventory service provided by the EPA under the direction of the IPCC reporting guidelines. Having established in the previous chapter that information at a sub-national level is deemed as essential to inform effective local climate change policy, this chapter assesses the adequacy of the default inventorying system which reports aspatially at a national level and reviews the currently available options for the spatial modelling of greenhouse gas emissions.

In search of a solution to the deficit of local level spatial information on emissions, **Chapter 4** discusses the recent developments in the area of microsimulation modelling and traces the development of several types and forms (Clarke, 1996b; Ballas & Clarke, 2001; O'Donoghue et al., 2013) The chapter discusses the evolution and previous applications of the SMILE microsimulation model and highlights its potential use for the inventorying of greenhouse gas emissions at the micro level thus enabling a spatial distribution of emissions to be created.

Chapter 5 outlines the development of a baseline spatial emissions model for Irish-Agriculture. A comparison of the agricultural output captured in the Teagasc National Farm Survey (NFS) with the output reported in the national accounts is carried out in order to provide a basis for a valid comparison of emissions calculated in the National Inventory Report. It describes the development and validation of a novel method used to preserve the spatial heterogeneity of Irish agricultural emissions activities through an adaptation of the SMILE-NFS sampling process using a stocking rate ranking variable and concludes with a discussion on the benefits and limitations of the technique.

Chapter 6 describes the construction of the NFS-DSM, a dynamic spatial microsimulation model for Irish Agriculture using a system of panel equations constructed from data from the Teagasc NFS which facilitate the simulation of changes in agricultural output over time. In the context of ambitious targets for the agricultural sector in the form of the Food Harvest 2020 policy goals and Ireland's potentially conflicting emissions reduction obligations, these models are employed to simulate production forward to 2020 based on historical trends. The projected spatial emissions outcomes from a business as usual scenario are disaggregated to electoral district level using the adapted SMILE-NFS spatial microsimulation model. The chapter concludes with suggested options for further scenario analysis in the agri-sector.

Chapter 7 outlines the performance of a multi-scenario analysis in order to assess the potential spatial emissions impact of achieving the target for the expansion of the dairy sector outlined the Food Harvest 2020 programme. For all scenarios, the number and location of additional new entrants required to meet target is projected spatially and disaggregated to electoral district level using the SMILE-NFS spatial microsimulation model. The resultant emissions outcomes are mapped and compared at an aggregate level to assess the implications for Ireland's 2020 emission obligations. The chapter concludes with an assessment of the level of structural change required in the dairy sector in order to meet targets set out in Food Harvest 2020.

Chapter 8 summaries the main findings of the thesis and discusses the potential future applications of the methodologies outlined and the opportunities for future research. Limitations of the approach and model are outlined and discussed.

1.4 Summary

The international community has recognised the need for urgent action in the face of compelling evidence that anthropogenic climate change presents a substantial threat to the planet and its long-term ability to sustainably support future generations. International agreement on climate change policies may go some way to mitigating the most deleterious effects of anthropogenic climate change, however, the effective implementation of these policies present a number of significant challenges. The pursuit by governments of market based climate change policies against the backdrop of the economic anxiety induced by the recent global recession may not however be politically acceptable. Policy conflicts may, and do, arise between the achievement of emissions reductions and demands for expansionary policies in emissions intensive areas, such as agriculture, in order to stimulate economic growth.

There are also practical difficulties which include the accurate measurement and availability of information on emissions not just nationally, but also at the local level against which, local authorities can set targets and assess progress. Therefore, there is a requirement for sophisticated analytical tools to effectively assess and inform the implementation of climate change policy. It is in the context of this requirement that this thesis seeks to provide a unique contribution to knowledge in establishing a framework under which economic and environmental policies for the agricultural sector can be assessed at a spatial scale of relevance in tandem with their consequences for national emissions.

The thesis outlines the development of a dynamic spatial microsimulation model for Irish agriculture and its use in providing a spatially disaggregated profile of agricultural emissions. A baseline spatial model of Irish agricultural emissions is first constructed, and is then simulated forward in time to provide an estimation of future emissions outcomes based on historical trends. Finally, a scenario analysis is undertaken in order to assess the potential emissions impact of achieving the target for the expansion of the dairy sector outlined the Food Harvest 2020 programme. Chapter 2 will undertake a comprehensive review of Ireland's national and international climate change commitments and investigate the role of local governance in the effective implementation of climate change policy. It provides the overarching policy context within which this work is framed.

CHAPTER TWO: IRISH CLIMATE CHANGE POLICY AND THE ROLE OF LOCAL NETWORK GOVERNANCE

In the context of meeting challenging national, international and European Union (EU) targets for climate change mitigation and adaptation measures for Ireland in the coming decade, this chapter considers the role of local authorities and the role of networked governance in the facilitation, implementation and adaptation of national and EU climate change policy. Following a brief summary of current policy, the form of co-operation between authorities, agencies and departments at the local level is considered, revealing that the delivery of targets relies on both the presence of a robust legislative framework and effective co-ordination between local authorities, regional authorities and agencies. A deficit of information however, on emissions related activities at the local level, is identified as a key barrier to the effective implementation of climate change policy by agents at the local level. The need for an efficient, effective, analytical policy tool for the assessment of policies at the local level is highlighted, not only in terms of effective inventorying, target setting and monitoring; but also in assessing mitigation and adaptation options and potential trade-offs for local authorities with limited resources.

2.1 Introduction

The nature of anthropogenic climate change and the resultant efforts towards mitigation are such that policies necessarily relate to a wide range of human activities across multiple sectors such as energy, agriculture, industry, buildings, forestry and waste (IPCC, 1995). Thus for cross-sectoral policies and measures, networked or joined up approaches involving the dense interaction of multiple state actors and departments are required to deliver collective goals (Agranoff, 2003). While the achievement of shared objectives across sectors through collaborative action between public bodies has been more broadly identified as the next phase of public governance, referred to as networked governance by Benington and Moore

(2010), the lack of joined up thinking and a networked approach between actors has been identified as a key barrier to progress on climate change measures at the local authority level (Allman et al., 2004).

Local authorities are typically responsible for the construction, maintenance and operation of civil, social, economic and environmental infrastructure. They are also charged with the eventual implementation of national policies at the regional or local scale (UN, 1992). As such, local governments have significant capacity to influence change across many sectors. At the 1992 Rio Summit the role of local government was identified as a key factor in successfully implementing sustainable development policies, with an agreement to develop Local Agenda 21 projects for local authorities. The United Nations (UN) viewed local authorities as a determining factor in fulfilling the programs objectives as they are the system of government closest to the people and as such play a vital role in educating, mobilizing and responding to the public in promoting sustainable development (UN, 1992).

In specifically examining the implementation of climate change policy, there has been an increasing focus in the literature on the role of local authorities in delivering policy objectives (Collier & Löfstedt, 1997). Furthermore, Kates et al. (1998) submit that it is at the local level where greenhouse gas emission reductions and mitigation measures will ultimately take place.

Significant progress has been made in the formation of climate change policy at national and international level. However, broad national and international policy goals such as those contained in the Irish National Climate Change Strategy (Department of Environment Heritage and Local Government, 2000), and the EU Commissions 20-20-20[3] project (European Commission, 2008) ultimately require the co-operation of local and regional authorities such as the county, city and town councils if they are to be successfully implemented (Allman et al., 2004).

There is however, an information deficit that local authorities suffer from (Allman et al., 2004). The International Council for Local Environmental Initiatives (ICLEI) has

[3] 20% EU-wide reduction in GHG emissions on 2005 levels, 20% reduction in projected EU energy and 20% of energy to come from renewable resources in the EU by 2020

identified the establishment of a baseline emissions inventory against which progress on climate change mitigation efforts can be measured as the first of 5 steps towards sustainable cities (ICLEI, 2006). Moreover, it has been suggested that there is a need for an analytical policy tool to assist local authorities in choosing appropriate mitigation and/or adaptation options (Laukkonen et al., 2009).

A substantial proportion of the literature on the role for/of local authorities has been conducted in the UK, however, there is a notable absence of literature analysing the effective dissemination of Irish climate change policy. In contrast to the more formalised institutionalised legislative implementation frameworks of the UK[4], there is a lack of such frameworks in Ireland. The Department of the Environment Heritage and Local Government (DEHLG) is the fiduciary state body charged with setting climate change policy. However, an over-arching framework to manage the required cross-coordination between many state and semi-state partners under several different Government departments is currently lacking. Significantly there are no targeted statutory obligations on Irish local authorities for the development and implementation of climate change policy and no framework of co-operation between agencies and state departments. While significant progress towards the development of an Irish Climate Change Response Bill was made (Climate Change Bill, 2009), a change of national government has put the passing of the Bill on hold and its future is now uncertain.

The deadline for a 20% reduction in greenhouse gas emissions (Council Decision, 2002) and 16% of energy to come from renewable resources is less than 6 years away. Considering the challenges associated with these targets, this chapter reviews the current local authority structure for the implementation of policy and investigates the linkages between the setting of national policy at departmental level and its adoption at local level (Benington & Moore, 2010; Department of Communications, 2010). This structure is compared to recent developments in the UK with the formation of the Department of Energy and Climate Change and the publication of

[4] Climate Change Act (c.27) 2008. UK: HMSO. Energy Act (c.27) 2010. UK: HMSO. Climate Change Act (c.27) 2008. UK: HMSO. and the establishment of the Department of Energy and Climate Change

the UK Climate Change Act 2008. The multi-governance approach and its suitability for environmental policy is considered. This chapter traces the development of climate change policies and strategies by local and regional authorities and discusses the challenges of information deficit (Laukkonen et al., 2009) and the opportunity for a spatial-analytical model of greenhouse gas emission to assist in the evaluation of measures and the achievement of shared goals.

2.2 Policy Background

Following a review of the global evolution of the climate change agenda this section tracks the development of International, Regional (EU) and national climate change policy and reviews the current Irish Climate Change Policy framework. In evaluating that framework the context in which the relevant authorities make their decisions must be understood. Ireland's commitments stem from a number of agreements both national and international which reflect the current stages of political consensus on climate change policy at both global and European level.

2.2.1 Evolution of the Global Climate Change Agenda

The first major appearance of the climate change debate on a global level was at the inaugural World Climate Conference (WCC) in Geneva in 1979, held under the auspices of the World Meteorological Organisation (WMO), from which the World Climate Programme (WCP) was developed. In a declaration noted as "An Appeal to Nations" the WCC called for the nations of the world to "take full advantage of man's present knowledge of climate... take steps to improve significantly that knowledge...[and] to foresee and to prevent potential man-made changes in climate that might be adverse to the well-being of humanity" (WMO, 1979:1).

While there was a general international consensus that a greater understanding of the issue was needed, it was almost 10 years before the United Nations Environment Programme (UNEP) and the WMO established the Intergovernmental Panel on Climate Change (IPCC); an international body comprised of scientists (currently numbering over 2,500) and policymakers to provide the world "with a clear scientific view on the current state of climate change and its potential environmental and socio-economic consequences" (IPCC, 2007:5). In the IPCC's first report, the First Assessment Report (1990), the panel expressed concerns about the growing body of scientific evidence supporting the theory of anthropogenic climate change brought about through direct radiative forcing caused by the increased concentration of greenhouse gases[5] in the earth's atmosphere (Houghton et al., 1990). The contents of this report greatly contributed to the establishment of the United Nation's Framework Convention on Climate Change (UNFCCC) at the UN Conference on Environment and Development (also known as the "Earth Summit") held in Rio de Janeiro in 1992, which was eventually adopted by 154 countries and the European Community (EC).

The stated objective of the Convention was "to achieve, in accordance with the relevant provisions of the Convention, stabilization of greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system" (UN, 1992:Art2). The convention also conferred upon signatories a number of commitments relating to the reporting and inventorying of greenhouse gas emissions as well as a number of measures requiring parties to commit to adopting national policies "...and take corresponding measures on the mitigation of climate change, by limiting its anthropogenic emissions of greenhouse gases (GHGs) and protecting and enhancing its greenhouse gas sinks and reservoirs" (UN, 1992:Art4). As part of these measures, developed (Annex I) countries were encouraged to cut their GHG emissions to 1990 levels with no binding commitment on developing (Annex II) countries on the principle of "...common but differentiated responsibilities..." This view was taken in the recognition that the developed Annex 1 countries were historically largely responsible for global GHG emissions.

While these commitments were viewed as essential steps, the lack of stated targets for parties meant that the convention lacked authoritative pressure. The release of the IPCC's Second Assessment Report in December 1995, stated that "…increases in greenhouse gas concentrations since pre-industrial times...have led to a positive

[5] CO_2, CH_4, N_2O, HFC's PFC's and SF6 (developed specifically for industrial applications)

radiative forcing[6] of climate, tending to warm the surface and to produce other changes of climate...and the balance of evidence suggests a discernible human influence on global climate…" (IPCC, 1995:21). The second assessment report was largely responsible for increased urgency among the international community surrounding climate change leading to the adoption of the Kyoto Protocol in 1997, the first legally binding international agreement on greenhouse gas emissions reductions. Parties to the protocol were faced with clear emissions targets during the commitment period 2008-2012. The protocol was ratified by the vast majority of nations with one major exception (UNFCCC, 2009b). Despite initially being a signatory to the protocol, the United States did not ratify the agreement domestically and as such the protocol was non-binding on the United States. Russia's decision to ratify was crucial as it resulted in the reaching of the 55% threshold allowing the protocol to come into effect on the 16th February 2005.

Since Kyoto, the international community has been attempting to establish agreement on a follow-on mechanism. Despite the publication of the IPCC's fourth (IPCC, 2007) and fifth (IPCC, 2013) assessment reports progress on further agreement has been slow. The UNFCCC's Copenhagen accord, stated *inter alia*, that parties "...agree that deep cuts in global emissions are required according to science, and as documented by the IPCC Fourth Assessment Report with a view to reduce global emissions so as to hold the increase in global temperature below 2 degrees Celsius, and take action to meet this objective consistent with science and on the basis of equity…" (UNFCCC, 2009:2). However, while it has been acknowledged that this was the first time there was effectively international consensus[7] on the risks associated with anthropogenic climate change, there was considerable disappointment with the failure to agree on any specified targets to curb emissions, a failure that was, mooted to be attributable to conflict between developed and developing countries over burden sharing (Vidal et al., 2009). Subsequent meetings

[6] Radiative forcing is a measure of the influence that a factor has in altering the balance of incoming and outgoing energy in the Earth-atmosphere system and is an index of the importance of the factor as a potential climate change mechanism. Positive forcing tends to warm the surface while negative forcing tends to cool it.

[7] Crucially including China and the U.S

of the conference of parties at Durban (2011) and Doha (2012) have resulted in incremental progress with a follow on agreement to the Kyoto Protocol currently[8] absent.

Aside from the burden-sharing political barriers, there have also been number of public challenges to the accuracy of the modelling of future climate change and the associated economic costs, which have led to the permeation of a considerable amount of climate change scepticism in the public sphere (Antilla, 2005; Poortinga et al., 2011; Webb, 2007; Whitmarsh, 2011). Such challenges have the potential to encourage nations to proceed with a more cautious “wait and see” approach.

While the examination of those arguments is outside the scope this thesis, it should be noted that the debate on climate change is likely to continue with the consequences for future international policy as yet unknown. Sudhakara and Assenza (2009:3006) state that “...the clash between sceptics and supporters is likely to endure, and may even become more pitched as the stakes on climate change are raised. The expansion of scientific knowledge is unlikely to end the debate, as each side will get more data to confirm their case. Sceptics will continue to assail supporters for blending science with environmental activism, and supporters will maintain their doubts about the scientific credibility of sceptics, because of their links to economic interests”.

2.2.2 Ireland’s National and International Policy Commitments

Ireland’s international climate change commitments stem from two main policy drivers, i.e. the Kyoto Protocol to the UNFCCC; and EU legislation which is applied either directly (through regulations) or indirectly (through directives) in Ireland.

Kyoto Protocol 1997

In line with the UNFCCC’s stated objective to reduce GHG emissions in order to prevent climate change, the Kyoto protocol sets out a range of policy measures

[8] As of Feb 2014

relating to *inter alia*. energy efficiency, renewable energy research and sustainable agriculture which parties must implement in order to comply; and includes a baseline emissions target of 5% below 1990 levels for all Annex I (i.e. developed countries). The protocol also included a number of "Flexible Mechanisms" such as International Emissions Trading, Clean Development Mechanism and Joint Implementation in order to allow parties to achieve their targets more practically (UN, 1998).

With all EC[9] Member States and the EC itself ratifying the protocol, the opportunity arose for burden sharing among countries under the principle of joint implementation. The EC's total emissions reduction target under Kyoto was set at 92% of 1990 base level emissions over the 2008-12 commitment period. Under the principle of burden sharing, Ireland's Kyoto target was to limit emissions to 13% above 1990 levels (Council Decision, 2002). In practical terms this represented a target of 62.8 Mtonnes of Carbon Dioxide equivalent (CO_2eq) per annum over the 5-year period 2008-12 (EPA, 2010). It should be noted that under the terms of the Kyoto protocol, the targets refer specifically to the greenhouse gases of CO_2, CH_4, N_2O, HFCs PFCs and SF_6 (developed specifically for industrial applications). CFCs and HCFCs are not included in Kyoto as they are included under the Montreal Protocol (UNEP, 2000).

European Community Legislation

The issue of climate change has long been on the European agenda with the EU playing a key role in the development of both the UNFCCC and Kyoto. In addition to those commitments the EU has continually introduced regulations and directives designed to curb GHG emissions and mitigate the effects of climate change. In the late 1990s the European Commission introduced measures such as the Commission Recommendation on the Reduction of CO_2 Emissions from Passenger Cars (European Commission, 1999). However, it was recognised that more robust

[9] There is a legal distinction between laws European Community (EC) law and laws enacted by the European Union, the appropriate citation of which has been preserved throughout this document for the purposes of accuracy.

measures would be needed in order to ensure that the EU would reach its Kyoto commitments and in response the Council of Ministers asked the Commission to propose a list of priority actions and policy measures, the result of which was the European Climate Change Programme (ECCP).

(i) European Climate Change Programme (ECCP)

The first ECCP was launched in 2000, with the aim of identifying and developing all the necessary elements of an EU strategy to implement the Kyoto protocol. It identified 36 different policies and measures for implementation covering eight different areas, namely; cross cutting measures, energy supply, energy demand, transport, industry including waste, agriculture & forestry, research & development and structural & cohesion funds. Details of existing, imminent and planned regulations[10] and directives[11] which formed the substantive body of the programme were outlined. The most significant measures included Council Directive (1996) on the prevention of GHG emissions from Industrial & Agricultural installations (bringing pre-1999 installations into conformity by October 2007); the EU Emissions Trading Scheme (Council Directive, 2003); and, the directives relating to promotion of renewable energy resources and the use of bio-fuels in transport. In addition, a number of key energy efficiency measures for the consumer including Council Directive (2002), on the Energy Performance of Buildings Directive and Council Directive (1992), on Appliance Labelling were included. The second programme, launched in 2005, is still in operation and is tasked with investigating further measures relating to aviation, CO_2 capture and storage, climate change adaptation and private transport emissions as well as performing a review of the 1st programme and the EU ETS.

(ii) EU Climate Action and Renewable Energy Package 2008

Following a firm commitment from the Spring 2007 European Council meeting on GHG emission reductions, the European Commission announced the agreement of a Climate Action and Energy package (Council Decision, 2009). The package outlines

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[10] Have direct effect in Member States

[11] Member States are obliged to implement deliver through domestic legislation

the EU's commitment to reducing GHG emissions to 20% below 1990 levels by the year 2020, primarily through a strengthening and expansion of the EU-ETS scheme (Council Directive, 2009b) and the promotion of the use of energy from renewable resources (Council Directive, 2009a). In addition, a directive on the geological storage of CO_2 was introduced to regulate the investigation of carbon sequestration as a bridging technology to ensure that the technology would be deployed in an environmentally safe way (Council Directive, 2009c)

The EU GHG emissions target for Ireland for non-ETS sector emissions is to reduce emissions by 20% by 2020 relative to 2005 levels which equates to 37.9 Mtonnes of CO_2eq emissions in 2020 (calculated by the EU Commission in 2008) (EPA, 2010). The renewable directive establishes a binding target of 20% of overall EU energy consumption coming from renewable sources by 2020, as well as a binding 10% minimum target for energy from renewable resources in the share of transportation fuels. The directive states that the aims are to be achieved through individual binding national targets which, if met, will be in line with the overall EU target. Ireland's national target under the directive is for renewable resources to account for 16% of total energy consumption by 2020.

In addition to existing targets, the European Commission (2014) has also outlined a proposal to legislate for a further binding target of a reduction of 30% of EU emissions relative to 1990 by 2030, indicating a commitment by Member States towards the continued decarbonisation of the European economy.

2.2.3 Irish National Policy on Climate Change

Ireland's ability to achieve its international, European and national commitments is dependent on the ability of national government to effectively delegate authority to the appropriate government departments, state agencies and semi-state bodies. This includes the role of government in ensuring that the appropriate mechanisms exist to enable the effective co-ordination between state-partners necessary to achieve cross-sectoral targets. To date, national policy on climate change and GHG abatement has been predominately based on statutory legislation and a National Climate Change Strategy (Department of Environment Heritage and Local Government, 2007).

Irish Legislation

Irish legislation relating specifically to Climate Change and the abatement of GHG emissions is covered by a number of Legislative Acts and Statutory Instruments. However, what is instantly noticeable about the Irish Statutory Legislation is that there are very few “Irish” measures initiated from the Irish Oireachtas with the majority of legislation coming from the adoption of EU Directives though statutory instruments, investing responsibility for legislative implementation with state bodies such as Sustainable Energy Ireland (SEI), The EPA and The Single Electricity Market (SEM) Committee.

(i) Acts and Statutory Instruments of the Oireachtas

There are five Acts of the Oireachtas which explicitly refer to the climate change agenda namely:

a. *Sustainable Energy Act (2002)* – Provides for the Establishment of Sustainable Energy Ireland whose functions include the promotion and assistance of measures to the reduce GHG emissions and transboundary air pollutants associated with the production, supply and use of energy.
b. *Protection of the Environment Act (2003)* – Integrated pollution prevention and control - providing for the implementation of Council Directive (1996), defines emissions including GHGs within the description, defines six GHGs and allows for the addition of any others as prescribed insofar as it contributes to Climate Change, amends the Environmental Protection Agency Act (1992), Waste Management Act (1996) and the Litter Pollution Act (1997).
c. *Carbon Fund Act (2007)* – Establishing Fund to acquire Kyoto units necessary to satisfy obligations under the UNFCCC
d. *Electricity Regulation (Amendment) (SEM) Act (2007)*– Establishes SEM and requires the SEM Committee to inter alia secure a diverse, viable and

environmentally sustainable long-term energy supply in the state and Northern Ireland where the latter "includes the need to guard against climate change".

e. *Finance Act (2008)* – Section 120: Regulations relating to the imposition/non-imposition of stamp duty on GHG emission allowances and Section 36: Definition of an allowance as a financial asset.

In addition, there are several other acts which are indirectly related to the climate change agenda, such as the Energy (Biofuel Obligation and Miscellaneous Provisions) Act (2010) and related amendments which give effect to certain provisions of Council Directive (2009a) on the promotion of the use of energy from renewable sources.

The above Acts are key moves towards the meeting of targets, the adoption of sustainable forms of energy and the forming of the administrative framework needed to support the NCCS. However, given climate change's current prioritisation on both the national and international political agenda in terms of targets, the absence of a specific climate change Act is conspicuous.

The eight statutory instruments[12] specifically related to climate change predominately deal with the regulation of GHG trading in compliance with the Kyoto protocol and the EU-ETS; the establishment of the EPA as Ireland's "agency" for GHG inventories and projections; waste management regulation; and a number of EC Directives.

National Climate Change Strategy (NCCS)

There have been two national climate change strategies. The first NCCS launched in 2000 outlined measures in energy, transport, built environment & residential, industry, commercial & services, agriculture, sinks (additional sequestration) and waste. This was followed by the second National Climate Change Strategy 2007-

[12] See Appendix A

2013. The stated purpose of this strategy was to ensure the achievement of Ireland's 2008-12 commitments under the Kyoto Protocol and to show how such measures position Ireland post 2012, with a view to meeting our eventual 2020 target commitments (Department of Environment Heritage and Local Government, 2007).

The 2007-2013 strategy is a comprehensive document outlining a broad range and type of market and non-market measures, including specific targets, procedures and behavioural and awareness campaigns across nine national sectors. It outlines Ireland's requirements in order to meet its commitments under the Kyoto protocol with a target of 63.032 Mt CO_2eq. The strategy projects emissions without any abatement measures to be 79,829 Mt CO_2eq with existing measures reducing that figure to 71.169 Mt CO_2eq. The strategy also identifies a further emission reduction target of 8.137 Mt CO_2eq and proposes that additional reduction measures of 4.953 Mt CO_2eq combined with flexible mechanisms allowing a further 3.607 Mt CO_2eq reduction, sufficient to meet targets.

The most apparent difficulty relating to the NCCS is the challenge of cross-sector compliance. While the Department of the Environment, Heritage and Local Government is the ultimate State body responsible for implementation of the NCCS, the ultimate success of the strategy relies on effective co-ordination between many state and semi-state partners under several Government departments[13]. Enforcement mechanisms and/or prescriptive implementation guidelines necessary to achieve cross-sectoral targets are absent.

Additional Key Initiatives

(i) Joint Oireachtas Committee 2007-2011

A number of additional steps have been taken by Government policymakers including the 2007 establishment of the Joint Oireachtas Committee on Climate Change and Energy Security (JOCCES) tasked with considering *inter alia.* the medium and long term climate change targets and the key measures needed; the role

[13] Including cross-border institutions such as in the case of the Single electricity market.

of the agriculture sector in providing bio-fuel and biomass crops and consequential implications; the levels of power supply from renewables or other new power supplies; the projected energy demand from transport and the implications for energy security and emissions targets (Dáil Eireann, 2007).

The JOCCES' second report in October 2009 focused on the case for climate change legislation. It reviewed and assessed the climate change legislative provision in 6 other jurisdictions[14] and having "...the shared belief that climate change legislation is needed..." it suggests 17 core provisions for which an Irish Climate Change act could provide the framework conditions (Joint Oireachtas Committee, 2009:11). On the basis of these provisions the Joint Committee report included an explanatory memorandum of an accompanying Climate Change Bill 2009. The report concludes that "…unless and until Government, State bodies, businesses, farmers, employees and householders operate and live within a legal framework, including binding climate change targets, changes in personal and corporate behaviour that are critical if GHG emissions reductions are to become a reality will not happen at the pace required..." (Joint Oireachtas Committee, 2009:11).

(ii) Framework for Climate Change Bill 2010

In response to the work of the JOCCES, the Irish Government's Climate Change Response Bill (2010) proposed among other measures an 80% cut on 1990 GHG Missions by the year 2050, the establishment of a climate change committee, and the introduction of domestic carbon offsetting schemes and trading. It proposed to put such measures on a statutory footing. However, following a change of government the legislative process has been postponed. Until the text of such a bill is published, finalised and passed, an analysis and appraisal of any implementation measures and the adequacy and/or provision of enforcement mechanisms would be premature.

(iii) National Renewable Energy Action Plan

[14] U.S, U.K, AUS, NZ, CAN, California. U.S

As part of their Member State obligations under Article 4 of Council Directive (2009b), the Department of the Communications, Energy and Natural Resources (DCENR) submitted a National Renewable Energy Action Plan (NREAP) to the European Commission consisting of 38 existing and planned measures, 10 of which were regulatory based (Department of Communications Energy and Natural Resources, 2010). The regulatory measures reported are a mixture of planned and existing measures across a variety of areas such as building and planning regulations, energy market trading and offshore licensing. While the NREAP is a comprehensive document that meets the requirements of Council Directive (2009b), it does not come under a broader national climate change or emissions reduction strategy. This may ultimately prove problematic when it comes to interdepartmental conflicts which may arise in the future as the hierarchy of competing interests remains unclear. Such conflicts may jeopardise the reaching of targets.

(iv) Carbon Tax

The 2010 budget from the Department of Finance marked the introduction of Ireland's first carbon tax. Annex E outlined the establishment tax of €15/Tonne carbon tax for transport fuels, non-transport fuels and solid fuels which does not apply to participants in the EU-ETS and consequently does not have an impact on electricity generators.

With regard to the carbon tax, set at €15/Tonne CO_2 [15], it is as yet unclear as to the adequacy of its level. Wissema and Dellink (2007:679) hypothesize using an applied general equilibrium model that "...the reduction target for energy related CO_2 emissions in Ireland of 25.8% compared to 1998 levels can be achieved with a carbon energy tax of 10–15 euros per tonne of CO_2...". However, it should be noted that their model included the application of a carbon tax to the ETS traded energy sector which currently falls outside the remit of the carbon tax.

(v) Appointment of the EPA as "the agency"

[15] The proposed National Recovery Plan 2011-2014 proposes increasing the carbon tax to €30/tonne by 2014

Statutory Instrument S.I.244 (2006) established the Environmental Protection Agency as “the agency” as the Irish Focal Point pursuant to Article 6, the national registry administrator pursuant to Article 7 and as the Irish National Authority pursuant to Article 12 of the Kyoto Protocol. It also delegates responsibility to the EPA as a national registry to ensure accurate accounting of emission reduction units (ERUs), certified emission reduction units (CERs), assigned amount units (AAUs) and removal units (RMUs).

The EPA is also tasked at the state body responsible for the inventorying of year on year GHG emissions and future projections in line with the Annual Inventories Reporting Guidelines from the UNFCCC.

(vi) 40% Renewable Electricity Target for 2020

In addition to existing targets, the Department of Communications, Energy and Natural Resources has set a target of 40% of electricity generation to come from renewable sources by 2020 (Department of Communications Energy and Natural Resources, 2010). Given that 16% of total energy consumption (and consequent GHGs) comes from the electricity sector, it is anticipated that achieving the 40% target in the electricity sector will be necessary if Ireland is to achieve its obligations under the renewables directive.

While there are a considerable number of policy instruments, it would seem that the absence of any over-arching legislative framework on climate change and emissions reductions is a notable omission. The lack of any firm statutory or regulatory structure for the majority of measures outlined in the NCCS may ultimately prove problematic in the absence of any enforcement/performance mechanisms, with cross-sector measures likely to pose the most difficulty.

The precise impacts some policy instruments such as the carbon tax will have in terms of the distributional and substitution effects, are as of yet unknown. Callan et al. (2009:1) discuss the distributional implications of the imposition of a €20/Tonne CO_2 carbon tax and conclude that “...if the tax revenue is used to increase social benefits and tax credits, households across the income distribution can be made better off without exhausting the total carbon tax revenue...”. However, without an accurate way to measure consumption spatially it is unclear as to how a social welfare or tax reallocation could counter-act the potentially unequal spatial distribution effects of a carbon tax on significantly inelastic consumption.

There is also the difficulty of attempting to ascertain or measure the effectiveness of public awareness campaigns designed to encourage behavioural change such as those relating to saving energy or recycling. A significant part of the NCCS centres around non-market mitigation measures. However, the benefits of such measures are typically difficult to quantify, which in turn makes it difficult to make cost benefit decisions in order to prioritise government expenditure.

2.3 Network Governance and Climate Change Policy

While governments have some recourse to market based mechanisms designed to reduce carbon emissions, they are limited both by the public acceptance of such policies in terms of their application and by their coverage due to the complexities involved in estimating the carbon cost of potentially millions of consumer products. Thus a key aspect of climate change policy is the promotion by governments of efficiency based mitigation measures for firms, households and individuals. This section examines the governance systems under which these measures have typically been implemented and discusses the role of multi-level governance in the implementation of climate change policy.

2.3.1 Evolving Governance Systems

Governments and Local Authorities are constantly subjected to changing ideological concepts of governance of which three phases have been identified (Benington & Moore, 2010). The first phase of governance was traditional public administration characterised by the theory of a public good identified and designed by “knowledgeable” professionals, provided by public servants to homogenous citizens and delivered through state and semi-state hierarchy top-down structures. This conception of governance was then largely superseded by the sweeping movement toward New Public Management (NPM). NPM describes the tendency of governments and their agents to more towards more market and customer orientated public administration in the 1980s and 1990s with the privatisation and contracting out of service provision a key feature (Benington & Moore, 2010).

However, Alford and Hughes (2008) report that NPM came under heavy criticism from public administration academia with a focus on the inappropriate likening of the public sector to the private sector and *inter alia* its “real” agenda of cutting government spending. In the search for an alternative approach, concepts of public management, dependent on networked or joined up approaches involving the dense interaction of multiple agents to deliver collective decision making emerged. This approach coupled with principles such as the development and achievement of shared goals through co-operation and through knowledge transfer gave rise to the third generation of governance ideology, termed Networked Governance.

While various different forms and types of network governance have been identified/proposed (Dunleavy et al., 2005; Osborne, 2006; Stoker, 2006), Alford and Hughes (2008) submit that while the area of networked governance is by no means fully developed, previous incarnations of networked governance still suffer the same one-best way problem as traditional public administration and NPM. In response, Alford and Hughes (2008) propose a system of Public Value Pragmatism which recognises that different circumstances demand different managerial tools and sets out a framework for a set of design rules for determining which managerial device is required, be it classical contracting, in-house production, partnering or provision by a service agency.

Despite these differences in approach, it seems clear that the role of modern governments, agencies and more significantly local authorities are changing with these ideological shifts as government bodies become less important in terms of direct service provision and more concerned with the fostering and management of a “diverse web” of multi-level organisational, multi-governmental and multi-sectoral relationships (Eggars & Goldsmith, 2003).

This shift towards networked governance has been identified specifically in the UK in parallel with the evolving political administrations (Bevir & Rhodes, 2003). In the US, Agranoff (2003) promotes the exploitation of networks for public managers working across organisations, highlighting informational, developmental, outreach and action networks.

These moves away from the more hierarchal and contract based construction of governance potentially increase the role, and subsequently opportunities, for local authorities to become contributors towards policy development and become co-ordinators of co-operation and collaboration. With respect to certain policy areas, local authorities may be in a better position to engage with local agents than national or regional organisations.

2.3.2 Multi-Level Governance & Climate Change Policy

While the general movement toward networked governance is acknowledged, the pragmatic approach proposed by Alford and Hughes (2008) would appear to support the recognition of opportunities for dissemination of climate change policy through a networked multi-level governance framework.

First espoused by Hooghe (1996) and subsequently by Hooghe and Marks (2001b), multi-level governance emerged as a framework which attempted to conceptualise the second wave of European integration with the EU's competencies on moving from strictly the management of international relations and co-operation towards the sphere of supranational policy formation. The importance of multi-level governance or the vertical and horizontal co-ordination of policy delivery has been increasingly highlighted by authors (Bulkeley et al., 2009) in the context of the dispersed nature of climate change governance (Betsill & Bulkeley, 2007).

Hooghe and Marks (2003) identify and distinguish two types of multi-level governance, Type I and Type II. Type I systems are characterised by a more traditional, inverted tree structured, system wide architecture of nested nonintersecting membership jurisdictions organized in a limited number of levels while Type II systems are defined as a more flexible multi-level governance design with task specific jurisdictions encompassing intersecting traditional jurisdiction memberships with no limit to the number of jurisdictional levels. More traditional examples of Type II systems would include the differentiated nations of the United Kingdom; Wales, Scotland and Northern Ireland; all of whom have different relations and interaction with the Crown with regard to policing, self-governance, etc. A more modern example of Type II governance can be viewed in some of the larger urban centres where responsibility for different public services and functions are divested in different organisations which may have different geographical boundaries or responsibility and require different levels of sub division.

Hooghe and Marks (2001a:16) argue that "…[in order]… to internalise externalities, governance must be multi-level…" and submits that "more decentralised institutions can better reflect the heterogeneity of preferences among citizens", assuming that is, that heterogeneity can be captured jurisdictionally. However, far from seeing Type I and Type II systems as being substitutes, Bache and Flinders (2004) submit that they can be complementary and used in parallel. Type I governance is orientated towards a set of policies which are strengthened by community and a strong sense of self-determination leading to jurisdictional competition. In contrast, Type II governance can deliver pareto-optimal outcomes to policies where additional efficiency gains can be made by combining resources over non-traditional areas due to some homogenous aspect of the region.

In an analysis of the UK transport sector and the related climate change policy adopted by UK government, Marsden and Rye (2010) use a multi-level governance analysis framework to consider the capability of governance structures to deliver changes required to limit the UK's greenhouse gas (GHG) emissions from transport. They assess the policies, powers and application for GHG emissions reduction from a modal shift in transport and outline a range of transport policies implementable at the local government level in the UK such as parking allocations for new development, smarter choices and improvements to walking, cycling and public transport (bus) infrastructure (Marsden & Rye, 2010). However, the authors note that without demand side restraint, such measures are unlikely to achieve their full potential in changing travel patterns. They also acknowledge an information deficit and note that "…there is, as yet, no guidance on how ambitious a local authority should be and little understanding of the marginal abatement costs in different authorities and areas... the analysis in this section suggests that there are few tools which are currently deemed practicable which would make the adoption of a substantial carbon reduction target a rational policy position to adopt…" (Marsden & Rye, 2010:676).

While the potential for networked multi-level governance gains with regard to climate change measures exists, there is a technical information deficit at the local authority level which needs to be addressed. The provision of such information is likely to improve the chances of the successful implementation of climate change measures at the local level (Marsden & Rye, 2010).

2.4 Local Authorities Matter

The role of local authorities in the implementation of climate change policy has been given increasing prominence in the climate change policy literature. Allman et al. (2004:273) submit that recent trends in the literature have focused on the potential role of local authorities in meeting climate change objectives and managing emissions over the last decade with a growing realisation that "measures to reduce greenhouse gases will be implemented locally and that this can only be achieved when climate change is accepted as a local issue".

The importance of settlements and the concentration of emissions in urban areas is highlighted by Mills (2007), who reports that while just 2-3% of the world's [non-ice] land mass is classified as urban; over half of the world's population live on urban land-cover. Mills (2007) identifies cities as chief causes of, and solutions to, anthropogenic emissions, with 50% of global emissions arising from just 3% of the global land mass and highlights the opportunities for mitigation, with greater geographic detail likely to show the bulk of emissions contained within urban administrative boundaries.

It would appear that as the over-arching climate change policy framework improves, the potential for local authorities to make mitigation and adaptation improvements also increases (Allman et al., 2004). In parallel, the emergence of transnational municipal network organisations, such as the ICLEI-Local Governments for Sustainability and the C40 Cities Climate Leadership Group, have increased the prominence of local authorities in the setting of the global climate change agenda. However, ultimately the potential impact of local authorities is highly dependent on the powers, responsibilities and powers afforded to them by national governments.

2.4.1 Evolving Role of Local Authorities and the Experience of the UK

Collier (1997) examines, within a framework of global, EU and national action, the role of local authorities in climate protection through examples of local strategies from five EU countries and submits that climate change, while a global environmental problem, requires action at all levels of government. In identifying the main obstacles to the implementation of climate change strategies at local level, Collier (1997:55) concludes that even with high levels of commitment from local authorities, an unfavourable policy context (e.g. through nationally imposed budget constraints or low energy prices) can "frustrate the best intentions". Advocating a more effective interpretation of the principle of subsidiarity[16] which should imply the co-operation and co-ordination of activities between relevant levels of government, the author submits that greater effort needs to be made to encourage local authorities to formulate climate change strategies and suggests providing grants for the drawing up of emission inventories and strategies (Collier, 1997).

In comparing the cases of local climate change policies in Sweden and the United Kingdom, Collier and Löfstedt (1997) contrast extensive powers afforded to Swedish

[16] Under Article 5 of the EC Treaty the principle of subsidiarity is intended to ensure that decisions are taken as closely as possible to the citizen i.e. that the EU will not legislate (apart from areas under its exclusive competency) where possibilities for legislation/regulation are available at national, regional or local level.

local authorities with the erosion of local powers in the UK. As a response to the 1970s oil shock, the Swedish government passed the municipal energy planning act which required local authorities to develop a municipal energy plan promoting energy efficiency and security of supply. This movement towards a more Type II governance system for energy supply gave local authorities greater autonomy in terms of energy management (with municipal companies serving the community shareholder) and consequently greater control over a sector usually associated with generating a high proportion of total emissions. In contrast, the privatisation and liberalisation of the UK energy sector has limited UK local authorities' roles in the energy sector. In addition, it was submitted that budget constraints and the lack of legislative competencies afforded to local authorities further limited their scope for local climate change policies. Collier and Löfstedt (1997) conclude that while considerable potential for climate change policies at local level exists the actual potential depends both on the competences and past achievements of local authorities in crucial areas. Greater autonomy afforded to local authorities in Sweden with regard to embedded generation and improvements in energy efficiency through community schemes, combined with previous experience of such activities, greatly increased their potential contribution toward climate change mitigation measures, while the erosion of local authority powers in the UK over the same period weakens their ability to make a significant impact (Collier & Löfstedt, 1997).

Allman et al. (2004) analyse the progress of local authorities in England and Wales in adopting mitigation and planning adaptation measures by considering the results of the 2000 Improvement and Development Agency (IDeA) survey and the 2002 Local Government Association (LGA), IDeA and De Monfort University survey, on the progress of local authorities on climate change. The results showed that while local authorities did make progress in areas under which they had direct control such as the use of renewable energy and the purchase of green electricity, more complex and strategic activities such as energy policy and greenhouse gas emissions inventories and targets had shown little progress with over 70% of authorities still without a dedicated climate change strategy (Allman et al., 2004). When the local authorities were asked to consider the main barriers to progress on the dedicated strategy the authors identified five main reasons for lack of progress citing;

- The lack of a statutory requirement for local authorities to tackle climate change, resulting in climate change not being a priority for local authorities
- The lack of availability of accurate energy use data at the postcode level
- The problem of inter-departmental cooperation: climate change is a multi-disciplinary issue therefore strategies or targets to reduce greenhouse gas emissions will only be achieved if there is cooperation between different council departments
- Problems engaging the wider community in activities to reduce climate change
- Staff and skills shortages: there may be sufficient technical level skills to address specific technical issues but there is a shortage of professionals with wide-ranging strategic skills in climate change

(Allman et al., 2004)

Allman et al. (2004) used the ICLEI-Climate Protection Programme (CPP) methodology to identify "successful" and "less successful" authorities and highlighted the key elements of support (funding and guidance) and co-ordination (other departments, authorities and the public sector) as the main differences between the two groups. The ICLEI-CPP's 5-step milestone methodology provides a simple and concise method of evaluating local authority progress on climate change policies encouraging local authorities to:

- Conduct an Emissions inventory
- Establish a target
- Develop a local Action Plan
- Implement policies and measures and
- Monitor and verify results

(ICLEI, 2006)

Acknowledging the work of Allman et al. (2002), Fleming and Webber (2004) assessed the impact and role of local government in GHG with considerable focus on the energy sector. The authors note the lack of clear guidance from the national government and the absence of specific legislation requiring local and regional government to produce GHG reduction strategies or to implement measures to reduce GHGs (Fleming & Webber, 2004). They report that where authorities have made significant progress in reducing emissions (>20%) the key factors which have contributed to their success were;

- Strong political/chief officer support
- Strong technical knowledge of the issues amongst energy professionals.
- Strong knowledge amongst other professionals.
- Increased awareness amongst the general public.

Fleming and Webber (2004:770) conclude that local authorities can "…be effective at reducing greenhouse gas emissions and targets could be achieved through partnerships with key stakeholders and more effective exchange of experience between the successful and less successful local authorities...". While opportunities exist for local authorities to make a real contribution to climate change policy and mitigation measures, deficiencies in the areas of legislative competency, the availability of emissions data and the lack of a coherent networked strategy, substantially diminish a local authority's ability to make and meet climate change policy targets.

It should be noted that the most recent Climate Change Survey of Local Authorities by the Local Government Group (LGG) reports that a climate change strategy or plan has been adopted by over 65% of local authorities; increasing from just 30% in 2002. This suggests a significant improvement in the implementation of national climate change policy goals at the local level (LGG, 2010). This may be attributable to changes in the over-arching UK policy framework discussed in the next section.

2.5 Climate Change Policy Governance in Ireland and the UK

With the potential of local authorities' contribution to climate change policy established and the networked multi-governance structure under which it may flourish recognised, the current Irish climate change governance structure is now considered and compared with the UK which operates a similar hierarchical authority structure. The analysis is followed by an appraisal of the involvement of Irish local authorities in climate change policy implementation.

2.5.1 UK Climate Change Framework

While Ireland's legislative provisions on climate change consist mostly of directly applicable EU regulations and adopted EC directives[17], the legislative framework in the UK is significantly more evolved. In addition to their international targets, the UK has developed additional legislative frameworks with regards to GHG emissions and renewable energy targets (e.g. the Climate Change Act 2008 which followed the Climate Change and Sustainable Energy Act 2006). The provisions of the Climate Change Act (2008) give legal and statutory effect to a wide range of GHG mitigation measures including a binding legal target to reduce emissions by 80% on 1990 levels by 2050; as well as establishing a Committee on Climate Change (CCC) and outlining reporting and dissemination mechanisms. In addition, subsequent energy legislation[18] takes account of certain definitions set out in the 2008 act and requires that reporting on the progress of de-carbonisation of the electricity generation sector and carbon capture and storage should have regard to any relevant points raised by the reporting of the CCC.

The publication of the 2008 Act in the UK was contemporaneous with the establishment of the Department for Energy and Climate Change (DECC) combining

[17] While Ireland's International Commitments are legally binding on the state, Ireland's dualist legal system means that any such international law only has legal effect within the state if it is adopted through a change in the constitution (i.e. specific assent to be bound by an international treaty) and/or complementary legislation passed/enacted by the Dáil.
[18] Climate Change Response Bill 2010.& Energy Act 2010. UK.

previous competencies of the Department of Business Enterprise and Regulatory Reform (DBERR) and the Department of the Environment Food Rural Affairs (DEFRA) and investing specific responsibility for UK policy on climate change within a single government department. A high level of sophistication exists both in governing the operation of the CCC and in the co-ordination of action across departments and the devolved authorities[19] In 2010, the DECC published the Committee on Climate Change Framework Document, outlining the roles and statutory responsibilities of the CCC and the Adaptation Sub-Committee (ASC) and their operations (Committee on Climate Change, 2010). In addition the Climate Change Act Concordat (HM Government, 2008) sets out the respective roles and responsibilities of each Government department and national authority and the procedure for consultation and resolution in the case of disputes. In comparison to the Irish framework, the UK has evolved a much more focused and deliberate mechanism for the delivery of climate change goals and targets.

2.5.2 Climate Change Governance: Ireland v UK

At the national level therefore, it would appear that the UK has a far more sophisticated system of climate change governance to rely upon for the implementation of its climate change policy. With an overarching legislative framework overseeing the formation and the creation of a system of networked departments via a guiding concordat, the UK would appear to have the necessary governance framework in place to facilitate and resolve policy impasses between conflicting departments and to achieve shared national climate change goals through climate change policy networks.

While some legislative measures have been adopted in Ireland, the chief over-arching framework is the National Climate Change Strategy which has no legal effect. While the strategy does provide for the establishment of a climate change commission to review progress and a high level group on climate change to co-

[19] Northern Ireland, Wales, Scotland

ordinate implementation of the strategy, to date, neither the commission nor the high level group have been established and the first Annual Implementation Status Report has yet to be published.

Consequently, it would appear that the continued absence of an overarching legal framework is hampering progress towards adequately co-ordinated climate change governance in Ireland.

2.6 The Devolution of Climate Change Policy in Ireland

Government policy in Ireland (Section 2.2) is primarily disseminated through local authorities and certain non-central government agencies. Noting the structure and form of local authorities and state agencies in Ireland, this section reviews the current status of climate change policy at the local authority level and considers the presence of and opportunities for multi-level climate change governance in Ireland.

2.6.1 Local Authorities

Ireland is served by a two-tiered local authority structure with 34 County and City (Tier 1) councils and 80 Town and Borough (Tier 2) councils. Tier 1 councils are responsible for the large scale provision and support of core public services and infrastructure with the Tier 2 nested authorities providing a smaller set of local services, typically in co-operation with their relevant county council. In parallel, there are also 8 regional authorities[20] which are responsible for co-ordinating larger scale infrastructure and development projects which are amalgamated into two regional assemblies for the purposes of EU structural fund projects.

In the area of climate change mitigation, local authorities have crucial competences in areas such as water and waste management, planning, housing regulation and can devise/support community projects designed to improve energy efficiency e.g. district heating. They are also responsible for transport infrastructure and traffic

[20] Established under Local Government Act 2001. *37.* Ireland.

management with the power to promote and incentivise the increased use of public transport and the creation of “green” lanes for non-motorised commuters.

In addition to the government structured nested co-ordination at the regional level, local authorities have identified commonalities and have grouped together to co-ordinate activities in areas where resources and expertise are scare. For the purposes of waste management, Ireland is divided into 10 different regions with management agreements established between the local authorities in each region (Department of Environment Heritage and Local Government, 2004). There have been also been progressive moves towards the establishment of energy agencies[21] by local authorities to act as advisory bodies to both the authority itself and local communities and businesses.

In the 2006 review of Ireland’s first climate change strategy (Department of Environment Heritage and Local Government, 2000) the DEHLG recognises the importance of local authorities in implementing climate change policy noting that local authorities have an important role in contributing to reduced GHG emissions, through their functions in relation to planning, transport, housing and waste disposal (Department of Environment Heritage and Local Government, 2006). As such, local authorities in Ireland have a potentially large influence in terms of effecting behavioural change when it comes to climate change mitigation measures.

2.6.2 Climate Change and Irish Local Authorities

In the Office for Local Authority Management’s 2008 Best Practice and Current Guidelines, the authors recognise that a number of different approaches to climate change have already been developed by local authorities with regard to local requirements but recommend that “all local authorities adopt a written climate change policy” (Office for Local Authority Management, 2008:1). In addition, the guidelines recommend that each policy should refer to the following, as outlined in the NCCS: energy use; housing/building projects; waste management; transport;

[21] Association of Irish Energy Agencies Reports 13 energy agencies serving 24 local authorities as of 13/02/2011

planning policies; procurement activities; raising awareness; and other statutory functions (Office for Local Authority Managment, 2008).

Approximately one third of County Councils[22,23] have a dedicated climate change strategy with another 6 reporting strategies in the pipeline. However, there is a large amount of variance in the scope and detail of county climate change strategies. While some strategies are quite detailed and set out specific targets and policy programmes for energy efficiency and community schemes, other strategies are comparatively quite weak and focus on basic information dissemination and awareness campaigns. Some strategies merely acknowledge the provisions of the NCCS and do not propose any individual measures. Of the councils that do not have a specific climate change strategy, there is substantial variance in the prominence that climate change policy receives in the county development plans; ranging from statements of strong deference to national policy objectives on climate change and renewable development; to declarations that the council will have regard to such policies when considering applications for renewable development.

2.6.3 Irish Local Authorities and Multi-level Climate Change Governance

With regard to the presence of multi-level governance in Ireland, both Type I and Type II arrangements could be said to be in operation. While Ireland's county councils operate for the most part, within a nested hierarchy of Type I multi-level governance, there are a number of examples of Type II governance in operation where county councils band together and co-operate in order to achieved shared climate change goals; the most prevalent of which are the waste management schemes some of which are managed by the regional authorities.

In addition, many county councils have sought the help of (and in some cases established) local energy agencies in developing and delivering on the energy goals

[22] In the 26 ROI counties there are 34 "County" Councils for the purposes of the DEHLG. The 34 include the city councils of Cork, Limerick, Galway and Waterford with the 4 Dublin councils and Tipperary North and South Riding.

[23] The Local Government Reform Act 2014 (No. 1 of 2014) provides for the future amalgamation of the city and county councils of Limerick and Waterford as well as Tipperary North and South Riding

outlined in their own climate change strategies. The Limerick Clare Energy Agency funded by both Clare and Limerick County Council is a typical example of a horizontal partnership between two councils whereby both reap the benefits of the shared knowledge and expertise of dedicated experts while sharing the burden of costs. Similarly, CODEMA acts as the main energy advisory to the four local authorities in Dublin city.

2.6.4 Agencies

There are a large number[24] of government agencies (predominantly made up of statutory bodies, departmental agencies and support/information agencies) involved in the dissemination of government policy. There are however, a small number of key large government agencies which have a potentially strong role to place in climate change policy. Agencies governing broad emissions sectors such as agriculture, public transport, planning, and energy and natural resources have a large potential to influence the development of appropriate and effective mitigation measures.

The nature of these agencies is such that their sphere of influence and competency is nationwide yet their application is experienced primarily at the local level. However, despite the potential for efficiency gains and the dissemination of mitigation incentives, many of these key agencies with large networks, resources and staffing do not have a specific climate change policy. Co-operation and co-ordination between these key agencies and the local authorities under an over-arching networked governance framework is essential if real progress towards the achievement of climate change objectives is to be made.

However, in evaluating the current and future potential of local authorities in Ireland to effectively contribute to climate change mitigation and adaptation we consider the findings of the evaluation of progress of the UK local authorities by Allman et al. (2004). Currently a number of the barriers to progress on climate change which

[24] Over 600 reported in 2005 McGauran, A.-M., Verhoest, K. & Humphreys, P. 2005. The Corporate Governance of Agencies in Ireland. Dublin: IPA.

Allman et al. (2004) identified are applicable in the Irish context. These are as follows:

- Currently there are no statutory obligations on climate change for local authorities. Thus there is a strong possibility of climate change not being considered a priority area for action.

- For those authorities that do consider it to be a priority action there is an information deficit in terms of accurate energy use (and consequent emissions) data at a spatially disaggregated level.

- With regards to co-operation and co-ordination at the national level, Ireland is lacking in comparison to the more institutionalised arrangements for inter-departmental co-ordination which have been advanced in the UK with the publication of the Committee on Climate Framework Document and the Climate Act Concordat.

Thus while it would appear that the potential is there for local authorities and agencies in Ireland to make a real impact towards the implementation of climate change policy, certain barriers to progress remain apparent. In addition to the absence of legislative provisions and a framework for collaboration and joined-up action between local authorities, agencies and government departments, the substantial information deficit raised by Allman et al. (2004) exists in relation to the lack of available and appropriate information against which local authorities and agencies can assess progress.

2.7 Assisting Local Policy and the Evaluation of Mitigation and Adaptation

While undoubtedly deficiencies exist in the Irish climate change policy framework, the progress shown by some local authorities in the development of individual climate change strategies is a positive step in the right direction. While the Irish system of governance remains predominantly hierarchal, the relative success of Type II networked governance approaches such as the multi-authority energy agencies and the waste management system show that there are opportunities to move the implementation of climate change and broader national policy forward through networked governance (McGauran et al., 2005). A more robust institutionalised framework for implementation and co-operation could see these systems replicated and repeated for other mitigation measures nationally.

However, even with a more robust over-arching policy framework, challenges for the implementation of policy and the assessment of mitigation measures at a local level remain. Laukkonen et al. (2009) consider these challenges and note that mitigation and adaptation measures are not necessarily complementary and may in some cases counter act each other. This may be due to the unavoidable carbon costs associated with certain adaptation measures. Such conflicts may necessarily create difficulties for authorities in their decision-making process as the costs and benefits associated with different mitigation and adaptation options would have to be calculated. Heterogeneity of outcomes for agents in the community could increase the complexity of such a calculation. Current methods for conducting climate change mitigation/adaptation cost-benefit analyses are likely to be overly onerous for poorly resourced local authorities while developing communities will also have to balance economic objectives with sustainable development. Cognisant of this, Laukkonen et al. (2009:291) argue for the development of a “methodology and a tool to help individuals, communities, countries or regions in the decision making process towards the best response to climate change…”.

In 2006, with the aim of providing nationally consistent estimates, AEA Energy and Environment provided DEFRA with a spatial map (Figure 2.1) of CO_2 emissions for the UK (Department for Environment Food and Rural Affairs, 2006). The high resolution map reported emissions at the local authority and regional level for 2004 and broadly grouped those emissions into 6 sectors[25]. The stated reasons for the initiation of the mapping project included an aspiration that the continued development of the dataset would facilitate action plans to reduce carbon emissions. Quoting the UK's Climate Change Programme, the document sees local authorities as vital contributors to national emissions reduction as they are "uniquely placed to provide vision and leadership to local communities" (Department of Environment Food and Rural Affairs, 2006:1).

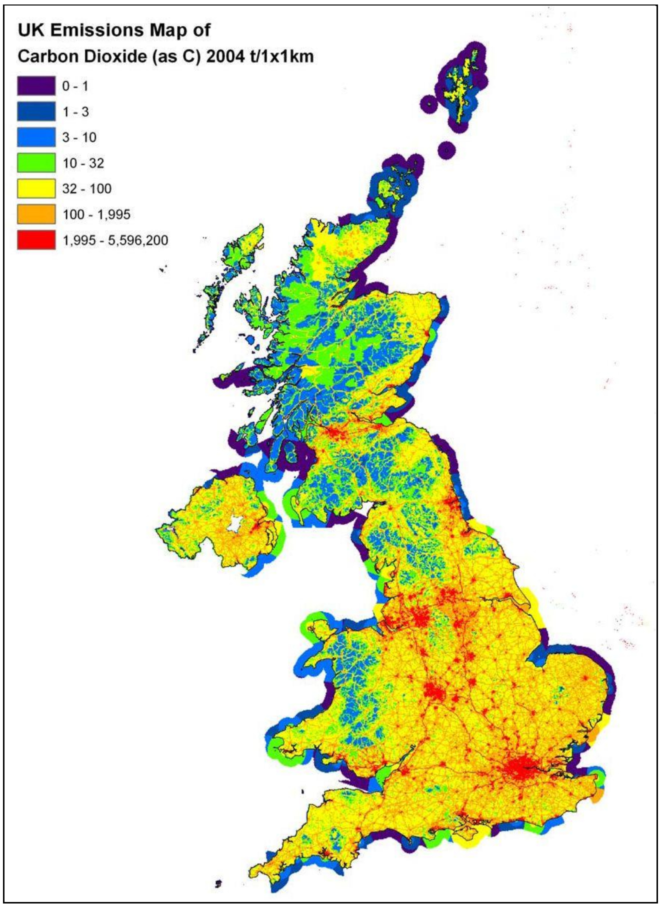


Figure 2.1 Spatial map of CO_2 emissions for the UK

(Source: Department for Environment Food and Rural Affairs 2006)

[25] Industrial and Commercial; Domestic; Road Transport; Land-Use, Land-Use, Change and Forestry; Unallocated emissions; Domestic Aviation, offshore Gas and Oil and emissions from shipping not included.

2.8 Discussion

It is clear from the literature and the continued growth of transnational associations such as the ICELI-CCP and the C40 that local authorities have a significant role to play, both in the formation of local climate change policy, and the implementation of broader national and international climate change strategies.

The results of the 2010 Climate Change Survey of Local Authorities for the Local Government Association, show considerable improvement in the engagement of local authorities with the climate change in the UK with over 65% of local authorities reporting the adoption of a climate change strategy or action plan while over one third of Ireland's county councils have adopted a climate change strategy with several other councils reporting it as a work in progress .

While the Department of the Environment Heritage and Local Government is currently the state body charged with setting climate change policy in Ireland, ultimately the delivery of targets relies on both the presence of a robust legislative framework and effective co-ordination between local authorities, regional authorities and agencies under several Government departments and their effective implementation of policy through networked multi-level governance.

The need for a policy tool to provide local authorities, agencies and departments with both a baseline emissions inventory for their respective areas of influence and a decision-making process to make informed choices when faced with competing mitigation and/or adaptation options is evident. Such a tool could also be used to consider the redistributive and localised economic impacts and assist in the wider development of optimal burden-sharing across sectors and regions resulting in more efficient and favourable outcomes both locally and nationally.

It is submitted that there is a clear need for an efficient, effective, analytical policy tool for the assessment of climate change policies at the local level, not only in terms of effective inventorying, target setting and monitoring but also to enable the assessment of both mitigation and adaptation options and the potential trade-offs for local authorities with limited resources.

CHAPTER THREE: MODELLING GREENHOUSE GAS EMISSIONS: A COMPARATIVE ANALYSIS OF NATIONAL AND INTERNATIONAL METHODS

3.1 Introduction

The primary motivation behind the requirement to model greenhouse gas emissions derives from the obligations conferred on parties to the United Nations Framework Convention on Climate Change (UNFCCC) in response to anthropogenic threats to the Earth's climate system. This chapter discusses the form, development and structure of various models designed to estimate anthropogenic greenhouse gas emissions in the context of reporting obligations under both the UNFCCC and the Kyoto Protocol. While an in-depth review of the Intergovernmental Panel on Climate Change (IPCC) assessment report structure is outside the scope of this work, Ireland's national emissions inventory submitted by the EPA under the IPCC reporting guidelines is considered. Having established that information at a sub-national level is deemed as essential to inform effective local climate change policy (Chapter 2) we assess the adequacy of a default inventorying system which reports aspatially at a national level and review current options both national and international for the spatial modelling of greenhouse gas emissions.

3.2 National Inventorying of Greenhouse Gas Emissions

The generation of a national emissions inventory is an onerous task. However, without information on past, present and potential future emissions, governments lack a framework under which they can balance the current costs of implementing mitigation and adaptation measures against the potential future costs of climate change through inaction (den Elzen & Meinshausen, 2005). Without such a framework, key economic questions such as how quickly countries should implement and/or enforce mitigation measures are extremely difficult to answer (Nordhaus, 2013). With the level of public concern relating to climate change at risk in the face of economic insecurity bought about by the recent global recession

(Scruggs & Benegal, 2010) the public acceptance of the implementation of market and/or regulatory climate change policies at the national level is not guaranteed (Lockwood, 2013).

In order to achieve stable atmospheric GHG concentrations while maintaining global political support, highly detailed information on past and current global emissions is required in order to create a baseline emissions inventory and project future emissions; thereby allowing policy makers to determine the highest acceptable future emission paths required to maintain stable atmospheric concentrations (den Elzen & Meinshausen, 2005). The accurate inventorying of emissions may facilitate policy makers in determining appropriate goals and targets to reduce or limit future emissions. The presence of these targets then allows individual nations to make informed economic decisions determining optimal mitigation paths by balancing the costs of mitigation against the costs of a business as usual scenario (BAU).

In response to the objectives of the UNFCCC, parties to the convention are obliged to submit a National Inventory Report (NIR) providing a high level of detail on annual emissions estimates from 1990-present in order to comply with the requirements of Articles 4 and 12 of the UNFCCC as per Decision 18/CP.8. In addition those parties who have also ratified the Kyoto protocol and assumed national emissions targets for the commitment period 2008-2012 are required to submit supplementary information required under Article 7.1 on emissions and removals from Land Use- Land Use change and Forestry (LULUCF) under Article 3.3.

3.2.1 IPCC Inventory Requirements

As an Annex 1 party to the UNFCCC, Ireland is bound by the requirements set out in the guidelines for the preparation of national communications for both the submission of an NIR and the reporting of GHG emissions by sources and removals by sinks in the common reporting format (CRF) (UNFCCC, 2003:13). In addition to the reporting guidelines, the IPCC publish accompanying guidance on uncertainty management, land use, land-use change and forestry activities under Article 3, paragraphs 3 and 4, of the Kyoto Protocol (UN, 1998). Parties to the convention are now obliged to consider the 2006 version of the IPCC guidelines. However, as yet, parties are only required to submit their reports in accordance with the provisions of the revised 1996 guidelines.

The IPCC (1996) guidelines for the formation of the National Inventory Reports are highly detailed, providing parties with a prescribed structure for the summary reporting of institutional arrangements, overall emission trends and emissions by sector as well as providing parties with a common reporting format (CRF) to be used for the quantitative data submission of annual emissions. In order to assist parties who experience information deficit with respect to any of the emissions factors for sectoral categories and sub-categories with their emissions calculations, the IPCC also provide standard 'default' emissions factors which parties may use. However, the guidelines state that "[in general]…default assumptions and data should be used only when national assumptions and data are not available" (IPCC, 1996:6). Parties' submissions are reviewed by an appointed Expert Review Team (ERT) which issues a report on the party submission.

In terms of the sophistication of any calculation methodology, the IPCC have identified three different ascending Tiers (1, 2 & 3) in order enable parties to use methods "consistent with their resources and to focus their efforts on those categories of emissions and removals that contribute most significantly to national emission totals and trends" (IPCC, 1996:8). The guidelines also require that parties develop and report on quality control/quality assurance (QC/QA) measures when using country-specific factors and provide decision tree guidance on the selection of the appropriate Tier method and emission factor based on the parties available resources.

The IPCC accounting methodologies and emissions factors are continuously being improved and updated, however, limitations of accuracy were noted by Subak (1999a) citing discrepancies between top-down validation models and self-reporting inaccuracies when forming comparisons of emissions associated with beef production in the US, UK and Canada. In addition, Subak (1999b) cites the format of the basket approach towards target and inventories as having the potential to allow countries to induce favourable outcomes and that in some cases countries may meet targets reducing emissions from sources with uncertain baselines such as methane associated with historical fertiliser application; thus allowing increases or non-reductions in emissions from sources that can be estimated more accurately such as emissions from energy.

While the likelihood of direct under-reporting in emissions inventories may be relatively small in the longer term, the incentive for counties to choose the more favourable tier methodology is present. While this may have a positive effect towards the development of more sophisticated sector methodologies for countries who suspect they are below average unit emitters in those sectors, the delay of the use of more accurate methodologies may benefit countries with above average unit emissions.

3.2.2 Ireland's Submission under the UNFCCC

The Irish Government established, by statutory instrument, the EPA as "the agency", the Irish focal point pursuant to Article 6, the national registry administrator pursuant to Article 7 and as the Irish National Authority pursuant to Article 12 of the Kyoto Protocol (Statutory Instrument S.I.244, 2006). It also delegated responsibility to the EPA as a national registry to ensure accurate accounting of emission reduction units (ERUs), certified emission reduction units (CERs), assigned amount units (AAUs) and removal units (RMUs).

In addition to its commitments under the UNFCCC and the Kyoto protocol, Ireland has also committed to submitting biennial greenhouse gas projection estimates to the EU commission. Submissions are carried out in compliance with Council Decision 280/2004/EC concerning a mechanism for monitoring Community greenhouse gas emissions and for implementing the Kyoto Protocol (Council Decision, 2004). Its purpose is to assist and to enable the commission to monitor progress in terms of the EU Kyoto commitments and in terms of its own targets under Council Decision

(2009) on the effort of Member States to reduce their greenhouse gas emissions to meet the Community's greenhouse gas emission reduction commitments up to 2020.

In order to complete Ireland's NIR and derive estimates of projected future emissions the EPA acquires a large amount of data from numerous government agencies. To facilitate this, institutional arrangements for co-operation between the EPA and data providers were established with Memoranda of Understanding (MOUs) developed for key data providers such as Sustainable Energy Authority of Ireland (SEAI), the Department of Agriculture, Food and the Marine (DAFM) Central Statistics Office (CSO). The available information is then examined to determine the appropriate tier methodology and emissions factors to be used based on the national data, research and studies available before the NIR is submitted for external review in advance of submission to the UNFCCC secretariat (EPA, 2010). An overview of the structure of the national inventory system is given in Figure 3.1.

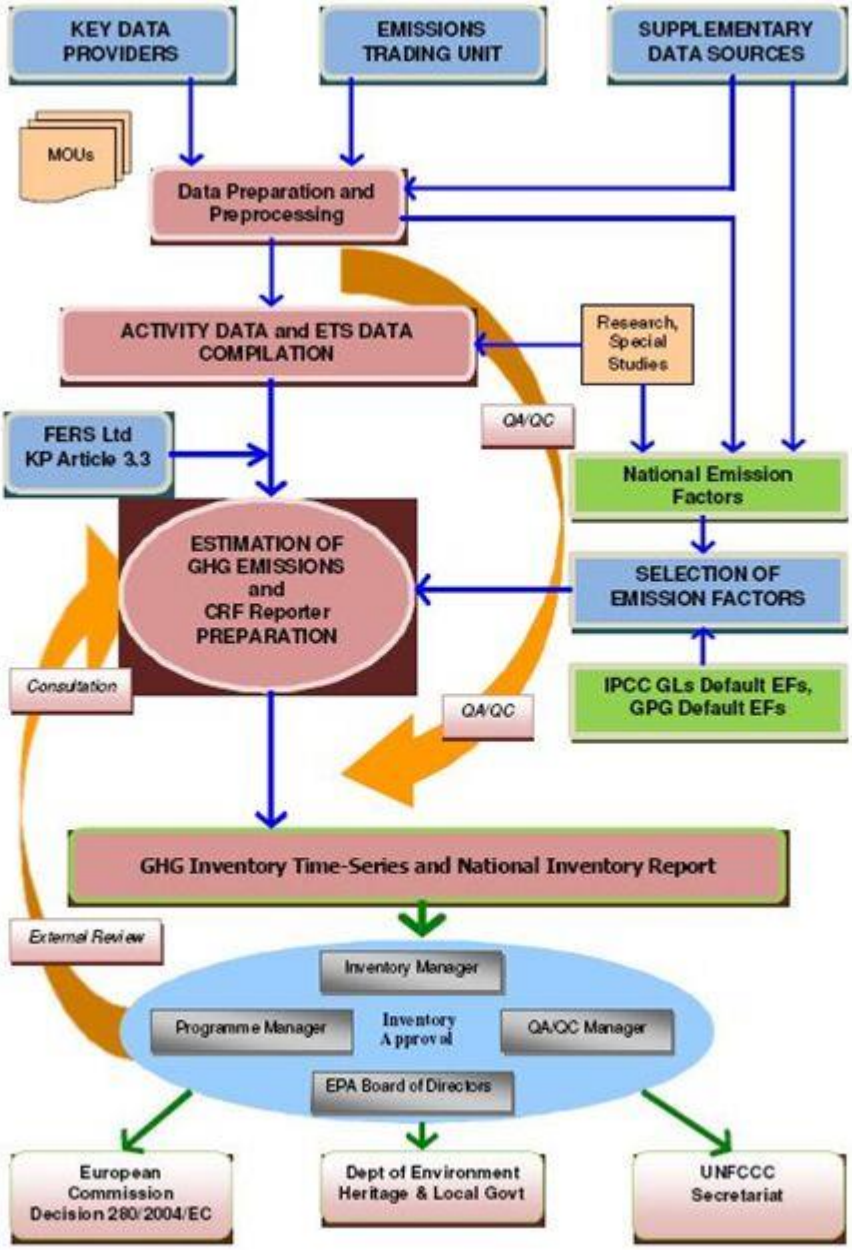


Figure 3.1 National inventory system overview

(Source: EPA, 2010)

Upon submission to the UN secretariat the report is then reviewed by a UNFCCC Expert Review Team (ERT) which then makes recommendations to the party in respect of any incompatibility with the reporting requirements. The party then responds/addresses the issues raised by the ERT in the following annual review.

While the IPCC's inventorying methodology may be appropriate in terms of its accuracy of reporting national incident emissions, its aspatial format does little to assist Member States in the design and implementation of effective mitigation policies at the local and regional level.

3.3 Alternative Approaches to Emissions Modelling

Internationally, the modelling literature has largely focused on the constant improvement and revision of emissions factors and the development of new emissions factors at an increasingly disaggregated accounting scale (Huang et al., 2006; Lovett et al., 2008; Mohareb et al., 2008). Scientific improvements with respect to more accurate and differentiated emissions factors can deliver the potential for higher tier methodologies to be used for inventory reporting either by a party adopting that method as a country-specific emissions factor (EF) or through the adoption of that EF by the UNFCCC through the National Greenhouse Gas Inventories Programme (NGGIP) thereby enabling more accurate emissions modelling.

However, the IPCC's Good Practice Guidance and Uncertainty Management in National Greenhouse Gas Inventories recognises the need for independent verification of the national inventories (IPCC, 2000) and while approaches to the modelling of greenhouse gas emissions have been dominated by improving emissions factors to help assist with the IPCC's bottom up accounting methods; alternative top-down backwards trajectory inverse modelling approaches have been used to estimate GHG emissions (Polson et al., 2010; Corazza et al., 2011).[26]

3.3.1 Top-Down Models

Top-down models have only been possible in recent years with the advent of modern computing. Optimum emissions estimates are calculated out on a large number of

[26] Total greenhouse gas and Nitrous Oxide (N_2O) emissions respectively

possible distributions using statistical theory (Janssen et al., 1999). Critically they provide an opportunity to investigate the efficacy and accuracy of bottom up approaches. These models are typically informed by aggregate observations measured at a limited number of data collection points which are then statistically modelled backwards to their point of origin (e.g. footprint analysis). Two inverse modelling methods have been prominently used in Europe. The first method involves the use of appropriate proxies to derive higher resolution inventories from aggregated estimates using bottom-up inventories as “a priori” constraints (Bergamaschi et al., 2005).

Working as part of the European Commission’s Joint Research Centre, Bergamaschi et al. (2005) use a two-way nested atmospheric model to estimate CH_4 emissions for the EU-15 countries aggregating modelled CH_4 emissions for a European wide domain, at a spatial scale of 1^o x 1^o. They compare the inverse modelled methane emissions to the national bottom up inventories and find overall agreement with national inventories and that EU-15 emissions are “very close” to the UNFCCC value for the year 2001 (Bergamaschi et al., 2005). However, the authors concede that as their model uses bottom-up estimated constraints it is not completely independent of the national inventories. Additionally, they conclude that while top-down approaches are an important element of inventory validation, the adequacy of the models in terms of verifying relatively small emissions reductions has yet to be established advocating a further expansion of the atmospheric observation network (Bergamaschi et al., 2005).

An alternative inverse modelling approach incorporating early Lagrangian trajectory (FLEXTRA) and dispersion (FLEXPART) models in order to backward track air parcels (backward trajectories) and spatially track GHG exchanges from the baseline background emissions level was used by Forster et al. (2001). Forster et al. (2001) used the Lagrangian models to track Canadian Forest Fire Emissions over Europe using baseline observations from Mace Head research station and a small number of observation stations in central Europe and showed that 2 periods of enhanced “black” carbon could be linked to the Canadian Forest Fires.

The spatial resolutions of the latest inverse models have been significantly improved. Corazza et al. (2011) makes use of an increased number of monitoring stations through the Continuous High PrecisOn Tall Tower Observations of Greenhouse Gases (CHIOTTO) programme in attempting to inverse model European N_2O emissions. Polson et al. (2011) use an inverse modelling technique to estimate the spatial apportionment of GHGs for the UK using a spatial sampling technique that involved the filling and subsequent analysis of telder bag observations collected during 5 hour flight plans circumnavigating the UK. Using the NAME Lagrangian dispersion model, Polson et al. (2011) attempt to independently validate the UK's national emissions inventory. Polson et al. (2011) report that for CO_2 emissions, the IPCC based National Atmospheric Emissions Inventory (NAEI) would appear to provide reasonable estimates while for N_2O and CH_4, employing the NAEI would appear to underestimate emissions significantly[27].

Polson et al. (2011) derived the 'history' or footprint of the air at each observation location, running until all air parcels had left the domain at a spatial scale of 0.3^o x 0.18^o. However, while this higher resolution spatial scale provided a much more detailed and accurate top-down estimation of emissions than previous models, the accuracy of its localised spatial data in terms of its suitability to aid policy development and implementation is questionable given the inability of the model to identify emission sources. Acknowledging non-uniform data quality and the averaging method used, Polson et al. (2011) concede that the spatial estimates are known to be less reliable than other types of modelling, citing regional disparities between the NAEI and the dispersion model. While regional disparities may exist, the improvement and use of top-down models are important in terms of validation of aggregate emissions reported by current bottom up modelling which are required in order to help nations design and implement abatement strategies.

[27] Polson et al., (2010) report mean CO_2 emissions at 2900 kt yr^-1 compared to 2400 kt yr^-1 reported in the NAEI. Mean CH_4 is reported at 3500 kt yr^-1 compared to the NAEI estimate of 2400 kt yr^-1 while mean N_2O emissions are reported at 500 yr^-1 compared 130 kt yr^-1 reported in the NAEI.

3.3.2 Bottom-up Approaches

While more sophisticated emissions factor methodologies may deliver more accurate IPCC national inventory reports they continue to be aspatial in nature. Given that information at a local and regional level can; better inform physical transport models (Zhang et al., 2009), account for spatially heterogeneous emissions (Li et al., 2010), and enable effective policy implementation and analysis (Allman et al., 2004); methods for spatially modelling emissions at a sub-national level have been developed.

In the area of emissions from agriculture, Li et al. (2010) note that significant errors can occur when applying the same Tier 1 emissions factors to heterogeneous geographical regions. Specifically in relation to emissions from soil, Li et al. (2010) review the role of the DNDC (Denitrification-Decomposition) model in predicting the soil fluxes of N_2O, CO_2 and CH_4. Developed for predicting carbon sequestration and trace gas emissions from upland agri-systems, the DNDC model provides a basis for constructing regional inventories for greenhouse gas emissions. Thus the DNDC model can identify high GHG emitting agricultural regions and enable the modelling of alternative practical management practices and mitigation methods suitable for each agricultural area. Similarly, Leip et al. (2010) use the DNDC model to develop spatially stratified N_2O factors for Europe by combining information on nitrogen application with the geographically varied environmental conditions. The authors simulate emissions fluxes for over 200,000 land units for 3 different crop types over 10 different meteorological years and report emissions at a national and EU-25 level. They conclude that while a single emissions factor is suitable for emissions assessments at a scale as large as the EU-25, “a stratified approach considering fertilizer type, soil characteristics and climatic parameters is preferable at scales from individual countries in Europe or smaller” (Leip et al., 2010:9)

The importance of geographical variations in differentiating emissions is also outlined by Zhang et al. (2009) who consider the variance of ammonia emissions from rice paddies. Zhang et al. (2009) submit that the development of a spatial emissions inventory would provide indispensible input data for atmospheric transport models, N deposition, critical load models and future abatement strategies for China in future research.

UK Spatial Emissions

In terms of a more comprehensive greenhouse gas emissions mapping methodology, the National Atmospheric Emissions Inventory (NAEI) uses a combination of point source data and a distribution map of diffuse emissions to construct a greenhouse gas emissions map across 11 source sectors for the UK, from which local statistics are compiled.

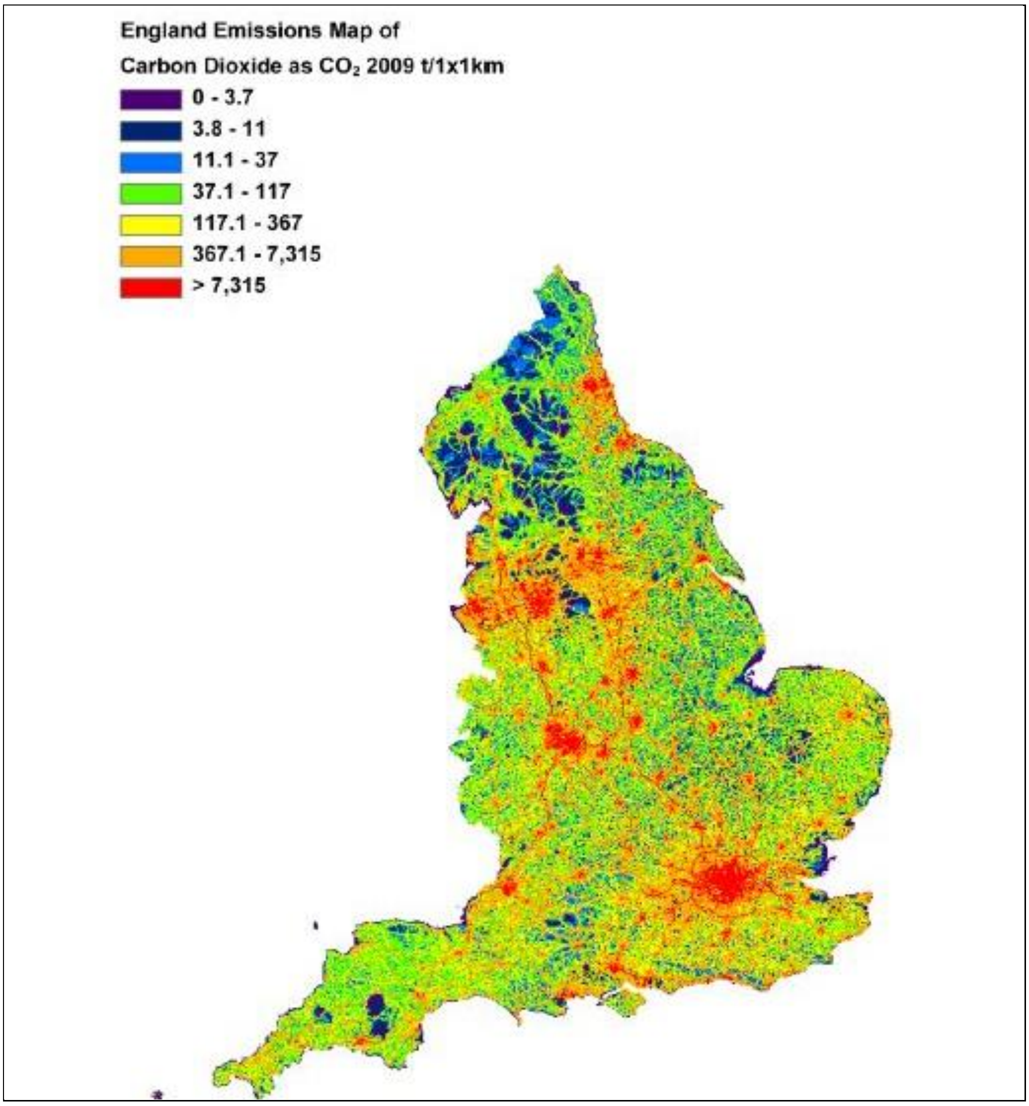


Figure 3.2 Spatial emissions map of CO_2 for England at 1km^2 resolution

Source: AEA Energy and Environment (2011)

Emissions are mapped using several data sources including the NAEI, the Centre for Ecology and Hydrology (CEH) (N_2O & CH_4) and local authority consumption data, which has been made available to the Department of Environment Food and Rural Affairs and the Department of Energy and Climate Change (AEA Energy and Environment, 2011). Emissions are then modelled at a resolution of $1km^2$, and draw on the structured compilation of numerous data sources. However it differs from the previous models in that some emissions have been redistributed from national inventory totals rather than having being modelled from the bottom-up directly.

3.4 Spatial Emissions Modelling in Ireland

There have been a number of studies which have attempted to model the spatial distribution of certain greenhouse gases in Ireland at varying resolutions and show the benefits and application of additional spatial information on emissions.

de Kluizenaar et al. (2001) describe a technique used to model the spatial distribution of SO_2 and NO_x emissions for 1995 which was carried out by assigning emission totals, from different emission-source categories, to a 1kmx1km resolution map of Ireland. Emissions were disaggregated by applying a spatially weighted distribution of emission sources onto matched suitable land cover types using the Co-Ordination of information of the Environment (CORINE) land cover map. The resultant map allowed the authors to investigate and identify emissions sources and sinks with the potential to contribute to improved long range transport models and aid in the evaluation of critical load exceedence for nitrogen in the form of both eutrophication and acidification in Ireland.

In discussing the distributional effects of a carbon tax in Ireland, Leahy et al. (2009) consider spatially modelled consumption (based on regressed averaged incomes) and production emissions (sector-weighted employment data) using an energy use income model and industrial EFs to calculate CO_2 emission totals disaggregated to electoral district (ED) level. The benefit of such studies allows policy makers to assess the likely impact of abatement strategies and balance reduced emissions benefits against potentially spatially inequitable welfare re-distributions.

Hynes et al. (2009) examine the spatial distribution of methane (CH_4) emissions across Irish farms using a technique called simulated annealing to match the Irish Census of Agriculture data to the National Farm Survey and develop a spatial microsimulation model (Chapter 4). Micro-datasets are primarily either official census publications or individual/household survey data. In general, census data includes a variety of socio-economic variables, such as age, marital status and education level, and a geographical component. However, variables such as income level, health, information on farming activity, etc. are not included due to data confidentiality. As such, using the census data for explanatory research is restricted due to data limitations. Microsimulation offers a useful technique to overcome some of these data limitations. Employing this method, Hynes et al. (2009) simulated the effects of a carbon equivalent tax on average family farm income at both the farm and regional level reporting the impacts for each quintile for both REPS and non-REPS farmers at ED level. Figure 3.3 illustrates the average tax take per farm per electoral district from a €7.50 per tonne of CO_2eq methane emissions tax. This spatial disaggregation of methane emissions by Hynes et al. (2009) enabled an analysis of the heterogeneity of welfare outcomes as a result of the tax across space and the impacts of a potential redistribution mechanism.

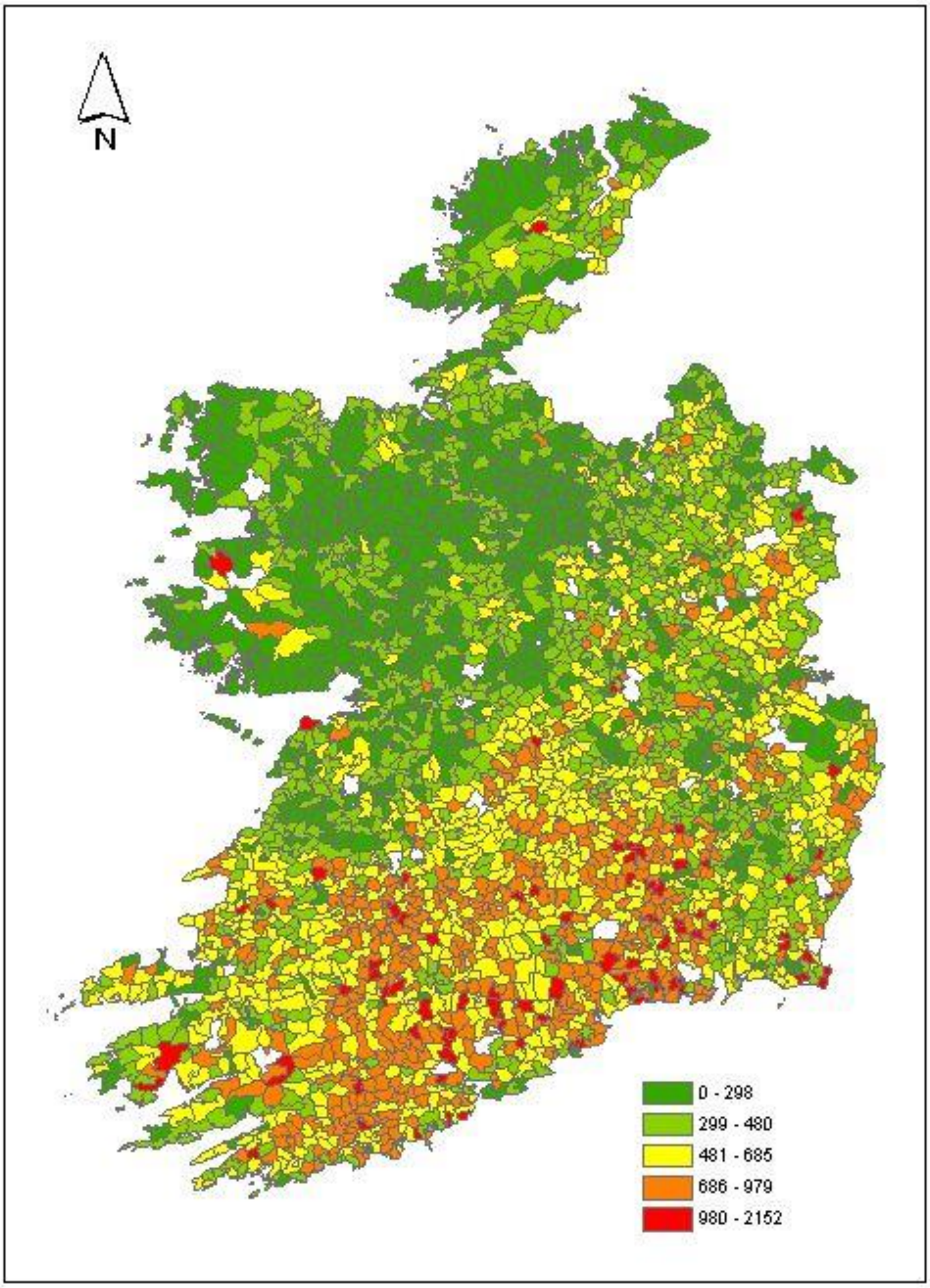


Figure 3.3 Average tax take per farm per ED from a €7.50 per tonne of CO_2eq methane emissions tax

(Source: Hynes et al., 2009)

3.5 Discussion

Having established the need for GHG modelling at a high spatial resolution in terms of the implementation of effective abatement strategies at the local level (Chapter 2), the adequacy of currently available modelling methods is considered. While the procedures and processes for the calculation of national emissions inventories may be comprehensive and provide accurate accounts for the purposes of calculating EU and indeed overall international emissions, the emphasis of the UNFCCC on an aspatial submission is perhaps questionable.

While the purpose of the national inventory accounts is to help parties and Member States, calculate total emissions, set reduction/limitation targets and analyse progress, the absence of a higher spatial resolution for a baseline emissions inventory against which local authorities can design, implement and manage abatement strategies is still a problem. If the ultimate use of UNFCCC emissions modelling is as an international accounting exercise rather than as effective tool to influence behaviour at the local level, than its purpose or more accurately its usefulness to end users i.e. policy implementers may be called into question.

It is clear from an analysis of the national and international literature, and a review of modelling techniques, that there is a need for a sophisticated analytical tool for modelling greenhouse gas emissions in order to enable the effective implementation of climate change policy at the local level. The following chapter investigates the potential use of microsimulation modelling in solving this information deficit.

CHAPTER FOUR: MICROSIMULATION MODELLING AND THE DEVELOPMENT OF SMILE

This chapter investigates the potential role for microsimulation modelling in providing a solution to the information deficit experienced by authorities in relation to greenhouse gas emissions (GHG) emissions at the local level. Following a review of recent developments in the area of microsimulation modelling and the emergence of several types and forms this chapter discusses the evolution and applications of the SMILE microsimulation model and highlights its potential use for the inventorying of greenhouse gas emissions at the micro level enabling the estimation of a spatially disaggregated distribution of GHG emissions.

4.1 Introduction

Public policy makers and implementation bodies have a difficult task. Where competition for public resources is high and the tolerance for mismanagement is low, policy makers are challenged with designing policies which satisfy certain basic evaluation criteria. Reviewing evaluation frameworks, Ballas (2001) states that when evaluating policy, basic questions include; Do the measures achieve the effect for which they were designed? If not, why not? What are the indirect and induced effects? What are the spatial impacts?

Unrau (1993) observed that the analysis of social policy requires an awareness of complex interrelations of societal conditions that include what individuals need, how institutional systems operate, and what social cultural and political actions are aimed at human survival. However Clarke (1996b) and Birkin et al. (1996) noted a lack of work on the evaluation of social and economic policies at the household or individual level. Yet macro level analysis tools (such as input-output modelling and income inequality using the Gini co-efficient) are still predominantly used today. While these models are useful and can give a good indication of the nature of impacts of a particular policy, they are somewhat blunt instruments. Such models do not observe the spatial and demographic distribution of benefits and may miss key interactions between individuals, households, and firms which can be important in determining outcomes. Ballas (2001) argues that there is a need to understand, estimate or predict which socio-economic groups and areas are mostly affected from a specific social or economic policy change.

Thus while social policy has long been evaluated at the aggregate or macro level, in order to more effectively evaluate and inform social policies, a greater understanding of interactions at the micro level is desirable. Morrissey (2008) argues that policy relevant modelling is a challenging research area which is better suited to a modelling framework which emphasises individual-level processes at the local level rather than aggregated process at the macro-level. Hynes (2007) highlights the need for impact assessment and analysis of either area-based or national socio-economic policies at the micro-scale. Ballas (2001) submits that these micro-level modelling requirements could be addressed in a spatial microsimulation framework.

This chapter will discuss the concepts, origins and demands of microsimulation modelling and traces the development of several types and forms as well as reviewing the current state of advancement of the methodology and the limitations of the modelling technique. It then considers the development of the Simulated Model of the Irish Local Economy (SMILE) which forms the substantive modelling framework of this thesis. The penultimate section discusses the applications of microsimulation modelling for the inventorying of greenhouse gas emissions at the micro level, enabling a spatial distribution of emissions to be created.

4.2 Microsimulation Modelling

Microsimulation modelling offers a solution to the practical difficulty relating to the availability of micro data to be used for more sophisticated analysis of the diverse and complex interactions within a large macro system. Typically at a national level, the availability of micro level data is confined to two sources; national census data and/or the availability of sample survey data. Census data generally includes a variety of demographic and socio-economic variables, such as age, sex, marital status, level of education and some spatial or geographical component. However due to issues surrounding the maintenance of data confidentiality, personal socio-economic variables such as income level, pension information, health status, and information on economic activity are not included. In addition, typically, as in the case of the Irish census of population, observations are also aggregated to a minimal spatial scale to preserve confidentiality. As such, using a population census or a firm census such as the Irish census of agriculture for explanatory research at the micro level is restricted due to data limitations (Hynes, 2007). Survey data on the other hand generally contains a wealth of socio-economic information at the micro-level for individuals, households and firms. However survey data by its nature is often difficult to obtain and can be prohibitively expensive. This has the effect of limiting survey sample size. With a small scale survey, inferences drawn from the resultant models may be misrepresentative of the total population due to selection bias and the non-capture of spatial heterogeneity.

4.2.1 Origins and Basic Principals

Originating in the early 1960s, microsimulation modelling was developed in response to the issue of data limitation and availability of adequately representative survey data. The idea evolved from Orcutt (1957) reflecting on the inadequacy of the use of macro or aggregate accounting methods being used to attempt to explain complex economic interactions. Orcutt (1957) submitted that there was an inherent difficulty in attempting to aggregate anything but absurdly simple relationships about elemental decision-making units into comprehensible relationships between large aggregative units such as industries, the household sector, and the government sector. Without knowing the micro-characteristics and being able to reasonably predict the individual unit response to input changes, aggregate estimate can suffer "disastrous loss of accuracy of representation" (Orcutt, 1957:116). Where relationships between inputs and outputs are non-linear and are dependent on other unit characteristics, inferences drawn from aggregate figures are in danger of missing the true relationships.

Orcutt (1957) envisaged that the achievement of a realistic model of the socio-economic system would require reinterpretation and reformulation of many existing research results, extensive research directed at filling in gaps, and involve considerable programming effort and computing time in connection with simulating the model on a “large electronic machine” (Orcutt, 1957:122). The solution proposed by Orcutt et al. (1961) was to pursue a microsimulation modelling approach which involved building synthetic, large-scale, attribute rich datasets from simulated data, using reweighting algorithms in order to match the synthetic data set to observed aggregate data as closely as possible while maintaining the integrity of the individual unit. While the principle involves the creation of a synthetic data set with many identical units (receiving identical input changes in the case of policy modelling) the outcomes for those units will not necessarily be the same. This is because the unit characteristics and given input changes only determine the probabilities associated with each possible output. Actual outputs are then determined by one or more random drawings from the specified probability distributions (Orcutt, 1957).

As such, microsimulation models seek not only to explain the mean E(Y/X) of endogenous models generating Y variables, such as farm/household disposable income, as macro-economic models do, but also their distribution, given exogenous variables X (for example, family farm incomes, and farm activity characteristics), and institutional policy variables P (for example hypothetical emissions tax rates or command and control policies). The joint distribution of the exogenous variable Y and the endogenous variables X conditional on the policy variables P can be described as follows:

$$f_{XY}(Y, X / P) = f_{Y/X}(Y / X, P_1) \cdot f_X(X / P_2) \qquad \mathbf{(4.1)}$$

where $f_{Y/X}(Y / X, P_1)$ is essentially the microsimulation describing how the exogenous X specify the distribution of Y and $f_X(X / P_2)$ the distribution of exogenously specified input variables, given institutional characteristics P_2 (O'Donoghue, 2001). The first microsimulation models were primarily focused on the tax-benefit systems and were concerned with the first-order effects of policy changes/impacts/shocks to that system. Early examples of the use of microsimulation models to predict tax-benefit impacts include the US Office for Tax Analysis (OTA) model for and the RIM model (Nelissen, 1993). The OTA model was used for personal income tax analysis and investigated potential outcomes by simulating the effects of thousands of proposals for tax changes. Additionally, Bekkering (1995) describes a microsimulation model to analyse the effect of abolishing marriage relief in the Dutch tax system on income tax individualization.

At their simplest, microsimulation models typically employ a method to initially create data at the individual, firm or household scale if such data is missing from available datasets (O'Donoghue et al., 2013a). Once created, the data from microsimulation models may be used to simulate the distributional impact of differing policies or a change in policy at the micro-level (Callan, 1991; Ballas, et al., 2006). In essence simulation techniques are used to generate a micro-level population enabling the individual unit to be used as the basis of analysis when assessing or predicting the impact of social or economic policies (Ballas et al., 2006a). Ballas (2001) maintains that it could be argued that the microsimulation method typically involves four major procedures: (i) The construction of a microdata set (when this is not available), (ii) Monte Carlo sampling from this data-set to 'create' a micro-level population, (iii) What-if simulations, in which the impacts of alternative policy scenarios on the population are estimated and (iv) Dynamic modelling to update a basic microdata set.

Microsimulation modelling can also use existing data, usually from individuals or households (Mot, 1992) but can also include firms (Eliasson, 1986), to build a data set based on the real-life attributes of those individuals, households and firms and then simulate the effect of changes in policy on each of those units. Household specific relationships between inputs and outputs can be estimated and used to predict the outcomes of policy changes through probabilistic modelling at the micro level. By permitting analysis at the individual unit, microsimulation enables researchers to model the distributional effects of different policies (Callan, 1991; Merz, 1991; Ballas et al., 2006a). By corollary it follows that microsimulation models can be used to inform policy making by defining the goals of economic and social policy, the instruments employed and also the structural changes of those affected by socio-economic policy measures (Krupp, 1986).

While a review of the main types of microsimulation models and a number of spatial matching methodologies has been carried below, an in-depth analysis of individual model methodologies is beyond the scope of this chapter. More generally it is useful to consider that if we assume that it is desired to create a synthetic data set as close as possible to the observed aggregate, the actual method for any particular microsimulation model is driven by obtaining the highest level of statistical accuracy possible for the alignment parameters available subject to practical computational constraints. The nature of these alignment parameters/constraints (e.g. size of farm, system, stocking rate) will determine the particular model structure required. For an extensive review and survey of microsimulation models see Mot (1992), Klevmarken (1997), O’Donoghue (2001) and Li and O'Donoghue (2013).

4.2.2 Types of Microsimulation Models

Traditionally microsimulation models could be classified into two types, static or dynamic (Mitton et al., 2000). However in recent times as microsimulation attempts to describe more complex economic and social events by modelling the behaviour of individual agents at aggregate spatial levels, a third type of microsimulation, spatial microsimulation modelling, is becoming increasingly useful (O'Donoghue et al., 2013a).

Static Microsimulation Models

Static microsimulation models simulate individual unit outcomes for “day after” first-order effects as a result of the application of a shock or treatment. Typically a static model consists of a cross-sectional database at a fixed point in time which is then “treated” with a policy measure (O'Donoghue et al., 2013a). Static models enable policy makers to evaluate the impact of that policy measure by studying the direct effect on the micro level unit (Equation 4.1). They generally have less complexity than their dynamic model counterparts, and are less expensive to construct (Hynes, 2007).

Figure 4.1 illustrates the typical sources of complexity in a static microsimulation model. First-order policy effects can be simulated on the micro population with a modelled behavioural response. For example, in a static model if we consider an environmental policy change on households such as the imposition of a carbon tax and/or a reduction in water charges, a static model enables us to study the direct income effects of each policy change and provides a means to identify household winners and losers

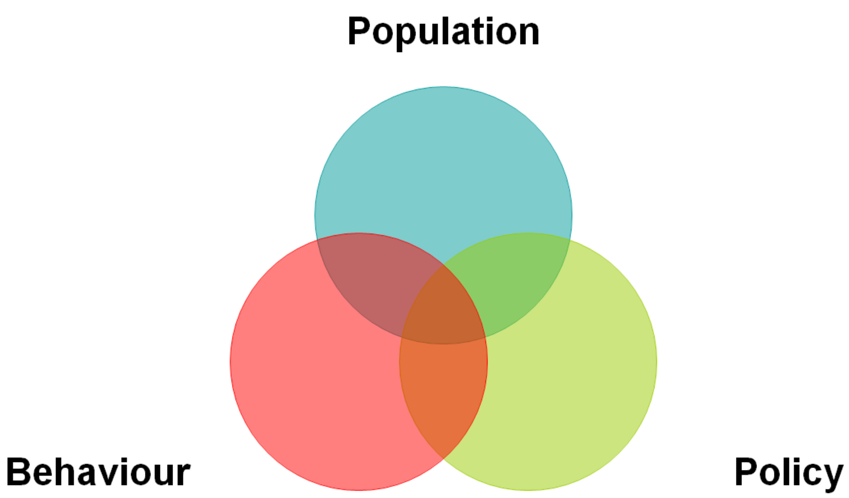


Figure 4.1 Typical sources of complexity in a static microsimulation model

Static models consider the effect for a snapshot in time and do not take account of effects resulting from event outcomes in future time periods such as a reduction in carbon consumption or an increase in water usage. Static models are therefore used principally to calculate the impact of institutional changes in the tax and benefit system (O'Donoghue, 2001).

Examples of static models include the TAXMOD model (Atkinson & Sutherland, 1988) and STINMOD, Australia's Static Incomes model (Lambert, 1994). TAXMOD, developed by Atkinson and Sutherland (1988) was initially used in order to calculate and analyse the impacts of changes to the tax and benefit system in the UK. In addition, Pudney and Sutherland (1996) used TAXMOD to simulate a series of individual attributes including income tax, employee and self-employed National Insurance Contributions (NICs), Income Support, Family Credit, Housing Benefit, Child Benefit and One Parent Benefit. STINMOD (Static Incomes Model) is a static microsimulation model of Australia's income tax and transfer system (Lambert, 1994). The model is updated annually incorporating the latest changes to the Commonwealth Tax and Transfer system.

Dynamic Microsimulation Models

Dynamic microsimulation models facilitate the simulation of micro unit populations such as individuals, firms and households forward through time at the individual level (Li & O'Donoghue, 2012a). For example, for a given time period each micro-unit of the sample is aged individually by an empirically based survivorship probability simulating life or death for the following year (Falkingham & Lessof, 1992; Merz, 1991).

In dynamic microsimulation modelling agents change their characteristics as a result of endogenous factors within the model. From equation 4.1 above, $f_X(X/P_2)$ is one example of a dynamic process, where the set of farm variables X are made endogenous in response to institutional characteristics P_2. Examples include models where farm labour supply responds to changes in agri-environmental policy. Another form of dynamic process is where a dynamic model projects a sample over time, modelling life course events such as demographic changes like marriage and birth, educational attainment or labour market movements (Hynes, 2007). In this case, the dynamics relate to the fact that characteristics in time (t), Y_t depend on characteristics in time (t-j) Y_{t-j} and exogenous characteristics X. This model gives estimates of both time dependent cross-sections and estimates of mobility over time (O'Donoghue, 2001).

Figure 4.2 illustrates the additional layer of complexity which may accompany the addition of a dynamic element to the microsimulation process. At their most basic level of complexity, dynamic microsimulation models may be used to simulate simple population transitions over time such as births, marriages, deaths etc. By adding more complexity to the model, effects on the population from policy changes, modelled behavioural change, or both can be simulated forward in time.

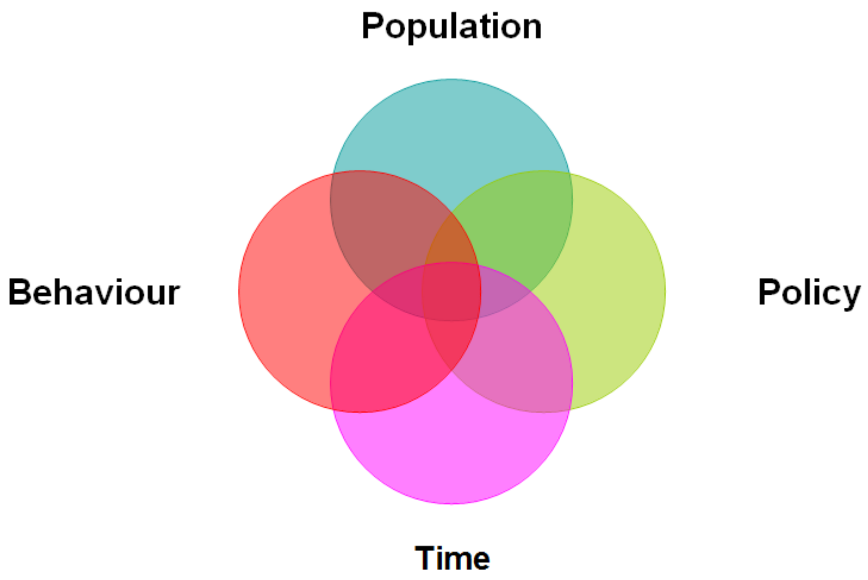


Figure 4.2 Additional layers of complexity in a dynamic microsimulation model

Li and O'Donoghue (2012b) state that dynamic microsimulation models in theory, could offer more insights than static models as they usually integrate long-term projections and behaviour simulations. Dynamic models are able to support attempts to forecast and, as a result, play an important role in informing social scientific thinking about the future (O'Donoghue, 2001). Examples of dynamic models include the dynamic population simulation model DYNOMOD (Antcliff, 1993) and the DESTINIE model used to study intergenerational transfers in Canada and France respectively (Bonnet & Mahieu, 2000).

Spatial Microsimulation Models

Spatial microsimulation models, which are also known as geographical microsimulation models, simulate 'virtual' or 'synthetic' populations of individuals (usually within households) in given geographical areas (Cullinan et al., 2011). The purpose of this is to ensure that the characteristics of these simulated populations will be as close as possible to their 'real-world' counterparts (Ballas et al., 2005a). Spatial microsimulation models link individuals, households or firms with a specific location and can be used to explore spatial relationships and to analyse the spatial implications of policy scenarios (Ballas et al., 2006b). Static spatial microsimulation is designed to analyse effects among regions and localities in order to project the spatial implications of economic development and policy changes in at a more disaggregated level (Holm et al., 1996; Hynes et al., 2006)

Figure 4.3 illustrates a typical spatial microsimulation process whereby a sample micro-level data set such as the Irish National Farm Survey or the Household Budget Survey is sampled to a spatially disaggregated population data set such as the Census of Agriculture or the Census of Population. The allocation is constrained to the national aggregate total by totals reported at a lower spatial level in order to preserve the spatial heterogeneity of the population distribution.

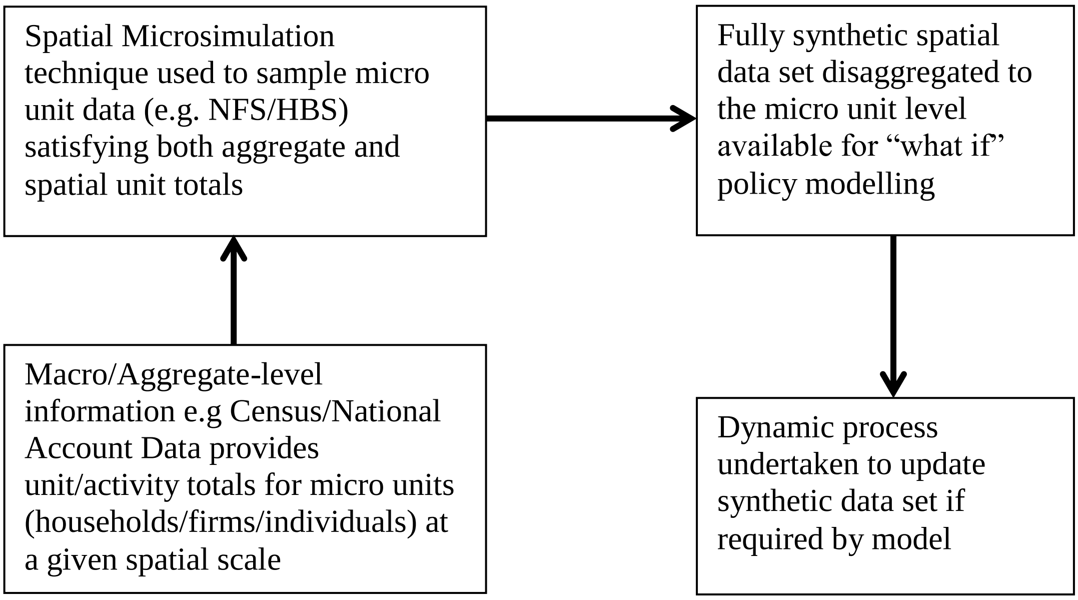


Figure 4.3 Illustration of a typical spatial microsimulation process

The development and application of spatial microsimulation models offers considerable scope and potential to analysis the individual composition of an area so that specific policies may be directed to areas with the highest need for that policy (Morrissey et al., 2008). This is a significant influencing factor in the context of the choice of model needed for the analysis of climate change policy with respect to greenhouse gas emissions mitigation strategies, considering the importance of emissions estimates at the local level (Allman et al., 2004).

There is however a potential trade off to be made with the addition of further layers of complexity to the microsimulation process. Figure 4.4 illustrates the additional layer of complexity that the inclusion of an additional dimension, in this case space, can bring.

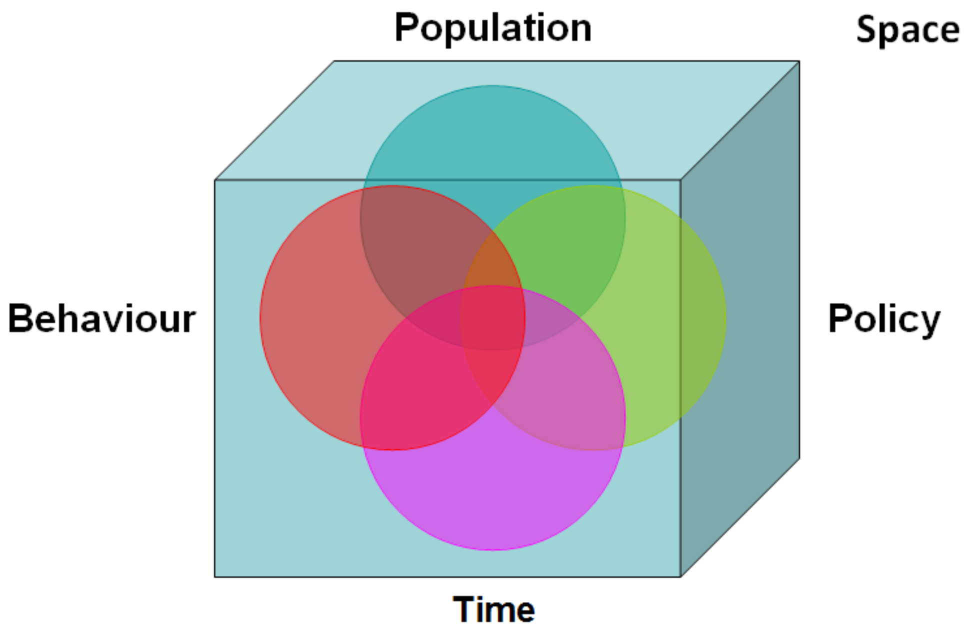


Figure 4.4 Additional layers of complexity in a dynamic spatial microsimulation model

While more sophisticated microsimulation methodologies provide new opportunities for researching impacts on micro-level populations their increasing complexity makes them more costly, time consuming and hard to interpret. In addition, there is no guarantee that a model with a high level of complexity will provide significantly more accurate results or insight than a more parsimonious version. The primary challenge for microsimulation designers is to incorporate the required level of complexity in order to make a model useful, while maintaining a level of parsimony which allows the model to be built and utilised efficiently.

4.3 Advantages and Disadvantages of Microsimulation Modelling

Microsimulation methodologies have become accepted tools in the evaluation of economic and social policy particularly in the area of tax-benefit models (Hancock & Sutherland, 1992) and with the continued advancement of modern computing, the practical barriers to increasingly complex microsimulation methods are gradually eroding. Williamson et al. (2009) anticipate that microsimulation models of all types will continue to become ever more firmly embedded as key tools in national policy making. However, it should be noted that all microsimulation models are constrained by both the quality of the base micro-data set used (if not constructed) and the availability of a sufficient validation methodology. The following section discusses the advantages, disadvantage and potential limitations of microsimulation modelling.

4.3.1 Advantages

One of the primary advantages of microsimulation as a modelling technique is that it artificially generates data for the most elemental units in a system and allows the conduction of analysis at a micro-level that was not possible previously. These elemental units may be individuals, farms, households, employers, housing stock, and in some cases are geographical areas (Hynes, 2007). Instead of focusing on aggregate behavioural relationships as in many macro-economic models (e.g., econometric, input-output, computable general equilibrium), these elemental units serve as the basic building blocks of the system and their behaviours can be modelled (Morrissey, 2008). Clarke and Holm (1987) note that microsimulation models permit micro unit relations and nested hierarchical relationships to be driving forces in micro unit growth and change while Ballas et al. (1999) highlight that complicated relationships can be represented with modern object-oriented programming languages in a way that is elegant, simple, and computationally efficient. Microsimulation models have advantages over both alternative micro and macro-based models.

Nelissen (1994) argues that microsimulation’s benefits stem from their ability to incorporate second-order (induced behavioural) effects in addition to the usual first-order (direct effects due to policy change) effects. One ramification is that household processes (i.e., demographic processes) are of greater importance to individual income development than socioeconomic changes such as becoming unemployed (Nelissen, 1994).

A further advantage of microsimulation modelling is the type and quality of potential outputs generated. These can be used to look at both aggregate and disaggregate/distributional effects of population and economic change (Merz, 1991; Ballas et al., 1999) and to generate longitudinal micro unit "biographies" that provide a better intuitive feel for the diverse outcomes of complex, non-linear economic-demographic processes. Because of their complexity and the variety of data elements that can be generated, perverse, unintended, or unexpected impacts of policies can be thoroughly investigated.

Specifically with regard to spatial modelling, Ballas et al. (2006b) submit that spatial microsimulation models also contain a number of structural advantages over comparable micro-based models. Firstly, microsimulation allows data from various sources to be linked if datasets contain at least one attribute in common, such as, the Irish Census of Agriculture and the National Farm Survey or the Household budget survey and the Census of Population (Hynes et al., 2006). Secondly, the models are flexible in terms of scale; that is data can be re-aggregated to higher levels of aggregation such as from individual to household to district and so on. This is especially beneficial in in cases where impacts are to be aggregated and analysed at varying spatial scales. Thirdly microsimulation models store data efficiently as lists, as opposed to other formats such as matrices; the lists generally consisting of unidentifiable units with associated characteristics obtained from a survey or census.

4.3.2 Disadvantages

Historic resistance to microsimulation modelling has focused on the practical and physical constraints of the modelling technique and on the complexities involved. The development of spatial microsimulation models also requires substantial additional time and resource investment (Haveman & Hollenbeck, 1980). For many years the computational requirements of microsimulation were beyond reach of modern computing power resulting in the slow progress of model development (Holm et al., 1996). While modern computing power and processor development have removed the computational barriers to development, microsimulation modelling requires intensive design investment in terms of human resources with development and maintenance costs remaining high in terms of man-years in the face of increasing complexity (Fredrickson, 1998; Williamson, 1992).

Complexity can be experienced in several different dimensions, including the characteristics of the population, the extent of potential behaviours, the lagged time response of those potential behaviours and interactions within the spatial dimension. Models abstracting from the real world can help to provide insights from complex systems. However, increased complexity may increase the cost of validation and lead to an over simplification of processes. Williamson (1999) comments that microsimulation models are regarded as “black boxes” by many. Klevmarken (1997) describes microsimulation as a data-intensive endeavour that is too disconnected from microeconomic theoretical foundations while Nelissen (1994) argues that microsimulation models do not usually incorporate “third-order” effects (i.e. induced changes in economic output because of markets, e.g., export-base, input-output multiplier effects). However this view is not shared by Isard et al. (1998) who describe several ways in which third order effects can be captured.

In summary many of the criticisms of large scale models cited by Lee (1973) retain their relevance for microsimulation modelling today. Outlining his “seven sins” Lee (1973) states that large models are computationally intensive, data hungry, make extreme demands on our theoretical understanding of spatial processes and our methodological capabilities for capturing that understanding within operational computer code, as well as being difficult to estimate and validate. These criticisms indicate that the future may not necessarily be one of bigger and more complicated models, but perhaps more on focused and targeted modelling structures.

4.4 Development of the SMILE Model

SMILE is an over-arching framework for a series of spatial microsimulation models developed by Teagasc's[28] Rural Economy Development Programme (REDP) in partnership with other external collaborators. These models are a means of synthetically creating large-scale micro-datasets for Ireland at various geographical scales in order to better understand the diverse and complex interactions of individuals, household and farms and how they might response to induced policies and/or change over time (Ballas et al., 2005b). The development of SMILE was an acknowledgement of the considerable change in the nature and scope of regional policy development in Ireland. The economic and social development of rural areas could no longer be taken as synonymous with agricultural development. Consequently, SMILE has incorporated demographic, economic and geographic components allowing for medium term population projections at a high spatial resolution, the simulation of labour market characteristics of individuals and the exploration of the relationship between an individual's place of work and their place of residency (Hynes, 2007).

SMILE has gone through several iterative processes which over time have contributed to improvements in the accuracy and computational efficiency of the spatial matching process moving from iterative proportional fitting (Ballas et al., 2005b) to simulated annealing (Morrissey, 2008) and then more recently, quota sampling (Farrell et al., 2010). Using several combinations of sample micro data and aggregate spatial data, SMILE has been used to assess the potential impacts of environmental policy on Irish farms (Hynes et al., 2009), access to health care services in rural Ireland (Morrissey et al., 2008) and more recently in the distributional analysis of the economic impacts of wave energy device deployment (Farrell, 2012). The modelling development of SMILE and its current format is outlined in the following section

[28] Teagasc is the agriculture and food development authority in Ireland.

4.4.1 Iterative Proportional Fitting

Ballas et al. (2005b) describe the development of the first SMILE model which was both a static and dynamic population spatial microsimulation model. The aim was to create a method of dynamically simulating the basic components of population change at a high spatial resolution using a two stage process. The first static process involved the synthetic reconstruction of a micro population data set from the 1996 Census of Population Small Area Populations Statistics (SAPS). The 1996 SAPS contained aggregate totals for key demographic characteristics such as age group, sex, employment status, marital status and industry for every electoral district (ED) in Ireland. These characteristics were cross-tabulated and categorised in terms of other demographics e.g. gender by 5-year age groups by marital status (SAPS table 2) and industry by employment status by gender (SAPS table 2). From these tabulations, conditional probabilities were calculated/attached to certain characteristics for each spatial unit. Where one set of conditional probabilities overlaps with another set via a common variable (or multiple sets overlap via at least one common), the opportunity to create conditional probabilities for a larger set of demographics exists. For example, the conditional probabilities for individual *i* in area *x* of age, marital status and gender can be expressed as *px,i(A, MS, G).* The conditional probabilities for gender, marital status and employment status can be expressed as *px,i(A, MS, G)*. Similarly the conditional probabilities for individual *i* in area *x* for gender, employment status and industry can be expressed as *px,i(G,ES,IND).* Using Iterative Proportional Fitting (IPF), the known conditional probabilities, for individual i in area x can be used to estimate the probability *px,i(A,G,IND,MS,ES),* whereupon Monte Carlo sampling is used to assign age, gender, marital status and employment status attributes to each individual in each spatial unit (Ballas et al., 2005b). The second dynamic process involved the dynamic simulation of mortality, fertility and migration forward in time using mortality and fertility probabilities from the 1991 Report on Vital Statistics and calculated migration probabilities derived from the 1991 and 1996 Census of Population data at county level. Ballas et al. (2005b) reported a mean error at the ED level of circa 6% for both the 1996 and 2002 models.

However, IPF can potentially produce unrealistic data as probabilities are used to create synthetic micro data from regional aggregates, rather than using real survey data (Norman, 1999). While the IPF methodology has been used widely in spatial microsimulation models (e.g. Birkin, 1987; Clarke, 1996a; Williamson et al., 1996; Ballas et al., 1999; Ballas & Clarke, 2000) there has been a gradual recognition that reweighting techniques have some advantages over the synthetic reconstruction of micro-data (Rahman et al., 2010). In addition, difficulties arise when attempting to carry out policy analysis on economic and welfare micro-units such as household or firms. This is due to the fact that IPF creates individual data based on individual constraints rather than a grouped socio-economic unit such as a households or farm. However, many policy analyses require modelled outcomes at the household-level, using micro data of individuals grouped into households. The IPF procedure is somewhat deficient in handling the additional degree of dimensionality imposed by reweighting individuals grouped into households according to individual level constraints, and thus is unsuitable for synthesising SMILE (O'Donoghue et al., 2013b).

4.4.2 Simulated Annealing-Combinatorial Optimisation

Reweighting is a procedure used in spatial microsimulation modelling in order to transform micro-unit information contained in a sample survey to estimates for the micro population (Chin & Harding, 2006). Two prominent methods of reweighting are the deterministic GREGWT approach (Bell, 2000; Chin & Harding, 2000; Rahman et al., 2010) and probabilistic combinatorial optimisation techniques (Ballas et al., 2003; Williamson, 2007; Hynes et al., 2009). GREGWT is a constrained distance minimisation function which uses a generalised regression technique to get an initial weight and iterates the regression until an optimal set of household or individual weights for each small area is derived (O'Donoghue et al., 2013a). Using a regression approach to minimise the difference between census total and the estimated total, the iterations stop when the residual difference is at or close to zero, (Chin & Harding, 2006). This process is known as convergence (Tanton et al., 2007a). However, while the method is suitable for larger spatial scales one of the drawbacks of GREGWT approach is that for some small areas convergence does not exist. That means that the GREGWT algorithm is unable to produce estimates for those small areas (Rahman et al., 2010). As many Irish EDs are of low population density (25% contain less than 100 households, 57% contain less than 200), significant barriers to convergence may exist if a generalised regression weight based method such as GREGWT were to be used for SMILE. (O'Donoghue et al., 2013a).

An alternative approach to reweighting is Combinatorial Optimisation techniques which include methods such as deterministic reweighting, probabilistic reweighting and simulated annealing (Ballas et al., 2005a). Combinatorial Optimisation allows microsimulation models to overcome dimensionality issues where survey data for the unit of interest is reweighted to fit small area population data (Ballas et al., 2005a). One of the key advantages in using a combinatorial optimisation technique is that it results in a more realistic representation of micro population as it generates simulated cases based on "real" people living in "real" households, and does not produce synthetically reconstructed individuals (Ballas & Clarke, 2001).

Combinatorial optimisation involves the selection of an appropriate combination of micro-units from a sample survey data to attain the defined combined "benchmark" in totals at the small area level using an optimization tool (Tanton et al., 2007b). A combination of sample units e.g. households, are selected. Then a random household from the initial set of combinations is replaced by a randomly chosen new household from the remaining survey data to assess whether there is an improvement of fit. The iterative process continues until an appropriate combination of households that best fits known small area benchmarks is achieved (Williamson et al., 1998a; Voas & Williamson, 2000; Huang & Williamson 2001; Tanton et al., 2007a) While it is theoretically possible to find an optimal single "solution", Rahman et al. (2010) note that in practice, it is almost unachievable, due to computing constraints for a very large number of all possible solutions.

Simulated annealing is an "intelligent searching" combinatorial optimisation technique which is also less sensitive to convergence issues (Rahman et al., 2010). Williamson et al. (2009) found that in an Australian simulation, SA performed slightly better at matching than GREGWT for both constrained and unconstrained variables. This was particularly the case in districts where there was no convergence. It also contains mechanisms to avoid becoming trapped at local minima (Wang et al., 1998). In the second stage of development of SMILE, Morrissey et al. (2008) use a simulated annealing approach which draws on SimLeeds Spatial Model. Like other combinatorial optimisation approaches, an initial combination is selected from the sample data set to fill the small area target numbers and calculates the error. Once filled a number of cases are replaced at random and the error is recalculated. If the error is smaller the changes are accepted and the model moves to the next iteration. If the error is larger, the originally selected cases are kept and a new selection of cases is chosen to be replaced. The process continues until error is less than a selected value or the number of iterations reaches a preset maximum. While simulated annealing provides a high level of statistical accuracy at smaller spatial scales it is computationally intensive technique due to the repeated sampling process. Hynes et al. (2009) found that it took two days to generate almost 140,000 individual farm records from 1200 survey data points on a 2G Dell workstation. O'Donoghue et al. (2013a) note that using this process to simulate a micro-level population of over 4 million individuals with a number of additional constraints would take a considerably longer period of time. The time cost of this level of computational intensity is prohibitively expensive and onerous, and can be accentuated by the requirement to perform repeated simulations for sensitivity analyses and simulations of future population projections (Farrell et al., 2010).

This computational limitation was a key motivation in the development of a more efficient matching process for the SMILE model. This resulted in the development of Quota Sampling; a more efficient spatial matching algorithm achieved through a reduction in the number of required computations. This methodology represents the the third stage of development of the SMILE model.

4.4.3 Quota Sampling

Quota Sampling (QS) is a probabilistic reweighting methodology developed by Farrell et al. (2010). A novel adaptation of this method provides the spatial microsimulation framework for the static and dynamic emissions modelling carried out in this thesis. Like simulated annealing, this matching procedure reweights survey data according to key constraining totals for each small area provided by a second aggregate spatial data set such as census of population or farms. However, unlike simulated annealing, when cases are selected from the sample data set and allocated to a spatial unit they are not replaced and are deemed to be selected. This mechanism of sampling without replacement avoids the repeated sampling procedure of SA and is fundamental to the efficiency gains of the quota sampling procedure (O'Donoghue et al., 2013b).

Running totals, termed "bins" are created for all match constraint variables. Each bin is assigned a constraining quota total provided by the aggregate spatial data set. All bins are updated after each individual case is selected and allocated to each spatial unit. This process continues until one of the quotas filled. The process is illustrated in Table 4.1 below.

Table 4.1 Quota Sampling selection process

Spatial Match Variables	**Sex (Female)**	**Age 25-44**	**Education Level ($3^{rd)}$**	**Household Size 2-5**	**No. Of Children**
Running Total	X-10	Y-15	Z-6	H-3	C
Spatial Unit *i* Quotas	X	Y	Z	H	C

Spatial unit *i* is assigned quotas for sex (X), age(Y), education level (Z), household size (H) and number of children (C) respectively. The quota totals are summed simultaneously with the addition of each observation until the first quota is filled in this case the number of children (C). Once the quota for any of the match variables is reached, the model then reduces the sample space from which observations are drawn by dropping those observations which would "overfill" the quota for that match variable. This process continues with more observations dropped in a similar manner as more quotas are filled. Cases are again selected without replacement until a second quota is filled and the sample space is further reduced. It is possible that this process can be repeated until all quotas are filled; however it is more likely that sample space will shrink to zero with the last few quotas remaining unfilled. This is usually because the characteristics required for the last few remaining cases are so specific, no such cases exist in the survey data that satisfies the constraints required to fill the remaining quotas (e.g. a five person household, containing 5 females aged over 65, all with third level education).

It is at this point that the quota constraints are relaxed to expand the sample space. Constraints should be lifted in reverse order of those variables which are the most influential determinants of the key characteristic(s) the method is attempting to model. While this may result in some quotas being overfilled for some spatial units the methodology also contains mechanisms to counteract practical convergence problems and minimise the accuracy vs. efficiency trade off. One of these methods involves the profiling of each constraint in each spatial unit in terms of the national distribution. In this way, the initial fill order for spatial units which are particularly "unusual" can be manipulated so that the most difficult constraint quota is filled first. For example a particular urban spatial unit could contain an unusually high number of young households due to its proximity to an educational institution. The model would then attempt to fill this constraint quota first by selecting young households from the sample survey first. The model then moves on to next most unusual constraint in terms of the national distribution and repeats the process.

4.5 Previous Applications of the SMILE model

The Teagasc SMILE methodology has evolved through a number of development phases moving from IPF to simulated annealing and currently to quota sampling. During that time, the SMILE-framework has been used for a variety of applications.

In the first phase of development Ballas et al. (2005a), used the IPF SMILE model to dynamically simulate mortality, fertility and migration in the Irish population forward in time from 1991-1996 and compared results from the SMILE model to the 1996 census of population in order to calculate the accuracy of the modelled demographic transitions. Ballas et al. (2005a) report a mean population error of 6.4% at ED level and just 2.7% at the higher county level spatial scale. Ballas et al. (2006b) use the SMILE model to study the implications of CAP reforms for the National Spatial Strategy (NSS) outlining the potential of microsimulation to address small-area impacts of major national or international rural policy changes. By examining the likely spatial distribution of winners and losers from CAP reform and the spatial distribution of employment, Ballas et al. (2006b) show that the spatial effects of decoupling on rural farm incomes in areas of low employment density could have the potential to frustrate regional development policy goals and highlights the potential use of the SMILE framework in identifying policy conflicts.

Hynes et al. (2009) used the second generation of the SMILE model based on simulated annealing, to statistically match data from the annual Teagasc NFS to aggregate spatial farms totals contained in Census of Agriculture (CoA) creating the SMILE-NFS. The Teagasc NFS is a highly detailed farm-level survey which collects farm-level data for circa 1000+ farms on an annual basis and contains variables on inputs and outputs, costs and incomes and stocking rates. The CoA classifies farms by size, economic type and geographical location reporting aggregate totals at the electoral district (ED) level. The CoA 2000 presents aggregate totals for a total farm population of circa 140,000 farms. By creating a baseline methane emissions model for the resultant SMILE-NFS farm micro-population, Hynes et al. (2009) studied the static effects of a €7.50 carbon equivalent methane emissions tax and calculated that such a tax could raise approximately €64m in tax revenue. Hynes et al. (2009) report the spatial outcomes on average family farm incomes and the spatially heterogeneous welfare outcomes as a result of a redistribution scheme based on participation in an environmental protection scheme, showing the potential use of the SMILE framework in informing rural policy analysis. In an analysis of responses to subsidy reform, Shrestha et al. (2007) use the SMILE-NFS model to dynamically study the regional effect of decoupling on farming in Ireland by using price and cost projections from the FAPRI[29] model in a linear programming model to estimate farmers' likely response to policy change. Shrestha et al. (2007) highlight differential regional impacts with farmers in South-West, West, Midland and Border regions likely to engage de-stocking in contrast to those in the mid-East and South-East.

Morrissey et al. (2008) use the SMILE simulated annealing framework to statistically match the LII survey to the SAPS, creating the SMILE-LII in order to analyse both demand for, and supply of, health care services at the ED level in Ireland. The Living in Ireland (LII) survey is a 7-year panel data set containing individual, demographic and socio-economic characteristics including detailed information on individual health status and health service utilisation rates from 1994-2007. The survey captured information from individuals from approximately 4,000 households annually. The SMILE-LLI model matches the LII survey to the Small Area Population Statistics SAPS; a rich set of aggregated demographic census information for over 3,400 EDs. Using the SMILE-LLI, Morrissey et al. (2008) examine access to both acute and community psychiatric facilities for individuals who reported suffering from depression and find a spatial mismatch between service need and service provision with areas with the highest rates of depression suffering from low levels of access to mental health services (Morrissey et al., 2010).

Using quota sampling (the latest iteration of the SMILE spatial matching framework), Farrell (2012) uses the SMILE-EUSILC to perform an economic evaluation of wave energy devices by considering the localised economic impacts

[29] Food and Agriculture Policy Research Institute of Missouri

for those areas near deployment zones and re-distributional impacts of the cost of support schemes and concludes that the employment benefit deployment of renewable energy technologies may help alleviate between-region inequality. The EU Survey of Income and Living Conditions (EUSILC) contains in-depth micro data detailing income, poverty and other such indicators of welfare. The SMILE-EUSILC statistically matches the SAPS with EU SILC to create a spatially explicit dataset of individuals grouped into households through which distributional welfare analyses may be carried out.

4.6 Conclusions

The SMILE framework has proved to be a useful method of creating simulated national level populations from sample survey data in Ireland. Various iterations of the model have been used to statistically match several sample data sets to aggregate national census data. The generation of these micro-populations facilitates the modelling of additional non-match variables in order to broaden the possibilities for the analysis of various economic, social and environmental policies. The nature of the modelling technique is such that the potential future number of applications in new policy areas is far-reaching. However the ability to validate outputs to both preserve spatial heterogeneity and to calibrate modelled outcomes is an essential restraining force which must be addressed.

CHAPTER FIVE: DEVELOPMENT OF A BASELINE SPATIAL EMISSIONS MODEL FOR IRISH AGRICULTURE

This chapter describes the construction of an analytical tool to assess the impact of policy measures on Irish agricultural greenhouse gas emissions. A baseline spatial emissions model for Irish agriculture is constructed from the SMILE-NFS model using a novel adaptation of the Quota Sampling (QS) microsimulation method. Activity data from a simulated farm population is used in conjunction with emissions factors from the Environmental Protection Agency (EPA) (based on the Intergovernmental Panel on Climate Change methodology protocol) to estimate greenhouse gas emissions for each farm and provide a spatial map of Irish agri-emissions reported at the electoral district level. Comparative results for the inclusion of a stocking rate ranking variable in the match process are reported. Estimates for greenhouse gas emissions from agriculture for 2008 are analysed and compared with the EPA's National Inventory Report (NIR), informed by a comparison of activity captured in the Teagasc National Farm Survey (NFS) with the national accounts.

5.1 Introduction

While its contribution to GDP has declined since the highs of the 1960s, agriculture and the related agri-food industry is still an important contributor to the Irish economy as Ireland's largest indigenous industry, contributing to around 7% of GDP (CSO, 2012). The majority of Irish agricultural produce is exported with Ireland's agri-food sector representing 10% of Ireland's entire export economy (Department of Agriculture Fisheries and Food, 2012). Considering current population projections, Bruinsma (2009) estimates that agricultural production would need to increase by 70% by 2050 to cope with a 40% increase in world population (Food and

Agriculture Organization, 2009). With the abolition of the milk quota in 2015 and increasing global demand for quality food produce, Ireland's agricultural sector has been identified as having high potential for growth in the medium to long term and has been targeted as one of several key sectors which have the capacity to contribute to Ireland's return to economic prosperity (Department of Agriculture Fisheries & Food, 2010). Ireland's agricultural sector has been earmarked for significant expansion under the aims of Food Harvest 2020 programme (FH2020) with targets outlined for the dairy[30], beef and sheep sectors[31] (Department of Agriculture Fisheries & Food, 2010).

Concurrently, the EU is committed to a 20% reduction in greenhouse gas (GHG) emissions on 1990 levels by 2020 under the terms of the 2008 Climate Action and Renewable Energy Package (Council Decision, 2009). As part of this target, Ireland is committed to reducing non-Emissions Trading Scheme (ETS) sector emissions by 20% by 2020 relative to 2005 levels (EPA, 2010). However, Ireland's agri-sector accounts for almost one third of Irelands' total reported emissions output, with agriculture representing 43% of emissions from the non-ETS sector in 2010 (EPA, 2012). Additionally, agriculture's contribution to total emissions from the non-ETS sector is currently projected to rise to 48% by 2020 (EPA, 2013b). Consequently, it is highly likely that the effective implementation of carbon abatement strategies and improved carbon efficiency measures in agriculture will be required if both these policy objectives are to be achieved.

The absence of spatial micro information on GHG emissions has been identified as a barrier to the effective implementation of mitigation policies, since it as at the local level where GHG reductions will ultimately take place (Kates, 1998; Allman, 2004). As outlined in Chapter 4, information at the micro level enables policy makers to study the dense interactions between agents at the smallest scale and model the magnitude and diversity of outcomes for individual firms and households arising as a result of policy changes. In the case of GHG mitigation policies, the presence of

[30] Target increase in quantity of output of 50%
[31] Target increase in value output of 20% set for both the beef and sheep sectors

spatial information further enables policy makers to examine the spatial equity of outcomes as well as providing the opportunity to design and tailor strategies to local and regional characteristics. A spatial microsimulation model for Irish agricultural emissions based on the IPCC methodology is considered.

5.2 Agricultural Emissions Modelling

5.2.1 Modelling approaches

As outlined in Chapter 3, a number of different methods for the modelling of greenhouse emissions have developed largely from two basic approaches; top-down (Bergamaschi et al., 2005; Corazza, 2011) and bottom up (O'Mara, 2006; O'Brien, 2011). Top-down approaches typically estimate emissions from aggregate observations measured at a limited number of data collection points which are then statistically modelled backwards to their point of origin, now possible due to the advancement of modern computing power and appropriate modelling techniques. Bottom-up approaches typically calculate emissions by applying emissions factors or weightings to certain activities or processes and aggregating those processes to the required scale of interest subject to the available source data. While top-down methods have been used to model point source emissions from specific environmental events (Forster et al., 2001) and as a validation reference point for national inventories (Polson et al., 2011), their use is limited in terms of modelling or apportioning emissions from specific sectors of an economy and are not considered in this thesis.

Considering bottom-up approaches, the scope of agricultural emission models is considerable. In line with the IPCC provision for participating nations to submit more detailed country specific emissions factors, O'Mara (2006) developed a tier 2 emissions methodology for the Irish cattle herd. Emission factors for methane from enteric fermentation (ENF) and manure management (MM) were calculated for categories of the Irish cattle herd for which data on animal numbers could be obtained from the Central Statistics Office (CSO). Focusing on the New Zealand dairy herd, Beukes et al. (2010) combine IPCC emissions factors, information on-farm management practices and methane emissions estimates based on a metabolizable energy intake model to investigate the impacts of management decisions on emissions and profitability with the goal of reducing unit emissions (per ha/kg) by improving production efficiency.

Kulshreshtha et al. (2000) use a "whole farm" approach to calculate emissions using activity data from the Canadian Regional Agriculture Sub-Model (CRAM) and project emissions to 2010 under alternative fertiliser application scenarios while Gibbons et al. (2006) model uncertainty in emissions estimates for UK agriculture using Farm-Adapt, a farm-level optimisation model using a monte-carlo simulation to estimate a resultant range of emissions scenarios.

In relation to modelling emissions from dairy farming, O'Brien et al. (2011) compare the current IPCC national inventorying method and a life cycle analysis (LCA) approach and find that when modelling emissions on a per hectare basis, both systems report that reductions in intensity of production result in lower emissions per unit area. However, O'Brien et al. (2011) submit that reporting emissions on a per hectare basis does not adequately reflect the impact that differential feed systems can have on milk production and conclude that farming systems should be assessed on an emissions per unit of product basis in order to ensure the lowest resulting GHG emissions for the projected increases in world meat and milk production.

From basic inventorying approaches such as the IPCC methodology to more complex life cycle analyses such as O'Brien et al. (2011), the applications of agricultural emissions models are diverse and cover areas such as the refinement of emissions factors, the modelling of more emissions efficient production systems and the projection of future emissions paths.

5.2.2 IPCC vs. LCA Approach

Due to its predominantly grass based production system, the Irish dairy and beef sectors are capable of producing some of the lowest emission agriculture produce per unit output available and could compare very favourably internationally in terms of a Life Cycle Analysis (LCA) approach to agri-emissions modelling (Schulte & Lanigan, 2011). However, while there has been a substantial shift in the literature towards whole farms systems analysis for modelling emissions at the farm level, significant challenges for using LCA in the construction of national inventories remain; such as the availability of accurate emissions information on indirect inputs, outputs and processes (Crosson et al., 2011).

The design of any emissions model is ultimately determined by its intended purpose. The IPCC employs a basic methodology to model national emissions from the traditional sectors of most modern economies. Its effect is to enable as many countries as possible to use a consistent methodology for the purposes of tracking national emissions over a period of time and use them as a basis for setting any country specific emissions targets set by international treaties. In addition to the emissions factors published by the IPCC, there is also a provision for countries to submit their own higher tier emissions factors to take into account national variations in processes and production systems such as in the case of Irish agriculture (O'Mara, 2006). The IPCC methodology provides each country with a structured baseline method for modelling GHG emissions and allows flexibility for the inclusion of country specific emissions factors.

A significant drawback to the IPCC methodology however, is that it seeks to accomplish an international objective within national boundaries. The IPCC methodology only requires countries to report emissions originating or emitted within national boundaries and thus does not necessarily seek to identify or reward countries which develop the most carbon efficient process, the exploitation of which may contribute greatly to that countries total emissions but result in lower overall global emissions. The IPCC method was developed to prepare transparent and simple inventories on a national scale (Schulte & Lanigan, 2011). Its purpose was not to determine precise levels emissions or assess strategies to reduce emissions on a lower scale, i.e. at micro/unit level (Schils et al., 2006). A typical example of this drawback is in the area of agriculture. While total emissions per unit area originating from the Irish dairy sector may be high, its emissions efficient grass-based production system means that emissions per unit of output are low. Thus reductions in Irish production levels, in order reduce Irish reported emissions, may result in less emissions efficient production elsewhere thus raising global emissions.

Life Cycle Analysis (LCA) can be used to assess and evaluate the impacts that products or processes have on the environment over their entire life span (Crawford, 2008). Emissions models based on LCA attempt to model the emissions arising from the entirety of the activity/process of interest including emissions involved in the delivery of inputs and outputs as well as emissions arising from the process itself. LCA can therefore be used to calculate the total global emissions arising from a specified activity or process. LCA allows for the comprehensive evaluation of alternative measures and/or changes to the production cycle which result in either reduced overall global emissions or lower emissions per unit output.

Casey and Holden (2006) use a life cycle assessment to estimate emissions from the Irish suckler-beef herd in order to evaluate a number of alternative management scenarios. The adoption of a LCA approach allows for the tracking of emissions changes as a result of a regime change. Using alternative approaches such as the IPCC methodology does not account for management practices which “export” emissions elsewhere. For example the importation of concentrate feed for animals may result in lower emissions for Ireland in terms of its NIR due to an offset in fertiliser emissions; however such a calculation does not consider the production and transport emission costs of the concentrate feed which may result in an overall increase in global emissions.

The use of LCA for inventory analysis is however somewhat problematic and presents considerable challenges. The modelling of emissions from any sector, activity or process involves the consideration of which activity/sinks are to be included and what emissions/sequestration factors are to be applied. The complexity involved in each LCA conducted means that each system needs to be individually assessed since no two situations are ever the same (Lee et al., 1995). While a standard for the principles and framework for LCA design has been created (ISO, 2006), international agreement on a consistent LCA method of emissions inventorying would require agreement on a vast amount of verifiable methodologies, agreement on the start and end point of each processes life cycle; as well as agreement on transport emissions and emission exchanges as a result of international trade.

O'Brien et al. (2011) examine the effect of methodology on GHG estimates from dairy systems and recommend the incorporation of LCA analysis into the IPCC methodology framework. As the current IPCC methodology does not include indirect GHG emissions from farm pre-chains such as concentrate production, future national decisions on production systems and mitigation strategies may be optimal in terms of the individual nation’s emissions inventory but sub-optimal in terms of achieving a net reduction in global emissions. However, Schulte and Lanigan (2011) note that full LCAs for individual farms can be laborious, time-consuming, subject to large uncertainties, and therefore difficult to verify.

The IPCC methodology is still the preferred method used for national emissions inventories in the absence of further international agreement and while an LCA analysis can provide valuable information on mitigation options for a variety of processes, currently its use as a practical tool for comparative national inventorying is limited.

5.3 Spatial Modelling of Emissions from Irish Agriculture

Ireland is faced with a significant challenge in terms of meeting its 2020 emissions targets. On the one hand, the FH2020 programme aims to increase agricultural output significantly while on the other, Ireland must reduce its emissions output in line with its EU commitments. Given that agriculture comprises almost 43% of Ireland's emissions form the non-ETS sector, the identification of further mitigation options and the effective implementation of current mitigation policy will be required to meet both objectives.

Spatial information on emissions at the local level has been identified as a key determinant in the effective implementation of climate change policy by Allman et al. (2004). The National Atmospheric Emission Inventory (NAEI) uses a combination of point source data and a distribution map of diffuse emissions to construct a GHG emissions maps across 11 source sectors for the UK. The maps are used by the AEA and other organisations for a variety of Government policy support work at the "national, regional and local scale" (AEA Energy and Environment 2011:23). de Kluizenaar et al. (2001) model the spatial distribution of SO_2 and NO_x emissions for 1995 by assigning emission totals, from different emission-source categories, to a 1kmx1km resolution identifying detailed information on the spatial distribution of emission sources.

Spatial information on emissions allows policy makers to identifying mitigation opportunities with a spatial dimension. It can help identify local initiatives which result in a more efficient use of resources; such as in the case of transport with Quinlan et al. (2006), who use a milk transportation model to calculate the optimal locations for milk processing, thereby reducing the costs of transport and associated emissions. The absence of spatial micro information restricts our ability to predict micro outcomes as a result of policy changes and analyse the spatial equity of redistributive effects such as in the case of a carbon tax.

5.3.1 Stocking rate as a key determinant of Agricultural Emissions

Neufeldt et al. (2006) used the EFEM–DNDC economic-ecosystem model to assess disaggregated regional GHG emissions from livestock and crop systems in Germany. Neufeldt et al. (2006) show that the distribution of GHGs strongly depends on the presence of livestock and state that stocking rates appear to be a useful indicator of total GHG emission levels. Neufeldt and Schäfer (2008) then use the EFEM–DNDC model to evaluating the effects of different agricultural mitigation policies on GHG abatement potentials and their cost efficiencies in Germany.

Foley et al. (2011) uses the BEEFGEM model as a means to compare the emissions efficiency of different management practices applied to beef production systems. Farm characteristics and output from the average beef farm identified from the NFS were used in conjunction with feed input factors to create a base farm scenario. Foley et al. (2011) found that the effect of increasing the stocking rate led to an increase in direct and total emissions in all scenarios modelled while higher stocking rates combined with higher levels of production efficiency led to lower emissions per unit output across alternative scenarios.

Emissions from livestock in the form of enteric fermentation and manure management accounted for over 90% of methane emissions and almost 60% of CO_2eq emissions attributed to the Irish agricultural sector in 2008 (EPA, 2010). Given its direct relationship to the primary sources of agricultural GHG emissions the farm level stocking rate is a key determinant of outcome in agri-emissions models. Consequently, in terms of the distribution of emissions in a spatial agricultural emissions model the preservation of the spatial unit’s stocking rate is a key consideration in attempting to reflect spatial heterogeneity

5.3.2 Proposed New Framework for Modelling Agricultural Emissions

In using a simulated annealing approach to create a spatial distribution of methane emissions from Irish dairy, cattle and sheep, Hynes et al. (2008) provided the first step towards providing a spatially disaggregated model of agriculture emissions for Ireland. However, the absence of a method of calibration for the stocking rate for each spatial unit is a notable omission. Expanding on this work, this chapter outlines a methodology for generating a baseline agricultural emissions model for Ireland and maps outcomes at the electoral district level. Using Quota Sampling, a new spatial methodology developed by (Farrell et al., 2010), an updated SMILE-NFS farm level model is created by sampling farms from the NFS to spatial totals reported in the Census of Agriculture. In addition, the inclusion of a match ranking variable based on the mean stocking rate is tested with results for its effect on the matching process reported. In the absence of any further agreement at an international level on the inventorying of emissions and in the interest of offering a comparison with the current national emissions inventory, the IPCC methodology has been adopted for the purposes of calculating emissions at the farm level, from which an aggregate emissions total is calculated and compared with Ireland's NIR.

5.4 Methodology

This section describes the construction of baseline spatial emissions model for Irish agriculture farms using an updated version of SMILE-NFS a spatial microsimulation model of the Irish Farm population. Farms from the 2008 NFS (Teagasc, 2009) are sampled to update the spatial totals reported in the CoA (CSO, 2000) using a novel adaptation of quota sampling, a spatial microsimulation technique developed by Farrell et al. (2010). Agricultural emissions for methane (CH_4) and nitrous oxide (NO_2) are calculated on the basis of emissions factors reported in the NIR. As the NIR's total reported emissions are based on activity data from the national accounts (NATACCs), activity captured in the NFS is aggregated and compared to the NATACCs in order to estimate the proportion of agricultural activity that is captured in the NFS. Emissions totals for captured activity in the NFS are then compared with the totals reported in the NIR, which are adjusted for the proportion of agri-activity covered by the NFS.

5.4.1 Data

Teagasc National Farm Survey

The Teagasc NFS is a comprehensive and nationally representative weighted panel data set compiled by surveying circa 1,000 Irish farms on an annual basis. First conducted in 1972, it contains a wealth of micro-level data (over 2,000 variables) relating to each farm's activity as well as providing details on each farm's physical characteristics and a demographic profile of the holder and farm household. As part of the Farm Accountancy Data Network (FADN) of the EU, the survey provides data on farm output, costs and income to the European Commission. In conjunction with the Central Statistics Office (CSO), a nationally representative random sample of farms are selected annually, with each farm assigned a weighting factor so that the results of the survey are representative of the national population of farms (Teagasc, 2009). The NFS records information on opening and closing stocks, purchases, sales, subsidies and grants, loans and overheads as well as information on inputs such as feed and fertiliser. The high level of detail contained in the NFS allows for the estimation of farm-level GHG emissions from enteric fermentation and from manure management based on animal numbers. Input quantity data allows for the estimation of nitrous oxide emissions from fertiliser use. In addition, information on electricity and fuel usage allows for the estimation of emissions from energy use, although for the purposes of comparison with the NIR, these emissions are not included due to their inclusion in the sectoral report for energy. While the NFS is a comprehensive data set on activity at the farm-level, it is a sample data set and does not contain information on some specific agricultural enterprises, i.e. those typically which have a very small number of farms producing the majority of national commercial output for the sector, such as in the case of horticulture, vegetable crops, pigs, and other speciality livestock.

Census of Agriculture

The Irish CoA is conducted approximately every ten years and provides aggregated information on every registered farm in Ireland. First conducted in 1847, the objective of the Census is to identify every operational farm in the country and collect data on agricultural activities undertaken on them (CSO, 2000). In addition to data on geographical location and aggregate input use, the census provides aggregate totals for the size, system and soil type of farms reported at the electoral district (ED) level. It reports aggregated demographics for all farm households within each ED and supplies information on livestock numbers enabling the calculation of an averaged stocking rate. The CoA classifies farms by size, economic type and geographical location reporting aggregate totals at the electoral district (ED) level, thus providing the spatially disaggregated allocation set for the SMILE-NFS spatial microsimulation model.

The National Accounts for Agriculture

The annual National Accounts for Agriculture (NATACCs) are published by the Central Statistics Office and provide an estimate of the annual value of income and expenditure activity in all primary sectors of agricultural activity. The NATACCs for output, input and income in agriculture provide figures for the total output value of all livestock and livestock produce sold as well as estimates for the total value of agricultural inputs giving an estimation of total agricultural income for a given year (CSO, 2009). The figures reported in the NATACCs are constructed from a large number of separate data sources and consist of a combination of observed volumes and prices and estimates based on survey data. For output, input and income in agriculture, data on slaughter numbers, prices, input volumes etc. are compiled from the Department of Agriculture, the CSO, Teagasc, the Office of the Revenue Commissioners and a number of other state and semi-state bodies. Since the NIR’s emissions estimates for agriculture are based on data from the NATACCs, it is necessary to first compare the NATACCs with activity captured in the NFS, as the NFS does not contain data on certain specific agricultural activities. A comparison with the NATACCs for agriculture informs an estimation of the share of total agricultural activity that is captured in the NFS. This is required in order to draw a reasonable comparison between emissions estimated from the SMILE-NFS model and emissions reported in the NIR.

The National Inventory Report

Ireland's NIR for greenhouse gas emissions is compiled by the EPA as Ireland's nominated statutory reporting body (Statutory Instrument S.I.244, 2006). The reporting format follows the guidelines adopted by the United Nations Framework Convention on Climate Change (UNFCCC), which requires the application of prescribed methodologies and procedures in order to provide consistent and comparable data on an annual basis (EPA, 2012). Greenhouse gas emissions estimates for methane (CH_4) and nitrous oxide (NO_2) are reported for seven source sinks and categories including agriculture. Ireland reports emissions for three of seven sub-categories for agriculture, namely enteric fermentation, manure management and agricultural soils, with the other 4 source categories not applicable as a feature of Irish agricultural activity. The EPA relies heavily on activity data compiled from numerous different sources with key contributors supplying data under prescribed memorandum of understanding. The key data contributors for the agricultural sector are the Central Statistics Office (CSO) (which provides the EPA with data on annual farm populations, livestock populations, and crop statistics) and the Department of Agriculture Food and Marine (DAFM) which provides estimates on fertiliser use. The CSO and the DAFM provide the majority of activity data for the EPA's estimation of emissions from Irish agriculture in the NIR. The same activity data from the CSO and the DAFM forms the basis for the output values recorded in the NATACCs for agriculture. It is on this basis that a comparison of activity recorded in the weighted Teagasc NFS and the NATACCs for agriculture is necessary in order to inform a comparison of emissions output from a baseline spatial emissions model for Irish agriculture and the NIR.

5.4.2 Comparison of Agricultural Output with the National Accounts

The NIR reports agricultural emissions on the basis of activity data obtained from the Central Statistics Office's (CSO) NATACCs for agriculture. However, while the NFS is a well-established survey of Irish Agriculture, it does not capture output for all sectors reported in the NATACCs. Thus in order inform a comparison between GHGs reported in the NIR and the SMILE-NFS spatial agri-emissions model, the differences between the level of activity or output reported for the NATACCs versus the output reported in the weighted NFS must be understood. The following explains the differences in reported gross outputs and inputs reported in the NATACCs value output table (AEA01) and the equivalent outputs calculated on the basis of the weighted NFS.

Comparable Sectors

When comparing the gross outputs and intermediate inputs reported in the NATACCs and the NFS it is important to understand the source of the differences between them. Firstly there are some sectors for which comparisons cannot be made. For several categories in NATACCs value output table (AEA01), some sectors gross outputs and inputs cannot be calculated from the NFS because of the unavailability of comparable data. This is partly due to the comparatively smaller size of those sectors and the small number of major producers in the country such as in the case of pigs and poultry. Consequently while the weighted NFS is regarded as nationally representative for the main sectors such as cattle, dairy and sheep, it is unable to capture the national picture for smaller sectors with a small number of large producers. It is also the case that there are other sectors in the NATACCs for which no equivalent data is collected in the NFS such as non-cereal food horticulture and information on contract work (treated as a contribution to both gross output and intermediate input)

Secondly, for comparisons of inputs and outputs that are contained in the NFS, at its most basic level, nominal differences occur due to the nature of the data source itself.

For the NATACCs the gross value output estimates are a combination of quantity/activity survey data and price data. These are compiled and sourced predominantly by the Central Statistics Office (CSO) and the Department of Agriculture, Food and the Marine (DAFM) with data from more sector specific organisations such as the Irish Horse Board (IHB) in the case of the horse industry. For the NFS, a national representative panel data set, the total aggregate weighted gross output estimates are based on output values reported directly at the farm level. At a more fundamental level, for some categories of inputs in particular, definitional differences in terms of what exact items are included, directly contribute to disparities in reported inputs and outputs between the weighted NFS and the NATACCs. Following a review of gross outputs and inputs for the NATACCs vs the NFS, comparable sectors were identified and are outlined below.

Outputs

(i) Livestock: The NATACCs report the gross output value of cattle, pigs, sheep, horses and poultry on the basis of DAFM data on export slaughterings, subsidies and levies, CSO trade statistics data on live imports and exports, and CSO data on local authority slaughtering and the change in livestock numbers. The weighted NFS reports the value for livestock on the basis of gross output at the farm gate, accounting for the value of sales, purchases and subsidies. While the NFS has sufficient coverage for the cattle and sheep sectors, no pig farms are included in the survey and poultry and horse reported outputs are minimal and are inadequate for national comparison.

Table 5.1 reports the 2008 weighted NFS total livestock gross output figures for cattle and sheep with figures of €1650m and €235m euro respectively. This compares with figures of €1682m and €171m reported in the NATACC. Output from the cattle sectors was found to be sufficiently comparable with the weighted NFS producing a slightly lower estimate for cattle outputs at 98% of the value estimated in the NATACCs. The weighted NFS reports a significantly larger estimate for gross output value from the sheep sector; 37% higher when compared to the NATACCs.

Given the sheep sector's contribution to trade livestock trade figures is less than 10%, potential explanations for this disparity include the possibility of sampling bias in the NFS given the relatively smaller size of the sector. Differences in output value may be attributable to a higher likelihood of the more productive sheep enterprises being sampled in the NFS. It is also possible that this disparity reflects the NFS's ability to more accurately capture inter-enterprise trade which is not sufficiently captured in the national accounts. Given that the purpose of the comparison is to ascertain which sectors are sufficiently captured within the NFS, the level of activity captured in the NFS is deemed to offer a reasonable basis for estimating national emissions from the sheep sector. The overall livestock gross output value for cattle and sheep sectors in the NFS is 2% over that reported in the NATACCs.

Table 5.1 Comparison of total agri-output reported in the NATACCs vs. NFS

(Euro Million) 2008	**NATACC**	**Weighted NFS**	**Weighted NFS/ NATACC Ratio**
All Livestock	*1,853*	*1,885*	*1.02*
Cattle	1682	1650	0.98
Sheep	171	235	1.37
All Livestock Products	*1,672*	*1,703*	*1.02*
Dairy(Milk)	1625	1698	1.05
Other Products (excluding Milk)	48	5	0.12
Crops	*229*	*207*	*0.91*

(ii) Livestock Products: For the purposes of the NATACCs, livestock products are divided into milk and "other products". The NATACCs report for milk consists of CSO surveying of processors for liquid and manufacturing milk with an own consumption estimate based on the number of farms, minus the superlevy. The NATACCs output report for "other products" includes data on eggs, wool and

honey. The weighted NFS reports the total value of milk output of €1698m at the farm gate (minus the superlevy), but can only contribute a wool output value of €5m for the other products sector. While the NFS output value for milk is comparable within the NATACCs (within 5%), the absence of comparable output in the NFS results in a considerably lower figure reported for other livestock products and as such is omitted from the analysis.

(iii) Crops: Due to the unavailability of data relating to non-crop horticulture and other crops in the NFS, reasonable comparisons with the NATACCs can only be drawn for the main cereal crops of wheat barley and oats. Overall weighted NFS cereal output is below that reported for the NATACCs from the Department of Agriculture Food and Marine (DAFM) by about 10%. Possible explanations for this include differences in assumptions relating to the quantity used for inter-farm feed from the DAFM and the representation of tillage in the NFS.

Inputs

Overall, aggregate agricultural input values reported in the NATACCs are higher than inputs reported in the NFS. This is anticipated due to the inclusion of inputs for agri-output not captured in the NFS. When adjusted to reflect this non-captured output, the inputs for which the NFS can provide comparable data are submitted to within an acceptable range when compared to the NATACCs. There are a number of comparable input categories reported in the NATACCs which are informed by the NFS. Specifically, NATACCs figures for energy and lubricants, maintenance and repairs, veterinary expenses and other goods and services inputs are calculated on the basis of price information from the NFS which are then combined with CSO data on the number of farms.

Of particular interest in terms of GHG emissions are the NFS figures reported for Energy and lubricants of €248m in Table 5.2 which provides a lower estimate than the €345m reported in the NATACC. While overall the weighted NFS figures for intermediate consumption compares favourably with the adjusted NATACCs, differences between the relative intensity of energy input required for different output sectors may be driving the differences reported. When adjusted for non-captured output, other inputs based on quantity data from DAFM such as feedstuffs, seeds and fertilisers (€432m Table 5.2) were found to be comparable or within range of the values reported in the NATACC with disparities again possibly due to the inclusion of forage plant value in the feedstuffs category in the NATACC and differences between the CSO prices and those reported at the farm-level.

Table 5.2 Comparable agricultural inputs captured in the NFS

(Euro Million) 2008	**Adjusted NATACC***	**Weighted NFS**	**Weighted NFS/ NATACC* Ratio**
Intermediate Consumption	*2,277*	*2,318*	*1.02*
Feedstuffs Feed & Fertilisers	507	432	0.85
Energy and Lubricants	353	249	0.71

In attempting to model GHG emissions and compare them to those in the NIR, the main comparable sectors of interest in the NFS are emissions from cattle, sheep and dairy and emissions from fertilisers. In addition, emissions from the comparable energy and lubricants sector are also of interest in terms of estimating emissions relating to the use of fuel and electricity use at the farm level. Overall, when adjusted for non-captured output, intermediate input values reported in the NFS were within 2.5% of the NATACC.

5.4.3 SMILE-NFS: A Spatial Microsimulation Model of Irish Agriculture

This section describes the matching process for the SMILE-NFS, a simulated model of the Irish local economy based on the 2008 Teagasc NFS, the 2000 CoA and an adaptation of the Quota Sampling methodology developed by (Farrell et al., 2010). In addition, an adaptation of the SMILE-NFS quota sampling methodology is described whereby the stocking rate reported for each CoA electoral district is used to rank and select farms from the NFS micro data which most closely resemble the stocking rate for that electoral district. This is done in order to preserve the spatial heterogeneity of the stocking rate which was previously found to be an influential variable in the determination of greenhouse gas emissions from agriculture when using the IPCC emissions inventorying methodology (Hynes et al., 2009).

Data Preparation

As outlined in Chapter 4, in designing a framework for spatial microsimulation models, the basic goal is to ensure that units from the micro data are simulated to the destination spatial unit by matching the characteristics of the micro units selected to the spatially heterogeneous characteristics of the spatial unit. In the SMILE-NFS model, farms from the weighted Teagasc NFS are simulated to an electoral district (ED) on the basis of aggregate farm totals reported for that ED in the CoA.

In order to have a basis for the application of any microsimulation sampling methodology, match variables common to both the micro data and the spatial data must first be identified. For the SMILE-NFS model, farms are matched to destination EDs by the main basic farm characteristics i.e. farm size, speciality and soil type. The CoA provides the aggregate totals for these match variables for each ED. A part-time rate variable by region and speciality is also simulated and applied to the CoA totals on the basis of information from the NFS.

A problem occurs however, where there is a time lag between the nationally representative micro data and the spatially representative aggregate data. While the NFS Survey is conducted annually, the Irish CoA is conducted approximately every ten years with the last two censuses conducted in 2000 and 2010 respectively. This means that while the annual weighted NFS micro-data changes over time to reflect national changes in agriculture, the spatially representative CoA aggregate data is only valid for the census year. Thus in order to perform a legitimate microsimulation match of the NFS and the CoA in non-census years an adjustment must be made to the aggregate ED totals in the CoA that reflect the changes over time captured in the NFS. To solve this problem, uprating factors are calculated from the NFS on the basis of comparisons with the NFS from the base census year. Due to the limited spatial information available in the NFS, regional uprate factors for the number of farms by size, specialty, soil code and part-time are created for each of the match variables. This is done by calculating the change in the weighted regional totals of the match variables from the base census year to the match year. These regional uprate factors are then applied to the CoA match variable ED totals within each region. It should be noted however that the accuracy of the uprate factors employed are dependent on the accuracy of the weightings applied to the NFS. The greater the time lag between the census year and the baseline simulation year, the greater the potential for considerable disparities between the weighted sample and the total population.

Quota Sampling Matching Process

The quota sampling matching process generally has been described in detail in the previous chapter in Section 4.4.3. The following describes the sampling process specifically as it has been applied to sampling unit farms from the NFS to aggregate spatial totals for each ED reported in the CoA

-Step1. Prepare data

The 16 year NFS panel data set is merged with the regional weighting factors provided by the CSO (informed by the farm structures survey) to provide a 16 year nationally representative weighted sample data set of Irish farms. Farms are identified, categorized and dummied by the farm speciality (7 categories), farm size (6 categories), soil code (6 categories) and whether the farm is part-time or full-time. These are the match variables which are used for the spatial microsimulation match/sampling procedure. In addition, each farm’s stocking rate per hectare is calculated based on the total number of livestock units per hectare. The regional uprate factors for the match year from the base census year are then calculated using the NFS for the following categories displayed in Table 5.3 below.

Table 5.3 Regional uprate categories

2008/2000 Regional Uprate Factors	No. of Categories
Tot. No. of Farms by: Region	8
Tot. No. of Farms by: Speciality & Region	56
Tot. No. of Farms by: Farm Size Group & Region	48
Tot. No. of Farms by: Soil Type Group & Region	48

Following the creation of the regional uprate factors, the unweighted micro data file of simulated farms from the NFS match year (from which the SMILE-NFS model will sample simulated farms) is created. In addition, due to the presence of several large EDs containing a large number of farms and the presence of outliers (EDs which may contain an unusually high number of a certain farm size, system or soil type), the micro data set is multiplied nominally in order to ensure that a sufficient number of farms exist in the sample space are able to be selected to fill the remaining places.

-*Step2. Create target totals*

The regional uprate factors created for the match year are then applied to the match variables in the CoA. The summed totals for speciality, size and soil type in the CoA are then proportionally adjusted to match the total uprated number of farms for that ED. The regional part time rates for all specialities for each region calculated from the NFS are applied. To ensure the summed totals for each category of the match variables are consistent with the target total number of farms, minor reweighting adjustments are made based on the relative proportions. This gives an integer total for each category with the sum of all categories equalling the EDs target farm total.

-*Step 3. Preparation and Selection for each ED*

Separately and sequentially, each individual ED containing the target totals for each match variable from the uprated CoA file is merged with the sample survey micro data file (i.e. the individual unit farm observations from the NFS) and the sampling process begins. To preserve the spatial heterogeneity of soil types the sample is limited to those farms matching the dominant soil type for the target ED. Target totals or "bins" for the match variables and the part-time rate are then created and updated each time a farm is selected. Farms are then sorted randomly and selected without replacement for inclusion until any one of the totals or "bins" for that ED is filled. The model then skips all farms with the characteristic of the filled bin and fills the ED sequentially with the remaining farms until a second bin is filled. The process then repeats until all bins are filled or until the remaining farms which can be selected has shrunk to zero, i.e. there is no farm remaining in the micro data that can be added without overfilling one of the already filled bins. If the target total number of farms for the ED has not been reached within two iterations of searching the micro data file, the part-time constraint is relaxed and the model moves to the next iteration. This process repeats until either the total target number of farms for the ED has been reached or the number of iterations reaches a predetermined terminus.

SMILE-NFS Validation Results Method 1

The statistical accuracy of the sampling procedure is crucial as it provides the synthetic baseline population from which the model proceeds to perform the microsimulation i.e. (the simulation of each individual micro unit). For each spatial unit (in this case each ED), it is desirable that the summed totals for each match category in the simulated population is as close as possible to the aggregate totals reported for each ED in the census data.

A simplified example of a statistically perfect sampling procedure is shown in Table 5.4 whereby the summed characteristics of each individually sampled farm matches the summed aggregate totals in the census. In Table 5.4 the census reports there are 6 farms in total in ED001, 2 of which are dairy, 3 of which are cattle and one of which is a sheep farm. It also reports that 3 of the 6 farms are part time. In this example, the first four farms are selected as none of the aggregate totals or “bins” for the ED would be exceeded by their addition. With the addition of farm 4, the aggregate ED001 total for the number of cattle farms has been reached. The model then proceeds to remove all remaining cattle farms (i.e. farm 5) from the sample space and continues the sampling process. With the selection of farm 6, the aggregate ED001 totals for both Sheep and Part-time have been filled. The model then removes all remaining part-time and/or sheep farms from the sample space (i.e. farms 7 and 8) and then proceeds to add farm 9, which satisfies the final remaining constraints, i.e. is a dairy farm and does not operate part-time. With the addition of farm 9, the total number of farms selected (6) has reached the total aggregate number of farms for ED001 and a statistically perfect sampling outcome has been achieved for the constraints selected.

Table 5.4 Simplified example of a statistically perfect sampling outcome

Farms Sampled to ED001	Dairy	Cattle	Sheep	Part-Time	Selected
Farm 1	1	0	0	1	YES
Farm 2	0	1	0	0	YES
Farm 3	0	1	0	0	YES
Farm 4	0	1	0	1	YES
~~Farm 5~~	~~0~~	~~1~~	~~0~~	~~0~~	~~NO~~
Farm 6	0	0	1	1	YES
~~Farm 7~~	~~0~~	~~0~~	~~1~~	~~1~~	~~NO~~
~~Farm 8~~	~~1~~	~~0~~	~~0~~	~~1~~	~~NO~~
Farm 9	1	0	0	0	YES
Farm 10	1	0	0	0	N/A
Total	**2**	**3**	**1**	**3**	**-**
Census Totals Reported for ED001	**2**	**3**	**1**	**3**	**-**
Match Accuracy	100%	100%	100%	100%	-

With additional constraints however, the achievement of a statistically perfect sampling outcome for each spatial unit becomes more difficult as a greater number of conditions must be met in order to fill the last few remaining farms in each ED.

The SMILE-NFS match for 2008 achieves the target total number of farms for all EDs and yields the simple correlation matrix of the targeted totals and simulated outcomes for the match variables across all simulated EDs is reported in Table 5.5.

Table 5.5 Correlation matrix for target totals and simulated outcomes for SMILE-NFS

Correlation Matrix target totals and simulated outcomes (Simulated outcome / Target Totals)	Specialist Tillage	Specialist Dairy	Specialist Beef	Specialist Sheep	Mixed Grazing	10-20 ha.	20-30 ha.	30-50 ha.	50-100 ha.	>100 ha.	Part Time Farms	Rate Stock no/ha. (non-match variable)
Specialist Tillage	1.00											
Specialist Dairy		1.00										
Specialist Beef			1.00									
Specialist Sheep				1.00								
Mixed Grazing					1.00							
10-20 ha.						0.81						
20-30 ha.							0.54					
30-50 ha.								0.56				
50-100 ha.									0.41			
>100 ha.										0.16		
Part Time Farms											0.86	
Stock Rate no/ha. (non-match variable)												0.12

With regard to the speciality variables a correlation coefficient of 1.00 is reported across all specialities. This is anticipated as speciality is the first constraint examined in the sampling process. This does not mean that in any given ED a speciality bin will necessarily be filled first, rather, that as the number of simulated farms reaches the population target for the ED the remaining sample space from which selections can be made is determined by specialty first.

In relation to size categories, Table 5.5 shows a correlation co-efficient of 0.81 for the smallest size category. While independently this could be considered a low yet reasonable result for a standard microsimulation model, the remaining co-efficients decline rapidly towards the larger farm size categories with a co-efficient of just 0.16 reported for the largest farm size category. The reason for this decline is that as the model fills the speciality bins, generally for each ED, the remaining micro data sample space is still populated with a sufficient number of farms in the lower size categories such that it is able to fill the first 4 farm size group bins with a higher degree of accuracy while satisfying all conditions. For the 500 or so EDs containing farms in the largest size category, the match is much less accurate. This is particularly pronounced for EDs containing a smaller number of total farms as the relative diversity of match characteristics for the smaller number of large farms in the sample is lower that than that for the smaller farm sizes. The part time co-efficient is reported in Table 5.5 at 0.86 which again could be considered a low yet reasonable result.

Of most concern however is the result for the ED stocking rate. A co-efficient of just 0.12 is reported indicating an extremely poor correlation between the actual and simulated stocking rates outcomes across all EDs. This is a particularly challenging outcome for the development of a credible spatial model of emissions for agriculture. Preserving the spatial heterogeneity of each ED stocking rate is a key requirement as it is the most influential variable in the determination of greenhouse gas emissions from agriculture at the farm level.

SMILE-NFS Validation Results Method 2: The inclusion of Stocking Rate Ranking Variable

In the previous method (Method 1), farms are sorted randomly before the sampling process, summarised in Table 5.4, begins. However this random sorting results in a significant decline in sampling accuracy across the match variables and crucially the resultant stocking rate for each ED (Table 5.4). In order to preserve the spatial heterogeneity of the stocking rate the SMILE-NFS quota sampling procedure has been adapted to include a ranking mechanism based on a predicted stocking rate residual for each electoral district recorded in the CoA.

A linear regression model (Equation 5.1) for the ED stocking rate is first performed on the CoA for all EDs in order to estimate and predict a stocking rate and a residual for each ED based on the aggregate totals of the match variables of size, system, and soil type.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \ldots\ldots + e \quad \textbf{(5.1)}$$

Where Y = stocking rate, X_1, X_2…etc = aggregate total of match variables for each ED, B_1, $B_{2\ldots}$ etc = the marginal contribution to the stocking farm of each additional farm in that match category.

The model is used to predict a stocking rate (R_{ed}) and a residual (r_{ed}) for each ED based on the aggregate totals of the match variables of size, system, and soil type. The regression coefficients are then applied to each individual farm in the sample data in order to return a predicted contribution to the stocking rate (R_f) and a residual (r_f) for each individual farm.

By applying the aggregate model coefficients to each sample farm in the NFS micro data, an estimation of each farms predicted contribution to that EDs stocking rate in the context of the total farm profile of that ED is made. These predictions are used to generate a stocking rate contribution residual for each sample farm in the micro data which will be used to rank available selections.

Before selection commences, farms are ranked by the smallest absolute difference between the stocking rate residual for the current ED (R_{ed}-r_{ed}) and the stocking rate residual contribution reported for the sample farms (R_f-r_f) (Equation 5.2).

$$Rnk = Min|(R_{ed} - r_{ed}) - (R_{f-}r_f)| \quad \textbf{(5.2)}$$

This step means that farms with residuals which most closely resemble the residual stocking rate of the target ED are more likely to be selected first. The SMILE-NFS model then considers each ranked farm in the micro data file for inclusion in the target ED. The application of this ranking is designed so that each target ED's residual stocking rate, unexplained by the linear regression model, can be somewhat preserved.

Table 5.6 shows the simple linear relationship between the original target ED totals and the summed total for each ED from the simulated match with the inclusion of the stocking rate residual ranking mechanism. As expected, the correlation co-efficient reported for all specialities is reported as 1.00 as the target bin totals for each speciality have been filled with a high degree of accuracy for all EDs.

Table 5.6 Correlation matrix for target totals and simulated outcomes for SMILE-NFS (with the use of a stocking rate ranking variable)

Correlation Matrix target totals and simulated outcomes (Simulated outcome) / Target Totals	Specialist Tillage	Specialist Dairy	Specialist Beef	Specialist Sheep	Mixed Grazing	10-20 ha.	20-30 ha.	30-50 ha.	50-100 ha.	>100 ha.	Part Time Farms	Stock Rate no/ha.
Specialist Tillage	1.00											
Specialist Dairy		1.00										
Specialist Beef			1.00									
Specialist Sheep				1.00								
Mixed Grazing					1.00							
10-20 ha.						0.98						
20-30 ha.							0.98					
30-50 ha.								0.98				
50-100 ha.									0.98			
>100 ha.										0.90		
Part Time Farms											0.97	
Stock Rate no/ha.												0.88

With regard to the size categories, when compared to the results in Table 5.5, the adapted SMILE-NFS model delivers a high degree of accuracy for the farm size groups. Table 5.6 reports correlation coefficients for the first 4 farm size groups at 0.98 while the coefficient for the largest farm size group is reported at 0.90. Again, as the model fills the speciality bins, the remaining micro data sample space is still populated with a sufficient number of farms in the lower size categories such that it is able to fill the smaller farm size groups bins more easily, explaining the decline in the strength of the linear correlations as we move up the size categories.

The inclusion of the stocking rate residual ranking, results in a much higher degree of accuracy for the bigger size categories. This is because the stocking rate ranking increases the likelihood of filling the more dominant size categories in each ED first due to the direct relationship of size to the stocking rate. When compared to the results in Table 5.5, there is a significant deterioration in the correlation results for size, as without a ranking mechanism, the size bins are filled randomly as the model fills the speciality bins.

The correlation coefficient for the part-time rate is reported at 0.97 which indicates a high degree of correlation despite the part-time constraint condition being dropped after the first two iterations; however, it must be remembered that the part-time target total is calculated by applying the regional part-time speciality rates to the speciality totals for each target ED. This step is required as the CoA does not contain a measure of part-time for each speciality, comparable with the NFS.

The correlation coefficient reported for the stocking rate is 0.88. While this represents a slightly lower level of accuracy when compared to size, system and the part-time rate, it must be noted that the stocking rate is not a match variable. The stocking rate reported for any ED in the CoA represents an averaged stocking rate across all farms. In reality each ED is made up of a collection of individual farms with varying stocking rates. As outlined above, prior to the selection process the SMILE-NFS model ranks the sample farms by the smallest difference between the stocking rate residual calculated for the ED and the stocking rate residual for the sample farm. This means that if a target ED's residual stocking rate is considerably higher or lower than that predicted by the linear regression model, the selection of farms with correspondingly higher or lower residual stocking rates than those predicted by the linear regression model will ensure that spatial heterogeneity of stocking rate for the target ED is somewhat preserved. This is a key consideration in the development of a spatial baseline emissions model for agriculture as the stocking rate is the key variable in determining resultant emissions from animal rumination. Table 5.7 displays the match accuracy and chi-squared distribution test-statistics for the inclusion of a stocking rate ranking variable in the SMILE-NFS match for 2008

Table 5.7 Match accuracy and chi-squared distribution test-statistics for SMILE-NFS match 2008

Match Variables	**0**	**1**	**Match %**	**Pearson Chi^2 =**	**Pr =**
Specialist Tillage	5	2811	99.82	6.70E+04	0.000
Specialist Dairy	3	2813	99.89	1.20E+05	0.000
Specialist Beef	3	2813	99.89	1.30E+05	0.000
Specialist Sheep	3	2813	99.89	1.70E+05	0.000
Mixed Grazing	0	2816	100.00	1.10E+05	0.000
10-20 ha.	362	2454	87.14	6.31E+04	0.000
20-30 ha.	365	2451	87.04	6.10E+04	0.000
30-50 ha.	245	2571	91.30	7.90E+04	0.000
50-100 ha.	342	2474	87.86	7.80E+04	0.000
>100 ha.	422	2394	85.01	2.50E+04	0.000
Part Time Farms	871	1945	69.07	8.50E+04	0.000

The nature of the match-process is such that there is a trade-off between methodological complexity and computational efficiency. While it is possible a more accurate match for the match variables may have been obtained using the previous simulated annealing method developed by Hynes et al. (2008), the computational cost of simulated annealing approach is high (Chapter 4). The quota sampling method provides a high level of accuracy for the match variables and allows the simulation to be modelled in a number of hours. The inclusion of a ranking mechanism provides the added benefit of preserving much of the spatial heterogeneity of each EDs stocking rate; the most influential variable in the determination of greenhouse gas emissions from agriculture using the EPA methodology.

5.4.4 Calculation of Agricultural Greenhouse Gas Emissions

In this section emissions are calculated for the comparable output sectors identified above, namely; dairy, cattle and sheep for both enteric fermentation and manure management, while emissions are calculated for the relevant comparable input sectors for energy use (electricity & fuel) and synthetic fertilizers.

Livestock Numbers

The adapted SMILE-NFS spatial microsimulation model uses the 2008 NFS and uprated ED totals from the CoA to create a fully synthetic micro population of Irish farms based on the key match variables of farm size, system soil type and the part-time rate, including an additional mechanism for minimizing differences in the stocking rate. For the purposes of calculating emissions, the use of additional non-match variables from the simulated farms such as livestock numbers are required to estimate emissions for each ED. Livestock numbers are considered as they will be the eventual determinants of estimated emissions of methane (CH_4) from enteric fermentation and both CH_4 and nitrous oxide (N_2O) from manure management. Simple regression analysis performed on the NFS data reveals that, with respect to the livestock numbers, the match variables of farm size, system and soil type are key determinants. However, additional variables such as the demographic profile of the holder and the availability of additional labour influence the total number of livestock at the farm level.

In order to provide a reasonable estimation of spatial emissions using non-match variables, validation of the estimated non-matched output must be performed. One potential way of validating non-matched microsimulation model outputs is to re-aggregate estimated data sets to levels at which observed data sets exist and compare the estimated distributions with the observed (Ballas & Clarke, 2001). In a census year, this could be done with a comparison with the CoA. However, in a non-census year the livestock numbers reported are subject to the regional uprating methodology as (i) The spatial heterogeneity of livestock numbers can vary greatly within regions and (ii) the livestock numbers are not included as a match variable. A constant time-invariant relationship is assumed between size, system and soil type for the estimate of the stocking rate at the ED level, with the time variant changes captured by the regional uprating process. As such, livestock numbers reported from the CoA 2000 are thus unable to provide a suitable comparison for the 2008 SMILE-NFS model.

In order to provide a reasonable comparison with estimated national totals the aggregated output from the SMILE-NFS model is compared with the livestock numbers reported for the NIR, which are based on the average estimated populations for June and December calculated by the CSO.

Table 5.8 displays the total livestock numbers for the NIR and the SMILE-NFS model for dairy, non-dairy cattle and sheep respectively. Dairy cows numbers for the SMILE-NFS are reported at 90% of those used by the NIR. The numbers estimated for non-dairy cattle in the SMILE-NFS are 18% higher than those estimated in the weighted NFS with sheep numbers being estimated at 87% of the estimated total used by the NIR.

Table 5.8 Total livestock numbers reported for NIR (EPA, 2010) vs. SMILE-NFS

Total Livestock Numbers (1000s)	NIR	SMILE-NFS	Ratio
Dairy Cows	1,087	982	0.90
Non-Dairy Cattle	4,814	5,696	1.18
Sheep	5,105	4,416	0.87

With respect to dairy cows the SMILE-NFS model reports livestock numbers at 90% of those reported in the NIR. Comparing the weighted dairy output from the NFS and dairy output reported in the NATACCs, the weighted NFS reports a dairy output figure of 5% in excess of the NATACCs. One possible explanation for higher gross output reported coupled with lower livestock numbers could be the presence of sampling bias in the NFS towards slightly more efficient dairy producers. If the NFS sample includes slightly more efficient dairy farms with an average gross output per livestock unit higher than the national average, the total weighted gross output would be higher than anticipated, while the total livestock numbers would be kept artificially low.

With regard to the disparity between the totals for non-dairy cattle and sheep there are two possible explanations. Firstly, with regard to the sheep numbers, there are very few sheep only enterprises in the NFS i.e. farms identified as specialist sheep that do not have any additional livestock on the farm. These farms tend to have the largest number of sheep. The majority of farms identified as specialist sheep have additional enterprises with cattle enterprises being the most common. This means that for farms identified as specialist sheep farms or specialist mixed farms, the additional cattle component is a considerable determinate of the stocking rate for that farm. The converse is not true for specialist beef farms as there are a much smaller proportion of those farms containing sheep numbers. Consequently, as sheep farms are selected by the model, is it likely that the sheep only enterprises are being under selected as the stocking rate is diluted by the cattle numbers resulting in smaller total numbers for sheep and higher numbers for cattle. Additionally, there are a very small number of large specialist tillage farms in the NFS which also include a large sheep enterprise. Again, while in the NFS these farms contribute significantly to the weighted total numbers, in the SMILE NFS it is again likely that these farms are being under-selected as the individual farms stocking rates are ‘contaminated’ by the tillage area.

Secondly with regard to the non-dairy cattle numbers in terms of the SMILE-NFS spatial match, there are a number of non-dairy cattle (non-matched) sub-categories that are summed in order to produce the total livestock numbers (Table 5.9). These include cattle 0-6 months, 6-12 months, 1-2 years, 2 year + and breeding bulls. As stated previously, while it is assumed that the match variables are the key determinants of the stocking rate, the variables of interest in this case are the non-dairy cattle sub-categories.

Table 5.9 Non-dairy cattle sub-categories

Non-Dairy Cattle Sub-Categories	
Suckler cows	Bulls for breeding
Male cattle < 1 year	Female cattle < 1 year
Male cattle 1 - 2 years	Male cattle > 2 years
Female cattle 1 - 2 years	Female cattle > 2 years
Dairy in-calf heifers	Beef in-calf heifers

While differences between the target ED stocking rate and the simulated stocking rate are minimized in the SMILE-NFS, the stocking rate is based on the number of livestock units (LUs) per hectare. Since a livestock unit equivalent of 1.0 is applied to dairy cows this problem does not affect the total dairy cow numbers. However for non-dairy cattle, livestock numbers in the younger age categories with lower LU equivalents such as calves under 6 months (0.2 LU) and cattle1-2 years (0.7 LU) mean that while the stocking rate may be being maintained higher total numbers are reported. In terms of stocking rate, the SMILE-NFS model does not distinguish between a 10 hectare non-dairy enterprise with e.g. 22 cattle (17 cattle over 2 years (1.0 LU) and 5 cattle 1-2 years), and similar sized enterprise with 25 cattle (10 cattle over 2 years, 15 cattle 1-2 years).

Overall the total livestock numbers reported in the SMILE-NFS model are deemed to be within range (+/-20%) of the estimated numbers reported in the NIR to offer a credible alternative estimation of emissions from Irish agricultural.

Livestock Emissions

Methane Emissions for each livestock category for each simulated farm are calculated by applying the emissions factors and Global Warming Potential (GWP) supplied by the EPA's NIR for 2008 (EPA, 2010). The tier 2 emissions factors used for calculating cattle methane emissions from ENF and MM developed by O'Mara (2006) are displayed in Table 5.10.

Table 5.10 Tier two emissions factors for Irish cattle (O'Mara, 2006)

	Methane produced from Enteric Fermentation (kg/head)	Methane produced from Manure Management (kg/head)
Dairy cows	109.21	20.5
Suckler cows	75.92	14.25
In-calf heifers**	51.60	11.72
Cattle <1 year**	28.73	8.46
Male cattle 1 - 2 years	59.07	13.78
Female cattle 1 - 2 years	47.00	9.95
Male cattle > 2 years	36.98	1.82
Female cattle > 2 years	22.55	0.34
Bulls for breeding	81.55	18.95
Lambs	3.38	0.11
Sheep	8.00	0.19

(Source: O'Mara, 2006)

Nitrous Oxide emissions from manure management are calculated in a similar fashion. Nitrogen output emission factors are applied to each animal category and are converted to nitrous oxide emissions. However, the rate at which nitrogen volatises to N_2O varies depending on the waste management system (WMS) used; i.e., liquid, solid or pasture. As detailed information on WMS is not available in the NFS, animal specific averages were taken from the NIR and applied to Nitrogen output for each animal category for each simulated farm. An N-N_2O conversion factor was then applied to calculate the total N_2O emissions from livestock.

*Total N_2O Livestk. Emissions (CO_2eq) = ∑ac(i-j):[(ac(i)*efNmm_ac*liq_ac (ac(i)*efNmm_ac*sol_ac + (ac(i)*efNmm_ac*pas_ac)*N\N_2O]*N_2OGWP*

Where: *mm* = Manure Management, *liq_ac,sol_ac,pas_ac* = Animal specific WMS ratios for Liquid, Soil Pasture; *GWP* = Global Warming Potential (N_2O = 310) and *ac* = Animal Category

N_2O Emissions from Agricultural Soils

Nitrous Oxide emissions from agricultural soils are also calculated. The NIR reports N_2O emissions from soils from the application of synthetic fertilizers, animal manure applied to soils, N-fixing crop, crop residue, indirect emissions and other (EPA 2010). For the SMILE-NFS emissions model, N_2O emissions are calculated for the application of synthetic fertilisers and indirect soil emissions only. There is insufficient information in the NFS, particularly with regard to non-cereal crops in order to provide reasonable estimates at appropriate spatial scales for, N-fixing crop and crop residue.

Direct Soil emissions from the application of synthetic fertilisers = Nfert(1-FracGASF)*N_soil_EF*

Where *Nfert* = Nitrogen Applied (kg), *FracGASF* = fraction of synthetic fertilizer nitrogen that volatilizes as NH3 (0.016 in 2008), *N_soil_EF* =N_2O-N/kg N emission factor (0.012)*44/28

The IPCC methodology for indirect emissions allocates emissions of N_2O due to nitrogen deposition resulting from NH_3 and NO_X emissions in agriculture and from nitrogen leaching.

Indirect Soil emissions = N_2Oindirect-deposition+N_2Oindirect-leaching

*N_2Oindirect-dep= [(Nfert*FracGASF) + ((Nex*(1- FracGRAZ)*FracGASM1)) + (Nex*FracGRAZ*FracGASM2)] * EF4]*

*[N_2Oindirect-leach = [Nfert + F_{AW}^{**} + Nex*FracGRAZ)] * FracLEACH * EF5]*

Where *Nex* = total amount of animal manure nitrogen excreted by livestock (kg N), *FracGRAZ* = fraction of Nex that is excreted by livestock during grazing (0.66 in 2008), *FracGASM1* = fraction of animal manure nitrogen that volatilizes as NH3 during housing, manure storage and land spreading (0.485 in 2008), *FracGASM2* = fraction of animal manure nitrogen that volatilizes as NH3 during grazing (0.036 in 2008) and *FracLEACH* = fraction of synthetic fertilizer nitrogen and animal manure nitrogen that leaches from agricultural soils (0.1 in 2008). F_{AW} ** (the indirect amount of N_2O from sludge spreading is not included in this analysis)

Electricity

Emissions attributable to electricity use are also calculated for each simulated farm. In the NFS each farm reports an annual amount spent on electricity. Apart from a small number of larger farms with a separate connection, in most cases, this figure is based on an estimation of the share of electricity used by the farm household which is related to farm activities. The model estimates total energy use, using the average price of €0.1597 per/kWh reported by the Commission for Energy Regulation (CER) for 2008. Total emissions are then calculated using the CER's electricity emissions factor of 0.538 $kgCO_2/kWh$ (CER, 2009).

$$Total\ Elec\ Emissions\ (CO_2eq) = ElecExp/(price/kWh)*KgCO_2/kWh$$

Where *ElecExp* = Farm expenditure on Electricity

However, one quarter of farms in the NFS report electricity costs below that reported for the standard general purpose annual standing charge. Due to an inability to elicit the ratio of farm electricity use to household electricity it is assumed that the proportion of electricity expense allocated to farms does not include the standing charge. A consequence of this is that the model will slightly over-estimate electricity emissions for all farms. This effect will be more pronounced for smaller farms where the ratio of the standing charge to overall electricity costs will be far higher. However, the impact on total emissions will be relatively small as the majority of over-estimation of shares will occur for farms with very low electricity use.

Fuel

The NFS reports farm level expenditure on fuel but does not provide information on the quantity of fuel used or the fuel mix. In order to provide a basis for the calculation of fuel related emissions a number of assumptions are made. It is assumed for the purposes of calculating quantities and the application of emissions factors that diesel is the predominate fuel used on farms. Averaged diesel prices for 2008 are taken from the Energy in Transport Report (SEAI, 2009a) and are used to calculate total fuel quantity consumed. Energy output is then calculated with emissions factors based on energy output from the SEAI report for diesel used to calculate the resultant emissions.

*Total Fuel Emissions (CO_2eq) = [FuelExp/(dieselprice/l)]*diesel (kWh/l)*diesel(kgCO_2kWh)*

Where, *FuelExp* = Farm expenditure on Fuels, *kWh/l* = 10.169, *diesel(kgCO_2kWh)* = 0.2639, *dieselprice/l* = 1.4c/l

5.5 Results

Results for a spatially disaggregated baseline microsimulation model of Irish agricultural emissions are presented in this section. Total aggregated output from the model is compared with estimates reported in the National Inventory Report with resultant outcomes mapped spatially at the ED level.

5.5.1 Emissions Output: SMILE-NFS vs. NIR

Using the SMILE-NFS spatial microsimulation model, a synthetic population level data set of Irish farms has been created from which a spatial baseline emissions inventory for Irish Agriculture has been estimated. In order to evaluate the validity of the simulated population level emissions from enteric fermentation (ENF), manure management (MM) and fertiliser usage, a comparison is carried out between the aggregated results from the SMILE-NFS model and the NIR report. Maps from the SMILE-NFS model, detailing emissions output at the electoral district level are also presented with the inclusion of results estimating emissions from electricity and fuel used in Irish agriculture.

Table 5.11 reports emissions totals from the NIR for comparable agricultural activity captured in the NFS (based on a comparison of activity between the weighted NFS and the NATACCs as discussed in Section 5.4.2)

Table 5.11 Total livestock numbers (000s) and GHG emissions (Gg) reported for all farms: Comparison of SMILE-NFS with the NIR 2008

	NIR*	**SMILE-NFS**	**SMILE NFS/NIR Ratio**
	Livestock Numbers '000s**		
Dairy Cows	1,087	982	**0.90**
Non-Dairy Cattle	4,814	5,696	**1.18**
Sheep	5,105	4,416	**0.87**
	CH_4 Enteric Fermentation (Gg)		
Total	416.70	404.80	**0.97**
Dairy Cows	120.20	107.00	**0.89**
Non-Dairy Cattle	266.35	271.00	**1.02**
Sheep	30.15	26.80	**0.89**
	CH_4 Manure Management (Gg)		
Total	78.07	79.69	**1.02**
Dairy Cows	22.59	20.10	**0.89**
Non-Dairy Cattle	54.70	58.90	**1.08**
Sheep	0.77	0.69	**0.89**
	N_20 Manure Management (Gg)		
Total	9.01	9.09	**1.01**
Liquid Systems	0.17	0.16	**0.94**
Solid and Dry Lot	1.00	0.99	**0.99**
Pasture Range and Paddock	7.84	7.94	**1.01**
	N_20 Soil Emissions (Gg)		
Total	9.92	9.64	**0.87**
Synthetic Fertilisers	5.96	5.08	**0.85**
Indirect Soil Emissions	3.96	3.56	**0.90**
**Livestock Numbers for the NIR are based on biannual population estimates			

**For comparable outputs/inputs (Section 5.4.2)*

Methane emissions from Livestock

Differences in the farm system totals between the NIR and the SMILE-NFS for CH_4 are predominantly driven by the differences in the reported livestock numbers. For dairy cows, total emissions of CH_4 from both ENF and MM from the SMILE-NFS model are reported at 107Gg and 20.10Gg respectively. In both cases, this represents 89% of the estimates reported in the NIR. This result is consistent with the result for the dairy livestock number with the 1% difference in output explained by the livestock population methodology adopted in the NIR. While the SMILE-NFS emissions model provides an emissions estimate on livestock numbers for the calendar year, the NIR provides emissions estimates based on two, bi-annual livestock population estimates from the CSO. While the NIR does provide an annual population total, the emissions are based on the bi-annual estimates. This results in the apparent disparity in the NIR with higher than expected figures of 120.20Gg and 22.59Gg of CH_4 reported for dairy cows from ENF and MM respectively.

While the estimate for total livestock numbers for cattle in the SMILE-NFS is 18% higher than the figure reported in the NIR, the resulting emissions comparisons are not as pronounced. This is due to fact that the simulated farms from the SMILE-NFS contain a larger amount of animals in the younger cattle sub-categories. One possible explanation for this difference is that while farms are surveyed in the NFS all year round, the CSO population estimates are for two fixed points in the production cycle. For CH_4 from ENF, the SMILE-NFS reports a total of 271Gg, representing a difference of just +2% from the estimate from the NIR. For CH_4 from MM the SMILE-NFS reports a total of 58.9Gg, representing a difference of +8%. The reason for the increased difference is because of the difference in relative weightings between each cattle sub-category of the emissions factors for ENFT and MM respectively (Table 5.10).

With regard to sheep, the SMILE-NFS model estimates 26.8 and 0.69Gg for CH_4 emissions from ENF and MM both representing around 89% of the emissions estimates from the NIR. Again, small differences between the NIR/SMILE-NFS ratio of livestock numbers and the ratio of emissions output can be explained by the differences in the ratios of sheep >1 year and lambs with the SMILE-NFS reporting slightly larger adult sheep numbers.

Figures 5.1 and 5.2 display methane emissions in kilograms per hectare for enteric fermentation and manure management from livestock in the dairy, cattle and sheep sectors respectively. Both maps illustrate an expected West-South-West, North-North-East dividing line in terms of the more productive agriculture regions of the country. Electoral districts which report the highest levels of average emissions per hectare are predominantly located in the south where the majority of dairy production is concentrated. Better soil quality and more favourable environmental conditions facilitate higher stocking rates contributing to higher emissions on a per hectare basis. In the north, north-west and in more mountains areas, the presence of higher numbers of cattle and sheep farms with lower stocking rates results in lower emissions per hectare. Slight differences in the relative emissions intensity of some EDs can be seen in the two maps presented. This is due to differences in the relative intensity of the emissions factors for enteric fermentation vs. manure management between the different animal sub-categories in Table 5.10 resulting in some EDs moving one step to higher or lower emissions per hectare category.

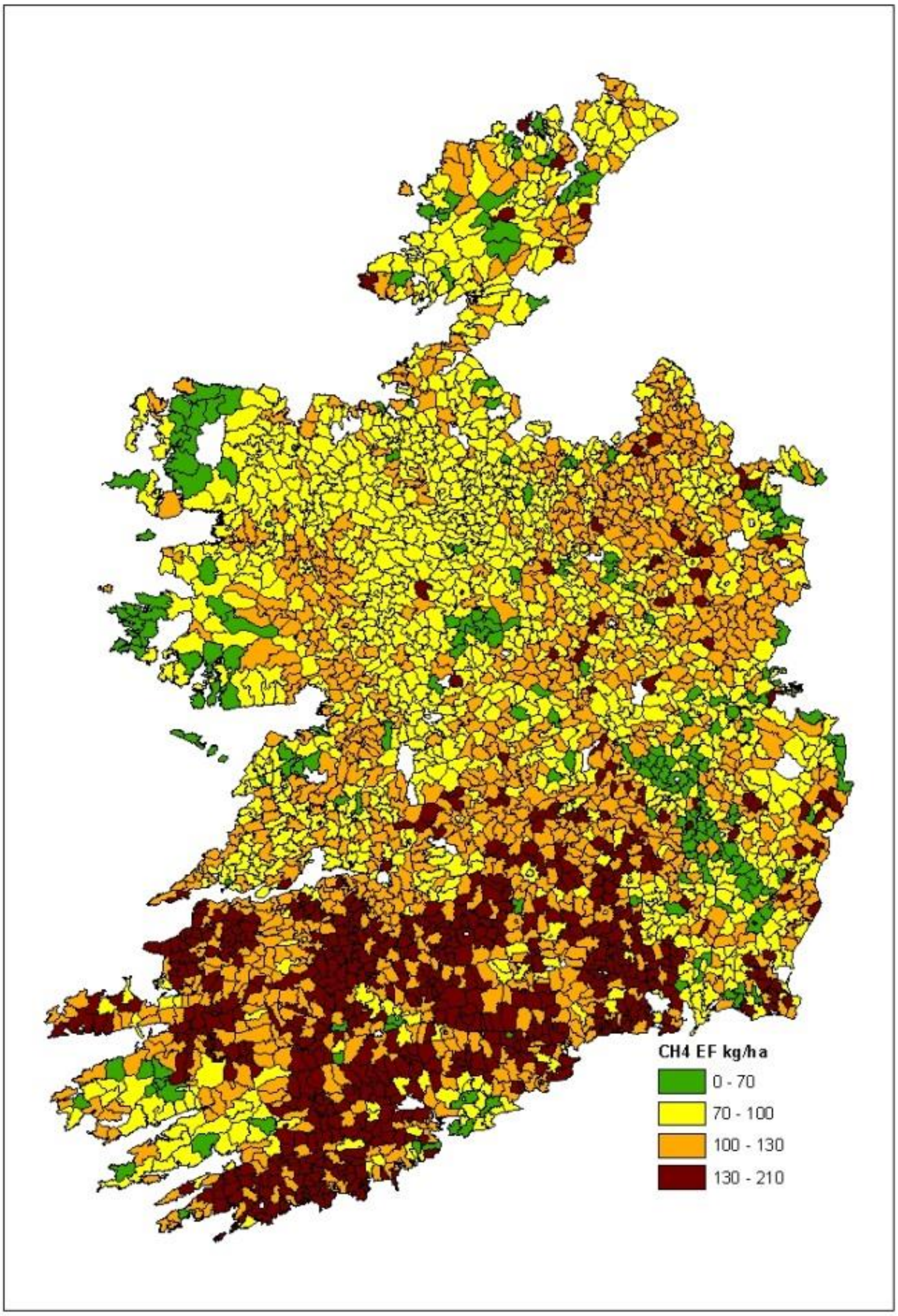


Figure 5.1 Estimated Methane (CH_4) emissions from enteric fermentation kg/ha by electoral district

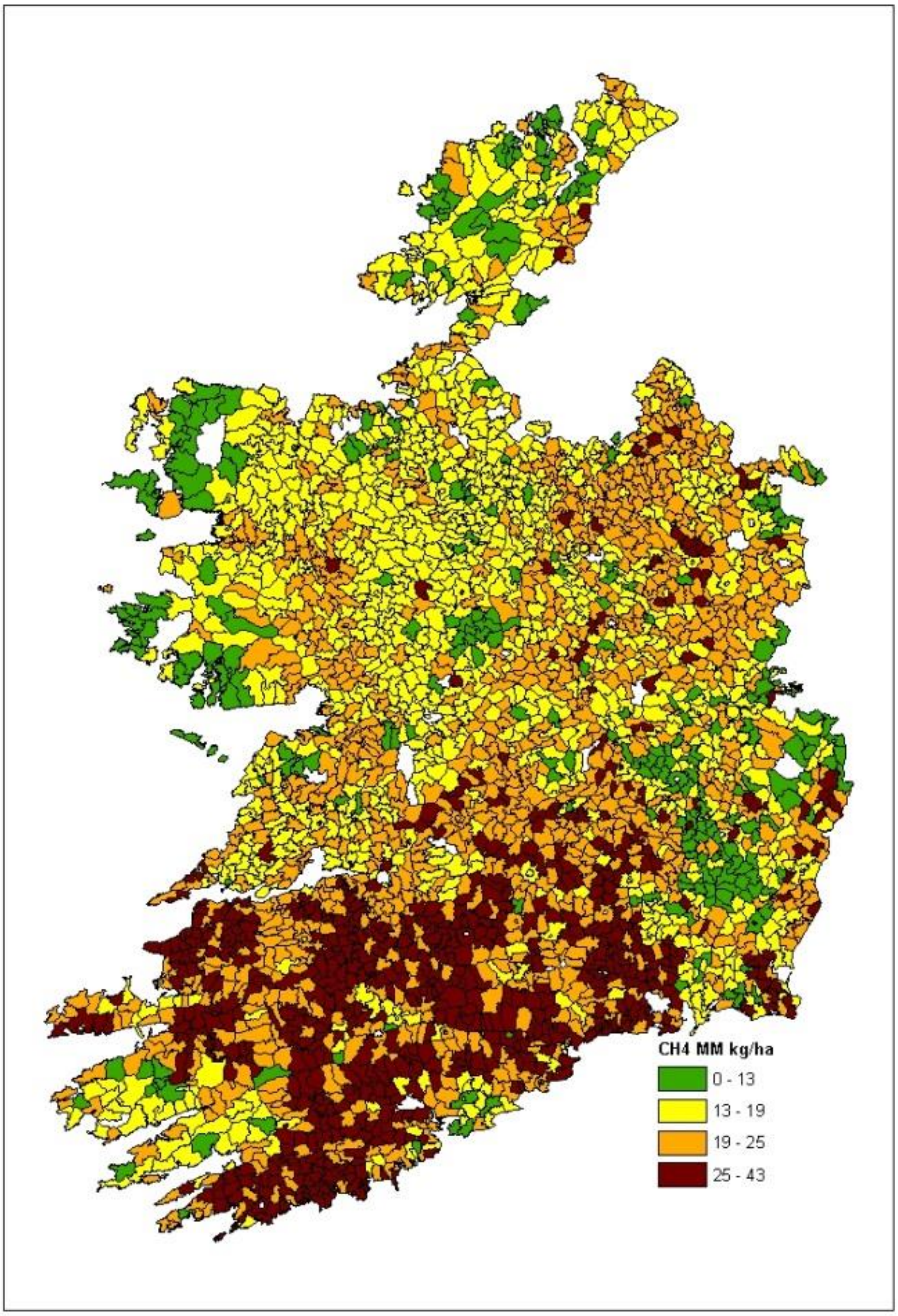


Figure 5.2 Estimated Methane (CH_4) emissions from manure management kg/ha by electoral district

Nitrous Oxide Emissions

With regard to N_2O emissions from manure management, a three stage approach is used. The first step involves the application of N excretion factors for all animal categories. The NIR report allocates the resultant N to the 3 different WMSs in accordance with national averages. Finally, for solid, dry lot, pasture and paddock it is assumed that N_2O volatizes from N at a rate of 0.19 kg N2O-N/kg N, while for liquid WMSs it is assumed that N_2O volatizes from N at a much lower rate of 0.009 kg N_2O-N/kg N (EPA, 2010). The NFS for 2008 however does not contain information on the WMS employed on each farm. As a result, the national average shares between the 3 WMSs are applied at the farm level. While at the individual farm level this is not a realistic representation of WMSs employed, it is assumed that emissions are sufficiently aggregated at the ED level in order to provide a reasonable estimate of emissions from N_2O for that ED. The inability of the model to correctly identify the WMS employed on each farm does, however, result in a loss of spatial heterogeneity with respect to emissions from liquid vs solid systems creating a smoothing effect across EDs and those EDs with a higher prevalence of liquid storage systems will experience an overestimation of N_2O, while EDs with very few liquid WMSs will benefit from some underestimation.

The output results for N_2O from soil emissions from the use of synthetic fertiliser is an interesting result as fertiliser usage is a non-matched variable which was not used either directly or indirectly in the SMILE-NFS microsimulation process. While the stocking rate ranking method preserves much of the spatial heterogeneity of livestock numbers and thus resultant emissions, the figures for synthetic fertiliser usage are the first non-match variable returned from the microsimulation process. Table 5.11 reports that the SMILE-NFS model estimates N_2O emissions from synthetic fertilisers of 5.08Gg. This figure represents about 85% of N_2O emissions estimated in the NIR of 5.96Gg. This is consistent with the figures reported in Table 5.2 where fertiliser usage from the weighted NFS is compared with that recorded in the NATACCs. Similarly, Table 5.11 reports indirect emissions of N_2O due to atmospheric nitrogen deposition and nitrogen leaching are reported at 3.56Gg representing around 90% of 3.96Gg estimated in the National Inventory Report.

Figure 5.3 displays estimated nitrous oxide emissions in kilograms per hectare from manure management and synthetic fertilisers. Again, as in Figure 5.1 an expected West-South-West, North-North-East divide is illustrated. The emissions of N_2O from manure management are largely driven by the livestock numbers and experience a smoothing effect across all EDs with the application of waste management systems based on national average shares reported in the NIR. However there are some observable differences. The impact of the location of tillage farms, which report higher levels of synthetic fertiliser use, can be seen in counties such as Louth and Meath in the North-East and counties Carlow, Kilkenny and Laois in the South East. Counties with low levels of tillage farming in the West and North-West will such as Mayo, Sligo-Leitrim and Cavan report very low average N_2O emissions per hectare. Generally, emissions of N_2O are more concentrated geographically and are centred in the main tillage areas when compared with CH_4 emissions reported in Figures 5.1 and 5.2

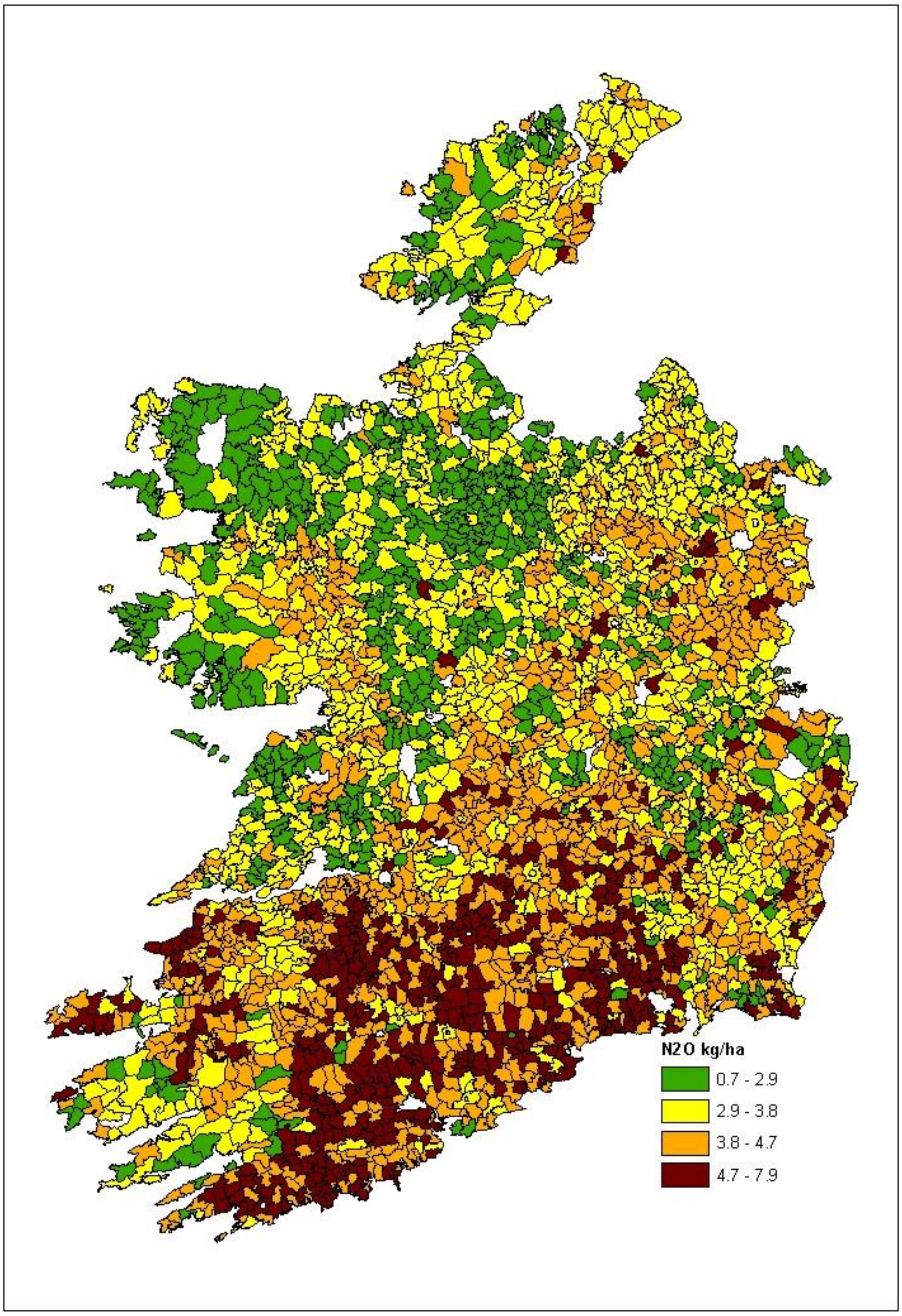


Figure 5.3 Estimated N_2O emissions from manure management and synthetic fertilisers kg/ha by electoral district

5.5.2 Agriculture Energy Emissions Output: Fuel and Electricity

In addition to emissions from livestock and agricultural soils, estimates were also derived on the emissions attributable from fuel and electricity usage (Section 5.4.). While is it assumed that farm system size and soil type are key determinants of fuel and electricity use and thus will indirectly persevere the spatial heterogeneity of consumption, fuel and electricity usage are not match variables in the SMILE-NFS microsimulation process and thus a certain amount of error is anticipated.

Figure 5.4 illustrates that agricultural emissions from fuel usage are substantially dispersed with higher concentrations witnessed in areas associated with tillage farming in the East, South East and South. In contrast, the national distribution of emissions from electricity consumption displayed in Figure 5.5 is much more pronounced with higher levels of consumption confined to areas which are dominated by highly productive dairy enterprises, e.g. in the South and South-East.

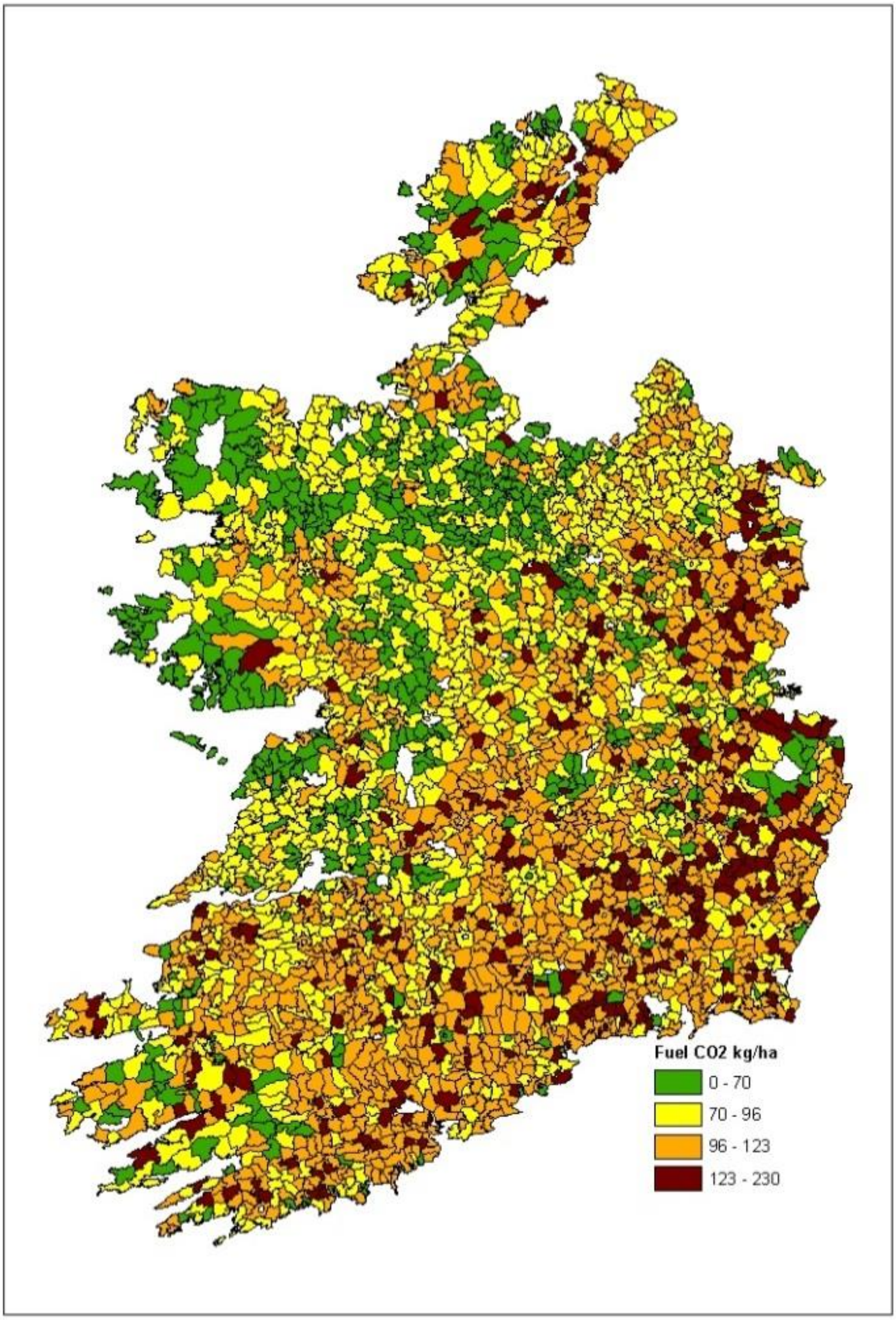


Figure 5.4 Estimated CO_2eq emissions from fuel kg/ha by electoral district

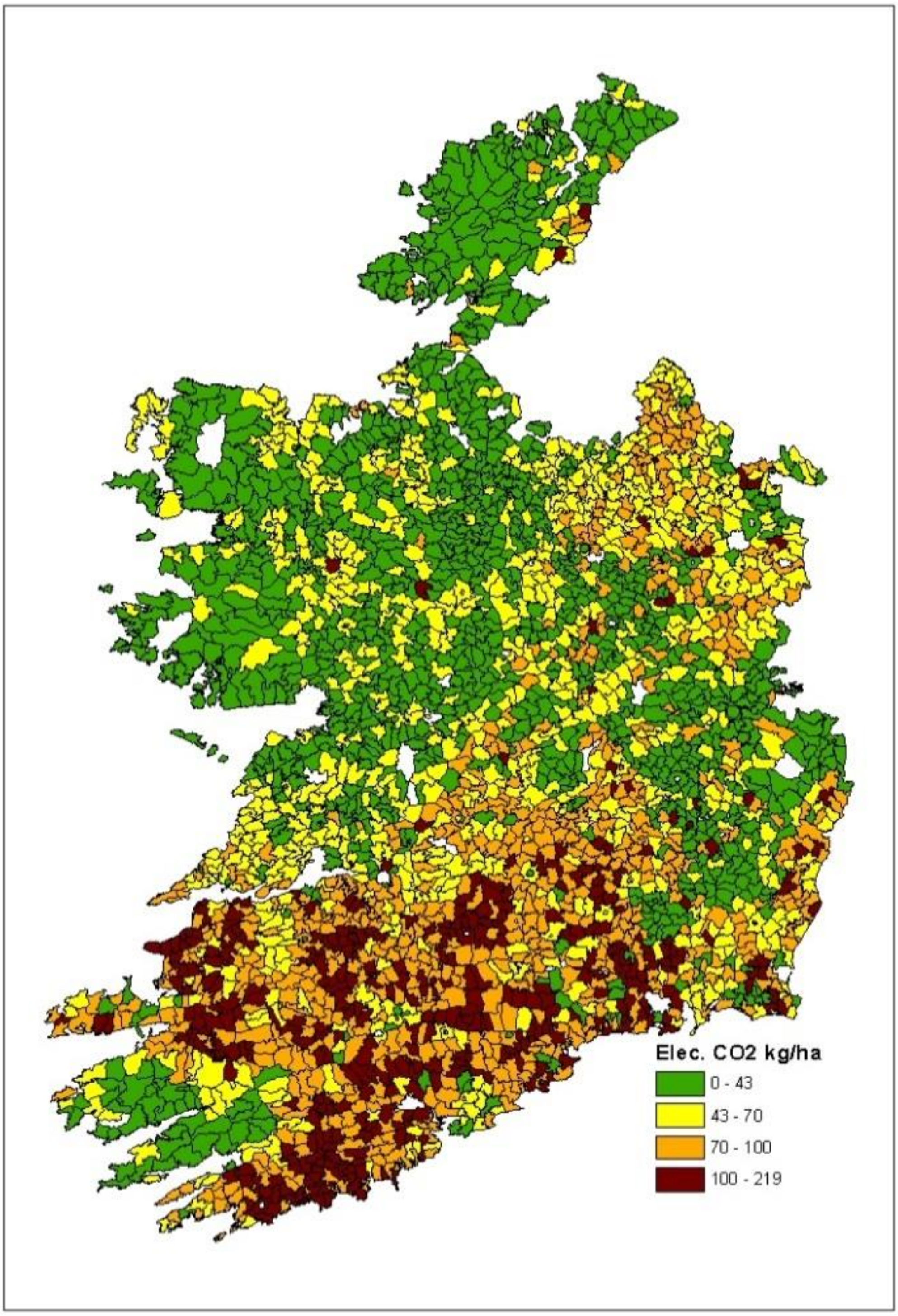


Figure 5.5 Estimated CO_2eq emissions from electricity consumption kg/ha by electoral district

A difficulty arises however when attempting to perform a reasonable validation of the estimated non-matched output as a suitable comparable aggregation of agri-emissions from fuel and electricity consumption is absent. Emissions for fuel and electricity usage from agriculture are not reported independently in the NIR. The NIR reports energy emissions from agriculture, forestry and fishing based on data contained in the National Energy Balance Report (NEBR) (SEAI, 2009b). However, from informal discussions with staff members from the SEAI's statistical unit, the assumptions surrounding agri-energy consumption make a fair comparison of emissions from the SMILE-NFS model with the NIR problematic. While the SMILE-NFS emissions are based on fuel expenditure at the farm level, with respect to fuel consumption, the SEAI estimates for fuel use are based on approximated GasOil/Diesel consumption shares supplied by the Department of Communications Energy and Natural Resources (DCNER).

Table 5.12 displays the SMILE-NFS model reporting emissions at just 46% of emissions calculated from SEAI consumption figures. While it is submitted that the data sources for this calculation are not directly comparable, a possible explanation for such a result is proffered. The NEBR figures for fuel consumption in the agricultural sector include consumption from fuel intensive agri-sectors such as vegetable crops and horticulture. Since these sectors are not captured in the NFS and a share basis on which to adjust down the SEAI figure is not available the SMILE-NFS model reports a lower level of agri-emissions from fuel use. With respect to electricity the SMILE-NFS reports emissions estimates 38% higher than those calculated from electricity consumption in the NEBR. Again, while emissions from the SMILE-NFS are based on farm-level expenditure data, the SEAI electricity estimates are based on an historical Rural/Domestic tariff surveyed ratio previously reported from the state electricity supplier.

In order to offer a reasonable comparison for the purposes of validation, emissions calculated from the SMILE-NFS are compared with results from the weighted NFS included in Table 5.12 below in order to inform a reasonable comparison of simulated output.

Table 5.12 Tons of CO_2 (000s) emitted from fuel and electricity usage SMILE-NFS vs. weighted NFS 2008

Gg of CO_2	**SEAI**	**Weighted NFS**	SMILE-NFS	**SMILE/ SEAI %**	**SMILE/ WNFS%**
Fuel Consumption	762.4	349.3	354.6	0.46	1.02
Electricity Consumption	147.3	203.4	217.0	1.38	1.07

The SMILE-NFS model reports emissions from electricity consumption of 217.0Gg of CO_2eq, 7% higher than that compared with electricity emissions calculated from the weighted NFS of 203.4Gg. Two possible explanations for this higher estimation of agricultural electricity use are as follows. Firstly, the weighted distribution of electricity usage is skewed towards and bound at zero while a number of larger outliers exist for electricity use especially in the dairy sector. Since the sampling process depends on a stocking rate residual ranking method and does not apply farm weightings the SMILE-NFS model will tend to select farms surrounding the mean first with the selection of outliers less likely. However, where outliers are selected, the tendency will be to artificially increase the mean since negative outliers are bounded at zero. Secondly, as illustrated Table 5.6 above, the correlation co-efficient for the match rate for the large farm size (>100ha) category is slightly less accurate than the lower farm size. The mean residual for the simulated against the actual largest farm size is positive meaning that across all EDs the total number of large farms sizes simulated is slightly above the total target bin totals. Since the largest electricity consumers are typically dairy farms in the largest size category this slight over selection of the largest size category will tend to increase the overall estimated electricity consumption.

With regard to fuel consumption the SMILE-NFS model reports emissions from fuel consumption of 354.6 Gg of CO_2eq representing an estimation of fuel use just 2% higher when compared with total fuel consumption emissions calculated from the weighted NFS of 349.3 Gg. As for electricity consumption, possible explanations for this disparity include the slight oversampling of high consumption tillage farms in the largest farm size, resulting in a slight overestimation of emissions from fuel consumption.

5.5.3 Spatial Mapping of Emissions from Irish Agriculture

Figure 5.6 displays the results of the first baseline spatial emissions model for Irish agriculture. Emissions are reported on a per hectare basis for each electoral district in tonnes of CO_2eq. Overall, the simulated emissions for agriculture are concentrated in the more production agricultural regions of Ireland with the highest emissions per hectare reported in areas primarily associated with dairy and tillage farming.

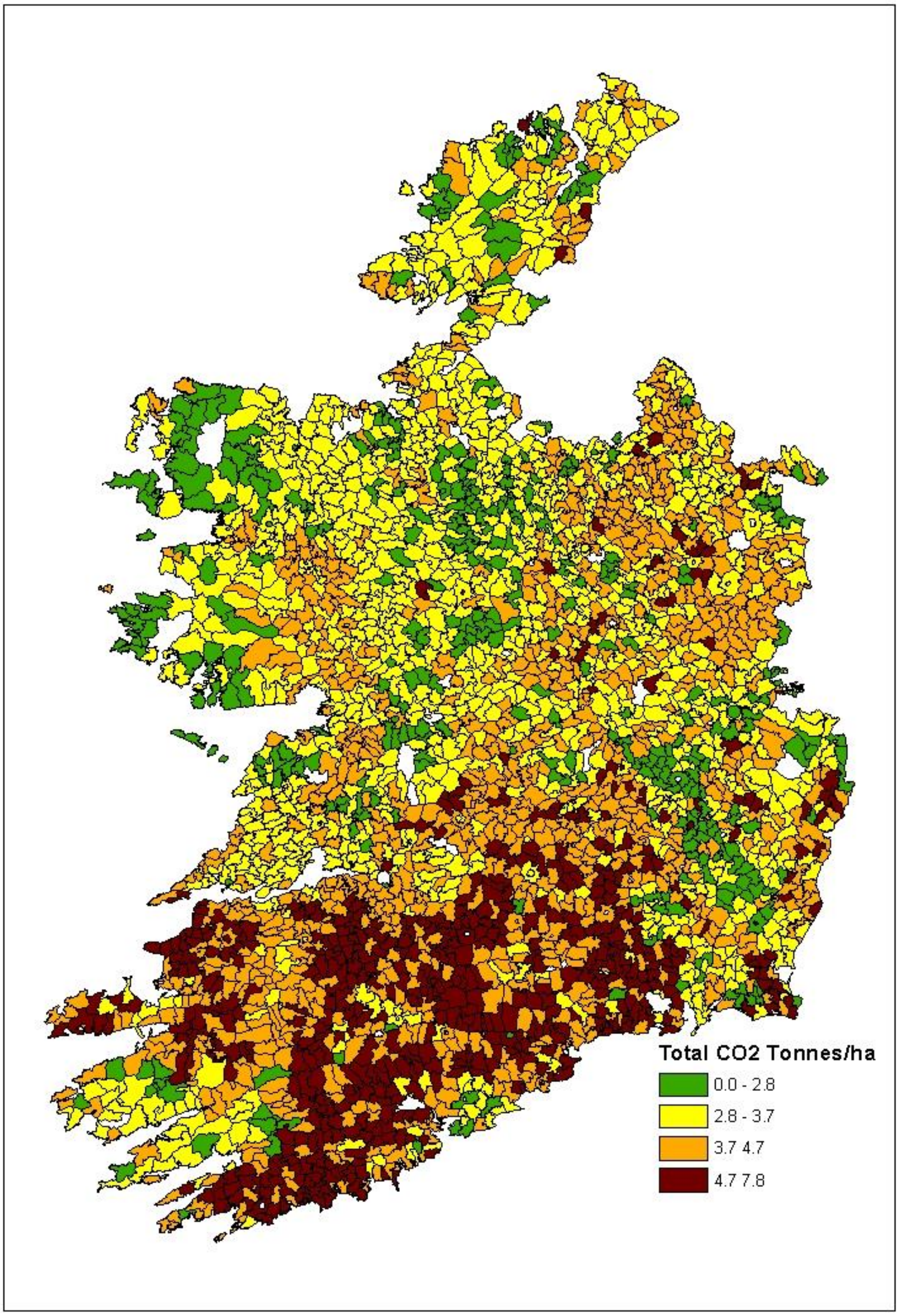


Figure 5.6 Total CO_2eq emissions tonnes/ha by electoral district: a baseline spatial emissions model for Irish agriculture 2008

Table 5.13 reports estimates for methane, nitrous oxide and total carbon dioxide equivalent emissions from agriculture from the NIR and the SMILE-NFS model (for the purposes of direct comparison with agri-emissions section of the NIR, emissions from energy use are excluded from this table).

Table 5.13 CH4, N2O and CO_2eq emissions from agriculture SMILE-NFS vs. NIR and NIR (Gg)*

	NIR	**NIR***	**SMILE-NFS**	**NIR%**	**NIR*%**
CH_4	523.01	494.77	444.65	0.85	0.90
N_2O	21.53	18.93	17.07	0.79	0.90
Total Gg CO_2eq	17657.35	16258.60	14628.04	0.83	0.90

The SMILE-NFS model estimates total national emissions from enteric fermentation, manure management and agricultural soils at 14,628Gg. This figure equates to 90% of total agri-emissions reported in the adjusted NIR* of 17,657Gg and 83% of total emissions reported in the unadjusted NIR.

5.6 Discussion

The new quota sampling microsimulation methodology adopted offers a number of benefits over previous versions of the SMILE-NFS model. In practical terms the computational efficiency of the spatial microsimulation process has improved. The simulated annealing methodology used by Hynes et al. (2008) took over two days to run on a DELL workstation with a single 3.2GHz processor, 1 MB on chip cache, 4GB (4x1024) RAM and a Windows XP operating system. Using similar hardware specifications, the quota sampling methodology delivers a simulated farm population in 6-8 hours enabling the completion of overnight model runs. This has the effect of not only reducing the computational time cost but also has practical benefits in terms of reducing the time cost associated with model attenuation and debugging. In addition the ability to deliver model output on relatively modest hardware in a reasonable time frame increases the accessibility of this method to the wider research community.

The preservation of the spatial heterogeneity of the stocking rate is a key improvement on the work of Hynes et al. (2009). The use of a residual ranking provides a means of tailoring the methodology to achieve an accurate simulation of the variability of the stocking rate for each electoral district, the key variable of interest in terms of agricultural emissions. The ranking methodology adopted means that the model is deterministic and delivers consistent results eliminating the requirement for repeated model runs.

The model represents the first baseline spatial emissions model for Irish agriculture which simulates emissions from all agricultural categories identified in the IPCC methodology. The modelling of CH_4, N_2O, and CO_2 emissions from enteric fermentation, manure management, synthetic fertilisers and carbon dioxide emissions from agricultural energy consumption at the farm level allows for possibility of studying the complex interactions and spatial diversity of outcomes associated with the implementation of national climate change policy and agricultural output targets for 2020 and beyond (Department of Agriculture Fisheries & Food, 2010). Singular or combinational policy changes can be simulated at the smallest scale with the magnitude and diversity of outcomes for individual farms available for examination; facilitating the selection of mitigation policies which will have the largest impact on emissions with the least impact on agricultural output.

While the current framework bases its emissions estimates on the IPCC methodology, the model has the capacity to be used for whole farm systems/life-cycle analysis should international agreement be reached on the interpretation of boundaries, assumptions, limitations and impacts for agricultural emissions in the future.

5.6.1 Model Limitations

With respect to the allocation of N_2O from manure management it is recognised that the application of national average shares for the waste management systems will result in a loss of spatial heterogeneity of emissions across EDs. With N_2O from manure management comprising 17% of overall agri-emissions this loss has a significant diluting effect. As a result, caution must be exercised in terms of predicted model output in determining the outcome of a policy change with respect to N_2O emissions from manure management. The inclusion of information on the farm waste management system employed in the NFS in the future would help eliminate this loss in spatial heterogeneity.

The stocking rate regression equation is performed on basis of stocking rates from the 2000 Census of Agriculture. While the regression estimates are performed on the regional uprated target totals calculated on the basis of the 2008 NFS, the time variant factors including policy decisions effecting stocking rate decisions in 2008 are not captured. Unless future agricultural policies are harmonised to achieve both environmental and productivity aims, this limitation will also apply to future predictions, as goals, changes relating to stocking rate requirements for the qualification for various agricultural schemes will affect future outcomes.

Since the stocking rate residual ranking system is based on distance between the actual mean stocking rate of the ED and it's predicted value, the SMILE-NFS model tends towards an over selection of mean farms at a national level, large outliers (in terms of the stocking rate) are much less likely to be added to any given ED. While this is a positive impact in terms of the preservation of spatial heterogeneity at the ED level, it does result in a substantial loss of intra-ED variability. This problem could be solved by limiting a farm's overall number of selections to its weighted total or perhaps a maximum multiple. However, the application of this solution could be problematic and could potentially introduce even more onerous problems such as

ED ordering. This could potentially be solved by attempting to fill all EDs simultaneously, however, the complexity and computational powers required for such an undertaking would be substantial.

A key assumption in the SMILE-NFS model is that that strength of the relationship of the match variables preserves the spatial heterogeneity of the non-matched variables of interest. The stocking rate ranking mechanism preserves the spatial heterogeneity of agricultural emissions relating to livestock. However, emissions relating to the application of synthetic fertilisers and energy consumption are based on non-matched variables from the simulated farm population. While regression models from the NFS show that farm size, soil and system are key determinants, the omission of additional factors affecting fertiliser and energy in the matching process affects the accuracy and variability of the spatial output. The selection of the match variables involves a decision process based on the availability of match data, the relationship of the match variables to the non-matched variables of interest and a pragmatic decision on the computational costs versus the associated returns from the inclusion of additional match variables. While spatial totals are not available for fertiliser and energy use at the ED level in the census of agriculture, totals for the livestock sub-categories described in Table 5.10 are available. The inclusion of an additional 13 match variables however, would have a potentially severe impact on computational cost with time frames increasing substantially with the addition of each additional constraint. It is unlikely that improvements if any on the correlations reported in Table 5.6 would be of a magnitude which would justify such cost. While the imposition of additional constraints may provide a framework to validate the spatial output of the livestock sub-categories the overall accuracy of the match across all variables is likely to decrease. As the computational costs of additional match variables decreases with the increased availability of more advanced computing power, the investigation of this option and its effect on the overall match accuracy should be investigated in the future.

5.7 Conclusions

The provision of a spatial emissions inventory has long been identified as a key aid to the design and implementation of climate change mitigation measures (Kates et al., 1998). The provision of a spatially disaggregated baseline model of greenhouse gas emissions for Ireland could play an essential part in the design and implementation of effective mitigation strategies in the future. With regard to agriculture, the National Economic and Social Council (NESC) acknowledges the climate change policy challenges facing Ireland and notes that achieving a 5% reduction in emissions by 2020 will be difficult (National Economic and Social Council, 2012). It highlights the need for a national database of scientific options and a constant review of new and existing mitigation measures. The NESC report also notes that identifying measures that reduce global emissions (LCA), can be captured and measured for the purposes of inventory, and that have costs below the carbon price, is a key priority (National Economic and Social Council, 2012).

A new methodology for the SMILE-NFS spatial microsimulation model is presented with the inclusion of a residual ranking variable designed to preserve the spatial heterogeneity of the electoral district stocking rate, a key determinant of farm-level agri-emissions. The model generates a simulated population of Irish farms from which farm-level emissions are calculated and aggregated at ED level providing an alternative methodology for the calculation of total national agricultural emissions. Results are compared with emissions calculated in the National Inventory Report and are found to be within a comparable range. Considering the two approaches rely on substantially different aggregation methods and data sources this is an important result and offers a credible basis for the spatial disaggregation and calculation of national emissions from agriculture. Results of SMILE-NFS model of farm-level emissions are presented as a standalone alternative methodology for the purposes of calculating Ireland’s total agricultural emissions output with the ability to analysis mitigation option at the local-level a significant value added component.

CHAPTER SIX: USING A DYNAMIC SPATIAL MICROSIMULATION TO ESTIMATE FUTURE EMISSIONS SCENARIOS FOR IRISH AGRICULTURE

The following chapter describes the construction of the National Farm Survey Dynamic Simulation Model (NFS-DSM), a dynamic spatial microsimulation model for Irish Agriculture using a system of panel equations constructed from data from the Teagasc National Farm Survey which facilitate the simulation of changes in agricultural output over time. Projected spatial emissions outcomes are disaggregated to electoral district level using the SMILE-NFS spatial microsimulation model and greenhouse gas emissions calculation methodology described in Chapters 4 and 5. Production, cost, and income models are estimated for the primary production sectors from panel data contained in the Teagasc National Farm Survey. In the context of ambitious targets for the agri-food sector in the form of the Food Harvest 2020 (FH2020) policy goals, and Ireland's 2020 emission obligations under the EU's Climate Action and Renewable Energy (CARE) Package these models are used to simulate production forward to 2020, using price projections from the FAPRI-IRELAND model. A number of assumptions relating to rates of exit, productivity in the dairy herd and future price projections are used to estimate future output and present a scenario for 2020 emissions outcomes for agriculture. Changes to the land base over time are simulated with resultant emissions outcomes spatially mapped to the electoral district level. The model presents a potential plausible spatial emissions output for 2020 from Irish agriculture under a business as usual (BAU) scenario. The chapter concludes with suggested options for further scenario analysis in the agri-sector.

6.1 Introduction

Ireland is seeking to rapidly expand its agricultural output in line with the aims set out in the FH2020 vision for Irish agriculture (Department of Agriculture Fisheries

& Food, 2010). The programme contains a combination of volume and value targets for the dairy and beef sectors respectively as well as targets for crops and other enterprises. The FH2020 strategy is part of a suite of Government policy initiatives designed with a view to aid Ireland's economy recovery in the wake of the 2007 financial crisis (Irish Government, 2011). Presently, agriculture remains Ireland's largest indigenous industry contributing over 7% of Ireland's GDP with the agri-food sector contributing over €24 billion to the Irish Economy (CSO, 2012) and accounting for 10% of Ireland's exports (Department of Agriculture Fisheries and Food, 2012).

However, under the terms of the EU's 2008 Climate Action and Renewable Energy (CARE) Package (Council Decision, 2009), Ireland has also made significant commitments to reduce non-ETS sector emissions by 20% by 2020, relative to 2005 levels (EPA, 2010). With Irish agriculture accounting for over 40% of Ireland's non-ETS reported emissions in 2011 there is a clear requirement for Irish agriculture to improve emissions efficiency if it is to both satisfy the aims and objectives of the FH2020 programme while supporting Ireland's emissions reduction obligations.

As outlined in Chapter 2 the presence of spatial information on greenhouse gas emissions has been identified as a key determinant in the effective implementation of climate change policy at the local level by Allman et al. (2004). The presence of micro-level information also allows for the study of the impacts of policy measures on the fundamental economic units of the state i.e. individuals, firms (farms) and households (Chapter 4). The creation of a baseline inventory of agricultural emissions as described in Chapter 5 allows for the estimation of future potential spatial emissions outcomes as a result of agricultural policies while the presence of micro-level information also allows for the estimation of the economic impacts of such measures on farm households. For example, Quinlan et al. (2006) show that spatial information on agricultural activity could be used to reduce transport emissions associated with the dairy sector with the optimal location of processing facilities. The mapping of an agri-emissions scenario for 2020 provides an opportunity for decision makers to identify potential future mitigation opportunities and develop policies at appropriate spatial scales.

Projecting a spatial 2020 emissions scenario for Ireland requires estimation of the most likely, or at minimum, plausible future development path for individual Irish farms both in terms of changes in output and the likelihood of entering or exiting the market. Previous studies on future output (Läpelle & Hennessy, 2012) and emissions (Donnellan & Hanrahan, 2011b) scenarios have been conducted at the national or macro level and while they are instructive in terms of assumptions surrounding future production paths they are inadequate in terms of providing an estimation of future output and resultant emissions at a spatially disaggregated level.

An estimation of the future growth path for the spatially disaggregated SMILE-NFS model outlined in Chapter 5 would provide a micro or farm level estimation of Ireland's likelihood to meet its future agricultural targets within existing farm structures as well provide a spatial map of emissions from the sector. The potential exists for such information to contribute to the adaptation of policy to encourage more emission efficient solutions at a local level as well as enabling integrated planning for future mitigation options. Using the SMILE-NFS baseline spatial emissions model for agriculture outlined in Chapter 5, a BAU scenario for the expansion of Irish agriculture to 2020 and the resultant spatial emissions outcomes is investigated.

6.2 FH2020 and wider policy implications

The FH2020 programme, developed by the Department of Agriculture Food and Fisheries, is a policy strategy intended to substantially increase output from the agri-food, fishery and forestry industries over the next 6 years (Department of Agriculture Fisheries & Food, 2010). Developed through a policy committee comprising of representatives from state agencies, industry representatives, academia and farm groups, the programme combines value and output targets for various sub-sectors within each industry and states that these goals should be reached sustainably; achieving the targeted growth through “smart” and “green” practices (Department of Agriculture Fisheries & Food, 2010). While the relative contribution of agriculture to Ireland’s GDP has declined considerably from the height of the mid-twentieth century, it remains one of Ireland’s largest indigenous industries with half of all exports (€10 billion in 2013) from indigenous Irish companies coming from the agri-food sector (Department of Agriculture Fisheries & Food, 2013) The development of a medium term expansion strategy for one of Ireland’s largest indigenous sectors was viewed by the Irish Government as a key component of Ireland’s strategy to recover from the economic recession attributed to the banking crisis of the late 2000’s (Irish Government, 2011). However, the achievement of future increases in agricultural output may have unintended adverse consequences in other areas of national and EU policy; namely in the form of Ireland’s international greenhouse gas emissions obligations; the potential impacts of which will depend on the nature and extent to which increases in output are offset by improvements in emissions efficiency.

6.2.1 Complementarities with Ireland’s Emissions Obligations

The FH2020 programme aims to achieve an increase in the value of primary output in the agriculture, fisheries and forestry sector by €1.5 billion (a 33% increase on the 2007-2009 average). It also aims to increase the value-added in the agri-food, fisheries and wood products sector by €3 billion (40% increase on 2008) and achieve a total export target of €12 billion for the sector (Department of Agriculture Fisheries & Food, 2010). These increases are dependent on the achievement of specific targets in a number of different sectors. These targets are predominantly focused on primary production with the wider agri-food sector benefiting from downstream processing of the increased output.

At the agricultural sub-level, the FH2020 programme outlines targets for beef, dairy, sheep, pig and poultry production as well as organics and aquaculture (Department of Agriculture Fisheries & Food, 2010). In particular, a 50% increase in the volume of milk output and a 20% increase in the value of beef output have been targeted.

These represent the key targets in terms of potential impact on future greenhouse gas emissions from Irish agriculture as these two sectors directly accounted for almost 68% of emissions in 2011 (EPA, 2013a).

Figure 6.1 shows the agricultural GHG emission shares by sector for 2011. The dairy and cattle production systems account for 22% and 46% of total emissions respectively. Sheep and other livestock including pigs and poultry account for 9% while 23% of agri-emissions are attributed to the nitrous oxide emissions from agri-soils arising as a result of the application of fertilisers for crop production including grass fodder for livestock. The IPCC methodology for agriculture, outlined in Chapter 5, primarily consists of the application of methane emissions factors to animal numbers in various classifications and the calculation of emissions arising from the application of chemical and organic nitrogen to agricultural soils (EPA, 2013a).

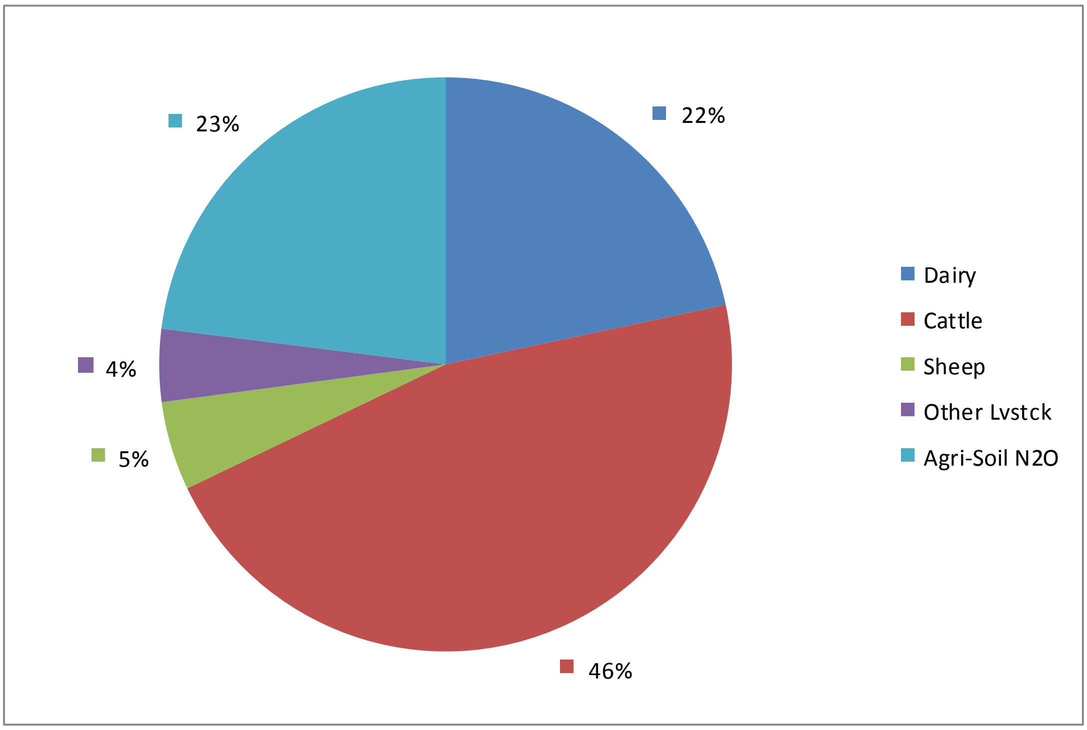


Figure 6.1 Agricultural GHG emissions shares by sector for 2011

(Source: EPA, 2013)

With the cattle and dairy sectors directly contributing to almost 70% of Ireland's agri-emissions, complementarities between the objectives of the FH2020 programme and Ireland's environmental targets are a matter of considerable debate.

Table 6.1 shows the total agricultural CO_2eq emissions by sector with total emissions from agriculture reported at 17,691 Gg for 2011 (EPA, 2013a). This accounts for 30.8% of total national emissions of 57,512 Gg.

Table 6.1 Total agricultural GHG emissions by sector 2011

Sector	**CO_2eq (Gg)**	**% Total Emissions**
Dairy*	3834	21.7%
Cattle*	8179	46.2%
Sheep*	885	5.0%
Other Livestock*	724	4.1%
Agri-Soil N2O**	4070	23.0%
Total Emissions from Agriculture* **	**17691**	**100%**

CH_4 & N_2O from ENT and MM **Includes direct and indirect soil emissions * Based on current IPCC Methodology adopted by the EPA*

(Source EPA, 2013)

Figure 6.2 illustrates that this proportion has decreased in relative terms from 35.5% in 1990 as the emissions from energy use increased significantly while emissions from Agriculture decreased by 9.9% (Duffy, 2013).

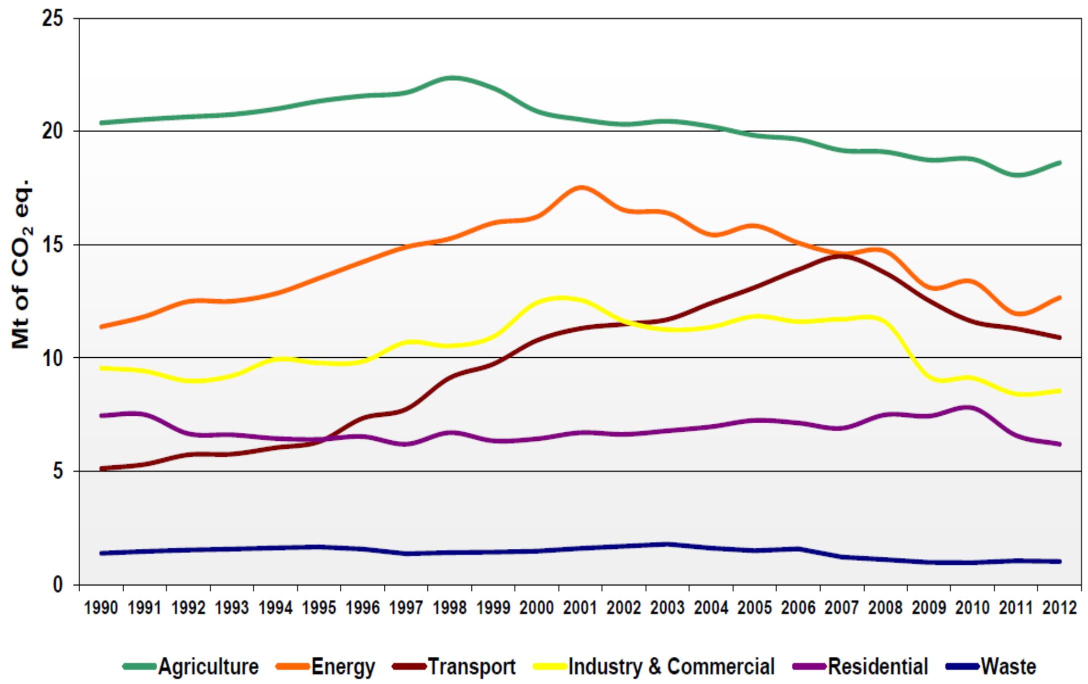


Figure 6.2 Mt of CO_2eq by sector for Ireland 1990-2012

Source: Duffy (2013)

However as shown in Table 6.2, when only the non-ETS sector is considered, agriculture accounts for over 40% of national emissions.

Table 6.2 Share of total and non-ETS emissions for 2011 from agriculture

	Total Emissions Mt CO_2	**Agri-Emissions Mt CO_2**	**%**
Total Emissions	57.3	17.7	30.9
Non-ETS Emissions	41.6	17.7	42.3

(Source: EPA, 2013)

As part of its commitment under the terms of the EU's 2008 Climate Action and Renewable Energy (CARE) Package (Council Decision, 2009), Ireland has agreed to reduce non-ETS sector emissions by 20% by 2020, relative to 2005 levels (EPA, 2010). Thus the achievement of a 20% reduction in total non-ETS related emissions while targeting a considerable expansion in a sector which contributes over 40% of those emissions would appear to be extremely challenging under the current accounting framework. To facilitate the investigation of the consequences of such a rapid expansion and its implications for future emissions scenarios, a methodology for the simulation of the changes in agricultural output over time must be developed. Furthermore, in order to provide a spatial disaggregation of future emissions, a methodology for the forward simulation of the farm population created using the SMILE-NFS microsimulation model is required. The following section describes the construction of dynamic simulation model (DSM) for the primary determinants of inputs, outputs, and incomes in the Teagasc NFS and its simulation forward to 2020. The model is then spatially disaggregated to a farm level population using the SMILE-NFS microsimulation model and the resultant emissions output under a business as usual scenario is reported with a comparison of simulated output and the primary FH2020 targets for the dairy and beef sectors are made.

6.3 Methodology

The Teagasc NFS-DSM model consists of a series of both fixed and random effects panel regression models designed to capture changes in inputs and resultant outputs and its effect on family farm incomes over time. Production and costs functions for the primary sectors contained in the NFS for dairy, cattle, sheep and tillage are formulated and inform the dependent and independent variables choosen for the panel regression models (these models are discussed in detail in the following Section 6.3.1). Output per livestock unit is modelled for the primary agri-livestock sectors captured in the NFS which is combined with modelled stocking rates to produce farm level output. Gross output per hectare is also modelled for the tillage sector. Expenditures on primary inputs such as bulk and concentrate feed, veterinary and artificial insemination (A.I) expenses, fertiliser and seeds are estimated on a per hectare basis while the model also contains an expansion model for the total adjusted farm size with land use shares recalculated annually.

Each panel regression is performed on the NFS over a ten year period 2001-2010 and validated over the same period. The model is then simulated forward from 2010 to 2020 with the aid of price projections from the FAPRI-Ireland model (Donnellan & Hanrahan, 2011b). The FAPRI-IRELAND model is an aggregate sector modelling research programme developed by Teagasc in partnership with the Food and Agriculture Policy Research Institute of Missouri (FAPRI). It was developed in order to inform analysis of future prospects for the agricultural and food sectors in Ireland. The model simulates forward dynamically such that with each iteration, values modelled for each simulated year are used as input variables for simulation for the following year where applicable.

Production changes are modelled initially with required input costs modelled for the level of simulated output. Finally, family farm incomes are calculated. The resultant output is disaggregated using an updated version of the SMILE-NFS spatial microsimulation model which statistically matches the 2010 NFS to spatial totals reported in the 2010 Census of Agriculture[32] using the novel stocking rate ranking method outlined in Chapter 5. Projected stocking rates for 2020 for each modelled farm are then used to estimate the total number of animals and consequent methane emissions from enteric fermentation and both methane and nitrous oxide emissions from manure management. Projected fertiliser usage is used to measure nitrous oxide emissions while energy and fuel use is also used to estimate carbon dioxide emissions. These projected emissions outcomes for 2020 are then presented on a per hectare basis at the electoral district level.

6.3.1 Panel Regression Models

Panel data sets have a number of advantages over individual time series or time invariant cross sectional data. The availability of repeat observations provides the opportunity to study changes of variables of interest over time accounting for the

[32] Results from the 2010 census of agriculture were released on a staggered basis from 2012 onwards and became available post the establishment of the baseline methodology outlined in Chapter 5. It was decided to update the spatial match using 2010 Census for the dynamic analysis in Chapters 6 & 7 while using Chapter 5 to illustrate a methodology for performing the sampling process in non-census years.

unique characteristics of individual micro units, be they individuals, firms, households or regions. They provide the opportunity to study dynamic change as well as more complex behavioural phenomenon such as technological change or economies of scale (Gujarati, 2003).

Equation 6.1 describes a Fixed Effects (FE) panel regression model for the *i*th individual in the *t*th time period where the dependent variable Y for individual i in time period t is a function of; the unique intercept β_{1i} for individual i, the common slope co-efficients $\beta_2$and $\beta_3$for the explanatory variables $X_{2it}$and X_{3it} and the error term u_{it}.

$$Y_{it} = \beta_{1i} + \beta_2 X_{2it} + \beta_3 X_{3it} + u_{it} \quad \textbf{(6.1)}$$

The fixed effects panel regression model assumes that the effect or slope of the explanatory variables X_2 and X_3 is common to all individuals and does not change over time. A fixed panel regression model also assumes that for each individual unit *i* there is a unique intercept β_{1i} and that while each unit's intercept is unique it does not vary over time, i.e. its effect is in essence "fixed". This may be due to certain characteristics which are unique to the individual. In the case of the farm, certain enterprises may have a more natural advantage than others which we cannot observe in the data such as the nature of the surrounding drainage, the farmland relief or the proximity to markets and local processing facilities.

In addition to controlling for individual characteristics, there may also be the need to control for external effects individual to each time period. In the case of farming, the differences in seasonal weather patterns can cause shifts in yields with for example, an extremely good summer resulting in abnormally high production levels (O'Neill & Matthews, 2001). This in turn can result in higher direct costs such as in the case of the purchase of bulk fodder in years of poor forage yields. Other changes such as shifts in government regulations and or agricultural policies may also suddenly impact changes in the dependent variable in different time periods. The inclusion of individual time dummies (D_{t1} for time period one, D_{t2} for time period two etc…) for n time periods allows the model to control for such factors (Equation 6.2).

$$Y_{it} = \beta_{1i} + D_{t1} + D_{t2} + \cdots D_{tn} + \beta_2 X_{2it} + \beta_3 X_{3it} + u_{it} \quad \textbf{(6.2)}$$

Further, it may be assumed that there is a certain rate of technological progress which affects yields or efficiency over time which is not captured in the data. While the inclusion of variables such as a farm holder's age could be assumed to be a proxy measure for experience or improvement in management skills, this does not capture increases in the general knowledge stock and can also be misleading where transfer of ownership occurs during the period of study. Changes such as the spread of knowledge of better management practices and improvements in production methods are hard to quantify. Other factors may be quantifiable but may also be expensive to measure or simply not included in the available data, for example, changes in the genetic merit of the individual farm herd (a key factor in terms of productivity) over time are not included in the NFS.

In order to attempt to capture the effect of technological progress an incremental linear time variable t is included in the model. It should be noted that as before, it is assumed that the slope or effect of the explanatory variables X_2 and X_3 is common to all individuals and does not change over time (Equation 6.3). If this assumption is violated, the problem of multi-collinearity arises.

$$Y_{it} = \beta_{1i} + t + D_{t1} \ldots D_{tn} + \beta_2 X_{2it} + \beta_3 X_{3it} + u_{it} \quad \textbf{(6.3)}$$

There is however, a further complication. It may be unreasonable to assume that the slopes of all explanatory variables are the same for all units. For instance the effect of the application of a fixed unit of fertiliser may differ slightly from farm to farm due to relief effects. While these effects can be controlled for by the inclusion of interaction dummies for each unit, this can result in a large increase in the number of variables included in the model which reduces the model's degrees of freedom and has the potential to cause further problems of multi-collinearity. Additionally, when applying this methodology to farm level data, a fixed effects model is unable to capture the effect of important time invariant production factors such as region and soil type. The preservation of farm heterogeneity in terms of these key environmental variables is an essential requirement in the development of future spatial emissions scenarios for Irish agriculture.

An alternative approach to the fixed effects approach is the Random Effects (RE) Model. Here it is assumed that it is not possible to accurately measure the individual slope coefficient for all explanatory variables. It is assumed that the individual intercept term β_{1i} is not fixed for each individual unit but is in fact composed of a random variable with a mean of β_1 and an individual error term ε_i (Equation 6.4).

$$\beta_{1i} = \beta_1 + \varepsilon_i \quad \textbf{(6.4)}$$

The Random Effects model assumes that the error term consists of two components, the individual specific error ε_i and the combined cross sectional error component u_{it}. Substituting this into Equation 6.1 gives the following equation.

$$Y_{it} = \beta_1 + \beta_2 X_{2it} + \beta_3 X_{3it} + \varepsilon_i + u_{it} \quad \textbf{(6.5)}$$

Maintaining the assumptions relating to the inclusion of time dummies and a linear time trend outlined in Equation 6.3 gives the following equation for an adapted Random Effects Model.

$$Y_{it} = \beta_1 + t + D_{t1} \ldots D_{tn} + \beta_2 X_{2it} + \beta_3 X_{3it} + \varepsilon_i + u_{it} \quad \textbf{(6.6)}$$

The random effects approach offers a solution to the problem of time invariant explanatory variables but there is a trade-off. The random effects model assumes that the individual error component ε_i is not correlated with any of the regressors. If the individual error component is in fact correlated with any of the regressors then the random effects estimators will be biased. However, if the assumption holds then the random effects estimates may be more efficient (Gujarati, 2003).

The Hausmann specification test was performed for all output (7) and cost (10) models used in the NFS-DSM model. The null hypothesis was rejected for all models except for other overhead costs, suggesting the use of a fixed effects model for all other cases. However, while the Hausman test (Hausman, 1978) offers a formal method to help choose between fixed effects or a random effects approach Johnson and DiNardo (1997) warn that there is no simple method to definitively navigate the choice between a fixed and random effects approach.

Variants of both fixed effects and random effects models have been used extensively in the Irish agricultural literature. Using fixed effects models, Breen et al. (2012) examine the production response of nitrogen while Smyth et al. (2009) investigate the seasonality of costs of production on dairy farms. Läpelle et al. (2012) use a random effects approach to examine the effects of extending grazing on dairy production. Loughrey and Hennessy (2013) also use a random effects approach to investigate hidden under employment in Irish farming, concluding that hidden forms of underemployment are of greater relevance than the more established time-related underemployment.

As discussed above a significant drawback of the fixed effects approach for use in this research is that it is unable to capture the effects of time-invariant variables such as soil and region, which are important variables in maintaining the spatial heterogeneity of simulated production outcomes and resultant emissions. Thus where possible, a random effects approach was favoured.

In order to validate the decision making process, the NFS-DSM validation process discussed in Section 6.4 was performed for both fixed and random effects for each production and cost model, with both simulation results compared to the observations over the ten year period of study (2001-2010). A multi-decision criterion was established for each model whereby the fixed effects model was used if it considerably outperformed the random effects approach. Decisions for each model were made on the basis of both annual trend line performance and the mean absolute differences between the simulated and actual outcomes over the period of validation. As a result, following this comparison a fixed effects approach was selected for four cost functions. The costs functions which use a fixed approach method are identified in the following section.

6.3.2 Key Modelling Components

The NFS-DSM model consists of a series of fixed and random effects panel regression models which estimate the effect of a series of independent variables on the key determinants of agricultural outputs, inputs and overhead costs. The following section describes the key modelling components used in the NFS-DSM model. It outlines the modelling of seven determinants of outputs and ten inputs which use both fixed effects and random effects panel estimates. The main independent variables associated with each modelled dependent variable are highlighted with full estimates for each model reported in Appendix B.

FAPRI-IRELAND Price Assumptions

The FAPRI-IRELAND model uses projections on prices, production and quantities traded in order to estimate future volume and value growth paths for agricultural inputs and outputs at a macro level (Binfield et al., 2008). It has been used extensively in the analysis of agricultural and trade policy changes in Ireland (Eg. Binfield, 2006; Donnellan & Hanrahan, 2006; 2011a).

The NFS-DSM model uses price projections from the 2010 FAPRI-Ireland model in order to provide estimated output and input prices for each sector in 2020. As the model simulates forward to 2020 from the base year (2010), movements in price are scaled linearly year on year. Prices are used to re-calculate costs and output at the end of each simulation year and are also used as dependent variable inputs where applicable.

Modelling of Gross Output

The NFS-DSM model calculates random-effects panel regression estimates for the primary determinants of output on a per hectare basis. For tillage systems, crop gross output is modelled. For the livestock sectors, value estimates for gross output per livestock unit and the number of livestock units per hectare are combined to predict gross output from the sector for each individual farm. Table 6.3 shows the seven modelled output variables for all farms by sector.

Table 6.3 Components of modelled output by sector

Dairy	Litres per livestock unit (Q) Dairy livestock units per hectare (Q)
Cattle	Gross output per livestock unit (€) Cattle livestock units per hectare (Q)
Sheep	Sheep gross output per livestock unit (€) Sheep livestock units per hectare (Q)
Tillage	Crop gross output per hectare (€)

Modelled gross output values are based upon, expenditure on feedstuffs (in the case of the livestock sectors) fertiliser usage, the area devoted to the enterprise, the presence of other enterprises as well as other farm and farm holder characteristics. Tillage output is based upon mean annual prices, fertiliser usage, the area devoted to tillage, the presence of other enterprises as well as other farm and farm holder characteristics.

It should be noted that for the gross output (value) per livestock unit models for cattle and sheep respectively, the unit price is necessarily omitted as an explanatory variable. This is due to the fact that by construction, the dependent variable is highly and perfectly correlated with the unit price. While an alternative output model on the basis of volume was considered, it is submitted that the use of livestock sales and slaughtering numbers for both cattle and sheep would be too crude a measure and therefore incapable of distinguishing between high-value and low value producers.

In the case of dairy however, the gross output volume is estimated by the average number of litres per livestock units available for each dairy farm over the ten year period of study. This approach is taken as the FH2020 target for dairy under consideration is a volume rather than a value target, thus the modelling of physical milk output and the required number of livestock units is required. The average productivity of the herd (i.e. number of litres per livestock unit) is modelled based on the stocking rate, the farm size (total area devoted to dairy is used in order to capture economies of scale), the presence of other enterprises on the farm and other characteristics of the farm and farm holder with respect to age and the presence of an off-farm income. This modelled productivity is then scaled by the number of livestock units per hectare to calculate total milk output. The total milk output is then scaled by the average annual unit price to calculate gross output for the dairy system on each farm.

Estimates for all seven determinants of farm gross output are calculated and simulated year on year with the gross output of each sector calculated as follows:

$$Dairy\ Gross\ Output = \ l_{lu} \times lu_{ha} \times ha_{dairy} \ \times P_{dairy}$$
$$Cattle\ Gross\ Output = \ fcatlego_{lu} \times fcatlelu_{ha} \times ha_{cattle} \ \times P_{cattle}$$
$$Sheep\ Gross\ Output = \ fsheepgo_{lu} \times fsheeplu_{ha} \times ha_{sheep} \times P_{sheep}$$
$$Tillage\ Gross\ Output = fcropgo_{ha} \times tillage_{area} \times P_{crop}$$

Where *ha* = hectare, *P* = unit price, *lu* = livestock unit and *l* = litres.

Direct Costs and Overheads

All direct costs are modelled on a per hectare basis for each farm. These costs are summarised in Table 6.4. The costs of purchasing of feedstuffs, veterinary expenses and A.I fees are modelled for the dairy, cattle and sheep systems. The purchase of seeds and expenditure on crop protection plans are modelled exclusively for tillage systems while expenditure on fertiliser, energy (fuel & electricity), repairs and other miscellaneous direct costs are modelled for all farms.

Table 6.4 Modelled costs by sector (€)

All Sectors	Purchase of fertiliser per hectare Direct costs including. expenditure. on repairs, fuel & electricity Other direct and overhead costs
Livestock	Purchase of Bulk Fodder Purchase of Concentrates Veterinary Expenses and Medicines A.I Fees
Tillage	Purchase of Seeds Purchase of Crop Protection Plans

For all sectors, fertiliser costs per hectare are modelled on unit prices, the share (if any) of the farm area devoted to tillage, the presence of livestock, environmental characteristics such as region and soil type and other farm characteristics effecting the quantity fertiliser applied per hectare such as the participation of the farm in the Rural Environmental Protection Scheme (REPS).

Direct costs comprising expenditure on repairs, fuel & electricity (RFE) are modelled on prices, the presence of livestock, farm size and other farm characteristics such as the presence of an off-farm occupation and the age of the farm holder. Both age and the presence of an off-farm income are found to be positively associated with direct RFE costs with younger farmers without an off-farm occupation assumed to able to supply more repair and maintenance labour hours and reduce costs associated with external labour hours. The presence of dairy livestock is also identified as a significant factor in relation to electricity expenditure due to the energy requirements associated with milking parlours. Region is not identified as a significant factor in direct RFE costs.

Other direct and overhead costs are again modelled on input prices, the presence of livestock, share of farm devoted to tillage, participation in REPS and other farm characteristics. Both direct and overhead costs per hectare were negatively associated with increases in farm size indicating anticipated economies of scale. The independent region variable dummies were not found to be a significant factor however better soil types were positively associated with lower direct costs per hectare.

Livestock related costs are modelled on unit prices, the area devoted to each livestock enterprise, the stocking rates associated with each enterprise as well as other farm characteristics. In the case of livestock feed inputs (bulk fodder and concentrates), farm environmental characteristics such as region and soil type are included in the model. These variables are included in order to control for effects of the localised environment on each farm's capacity to produce the majority of their livestock feed requirement on farm. If a farm's ability to provide the majority of its livestock primarily from fodder grown on farm is high (due to an extended growing season and favourable soil conditions) this will limit required expenditure on bought in feedstuffs. The inclusion of regional and soil type variables preserve the spatial heterogeneity of feed costs across the country controlling for other farm characteristics. Expenditure on veterinary expenses, medicines and A.I. are as expected to be strongly and positively associated with the stocking rates for each livestock sector.

For the tillage sector, positive associations with tillage area, and the better soil types were apparent for both the purchase of seed and crop protection plans. As expected, negative associates were identified with the presence of other enterprises on the farm while a negative association for expenditure per hectare was identified with an increase in the age of the farm holder.

Changes to farm size

In order to capture the gradual changes in the land area utilised by each farm over time the determinants of the total adjusted farm size are estimated using a random effects regression for the period 2001-2010 and modelled forward to 2020. The adjusted farm size has gradually increased over the 10 year period 2001-2010. An important distinction between the total physical agricultural area on the farm and the total adjusted farm size is made. The adjusted farm size comprises the total forage and tillage areas devoted to the four primary sectors captured in the NFS namely the dairy, beef, sheep and tillage sectors. This includes the equivalent forage area required to produce purchased fodder. For the livestock sectors this allows for a consistent modelling of the stocking rate across farms reflecting the intensity of production. The adjusted farm size is the total land equivalent that is farmed by the holder in each year and is estimated for all farms on the basis of region, soil type, the presence of livestock, tillage and/or other enterprises, the characteristics of the farm and farm holder. The adjusted farm size is modelled for all farms and is simulated year on year for each farm in the NFS.

Table 6.5 summarises the 7 output variables and 11 input/cost variables included in the NFS-DSM model, their abbreviations used in the later analysis and whether a fixed effects or random effects model was employed. Changes to farm capital assets and long term liabilities are assumed to be fixed and are not considered in the simulated production model.

Table 6.5 Summary of all modelled output, inputs and change in land base

Sector	**Input Variables**	**Abbrev.**	**Model (Fixed (FE) or random effects RE)**
Dairy	Litres/Livestock Unit Livestock Units/Hectare	l_lu lu_ha	RE RE
Cattle	Gross Output/Livestock Unit Livestock Units/Hectare	cattlego_lu cattlelu_ha	RE RE
Sheep	Gross Output/Livestock Unit Livestock Units/Hectare	fsheepgo_lu fsheeplu_ha	RE RE
Crop	Crop Gross Output/Hectare	fcropgo_ha	RE
Sector	**Output Variables**	**Abbrev.**	**Model (Fixed (FE) or random effects RE)**
Livestock Sectors	Purchase of Concentrates Purchase of Bulk Fodder A.I Costs Veterinary Costs	fdpurcon_ha bulkfodder_ha fdaifees_ha fdvetmed_ha	RE RE RE FE
All Sectors	Fertilizer Costs Other Direct Costs Car/Elec/Tel Costs Other Overhead Costs Total Adjusted Farm Size	fertiliser_ha oth_dc_ha car/tel/elc_ha oth_oc_ha totadjfarmsize	RE FE FE FE RE

Exit from Dairy

In the ten year period of study of the weighted Teagasc NFS, there were 95 exits from the dairy sector recorded in the national survey representing approximately 2%

of the total number of observations and a weighted annual exit of approximately 3% per annum. It should be noted that these were not exits from the survey but instances where milk was produced in one year and ceased in the following year with the remaining farm area devoted to the remaining enterprises. In order to ensure a plausible representation of future milk volume output, the NFS-DSM model incorporates a stochastic component for the probability of exit from the sector

Logistic regression estimates for exiting dairy are calculated from the NFS panel and are then simulated on the base year, identifying those dairy farms most likely to exit. Bragg and Dalton (2004) identified that the age of the farmer, the presence of an off farm income, lower returns over variable cost and a greater diversification of farm income significantly influence the exit decision while Läpelle et al. (2012) model dairy exit on those farms with the lowest net margin return. The likelihood of exiting dairy for the FH2020 model is assumed to be a function of farm characteristics (region, soil type, farm size, land value, share of land devoted to dairy), profitability (gross margin quintile) and additional socio-economic characteristics such as the age of the holder and the presence of off-farm income. Given the relatively small sample size the following simple pooled logit regression for dairy exit is performed (Equation 6.7).

$$\ln\left[\frac{p}{1-p}\right] = \alpha + \sum\beta x + e \quad \textbf{(6.7)}$$

Where ln[p/(1-p)] = log odds ratio of exiting dairy.

Used in conjunction with a stochastic component, farms are then simulated to exit the sector for the following year. The rate at which farms exit is determined by setting an alignment condition based on historical rates of exit. Farms are ranked in order of those most likely to exit and are then stochastically selected using a random number between 0-1 drawn from a uniform distribution. A farm is determined eligible for selection to exit if the randomly drawn number is less or equal than the probability of exit (Equation 6.8, 6.9), otherwise the farm is deemed ineligible for selection.

$$if\ rand < Prob_{exit}\ , let\ exit_{dairy} = 1 \quad \textbf{(6.8)}$$
$$if\ rand\ \geq Prob_{exit}\ , let\ exit_{dairy} = 0 \quad \textbf{(6.9)}$$

The model then selects the ranked order of farms eligible to exit until the alignment total is reached. While the average annual rate of exit over the ten year period was approximately 3%, the rate of exit is skewed towards the early part of the decade with the rate of exit decreasing as the rate of restructure within the dairy sector slows. Thus, an annual exit rate of 2% p.a was simulated for the dairy sector falling to 1% post the abolition of the milk quota in 2015. It is important to note that when a dairy farm is selected to exit, it is assumed that the total area vacated by the dairy enterprise will be consumed by the remaining enterprises on the farm. The former dairy area is transferred pro-rata to the remaining enterprises on the farm.

In terms of considering the modelling of exit from other sectors, in the case of cattle, recorded historical exits from cattle enterprises are much lower than dairy with just 29 exits observed in the weighted sample over the 10 year period. This presents a substantially static picture in terms of cattle enterprise and the number of observations was deemed insufficient in terms of sample size to simulate exit from the sector. Similarly while a relatively high number of exits from the sheep sector were recorded in the early 2000s, exits dropped considerably by end of the survey period leaving sheep farms numbers largely static. In respect of the tillage sector, given the small number of tillage farms in the weighted sample, and the low levels of recorded exits, simulating exits would introduce an unjustifiably high margin of error in terms of simulated crop output and was therefore not undertaken.

Considering the challenges relating to sample size and other methodological issues, it was considered that the simulation of exit from other farms sectors would substantially increase the modelling complexity and increase the variability of outcomes due to the additional stochastic components involved, with no guarantee of the addition of accuracy and subsequent value to the model.

6.3.3 The effect of quota on productivity in the dairy sector

In constructing the panel model for productivity in the dairy sector, the random effects model for litres per livestock unit includes a linear time trend variable outlined in Equation 6.3 above. The linear time trend variable, *year,* was found to have a significant positive effect on litres per livestock unit. It is presumed that this effect represents the natural rate of efficiency improvement due to technological progress, be that as a result of an improvement in management practices or a gradual increase in the genetic merit of the herd. However, while the effect of *year* is both positive and significant its magnitude is extremely small. There are a couple of possible reasons for this. Firstly, while a farmer may control productivity per animal within certain ranges (i.e. through feed restriction or the use of concentrates) in response to changes in milk prices, productivity per animal on each farm is physically limited or upper-bounded to the generic merit of each individual herd (Mee et al., 1999) and it may well be that in certain years and at certain price levels some dairy farms are already producing at the upper limit bound for the genetic merit of their particular herd. More likely however, is that productivity per animal may also be effectively upper-bounded on many farms due to the existence of the milk quota[33]. The presence of a quota makes it very difficult to estimate from historical data which farmers are likely to make productivity gains and at what rate (Läpelle & Hennessy, 2012).

While improvements in unit output per animal can be achieved gradually over time through both increases in the genetic merit of the herd and the refinement of management practices through greater experience, these effects are hard to elicit with quota in effect. The extent to which the farmer is able to balance efficiency gains

[33] The Milk Quota Regulations (SI 227/2008) provide for the payment of a levy, on milk deliveries in excess of Ireland's annual national quota. The liability of individual producers who have exceeded their quota is established after the reallocation of unused quota. (DAFM, 2014; Irish Government 2008)

through adjustments in stocking rate or feed mix while maintaining levels of productivity in line with quota would also weaken the relationship of the time trend and productivity per animal. Ultimately, the complex range of management options open to the dairy farmer in response to changes in annual milk prices in a pre-abolition quota era are likely to explain why a highly significant but weak relationship between the annual time trend and productivity per animal was found.

6.3.4 Overall Structure

It should be noted that the panel model estimates and subsequent simulations are independent of the microsimulation sampling process itself. The panel models are estimated on the weighted NFS, over the period 2001-2010. Each individual sample farm is then simulated forward to 2020. Independent of this process, the 2010 NFS is repeatedly sampled to aggregate spatial totals for each ED in the 2010 CoA using the novel stocking rate ranking methodology outlined in Chapter 5 (Section 5.4) providing a spatially disaggregated farm population for 2010. Each farm has a unique identification number which allows the model to record which farms have been sampled to each ED. For computational efficiency, this information on the original 2010 disaggregation is recorded in a separate data set which is then later used to spatially disaggregate the NFS after is has been simulated forward to 2020. This means that only circa 1,000 farms rather 100,000 farms are required to be simulated forward to 2020 with the 2020 farms disaggregated post simulation to the original 2010 spatial disaggregation. This ensures that the sampled farm profile of each ED in 2020 is the same as in the base year of 2010, i.e. no switching has occurred. This provides the basis for a consistent simulation and a legitimate like for like comparison of outcomes between 2010 and 2010. Since each NFS sample farm is only sampled to EDs within their own region and with the same soil type, spatial heterogeneity in terms of simulated future outcomes is predominantly preserved.

With regard to the simulation process itself, estimates on the 2001-2010 weighted panel of the NFS are used to simulate each farm in the 2010 NFS sample data set forward year on year to 2020. This happens in the following order for each simulation year. Firstly, the year (a dummy variable used to reflect the marginal technical rate of progress in terms of increasing outputs or reducing costs) and the age of the farm holder are increased by one year. Additionally, prices for all farm outputs are changed to the projected price for that simulation year based on the scaled price projections from the FAPRI-IRELAND model. Secondly, any transitions modelled from the previous year are applied. Thus if, a farm in the previous year has simulated to exit in the following year, they are no longer identified as a dairy farm, the models for dairy production are no longer applied to the farm and the remaining land base is distributed to the remaining enterprises on the farm. Thirdly, saved estimates from the panel regressions are used to predict the new outputs and the amount of inputs required for the new output. The order of simulation for each of the 17 panel models follows the order of the model estimates reported in Appendix B. Estimates from a logit regression on the probability of exiting dairying are applied with a number of farms simulated to exit the following year (Section 6.3.2). Finally, incomes and costs are recalculated to provide an estimate of the change in family farm incomes while changes in stocking rates are used to recalculate resultant emissions outcomes.

6.4 Validation

In assessing the validity of model specification and the assumptions relating to rates of exit, a validation procedure was carried out on the NFS-DSM model. All models were estimated over the ten year study period 2001-2010. The independent variable estimates are saved and then simulated over the same period using 2001 as the base year.

The validation procedure is predominantly stable with a random element introduced through the stochastic selection of dairy exits limited by the prescribed exit rate of 2% per annum. With the dairy, cattle and sheep livestock sectors accounting for almost three quarters of emissions from the agri-sector (EPA, 2013a) the accurate estimation and plausible simulation of future stocking rates is a primary requirement in order to provide a plausible estimation of future spatial disaggregations of emissions from Irish agriculture. Results from the validation procedure for the simulation of stocking rates for the dairy cattle and sheep sectors are presented below with model validation outcomes for all models used in the NFS-DSM presented in Appendix C.

In Figure 6.3 the red line displays the simulated mean annual values for dairy livestock units per hectare while the blue line represents the actual values reported in the NFS for the 10 year period 2001-2010.

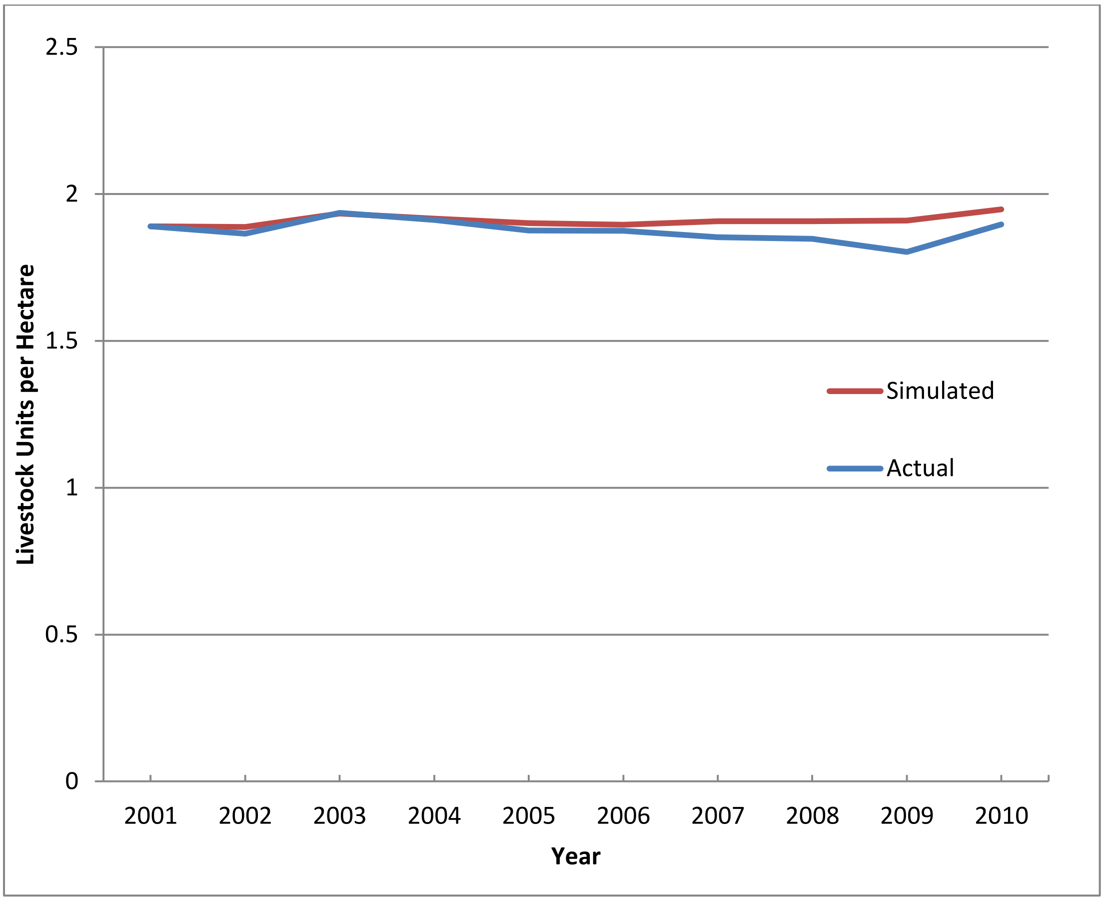


Figure 6.3 Dairy: Simulated vs. actual mean values for dairy livestock units per hectare 2001-2010

Table 6.6 shows that the NFS-DSM model returns a value of 1.957 livestock units per hectare in the final simulation year of 2010 with an actual value of 1.896 reported in the NFS. This represents a 3.2% overestimation of the mean stocking rate for dairy with a mean absolute difference of 3.1% recorded over the 10 year period.

Table 6.6 Simulated vs. actual mean values for dairy LUs per hectare 2010

Year	Simulated	Actual	Ratio sim/act
2010	1.957	1.896	1.032

In Figure 6.4 the red line displays the simulated mean annual values for cattle livestock units per hectare while the blue line represents the actual values recorded in the NFS for the simulation period.

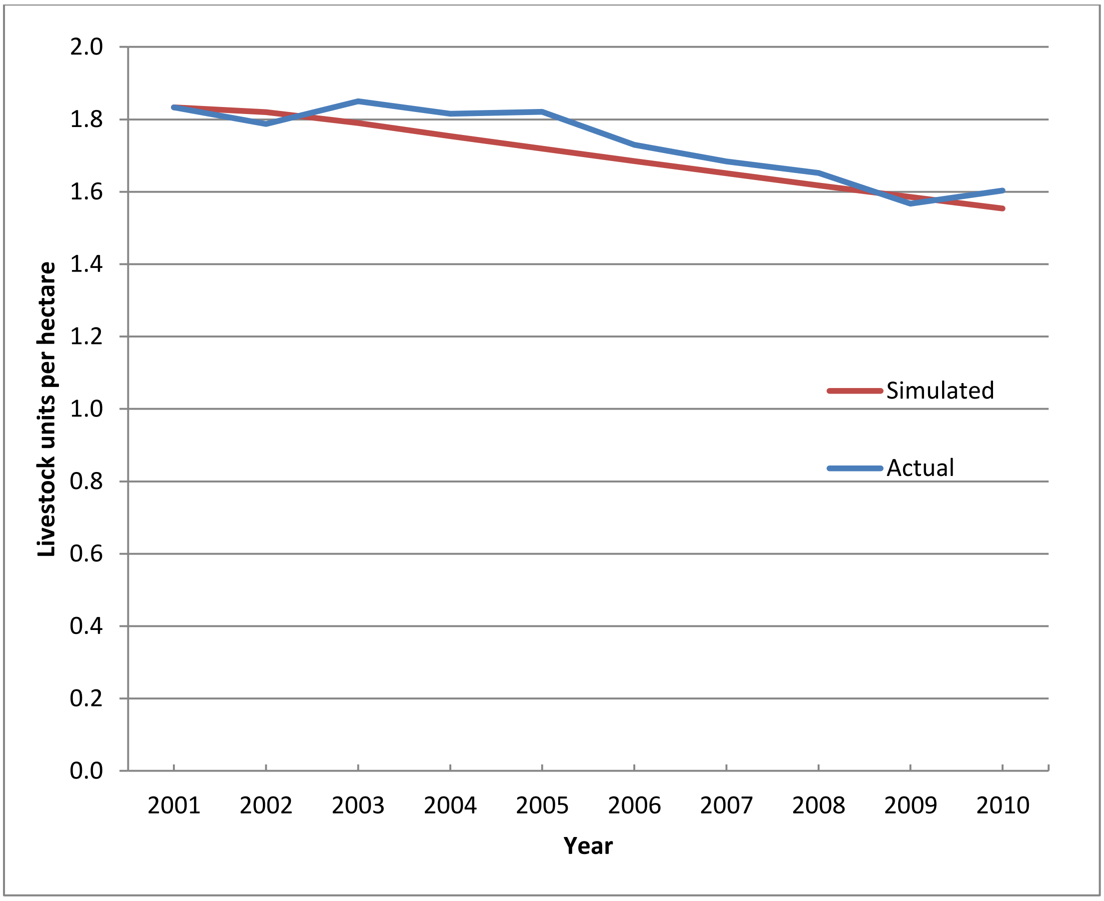


Figure 6.4 Cattle: Simulated vs. actual mean values for cattle livestock units per hectare 2001-2010

Table 6.7 shows a value of 1.359 livestock units per hectare in the final simulation year of 2010 with an actual value of 1.423 reported in the NFS. This represents a 4.5% underestimation of the mean stocking rate for cattle with a mean absolute difference of just 2.5 % recorded over the 10 year period.

Table 6.7 Simulated vs. actual mean values for cattle LUs per hectare 2010

Year	Simulated	Actual	Ratio sim/act
2010	1.359	1.423	0.955

In Figure 6.5 again the red line displays the simulated mean annual values for sheep livestock units per hectare while the blue line represents the actual values recorded in the NFS.

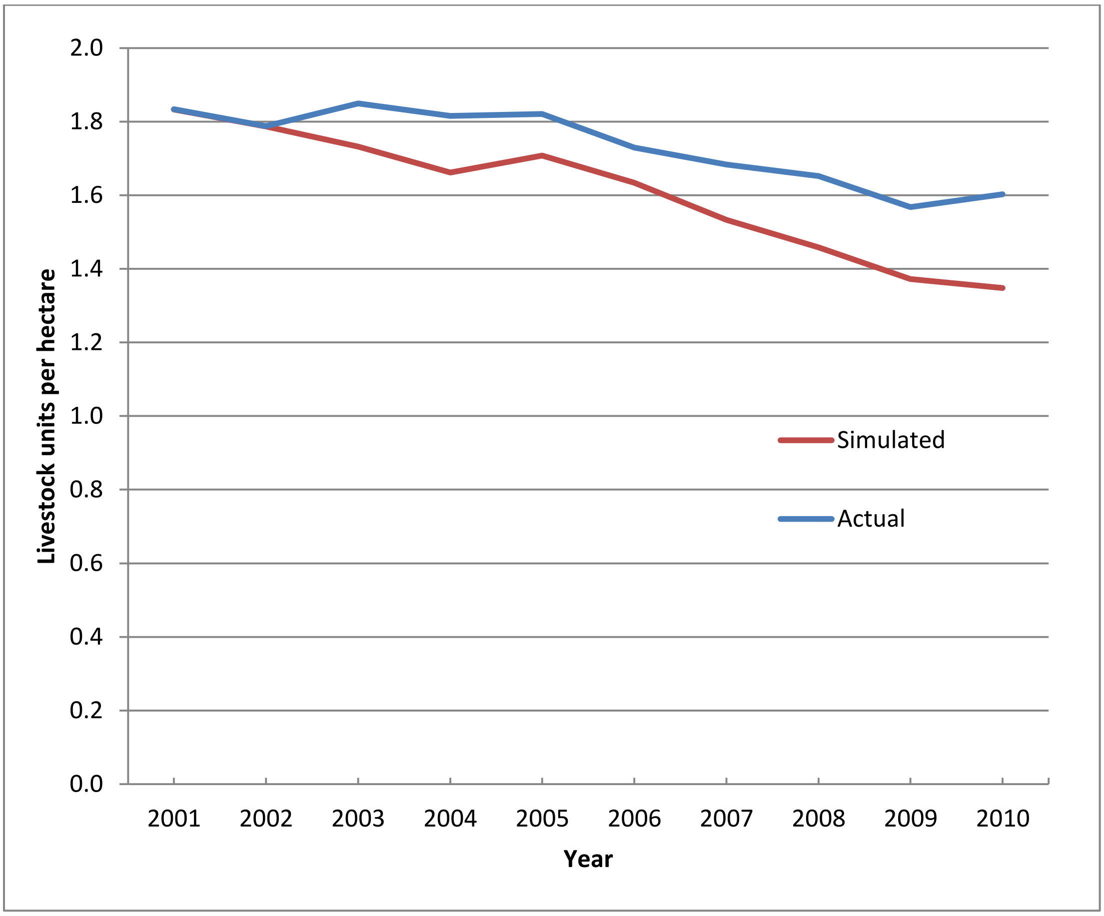


Figure 6.5 Sheep: Simulated vs. actual mean values for sheep livestock units per hectare 2001-2010

Table 6.8 shows a value of 1.348 livestock units per hectare in the final simulation year of 2010 with an actual value of 1.603 reported in the NFS. This represents a 16% underestimation of the mean stocking rate for sheep with a mean absolute difference of 7.1 % recorded over the 10 year period. While the annual simulated stocking rates for dairy and cattle are deemed to be reasonably accurate the simulated stocking rate for sheep indicates that the model is overestimating the negative annual trend.

Table 6.8 Simulated vs. actual mean values for sheep LUs per hectare 2010

Year	**Simulated**	**Actual**	**diff**
2010	1.348	1.603	0.84

One possible explanation for this is that the gradual growth in the adjusted farm size (outlined in Section 6.3.1), is allocated pro rata to all farm enterprises. In instances where farms are operating a mixed enterprise system, the sheep enterprise may typically have the largest share of total farm size due to large areas under marginal grazing such as hillsides and commonage. Thus it may be unrealistic to increase the forage area devoted to sheep enterprises pro rata, with the implicit negative relationship between increases in sheep forage and the resulting simulated stocking rate. In order to preserve the stocking rate levels while also preserving the heterogeneity of outcomes an attenuation factor was introduced in the model where a change in stocking levels of no greater than 3% per annum would occur. Figure 6.6 illustrates the effect of this measure.

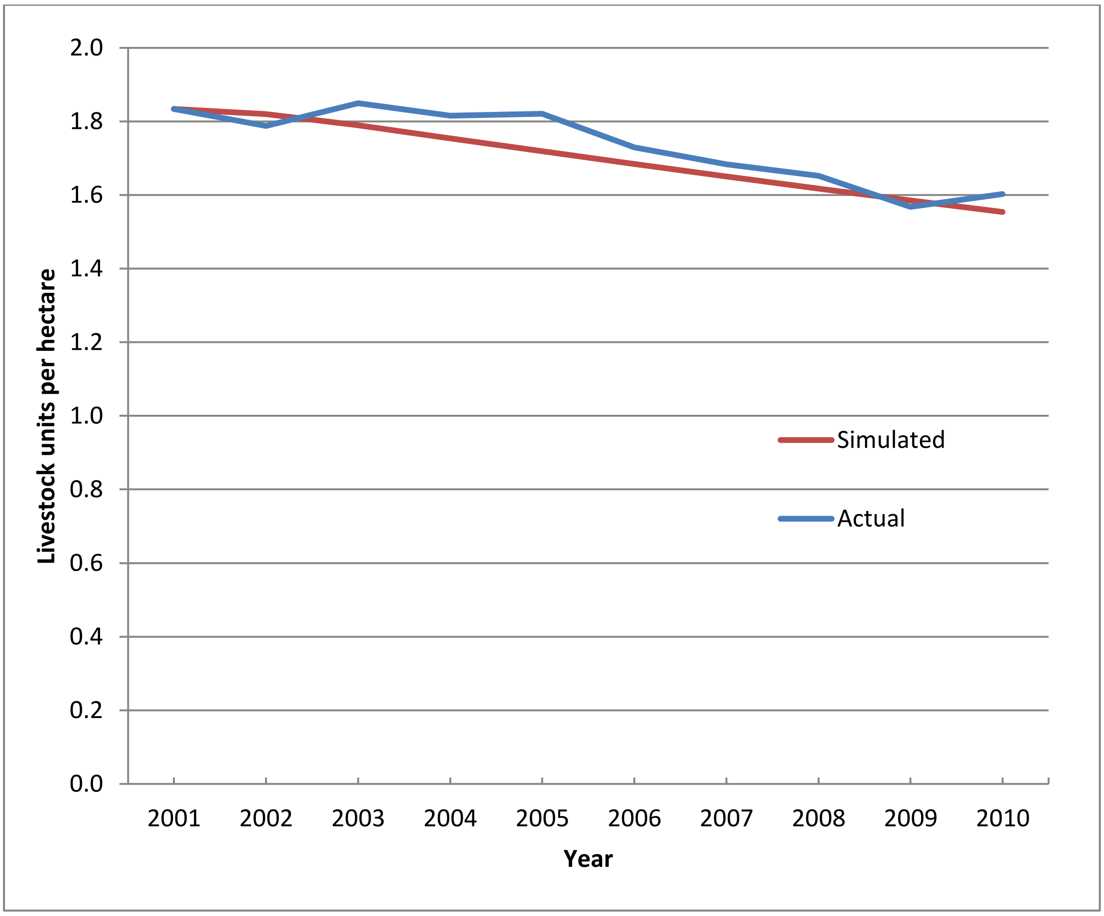


Figure 6.6 Sheep: Simulated vs. actual mean values for sheep livestock units per hectare 2001-2010 adjusted

The attenuation measure to limit annual stocking rate changes to no greater than 3% per annum, results in improvement in the projected stocking levels. Table 6.9 shows the adjusted mean value of 1.518 livestock units per hectare in the final simulation year of 2010 with an actual mean value of 1.603 reported in the NFS resulting in a 5% underestimation of the mean stocking rate for sheep over the ten year period.

Table 6.9 Adjusted simulated vs. actual mean values-sheep LUs per hectare

Year	Simulated	Actual	diff
2010	1.518	1.603	0.95

While the attenuation of the stocking rate model for sheep introduces an additional deterministic component into the model, it is submitted that its inclusion improves the likelihood of a more realistic outcome for mean stocking rate levels. While still allowing for some measure of heterogeneity among farm outcomes the inclusion of this attenuation measure will result in some smoothing of outcomes. The decision to include any attenuation measure involves balancing the preservation of heterogeneity with the preservation of reasonable national total outcomes for emissions.

As outlined in Chapter 5, spatial information on emissions at the local level has been identified as a key requirement for the effective implementation of climate change policy, by increasing the ability of policy makers to create targeted mitigation strategies at sub-national/regional scales and track progress at the local level (Allman et al., 2004). Thus a key requirement in providing a spatial emissions model for 2020 under a business as usual scenario is the preservation of regional and local level heterogeneity. However, this chapter also aims to assess total emissions projected under a business as usual scenario in the context of the aims of the FH2020 programme. With the sheep sector making up 5% of total national emissions, the marginal loss in heterogeneity in this sector can be justified in order to provide a more accurate estimate for future national sheep numbers providing the opportunity for a more accurate assessment of the change in total national agri-emissions under a business as usual scenario.

6.5 Results

Results are presented for the outcome of a business as usual (BAU) scenario for Irish agriculture for 2020. In terms of emissions, the overall trend is of a slow gradual decline in activity across all sectors with total livestock numbers falling for the dairy, cattle and sheep sectors. Coupled with declines in gross output per livestock unit this leads to a considerable reduction in gross value output for the cattle and sheep sectors despite marginal increases in the total adjusted farm size devoted to both enterprises. The dairy sector however is projected to offset the reduction in stocking rate levels through increases in productivity and while it presents a largely static picture in terms of value output, total milk output is projected to increase by approximately 3%.

6.5.1 Changes at Farm Level

The following figures display the changes of mean output, stocking rates and changes in farm size at farm level. The black vertical line displayed on all trend graphics indicates the start of the simulated outcomes. All information to the left of the black line is actual data taken from the Teagasc National Farm Survey with all information displayed to the right is produced from the NFS-DSM.

Stocking Rates and Productivity

Figure 6.7 displays the mean stocking rates simulated for dairy, cattle and sheep respectively over the ten year period 2010-2010. For comparative purposes the graph also includes the actual change in the mean stocking rate recorded for the estimation years 2001-2010. The graph shows a gradual decline in stocking rates for both the dairy and cattle sectors with a more pronounced decline in stocking rate for the sheep sector. For all graphs, data left of the vertical black line indicates observed data while date on the right represents the modelled outcomes from the NFS-DSM model

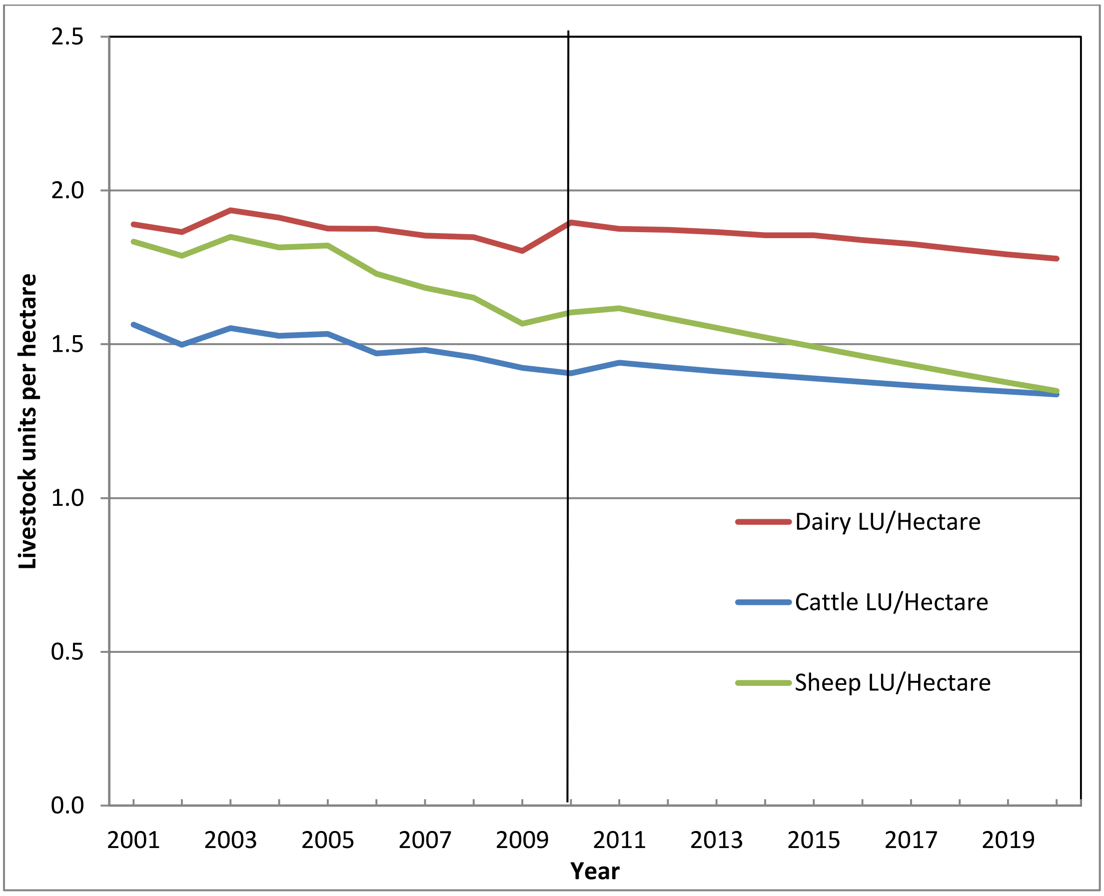


Figure 6.7 Simulated mean stocking rates for dairy cattle and sheep 2010-2020 under BAU scenario

Table 6.10 summarizes the change in mean stocking rate values for all three sectors. The mean stocking rate for dairy falls from 1.896 LUs/hectare to 1.778 representing a decline of 6.2%. For cattle the mean stocking rate falls from 1.405 LUs/hectare to 1.336 representing a decline of 4.9% while for sheep the mean stocking rate falls from 1.6 LUs/hectare to 1.348 representing a decline of 15.9%.

Table 6.10 Simulated change in mean stocking rates for dairy cattle and sheep

Year	Dairy LU/Hectare	Cattle LU/Hectare	Sheep LU/Hectare
2010	1.896	1.405	1.603
2020	1.778	1.336	1.348
% change	-6.2	-4.9	-15.9

Gross Output

In terms of mean gross output per livestock unit Figure 6.8 displays the mean gross output per livestock unit for the cattle and sheep sectors. The data shows a largely static picture for the cattle sector, with a consistent decline in the order of 1-2% per annum projected for the sheep sector.

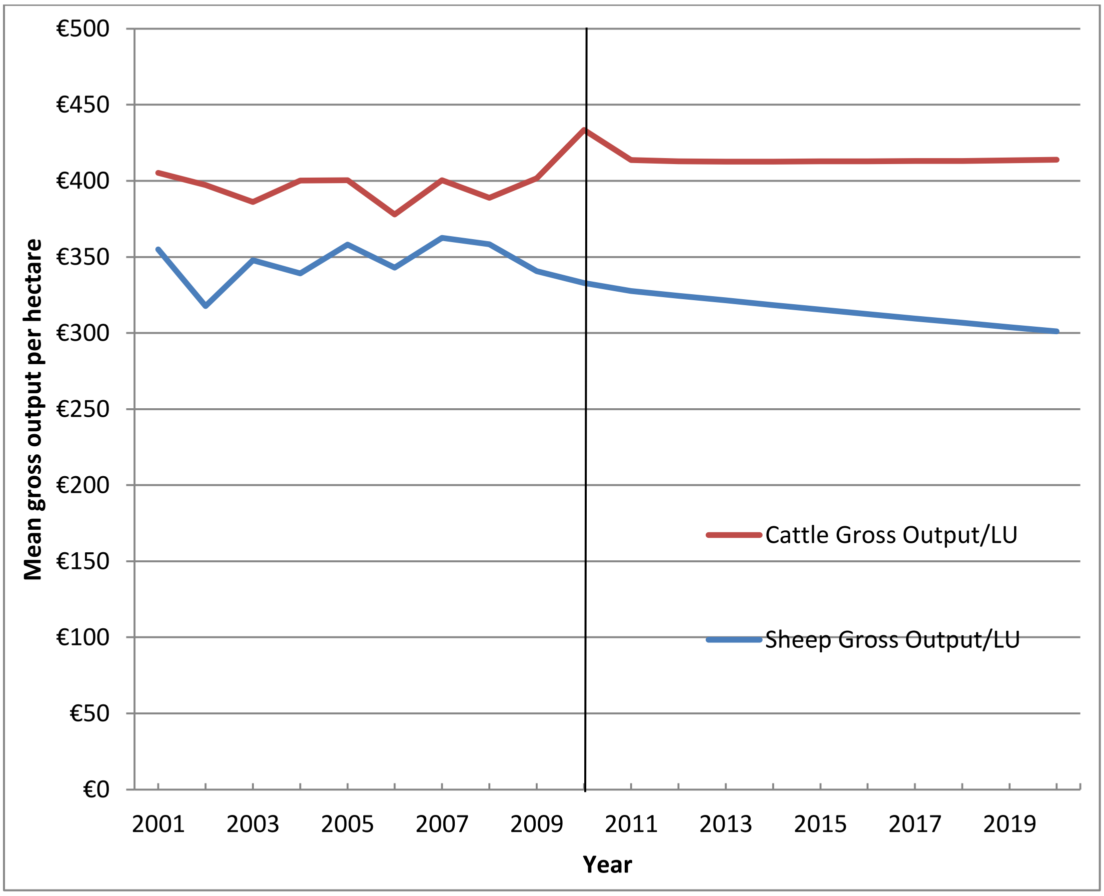


Figure 6.8 Simulated mean gross output for cattle and sheep 2010-2020 under BAU scenario

Table 6.11 summarizes the change in mean gross output per livestock unit for cattle and sheep. The mean gross output per livestock unit for cattle falls from €433/LU to €413/LU representing a decline of 4.5%. However, all of this decline is accounted for in the first year of simulation as the positive dummy effect (Equation 6.2) for 2010 is removed, leaving a marginal gradual increase in gross output for the remaining years of the simulation. The mean gross output per livestock unit for sheep falls from €333/LU to €301/LU at a rate of approximately 1-2% per annum representing an overall decline of 9.5%.

Table 6.11 Simulated change in mean stocking rates for dairy cattle and sheep

Year	Cattle Gross Output/LU	Sheep Gross Output/LU
2010	€433.42	€332.95
2020	€413.81	€301.02
% change	-4.523	-9.590

With respect to dairy, given that the FH2020 target consists of a volume rather than a value target the annual mean change in litres per livestock unit is displayed in Figure 6.9. The graph shows a gradual increase in productivity over the period with a per annum increase of approximately 0.5-1.0% over the period.

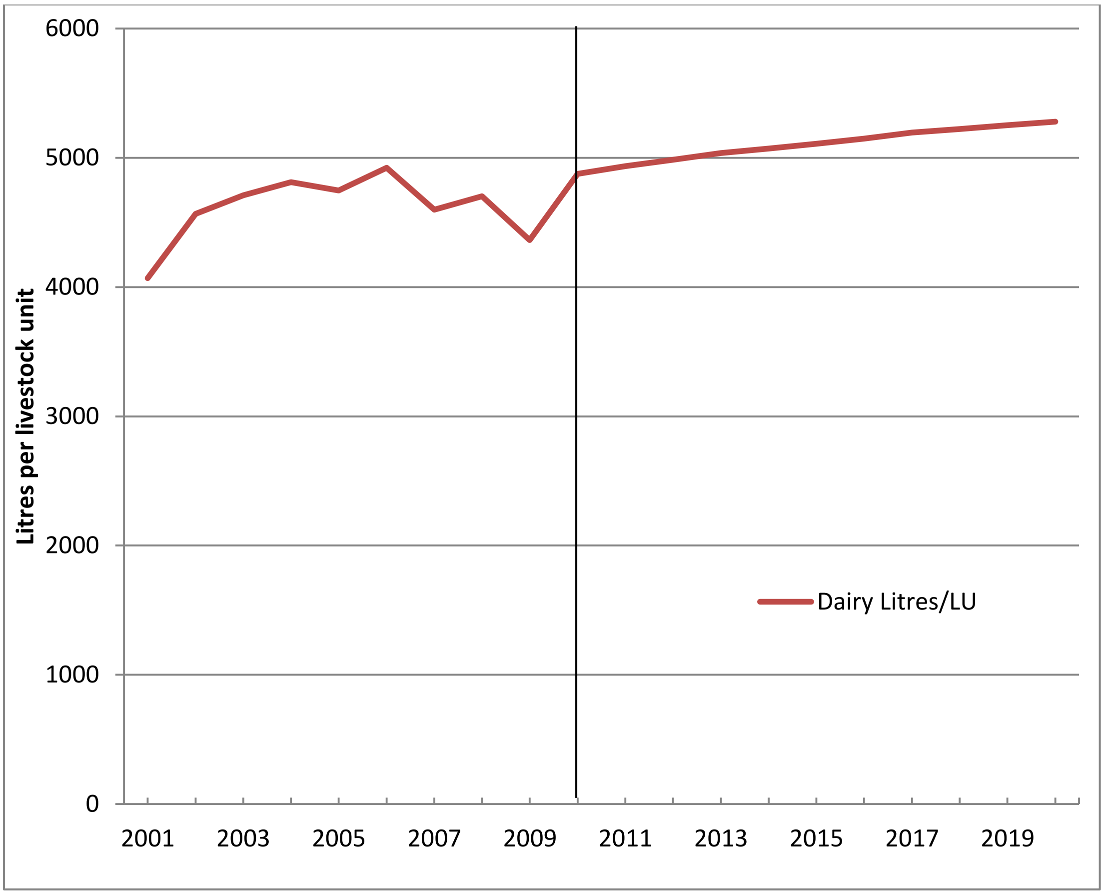


Figure 6.9 Simulated mean litres per livestock unit for dairy 2010-2020 under BAU scenario

Table 6.12 displays the change in mean litres per livestock unit for the dairy sector from the base year 2010 to the end of the simulation period. Mean litres per livestock unit increases from 4874.7 litres/LU to 5279.6 litres/LU representing a overall increase of 8.3%.

Table 6.12 Simulated change in mean litres per livestock unit for dairy

Year	Dairy Litres/LU
2010	4874.678
2020	5279.612
% change	8.307

For the crop sector, Figure 6.10 displays the change in crop gross output per hectare over the simulation period. The graph shows a steady decrease in crop gross output per hectare with a per annum decrease of approximately 3% over the period.

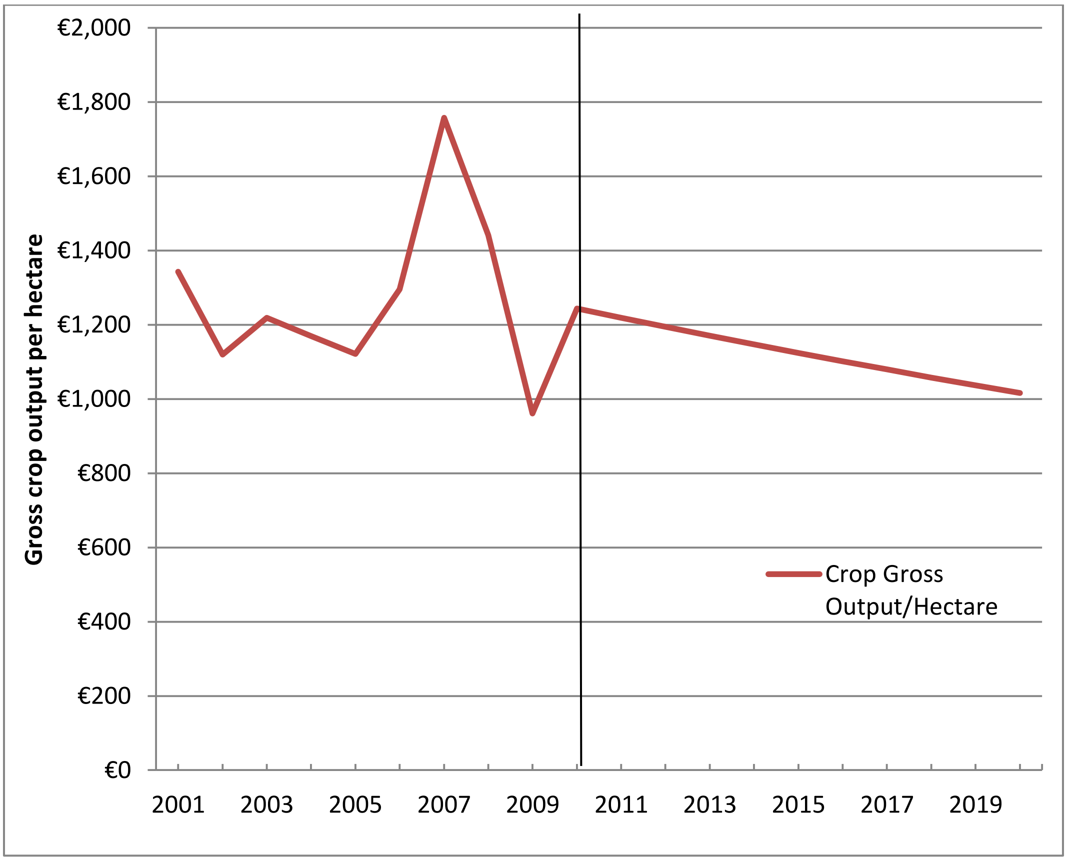


Figure 6.10 Simulated mean gross crop output per hectare 2010-2020 under BAU scenario

Table 6.13 displays the change in mean crop gross output per hectare litres for the tillage sector from the base year 2010 to the end of the simulation period. Mean output per hectare decreases from €1,243/hectare to €1,016/hectare representing a overall decrease of 18.3%.

Table 6.13 Simulated change in mean crop gross output per hectare

Year	**Crop Gross Output/Hectare**
2010	€1,243
2020	€1,016
% change	-18.293

Land Base

Figure 6.11 displays the change in mean adjusted farm size from 2010-2020 projected from the NFS-DSM model. The graph shows a slight gradual increase the mean adjusted farm size in line with the historical trend with a per annum increase of approximately 0.3% over the period.

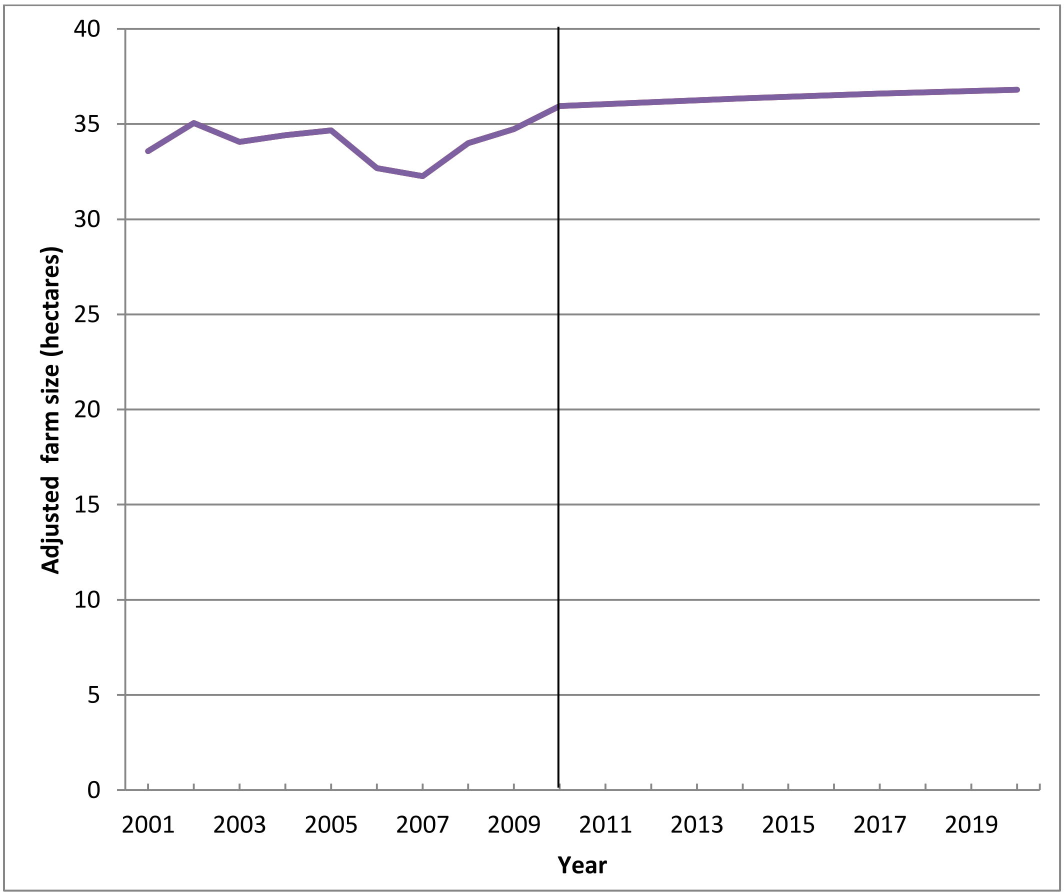


Figure 6.11 Simulated mean adjusted farm size (ha) 2010-2020 under BAU scenario

Table 6.14 displays the change in mean adjusted farm size for the ten year simulation period. Mean adjusted farm size increases from an average of 35.9 hectares in 2010 to 36.8 hectares in 2020 representing an overall increase of 2.3%.

Table 6.14 Simulated change in mean adjusted farm size per hectare

Year	Total Adjusted Farm Size (Ha)
2010	35.952
2020	36.800
% change	2.361

Family Farm Income

Figure 6.12 displays the change in mean family farm income from 2010-2020 projected from the NFS-DSM model.

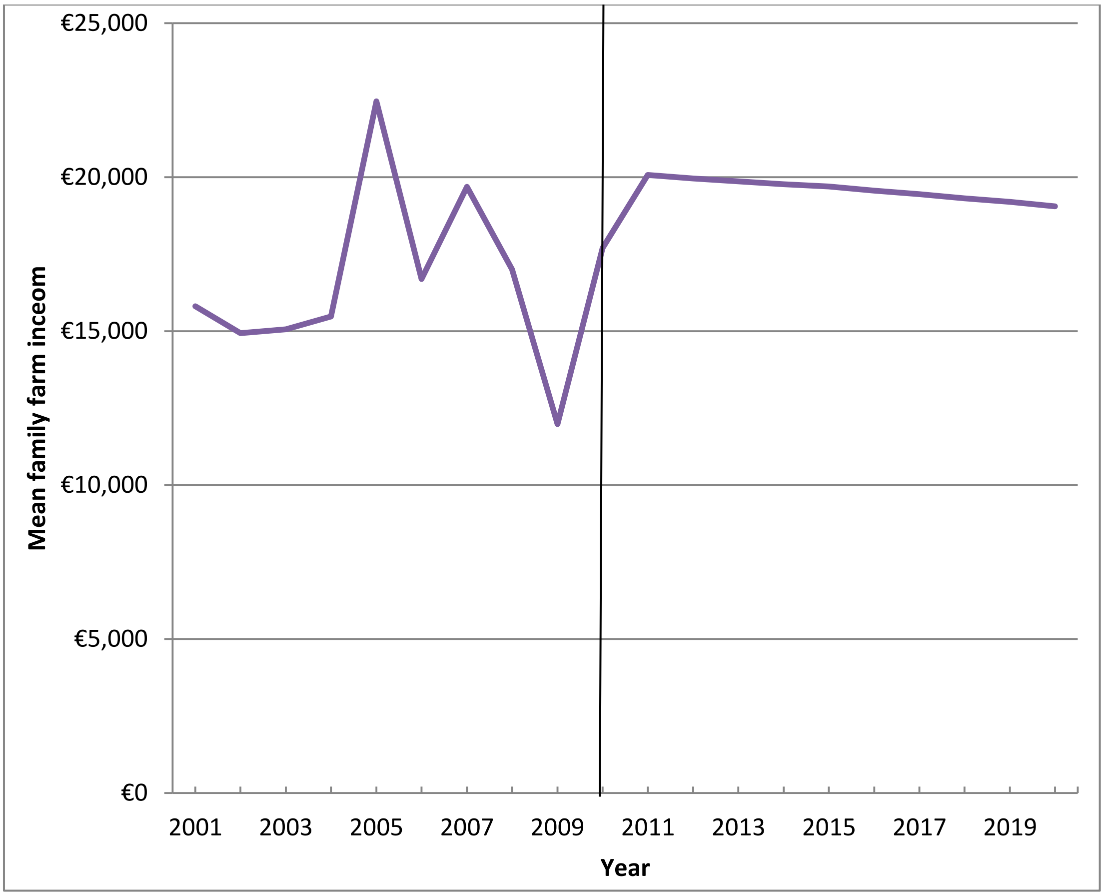


Figure 6.12 Simulated mean family farm income 2010-2020 under BAU scenario

While Table 6.15 below shows an overall increase in family farm income of 7.6% over the period, Figure 6.12 reveals that this increase is accounted for in the first year with the graph showing a subsequent annual decline in family farm income as gross output falls over time. It should be noted that family farm income is not directly modelled in the NFS-DSM but is re-constructed annually from simulated changes in outputs and costs across all sectors. As such, these results should be treated with a degree of caution. The explanation for the large increase and subsequent decrease of family farm income is directly related to the combined impact of the removal of the dummy effect in the first simulation year for all outputs and costs (Equation 6.2).

Table 6.15 Simulated change in mean family farm income

Year	Mean Family Farm Income
2010	€17,702
2020	€19,050
% change	7.618

6.5.2 Total Agri-Output

Figure 6.13 shows the change in total agri-output projected to 2020 by the NFS-DSM model. In terms of dairy, the picture is largely static with decreases in stocking rate levels offset by productivity gains in terms of litres per livestock, marginal increases in total adjusted farm size and the unit price per litre projected by the FAPRI-Ireland model, resulting in an overall marginal increase in dairy output. This projection for the dairy sector is in contrast with significant declines in total gross output in the cattle sheep and tillage sectors.

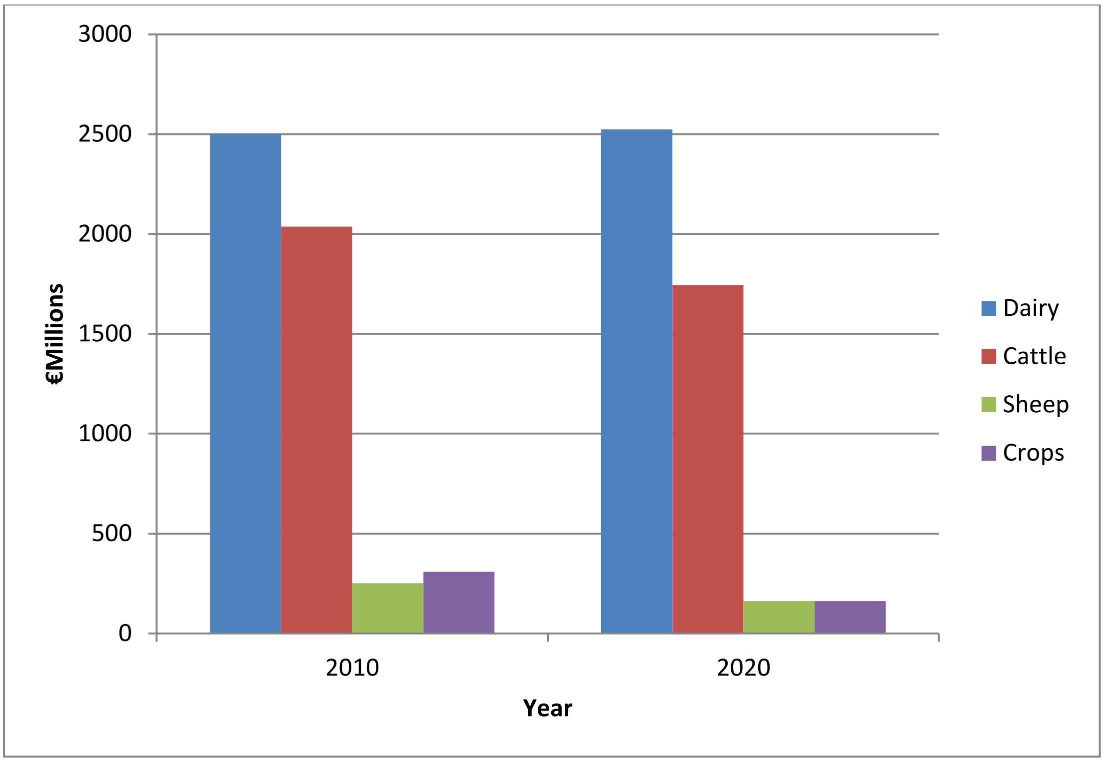


Figure 6.13 Simulated total agri-output 2010-2020

Table 6.16 shows an increase in projected dairy output of 1%, with declines of 14%, 35% and 48% projected for the cattle, sheep and crop sectors respectively. For the cattle sector this outcome is anticipated when the effects of decreases of 4.9 % (stocking rate) and 4.5% (gross output per livestock unit) outlined for the cattle sector in the previous section are combined. A marginal price increase of 3.2% is not enough to offset this decrease in projected output. Similarly, for the sheep sector, the effects of decreases of 15.9 % (stocking rate) and 9.5% (gross output per livestock unit) result in a 35% decrease in total output. The decrease of 48% for the tillage sector seems prohibitively high considering a mean decrease of 18.3% for gross crop output per hectare until we combine the effect of a projected 8% decrease in unit prices from the FAPRI-Ireland model.

Table 6.16 Simulated change in mean adjusted farm size per hectare

Gross Output €M				
	Dairy	**Cattle**	**Sheep**	**Crops**
2010	2501.4	2036.1	251.6	308.6
2020	2523.2	1744.5	162.4	161.7
FAPRI prices	+3.6%	+3.2%	+3.3%	-8.2%
Change in output	1%	-14%	-35%	-48%

In terms of total milk output Figure 6.14 shows an overall decrease in total milk output from 5.49 billion litres in 2010 to 5.173 billion litres in 2020. This represents a total decrease of 5.7% over the simulation period.

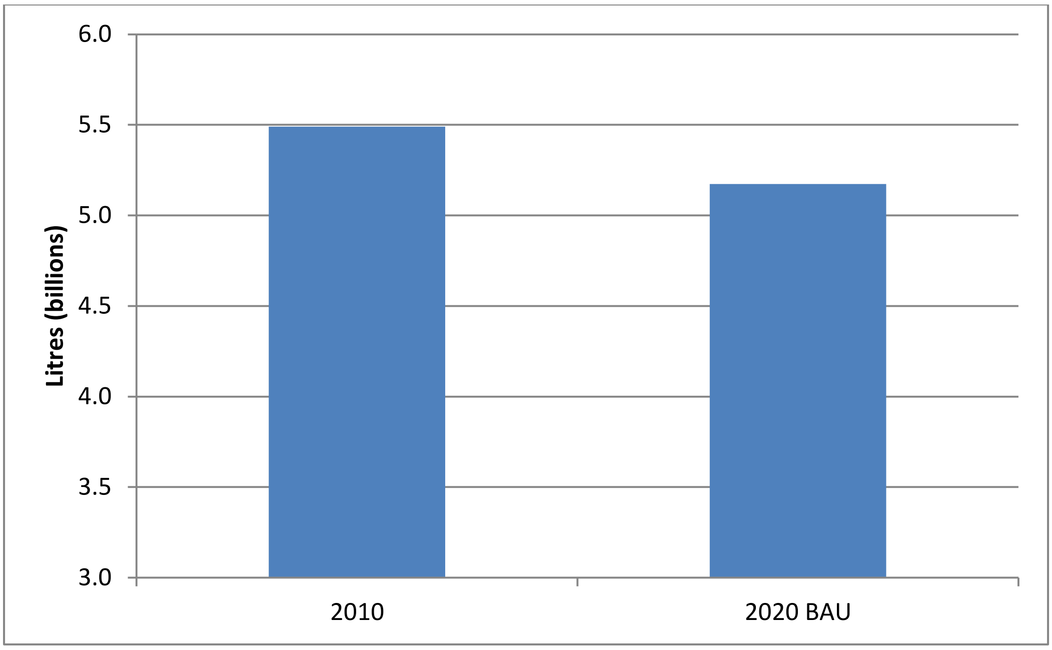


Figure 6.14 Total milk litres (billions) 2010 and 2020 BAU

6.5.3 Consequences for National Agri-Emissions Totals

As outlined in Chapter 5, the IPCC methodology is still the method used for national emissions inventories and in the absence of further international agreement is applied for the purposes of calculating the change in national agri-emissions projected by the NFS-DSM model. As described in Section 5.3.2, under the IPCC methodology the stocking rate is the key determinant of national agri-emissions as direct and indirect emissions from livestock account for approximately 75% of total agri-emissions in Ireland. Emissions factors for methane (CH_4) from enteric fermentation and manure management and for nitrous oxide (N_2O) from manure management are applied to total herd numbers.

Table 6.17 summaries the change in total livestock numbers for the dairy, cattle and sheep sectors over the simulation period. From a total of 1.553 million in 2010, the total number of dairy cows is projected to fall to 1.410 million in 2020 representing an overall decrease of 9.2% primarily due to a decline in stocking rates and a simulated rate of exit of 2% p.a. Cattle numbers are projected to fall slightly from 6.913 million in 2010 to 6.516 million in 2020 representing an overall decrease of 1.1% while total sheep numbers are anticipated to drop from 5.051 to 4.347 million representing a 13.9% decrease over the simulation period reflecting the fall in mean stocking rates outlined in Section 6.5.1. For both the cattle and sheep sectors the fall in livestock numbers is slightly less than anticipated from the results for changes in total agri-output outlined in Section 6.5.2.

Table 6.17 Simulated change in total livestock numbers (millions) for dairy, cattle and sheep 2010-2020

Year	Tot. Dairy No.	Tot Cattle No.	Tot. Sheep No.
2010	1.553	6.591	5.051
2020	1.410	6.516	4.347
% change	-9.2	-1.1	-13.9

As outlined in Section 6.3.1, this can be explained by the following. In the NFS-DSM model, animal numbers are recalculated year on year reflecting changes in the stocking rate and pro-rata changes in the total area apportioned to each enterprise through increases in the total adjusted farm size. Additionally in the case of dairy, when a dairy farm exits, the total area vacated by the dairy enterprise is assumed to be consumed by the remaining enterprises on the farm. It is transferred pro-rata to the remaining enterprises on the farm resulting in an increase in livestock numbers where cattle and sheep enterprises remain.

Figure 6.15 summaries the change in total agri-emissions over the simulation period, showing an overall 6% decline from 19.881 Gg of CO_2eq in 2010 to 18.650 Gg of CO_2eq in 2020.

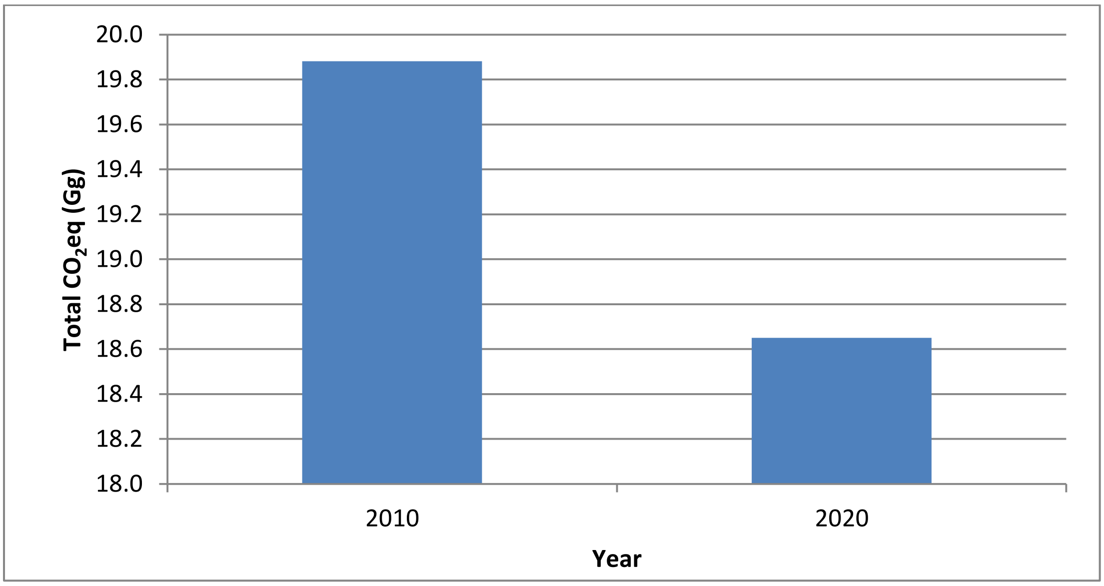


Figure 6.15 Simulated total CO_2eq agri-emissions (Gg) 2010-2020

Table 6.18 outlines the change in total emissions by emissions category with total methane emissions from enteric fermentation and manure management falling from 606.443Mt to 578.398Mt in 2020, a decrease of 4.24%. Nitrous oxide emissions from manure management and the application of synthetic fertilisers fall from 23.051Mt to 20.978Mt, a decrease of 8.9%. Using the relevant global warming potential factors for methane (21) and nitrous oxide (310) respectively, the model estimates an overall decrease of 1.232 Gg of CO_2eq, representing a 6.6% reduction.

Table 6.18 Summary of changes in total emissions by emissions category methane and nitrous oxide emissions (Gg) 2010-2020

Category	2010	2020	%change
Methane (CH_4)(Mt)	606.443	578.398	-4.624
Nitrous Oxide (N_2O) (Mt)	23.051	20.978	-8.994
Total CO_2eq Emissions (Gg)	19.881	18.650	-6.60
Carbon Dioxide (CO_2) from Diesel. (Mt.)	447.13	421.827	-5.659
Carbon Dioxide (CO_2) from Elec. (Mt.)	285.488	300.306	5.191
Tot. CO_2eq Emissions (Gg) inc Elec & Diesel	20.613	19.371	-6.026

As outlined previously in Chapter 5, the model includes the capacity to estimate emissions from electricity and diesel usage. Table 6.17 shows carbon dioxide emissions from diesel are projected to fall from 447.13mt in 2010 to 421.83Mt in 2020, a decrease of 5.6% broadly reflecting decrease output among the cattle, sheep and tillage sectors across all enterprises. Conversely a 5.2% increase in carbon dioxide emissions due to electricity usage is projected with emissions rising from 285.5 Mt in 2010 to 300.3 Mt in 2020 reflecting the increase of milk output of 3% in in the dairy sector. The results for both diesel and electricity usage should be interpreted with caution however as they are not modelled directly in the NFS-DSM model and are calculated based on historical shares observed in 2010 and the projected changes in overhead costs outlined above (Section 6.3.1)

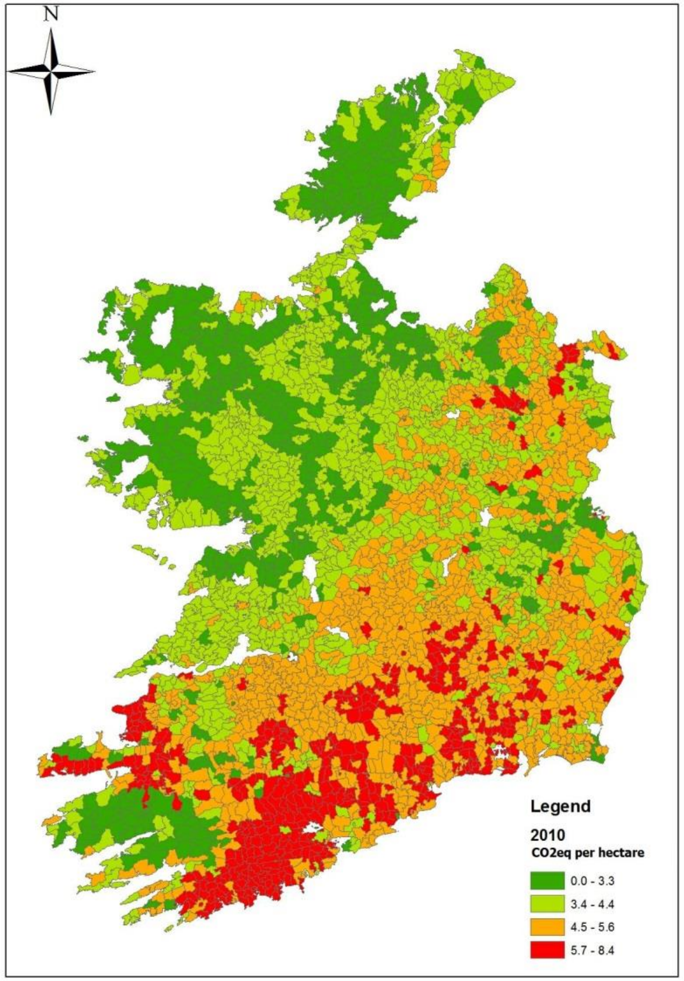
6.5.4 Spatially Disaggregated Emissions Outcomes for 2020

Outputs from the NFS-DSM model are spatially disaggregated to the ED level using the stocking rate adapted SMILE-NFS spatial microsimulation methodology outlined in Chapter 5 and updated to 2010. Spatial emissions outcomes for Irish Agriculture for 2020 are presented below. Figures 6.16 and 6.17 present CO_2eq emissions on a per hectare basis for over 3000 electoral districts for 2010 and 2020. As anticipated the spatial pattern of emissions for 2020 is consistent with pattern for 2010 with broadly speaking a clear division between the traditionally more productive South and East regions and the traditionally subsistence based farming associated with the North and West.

While the overall reduction of emissions is hard to discern from Figures 6.16 and 6.17, Figure 6.18 displays the ratio of change of CO_2eq emissions per hectare for each electoral district over the period of the simulation from 2010-2020.

Figure 6.18 reports that all EDs experience a reduction in emissions per hectare with a large amount of (yellow) EDs in the midlands, west and northwest experiencing the lowest level of reduction of between 2-7%. This is most likely explained by cattle being the dominant systems in those areas. A gradual decrease in the mean stocking rate reported in Section 6.5.1 coupled with the absorption of land from dairy exits has resulted in overall cattle numbers declining by just 1.1% (Table 6.16). Thus in areas where cattle systems are more dominant the reduction in overall emission per hectare is likely to be similarly low.

Figure 6.18 also indicates more pronounced changes in areas traditionally associated with dairying, tillage and in the more peripheral areas. The large 9.2% reduction in overall dairy livestock numbers reported in Table 6.16 occurs as a result of declining stock rates and an exit rate of 2% p.a. from the sector resulting in a larger reduction in emission. In areas associated with tillage such as Meath and Louth in the North East and Carlow Kilkenny and Laois the decline in tillage activity reported in the sector in Section 6.5.2 translates into lower levels of synthetic fertilisers associated with tillage production. The areas trade associated with dairy in the South and South-East and tillage in the North East and South (Carlow, Kilkenny and Laois) contain a considerable number of (green) EDs reporting a reducing in emissions of between 8-11%.



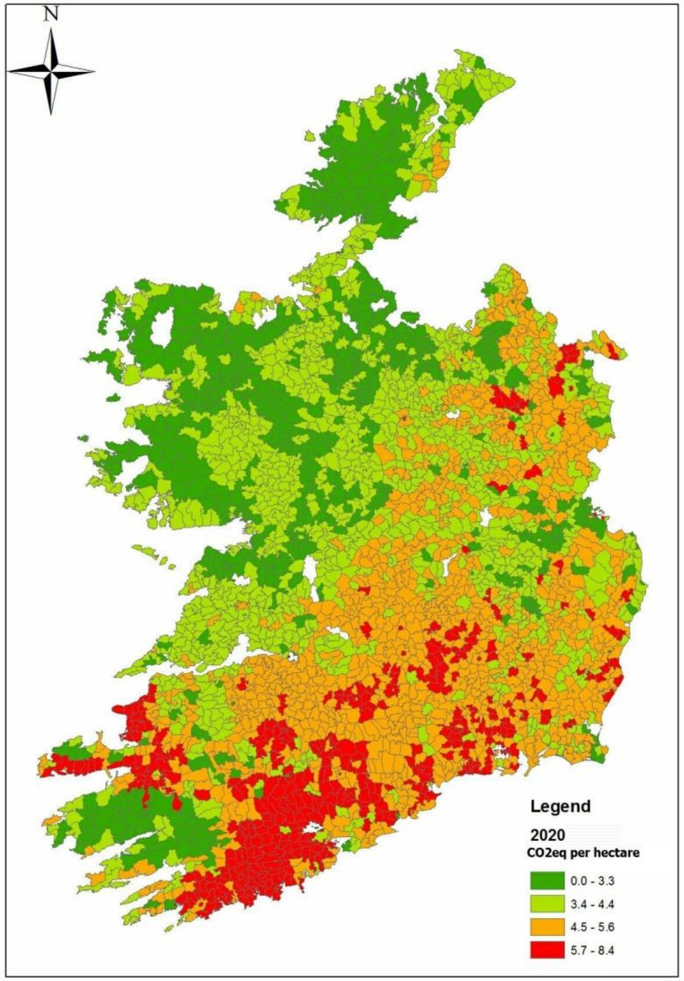


Figure 6.16 CO_2eq emissions per hectare 2010

Figure 6.17 CO_2eq emissions per hectare 2020

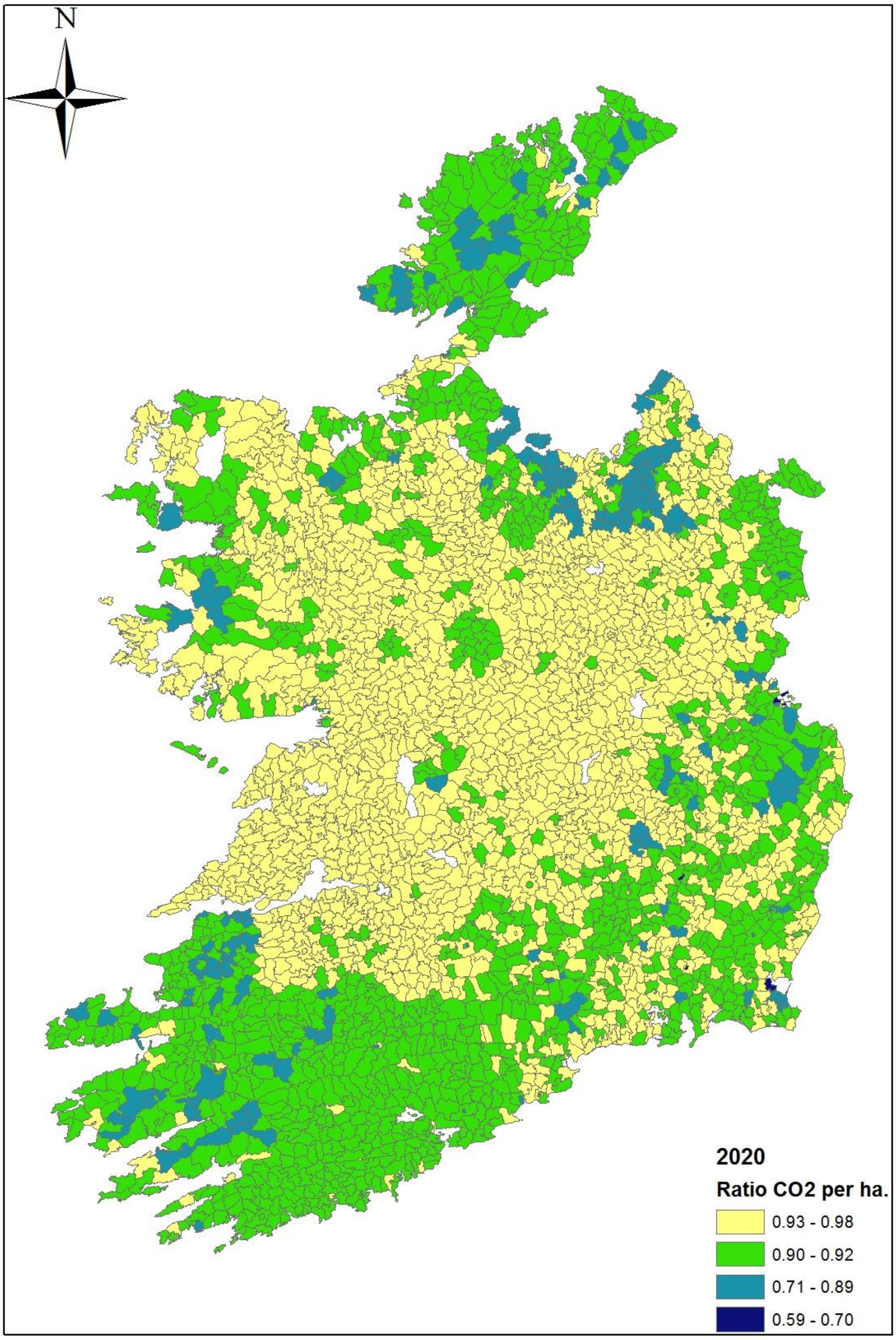


Figure 6.18 Ratio change of total CO_2eq emissions per hectare at the electoral district level from 2010 to 2020.

There are a small number of (light blue) EDs displaying larger reductions of between 12-29%, with a small number of very small (in terms of farm area) outlier EDs reporting more than a 30% drop in emissions. Reductions of between 12-29%, may occur in EDs where the effects of both a decrease in dairy cattle numbers and a decrease in tillage output combine to a substantial reduction in emissions, or in more peripheral and marginal upland areas where sheep is the dominant enterprise and a more pronounced reduction in emissions is witnessed due to falling sheep stocking rates. The 3 or 4 EDs reporting reductions of great than 30% are extremely small EDs with a small number of farms, and have experienced a one or more exits from the dairy sector in the simulation period.

Figure 6.19 shows the distribution of ED ratio of emissions changes per hectare from 2010 to 2020, with the blues lines representing the natural (jenks) breaks used to display the data spatially in Figure 6.16. The mean ED ratio of emissions change per hectare from 2010 to 2020 was 0.92 or a reduction in emissions of 8%. The standard deviation from the mean was 0.02 with the vast majority of EDs experiencing emissions per hectare reductions of between 4 and 12%.

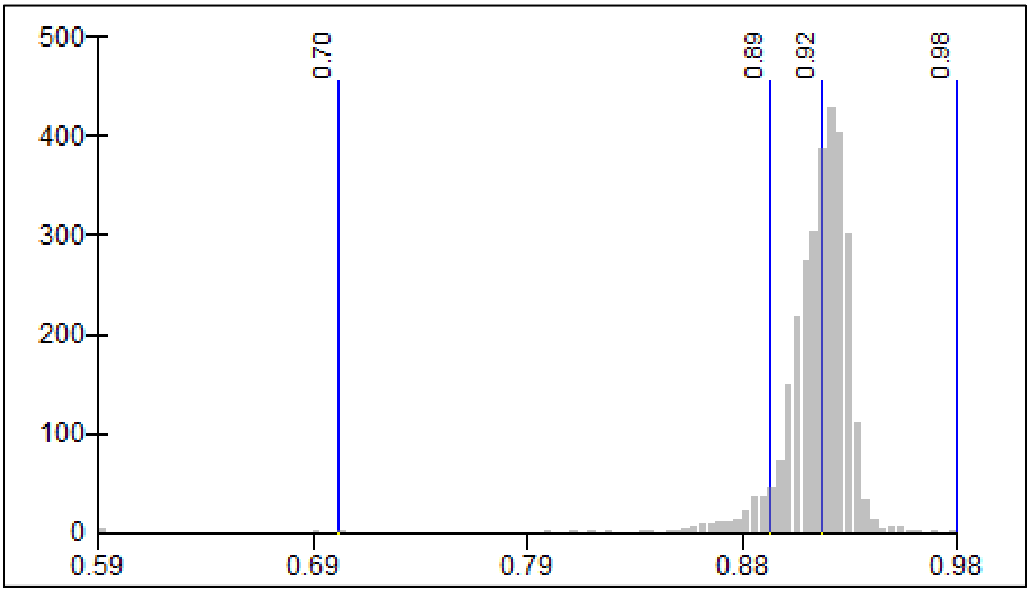


Figure 6.19 Distribution of ED ratio of emissions changes per hectare from 2010 to 2020.

6.6 Conclusions

This chapter outlines the construction of a dynamic spatial microsimulation model for the Teagasc National Farm Survey, its simulation under a business as usual scenario following historical trends and its use in presenting a spatially disaggregated emissions map for Irish agriculture in 2020. Overall, the model estimates a gradual decline in agricultural activity over the 10 year simulation period with a concomitant marginal reduction in associated emissions.

In terms of implications for current agri-policy, the results indicate that the achievement of the headline FH2020 target of a 50% increase in milk volume is unlikely without a significant shift in historical trends witnessed in the sector. Similarly the target to increase the value of the cattle sector by 20% is unlikely to be met without some combination of a significant shift in future prices and/or productivity trends.

In terms of the impacts on emissions associated with agriculture the NFS-DSM model projects an overall decrease in CO_2eq of 6.6%. Agriculture currently accounts for almost 43% of non-ETS sector emissions. While a specific target for emissions for agriculture has not been declared, it is likely that this reduction does not represent the required contribution from agriculture if Ireland is to meet its commitment to reduce non-ETS sector emissions by 20% by 2020.

These results should, however, be treated with caution as there are a number of limitations to the NFS-DSM model which may result in the under estimation of future agricultural output. In particular, the simulation of productivity increases in the dairy sector in line with historical trends may be naïve in the face of the abolition of the milk quota in 2015. As outlined in Section 6.3.3 it is extremely difficult to predict what is likely to happen in the post quota era.

Additionally in terms of the other livestock sectors the simulation of value estimates (as opposed to a volume estimates) for cattle and sheep respectively is a significant limitation in the model. While physical productivity can be modelled in the dairy sector and informed by the unit price, detailed physical productivity data in terms of kg/lu for the cattle and sheep sectors are not available in the NFS. Thus estimates carried out for gross value output present a difficulty in that they are generally highly and strongly correlated with the unit price which presents a methodological difficulty in that the true effect of unit price increases on productivity response is hard to quantify.

In summary, a question remains with regards to the uncertainty in the future growth paths for dairy as a result of the abolition of quota in 2015. It is possible that a large proportion of dairy farms are currently under producing due to quota constraints and that the abolition of quota in 2015 will result in a substantial increase in output. The nature of that increase will have knock-on effects for emissions outcomes with higher productivity rates having the potential to offset emissions increases due to an overall increase in activity. It is submitted that there is a requirement for a multi-scenario analysis of potential growth paths for the dairy sector in a post quota era.

CHAPTER SEVEN: FOOD HARVEST 2020 TARGETS IN THE IRISH DAIRY SECTOR: ESTIMATING FUTURE DAIRY FARM LOCATIONS AND RESULTANT EMISSIONS OUTCOMES

The following chapter describes the construction of a multi-scenario analysis for the expansion of the Irish dairy sector and its use in predicting the spatial pattern of new entrants required in order to meet the targets outlined in the Food Harvest 2020 (FH2020) Programme. By adapting the National Farm Survey Dynamic Spatial Microsimulation Model (NFS-DSM) described in Chapter 6, three alternative productivity scenarios for the expansion of the dairy industry are simulated to 2020 and compared against the business as usual case. For all four expansions scenarios, the total milk output is calculated and compared to the target outcome informing the number of additional new entrants required to meet target. The location of these selected new entrants is then projected spatially and disaggregated to electoral district level using the SMILE-NFS spatial microsimulation model. The resultant emissions outcomes are mapped using the methodology described in Chapters 4 and 5 and compared at an aggregate level to assess the implications for Ireland's 2020 emission obligations under the EU's Climate Action and Renewable Energy (CARE) Package. The chapter concludes with an assessment of the level of structural change required in the dairy sector in order to meet target.

7.1 Introduction

Attaining FH2020 targets has been identified as a key aspect of the Irish Government's strategy towards economic recovery following one of the largest economic recessions in the state's history (Irish Government, 2011). However, while the economic benefits of attaining Food Harvest 2020 are significant for both the agricultural sector and the wider economy, the possible consequences for Ireland's international commitments to reducing greenhouse gas emissions must also be considered. As outlined in Chapters 5 & 6, with the dairy sector contributing to 22% of agricultural emissions and circa 9% of total emissions from the non-ETS sector, key questions in terms of Ireland's EU 2020[34] commitments are; which development paths are considered the most likely and what are the resultant emissions outcomes associated with those paths? The conclusions arising from these questions have important implications in terms of resolving the apparent policy impasse between the expansionary policies outlined in the FH2020 programme and Ireland's commitments to emissions reductions.

In investigating potential development paths the FAPRI-Ireland model (Binfield et al., 2008) has been used to estimate future volumes and values for agricultural inputs and outputs under the FH2020 programme. By modelling the agricultural production volume required to reach FH2020, and determining the associated costs and volumes of input usage, the FAPRI-Ireland model identifies the critical market conditions required in order for targets to be achieved (Donnellan & Hanrahan, 2011a). Additionally, Miller et al. (2013) consider the knock-on benefits for the wider economy of achieving the FH2020 growth targets by studying the linkages between agriculture and other economic sectors using a social accounting matrix.

A small number of studies have investigated the consequences for agri-emissions as a result of reaching the FH2020 targets (Donnellan & Hanrahan 2011; Curtis, 2012) but these studies have focused on potential emissions outcomes at the aggregate level and a spatial dimension to the future outcomes for agri-emissions is notably absent in the current literature.

As outlined in Chapter 2 the availability of resolved spatial information on greenhouse gas emissions has been identified as a key determinant in the effective implementation of climate change policy at the local level (Allman et al., 2004). The potential also exists for such information to contribute to the development and

[34] Ireland has committed to reducing non-ETS emission by 20% by 2020 under the terms of the EU's 2008 Climate Action and Renewable Energy (CARE) Package (2009/29/EC) (EPA, 2009)

subsequent adaptation of policy which encourages more emission efficient solutions at a local level as well as enabling integrated planning for future mitigation options.

There is, however, a significant gap in the literature with regards to the spatial disaggregation of the potential future outcomes for dairying in Ireland. The restructuring and possible expansion of the dairy sector to meet target may, over time, result in considerable shifts in the spatial concentrations of dairying activity. This, in turn, will have important consequences on the future location of emissions, not only those attributable to the dairy herd but also in terms of the emissions associated with transportation to processing facilities as identified by Quinlan et al. (2006). Previous studies on the expansion of the dairy sector also lack a spatial element in relation to the potential location of future dairy sector entrants. The number and location of potential new entrants will also have important consequences for emissions from dairying in the future and could inform future mitigation strategies (Quinlan, 2013).

As part of the FH2020 programme, a 50% increase in milk output has been targeted specifically for the dairy sector (Department of Agriculture Fisheries & Food, 2010). If realised, this significant expansion of Irish dairy production will require some combination of increased productivity per cow and/or an increase in the active agri-land base and is likely to require a significant number of new entrants to the sector (Läpelle & Hennessy, 2012). Considering the primary determinants of milk output in conjunction with different levels of efficiency improvements, a 50% increase in milk output could be achieved along a number of different potential development paths each with a different outcome for agri-emissions.

The mapping of a multi-scenario analysis for 2020 for the dairy sector provides an opportunity for policy makers to identify future such mitigation opportunities at appropriate spatial scales. It also presents the opportunity to provide advanced insight into the potential future locations of new dairy entrants and could inform future planning decisions in relation to the optimal location of future processing facilities, the provision of which has been identified as a key requirement (Irish Dairy Board, 2010).

Using the NFS-DSM model outlined in Chapter 6, a multi scenario-analysis for the expansion of the dairy industry is investigated. Analysis of the spatial distribution of potential new entrants will be undertaken and the consequences for future emissions from agriculture as a result of meeting the FH2020 targets will be assessed.

7.2 The Irish Dairy Sector

To inform the design and selection of future expansions scenarios for the dairy sector a review of the recent trends in the dairy sector is required. This section describes the historical trends recorded in the Teagasc National Farm Survey for the Irish dairy sector over the ten year period 2001-2010. This section also outlines the challenge faced by the industry in meeting the targets outlined in the FH2020 programme and draws on the work of Läpelle and Hennessy (2012) to inform the development of future expansions scenarios.

7.2.1 Recent Trends

Irish dairy farms have been involved in considerable structural change in recent years. Figure 7.1 shows the total weighted number of farms recorded in the Teagasc National Farm survey as operating a dairy enterprise has fallen by over 40% between 2001 and 2010.

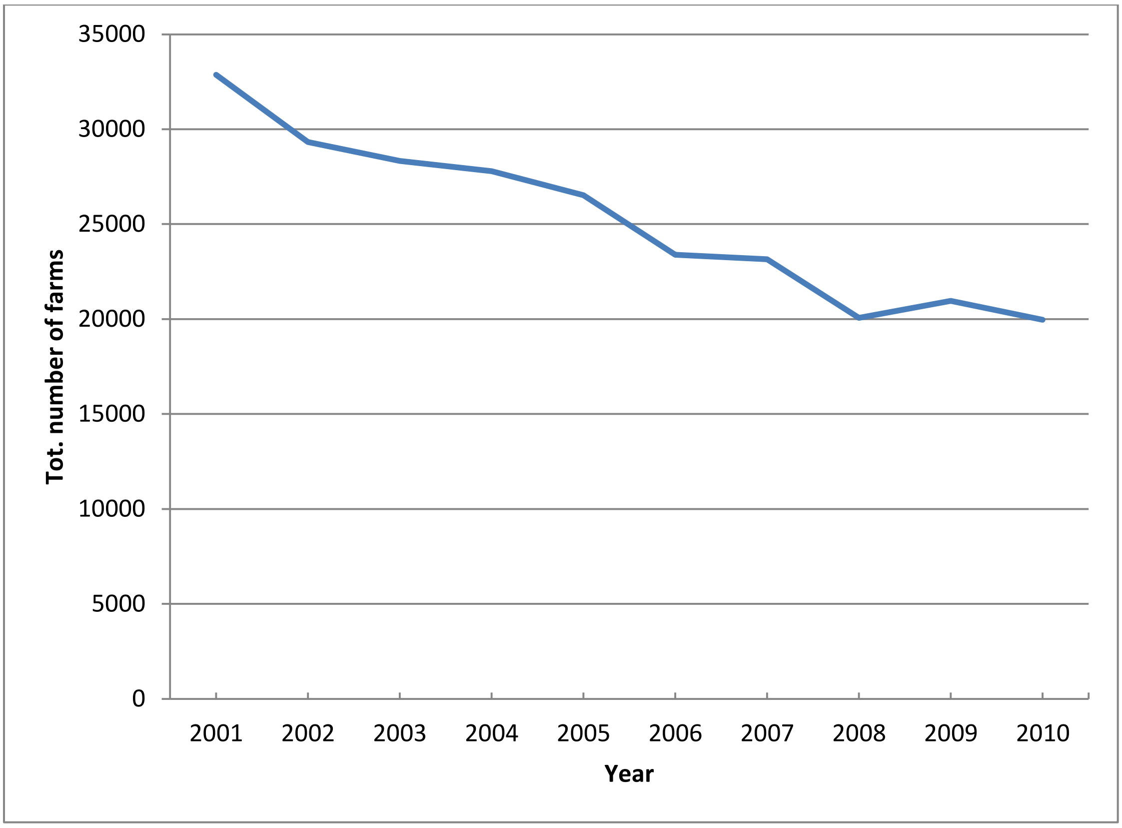


Figure 7.1 Total number of farms with a dairy enterprise 2001-2010

(Source: Teagasc NFS)

Despite the decline in dairy farm numbers, the level of total milk output has been maintained, averaging 5.4bn litres over the 10 year period. This has primarily been due to increases in productivity and increased specialisation on those farms continuing to operate a dairy enterprise. Figures 7.2-7.6 profile the changes at farm level in terms of mean values for milk output and its constituent determinants (i.e. productivity, stocking rate and forage area) for the Irish dairy sector from 2001 to 2010.

Figure 7.2 shows the mean values for annual milk output per farm from the dairy sector over the ten year period 2001-2010, increasing from 150,000 litres p.a in 2001 to over 260,000 litres in 2010, representing an increase of 66.9% mean output over the period with an average growth rate of approximately 6.1% per annum.

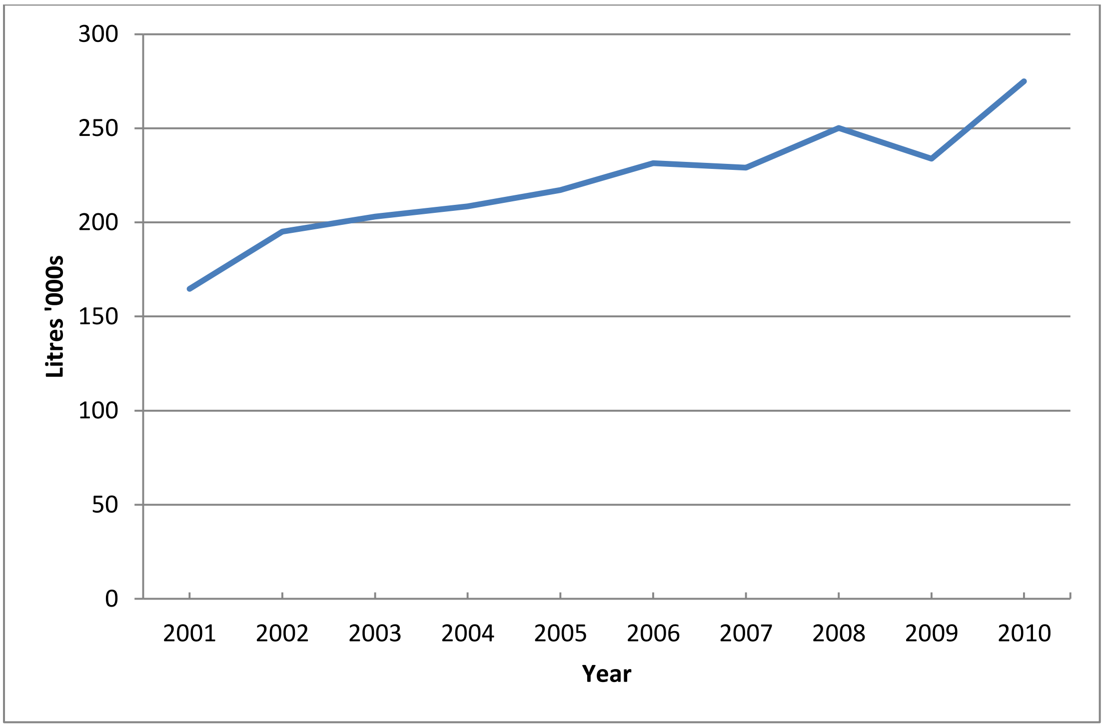


Figure 7.2 Mean annual milk output (Litres '000s) per farm 2001-2010

(Source: Teagasc NFS)

Figure 7.3 shows the trend in productivity per cow in terms of litres of milk per livestock unit over the 10 year period. Mean productivity per dairy cow has increased from an average of 4,067 litres per livestock unit in 2001 to 4,874 litres in 2010, an increase of 19.8%, or approximately 2.3% per annum.

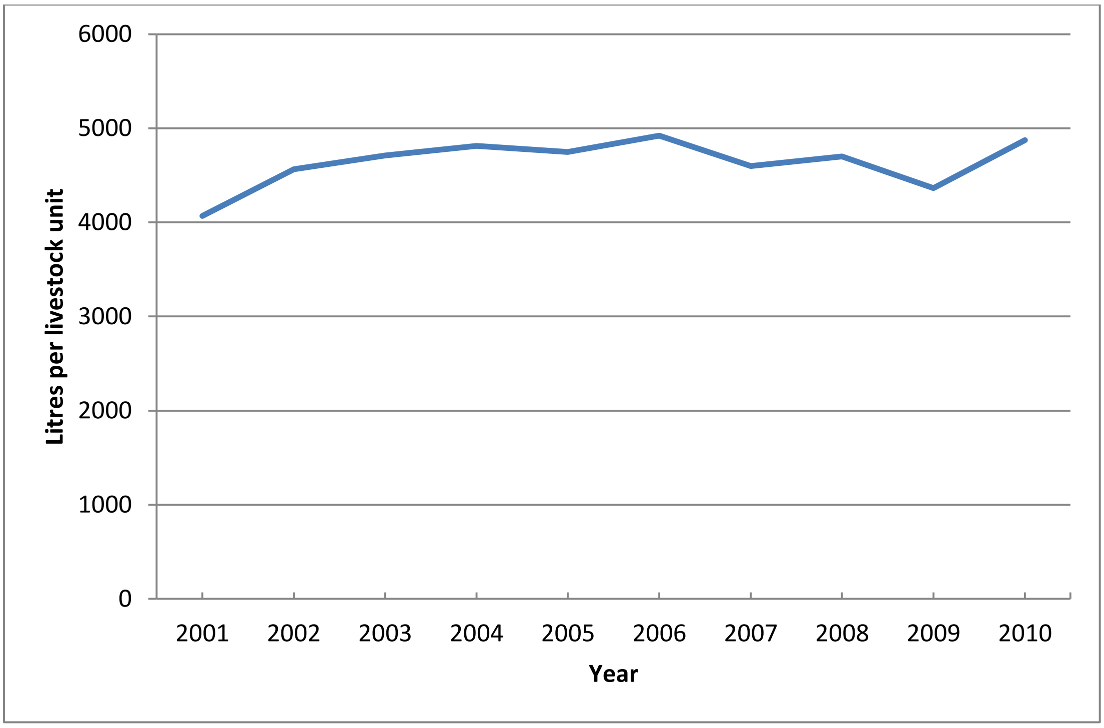


Figure 7.3 Dairy litres per livestock unit 2001-2010

(Source: Teagasc NFS)

The changes in mean stocking rate shown in Figure 7.4, present a largely static picture over the 10 year period with mean stocking rates virtually unchanged from 1.890 livestock units per hectare in 2001 to 1.896 in 2010. The annual mean stocking rate does however fluctuate annually around a mean 1.87 for the period. This fluctuation is likely due to a management response when faced with year to year adverse environmental[35] or market conditions such as the sharp fall in milk prices in 2009. The use of stocking rate as a management tool for milk production, pasture production and profitability has been well documented by Macdonald et al. (2008).

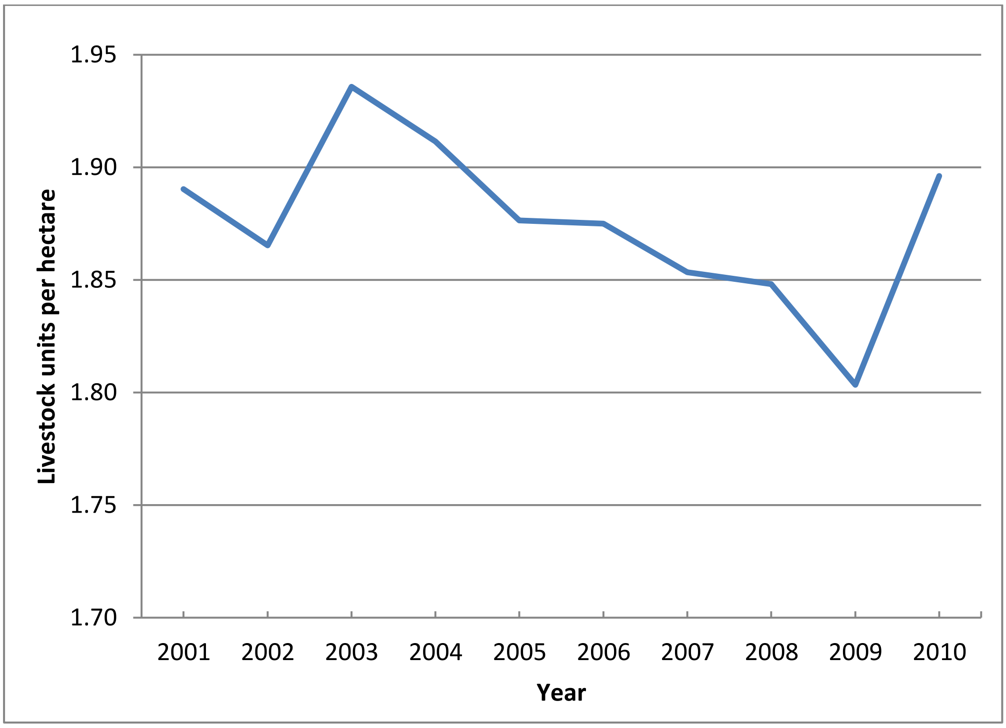


Figure 7.4 Dairy livestock units per hectare 2001-2010

(Source: Teagasc NFS)

[35] Such as in the case of below or above average pasture growth due to annual weather fluctuation

If we consider the mean share of total farm size under dairy, we can see that in addition to increased productivity, the increase in mean farm milk output over the period is also attributable to an increase in the mean area per farm devoted to dairy over the same period. Figure 7.5 shows an increase in the mean agricultural area devoted to dairy from 19.5 hectares in 2001, to 28.2 hectares in 2010, representing an increase of 44%.

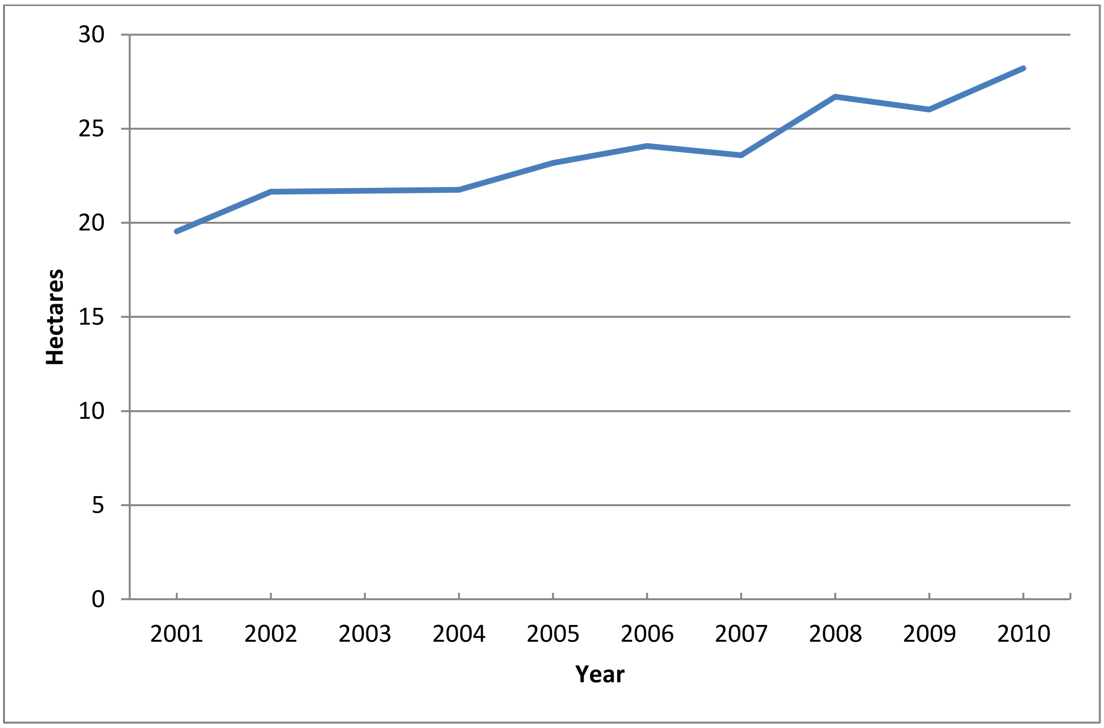


Figure 7.5 Mean farm area devoted to dairy (hectares) 2001-2010

(Source: Teagasc NFS)

This represents a shift in the average share of the total adjusted farm size devoted to dairy from 50% in 2001 to 61% in 2010, which is displayed in Figure 7.6.

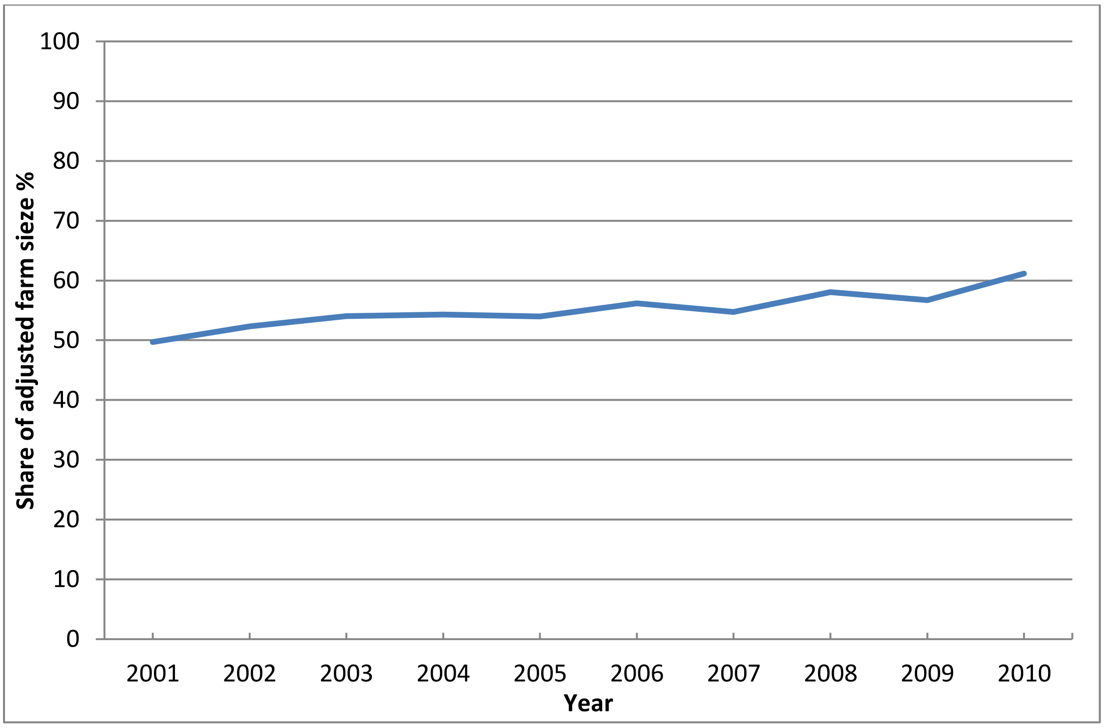


Figure 7.6 Mean share of adjusted farm size (%) devoted to dairy enterprise (Source: Teagasc NFS)

In terms of total agricultural area, the area under dairy has fallen from 641,995 hectares to 563,101 hectares representing a fall of 12% from 2001 to 2010. However the restructuring of the dairy sector has resulted in the level of milk production being maintained at around 5.5bn litres per hectare (Figure 7.7).

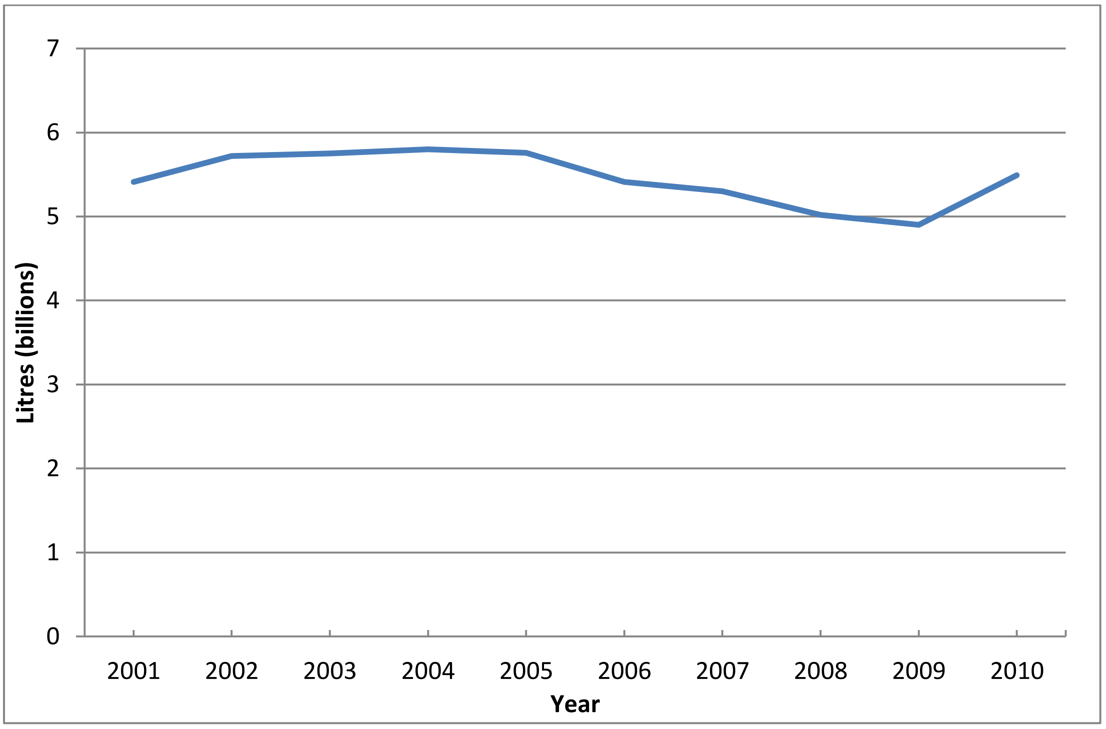


Figure 7.7 Total national milk output (Billion Litres) 2001-2010

(Source: Teagasc NFS)

In summary, over the last ten years while the number of farms operating a dairy enterprise has fallen considerably, total milk output has been maintained due to considerable restructuring within the sector. This is primarily due to a combination of the exit of the least efficient (and typically smaller) dairy farms coupled with efficiency increases through increase specialisation from the remaining farms that were able to take up quota vacated by those exiting the sector.

7.2.2 Food Harvest Target for Dairy

In the BAU scenario outlined in Chapter 6, despite a reduction in the rate of exit from the dairy sector as the rate of restructuring decreases (Section 6.3.2), total milk output decreases by 5.7% from 5.490bn litres in 2010 to 5.173bn litres in 2020. This projected decrease in output is based on previous historical trends with respect to productivity, stocking rates and the total adjusted farm size. Figure 7.8 outlines the scale of the challenge for the industry with a target of 7.254 bn. litres set for 2020 based on milk output for the base year of 2008[36,37].

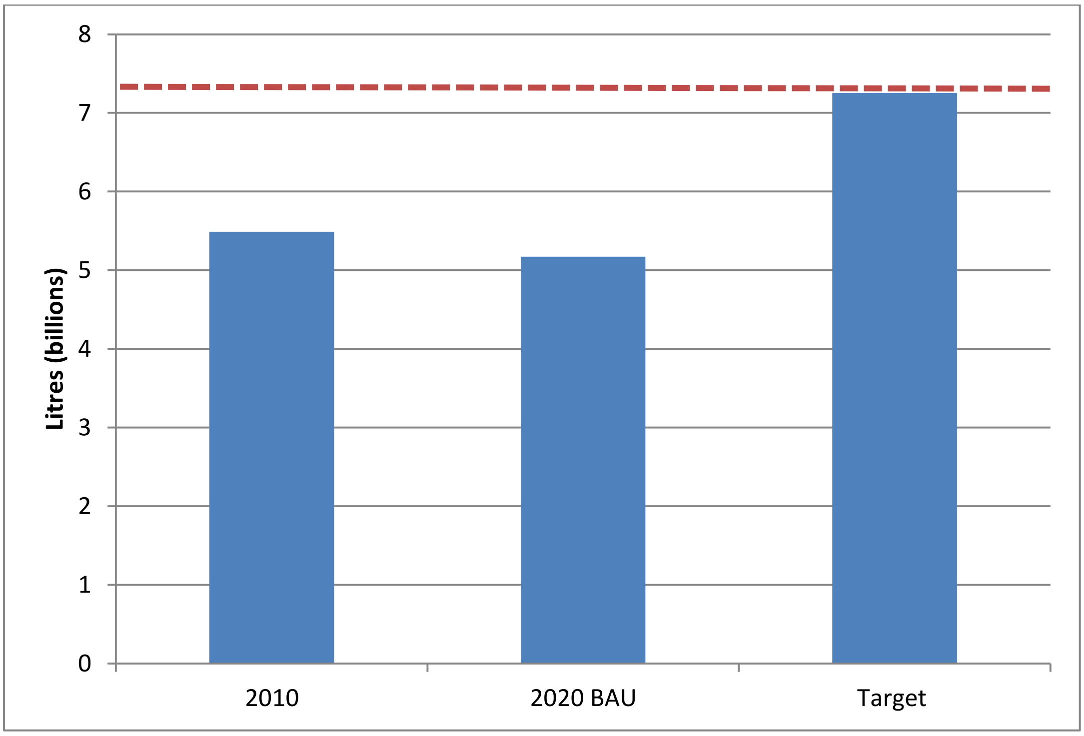


Figure 7.8 Distance to milk target under BAU scenario from NFS-DSM model

[36] The reference year for the purpose of the calculation of FH2020 targets is 2008.
[37] The weighted NFS calculation of the target milk output for 2020 based on the base year of 2008 was compared to the FAPRI-IRELAND model and found to be within 1% and thus deemed to be a reasonable estimation for the purposes of estimating the distance to target.

Under the business as usual scenario outlined in Chapter 6 overall milk output is projected to fall by approximately 6%. This represents a substantial shortfall in the production levels required to meet the 2020 target. However a significant question mark which remains over the future expansion of the Irish dairy sector is the impact of the abolition of the milk quota in 2015 and its impact on productivity (Section 6.3.3).

At an aggregate level, previous studies such as Binfield et al. (2007) and Donnellan et al. (2009) have attempted to assess the impact of a progressive increase and ultimate abolition of quota in 2015 on the volume and value of milk output using various estimates of quota rent[38]. At farm level, Hennessy (2007) investigates mean production outcomes and the potential resultant impacts on family farm incomes from the scenarios proffered by Binfield et al. (2007). Further, Läpelle and Hennessy (2012) conduct a scenario analysis of farm viability under different productivity growth outcomes in the post quota period. For all scenarios, Läpelle and Hennessy (2012) estimate that the dairy target is unlikely to be reached and that to do so would require the addition of a varying number of additional model[39] farms in order to achieve the dairy target for FH2020.

With the effect of the abolition of quota on future productivity in the dairy sector uncertain, the NFS-DSM (Dynamic Spatial Microsimulation) model outlined in Chapter 6 presents the opportunity to investigate the spatial impact of alternative productivity scenarios and resultant emissions arising from the abolition of quota in 2015. Additionally, in contrast with the model farm approach taken by Läpelle and Hennessy (2012), the NFS-DSM model provides a basis for the selection of new entrants from within the existing population of non-dairy farms. A 50% increase in milk output could be achieved along a number of different possible development pathways, using different combinations of the primary determinants of output in conjunction with efficiency improvements and a number of new entrants.

[38]. Quota rent refers to an estimation of the production levels that would occurred if the quota system was not in place.
[39] The model farm was defined as a 100 livestock unit dairy enterprise on good soils with stocking densities of 2.6 LU/ha.

7.3 Methodology

The study of four dairy productivity scenarios as a result of the abolition of quota in 2015 is undertaken using the NFS-DSM model framework outlined in the previous chapter. This methodology introduces a new dimension, and expands on the previous work of Hennessy (2007) and Donnellan and Hanrahan (2011a) by providing a spatial disaggregation of potential future dairying activity and resultant emission outcomes following the abolition of quota. In addition, the identification of potential new entrants within the existing farm population and their spatial location progresses the literature from the standard model farm entrant approach taken by Läpelle and Hennessy (2012).

The data, methodology and simulation process for the NFS-DSM model has been outlined previously in Section 5.4. What follows is a brief synopsis of a two stage modelling process, which involves the simulation of four alternative productivity growth scenarios using the NFS-DSM model and the use of a logistic regression model to rank and select the number of non-dairy farms required to meet the FH2020 dairy targets.

7.3.1 Productivity Scenarios

The model employs four alternative productivity scenarios for the dairy sector which are summarised in Table 7.1 below. For each scenario, assumptions relating to the rate of productivity change are made for the pre-abolition period (2010-2014) the immediate post-abolition period (2015-2016) and the remaining post abolition period (2017-2020). The design of each productivity scenario was informed by the work of Läpelle and Hennessy (2012) and by conversations with dairy experts within Teagasc, the Irish agricultural advisory authority.

Table 7.1 Productivity scenarios for the abolition of milk quota

Scenario 1	Productivity changes at the historical modelled rate (BAU)
Scenario 2	Productivity increases at **1% per annum**, rising to **3%** immediately in the post quota years of 2015 & 2016, returning to **1%** thereafter
Scenario 3	Productivity increases at **2% per annum**, rising to **3%** immediately in the post quota years of 2015 & 2016, returning to **2%** thereafter
Scenario 4	Productivity increases at **2% per annum**, rising to **4.5 %** immediately in the post quota years of 2015 & 2016, returning to **2 %** thereafter

For all scenarios, it is assumed that annual productivity will increase by between 1-2% given an annual 1% quota increase per annum (p.a) designated for Ireland through the EU Health Check Agreement (Council Regulation, 2009). This assumes the take up of additional quota and the continued restructuring of the dairy sector in the pre-quota period.

Scenario 1 is a business as usual scenario, with productivity changes modelled at the historical rate. Scenario 2 assumes that productivity increases at 1% p.a. annum, rising to 3% p.a. in the two years post quota abolition before returning to 1% p.a. thereafter. Alternatively, Scenario 3 assumes productivity increases of 2% p.a., again rising to 3% p.a. in the two years post quota abolition before returning to 2% p.a. Scenario 4, assumes the highest level of productivity increase with a rise of 2% p.a. assumed for the pre-abolition period, rising to 4.5% p.a. in the two years post abolition before finally returning to 2% p.a. For all scenarios, the baseline assumptions relating to the rate of exit from the dairy sector were maintained with an exit rate of 2% per annum for the pre-abolition period falling to 1% following the abolition of quota restrictions post 2015.

It should be noted that while, Läpelle and Hennessy (2012) investigated economic outcomes for dairy farms from a number of milk price scenarios for 2020, the focus of this thesis is on the consequences for spatial agri-emissions resulting from the restructuring of dairying activity in Ireland and the potential emissions outcomes arising from the meeting of targets. As such, price projections for 2020 from the FAPRI-IRELAND model outlined in Chapter 6 were maintained for all outputs across all four scenarios.

7.3.2 Two-Stage Modelling Process

In order to estimate future dairy farm locations and resultant emissions outcomes as a result of meeting targets in the Irish dairy sector a two stage modelling process is undertaken.

Stage One: The Simulation Process

The NFS-DSM model simulates agricultural outcomes for the national farm population for 2020. The weighted Teagasc National Farm Survey is dynamically simulated forward by using a system of equations designed to predict structural and productivity changes year on year, from which each farms gross output, net margin and family farm income can be recalculated. A mixture of random and fixed effects models are estimated on the primary determinants of output and on direct and overhead costs with the rate of time variant technological progress captured using the nominal year value as an explanatory variable. These models are then used to simulate outputs and costs forward in time. As the model simulates forward, the year and the age of the holder is increased year on year while input and output prices are recalculated on the basis of price projections from the FAPRI-Ireland model (Binfield et al., 2008). Exits from the dairy sector over the estimation period 2001-2010 are modelled and simulated from the base year of 2010 to 2020. The modelled rate of exit, together with projections for changes in yield, intensity of production and the land base, produces a baseline business as usual (BAU) scenario for all sectors.

In addition to the baseline scenario, due to the uncertainty surrounding the effect of the abolition of quota in 2015, three alternative productivity growth scenarios are simulated for the dairy sector. The resultant total milk yield is then calculated for all four scenarios and compared with the FH2020 dairy target outlined in Section 7.2.2. The model then calculates the distance or shortfall to achieving the FH2020 dairy target based on the total milk production simulated for each scenario.

Stage Two: The Selection of New Entrants

The number of new entrants required is dependent on the projected output from existing farms which are simulated to remain in dairy until 2020 under all four productivity growth scenarios. The distance or gap between the projected output and the target output determines the number of farms that are required to enter the sector by 2020 under each scenario modelled in stage one. The amount of farms simulated to enter is also dependent on assumptions related to the estimated output from new entrants. New entrants are assumed to devote at least 65% of the farm area to dairy and are assumed to be specialist dairy with the remaining farm area allocated pro rata to the existing enterprises. The total potential milk output is simulated by applying the output estimates for productivity and stocking rate from existing dairy farms to all non-dairy farms.

Due to the extremely small number of farms entering the dairy sector in the period of the panel analysis, the model simulates entry by selecting farms who characteristics most closely match existing dairy farms. The probability of being a dairy farmer is estimated based on farm characteristics such as region, soil type, farm size, land value, the age of the farm holder and the existing stocking rate. The estimates are used to rank the non-dairy farms in terms of the probability of being a dairy farm (it is assumed that those farms with characteristics most similar to existing dairy farms are the most likely to enter). The model then adds farms sequentially in order of those most likely to enter and incrementally recalculates total output. The process is repeated until the target total milk output is reached with the required number of new entrants selected.

Each alternative expansion scenario is disaggregated using the SMILE-NFS spatial microsimulation model, with resultant emissions outcomes and the spatial disaggregation of predicted new entrants presented at the electoral district level.

7.3.3 Probability of Entering Dairy

Läpelle and Hennessy (2012) note that even in their most optimistic price and productivity scenarios, a substantial number of new entrants would be required to meet the milk volume target. However, the authors' use of a homogenous model[40] farm to determine the number of additional entrants does not take into account the likely heterogeneous nature of those new entrants; given that they will almost certainly come from within the existing farm population. Additionally, the likely location of those new entrants will have important impacts in terms of the consequences for spatial emissions, not only in terms of the emissions associated with changes in dairying activity but also in terms of the emissions offset from other sectors as a result of a move into dairy.

Studying extended grazing on Irish dairy farms, Läpelle et al. (2012) note the importance of environmental characteristics such as region and soil type on the economic characteristics related to dairy farming. An examination of the National Farm Survey over the estimation period reveals that dairy farms are typically located on larger farms, with better soils and typically the more productive south and south-west regions of Ireland (Teagasc, 2011). Given the relative labour intensive nature of the dairy industry, the farm holder's age and the availability, and use of unpaid labour hours on the farm is also assumed to be a key factor influencing the likelihood of operating a dairy enterprise (Egan, 2013).

To provide a reasonable estimate of the number, nature and location of new entrants, the question of what farm characteristics are associated with existing dairy farms is a crucial concern. While there is a subtle distinction between the probability of being a dairy farmer and the probability of entering dairy, due to the extremely small number

[40] defined as a 100 livestock unit dairy enterprise on good soils with stocking densities of 2.6 LU/ha

of farms entering the sector in the period of analysis it is assumed that those non-dairy farms/farmer holders, whose characteristics most closely match existing dairy farms, are the farms that are deemed the most likely to enter the dairy sector.

In order to calculate predicted probabilities for non-dairy farms entering the dairy sector a pooled logistic regression on the probability of having a dairy enterprise is performed on the NFS for the period 2001-2020 taking the form of:

$$\ln\left[\frac{p}{1-p}\right] = \alpha + \sum\beta x + e \quad \textbf{(7.1)}$$

Where ln[p/(1-p)] = log odds ratio of having a dairy enterprise.

Estimates are calculated for the probability of being a dairy farm based on farm characteristics such as region[41], soil[42] type, farm size and the existing stocking rate with farm holder characteristics relating to the availability to supply the necessary labour requirements and the membership of the age of the national agricultural advisory service also included. Table 7.2 summarises the results from a pooled logistic regression on the probability of having a dairy enterprise.

[41] Region 1: Louth, Leitrim, Sligo, Cavan, Donegal, Monaghan Region 2: Dublin Region 3: Kildare, Meath, Wicklow Region 4: Laois, Longford, Offaly, Westmeath Region 5: Clare, Limerick, Tipperary North Region 6: Carlow, Kilkenny, Wexford, Tipperary South, Waterford Region 7: Cork, Kerry Region 8: Galway, Mayo, Roscommon

[42] Soil 1 = Good, Soil 2 = Fair, Soil 3 = Poor

Table 7.2 Coefficients for probability of having a dairy enterprise (hasdairy)

Independent Variable	Description	hasdairy	(stnd.error)
landvalue_ha	(Land Value Per Hectare)	-.0098488	(.0462581)
farmsize1_<10	(Farm Size Less than 10 ha.)	-0.669***	(0.183)
farmsize2_10-20	(Farm Size 10-20 ha.)	-0.762***	(0.104)
farmsize4_30-50	(Farm Size 30-50 ha.)	0.463***	(0.0682)
farmsize5_50-100	(Farm Size 50-100 ha.)	0.660***	(0.0685)
farmsize6_100+	(Farm Size over 100 ha.)	0.170*	(0.0867)
ageofholder	(Age of farm Holder)	0.0619***	(0.00941)
ageofholder2	(Age of farm Holder Squared)	-0.000940***	(0.0000883)
teagasc_member	(Member of Teagasc)	0.521***	(0.0420)
labour_hrs	(No. of non-Paid Labour Hrs)	1.243***	(0.0479)
stock_rate	(Stocking Rate)	1.991***	(0.0398)
year	(time trend)	-0.0184***	(0.00387)
region1		1.774***	(0.0939)
region2		0.873**	(0.275)
region3		1.099***	(0.0994)
region4		1.002***	(0.101)
region5		2.002***	(0.101)
region6		1.753***	(0.0919)
region7		2.744***	(0.0927)
soil1		0.390***	(0.102)
soil2		0.219*	(0.104)
off_farm_inc	(Presence of Off-Farm Inc.)	-1.323***	(0.0589)
_cons		28.80***	(7.760)
N		22185	
pseudo R^2		0.416	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The model reports that farms in the larger size categories are more likely to operate a dairy enterprise relative to the reference category (farm size of between 20-30 hectares) while smaller farms are estimated to be less likely. As expected, farms operating on the high (soil1) and medium (soil2) soil categories are predicted to be more likely to operate a dairy enterprise relative to those operating on the poorest (soil3) soil category. With regard to region, the coefficients are reported with respect to region 8,[43] the poorest in terms of current milk production. As anticipated, positive and significant coefficients are reported for regions more typically associated with dairying. The amount of unpaid labour (labour_hrs) supplied to the

[43] Mayo, Roscommon, Galway

farm is also positively and significantly associated with the probability of having a dairy enterprise while the presence of an off-farm income (off_farm_inc) is significantly negatively associated. A significant negative association is also reported for the time trend (year), however this is likely to be simply reflecting the effect of a reducing number of dairy farms over the estimation period as a result of exits from the sector. The collective farm-level stocking rate was both found to significantly and positively associated with the presence of a dairy enterprise possibly reflecting the farms existing land carrying capacity for intensive production. Membership of the Teagasc advisory service was also found to be positively and significantly associated with being a dairy farmer.

The findings of McDonald et al., (2012; 2013) in examining the profile of new entrant applicant farmers appear to support the results relating to region, farm size and the availability of unpaid labour. McDonald et al. (2012) observe a concentration of new entrant applicants in regions traditionally associated with dairy and note that new entrant applications typically came from younger farmers on larger farms, with younger farmers able to supply higher amounts of unpaid on-farm labour. It should be noted however that these profiles were constructed from information on applicants to the new dairy entrant scheme (McDonald et al., 2012) and do not represent observed dairying activity.

The estimates reported in Table 7.2 are used to rank non-dairy farms in terms of the probability of being a dairy farm. The model then adds farms sequentially in order of those most likely to enter and incrementally recalculates total output. The process is repeated until the target total milk output is reached with the required number of new entrants selected. In contrast to the simulation of exit from the sector discussed in Section 6.3.2 a stochastic selection component to the model is purposely omitted as those farms who are deemed most likely to enter dairy from the non-dairy cohort may not necessarily return high nominal probabilities. This also allows for the consistent examination of new entrants across all four productivity scenarios discussed in the previous section.

7.4 Results

Results are presented for outcomes arising from the simulation of the four dairy productivity scenarios described in Section 7.3.2. Outcomes for the impacts on mean productivity rates for each scenario are reported with the resultant impacts on family farm incomes illustrated. For each scenario, the required number of new entrants to meet the dairy target from the existing non-dairy farm population is calculated and each selected is simulated to enter dairy. Using the SMILE-NFS methodology outlined in Section 5.4.3, these new entrants are mapped and identified at the ED level along with the subsequent change in emissions per hectare arising from a movement into the dairy sector from other non-dairy enterprises.

7.4.1 Impacts at Farm Level

Figure 7.9 shows the projected growth in mean litres per livestock unit from 2010-2020 for all four productivity scenarios. By construction, the estimated mean litres per livestock unit increases ranges from the baseline (BAU) scenario (Scenario 1) to the most efficient productivity scenario (Scenario 4).

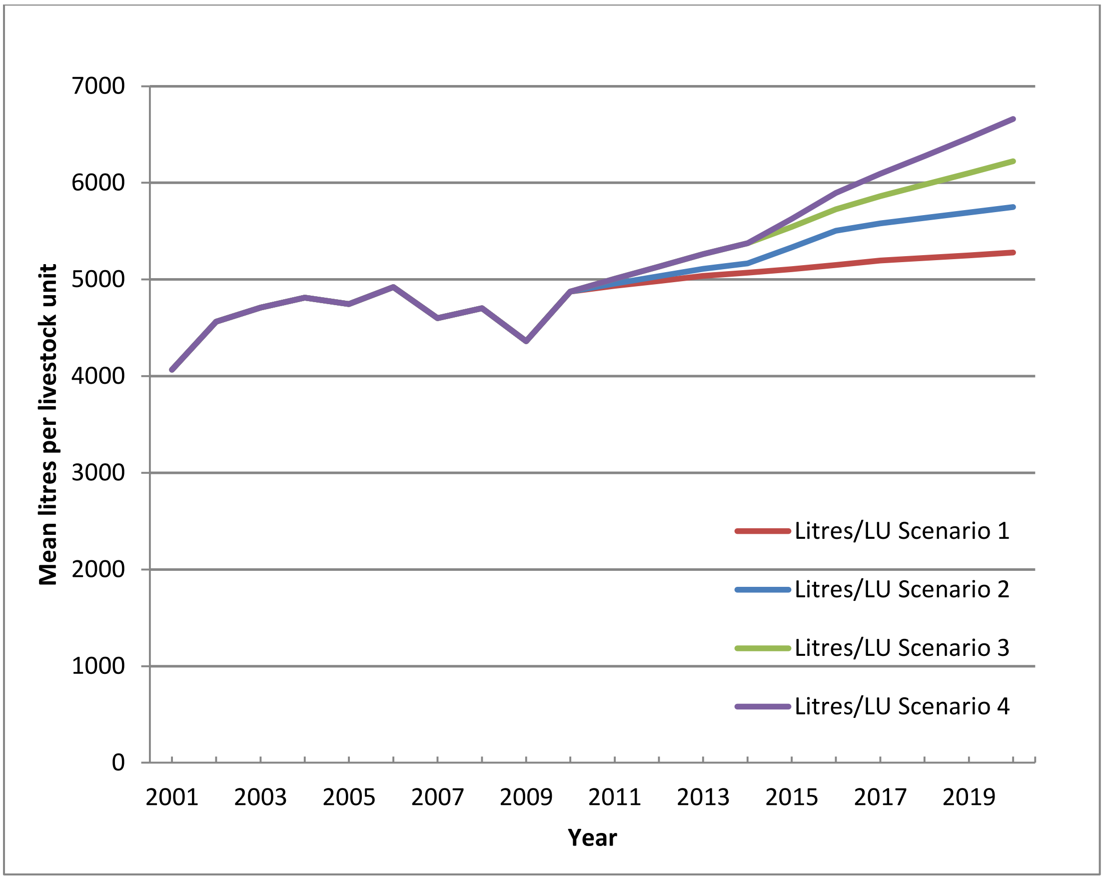


Figure 7.9 Outcomes for mean productivity (litres per livestock unit) 2010-2020

Accompanying Figure 7.9, Table 7.3 below displays the changes in mean productivity for all four scenarios. For the base year of the simulation (2010) the mean productivity value for litres per livestock unit (Litres/LU) is reported at 4,874 Litres/Lu. Mean productivity levels for 2020 range from 5,279 Litres/LU in the lowest productivity growth scenario (Scenario 1) to 6,660 Litres/LU in the highest productivity growth scenario (Scenario 4). These figures represent increases on the 2010 base year of 8.31% and 36.62 % respectively.

Table 7.3 Change in mean productivity (litres per livestock) 2010-2020

	Scenario 1	**Scenario 2**	**Scenario 3**	**Scenario 4**
2010	4874	4874	4874	4874
2020	5279	5750	6222	6660
% change	8.31	17.98	27.65	36.62

In the NFS-DSM model, increases in productivity improvements translate to higher milk volumes reported for 2020, leading to lower emissions and lower number of new entrants required to meet target.

Effects on Family Farm Income

The reaching of the dairy target will also have considerable benefits to family farm income. Figure 7.10 shows the outcomes for mean family farm income for all three productivity scenarios before the addition of new entrants required to meet target. Mean incomes range from €19,050 for Scenario 1 to 23,752 in Scenario 4, the highest productivity improvement scenario.

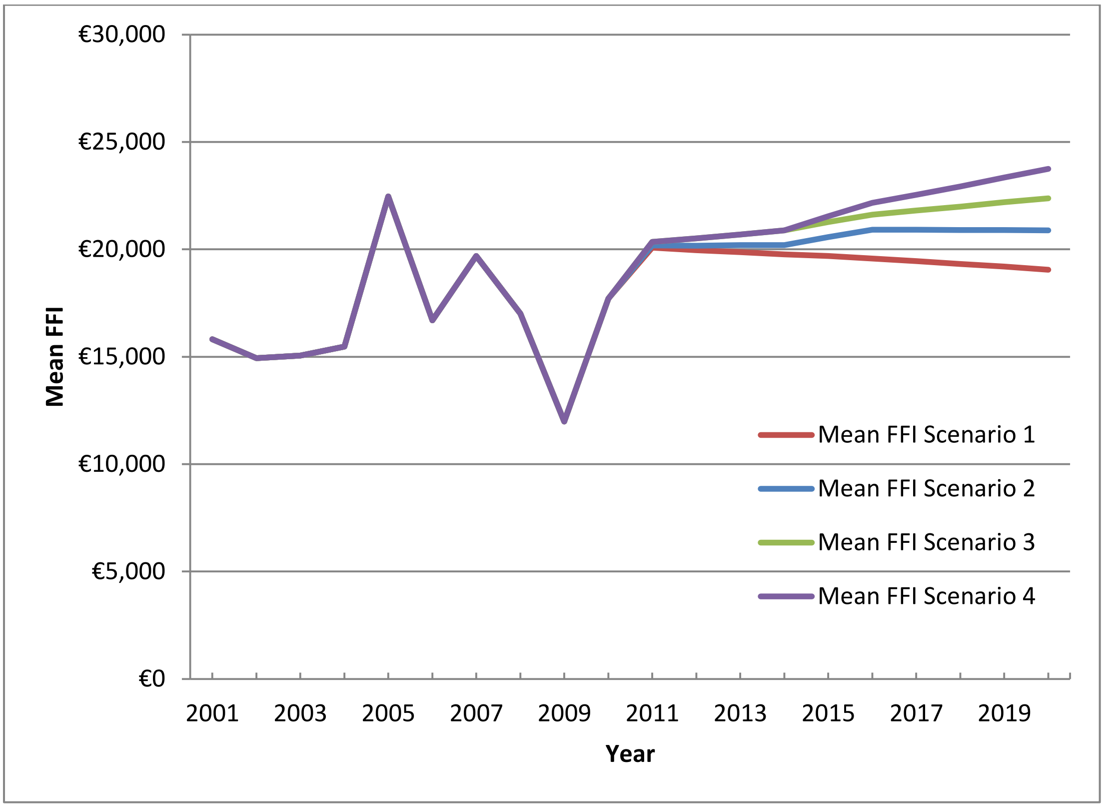


Figure 7.10 Outcomes for mean family farm income (FFI) 2001-2020

Table 7.4 reports the percentage change in mean Family Farm Incomes (FFI) for the period for all four productivity scenarios, again before the addition of new entrants and without reaching the FH2020 dairy target. For the base year of the simulation (2010) the mean family farm income is reported at €17,102. Under Scenario 1 (BAU) mean family farm incomes increase 7.62% to €19,050, while mean incomes increase by 17.98%, 26.38% and 34.18% for Scenarios 2,3 and 4 respectively over the 10 year simulation period.

Table 7.4 Change in mean family farm income (FFI) 2010-2020

€	**FFI Scenario 1**	**FFI Scenario 2**	**FFI Scenario 3**	**FFI Scenario 4**
2010	17,702	17,702	17,702	17,702
2020	19,051	20,885	22,372	23,752
% change	7.62	17.98	26.38	34.18

It should be noted that a significant portion of the increase in mean FFI for all scenarios is accounted for in the first year with Scenario 1 showing a subsequent annual decline in family farm income as gross output falls over time. The explanation for this is directly related to the combined impact of the removal of the dummy effect in the first simulation year for all outputs and costs (Section 6.4.1 and Equation 6.2).

Figure 7.11 represents the uplift in mean family farm incomes simulated as a result of achieving the FH2020 dairy target through the addition of new entrants in the dairy sector. Across all scenarios the movement of existing non-dairy farms into dairy results in an uplift of incomes with the greatest relative uplift being experienced in Scenario 1 (BAU). This result is anticipated as historically the dairy sector has consistently out-performed the other sectors in terms of mean FFI (Teagasc, 2010). Scenario 1 experiences the lowest level of productivity increases, thus a far greater number of farms are required to enter the dairy sector resulting in the most substantial movement in mean incomes. Despite this movement, the baseline scenario still retains the lowest level of mean family farm income from reaching the FH2020 dairy target as it experiences the lowest rate of productivity growth. The dashed lines represent mean FFIs for all four scenarios as displayed in the previous figure (Figure 7.10) before the addition of new entrants.

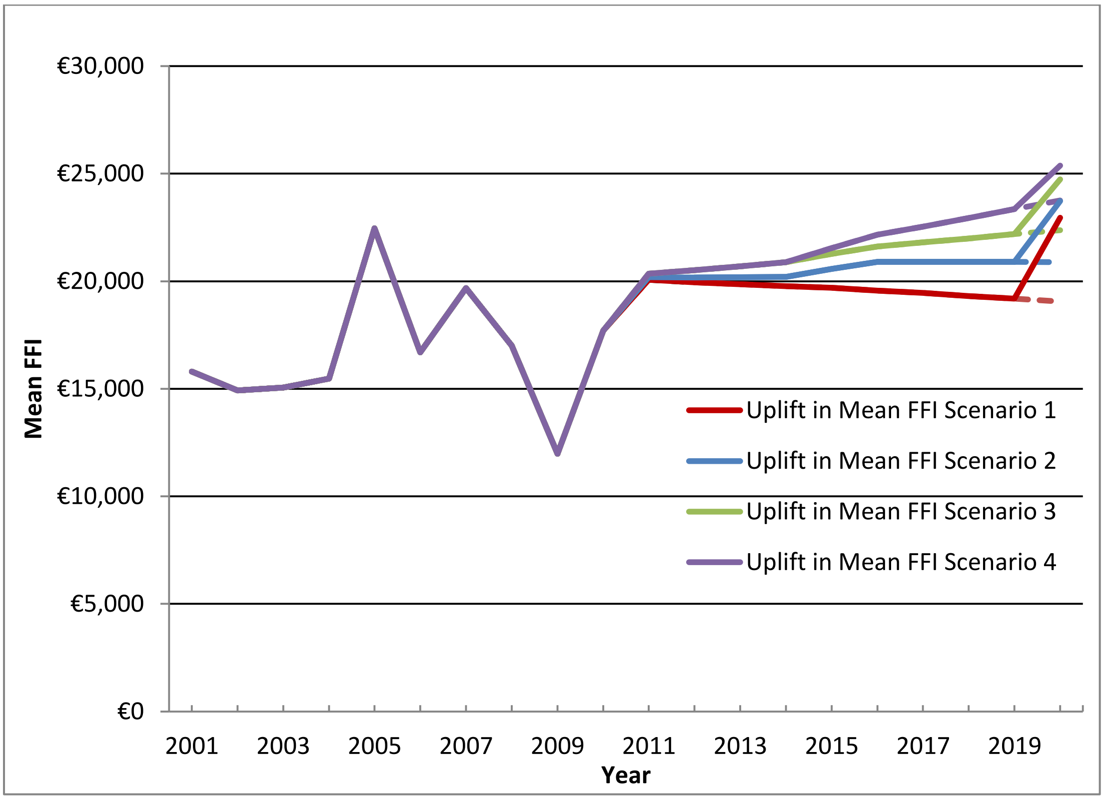


Figure 7.11 Uplift in mean FFI as a result of meeting FH2020 dairy target

Table 7.5 reports the percentage change in mean family farm incomes as a result of meeting the FH2020 dairy target for all four productivity scenarios. Under Scenario 1 (BAU) mean family farm incomes increase 29.69% to €22,958 while mean incomes increase by 34.03%, 39.79% and 43.32% for Scenarios 2, 3 and 4 respectively over the 10 year simulation period.

Table 7.5 Change in mean FFI as a result of meeting dairy target 2010-2020

€	Scenario 1	Scenario 2	Scenario 3	Scenario 4
2010	17,702	17,702	17,702	17,702
2020	22,958	23,726	24,740	25,370
% change	29.69	34.03	39.76	43.32

As outlined in Chapter 6 it should be noted that family farm income is not directly modelled in the NFS-DSM but is constructed annually from simulated changes in outputs and costs across all sectors. As such, these results should be treated with a degree of caution.

Effects on Dairy Numbers

The amount of dairy cows required to meet the FH2020 targets will have a direct impact on the amount of emissions attributed to the agri-sector in 2020. In all four productivity growth scenarios, the FH2020 milk target of 7.254bn litres cannot be reached without the addition of new entrant farms (and their modelled number of dairy cows) to the dairy sector. Figure 7.12 below displays the total number of dairy cattle required to meet the FH2020 targets in all four productivity growth scenarios. In addition the first column displays a total of 1.41 million dairy cows projected for 2020 in the BAU scenario[44] outlined in Chapter 6, i.e. without the addition of new entrants.

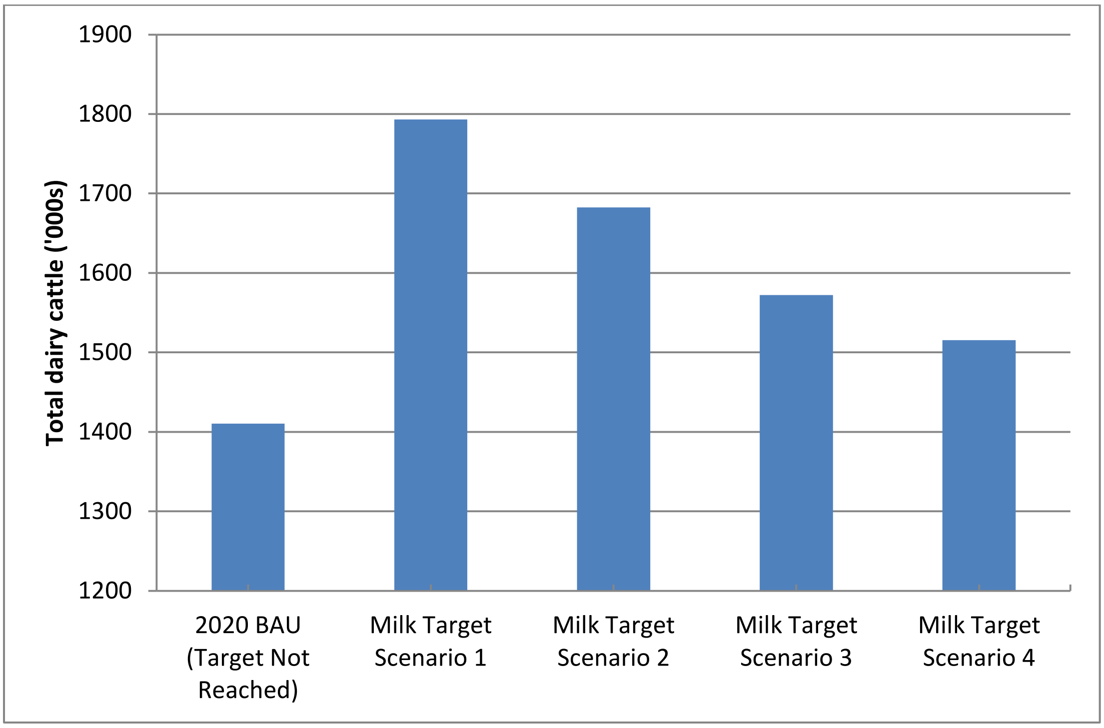


Figure 7.12 Total dairy cattle required to meet FH2020 dairy target

[44] resulting in a total milk output of 5.173bn litres, approx. 2.018bn litres short of the 7.254bn litre dairy target

For all four scenarios, Table 7.6 shows the percentage change in the number of dairy cows required to meet the FH2020 dairy target compared to the BAU scenario outlined in the previous Chapter 6. The number of additional dairy cows required to meet target for Scenario 1 is estimated at 1.793m cows signifying a 27.2% increase. The total number of dairy cows estimated to be required to meet target in Scenarios 2 and 3 are 1.682m and 1.572m, representing a 19.3% and 11.5% increase respectively. In the highest productivity scenario (Scenario 4), the total number dairy cows required to meet the FH2020 dairy target is estimated at 1.515m representing just a 7.4% increase in total dairy cow numbers.

Table 7.6 Total dairy cattle (millions) required to meet dairy target 2020 compared to 2020 BAU scenario

	Milk Target Scenario 1	**Milk Target Scenario 2**	**Milk Target Scenario 3**	**Milk Target Scenario 4**
2020	1.793	1.682	1.572	1.515
2020 BAU	1.410	1.410	1.410	1.410
%change	27.2	19.3	11.5	7.4

7.4.2 Spatial Disaggregation of Required New Entrants

Figure 7.13 displays the total number of new entrants required to meet dairy target under all four productivity scenarios. In Scenario 1, the lowest productivity scenario, a total of 4,465 new entrants are projected to enter the dairy sector in order to meet target. As productivity rates increase the number of farms required to enter the sector declines considerably with just 1,031 new entrants required to enter in Scenario 4.

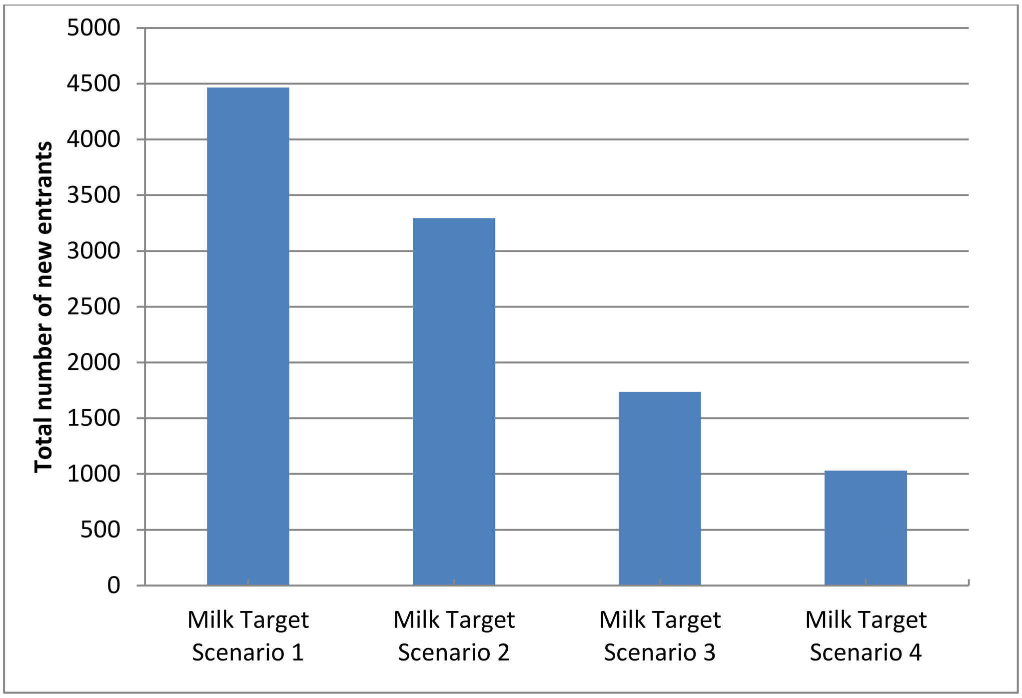


Figure 7.13 Total number of new entrants required to meet dairy target 2020

Table 7.7 shows the change in the total number of dairy farms required from the BAU scenario outlined in Chapter 6 (where the dairy target is not met). For Scenario 1, the lowest productivity scenario, the total number of dairy farms projected to be required to meet target is 32,369, an increase of 16% on the BAU scenario. For Scenario 4, the highest productivity scenario, the total number of farms required drops to 28,935 representing just a 3.7% increase on the BAU scenario.

Table 7.7 Change in total number of farms required to meet dairy target 2020

No. of Dairy Farms	**Scenario 1**	**Scenario 2**	**Scenario 3**	**Scenario 4**
New Entrants Required	4,465	3,295	1,736	1,031
BAU 2020	27,904	27,904	27,904	27,904
Tot. Required to Meet Target	32,369	31,199	29,640	28,935
% Increase Required	16.0	11.8	6.2	3.7

Figures 7.14-7.17 display the spatial distribution of new entrants required to meet the dairy target under all four productivity scenarios. The maps are ordered from the highest productivity scenario (Scenario 4) to the lowest (Scenario 1) in order to reveal the increased geographical dispersion of new entrants required as productivity

decreases. For Figure 7.14 representing the highest productivity scenario, a small number of new entrants are concentrated predominantly in those areas traditionally associated with dairying, where farms not currently engaged in dairy farming are simulated to enter. As productivity declines through Scenarios 4 to 1, the required number of new entrants increases with the geographical spread of new entrants broadening substantially as the available farms deemed most likely to enter are exhausted in those areas.

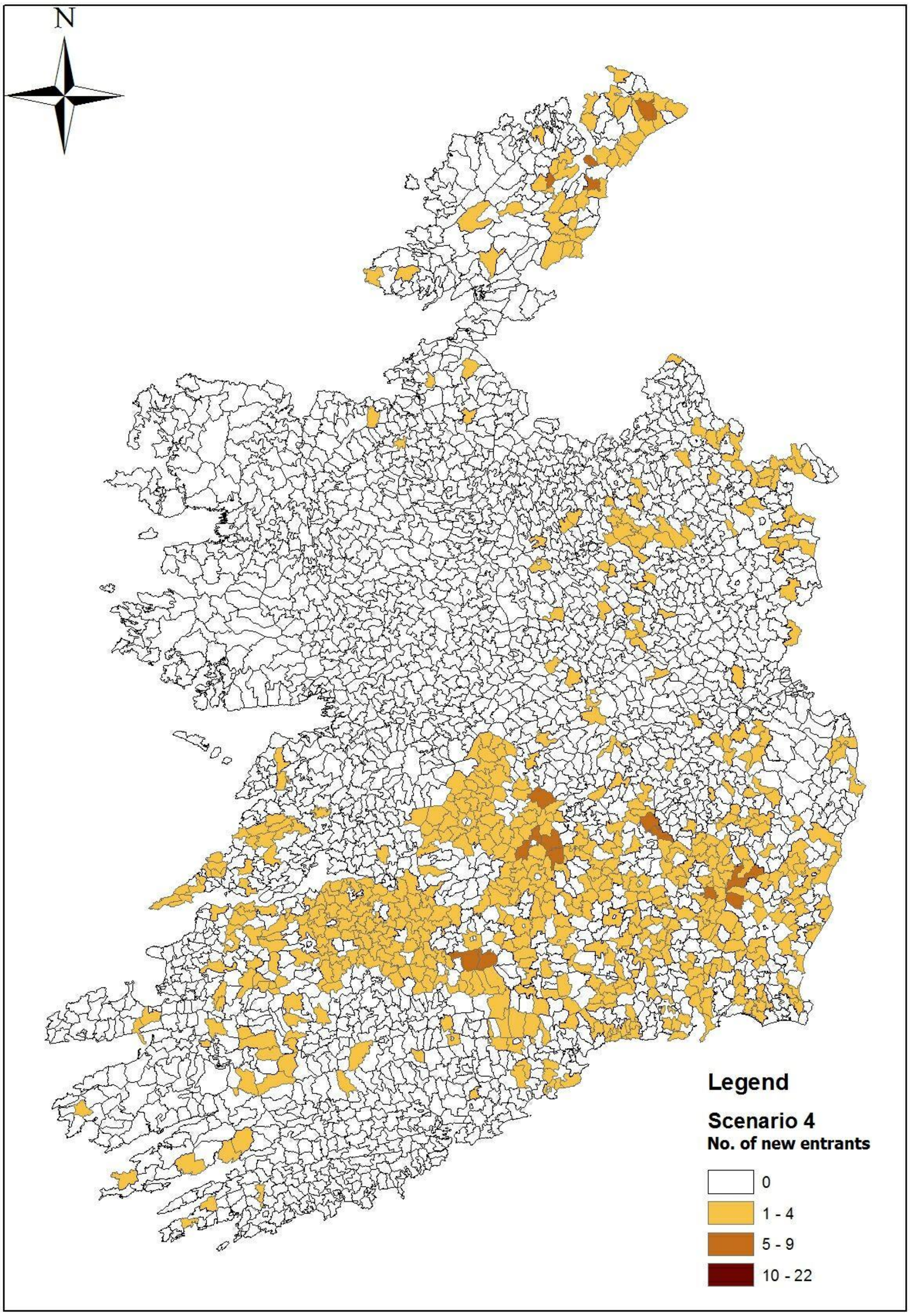


Figure 7.14 Spatial distribution of 1,031 new entrants required to meet dairy target 2020 under Scenario 4

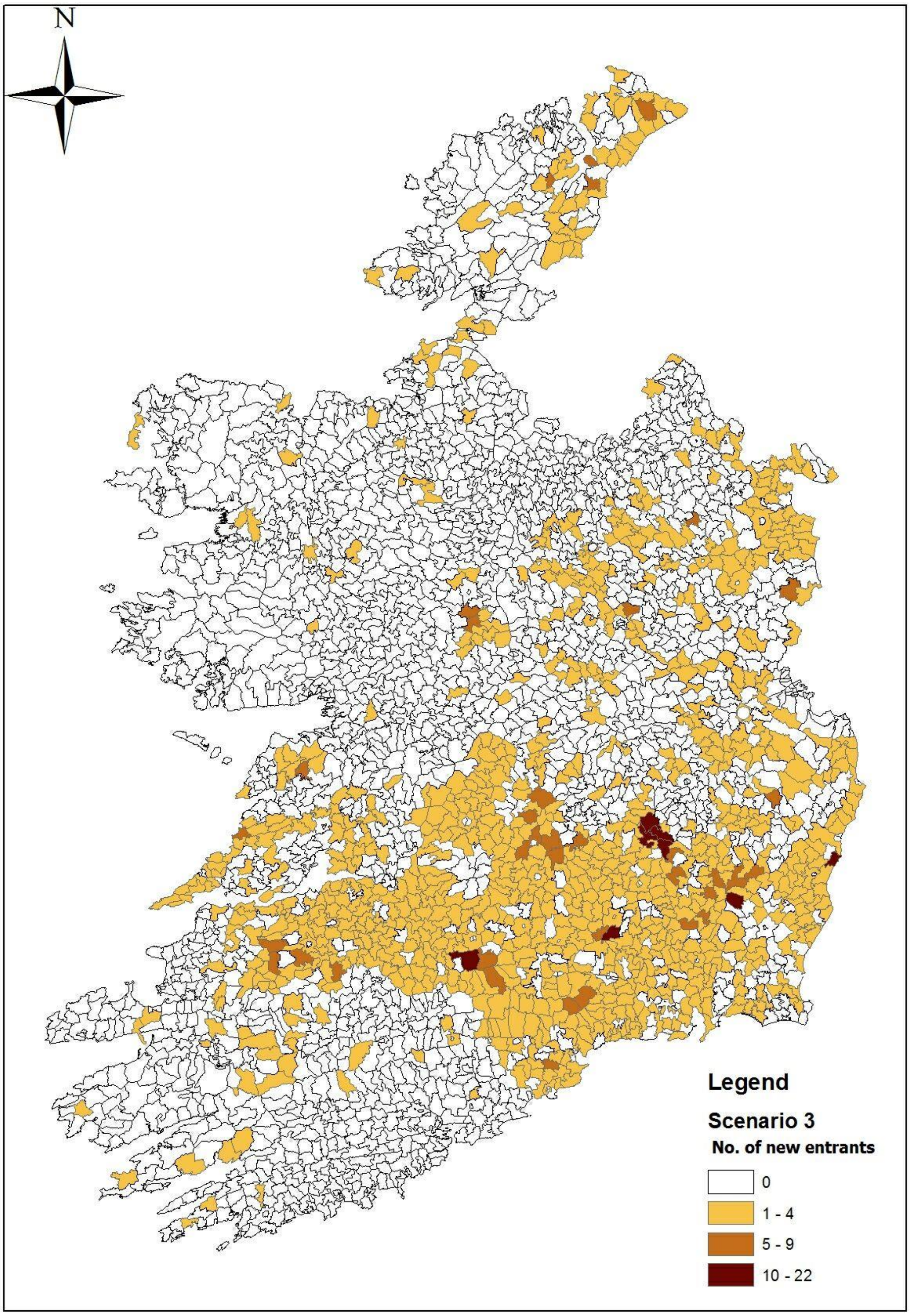


Figure 7.15 Spatial distribution of 1,736 new entrants required to meet dairy target 2020 under Scenario 3

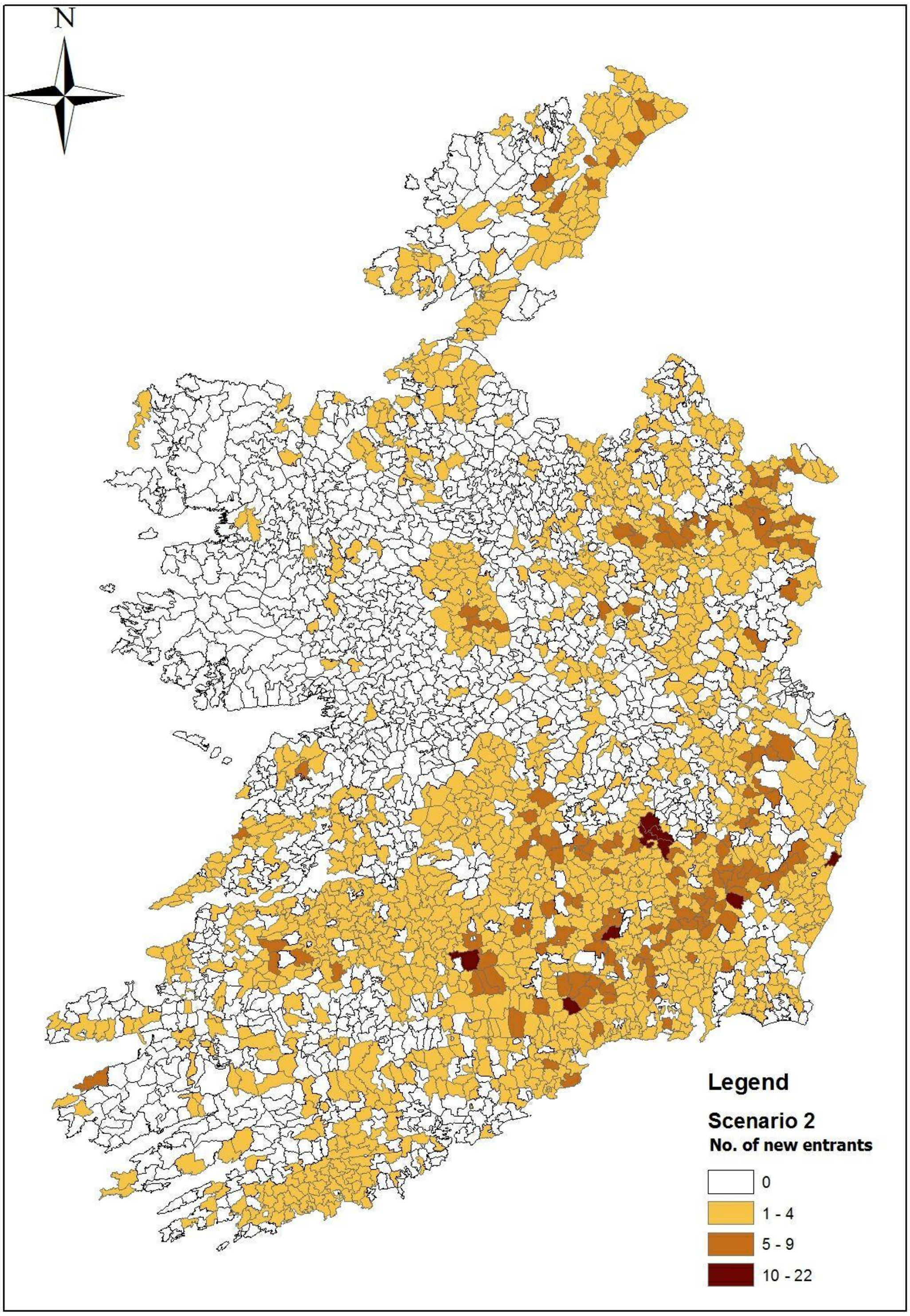


Figure 7.16 Spatial distribution of 3,295 new entrants required to meet dairy target 2020 under Scenario 2

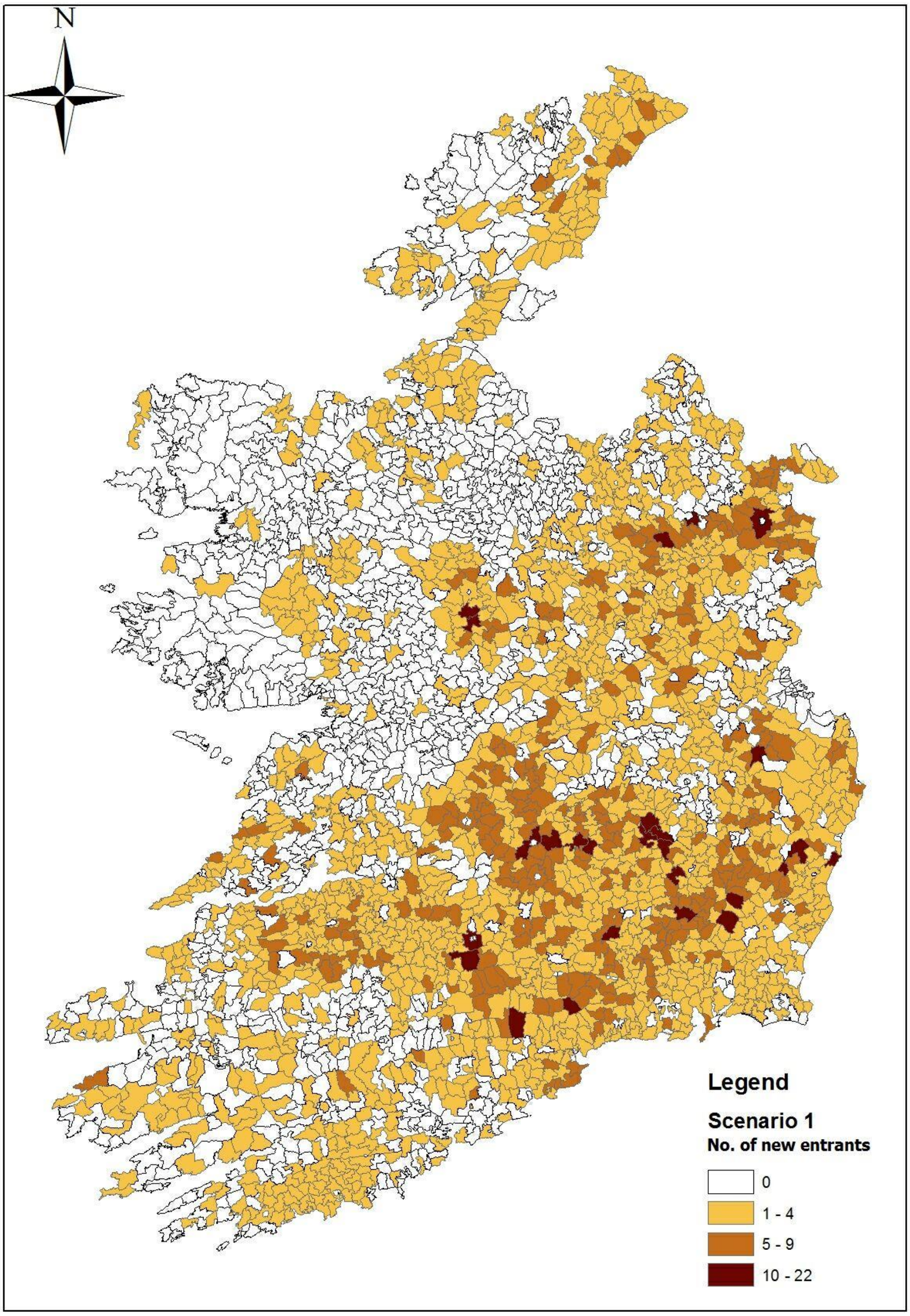


Figure 7.17 Spatial distribution of 4,465 new entrants required to meet dairy target 2020 under Scenario 1

7.4.3 Impacts on National Emissions

As outlined in the previous chapter, the IPCC methodology is the method used for the calculation of national inventories and in the absence of further international agreement is applied for the purposes of calculating the change in national agri-emissions projected by the NFS-DSM model. Tables 7.8-7.10 display the percentage change in total livestock numbers for dairy, cattle and sheep respectively from all four milk target scenarios compared to the BAU scenario outlined in Chapter 6.

Scenario 1 projects that at the lowest rate of productivity growth for the dairy sector, 1.793m dairy cows will be required to meet the target milk output volume in 2020 representing an overall increase on 2010 levels of 27%. In contrast, Scenario 4 projects that assuming the highest rate of productivity growth, the total projected dairy numbers required to meet the dairy target will be 1.515m, representing an increase of 7.4%.

Table 7.8 Total dairy numbers 2020

(000s)	Scenario 1	Scenario 2	Scenario 3	Scenario 4
2020	1793	1682	1572	1515
2020 BAU	1410	1410	1410	1410
%change	(27.2)	(19.3)	(11.5)	(7.4)

For cattle, Scenario 1 projects that at the lowest rate of productivity growth for the dairy sector, around 415,000 cattle will be displaced by the dairy sector leaving a total of 6.102m cattle in 2020 representing an overall decrease of around 6.4%. Scenario 4 projects that assuming the highest rate of productivity growth, the total projected cattle displaced by new dairy entrants will be in the order of 126,000 representing a decrease of just 1.9%

Table 7.9 Total cattle numbers 2020

(000s)	Milk Target Scenario 1	Milk Target Scenario 2	Milk Target Scenario 3	Milk Target Scenario 4
2020	6102	6222	6339	6391
2020 BAU	6517	6517	6517	6517
%change	(-6.4)	(-4.5)	(-2.7)	(-1.9)

For sheep, Scenario 1 projects that at the lowest rate of productivity growth for the dairy sector; around 491,000 sheep will be displaced by the dairy sector leaving a total of 4.347m sheep in 2020 representing an overall decrease of around 11.4%. Scenario 4 projects that assuming the highest rate of productivity growth, the total projected sheep displaced by new dairy entrants will be in the order of 96,000 representing a decrease of just 2.2%

Table 7.10 Total sheep numbers 2020

(000s)	Milk Target Scenario 1	Milk Target Scenario 2	Milk Target Scenario 3	Milk Target Scenario 4
2020	3856	3968	4159	4251
2020 BAU	4347	4347	4347	4347
%change	(-11.3)	(-8.7)	(-4.3)	(-2.2)

Figure 7.18 reports the total CO_2eq emissions (Gg) for all 4 Scenarios for 2020, compared to the 2020 BAU scenario reported in Chapter 6 and total agri-emissions reported for 2010 with emissions ranging from 19.35Gg CO_2eq under Scenario 1 to 18.83 Gg CO_2eq under Scenario 4.

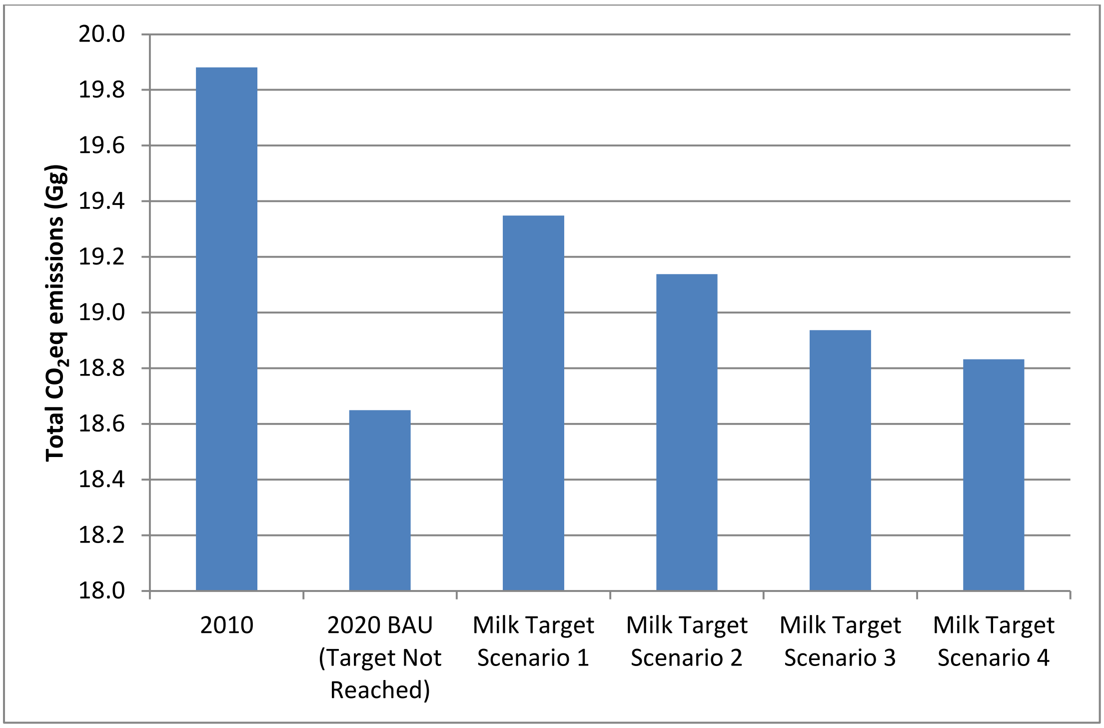


Figure 7.18 Total CO_2eq agri-emissions (Gg) for all scenarios compared to 2010

Table 7.11 reports the total change in Methane, Nitrous Oxide and total CO_2eq Emissions (Gg) for all 4 Scenarios and the 2020 BAU scenario, compared to 2010. Total emissions show a decrease in the baseline values across all scenarios and the BAU compared to 2010. In terms of meeting the dairy target, the highest rates of decrease are seen in Scenario 4 where the high annual increase in productivity per cow post quota translates into the fewest number of dairy cows required.

Table 7.11 Change in total CO_2eq emissions (Gg) 2010-2020

	2010	**2020 (BAU)**	**Scenario 1**	**Scenario 2**	**Scenario 3**	**Scenario 4**
Tot. CO_2eq (Gg)	19.88	18.65	19.35	19.14	18.94	18.83
% (2010)		(-6.20)	(-2.68)	(-3.74)	(-4.75)	(-5.28)
Tot. CH_4 (Mt)	606.44	578.40	600.36	593.78	587.84	584.25
% (2010)		(-4.62)	(-1.00)	(-2.09)	(-3.07)	(-3.66)
Tot. N_2O (Mt)	23.05	20.98	21.75	21.51	21.27	21.17
% (2010)		(-9.00)	(-5.67)	(-6.68)	(-7.75)	(-8.17)

While the range of values for the four milk target scenarios reported in 7.11 would appear comparatively small, it should be remembered that the table reflects total emissions across all sectors. For all four dairy target scenarios, as productivity increases, emissions savings from the reduction in the number of dairy cows required to meet target are offset by a reduction in the displacement experienced in other sectors. For the lowest productivity scenario (Scenario 1) the additional emissions associated with an additional 383,000 dairy cows (the highest per LU CO_2eq emitters) (Table 7.8), are substantially offset through reductions in livestock numbers in the cattle (Table 7.9) and sheep sectors (Table 7.10) of 415,000 and 491,000 respectively. For the highest productivity scenario (Scenario 4) only 105,000 additional dairy cows are required with those increased emissions partially offset through reductions of 126,000 and 96,000 in livestock numbers for cattle and sheep respectively. While a rise in overall emissions occurs despite seemingly larger numerical reductions in the livestock numbers of the other sectors, it should be remembered that emissions factors are understandably different for different livestock categories and are not weighted equally. The highest emissions factors are attributed to dairy cattle under the current methodology. For further information see Section 5.4.4.

7.4.4 Spatial Impacts on Emissions per Hectare

Figures 7.19 to Figure 7.22 report the ratio of change of total CO_2eq emissions per hectare from 2010 to 2020 for Scenarios 1,2 3 & 4 respectively. Both figures show that while most of Ireland experiences a decline in emissions per hectare, those areas experiencing considerable entry into the dairy sector (Section 7.4.2) show an increase in overall emissions per hectare.

For Scenario 4, the highest productivity scenario, increases are observed for a small number of EDs predominantly concentrated in areas traditionally associated with dairy, where farms not currently engaged in dairy farming convert to dairy. For Scenario 1, the required number of entrants is much greater with a considerably higher number of EDs experiencing a rise in emissions per hectare. While the geographical spread of new entrants is broadened substantially, simulated entrants are still primarily concentrated in areas traditionally associated with dairy.

Spatial information on agricultural activity and associated emissions provides an opportunity to design and effectively implement mitigation strategies at various spatial scales. These results illustrate the potential for a dynamic spatial microsimulation model for agriculture to provide an essential input into the development of mitigation options for the future, particularly where certain mitigation options may only be feasible on a medium to long term planning horizon such as the optimal location of processing facilities and distribution centres.

With agriculture's contribution to total emissions from the non-ETS sector projected to rise to 48% by 2020 (EPA, 2013b), the ability to plan strategically for the future mitigation of greenhouse gases from the agricultural sector is of crucial importance, not just in terms of Ireland's ability to meet its immediate EU commitment to reduce national emissions by 20% by 2020 (Council Decision, 2009) but also in terms of the likely requirement to meet more ambitious targets in the future (European Commission, 2014).

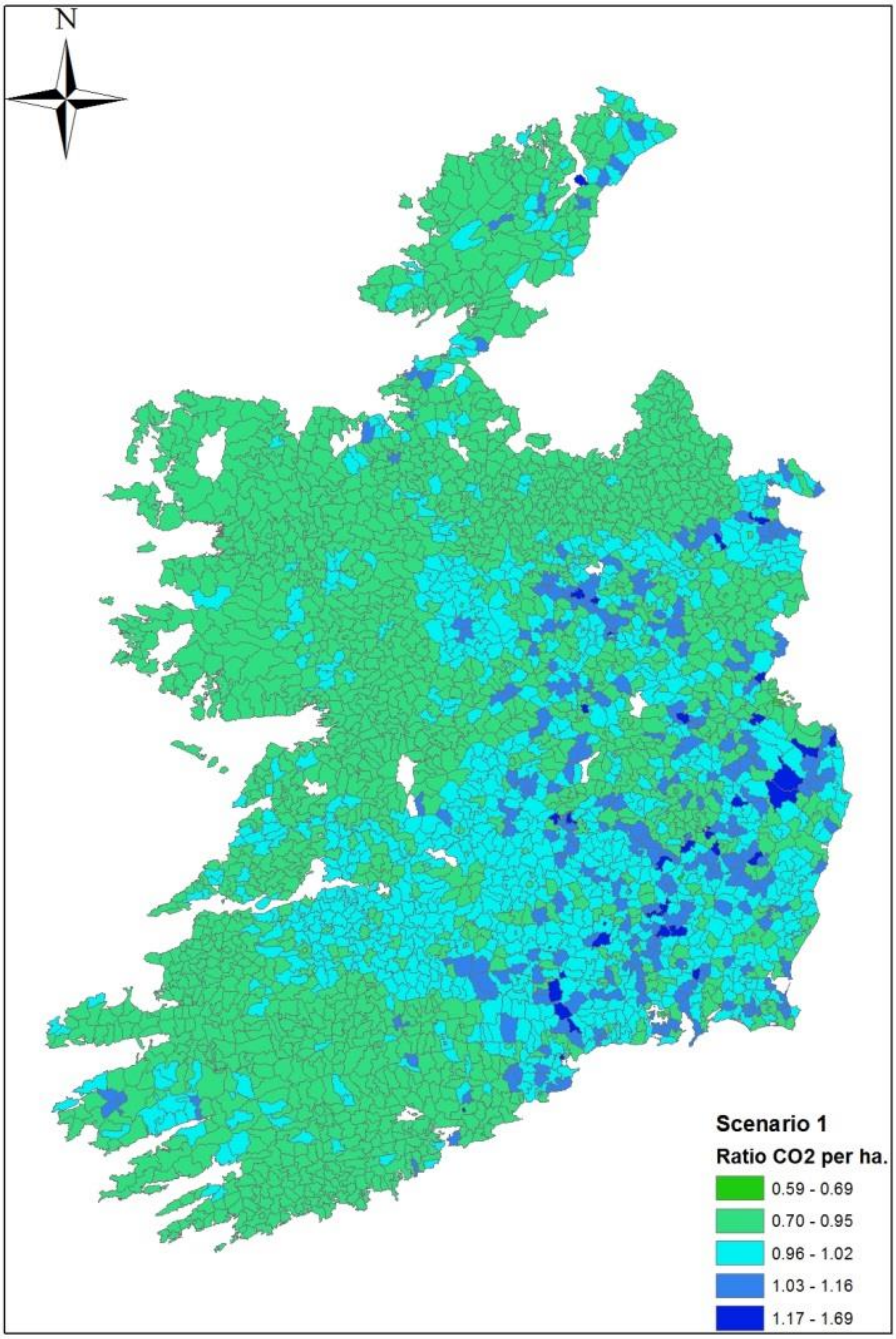


Figure 7.19 Ratio change of total CO_2eq agri-emissions per hectare 2010 to 2020 for Scenario 1

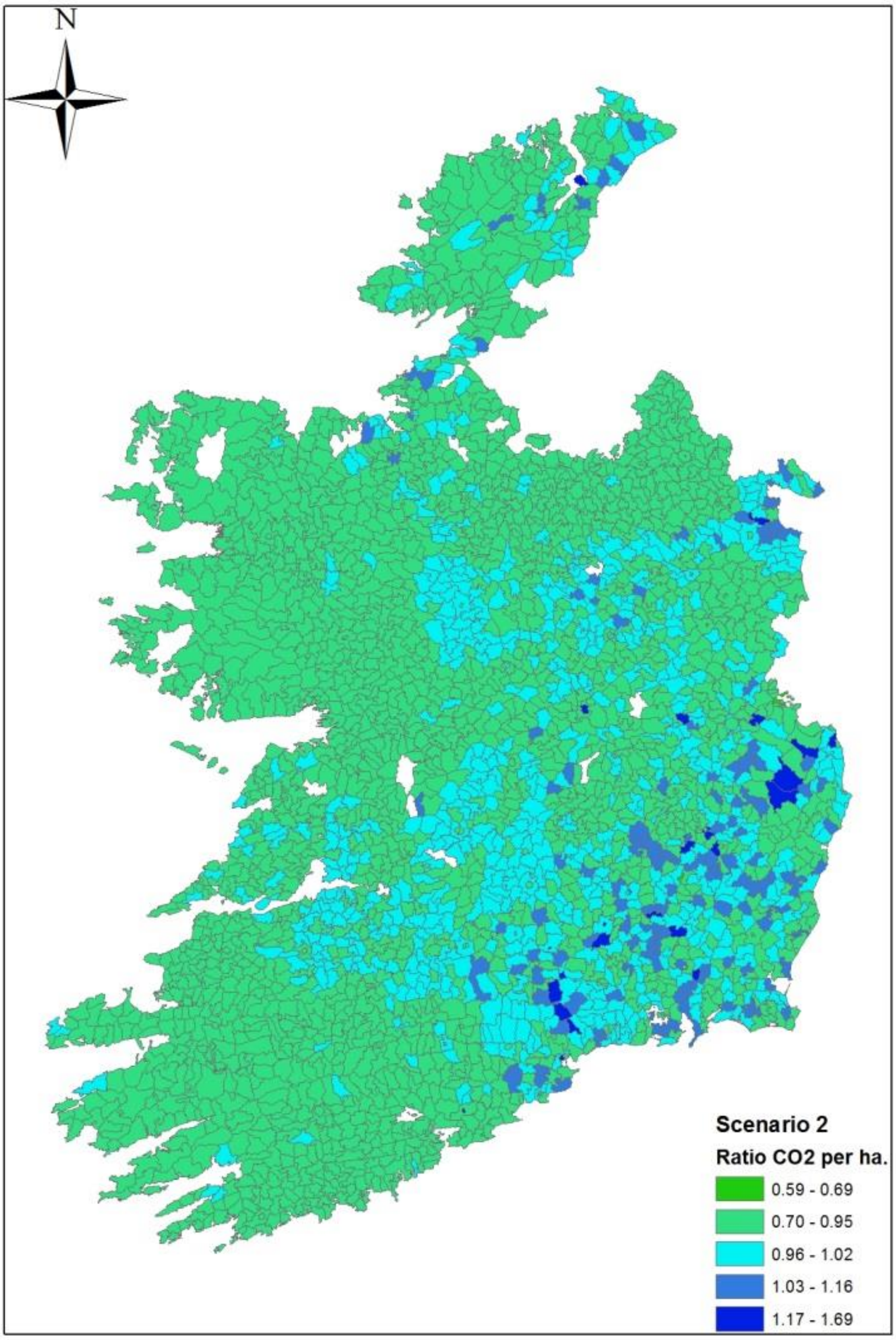


Figure 7.20 Ratio change of total CO_2eq agri-emissions per hectare 2010 to 2020 for Scenario 2

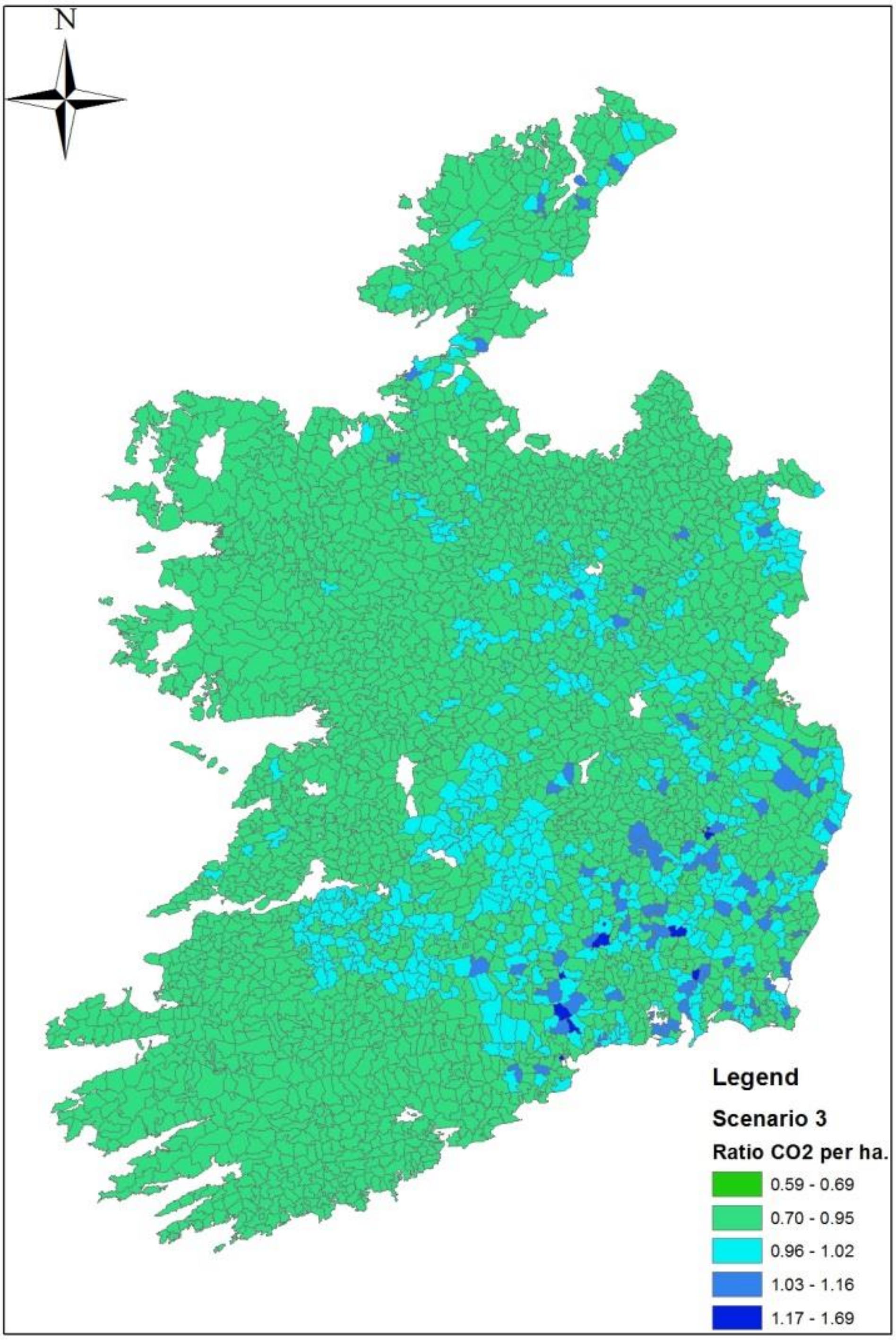


Figure 7.21 Ratio change of total CO_2eq agri-emissions per hectare 2010 to 2020 for Scenario 3

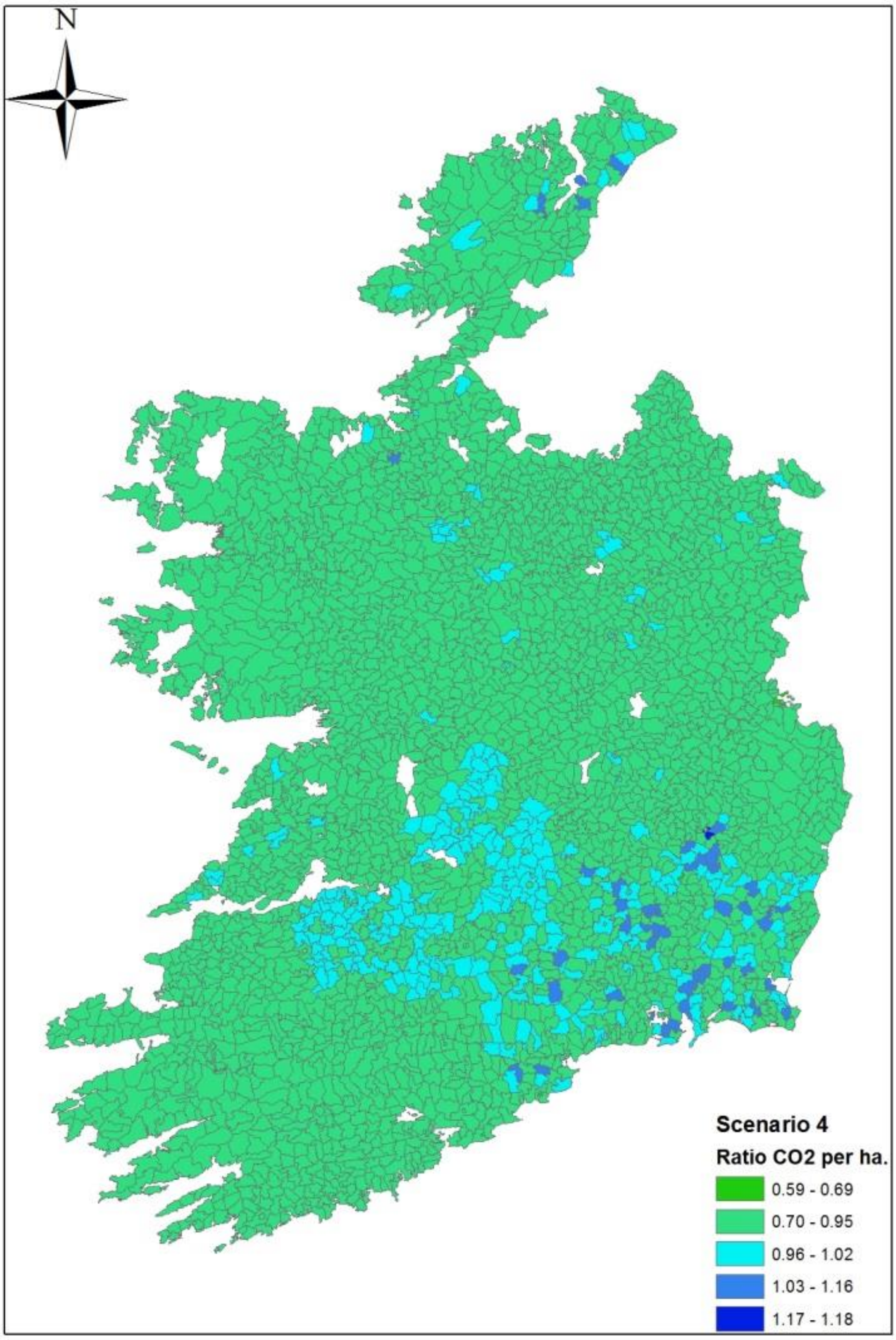


Figure 7.22 Ratio change of total CO_2eq agri-emissions per hectare 2010 to 2020 for Scenario 4

7.5 Conclusions

Given the regional heterogeneity of agricultural activity in Ireland, a key component of policy analysis for the impact of reaching the FH2020 dairy target is currently absent. Spatial information on farming activity can provide policymakers with a basis for predicting where the increased agricultural activity is likely to be centred. Future economic, environmental, and labour outcomes at the local level can be undertaken with the objective of identifying local constraints/barriers to growth. Spatial information on agricultural activity can help also help policymakers identify local efficiency opportunities and productivity gains which can reduce overall emissions levels.

This NFS-DSM model has been used to display the potential future spatial locations of new dairy farms required to enter the sector in order to meet the FH2020 target of a 50% increase in milk output under a number of different productivity growth scenarios. The model simulates new entrants initially in the more traditional dairy areas with the geographical spread and number of new entrants required widening and increasing with lower productivity growth rates. Advanced knowledge of the potential spatial disaggregation of dairying activity could help inform future greenhouse gas mitigation strategies such as informing the optimal location of future processing facilities to reduce associated transport emissions as outlined by Quinlan et al. (2006). The NFS-DSM model also calculates the resultant spatial change in total agri-emissions as a result of meeting the dairy target and projects that while the majority of EDs will experience an overall decline in emissions over the simulation period 2010-2020, those EDs which experience a significant amount of non-dairy farms entering the dairy sector will experience higher emissions per hectare.

A significant advantage of the use of the NFS-DSM model for this scenario analysis is that it is internally consistent and allows the user to observe the impacts on the cattle, sheep and (to a lesser extent) the tillage sectors resulting from a move into dairy. Of notable significance in this scenario analysis is that the achievement of the dairy target may not just have implications for emissions from the dairy sector but also for the other competing sectors. Lower rates of productivity growth result in higher overall emissions if the dairy target is to be achieved. However, the achievement of target under the lower productivity scenarios will require a higher level of displacement of livestock from other enterprises thus mitigating the overall increase in emissions. As a consequence, a large expansion in production in the dairy sector need not necessarily directly translate to a large increase in over-all emissions. The rate at which productivity gains are made will be a crucial determinant of future emissions profiles for the dairy sector.

From these results, it is clear that while the future rate of productivity growth in the dairy sector will have a substantial impact on the future spatial disaggregation of agri-emissions, the overall effect of reaching the FH2020 targets on total emissions from the agri-sector may not be as pronounced as may have been previously anticipated. Rather, the potential growth paths for the expansion of the Irish dairy sector may tell us more about the change in the spatial concentration of emissions from the agri-sector in the future; an important consideration in the design and development of medium-long term mitigation options.

CHAPTER 8: DISCUSSION

This chapter summarises the findings of this thesis in relation to the objectives outlined in the opening chapter and is structured as follows; Section 8.1 highlights the important findings of this thesis and their impact in expanding the base of knowledge in relation to the spatial modelling of Irish agricultural emissions. Section 8.2 provides a brief description of the limitations of this research. Section 8.3 describes the opportunities for further research in this area before section 8.4 arrives at some concluding comments.

8.1 Important Findings of this Thesis

The primary objective of this thesis involved the investigation of the conditions for the effective implementation of climate change policy and the construction of an analytical policy tool which will assist decision makers in making informed decisions in relation to the design and implementation of mitigation strategies at various spatial scales. A new framework for the spatial modelling of GHG emissions from Irish agriculture has been proposed and its potential usefulness demonstrated.

In Chapter 2, an investigation into the role of local governance in the implementation of climate change policy was conducted. In the context of continually evolving governance regimes, it was found that with regard to climate change policy, the presence of multi-level governance structures have the potential to foster the successful co-ordination and planning of mitigation strategies both within and across traditional spatial administrative boundaries and at multiple governance levels where appropriate. Evidence of such structures has been found in Ireland in relation to the establishment of cross county renewable energy agencies and in co-ordination of public waste management strategies. However, targeted legislative provisions and a framework for collaboration between local authorities, agencies and government departments, are notably absent. Furthermore, a substantial information deficit was raised by Allman et al. (2004) in relation to information on emissions at the local level. The absence of an analytical tool against which local authorities can set targets and assess progress was identified as a key barrier to the effective implementation of climate change policy at the local level.

In Chapter 3, the current IPCC framework for the reporting of national GHG emissions inventories, and a number of alternative approaches to emissions modelling, were investigated. Two primary issues arose. Firstly, the current reporting structure attempts to confine emissions to national boundaries. This structure has the potential to encourage and result in suboptimal global emissions outcomes. Where a high level of emissions efficient production is curtailed in order to meet targets, a net increase in global emissions may occur as a result of less emissions efficient production elsewhere. However, the level of complexity involved in alternative LCA approaches to emissions inventorying is considerable and its implementation within an international reporting framework may be impractical within the globalised nature of international trade[45]. Secondly, having established the need for GHG modelling at various spatial resolutions (Chapter 2) in order to aid the implementation of climate change policy at sub-national level, the emphasis of the UNFCCC on an aspatial inventory structure was identified as a potential weakness. Following an analysis of the national and international literature, a review of modelling techniques and a review of previous examples of spatial emissions modelling in Ireland, the need for an alternative approach to modelling GHG emissions incorporating a spatial component for the purposes of climate change policy analysis was identified.

Chapter 4 identified the potential use of microsimulation modelling in providing a framework for the spatial disaggregation of national GHG emissions. The availability of detailed micro-level information on individuals/firms and households is typically restricted due to data confidentiality issues. The use of this technique in

[45] For clarity and convenience , the analysis in relation to the use of an IPCC vs. LCA approach in the inventorying of emissions from agriculture is placed conducted in Section 5.2.2

the creation of synthetic disaggregated population data sets offers a solution to this problem enabling the modelling of dynamic, behavioural and political (policy) change across space at the micro-level. However, a trade-off between the level of complexity employed and the effective utilisation of the technique was identified. A balance must be struck between the level of complexity required in order to make a model useful against a level of simplicity which allows the model to be built and utilised efficiently. In relation to a previous application of the SMILE model, the use of simulated annealing by Hynes et al. (2009) to provide a spatially disaggregated profile of the income effect of a tax on methane emissions from Irish farms, SMILE was found to be subject to considerable computational constraints. In addition, a specific targeted measure to preserve the spatial heterogeneity of stocking rates (a key determinant in terms of emissions) was notably absent. This demonstrates the need for a novel solution, and the development of an improved sampling methodology in order to preserve the spatial heterogeneity of stocking rates while proving a computationally efficient solution.

Chapter 5 presented the first methodological contribution of this thesis by proposing a solution to the methodological constraints outlined in Chapter 4 and the need for a spatial analytical policy tool for modelling GHG emissions (Chapter 2 & Chapter 3). A novel adaptation of the sampling methodology used in SMILE-NFS spatial microsimulation model was presented with the inclusion of a residual ranking variable designed to preserve the spatial heterogeneity of the electoral district stocking rate, a key determinant of farm-level agri-emissions. The adapted quota sampling method reported a high level of accuracy for all match variables and enabled the simulation to be modelled in a number of hours representing a substantial methodological advancement. Aggregate results from the model were compared with emissions from the National Inventory Report and were found to be within a comparable range. The SMILE-NFS baseline model of farm-level emissions presents a credible alternative methodology for the purposes of calculating Ireland's total agricultural emissions output with the ability to analyse mitigation options at the local-level, a significant value added component. The inclusion of results for fuel and electricity emissions also highlighted the potential future application of the model in an LCA context.

In the context of potentially conflicting agricultural and environmental policies for Ireland, Chapter 6 presents a unique framework under which economic and environmental policies for the agricultural sector can be assessed in tandem, in terms of their future consequences for national GHG emissions. The creation of the NFS-DSM model for Irish agriculture and its use in dynamically simulating the farm population forward in time enabled the presentation of a BAU scenario for Irish agricultural activity and related spatial emissions outcomes in 2020. Overall, the model estimated a gradual decline in agricultural activity over the 10 year simulation period with a concomitant marginal reduction in associated emissions. These results reveal that without a significant shift in historical trends, the achievement of the headline FH2020 target of a 50% increase in milk volume is unlikely. Similarly the 20% increase in value targets outlined for the cattle and sheep sectors are unlikely to be met without a significant shift in prices and/or productivity trends. With regard to emissions the NFS-DSM model projects an overall decrease in CO_2eq emissions from agriculture of 6.6%. With agriculture currently accounting for almost 40% of non-ETS emissions it is likely that this reduction does not represent the required contribution from agriculture if Ireland is to meet its commitment to reduce non-ETS sector emissions by 20% by 2020.

Finally, in the context of uncertainty surrounding the effects of the abolition of quota (Section 6.3.3) Chapter 7 reports results for a multi-scenario analysis for the expansion of the Irish dairy sector and its use in simulating the spatial pattern (and related emissions) of potential new entrants required in order to meet the targets outlined in the FH2020 Programme. The NFS-DSM model was adapted to incorporate 3 improved dairy productivity expansion scenarios relating to the abolition of quota. Outcomes for all three scenarios were simulated to 2020 and compared to the BAU scenario outlined in Chapter 6. The total amount of additional milk and concomitant new entrants required to meet the FH2020 dairy target was also calculated. The scenario analysis projected that between 1,031 (highest productivity scenario) and 4,465 (BAU scenario) new entrants would be required in order to meet the dairy target. It was also found that for the highest productivity scenario, new entrants were predominantly located in the traditional dairy regions. However, as the outlook for productivity declines, the number and geographical spread of new entrants’ increases as the available farms deemed most likely to enter are exhausted in traditional areas.

This model demonstrates a significant departure from the model farm approach adopted by Läpple and Hennessey (2012) through the selection of sample farms from within the existing farm population with the added value of an additional spatial component. Additionally, in relation to emissions outcomes, the model projects that for all scenarios, the achievement of the dairy target will not necessarily result in an increase in overall emissions. In the highest productivity scenario, emissions are projected to decrease by 5.28% in comparison to 2010 while for the lowest productivity scenario emissions are projected to decrease by 2.68%. While this may initially seem counter-intuitive, for all four dairy target scenarios, as productivity increases, emissions savings from the reduction in the number of dairy cows required to meet target are offset by a reduction in the displacement experienced in other sectors. This demonstrates the capacity of the NFS-DSM to conduct scenario analyses for Irish agriculture in an internally consistent manner, accounting for transfers, exits and observing practical constraints within the confines of a simulated population.

8.2 Implications for Policy Development

There are a number of implications for policy development which arise from this research. It has been demonstrated that a dynamic spatial microsimulation model can be used to construct a disaggregated profile of agricultural emissions which has been validated against the National Inventory Report. This may be the first step towards the construction of a disaggregated profile of emissions from all sectors. With this information, mitigation policies can be designed and implemented at the most appropriate spatial scales.

Local authorities can be tasked with setting local emissions reductions targets for sectors and activities for which they have been given responsibility. The potential exists for the incentivisation of local authorities to both co-operate and compete for additional resources upon the achievement of environmental improvement targets. The devolution of responsibility for reductions in emissions to the lowest tier of governance would likely increase the importance and relevance of climate change policy to individuals/households and firms as they would be are in direct contact with those tasked with implementing policy. This would in turn increase the likelihood of achieving the required changes to conserve energy, reduce waste and engage in more emissions efficient behaviours. This would be most relevant for mitigation measures which require greater levels of awareness, education and co-operation in contrast to nationally implemented command and control measures which may not be appropriate or indeed politically acceptable.

The potential also exists for the use of a spatial emissions framework to facilitate the design of more sophisticated mitigation strategies at the most appropriate spatial scales. In the areas of industry, transport, energy and waste management, the opportunity exists for the identification and demarcation of appropriate zones or bespoke regions for policy implementation within a multi-level governance framework. A small number of these zones are already in evidence in Ireland in the areas of energy and waste management (Section 2.6.3)

8.3 Limitations of this Research

There are a number of limitations which must be recognised when interpreting the results outlined in this thesis. Firstly, as outlined in Chapter 5, the SMILE-NFS model tends towards an over selection of mean farms at a national level while substantial outliers (in terms of the stocking rate) are much less likely to be allocated to any given ED. While this has a positive impact in terms of the preservation of spatial heterogeneity of stocking rates at the ED level (and a significant reduction in the probability of simulating outliers EDs), it does result in a substantial loss of intra-ED variability at the micro level. While this problem could potentially be solved by limiting a farm's overall number of selections to its weighted total or perhaps a maximum multiple, the application of these solutions could be problematic and could potentially introduce even more onerous problems such as ED ordering. This limitation highlights an important feature of the sampling methodology employed i.e. that the optimal design of the sampling process is informed by the requirement to maintain the spatial heterogeneity of the key variable(s) of interest; in this case the stocking rate.

This compromise reflects a trade-off between the computational efficiency of the sampling process and the computational intensity necessarily involved in adoption of alternative multi-dimensional optimisation methodologies. It should also be noted that while total output and emissions from the model are compared to the National Accounts and the National Inventory Report and are deemed to be within an acceptable range, this application of the SMILE-NFS model does not include calibration of the non-matched variables. While by design, the model preserves the spatial heterogeneity of stocking rate and thus indirectly the consequent national totals for livestock output and emissions, the results for non-calibrated output such as family farm income should be treated with caution[46]. In addition, it should be remembered that while the model contains a structure for the spatial disaggregation of the NFS in non-census years, the longer the time lag between the subject year and the census, the greater the potential for significant error.

Secondly, outputs from the NFS-DSM model for both the business as usual scenario in Chapter 6 and the scenarios analyses in Chapter 7 rely on several assumptions about the future development of Irish agriculture including the rate and form of restructuring in the dairy sector, the possible impacts of the abolition of quota and the future production profile of new dairy entrants. While these assumptions constitute the "best guess" given the currently available information on agricultural activity, the model does not account for several external factors which may impact on the validity of these assumptions. Such factors include; the impact of the credit

[46] For a full description of a calibration processes applied to the SMILE-SILC household model see O'Donoghue et al. (2013)

crisis on the availability of credits for both the expansion of current enterprises and the establishment of new entrants; the ease of transfer of knowledge to new dairy farmers; exits from farming and the effect of changes to the current subsidy structures[47].

Thirdly, while the cattle and sheep sectors are responsible for a large share of total agri-emissions, both of these sectors faces a value target for FH2020 as opposed to the volume target for dairy. Thus the achievement of these targets is largely dependent on future price scenarios. With static production levels an increase in prices of just 2% per annum would be sufficient to achieve a 20% overall increase in value by 2020. Ultimately, the execution of a plausible multi-scenario analysis for the future value of the cattle and sheep sectors in 2020 is heavily reliant on future price paths for the sector and its effect on gross livestock output. As outlined above and in Section 6.6, the reliable simulation of future value estimates (as opposed to a volume estimates) raises signification challenges for the NFS-DSM in that the true effect of unit price increases on productivity responses at the micro-level is extremely difficult to quantify. Given this limitation, it was felt that further investigation of outcomes for the cattle sector in relation to value targets would be unlikely to yield definitive results. The additional complexity this would have involved in attempting to balance competing volume and value target outcomes at the micro-level was deemed beyond the scope of this thesis and was not considered in this analysis.

8.4 Potential Future Research Areas

The development of a computationally efficient sampling methodology and a dynamic microsimulation framework for the spatial disaggregation of agricultural activity in Ireland represents a significant progression of the methodological literature and opens a number of possible avenues for future research which may include the following:

[47] The NFS-DSM model assumes subsidies are fixed and does not consider the impacts of the recently announced CAP reform European Commission (2013)

Firstly, as the NFS is conducted as part of the European Farm Accountancy Data Network (FADN) the potential exists to replicate the methodology outlined in Chapter 5 in other European countries and compare outcomes both in terms of the results for the sampling methodology and in terms of a comparison of modelled emissions with their respective national inventory reports. Additionally, the application of the dynamic simulation model outlined in Chapter 6 may help to improve our understanding of the differences in productions trends within the FADN membership.

Secondly, with regard to the microsimulation of agricultural output, the current NFS-DSM model uses a series of regional dummy variables in order to attempt to capture the spatially heterogeneous effects associated with each region. This places significant demand on the region dummy to explain unobserved regional differences which may include factors such as differences in local environmental characteristics, average distances to markets, the density of local co-operatives etc. The inclusion of local environmental variables in relation to rainfall, temperature and average hours of sunshine through the overlaying of weather station data could help improve the accuracy of production models and help improve our understanding of differential outcomes at smaller spatial scales. Care must be taken however to ensure that the correct balance is struck between complexity and practical applicability.

Thirdly, while the emissions calculation methodology used in this thesis was based on the standard IPCC inventorying approach, the SMILE NFS-DSM model provides a framework for the performance of LCA based emissions estimates in the future. Currently available information on the fodder and concentrate feed ratios, energy use and stocking rates, may be complimented by future information on waste management systems and the genetic merit of the herd in order to provide farm specific emissions estimates.

Finally, in terms of linking agricultural activity to observed environmental outcomes, a further potential area of research could involve the overlaying of information from the land parcel information system (LPIS) and the animal identification system

(AIM) on water catchments areas in order to study the impacts of animal concentrations on water quality.

8.5 Concluding Comments

Ireland, and the international community at large, faces an extremely difficult challenge in the effective design and implementation of climate change policy. International evidence suggesting that the level of public concern relating to climate change issues has seen a decline in the face of economic insecurity brought about by the recent global recession is a worrying development. While governments have the option to design market instruments to attempt to reflect the cost of carbon, these instruments have been typically targeted at goods for which consumption is inelastic in the short-medium. Market based mitigation measures often result in immediate and visible income effects for citizens which are subject to political support. Additionally, the level of uncertainty surrounding the economic costs of climate and the emissions footprint of individual consumer products makes it extremely difficult to relate the "true" carbon cost to the individual consumer. Therefore, the successful implementation of non-market policies designed to encourage individuals, households, firms and farms to engage in more emissions efficient behaviour comprises a central pillar of climate change policy.

While Ireland's ambition to considerably increase output from the agricultural sector in the aftermath of the economic recession would appear to have broad political support domestically, it also has the potential to frustrate the achievement of longer term environmental obligations at the national, EU and international level. The findings of this research indicate that even in the most optimistic emissions scenario for dairy expansion, the achievement of FH2020 targets will limit any significant decrease in overall agricultural emissions by 2020. This indicates a significant impasse between current agricultural policy and Ireland's commitments to reduce emissions under the current accounting framework. The absence of a specific emissions target for agriculture is conspicuous, and with a continued emphasis on expansion in the sector, it is likely that considerable reductions will have to be found elsewhere if Ireland is to meet its emissions reductions targets in the future.

There is, however, a question mark over the suitability of the current accounting framework in incentivising emissions efficiencies throughout the agricultural production system. While an LCA analysis was not employed in this study, substantial efforts towards the recognition of Ireland's low emissions per unit production system are being undertaken. While in absolute terms Ireland's agricultural emissions footprint may be comparatively high on a per capita basis, this is largely due to Ireland's status as a major exporter of agricultural produce. In relative terms, Ireland's emissions per unit of output for the beef and dairy sectors have been stated to be among the lowest in the world due to the low emission cost of a grass based system relative to primarily concentrate based systems. Thus displacement in output from Irish agriculture in order to meet national emissions targets may result in less efficient production occurring elsewhere, resulting in an overall increase in global emissions. However, while the adoption of an LCA approach to emissions inventorying and recognition of the value of emissions efficient production could highlight gains to be made in Irish agriculture, it may result in losses elsewhere. Ireland is a small open island economy heavily dependent on international trade. If emissions from the transport of inputs/exports are included in the LCA this may have considerable impacts for Ireland. Apart from the methodological issues concerning LCA it is unclear what the net effect of moving to an LCA system for Ireland might be.

The provision of information on the spatial disaggregation of GHG emissions is the first step towards the potential development and implementation of climate change policy at the local level since it as the local level where GHG reductions will ultimately take place. Knowledge of the spatial distribution of agricultural activities could help local authorities to facilitate co-operation between farmers. The design of optimal routes for produce collection and co-operation in areas such as the establishment of shared machinery could yield a double dividend of both a reduction in associated emissions and cost savings due to increased efficiencies.

The presence of spatially disaggregated information on emission levels, as has been outlined for agriculture in this thesis, provides an opportunity to assist decision makers in the design and implementation of mitigation policies through co-ordinated multi-level governance action at the regional, local and community level. However, while evidence of such co-ordination can already be seen in Ireland, the institutional barriers to the devolution of responsibility for the implementation of climate change policy remain. It is likely that such barriers will need to be addressed if Ireland is to meet its national and international commitments on climate change.

APPENDICES

Appendix A – Irish Statutory Instruments (S.I) on climate change

S.I. 244/2006-Kyoto Protocol Flexible Mechanisms Regulations 2006	Establishment of the EPA as "The agency" for the purposes of Art 6 and 12 of the Kyoto Protocol and the establishment of a registry with the EPA as the national registry administrator for the purposes of Article 7.
S.I.706/2005 - EC (GHG Trading) (Amendment) Regulations 2005 –	Amending the EC GHG Trading Regulations 2004 in order to provide for the linking of the Kyoto Protocol 's project mechanisms to the scheme for GHG emission allowance trading within the European Community
S.I.437/2004 – EC (GHG Trading) Regulations 2004	Providing for "the implementation in Ireland of a scheme for GHG emission allowance trading within the EC in order to promote reduction of GHG emissions in a cost effective and economically efficient manner."
S.I. 274/2009 EC (GHG Trading)(Aviation) Regulations 2009	Amending 2005 Regulations to provide for provisions to promote reductions in the Aviation industry.
S.I. No. 821/2007 — Waste Management (Facility Permit and Registration) Regulations 2007	Requires Registration with local authority or the EPA for activities involved in the reception and temporary storage of fluorinated GHG's
S.I. 820/2007 Waste Management (Collection Permit) Regulations 2007 –	Promoting Compliance with Regulation (EC) No. 842/2006, - outlines conditions necessary for non-application of Section 34(1)(a) of the waste management acts in relation to the collection and transportation of fluorinated GHGs
S.I 803/2007 EC (passenger car entry into service) (amendment) Regulations 2007	Given updated effect to EC regulations on HFC-134a
S.I. 281/2006 Control of Substances that Deplete the Ozone Layer Regulations	Giving Full effect to Regulation (EC) No. 2037/2000

Appendix B – Panel Regression Estimates

Adjusted Farmsize: Panel estimates for total adjusted farmsize

Random-effects log panel estimates for the adjusted farmsize

	lnadjfarmsize	(stnd.error)
year	0.00581^{***}	(0.000743)
region2	0.167	(0.127)
region3	0.464^{***}	(0.0505)
region4	0.221^{***}	(0.0487)
region5	0.0121	(0.0507)
region6	0.305^{***}	(0.0436)
region7	0.0811	(0.0422)
region8	-0.169^{***}	(0.0435)
soil1	-0.00138	(0.0183)
soil2	-0.00750	(0.0161)
age	0.00755^{***}	(0.00135)
age2	-0.0000918^{***}	(0.0000140)
landval_ha	-0.124^{***}	(0.00508)
hasmilk	0.0735^{***}	(0.0124)
hascattle	0.115^{***}	(0.0215)
hassheep	0.0514^{***}	(0.0107)
hashorses	-0.0324^{*}	(0.0151)
hastillage_area	0.0972^{***}	(0.0109)
hasforestry	-0.0537^{**}	(0.0182)
labour_hrs	0.128^{***}	(0.00914)
_cons	-8.425^{***}	(1.493)
N	11453	
R^2	0.070	
rho	0.925	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Dairy: Panel estimates for litres/LU and LUs/hectare

Random-effects log panel estimates for dairy litres/LU and LUs/hectare

	lnl_lu	(stnd.error)	lnlu_ha	(stnd.error)
lnPdairy	0.155***	(0.0387)	-0.0153	(0.0387)
lnlandval_ha	0.00556	(0.00861)	0.0393***	(0.00871)
lndairy_ha	0.324***	(0.0116)	0.0522***	(0.00910)
lnlabour_hrs	-0.00447	(0.0120)	0.0578***	(0.0123)
lnage	-0.00326	(0.0156)	-0.0265	(0.0161)
off_farm_inc	0.00257	(0.0110)	-0.0501***	(0.0112)
lnadjfarmsize	-0.160***	(0.0153)	-0.250***	(0.0156)
hasforestry	-0.0627***	(0.0168)	-0.0777***	(0.0187)
teagasc	0.0113	(0.00667)	-0.00683	(0.00670)
hasreps	0.00926	(0.00755)	-0.0269***	(0.00757)
region2	0.0775	(0.120)	0.0897	(0.147)
region3	0.0387	(0.0335)	0.226***	(0.0407)
region4	0.0191	(0.0331)	0.232***	(0.0400)
region5	-0.111***	(0.0293)	-0.0201	(0.0356)
region6	0.0222	(0.0265)	0.201***	(0.0320)
region7	-0.00302	(0.0242)	0.110***	(0.0293)
region8	-0.00548	(0.0363)	0.0303	(0.0439)
year	0.00435**	(0.00157)	-0.00857***	(0.00157)
year2	0.116***	(0.0102)	-0.0203*	(0.0101)
year3	0.129***	(0.00949)	0.00526	(0.00941)
year4	0.128***	(0.00865)	0.00707	(0.00855)
year5	0.0937***	(0.00856)	0.00435	(0.00845)
year6	0.111***	(0.00878)	-0.000335	(0.00866)
year7	0.0442***	(0.0103)	0.0142	(0.0103)
year8	0.00263	(0.0118)	0.0113	(0.0118)
year9	0	(.)	0	(.)
year10	0	(.)	0	(.)
soil1	0.0769**	(0.0241)	0.138***	(0.0263)
soil2	0.0403	(0.0225)	0.0870***	(0.0242)
_cons	-0.636	(3.096)	18.43***	(3.105)
N	4161		4161	
R^2	0.233		0.173	
rho	0.687		0.779	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Cattle: Panel estimates for gross output/LU and LUs/hectare

Random-effects log panel estimates for cattle gross output/LU and LUs/hectare

	lncattlego_lu	(stnd.error)	lncattlelu_ha	(stnd.error)
lnPcattle	0.00694	(0.0931)		
lnlandval_ha	0.0280*	(0.0127)	0.0576***	(0.00730)
lnfertiliser_ha	0.0669***	(0.00608)		
lncattle_area	-0.125***	(0.00960)	-0.158***	(0.00729)
lncattlelu_ha	-0.0658***	(0.0176)		
lnlabour_hrs	0.128***	(0.0156)	0.137***	(0.00953)
lnage	-0.0669***	(0.0185)	-0.0500***	(0.0102)
off_farm_inc	-0.0383*	(0.0151)	-0.0378***	(0.00915)
lndairy_ha_sh	-0.151***	(0.0167)	-0.0931***	(0.00955)
hasforestry	0.00460	(0.0228)	-0.0518**	(0.0173)
teagasc	0.0616***	(0.0113)	0.0197**	(0.00619)
hasreps	-0.00170	(0.0114)	-0.00873	(0.00623)
region2	0.0290	(0.103)	0.0600	(0.0972)
region3	-0.0712*	(0.0354)	0.339***	(0.0334)
region4	-0.0473	(0.0335)	0.217***	(0.0310)
region5	-0.0648*	(0.0330)	0.0287	(0.0315)
region6	0.0157	(0.0310)	0.300***	(0.0285)
region7	0.00264	(0.0287)	0.147***	(0.0269)
region8	-0.187***	(0.0294)	0.0304	(0.0276)
year	0.00313***	(0.000216)	-0.0204***	(0.00114)
year2	-0.0180	(0.0158)	-0.00628	(0.00789)
year3	-0.0671***	(0.0162)	0.0234**	(0.00762)
year4	-0.00880	(0.0148)	0.0204**	(0.00743)
year5	-0.0227	(0.0153)	0.0413***	(0.00755)
year6	-0.0456*	(0.0178)	0.0360***	(0.00780)
year7	-0.000901	(0.0168)	0.0444***	(0.00812)
year8	-0.0283	(0.0251)	0.0456***	(0.00860)
year9	-0.0382*	(0.0182)	0.0439***	(0.00922)
year10	0	(.)	0	(.)
soil1	0.0496	(0.0292)	0.154***	(0.0208)
soil2	0.0688*	(0.0267)	0.0906***	(0.0177)
lnadjfarmsize			-0.0922***	(0.0115)
_cons	0	(.)	42.04***	(2.277)
N	10603		10603	
R^2	0.012		0.262	
rho	0.402		0.763	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Sheep: Panel estimates for gross output/LU and LUs/hectare

Random-effects log panel estimates for sheep gross output/LU and LUs/hectare

	lnsheepgo_lu	(stnd.error)	lnsheeplu_ha	(stnd.error)
lnlandval_ha	0.0345	(0.0242)	0.109***	(0.0154)
lnfertiliser_ha	0.0333**	(0.0116)		
lnsheep_area	-0.0910***	(0.0129)	-0.128***	(0.00719)
lnsheeplu_ha	-0.0972***	(0.0287)		
lnlabour_hrs	0.0869**	(0.0303)	0.139***	(0.0195)
lnage	-0.0100	(0.0421)	0.00989	(0.0275)
off_farm_inc	-0.0424	(0.0311)	-0.0340	(0.0205)
lnadjfarmsize	0.0782**	(0.0265)		
hasforestry	-0.108*	(0.0468)		
teagasc	0.0342	(0.0223)	0.0238	(0.0141)
hasreps	0.0521*	(0.0211)	-0.0231	(0.0132)
region2	0.122	(0.172)	-0.237	(0.145)
region3	0.0466	(0.0645)	0.253***	(0.0530)
region4	0.104	(0.0696)	0.101	(0.0572)
region5	0.0966	(0.0897)	0.0193	(0.0754)
region6	-0.0839	(0.0623)	0.303***	(0.0507)
region7	-0.259***	(0.0684)	0.0340	(0.0568)
region8	-0.0396	(0.0544)	0.134**	(0.0451)
year	-0.00940*	(0.00426)	-0.0383***	(0.00260)
year2	-0.0486	(0.0292)	-0.0178	(0.0266)
year3	0.0101	(0.0285)	0.00839	(0.0267)
year4	0.00663	(0.0278)	0.0195	(0.0269)
year5	0.0570*	(0.0286)	0.0274	(0.0339)
year6	0.0904**	(0.0296)	0.0331	(0.0299)
year7	0.121***	(0.0309)	0.0162	(0.0263)
year8	0.0892**	(0.0324)	0.0210	(0.0211)
year9	0.0774*	(0.0350)		
year10	0	(.)	0	(.)
soil1	0.438***	(0.0546)	0.289***	(0.0389)
soil2	0.344***	(0.0476)	0.181***	(0.0322)
lPsheep			-0.279*	(0.136)
year9			0	(.)
_cons	24.09**	(8.536)	78.55***	(5.561)
N	3810		3810	
R^2	0.019		0.139	
rho	0.513		0.701	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Crops: Panel estimates for gross output/hectare

Random-effects log panel estimates for crop gross output/hectare

	lncropgo_ha	(stnd.error)
lPcrop	2.689***	(0.285)
lnlandval_ha	-0.0610*	(0.0272)
lnfertiliser_ha	0.148***	(0.0227)
lntillage_area	0.222*	(0.0870)
lnlabour_hrs	0.0141	(0.0264)
lnage	0.0117	(0.0359)
off_farm_inc	0.0206	(0.0393)
lntillage_sh	-0.333***	(0.0876)
lnadjfarmsize	-0.286***	(0.0796)
hasforestry	0.0473	(0.0666)
teagasc	0.00712	(0.0263)
hasreps	0.0129	(0.0260)
region2	0.410	(0.271)
region3	-0.0483	(0.125)
region4	-0.111	(0.129)
region5	-0.275	(0.226)
region6	-0.148	(0.107)
region7	-0.350**	(0.127)
region8	-0.156	(0.185)
year	-0.0786***	(0.00727)
year2	-0.0913**	(0.0300)
year3	0.0149	(0.0278)
year4	0.432***	(0.0463)
year5	0.195***	(0.0360)
year6	-0.261***	(0.0347)
year7	-0.516***	(0.0748)
year8	-0.213***	(0.0332)
year9	0	(.)
year10	0	(.)
soil1	-0.453**	(0.167)
soil2	-0.477**	(0.165)
_cons	151.3***	(13.40)
N	2222	
R^2	0.169	
rho	0.847	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Feed Costs: Panel estimates for feed costs/hectare

Random-effects log panel estimates for fodder direct costs (bulk fodder and concentrates)

	lnbulkfodder_ha	(stnd.error)	lnconcentrate_ha	(stnd.error)
lPbulkfodder	-1.082	(0.677)		
lnlandval_ha	-0.0465	(0.0429)		
off_farm_inc	0.122*	(0.0500)		
lntillage_sh	0.101***	(0.0275)	0.0203	(0.0108)
lnadjfarmsize	-0.938***	(0.0470)	-0.644***	(0.0235)
teagasc	-0.121**	(0.0382)	0.0610***	(0.0149)
hasreps	-0.154***	(0.0393)		
lnsheeplu	0.0629**	(0.0195)	0.162***	(0.00956)
lncattlelu	0.306***	(0.0277)	0.292***	(0.0134)
lndairylu	0.141***	(0.0161)	0.458***	(0.00836)
region2	0.385	(0.324)	-0.455*	(0.222)
region3	0.473***	(0.107)	-0.0146	(0.0765)
region4	0.195	(0.110)	-0.146*	(0.0726)
region5	0.0312	(0.107)	-0.384***	(0.0751)
region6	0.223*	(0.0966)	-0.144*	(0.0657)
region7	0.136	(0.0910)	-0.165**	(0.0627)
region8	0.0621	(0.0965)	-0.299***	(0.0641)
year	0.0639***	(0.0156)	0.00209***	(0.000256)
year2	-0.102	(0.0556)	0.0402*	(0.0199)
year3	-0.225***	(0.0568)	0.0633**	(0.0201)
year4	-0.269***	(0.0531)	-0.0203	(0.0181)
year5	-0.297***	(0.0659)	-0.0682***	(0.0184)
year6	-0.0500	(0.0640)	0.00364	(0.0186)
year7	-0.0577	(0.0567)	-0.170***	(0.0257)
year8	-0.0777	(0.128)	-0.126***	(0.0360)
year9	0	(.)	-0.0639*	(0.0252)
year10	0	(.)	0	(.)
soil1	-0.202*	(0.0934)	0.120*	(0.0488)
soil2	-0.153	(0.0854)	0.0981*	(0.0411)
lPconcentrate			0.214*	(0.109)
hasforestry			-0.132**	(0.0411)
_cons	-117.9***	(28.43)	0	(.)
N	5077		10947	
R^2	0.077		0.193	
rho	0.458		0.751	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Veterinary: Panel estimates for vet & med costs/hectare

Log panel cost estimates for vet (fixed-effects) and A.I (random effects)

	lnvetmed_ha	(stnd.error)	lnai_fees_ha	(stnd.error)
lPvetmed_ha	0	(.)		
lnlabour_hrs	0.0570**	(0.0205)		
off_farm_inc	0.0295	(0.0194)		
lnadjfarmsize	-0.838***	(0.0244)	-0.817***	(0.0478)
teagasc	0.0430***	(0.0125)		
hasreps	0.0239	(0.0124)		
lnsheeplu	0.0994***	(0.00971)	-0.0620***	(0.0176)
lncattlelu	0.260***	(0.0136)	0.0489	(0.0299)
lndairylu	0.226***	(0.00955)	0.380***	(0.0143)
region2	0	(.)	0.518	(0.336)
region3	0	(.)	-0.0200	(0.111)
region4	0	(.)	0.0323	(0.0984)
region5	0	(.)	-0.142	(0.101)
region6	0	(.)	0.160	(0.0902)
region7	0	(.)	0.00754	(0.0840)
region8	0	(.)	0.0280	(0.0860)
year	0.00847***	(0.00241)	0.0309	(0.0483)
year2	0.00776	(0.0154)	-0.0128	(0.0447)
year3	-0.00736	(0.0149)	-0.0235	(0.0756)
year4	0.0240	(0.0146)	-0.0851	(0.0491)
year5	0.0476**	(0.0150)	-0.139***	(0.0366)
year6	-0.0178	(0.0157)	-0.0627	(0.0541)
year7	0.0229	(0.0165)	-0.0215	(0.0605)
year8	0.0218	(0.0176)	-0.0273	(0.0537)
year9	-0.0188	(0.0190)		
year10	0	(.)	0	(.)
soil1	-0.126*	(0.0528)	0.0773	(0.0808)
soil2	-0.0949*	(0.0409)	0.0760	(0.0727)
lPai_fees_ha			-1.464	(1.822)
year9			0	(.)
_cons	-11.43*	(4.820)	-50.59	(88.22)
N	11163		5810	
R^2	0.164		0.077	
rho	0.756		0.644	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Fert & Other: Panel estimates for fert & other costs/hectare

Log panel estimates for fertilizer (random effects) & other direct costs (fixed-effects)

	lnfertiliser_ha	(stnd.error)	lnoth_dc_ha	(stnd.error)
lPfertiliser_ha	-0.405***	(0.0909)		
lnlandval_ha	0.0612***	(0.0120)		
off_farm_inc	-0.0267	(0.0151)	0.00650	(0.0233)
lntillage_area	0.236***	(0.00847)		
lnadjfarmsize	-0.531***	(0.0166)	-0.573***	(0.0292)
teagasc	0.0422***	(0.0105)	0.0132	(0.0150)
hasreps	-0.0506***	(0.0105)	0.000497	(0.0149)
lnsheeplu	0.00956	(0.00641)	0.0215	(0.0116)
lncattlelu	0.171***	(0.00854)	0.120***	(0.0161)
lndairylu	0.226***	(0.00584)	0.188***	(0.0115)
region2	0.282*	(0.126)		
region3	0.274***	(0.0493)		
region4	0.114*	(0.0476)		
region5	0.00152	(0.0489)		
region6	0.241***	(0.0429)		
region7	0.252***	(0.0409)		
region8	-0.0590	(0.0424)		
year	-0.0143**	(0.00486)	0.00315	(0.00288)
year2	-0.0260	(0.0154)	0.136***	(0.0184)
year3	0.0167	(0.0163)	0.0543**	(0.0179)
year4	-0.0163	(0.0178)	0.0541**	(0.0175)
year5	-0.000895	(0.0160)	0.0429*	(0.0180)
year6	0.0315*	(0.0150)	0.0160	(0.0187)
year7	-0.00742	(0.0166)	-0.00502	(0.0197)
year8	-0.0364	(0.0304)	-0.0487*	(0.0210)
year9	0	(.)	0.00674	(0.0226)
year10	0	(.)	0	(.)
soil1	0.292***	(0.0339)	-0.143*	(0.0636)
soil2	0.138***	(0.0290)	-0.0774	(0.0495)
lPoth_dc_ha			0	(.)
lnlabour_hrs			0.00331	(0.0235)
lntillage_sh			-0.0372***	(0.0111)
hasforestry			-0.0252	(0.0561)
_cons	35.48***	(9.310)	-0.215	(5.759)
N	10956		11378	
R^2	0.272		0.078	
rho	0.721		0.785	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Car/Elec/Tel & Other: Panel estimates for car/elec/tel & other costs/hectare

Fixed effects log panel estimates for car/elec/tel & other overhead costs

	lncar/tel/elc_ha	(stnd.error)	lnoth_oc_ha	(stnd.error)
lPcar/tel/elc_ha	0	(.)		
lnlabour_hrs	0.105***	(0.0175)	0.0443***	(0.0129)
lnage	0.0355*	(0.0171)		
off_farm_inc	0.0228	(0.0167)		
lnadjfarmsize	-0.854***	(0.0207)	-0.770***	(0.0165)
teagasc	0.0162	(0.0107)	0.0394***	(0.00828)
lnsheeplu	0.0266**	(0.00838)	0.00936	(0.00644)
lncattlelu	-0.00933	(0.0116)	0.0977***	(0.00891)
lndairylu	0.146***	(0.00828)	0.0769***	(0.00638)
year	-0.0425***	(0.00206)	-0.00511**	(0.00159)
year2	-0.00573	(0.0133)	-0.0421***	(0.0102)
year3	-0.0518***	(0.0128)	-0.0574***	(0.00987)
year4	-0.0540***	(0.0126)	-0.0243*	(0.00967)
year5	-0.0467***	(0.0129)	-0.0469***	(0.00992)
year6	-0.0263*	(0.0134)	0.0120	(0.0103)
year7	-0.0378**	(0.0141)	0.0444***	(0.0108)
year8	-0.000489	(0.0150)	0.0707***	(0.0115)
year9	-0.0698***	(0.0162)	-0.0987***	(0.0125)
year10	0	(.)	0	(.)
soil1	0.0738	(0.0456)	-0.0422	(0.0351)
soil2	0.0497	(0.0355)	-0.0382	(0.0273)
lPoth_oc_ha			0	(.)
lnlandval_ha			-0.0419***	(0.00984)
lntillage_sh			0.0180**	(0.00616)
hasreps			0.0770***	(0.00824)
_cons	91.77***	(4.116)	18.45***	(3.173)
N	11370		11447	
R^2	0.284		0.233	
rho	0.867		0.936	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Crop Costs: Panel estimates for crop costs/hectare

Random effects log panel estimates for purchase of seed & crop protection plans

	lnseed_ha	(stnd.error)	lncroprotect_ha	(stnd.error)
lPseed_ha	-0.478	(0.338)		
lnlandval_ha	0.0502	(0.0335)	0.0117	(0.0264)
lnage	-0.141**	(0.0460)	-0.0824*	(0.0373)
lntillage_area	0.509***	(0.0169)	0.893***	(0.0141)
lnadjfarmsize	-0.351***	(0.0422)	-0.576***	(0.0323)
lnsheeplu	-0.0662***	(0.0144)	-0.0339**	(0.0114)
lncattlelu	-0.0548**	(0.0184)	-0.0180	(0.0144)
lndairylu	0.0223	(0.0125)	0.0709***	(0.0101)
region2	0.348	(0.217)	0.329	(0.170)
region3	0.276**	(0.0867)	0.278***	(0.0646)
region4	0.125	(0.0869)	0.151*	(0.0640)
region5	-0.132	(0.0936)	-0.0367	(0.0680)
region6	0.263***	(0.0743)	0.200***	(0.0573)
region7	0.216**	(0.0739)	0.128*	(0.0552)
region8	-0.304***	(0.0900)	-0.0923	(0.0598)
year	0.00281***	(0.000792)	-0.0279	(0.0511)
year2	-0.112**	(0.0408)	-0.0583	(0.0476)
year3	0.0437	(0.0409)	0.112**	(0.0417)
year4	-0.0424	(0.0417)	-0.0294	(0.0940)
year5	0.0480	(0.0409)	0.0869*	(0.0353)
year6	-0.0267	(0.0459)	0.101	(0.169)
year7	-0.214***	(0.0643)	0.219	(0.221)
year8	-0.0727	(0.0874)	0.212	(0.122)
year9	-0.0557	(0.0651)		
year10	0	(.)	0	(.)
soil1	0.539***	(0.0811)	0.278***	(0.0611)
soil2	0.411***	(0.0782)	0.178**	(0.0575)
lPcroprotect_ha			7.633	(10.40)
off_farm_inc			-0.0162	(0.0327)
teagasc			0.0393	(0.0249)
year9			0	(.)
_cons	0	(.)	24.10	(54.66)
N	5129		7220	
R^2	0.050		0.119	
rho	0.471		0.365	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Dairy Logit Models: Determinants for probability of exiting dairy

Determinants for Probability of Exiting from Dairy

	exit_dry_1	(stnd.error)
landval_ha	0.480*	(0.211)
totadjfarmsize	-0.0385***	(0.0100)
totadjfarmsize2	0.0000971	(0.0000554)
age	-0.0832	(0.0637)
age2	0.000908	(0.000587)
teagasc	0.0901	(0.242)
labour_hrs	-0.201	(0.284)
stock_rate_tot	-2.439***	(0.298)
gross_margin_quintile_1	0.618	(0.507)
gross_margin_quintile_2	0.0843	(0.564)
gross_margin_quintile_3	0.0988	(0.629)
gross_margin_quintile_4	0.146	(0.685)
gross_margin_quintile_5	-0.319	(0.875)
year	0.0128	(0.0926)
year2	0.311	(0.597)
year3	-0.0711	(0.574)
year4	0.482	(0.515)
year5	0.953*	(0.445)
year6	0.408	(0.472)
year7	0.672	(0.471)
year8	0.250	(0.530)
year9	0	(.)
year10	0	(.)
region2	0	(.)
region4	-0.256	(0.550)
region5	-0.286	(0.351)
region6	-0.794*	(0.404)
region7	-0.739*	(0.313)
region8	0.378	(0.472)
soil1	0.386	(0.408)
soil2	0.253	(0.375)
_cons	-23.08	(185.4)
N	3824	
pseudo R^2	0.226	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Dairy Logit Models: Determinants for probability of having dairy enterprise

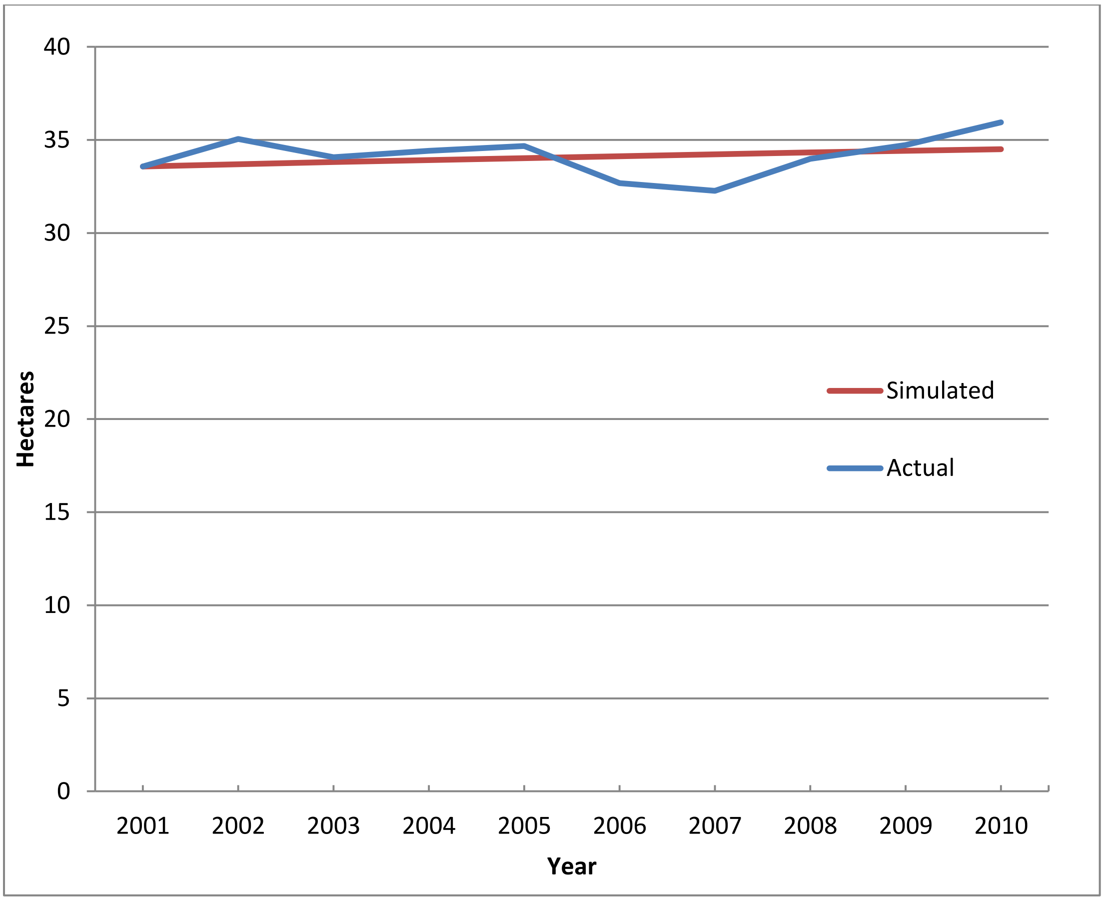
	hasdairy	(stnd.error)
landval_ha	-.0098488	(.0462581)
farmsize1	-0.669***	(0.183)
farmsize2	-0.762***	(0.104)
farmsize4	0.463***	(0.0682)
farmsize5	0.660***	(0.0685)
farmsize6	0.170*	(0.0867)
age	0.0619***	(0.00941)
age2	-0.000940***	(0.0000883)
teagasc	0.521***	(0.0420)
labour_hrs	1.243***	(0.0479)
stock_rate_tot	1.991***	(0.0398)
year	-0.0184***	(0.00387)
region1	1.774***	(0.0939)
region2	0.873**	(0.275)
region3	1.099***	(0.0994)
region4	1.002***	(0.101)
region5	2.002***	(0.101)
region6	1.753***	(0.0919)
region7	2.744***	(0.0927)
soil1	0.390***	(0.102)
soil2	0.219*	(0.104)
off_farm_inc	-1.323***	(0.0589)
_cons	28.80***	(7.760)
N	22185	
pseudo R^2	0.416	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix C – NFS-DSM Model Validation 2001-2010

Farm Size: Adjusted farm size

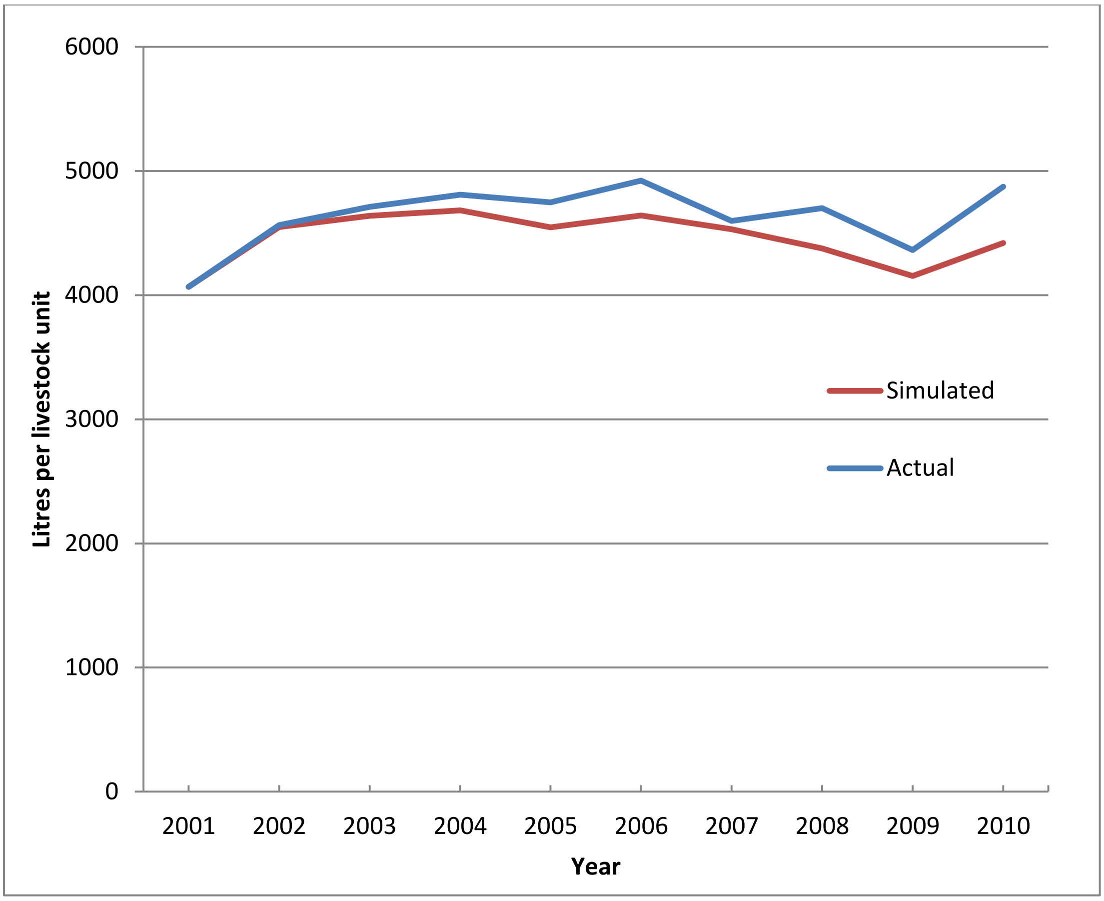
Simulated vs. actual mean values for adjusted farm size 2001-2010



year	Simulated	Actual
2001	33.574	33.574
2002	33.698	35.059
2003	33.815	34.068
2004	33.924	34.413
2005	34.030	34.674
2006	34.133	32.686
2007	34.233	32.269
2008	34.330	33.990
2009	34.419	34.732
2010	34.500	35.952

Dairy: Litres per livestock unit

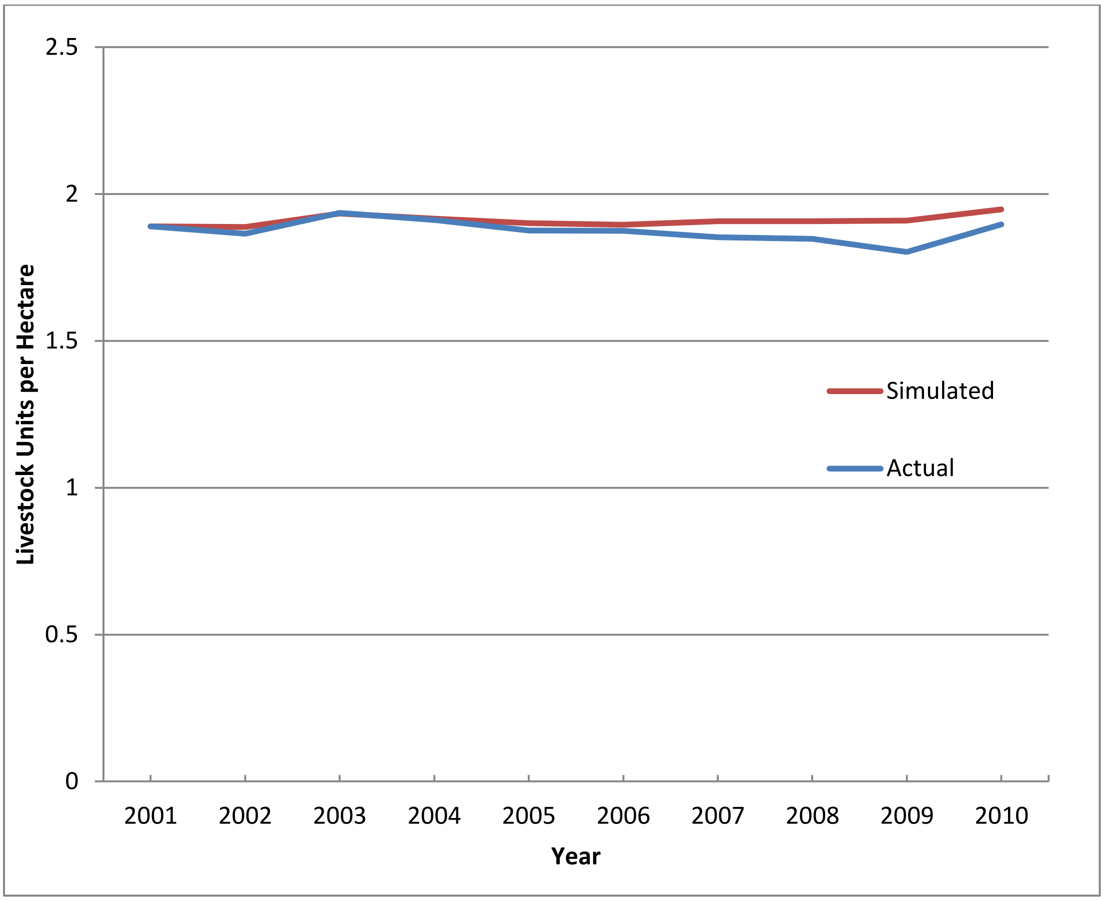
Simulated vs. actual mean values for dairy litres per livestock unit 2001-2010



year	Simulated	Actual
2001	4067.336	4067.336
2002	4550.500	4564.917
2003	4639.356	4710.772
2004	4683.619	4811.074
2005	4547.742	4747.208
2006	4643.174	4922.296
2007	4530.544	4599.031
2008	4377.575	4701.241
2009	4153.555	4362.904
2010	4420.023	4874.678

Dairy: Livestock units per hectare

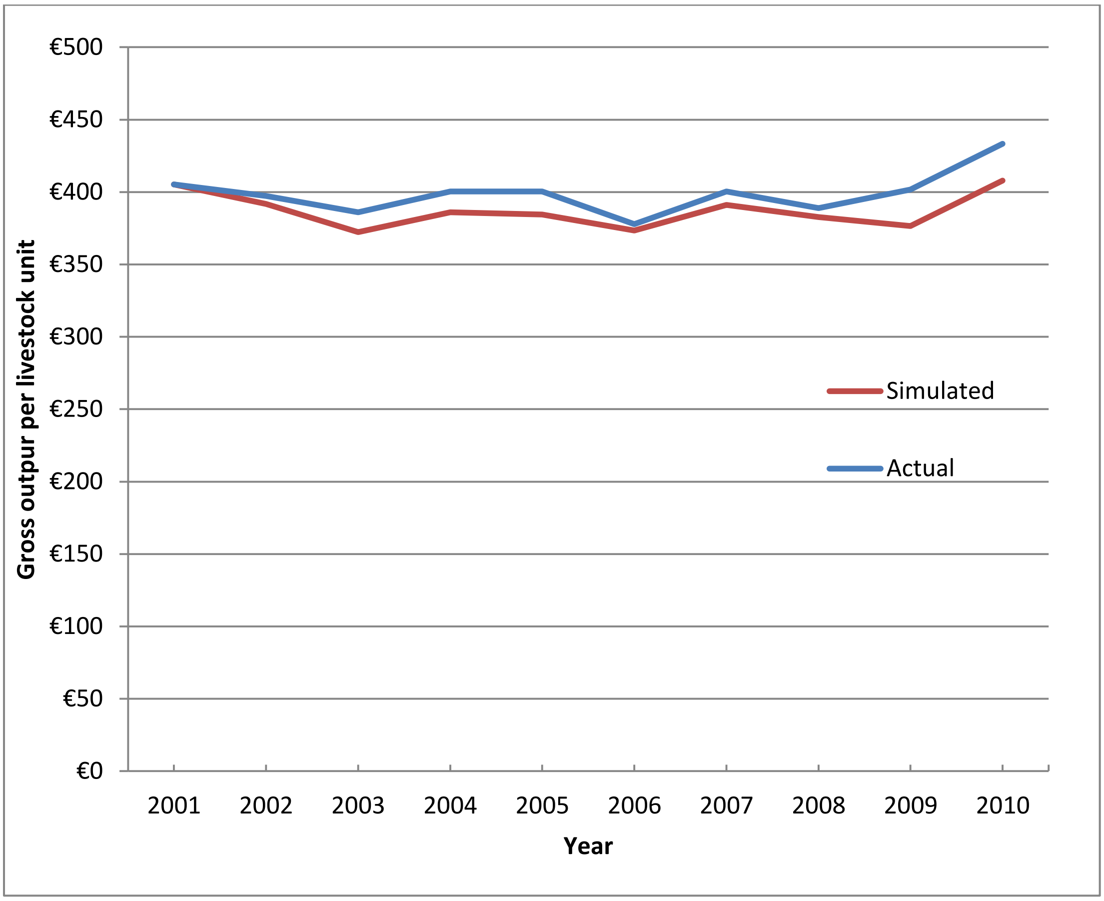
Simulated vs. actual mean values for dairy livestock units per hectare 2001-2010



year	Simulated	Actual
2001	1.890	1.890
2002	1.888	1.865
2003	1.934	1.936
2004	1.916	1.912
2005	1.901	1.876
2006	1.896	1.875
2007	1.908	1.853
2008	1.908	1.848
2009	1.909	1.803
2010	1.948	1.896

Cattle: Gross output per livestock unit

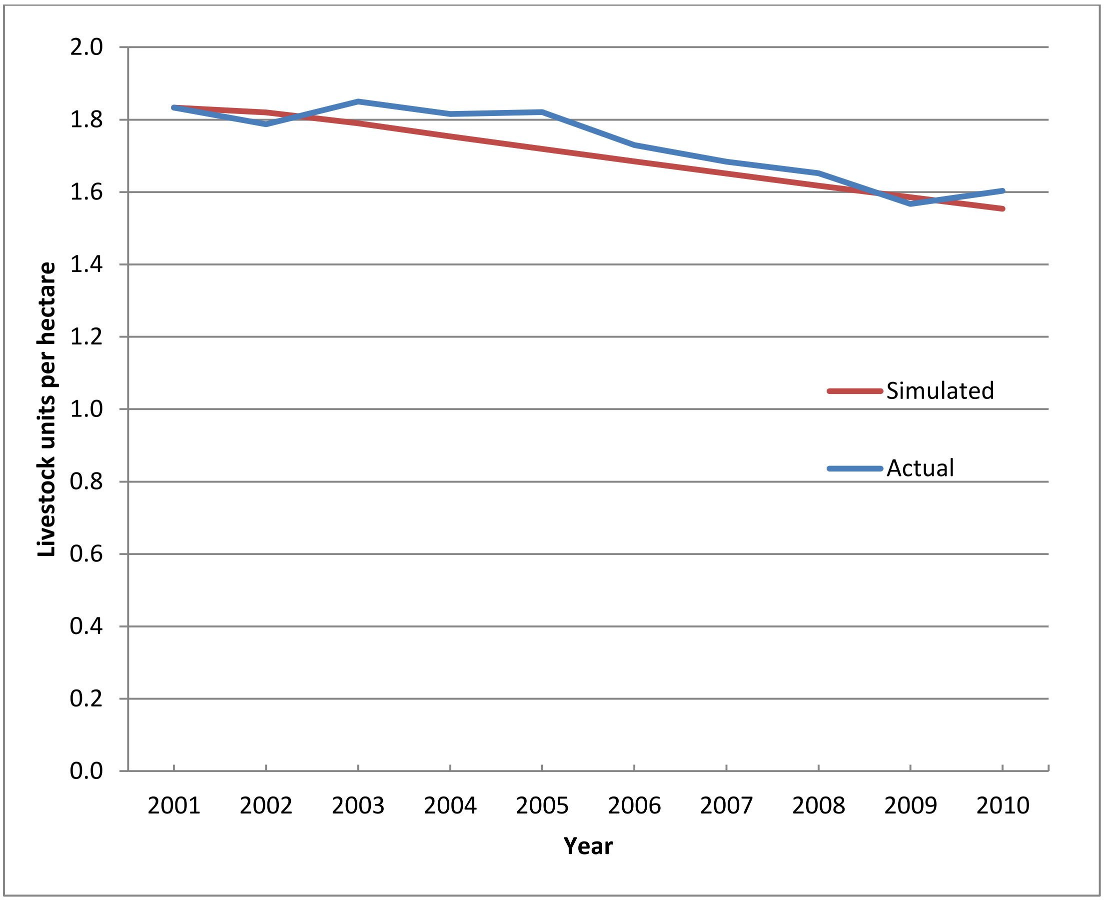
Simulated vs. actual mean values for cattle gross output per livestock unit 2001-2010



year	Simulated	Actual
2001	€405.28	€405.28
2002	€402.12	€397.37
2003	€402.83	€386.12
2004	€399.86	€400.29
2005	€384.71	€400.41
2006	€373.84	€377.81
2007	€391.68	€400.35
2008	€383.23	€388.92
2009	€377.73	€401.65
2010	€409.69	€433.41

Cattle: Livestock units per hectare

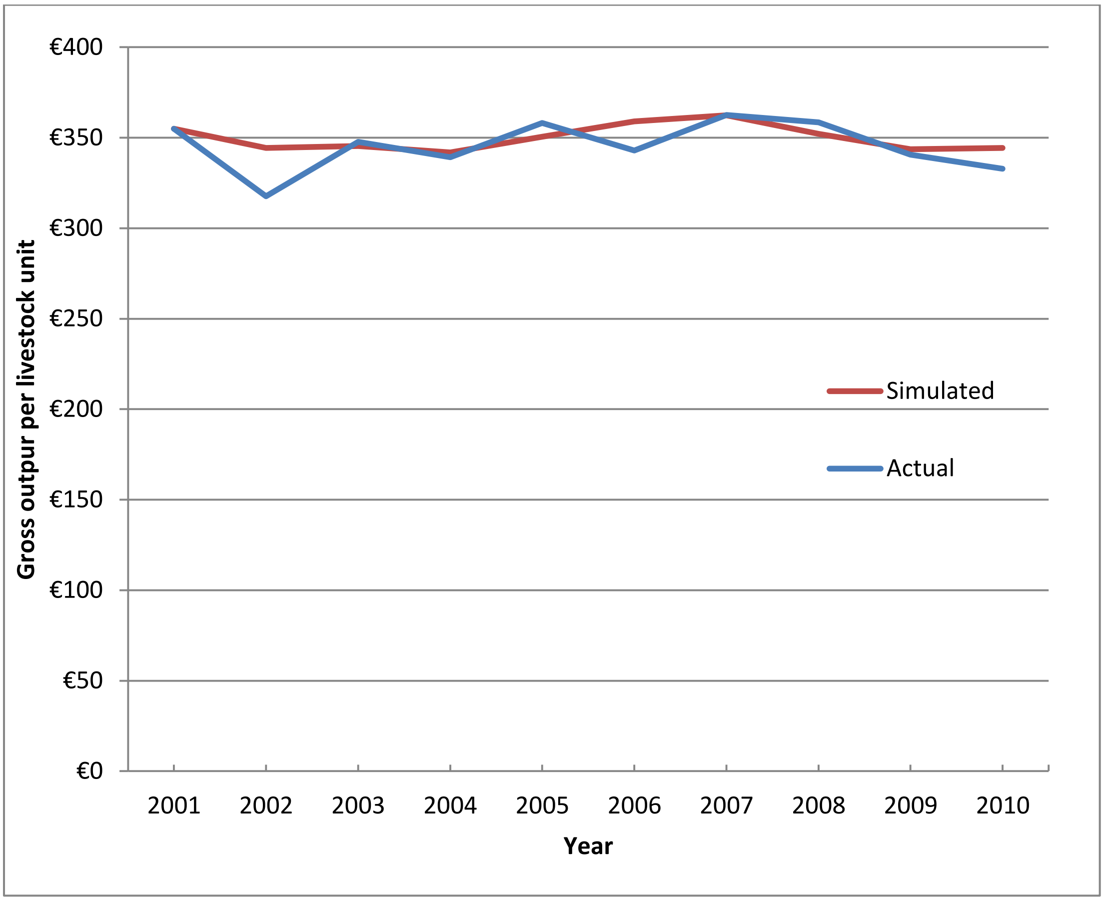
Simulated vs. actual mean values for cattle livestock units per hectare 2001-2010



year	Simulated	Actual
2001	1.563	1.563
2002	1.537	1.498
2003	1.535	1.552
2004	1.484	1.528
2005	1.475	1.534
2006	1.435	1.470
2007	1.404	1.481
2008	1.384	1.458
2009	1.354	1.423
2010	1.322	1.405

Sheep: Gross output per livestock unit

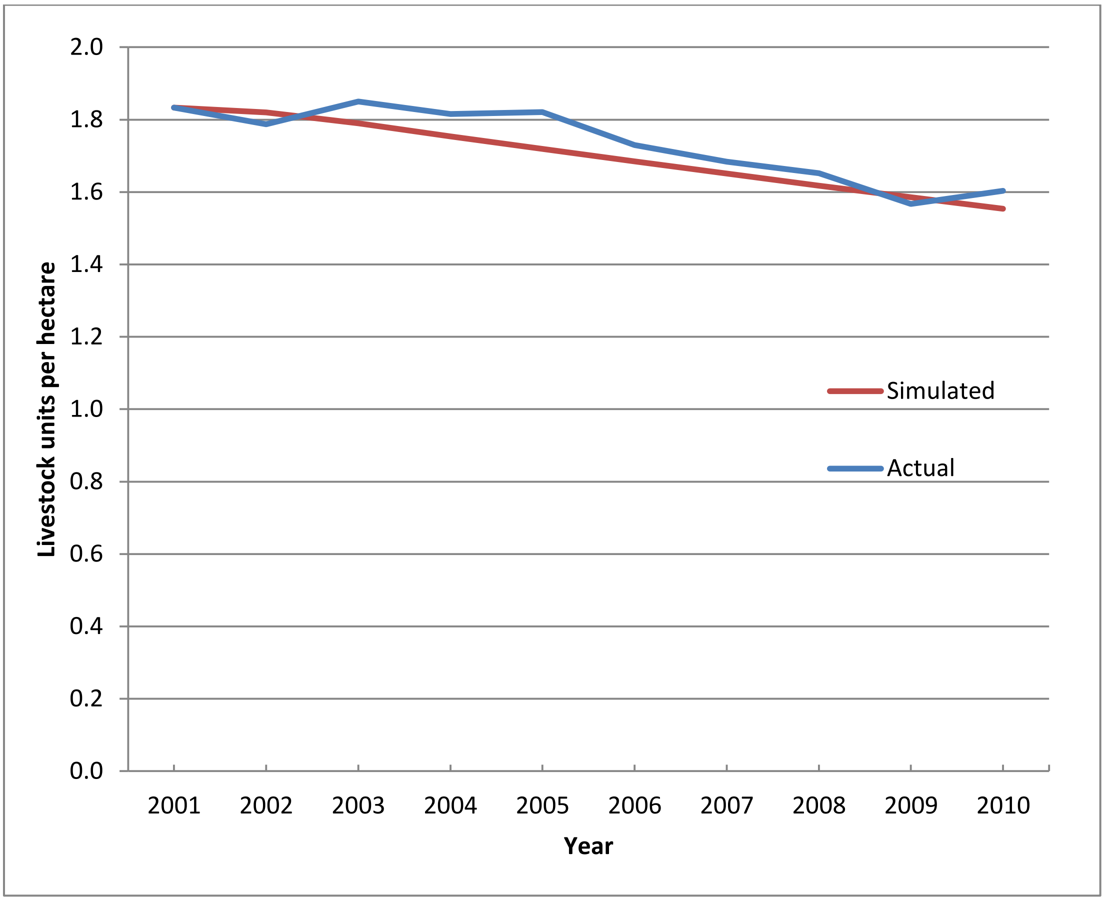
Simulated vs. actual mean values for sheep gross output per livestock unit 2001-2010



year	Simulated	Actual
2001	€354.95	€354.95
2002	€339.75	€317.65
2003	€339.27	€347.81
2004	€341.10	€339.18
2005	€351.83	€358.13
2006	€355.36	€343.02
2007	€359.20	€362.54
2008	€345.70	€358.43
2009	€344.02	€340.59
2010	€351.22	€332.95

Sheep: Livestock units per hectare

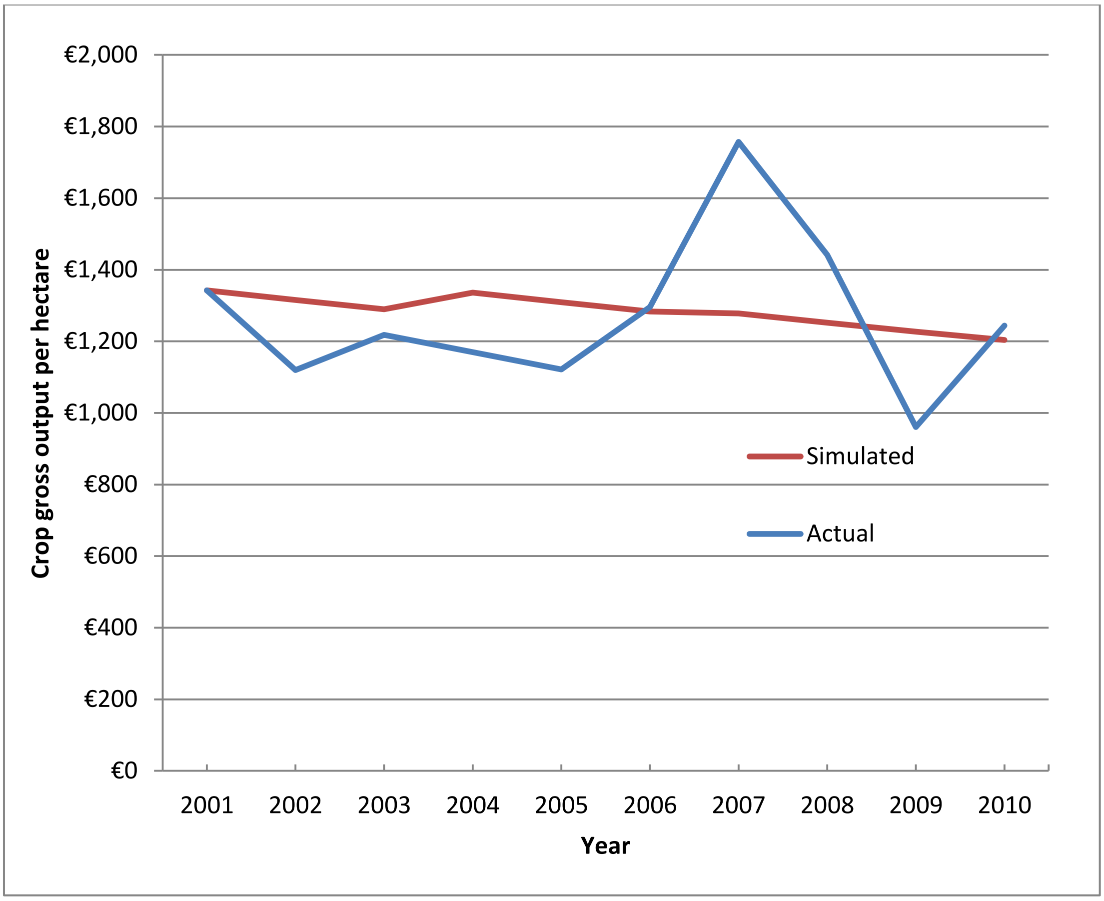
Simulated vs. actual mean values for sheep livestock units per hectare 2001-2010



year	Simulated	Actual
2001	1.833	1.833
2002	1.820	1.787
2003	1.790	1.850
2004	1.754	1.815
2005	1.719	1.821
2006	1.684	1.729
2007	1.651	1.684
2008	1.618	1.652
2009	1.585	1.567
2010	1.554	1.603

Crops: Gross output per hectare

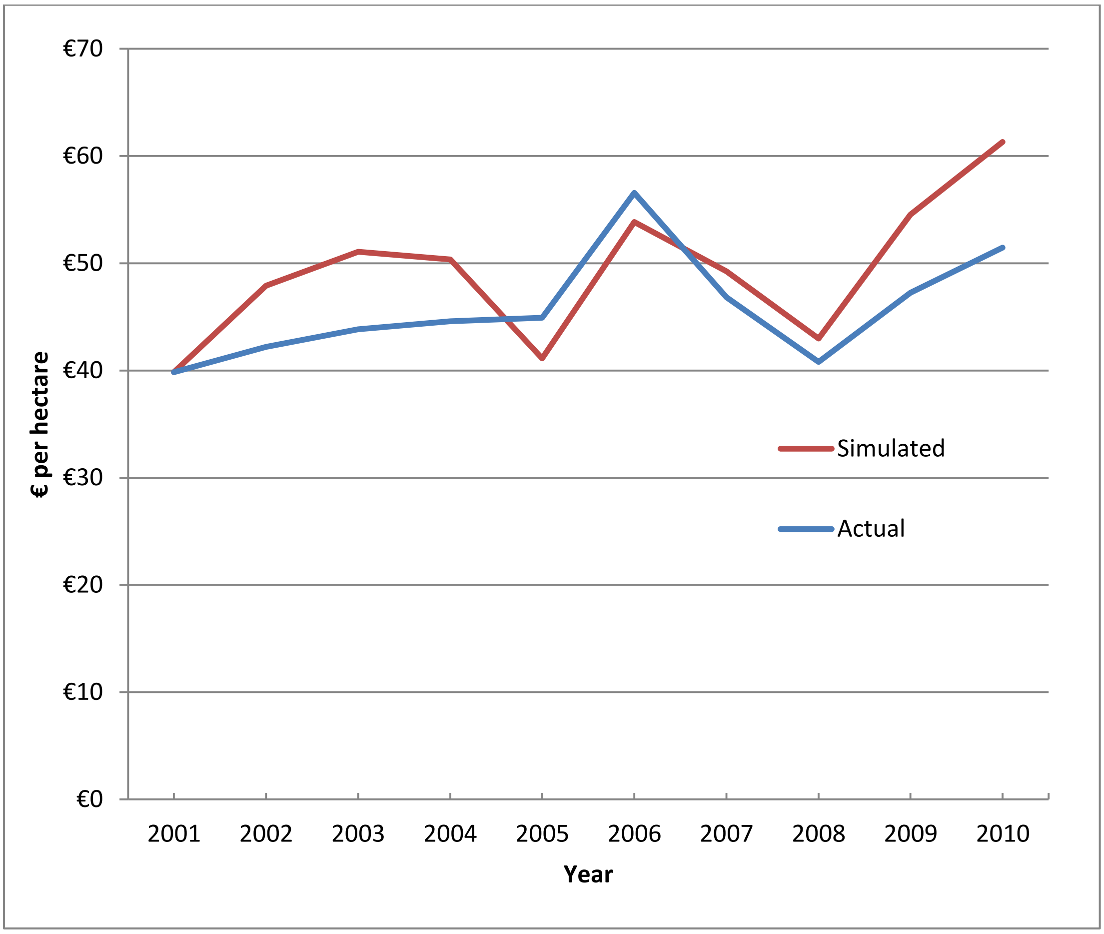
Simulated vs. actual mean values for crop gross output per hectare 2001-2010



year	Simulated	Actual
2001	€1342.71	€1342.71
2002	€1315.86	€1119.98
2003	€1289.54	€1218.43
2004	€1336.31	€1169.66
2005	€1309.59	€1121.22
2006	€1283.40	€1295.46
2007	€1277.70	€1757.46
2008	€1252.14	€1441.47
2009	€1227.10	€960.70
2010	€1203.37	€1243.51

Fodder: Expenditure on bulk fodder per hectare

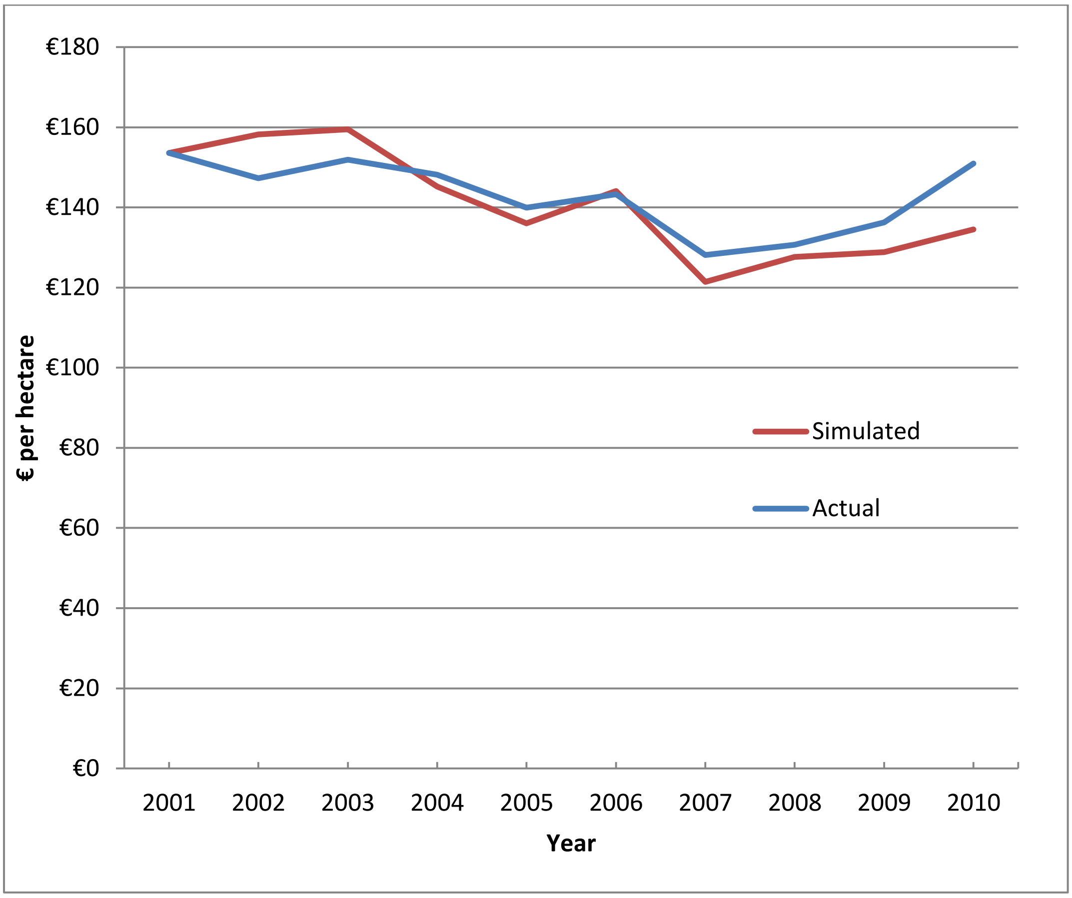
Simulated vs. actual mean values for expenditure on bulk fodder per hectare 2001-2010



year	Simulated	Actual
2001	€39.85	€39.85
2002	€47.91	€42.19
2003	€51.07	€43.84
2004	€50.34	€44.59
2005	€41.12	€44.92
2006	€53.84	€56.57
2007	€49.24	€46.82
2008	€42.99	€40.79
2009	€54.52	€47.23
2010	€61.30	€51.46

Fodder: Expenditure on concentrates per hectare

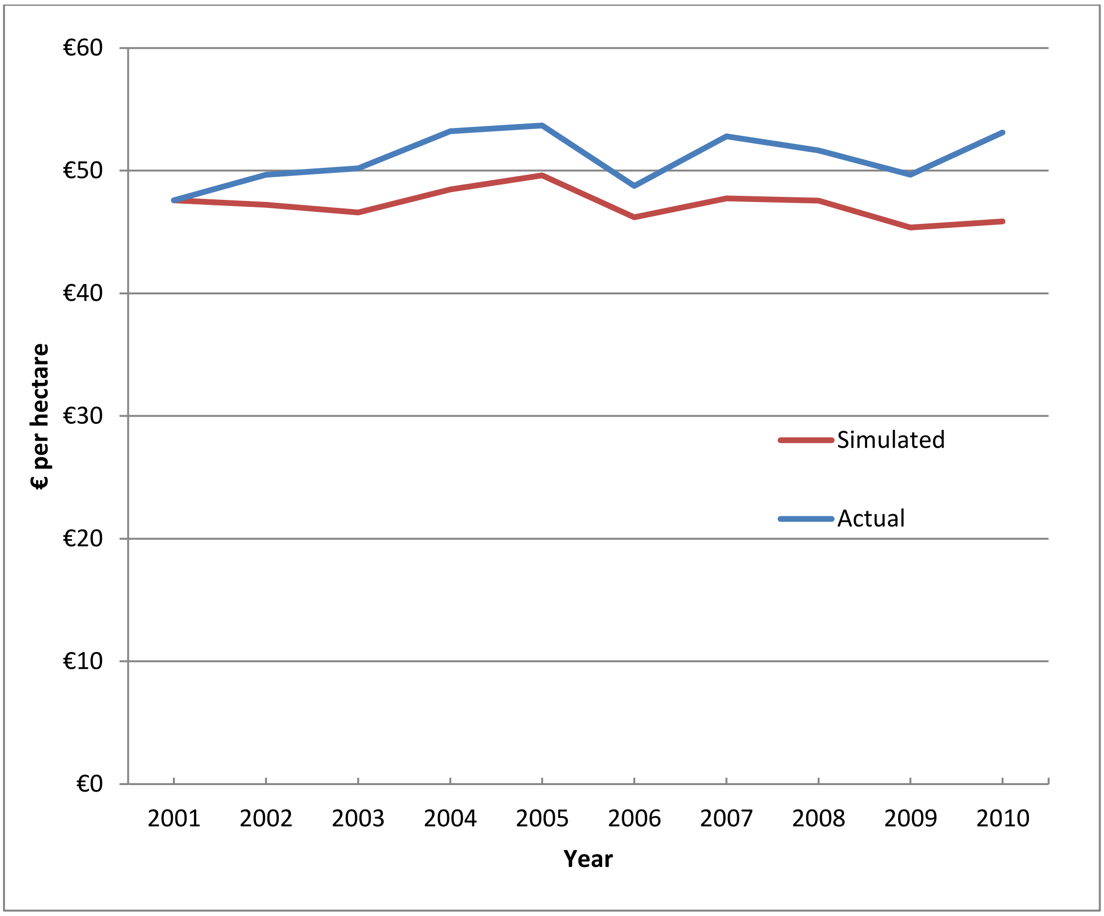
Simulated vs. actual mean values for expenditure on concentrates per hectare 2001-2010



year	Simulated	Actual
2001	€153.54	€153.54
2002	€158.20	€147.30
2003	€159.49	€151.93
2004	€145.17	€148.12
2005	€136.02	€139.93
2006	€144.11	€143.29
2007	€121.44	€128.10
2008	€127.62	€130.67
2009	€128.80	€136.29
2010	€134.53	€150.92

Veterinary: Expenditure on veterinary per hectare*

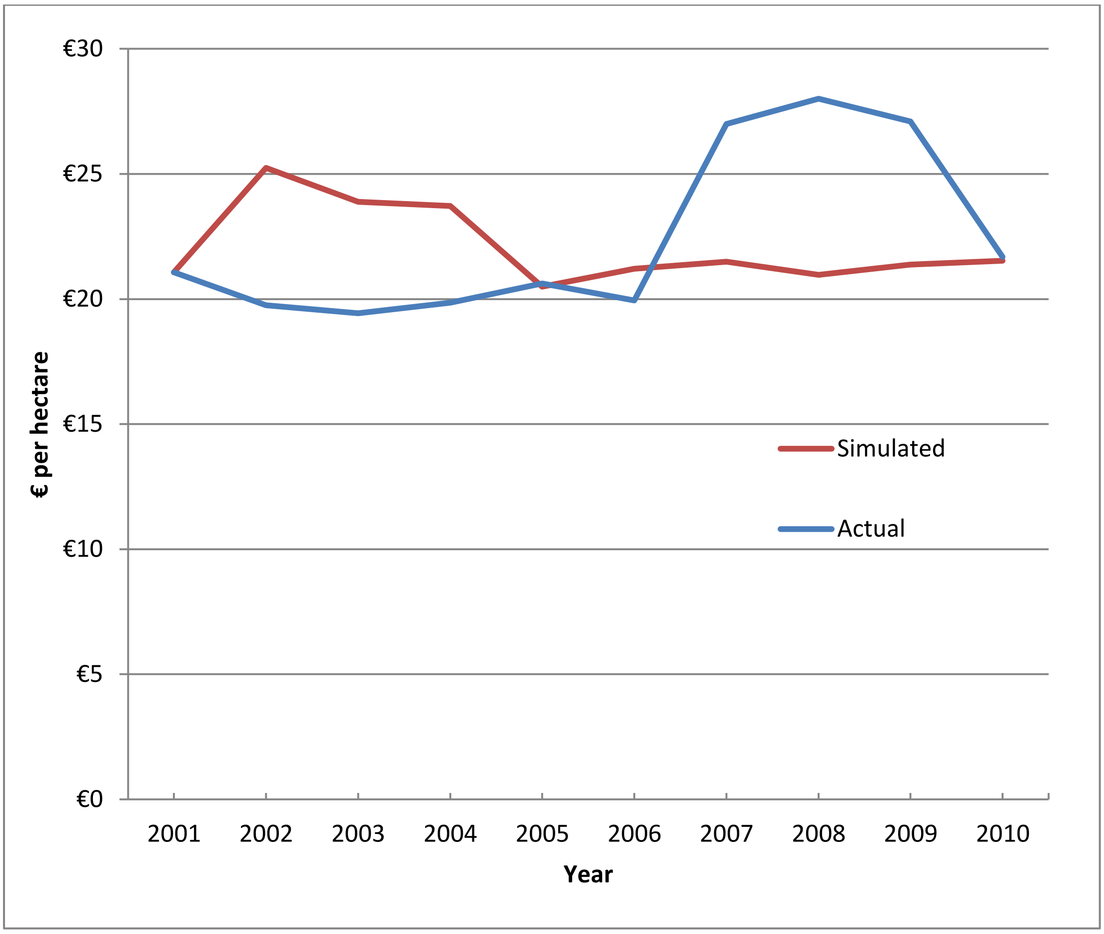
Simulated vs. actual mean values for expenditure on veterinary and medical per hectare 2001-2010



year	Simulated	Actual
2001	€47.58	€47.58
2002	€47.21	€49.67
2003	€46.60	€50.19
2004	€48.46	€53.20
2005	€49.62	€53.69
2006	€46.20	€48.76
2007	€47.74	€52.79
2008	€47.54	€51.64
2009	€45.35	€49.67
2010	€45.85	€53.11

A.I.: Expenditure on A.I. per hectare

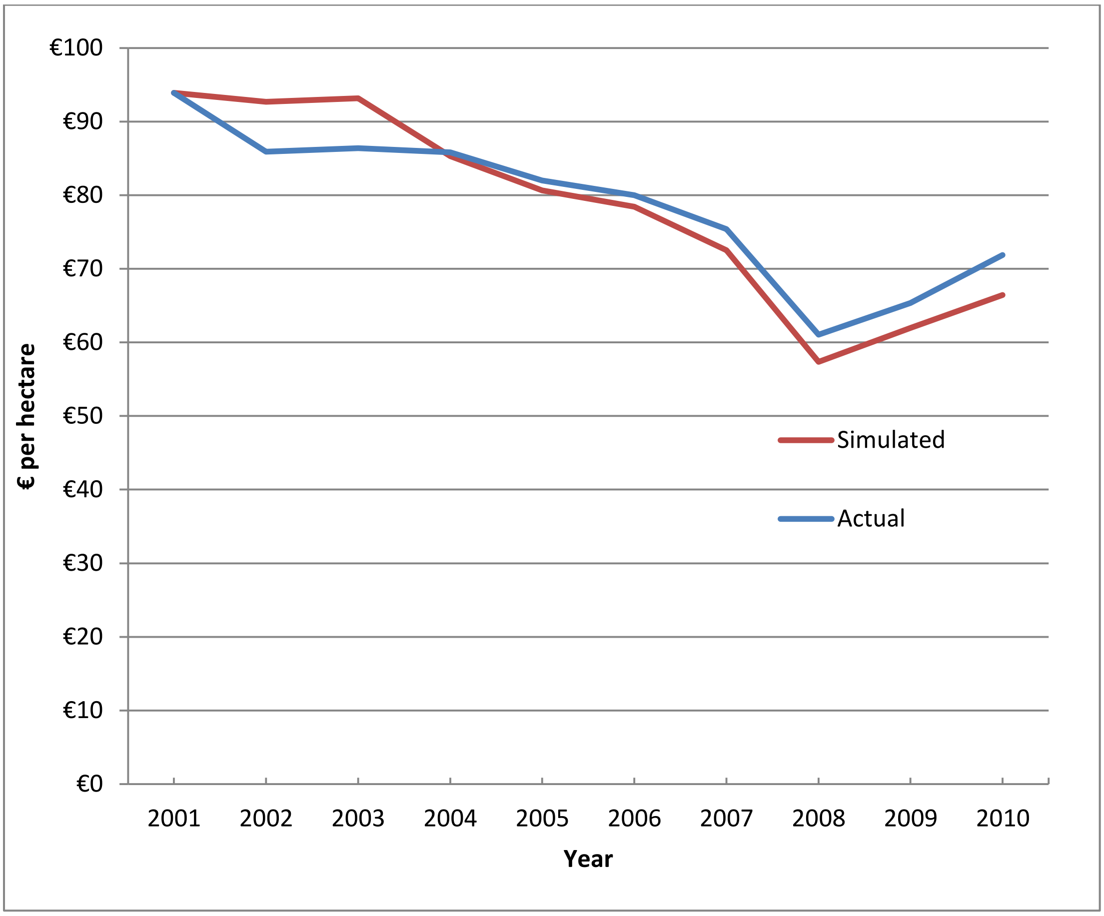
Simulated vs. actual mean values for expenditure on A.I. fees per hectare 2001-2010



year	Simulated	Actual
2001	€21.06	€21.06
2002	€25.24	€19.75
2003	€23.88	€19.43
2004	€23.71	€19.85
2005	€20.49	€20.62
2006	€21.21	€19.93
2007	€21.48	€26.99
2008	€20.96	€28.01
2009	€21.37	€27.09
2010	€21.52	€21.68

Fertiliser: Expenditure on fertiliser per hectare

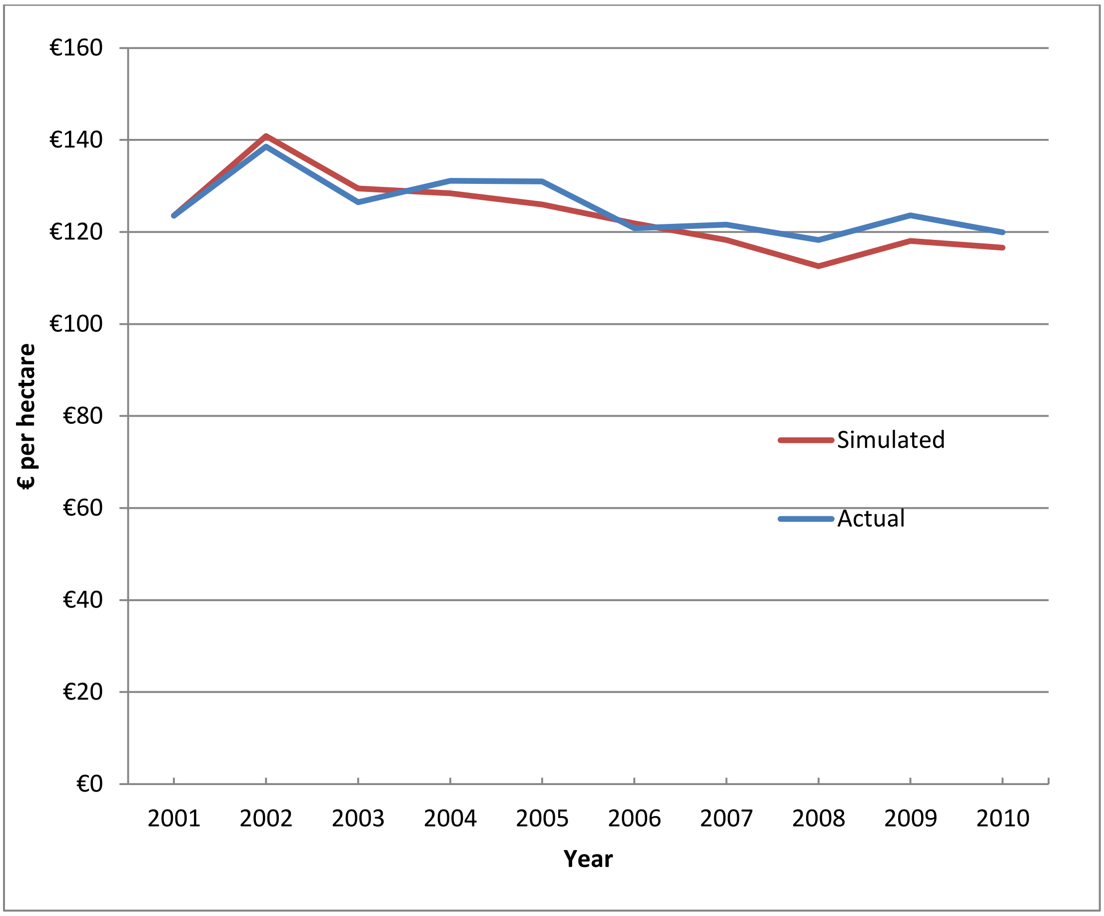
Simulated vs. actual mean values for expenditure on fertiliser per hectare 2001-2010



year	Simulated	Actual
2001	€93.89	€93.89
2002	€92.67	€85.91
2003	€93.17	€86.39
2004	€85.29	€85.80
2005	€80.67	€81.97
2006	€78.42	€80.01
2007	€72.54	€75.38
2008	€57.37	€61.06
2009	€61.97	€65.34
2010	€66.43	€71.87

Other Direct Costs: Expenditure per hectare*

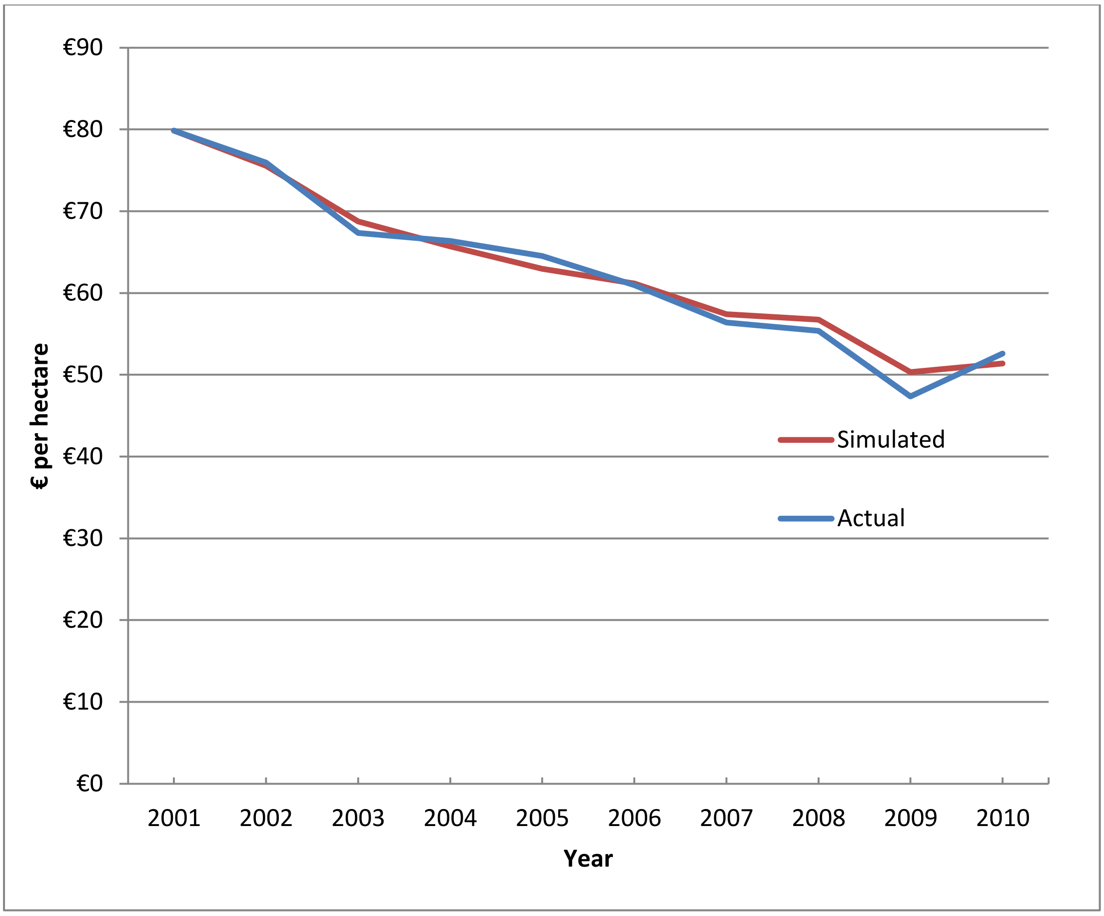
Simulated vs. actual mean values for expenditure on other direct costs per hectare 2001-2010



year	Simulated	Actual
2001	€123.52	€123.52
2002	€140.88	€138.57
2003	€129.45	€126.49
2004	€128.39	€131.11
2005	€125.97	€131.02
2006	€121.87	€120.80
2007	€118.25	€121.58
2008	€112.50	€118.24
2009	€118.08	€123.64
2010	€116.56	€119.91

Car/Elec/Tel: Expenditure per hectare*

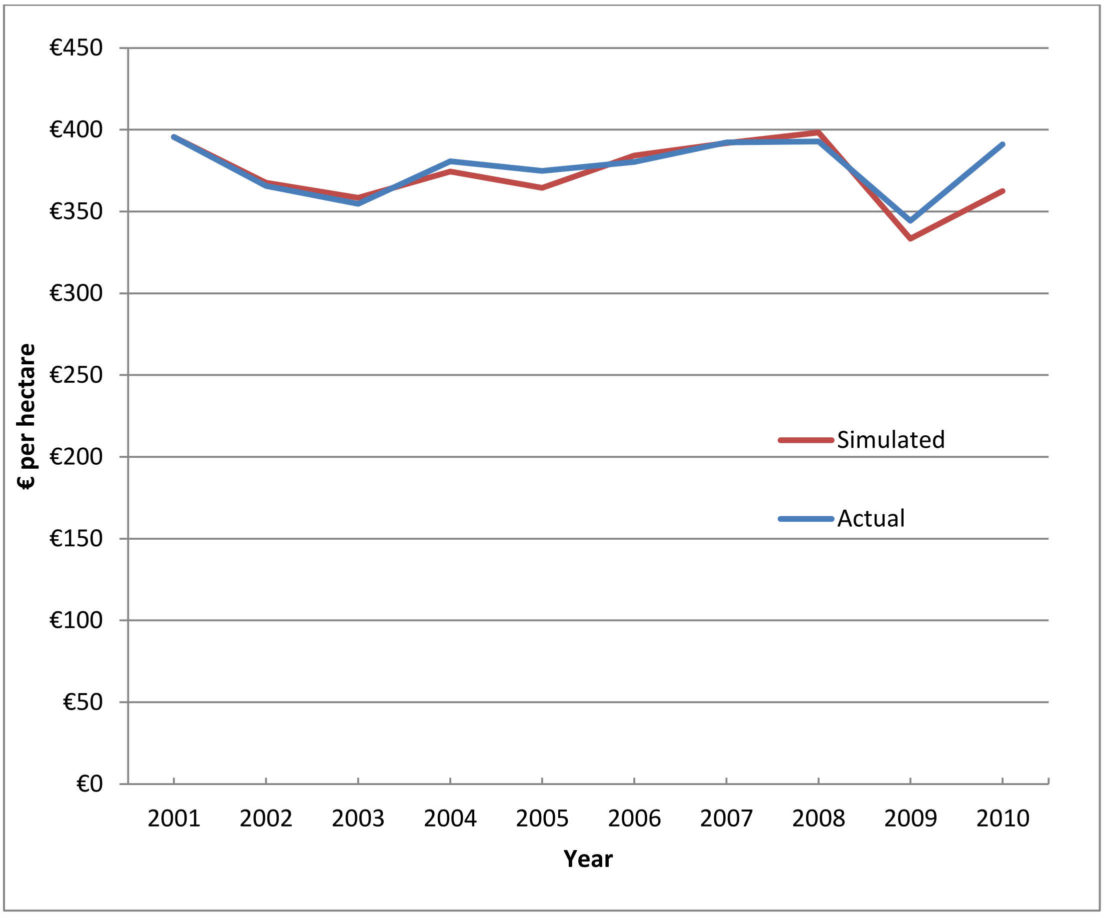
Simulated vs. actual mean values for expenditure on car/elec/tel per hectare 2001-2010



year	Simulated	Actual
2001	€79.87	€79.87
2002	€75.57	€75.95
2003	€68.75	€67.36
2004	€65.71	€66.35
2005	€62.95	€64.52
2006	€61.15	€60.98
2007	€57.41	€56.37
2008	€56.74	€55.38
2009	€50.32	€47.35
2010	€51.37	€52.61

Other Overhead Costs: Expenditure per hectare*

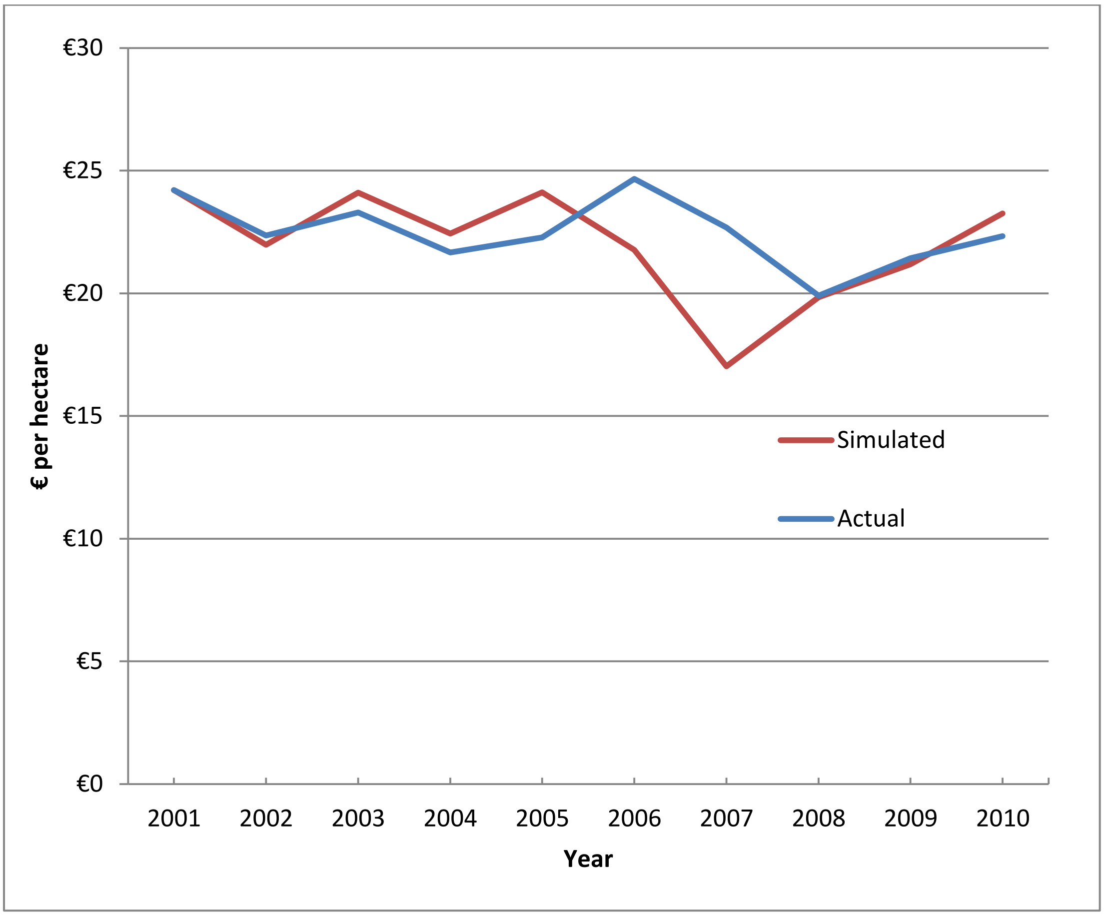
Simulated vs. actual mean values for expenditure on overhead costs per hectare 2001-2010



year	Simulated	Actual
2001	€395.59	€395.59
2002	€367.57	€365.65
2003	€358.47	€354.75
2004	€374.43	€380.72
2005	€364.49	€374.88
2006	€384.21	€380.34
2007	€391.79	€392.28
2008	€398.40	€392.85
2009	€333.34	€344.38
2010	€362.53	€391.16

Crop Costs: Expenditure on seed per hectare

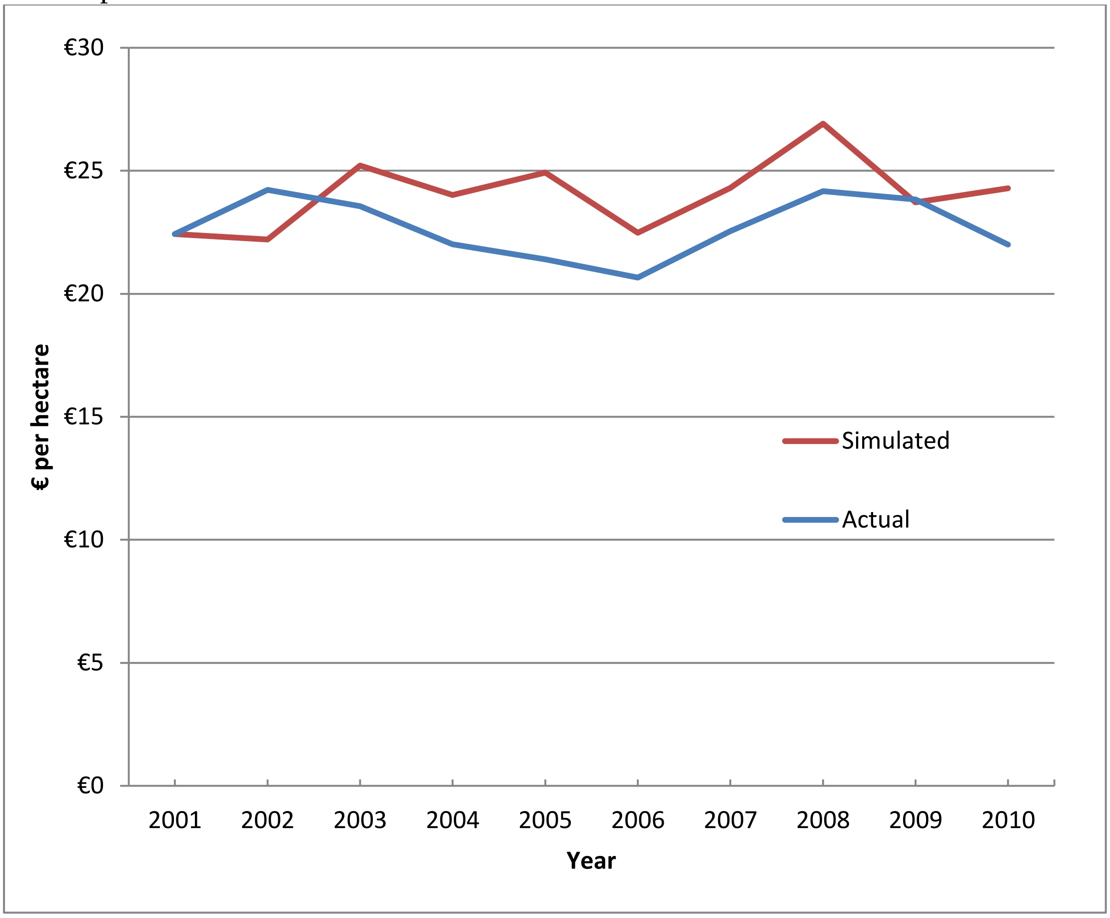
Simulated vs. actual mean values for expenditure on seed per hectare 2001-2010



year	Simulated	Actual
2001	€24.21	€24.21
2002	€21.97	€22.35
2003	€24.10	€23.29
2004	€22.43	€21.66
2005	€24.12	€22.27
2006	€21.76	€24.60
2007	€17.02	€22.68
2008	€19.84	€19.90
2009	€21.12	€21.43
2010	€23.25	€22.32

Crop Costs: Expenditure on CPPs per hectare

Simulated vs. actual mean values for expenditure on crop protection plans per hectare 2001-2010



year	Simulated	Actual
2001	€22.42	€22.42
2002	€22.20	€24.21
2003	€25.20	€23.56
2004	€24.01	€22.01
2005	€24.92	€21.39
2006	€22.48	€20.65
2007	€24.30	€22.54
2008	€26.91	€24.17
2009	€23.71	€23.83
2010	€24.29	€22.00

* Indicates Fixed Effects Model

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