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The Irish Land Mapping Observatory: Mapping and Monitoring Land Cover, Use and Change

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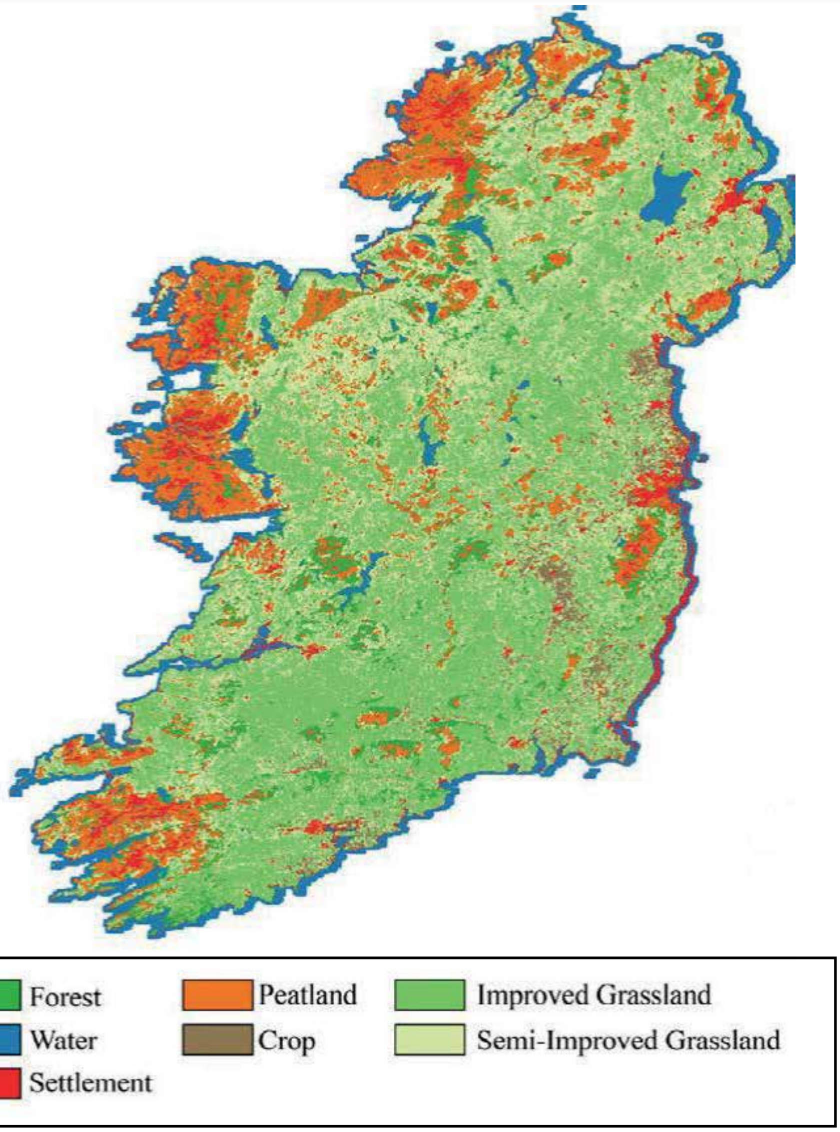

Roinn Cumarsáide, Gníomhaithe ar son na hAeráide & Comhshaoil
Department of Communications, Climate Action & Environment

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EPA RESEARCH PROGRAMME 2014–2020

The Irish Land Mapping Observatory: Mapping and Monitoring Land Cover, Use and Change

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Prepared for the Environmental Protection Agency

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

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Executive Summary

Within a number of European Union (EU) countries, there is ongoing discussion regarding how to map land use and land cover, and the changes to these landscape elements, in an objective, efficient, scalable and repeatable manner. This conversation is driven by the need to provide spatial information on a variety of aspects of national land use and cover for management- and policy-related decision making, as well as for inventory purposes. Although EU-wide mapping projects, such as the Coordination of Information on the Environment (CORINE) programme, have been undertaken since the 1990s, these have proven inadequate for many national- and local-scale applications because of their spatial resolution, restricted class categories and infrequent updates. The Irish Land Mapping Observatory (ILMO) project is part of Ireland's response to creating a national land cover map that can be generated on an annual basis, primarily using satellite imagery supplemented by ancillary field data, to populate the Ordnance Survey Ireland PRIME2 vector database. For the purposes of this project, the Counties of Longford and Sligo were used to test different methodologies.

Visible and near-infrared satellite imagery have long been used to discriminate ground features on the basis of their spectral reflectance; however, to account for the dynamics of Irish vegetation, several images per year are required. To achieve this in a frequently cloud-covered country, 16-day composite Moderate Resolution Imaging Spectroradiometer (MODIS) vegetation index images were used to separate elements on the basis of their phenological cycle. Although classification using machine-learning methods has proven to be very successful for homogenous regions, the Irish landscape is highly fragmented and, in both Longford and Sligo, problems were encountered with multiple land covers within the 250 m × 250 m pixel resolution used. A number of approaches were explored to derive the sub-pixel content of the images, and although the probability of a particular type of land cover being present within a pixel could be calculated as part of the classification process, atmospheric and geo-location instabilities contributed a significant error component to the image time series. It would thus appear that sub-pixel methodologies for land cover mapping in Ireland, using the currently available low-resolution (250 m × 250 m or lower) data, are not possible.

A further challenge presented by the MODIS data relates to assigning land cover classes to the sub-pixel PRIME2 objects. Given the problems with MODIS sub-pixel classification, two 30 m Landsat images of part of Longford, supplemented with the MODIS land cover probability data to account for temporal variation, were classified. Manual inspection of aerial photography proved to be the only near-contemporaneous ground truth source, but assessment of the resulting polygon classification accuracy demonstrated a better discrimination between improved and semi-improved grasslands than any other currently available dataset.

To overcome the limitations on optical data acquisition imposed by cloud cover, the value of synthetic aperture radar (SAR) imagery for land cover classification was also investigated. Although the temporal frequency of acquisitions is much lower than for MODIS and only one wavelength is available, which together prevent the full phenological variation from being derived, the 20 m spatial resolutions of Advanced SAR and Phased-Array L-band SAR data are far superior to MODIS. The same machine-learning algorithms were used to classify the SAR imagery as were used for the MODIS images, and the average classification accuracies for a single year of data exceeded 90% for both counties. Notably, however, the Longford results outperformed those for Sligo, which may be because of the more complex, small-scale mosaic landscape in the latter, as well as its higher degree of topographical variation.

Given that the motivation for land cover mapping is driven by carbon accounting, the land cover ascribed to the PRIME2 polygons for Longford and Sligo, from SAR imagery acquired in 1992 and 2008, was used to estimate greenhouse gas (GHG) emission/reduction profiles for croplands and grasslands. Methods were developed to estimate carbon stock changes for the land management and land cover and use transitions, based on existing methodologies and newly derived biomass and soil organic carbon

(SOC) activity data. The results showed that net emissions from croplands in the two study areas, between 1992 and 2008, were primarily associated with a loss of SOC after the conversion of grasslands to cropland. However, transitions between improved or semi-improved grassland and scrub sub-categories within the grassland category resulted in a large sink (sequestration) of carbon dioxide (CO_2), equivalent to 0.3 to 1 t CO_2/ha per year. The GHG reporting methodology developed as part of this project provides a basis to estimate the historic, present and future emissions/reductions associated with cropland and grazing land management under Article 3.4 of the Kyoto Protocol, and for future burden-sharing agreements. The pilot study, which represents only two counties, does suggest that it would be an advantage for Ireland to elect grazing land management under Article 3.4, but not cropland management. However, national mapping frameworks need to be implemented to assess the implications on a national level.

Based on the outputs of this project, it is recommended that high spatial resolution (better than 30 m resolution) satellite data are used for the land cover mapping of Ireland, but lower spatial resolution data acquired on a shorter update cycle could be used to inform the classification of more infrequently acquired imagery. Both SAR and optical high spatial resolution data can be used, but given the frequently cloudy conditions, SAR data offer a more reliable and consistent data source. Using the PRIME2 polygons as well-defined coherent objects enables a seamless land cover map to be generated; however, this cannot account for sub-object variation, such as strip grazing within a field. Furthermore, the polygon boundaries are not updated annually, so discrepancies may arise between the apparent edge of a feature and its appearance on a satellite image. Nevertheless, the combination of raster and object datasets makes it possible to perform a more complete carbon balance estimate for land use and cover transitions between two separate years in Ireland than is currently possible.

1 Introduction

1.1 The Need for Land Cover and Land Use Data

Globally, there has been a growing interest in monitoring land cover and land use, land use change and forestry (LULUCF) in recent years, in order to support policy-related decisions and ensure effective land management. Different countries and regions have adopted unique methods of addressing this issue, and currently there is no agreed single approach or any best practice guidelines. However, increasingly, LULUCF data are gaining importance in both European environmental directives and global initiatives. Among the key drivers behind a desire for accurate LULUCF knowledge are the needs to provide carbon budget and greenhouse gas (GHG) inventories, and to assess the efficacy of biodiversity, agriculture, habitat and water management targets. Ireland is one of many countries obliged to report an annual inventory of its GHG emissions and removals to the United Nations Framework Convention on Climate Change (UNFCCC), and in the second commitment period of the Kyoto Protocol (up to 2020) legally binding targets may be enforced. In addition, Member States of the European Union (EU) have agreed to reduce GHG emissions to levels at least 20% below those of 1990 by 2020; however, it is predicted that Ireland will be one of 13 Member States that will not reach this target without extra efforts. Indeed, as of 2011, Ireland's emissions were 110% of 1990 levels (CSO, 2012), but these values do not include emissions and removals related to LULUCF (EC, 2014).

To ensure that future estimates of GHG emissions and sequestration are as accurate as possible, reliable data on LULUCF are necessary. At present, land area and use estimates are based on an amalgamation of Central Statistics Office (CSO) data, the Coordination of Information on the Environment (CORINE) land cover map, the agricultural Land Parcel Information System (LPIS), the Forest Information and Planning System (FIPS), the general soil map of Ireland and other specialist sources, e.g. Bord na Móna for peatland area statistics (Table 7.3 in EPA, 2013). However, each of these data sources reports LULUCF in different ways and under different headings, making harmonisation of the values difficult.

Several reviews of the Irish National Inventory Report in recent years (e.g. EPA, 2013) highlight the problems that arise from the current reporting formats for LULUCF in Ireland. These include resolution and classification issues, the lack of a seamless land classification system, and the inability to track changes in land cover and use, including transitions between agricultural states.

1.2 European Land Cover Mapping

1.2.1 CORINE dataset

Many national LULUCF systems are derived from images acquired by satellites that orbit at altitudes of 400–800 km above the surface of the Earth. Such Earth observation data have been exploited for land mapping since the early 1970s as they are a relatively accurate and increasingly inexpensive source of information, which allows different land covers to be distinguished if they are spectrally discernable and separate on the imagery. From the late 1980s, more formalised attempts have been made within the EU CORINE project to generate land cover maps that are consistent, objective and repeatable on a timescale of several years. The resulting CORINE land cover maps are standardised into 44 classes at a 100 m resolution, based on interpretation of the spectral response for each pixel within the image using a semi-automated classification approach, followed by manual editing to create spatial parcels that represent the land cover units. The statistics that are derived from the map provide a snapshot of the state of EU land cover at a single point in time, and with maps generated in 1990, 2000, 2006 and 2012, changes over time can be identified. Although the CORINE dataset is recognised as a valuable reference dataset across Europe to illustrate land cover and its change at regional, national and European scales, it also has many limitations, especially with regard to detailed local mapping.

CORINE mapping was designed to be applicable across a wide range of land covers, with classes and spatial resolution compatible with European-scale needs, not those of any individual country. The landscape mosaic of Ireland is relatively fragmented compared with most other European countries, and the relatively low-resolution minimum mapping unit (MMU) within CORINE of 25 ha and the linear features of 100 m make some landscape units unmappable. The 2010 Census of Agriculture in Ireland found that the average farm size was 32.7 ha (CSO, 2010); therefore, a large proportion of individual fields within the average farm lie below the MMU scale and so different land covers may be aggregated inappropriately.

The CORINE land cover classes were designed to represent the predominant landscapes of all EU Member States and to be distinguishable on satellite images; however, only 26 of the 44 classes are present within Ireland (there are no vineyards or glaciers, for example). The map therefore is a simplification of the detail inherent within the landscape, and much of agricultural Ireland is designated within the single class of “pastures”. Although the 2010 agricultural census confirmed that approximately 91% of the agricultural area is grass based, this is split between pasture, silage, hay and rough grazing, and distinctions between these different types of land are not made within the CORINE dataset; however, such distinctions are of significant importance with respect to their relative carbon budgets. As an EU-wide project, CORINE also had to respect the technical limitations associated with acquiring and processing a large volume of data. Many of the images used in the most recent 2006 and 2012 iterations were acquired from SPOT (*Satellite Pour l’Observation de la Terre*), Indian Remote Sensing (IRS) and RapidEye satellite sensors, which operate at a 5–20 m scale, in the visible and near-infrared (NIR) regions of the electromagnetic spectrum. Although these wavelengths are useful for distinguishing different features on the basis of their reflectance properties, the timing and frequency of image acquisition is constrained by cloud cover. Thus, although a CORINE dataset is described as a snapshot of the land cover at a single point in time, that snapshot is itself the result of a number of images that may be separated by 2–3 years. Moreover, the land cover is typically determined from images acquired on one or two dates within the growing season, which, for a dynamic natural environment, may not be typical of the state of the land cover at other times of year.

Several papers have been published that highlight the limitations of CORINE for use in Ireland, including the following: Verbeiren *et al*. (2013), who “showed that consistent remote sensing derived land-use maps are preferred over alternative sources (such as CORINE) to avoid overestimation errors, interpretation inconsistencies and assure enough spatial detail for urban studies”; Sullivan *et al*. (2010), who stated that “Use of datasets such as CORINE Landcover Classes is widespread but it has been acknowledged that such datasets can significantly overlook fine-scale biodiversity features”; and Connolly *et al*. (2007), who found that the CORINE land cover had a reliability of 65% for the peatland classification, compared with 75% for a dedicated map. Given these, and other, limitations of the CORINE dataset, several European countries have developed their own national land cover mapping programmes, many of which also use satellite data, but in a way that is better suited to the landscape conditions of that country. For instance, these approaches use a variety of different satellite data, integrate satellite data with other ancillary data or use several images throughout the growing season to better distinguish individual land cover types.

1.2.2 Land cover mapping from space

Mapping in the optical domain

The visible and NIR wavelengths of the electromagnetic spectrum have long been regarded as the most suitable for distinguishing different land cover classes, as different features have very different reflectance patterns at these wavelengths. As a result, many land cover classifications have been generated globally using data from sensors that record in this domain, including Landsat (e.g. Zhu and Woodcock, 2014), SPOT (e.g. Rodrigues *et al*., 2013), MERIS (a low-resolution imaging spectrometer) (e.g. Carrao *et al*., 2010), Moderate Resolution Imaging Spectroradiometer (MODIS) (e.g. Ali *et al*., 2014) and IRS (Bhagyanagar *et al*., 2012). A variety of approaches have been adopted that exploit the difference in reflectance between one wavelength and another, with vegetation indices (VIs) using the red and NIR reflectance values common for many of the natural landscape classifications. For more detailed

local habitats, the same approaches are often used with higher spatial resolution sensors such as IKONOS (e.g. Holland and Aplin, 2013), Quickbird (e.g. Fernandez *et al*., 2013) and WorldView (e.g. Jawak and Luis, 2013), all of which can record ground detail at a resolution of less than 1 m.

However, the limited ground cover and infrequent overpass of these sensors, as well as the high cost of purchasing imagery from commercial companies, limits the potential to develop national or global maps from these instruments. Given that a single image of the ground may not be optimal for mapping the natural features of that surface, hyper-temporal mapping approaches have been developed that use images at bi-monthly or weekly intervals, thus capturing the dynamic changes that are associated with, for example, crops growing at different rates, a pasture being cut for silage or an area of forest being harvested. To achieve such regular coverage, the sensor typically needs to pass overhead daily, or several times per day, in order to acquire information on as many cloud-free opportunities as possible. This necessitates a much lower spatial resolution, of hundreds of metres, which precludes detailed habitat-scale information from being derived. Nevertheless, research has demonstrated that from a detailed time series of data, phenological changes can be observed within agricultural landscapes, and the start and end of the growing season can be determined (e.g. Potgieter *et al*., 2013).

Mapping in the microwave domain

In contrast to the optical domain, microwave wavelengths can penetrate through cloud cover and record the backscatter of energy from the ground beneath, making microwave sensors usable 24 hours a day in all weather conditions. Despite this advantage, microwave sensors have not been as widely used for land cover mapping as optical sensors because there are fewer of them, they have a shorter history of data collection, the processing of the data is more challenging and, critically, each sensor records at only a single wavelength, making it much harder to conclusively discriminate between land cover types. However, in recent years, a growing body of research has demonstrated that, from a time series of microwave images, different land cover types can be distinguished with as much reliability as can be achieved in the optical domain (e.g. Skriver *et al*., 2011; Niu and Ban, 2012; Ok and Akyurek, 2012).

Pixel and object mapping

Much of the work carried out using optical and microwave instruments to date has been pixel based, where each pixel is ascribed to a unique land cover class. However, this fails to recognise that, at all spatial resolutions, pixels almost always comprise more than one land cover type, and largely ignores the spatial relationship between neighbouring pixels; these factors can have significant impacts on the accuracy and reliability of the end result. To overcome these shortcomings, texture measures can be used to account for the similarity and difference between adjacent pixels (e.g. Rodriguez-Galiano *et al*., 2012a), and fuzzy classification can allow the probability of different land covers within a pixel to be calculated (e.g. Beekhuizen and Clarke, 2010). An alternative approach to classifying each pixel uniquely and in isolation is that of object-oriented classification whereby groups of pixels with similar spectral and spatial characteristics are segmented into objects. These are then labelled with a land cover class; however, although such an approach can result in greater accuracy than a purely pixel-based classification method, objects on an image may not equate to objects on the ground (Platt and Rapoza, 2008). Moreover, such image-derived objects do not necessarily maintain spatial integrity from one imaging period (season or year) to another because of natural changes in vegetation, shadow and other illumination effects, cloud and atmospheric scattering, or human intervention (Hofmann *et al*., 2008).

Such segmentation approaches have been investigated for land cover mapping at a national scale. For example, in the UK, the Land Cover Map 2000 defined areas of land based on the Ordnance Survey Mastermap boundaries and spatial attributes of area, length, etc., and the areas were then labelled according to the spectral characteristics of SPOT and Landsat imagery (Smith, 2008). Similarly, in Germany, the DeCover land cover mapping programme has exploited the fusion of satellite datasets, including time-series optical imagery to interpret phenology signals, with existing land parcels (Möller *et al*., 2010). In Spain, the Spanish Land Use and Land Cover Information System programme has adopted

an approach that takes cadastral objects from the mapping agency and uses satellite imagery, along with other relevant data from different agencies, to ascribe a land cover class to each object, allowing them to have multiple classes and attributes (Villaa *et al*., 2008). By using independently created and maintained objects that constrain segmentation and guide classification, these hybrid object–pixel approaches to classification can facilitate the reliable and accurate classification of land cover and land use at a national scale, or for specific land cover classes, if suitable object-based information exists.

1.3 Land Cover Mapping in Ireland

1.3.1 Current status

At present, no authority in Ireland has been charged with the responsibility of creating and maintaining a national database of land cover, land use or changes in land use or cover. As discussed, the CORINE maps are inappropriate for national-scale reporting purposes (Black *et al*., 2009) because of their generalisation, infrequency and inability to capture the dynamics of specific land uses. The only national land cover map developed explicitly for Ireland was created by Teagasc, as part of the soils and subsoils programme; this map shows land cover and habitats at a 1 ha scale, but was determined from satellite imagery acquired in 1995 (EPA, 2009). A number of maps have been produced for one-off purposes, such as MOLAND (Monitoring Land Use/Cover Dynamics) map for urban planning on the east coast (Van de Voorde *et al*., 2009) and the PIMLI (Peatlands of Ireland Mapped with Landsat Images) collection for peatlands (Cawkwell *et al*., 2010). Annual or periodic high-resolution datasets are also produced by the Department of Agriculture, Food and the Marine (DAFM) as part of the LPIS and the FIPS, with information on land use for parcels of relevance to that dataset.

Although these datasets are useful for dedicated activities, many challenges exist with regard to aggregating them for coherent national reporting because of their different spatial and temporal resolutions, and varied means of attributing land cover types. Accounting for nuances in grassland production and change is especially important in an Irish context given the far greater proportion of the agricultural area that is under pasture than other European countries. For Ireland to meet the challenges of providing annual carbon budget inventory data, assess the success of targets to reduce GHG emissions from agriculture and increase GHG sequestration from forestry, and administer policies on land management, it is essential that a single coherent mapping system that has the capacity to distinguish between subtly different land uses (e.g. between pasture that is cut for silage and pasture that is grazed) is developed. Given current developments within the Irish and European technological landscape, the potential to implement such an operational system in the coming years, using a hybrid approach of satellite imagery to populate vector objects, should be realised.

1.3.2 OSi PRIME2

Since 2006, the Irish national mapping authority, Ordnance Survey Ireland (OSi), has been designing a new geo-spatial database structure for the intelligent, seamless mapping of boundary information, which will support digital vector and cartographic products. Data capture resolution is between 0.1 m, in urban areas, and 0.5 m, in rural areas, but the resolution could be reduced to 3 m, 6 m or 15 m depending on the needs of a project. This national, spatial data platform, PRIME2, consists of layers of objects that can each be uniquely referenced by a globally unique identification (GUID) code, enabling the exchange and integration of OSi data between and with data from other sources. In addition, the attributes of all of these objects, including land cover classes, can be defined, and both the attributes and the objects themselves can be updated over a range of time intervals as necessary, with the history of changes being trackable for each individual object. During the lifetime of this project, a beta version of the PRIME2 dataset for Counties Longford and Sligo was available and complete national coverage was delivered in 2014.

1.3.3 Satellite imaging of Ireland

High-resolution optical sensors have been used for mapping a variety of LULUCF data and changes in these data for small regions within Ireland, but the persistent cloud cover associated with a temperate maritime climate precludes frequent acquisition of national data and, as a result, can fail to capture sufficient imagery to accurately distinguish different

classes or identify change on an annual basis. Daily overpasses by low-resolution sensors have been proven to acquire sufficient cloud-free data to allow the creation of time composites of key phenological stages (O'Connor *et al*., 2012), but the 250–1000 m resolution of these datasets is not compatible with the Irish field scale.

In 2014, the European Space Agency (ESA) embarked on an ambitious programme of satellite launches, which will result in 12 new Sentinel satellites for terrestrial, marine and atmospheric observation. The six Sentinel missions are each based on a constellation of two satellites, in order to increase the revisit time and data coverage, and each mission carries instruments for different applications. The first three Sentinel missions (six satellites in total) focus on terrestrial and marine applications, and can be incorporated with other operational and historic missions and sensors, such as Landsat. As a subscriber to ESA's Earth Observation Envelope Programme, Ireland is well placed not only to access and use the data from the Sentinel missions, but also to support and build capacity in the use of satellite data for a variety of national interests. Although the Sentinel missions were not operational during the lifetime of this project, similar data from other satellites were used to demonstrate the potential that can be offered, and to allow the development of concepts and algorithms that can be implemented across a range of different data types.

1.3.4 The importance of grasslands in Ireland

Globally, grasslands cover 37% of the total land area (O'Mara, 2012). They are valuable ecosystems that support a multitude of roles, most importantly food security, biodiversity conservation and GHG mitigation. In Ireland, grassland is the dominant land cover, occupying approximately 60% of the country's terrestrial area (Eaton *et al*., 2008), and represents over 90% (≈4,000,000 ha) of all agricultural land (pasture, grass silage or hay, and rough grazing). Given the extent of grasslands, there is considerable potential to increase carbon sequestration through improved land management and the restoration of degraded grasslands (Soussana *et al*., 2004; O'Mara, 2012). This is of particular relevance for Ireland, given the dominance of grassland and the expected trends with regard to the intensification of grassland management as a result of the implementation of the Food Harvest 2020 strategy (DAFF, 2011) by the Irish Government and the abolition of milk quotas across the EU-28 in 2015 (Läpple and Hennessy, 2012). Although these transitions will affect sequestration and emission processes, they also present significant implications for biodiversity (Benton *et al*., 2003; Walker *et al*., 2004) and water quality.

1.3.5 Land cover classes in Ireland

Sullivan *et al*. (2010) highlighted the need to develop a grassland classification system for use in Ireland that allows semi-natural grassland assemblages to be identified at the field level. The land cover categories and definitions used in this study are similar to those used by the EPA for LULUCF reporting (EPA, 2013), but whereas the current EPA system (see Table 1.1) acknowledges only "improved" and "unimproved" grassland, this project sees the former sub-divided into "improved" and "semi-improved" grassland. In practice, there is a continuum that relates to changes in phyto-sociological relationships across grassland types, from intensively managed *Lolium* and *Trifolium*-dominated pastures to less intensively managed dry calcareous (e.g. *Agrosits*-dominated) or wet (*Carex*-dominated) grasslands, through to rank grasslands

Table 1.1. Definitions of six major land cover categories

Land use	Definition and coverage
Forest land	All public and private plantation forests
Cropland	Permanent crops and tillage areas (including set aside)
Grassland	Areas of improved grassland (pasture and areas used for the harvesting of hay and silage), unimproved grassland (reduced silage cut and fertiliser input, no reseeding)
Wetlands	Natural unexploited wetlands and wetland areas commercially exploited for public and private extraction of peat, and areas used for domestic harvesting of peat
Settlements	Urban areas, roads, airports and the footprint of industrial, commercial/institutional and residential buildings
Other land	Water bodies, bare rock

and the occurrence of woody species such as gorse, bramble or even hazel in abandoned grasslands (White and Doyle, 1982). In reality, however, a satellite-based classification system needs to be more constrained, but still reflect different potential GHG emission/removal profiles, as management intensity across different grassland categories may increase or decrease. The grassland classes were defined using the Fossitt (2000) classification, which is the most widely utilised grassland classification in Ireland (O'Neill *et al*., 2009; 2010) and includes information on soils, geology and landscape features, in addition to information on plant communities. "Semi-improved" grasslands are defined as managed enclosures, which are less intensively managed than "improved" grasslands, but more intensively managed than upland natural grassland, for which the only "management" is grazing. The definitions, and some ground truth locations, of the semi-improved and improved grassland classes were taken from the Semi-Improved Grassland Surveys funded by the National Parks and Wildlife Service (NPWS) (O'Neill *et al*., 2009; O'Neill *et al*., 2010).

In light of the major changes now underway in Irish grassland practices, it is crucial that more detailed and precise inventories of grassland are obtained so that sustainable grassland management can be achieved. The collection of such data by traditional means (e.g. through field work) can be cost prohibitive and resource intensive. The use of satellite data can provide routine coverage over large and remote areas, and be readily incorporated into operational mapping or monitoring programmes to provide a cost-effective means of replacing or complementing field data collection. Therefore, for the purposes of this project, the focus of the land cover classification was on grasslands, which can be sub-divided into levels of complexity according to soil type and management practices (Table 1.2).

1.4 Aim and Objectives

The overall aim of this research was to develop an integrated geo-informatics approach to mapping land cover, land use and changes in land cover and use, with a focus on Irish grasslands, to enhance the accuracy of reporting national GHG emissions related to land dynamics. Counties Longford and Sligo (Figure 1.1) were the test areas for the bulk of the work. These areas were chosen because of the availability of PRIME2 data for these regions at the start of the project, and also because of the challenges they present in terms of the variety of land cover types, small agricultural fields, cloud cover and terrain variation. Specifically, this report will focus on:

- analysing time series of VI composites from MODIS, combined with ancillary ground data, to determine the extent to which intra- and inter-annual variations in land cover and land use can be reliably mapped given the 250 m spatial resolution of the sensor (Chapter 2);

Table 1.2. Hierarchy of grassland categories according to soil type and management practices

L0	L1	L2	L3	L4
Grassland	Improved grassland (GA)	Dry improved grassland (GAd)		Grazing (GAdg)
				Cutting (GAdc)
		Reclaimed improved grassland (GAr)		Grazing (GArg)
	Semi-Improved grassland (GS)	Dry semi-improved grassland (GSd)	Calcareous (GSdc)	Grazing
				Reverting
			Humic (GSdh)	Grazing
				Reverting
		Wet semi-improved grassland (GSw)		Grazing
				Reverting
Forest				
Water				
Settlement				
Peatland				
Cropland				

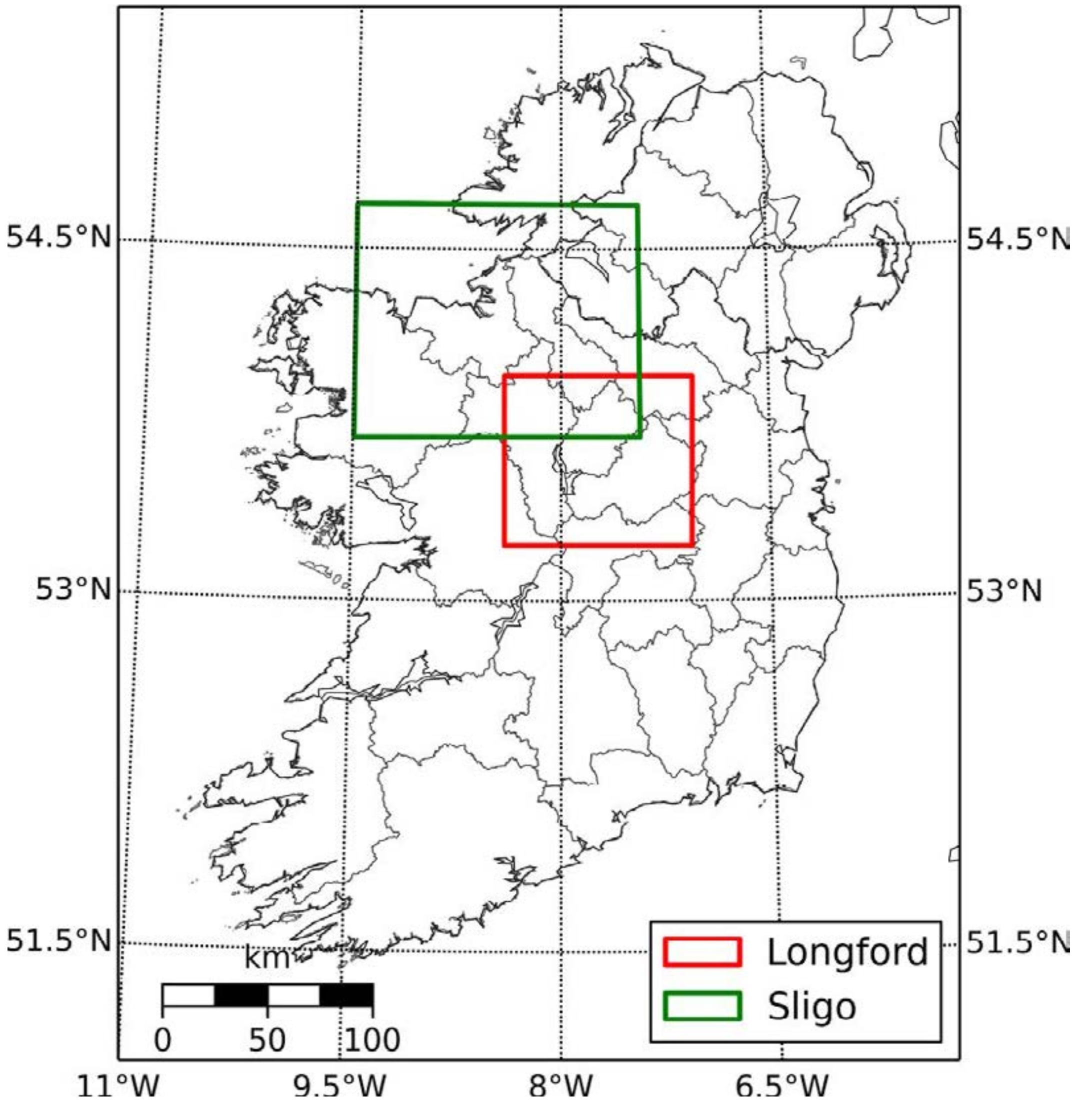

Figure 1.1. Map showing Counties Longford and Sligo, which formed the focus of this study.

- integrating pixel-based satellite products with vector-based objects from the PRIME2 database in order to assign land cover attributes to each parcel, and, in particular, to explore solutions to the attribution of classes to sub-pixel-sized fields (Chapters 3 and 4);
- analysing multi-temporal single frequency and multiple polarisation microwave data from the ENVISAT Advanced Synthetic Aperture Radar (ASAR) and Advanced Land Observing Satellite (ALOS) Phased-Array L-band Synthetic Aperture Radar (PALSAR) instruments, combined with ancillary ground data, to determine the extent to which agricultural lands can be distinguished at a 20 m spatial resolution (Chapter 5);
- evaluating the extent of land cover change between two separate years, and thus how GHG emissions related to land cover have changed during those reporting periods (Chapter 6);
- discussing the implications of these results and other developments for future national land cover mapping initiatives, including recommendations for the operationalisation of scaling-up from the county to national scale, and extending the land cover studied beyond grasslands (Chapter 7).

2 Time-series Analysis of Optical Satellite Data

Research highlights

- Low-resolution data (250 m) are valuable for regional-scale land cover mapping, but not at the field level for which inter- and intra-annual variations cannot be reliably determined.
- Time-series data can be used to show seasonal changes in the phenology of homogenous areas of vegetation in Ireland.
- An automated, objective and scalable machine-learning classifier approach is essential for the annual production of land cover datasets.

2.1 Introduction

The reflectance profiles in the visible and NIR regions of the electromagnetic spectrum enable different land cover classes to be distinguished with a high degree of certainty. If multi-temporal datasets for a single year are available, an even finer degree of separation of similar land covers can be achieved, as their different phenologies and land management practices can be incorporated into the classification rules. To achieve a sufficiently high-resolution temporal dataset in a persistently cloudy climate, time composites of daily data that have been normalised, for example through the use of a VI, are frequently used. In this study, three machine-learning classifiers [random forests (RFs), support vector machines (SVMs) and extremely randomised trees (ERTs)] are applied to 16-day composites of MODIS data for Counties Longford and Sligo. This chapter evaluates their potential and advantages and disadvantages with regard to creating grassland inventories over large heterogeneous areas, and makes the key distinction between grasslands that are subject to different management intensities (improved and semi-improved). The results, limitations and recommendations of using these data are presented.

2.2 Methodology

2.2.1 MODIS data

A number of sensors acquire imagery on a daily basis, such as MODIS, MERIS, SPOT Vegetation or AVHRR (Advanced Very High Resolution Radiometer), but the 1 km resolution of some of these instruments precludes their use for field-scale studies in Ireland. Only MODIS, at 250 m resolution, and MERIS, at 300 m resolution, are acceptable instruments for a heterogeneous landscape, and, of these, MERIS data ceased to be transmitted in April 2012 when communication with the ENVISAT platform was lost; therefore, MODIS is the primary source of imagery data for this study.

The MODIS instrument is mounted on two different satellites, Terra and Aqua, which have acquired data daily, with a spatial resolution of between 250 m and 1000 m, since 1999 and 2002, respectively. The data are pre-processed automatically to different products for a large range of applications. Time-compositing techniques can be applied to the daily data to determine the highest quality image within a specified period, thus reducing the influence of unfavourable weather conditions. As demonstrated by O’Connor *et al*. (2012), a compositing period of at least 10 days is required for a sufficiently cloud-free annual time series of the island of Ireland. Therefore, the free 16-day composite data (MOD13Q1) were chosen as the primary dataset and were acquired from the Earth Explorer portal of the United States Geological Survey (http://earthexplorer.usgs.gov). Within this dataset, low-quality images are filtered out automatically and the optimal date within the fixed 16-day period is determined by a constrained view-angle maximum-value composite algorithm (Huete *et al*., 2011). Each year consists of 23 datasets: the first period is from 1 January to 16 January, the next period starts on 17 January, and so on. The regular ongoing acquisition of images and the long time series makes it possible to monitor seasonal cycles, annual comparisons, and long- and short-term changes. Each dataset contains four spectral bands, as well as two VIs, namely the widely used Normalised Difference Vegetation Index

(NDVI) and the MODIS-specific Enhanced Vegetation Index (EVI). In addition to the spectral data, pixel-based supplementary information, such as VI quality, pixel reliability, and shadow and cloud masks, is available from these datasets and can be used for the assessment of the data quality, for example with regard to the degree of cloud cover.

2.2.2 *Vegetation indices*

VIs provide valuable information about the status (density and health) of vegetation, taking the difference in reflectance between the visible and infrared spectra into account. Several indices have been developed, but the NDVI is the most ubiquitous for all sensors; the EVI is specifically designed for the MODIS instrument. For all VIs, a high value represents dense, healthy vegetation, whereas low or negative values indicate a lack of vegetation. With the use of VI time series, vegetation cycles can be monitored on a range of different scales. Most land cover types are characterised by different temporal VI curves. The differences between them, for instance the absolute values and the seasonal pattern (e.g. green-up dates), can help to distinguish between land cover classes.

2.2.3 *Pre-processing*

Time-series data for the period January 2001 to December 2013 were extracted for the two study areas, County Longford and County Sligo (Figure 1.1), from the MOD13Q1 dataset. An example of a time series for one land cover type is shown in Figure 2.1; from this figure, it is apparent that the data still show substantial short-term fluctuations, despite the compositing and pre-processing steps.

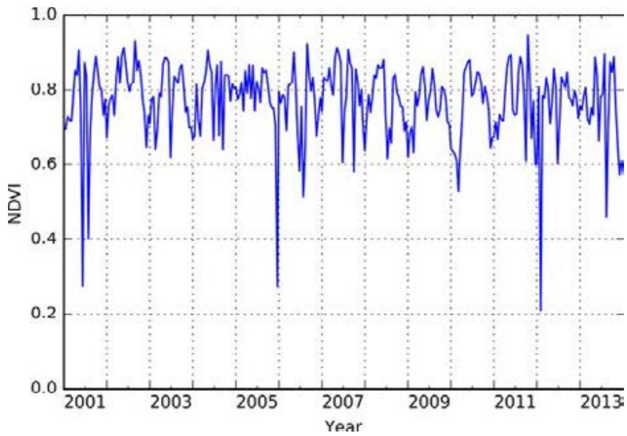

Figure 2.1. Raw 13-year NDVI time series for an improved grassland training sample in Longford.

Persistent atmospheric disturbances, snow or sensor noise are responsible for a high noise level, and although such fluctuations have been described for other regions (Bradley *et al*., 2007; Atzberger and Eilers, 2011), they seem to be particularly strong in the Irish study areas. Time-series filtering can overcome this issue by smoothing the signal over a longer period. This produces a result that is closer to the true land cover response, and different seasonality metrics, such as green-up date, brown-down dates and VI maximum, can be derived. Figure 2.2 illustrates the impact of cleaning the time-series signal of a single pixel.

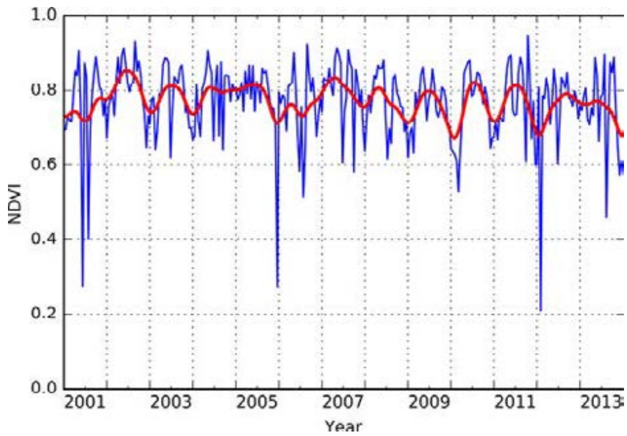

Figure 2.2. Raw 13-year NDVI time series (blue) of an improved grassland training sample in Longford, overlaid with its corresponding filtered time series (red).

2.2.4 *Classification*

For this study, a supervised classification approach was chosen, whereby an automated machine-learning model was trained for known locations with the data characteristics (e.g. VI time series) and associated class label for each land cover type. The model was then applied to locations (pixels) of unknown land cover within the study areas. The existence of locations with known uniform land cover is a pre-requisite for this process. Because of the large pixel size of the MODIS data, these sites must be a minimum of 6.25 ha, which proved to be a challenge for some classes within the study areas, particularly in agricultural and urban areas. In addition, the “crops” class (agriculture other than grassland) had to be excluded because of the insufficient extent of this land

cover within the study areas. Moreover, the land cover type had to be stable over the entire study period (2001–2013) to allow all years of data to be classified from a single ground truth dataset. The focus of the study was on grassland; however, land cover and land use are rarely completely independent from each other. For classification using remote sensing imagery in particular, it is necessary to collect information about other land cover types as this helps to improve the validation and provides knowledge of class confusions. Understanding the spectral signatures of the other land cover classes is also essential for calculating the probability of a land cover type (including grassland) existing within a pixel.

The first iteration of collecting ground truth samples was based on the visual inspection of high-resolution imagery from varying sources, namely OSi aerial imagery datasets from different years, Bing Maps and Google Earth. For the distinction of the grassland types (see Table 1.2), namely improved grassland (GA) and semi-improved grassland (GS), information from the NPWS Semi-Improved Grasslands Survey was added to improve the interpretation capabilities. However, it became apparent that the inspection of imagery from one point in time was not sufficient to ensure the validity of the class label over the entire study period. Therefore, the VI time series for each ground truth site was processed, plotted and inspected for temporal stability and potential changes. Samples that appeared to show changes in land cover during the study period were discarded from the dataset. Typical changes were transitions between the different grassland types, resulting from abrupt changes in the management regime from one year to another, which, in some cases, then reverted back to the original state. Other changes, not apparent in mono-temporal aerial imagery, were from grassland to urban, as many peri-urban areas were subject to building. Because of its significantly greater size, the number of training samples defined for Sligo was just over twice the number for Longford, with 946 sites for Longford and 2008 sites for Sligo, but the proportion of sites of each class from the total is similar for both regions (Table 2.1)

Table 2.1. The number and class of reference data points

Land cover type	Longford	Sligo
Forest	89	532
Water	297	582
Settlement/urban	62	112
Peatland	299	314
Improved grassland	103	301
Semi-improved grassland	96	167

The mean seasonal curves of the different land cover classes with their standard deviations are depicted in Figure 2.3. From this figure, it is apparent that each class exhibits a specific seasonal behaviour in conjunction with inter-annual variations of differing magnitudes. These time-series data are not only valuable for the distinction of different land cover types, but also for other applications, such as the analysis of seasonal changes in vegetation.

2.2.5 *Classification strategies*

The choice of classification method has a strong influence on the success of the process. Traditionally, statistical classifiers such as maximum likelihood (ML) have been the most popular algorithms in the remote sensing community. However, over the last decade, more sophisticated machine-learning methods, such as SVMs and RFs, have been increasingly applied, and have proven to be superior to the traditional algorithms in many regards. Classified land cover maps were produced for individual years for each county using the ML, SVM and ERT (which is a modification of the RF algorithm) classifiers for the whole study period.

In order to calculate the accuracy of the resulting land cover maps, a cross-validation procedure was carried out. The accuracy of the whole map was defined by calculating the overall accuracy (OA) and the kappa coefficient. Single-class accuracies were determined through the user's accuracy (UA), producer's accuracy (PA), f1 score and error matrix. These measures were used to illustrate the classification success of each individual class and the relationship of errors between classes. To identify the most reliable method, an automated classification procedure was developed, which allowed the direct comparison of the classification results and therefore the selection of the most suitable method for the purposes of the project.

2.2.6 *Process automation*

The automation of the production of land cover maps is an important element of creating an operational

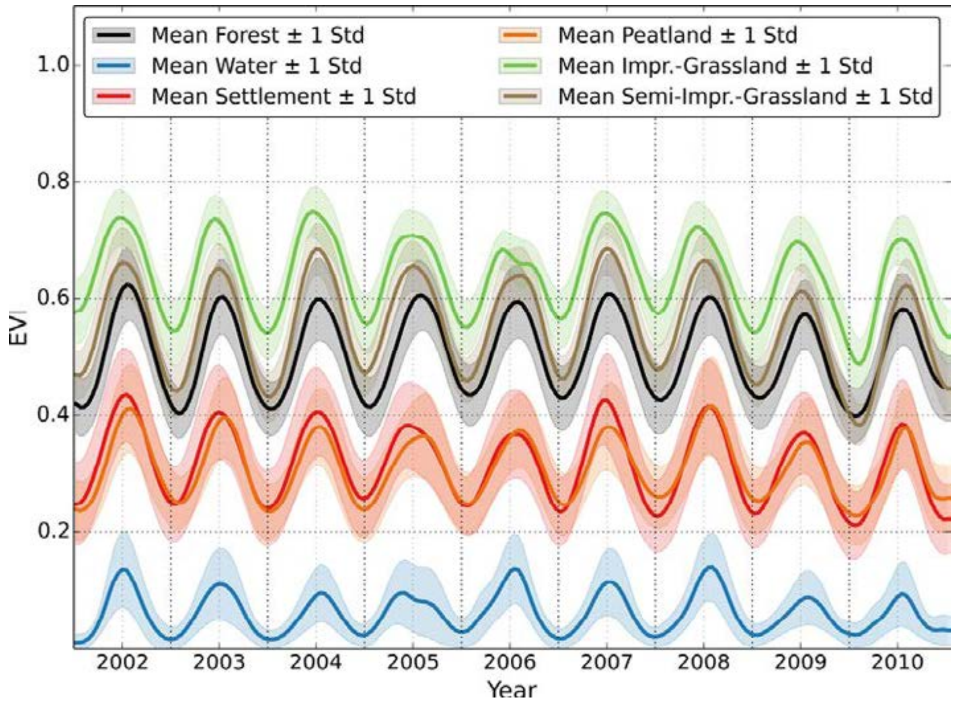

Figure 2.3. Smoothed EVI time series of training samples by land cover classes in County Longford.

system. The most important advantages of process automation are related to:

- repeatability;
- adaptability;
- processing speed;
- user independence.

Repeatability and adaptability play an important role in the scientific process, allowing the same result to be achieved when data are re-processed, but also allowing results to be compared and analysed if small changes within the process chain are made. For operational purposes, user independence and processing speed are important features. Instead of running every single task of the workflow manually, the user can trigger a pre-set workflow automatically, so that anyone can start the entire workflow with only little knowledge of the process.

The processing chain was written in the free, open-source programming language Python. This software offers numerous modules for specialised applications, such as machine learning, numerical processing and database access, in addition to the typical features like data and file management. Typical remote sensing software packages, e.g. ERDAS Imagine or ENVI, do not offer such a wide variety of cutting edge technologies, and such software packages also come at a price. However, a proficient programmer is required to write and maintain the automated software.

2.3 Results

2.3.1 Classified land cover maps

After evaluation of all the classifiers, ERT (Geurts *et al*., 2006) proved to be the most suitable method for producing land cover maps of Ireland from MODIS data as it yielded a very good level of accuracy, quick processing times and good usability. The classification process yielded some excellent results for all configurations and in both study areas. However, these results were achieved only in homogeneous areas, where uniform areas exceeded the pixel size. In these regions, an OA of more than 95% was achieved, and the only misclassifications were between settlement and peatland, and improved and semi-improved grassland (see Table 2.2). These errors can be attributed to the spectral similarity of these land types, as shown in Figure 2.3.

Despite the promising performance of the classifiers on the time-series data in homogeneous areas, major issues arose in heterogeneous agricultural lands and urban areas. First and foremost, the spatial resolution of the MODIS data is insufficient for the highly fragmented Irish landscape. Although lakes

Table 2.2. Classification results (error matrix) for 2008 in Longford

	F	W	S	P	GA	GS	UA	f1
F	96	0	0	0	0	2	0.98	0.99
W	0	318	0	0	0	0	1.00	1.00
S	0	0	66	11	0	0	0.86	0.92
P	0	0	0	319	0	0	1.00	0.98
GA	0	0	0	0	112	6	0.95	0.95
GS	0	0	0	0	5	116	0.96	0.95
PA	1.00	1.00	1.00	0.97	0.96	0.94	OA: 0.97	κ: 0.97

Reference data are shown in the columns, image data are shown in the rows.
F, forestry; f1, f1 score; P, peatland; S, settlement; W, water; κ, kappa coefficient.

and peatbogs extend over large areas, agricultural areas are characterised by much smaller parcel sizes. Average field sizes of 2 to 5 ha, hedgerows, different land use in adjacent fields and intra-field variations in vegetation constrain the classification process because of the mix of spectral information from the different surface conditions within a single MODIS pixel. If results from the same location, but from different years, are compared, the effect of such mixed pixels results in false and unstable class predictions. This issue can be partly overcome with the internal probability estimator of the classifier (*P*-value), which indicates the certainty of the classification results in values between 0 (very uncertain) and 1 (very certain) for each class. But although the class-specific *P*-value may also be used to indicate the fractional land cover, there are insufficient ground truth data to prove this hypothesis, although visual inspection indicates a good correlation in some cases. Even if specific land-cover fractions per pixel cannot be reconstructed, *P*-values still give useful information about the homogeneity of the land surface.

The homogeneity of the pixels (*P*-value of the class decision) is shown in Figure 2.6. The large lakes, peatbogs and homogeneous improved grasslands around Lough Ree, as well as the semi-improved grasslands on the border of Counties Longford and Leitrim, with high *P*-values, i.e. close to 1 (dark-red colour), and therefore a high level of homogeneity, are particularly prominent. Other regions, specifically the Shannon Callows in the south-west, suburban areas of Longford Town, central County Longford and some lakes in the Drumlin Belt with rather small basins, exhibit low *P*-values, i.e. of less than 0.5 (blue colour).

These low *P*-values could be explained either by changing surface conditions caused by flooding, e.g. in the Shannon Callows or the fringes of lakes, or by a strong heterogeneity of land cover inside the footprint of the MODIS pixels.

The error matrix shown in Table 2.2 highlights the accuracy with which all homogeneous pixels can be classified; the greatest degree of uncertainty exists between the two grassland classes (GA and GS).

2.3.2 Longford land cover maps

As an example of the nature of the output produced, the single-year classification results for 2008 in County Longford are shown in Figure 2.4. Areas around Lough Ree (on the borders with Counties Longford, Roscommon and Westmeath) have a strong dominance of improved grassland, and other clusters of the same type can be found in the south and east of the study area, whereas the Drumlin Belt in the north and north-west has a much larger proportion of semi-improved grasslands. These features and the different class-specific levels of homogeneity are highlighted in Figure 2.5.

2.3.3 Sligo land cover maps

County Sligo shows an even stronger spatial pattern in the distribution of different land cover types than Longford (Figure 2.7). The Ox Mountains, covered by blanket bog and forest patches, divide the County into two halves. Along the coastal plain in the north, improved grassland is the most dominant land cover type, whereas semi-improved grassland is found in only smaller patches on the northern foothills of the mountain range, where different soil type and moisture conditions result in a lower intensity of grassland management. By contrast, the south of the county exhibits the opposite behaviour in terms of grassland

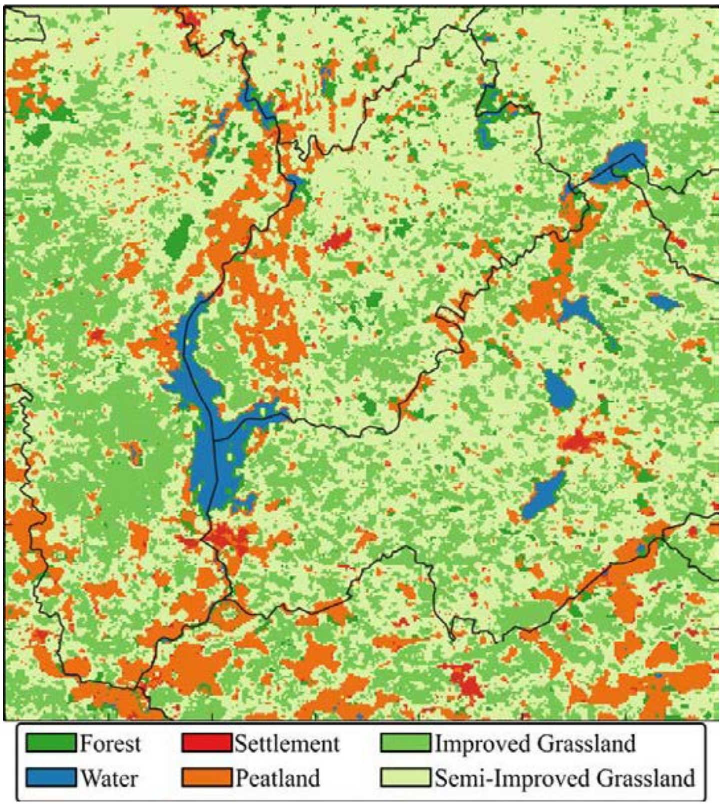

Figure 2.4. Classification results for 2008 in Longford.

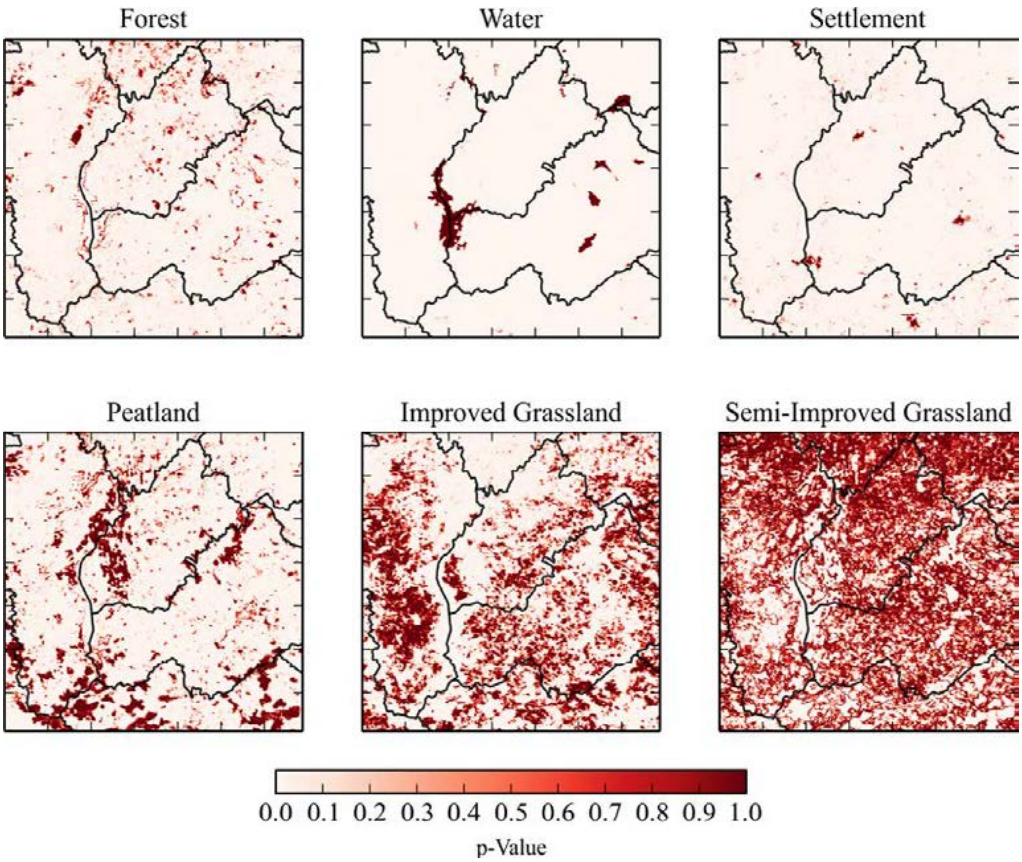

Figure 2.5. *P*-values for individual classes in Longford.

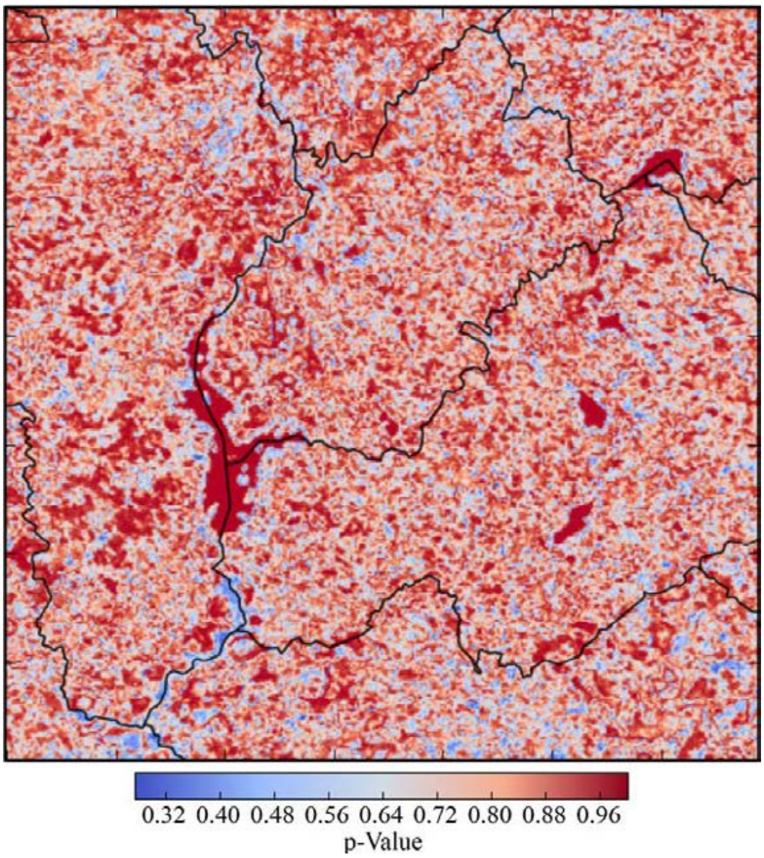

Figure 2.6. Classification *P*-values for all classes for 2008 in Longford.

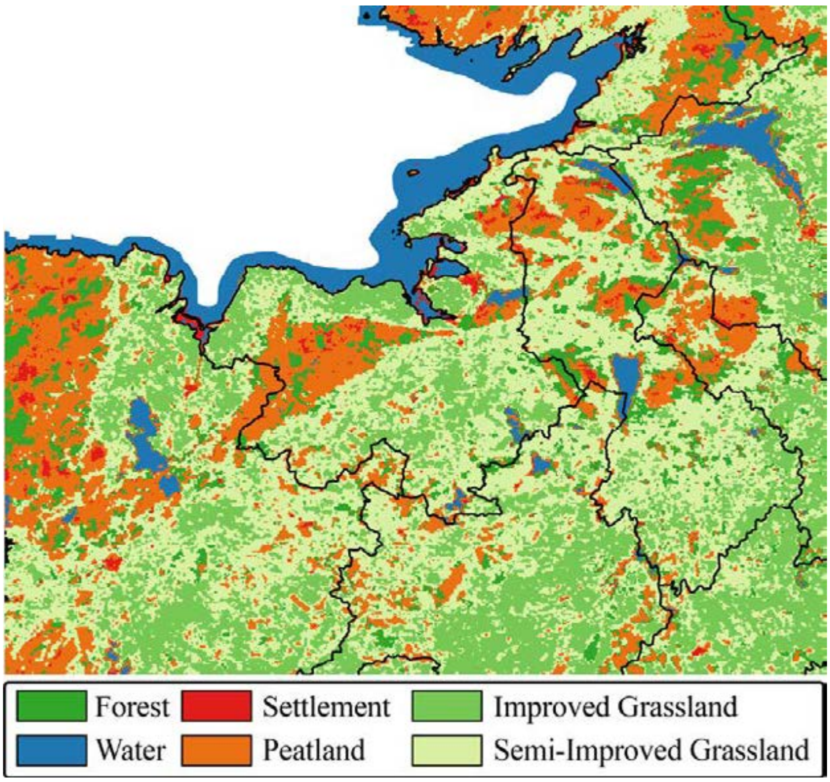

Figure 2.7. Classification results for Sligo in 2008.

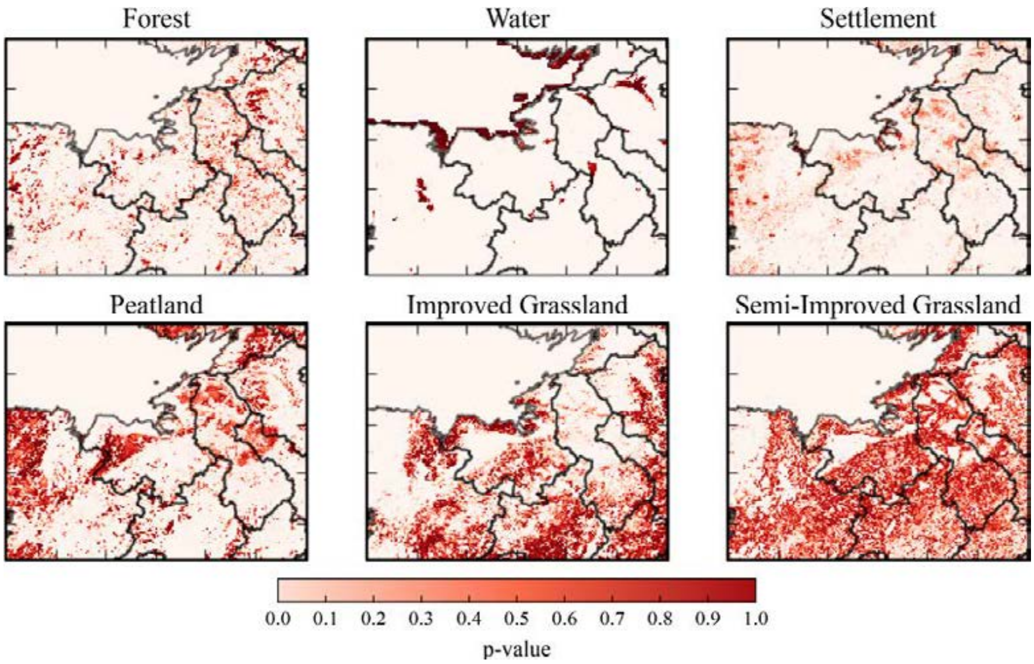

Figure 2.8. *P*-values for individual classes in Sligo.

management. These areas are much less intensely managed, with the exception of one larger cluster of improved grassland. Similar to Longford, the clustering behaviour of most land cover types is also apparent in Sligo (Figure 2.8).

Despite the encouraging results, some issues still arise. The settlement *P*-values show a confusion with peatland (mostly blanket bog), with a slight over-classification of settlement on the westernmost fringes of the map. However, this can be explained by the spectral similarities of these land cover classes, which are hardly distinguishable at the spatial resolution of the MODIS imagery (Figure 2.3).

2.3.4 Image acquisition timing and frequency

The optimisation of image acquisition timing and frequencies can help to increase the effectiveness of the classification process. For this purpose, the feature importance (FI) measure of the RF classifier was used to determine the optimal image acquisition periods for the classification. Taking into account all land cover types, the highest degree of spectral separability and the highest classification accuracies for both the NDVI and the EVI occurred in December and January, and the lowest separability and classification accuracies occurred in July and August (Figure 2.9). In general, the same distribution was observed in each individual year, with only small deviations in timing and intensity of the periods of high separability. The use of data from only the optimal acquisition period, as opposed to the whole year, produced overall classification accuracies of around 80%. The classification accuracies using the best and worst acquisition dates varied by only 6% when using the EVI, whereas use of the NDVI showed a larger difference of 12%. The addition of further images gradually increased the classification accuracy until an optimum was reached at 90% with around 8 to 10 images. In this instance, no significant differences were observed between EVI and NDVI data.

Both grassland classes were found to be most separable during spring and late autumn (i.e. the transition periods), at which times improved grassland had a significantly stronger VI signal (see Figure 2.10). With regard to distinguishing between the grasslands, EVI proved to be the better data source: single-date accuracies were between 65% and 82%, and were generally around 10% higher than those achieved with the NDVI data. Using multi-temporal datasets, EVI data achieved accuracies of around 90%, whereas NDVI data achieved accuracies up to only 85%.

2.3.5 Land cover changes

The use of a long time series of data allows changes to be monitored during a specified period. Using the dataset described in section 2.2, it was possible to analyse the period from 2002 until 2012; data from

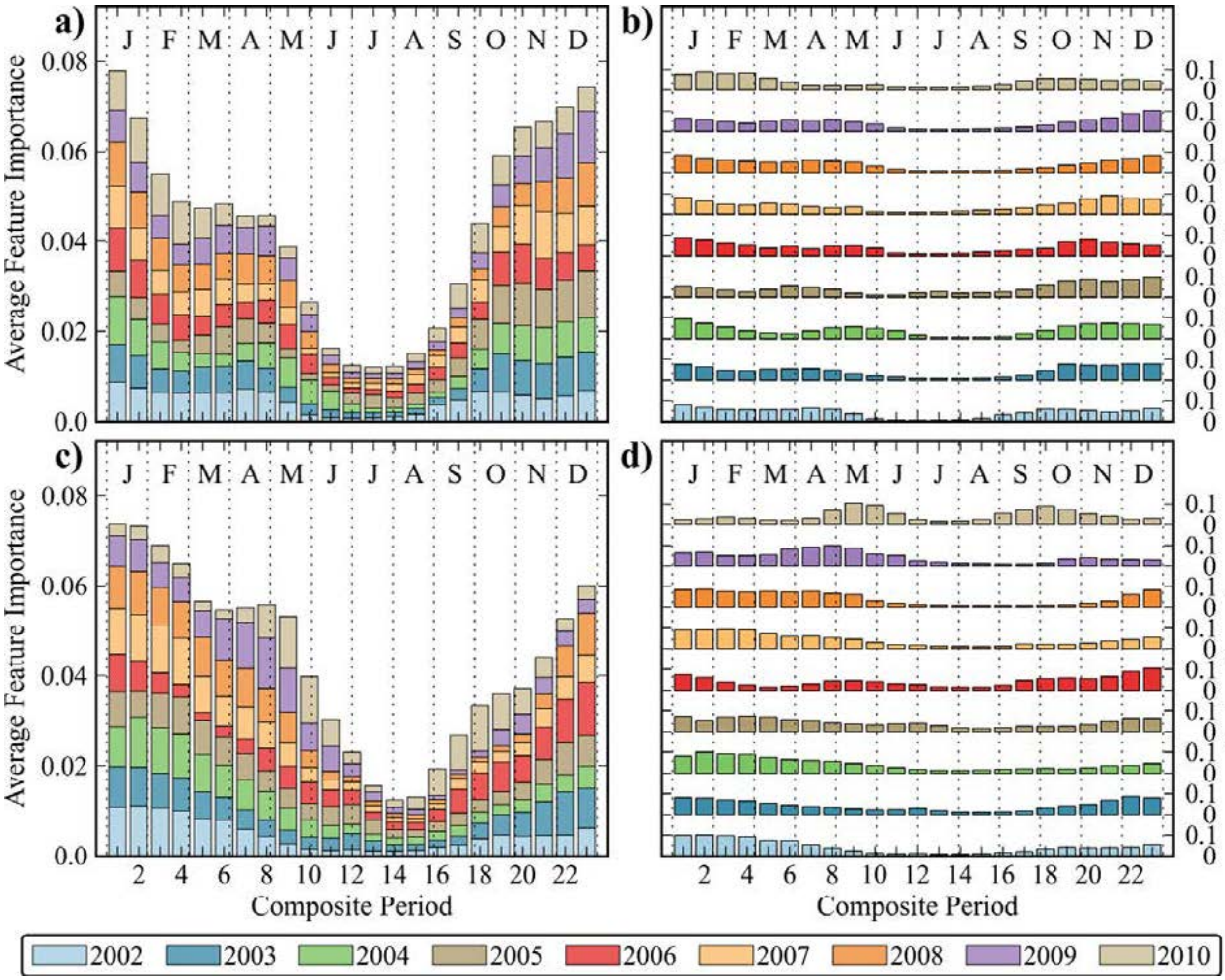

Figure 2.9. Temporal separability (FI) measures for general land cover classification in Longford: (a) NDVI average; (b) NDVI for a single year; (c) EVI average; and (d) EVI for a single year. Reproduced from Nitze *et al*., 2015, with permission from Elsevier.

2001 and 2013 were discarded because of possible edge effects of the time-series processing. Single-year classification maps were compared with each other, but because of the constraints of spatial resolution, only a small subset of homogeneous pixels could be analysed if the *P*-values exceeded 0.7 in most of the years. The land cover classes of these homogeneous areas were extracted, and they account for around 20% of the Longford study area.

None of the land cover classes analysed exhibited severe change. Nonetheless, according to the results in Table 2.3, some changes and trends do prevail. The largest changes are apparent between the two grassland types: a positive trend is apparent for GA (+0.82% of the total land surface), whereas the area of GS decreased (–0.77%). Forest exhibits a slight negative trend (–0.05%), whereas water, settlement and peatland remained practically stable.

2.3.6 Upscaling to national level

The preliminary results of upscaling this land cover classification process to the entire island of Ireland, using 2008 data and the ERT classifier, are shown in Figure 2.11. In most places, grassland dominates the land surface. The distinction between improved and semi-improved grasslands also shows an interesting pattern: the grassland management intensity is higher in the southern counties of Limerick, Cork and Tipperary, whereas in the west and north-west, as well as on the foothills of larger hill ranges, GS is much more prevalent. Other land cover types, such as peatland and crops/tillage, are unevenly distributed over the entire country. Although the former is the prevailing land cover type along the western seaboard, the latter covers large areas in the eastern and south-eastern regions.

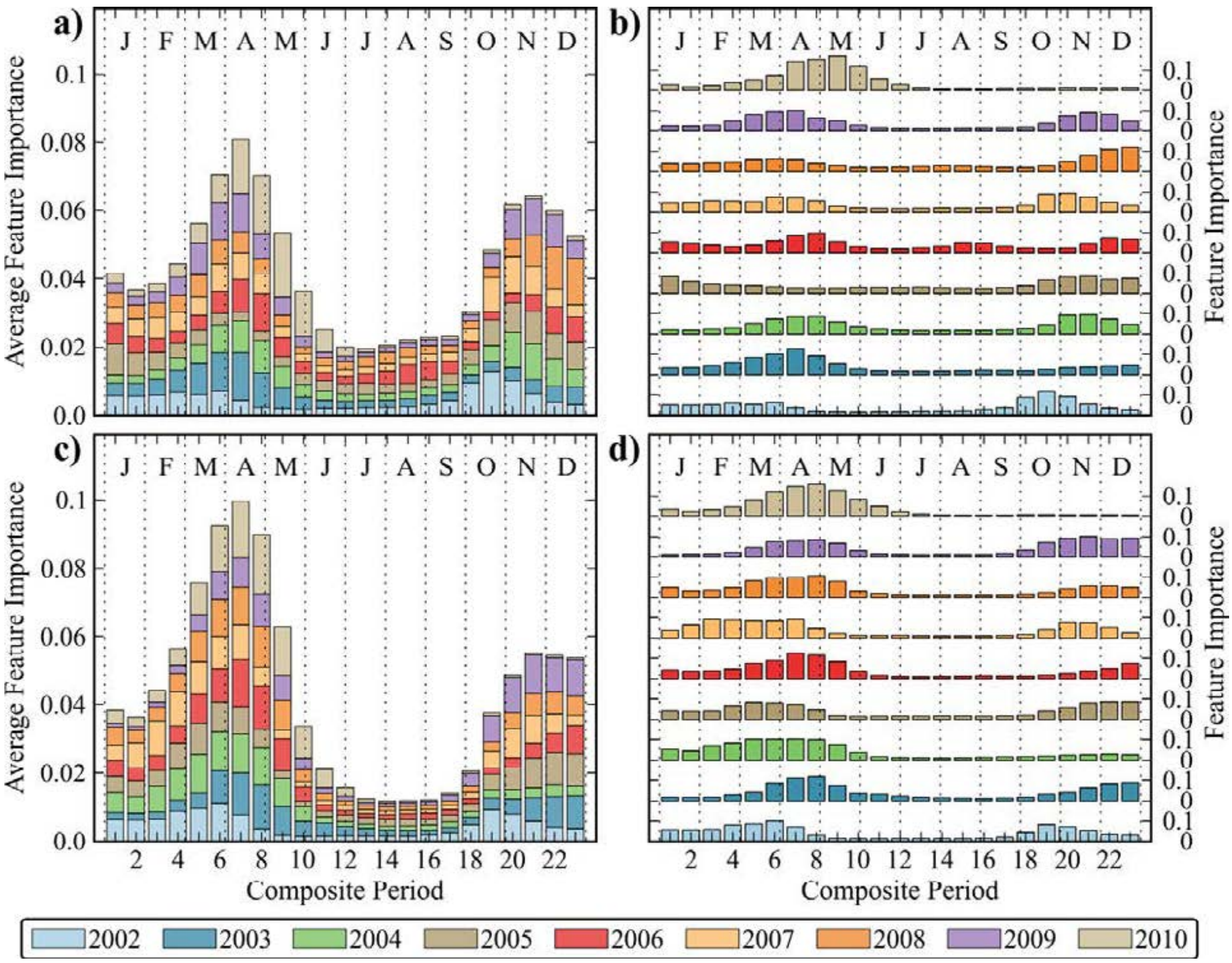

Figure 2.10. Temporal separability measures (FI) for grassland-specific classification in Longford: (a) NDVI average; (b) NDVI for a single year; (c) EVI average; and (d) EVI for a single year. Reproduced from Nitze *et al*., 2015, with permission from Elsevier.

Table 2.3. Number of homogeneous MODIS pixels per class from 2002 to 2012 with percentage change of land cover over that time

Year	F	W	S	P	GA	GS
2002	398	1860	149	4373	8073	10,453
2003	393	1860	145	4377	8180	10,351
2004	388	1860	145	4377	8153	10,383
2005	393	1860	145	4377	8144	10,387
2006	388	1860	146	4375	8114	10,423
2007	388	1860	145	4376	8151	10,386
2008	387	1860	145	4376	8152	10,386
2009	386	1860	145	4376	8134	10,405
2010	386	1860	149	4372	8212	10,327
2011	387	1860	145	4376	8159	10,379
2012	385	1860	144	4377	8281	10,259
Change over time (%)	–0.05	0	–0.02	0.02	0.82	–0.77

F, forestry; GA, improved grassland; GS, semi-improved grassland; P, peatland; S, settlement; W, water.

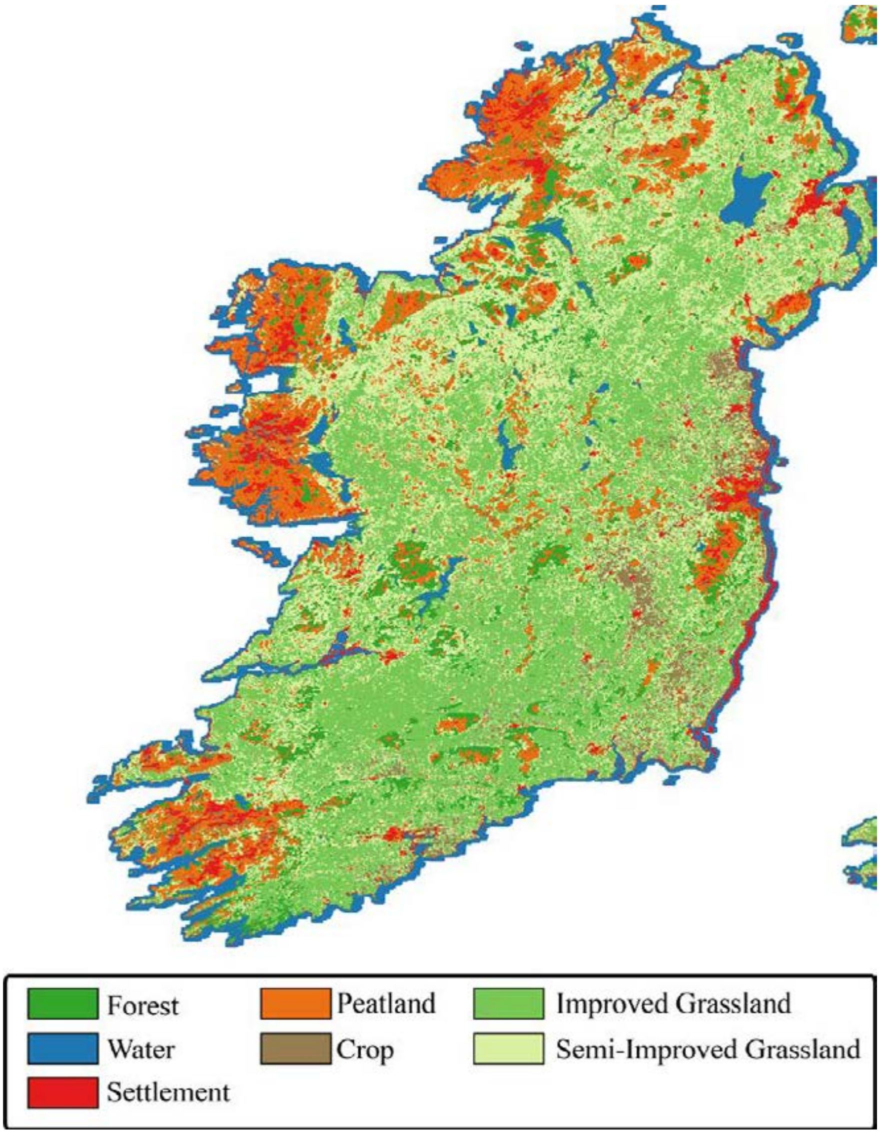

Figure 2.11. Classification map of the island of Ireland for 2008.

Minor issues deriving from extending the methodology beyond the conditions of the two initial study areas are also obvious. As already observed in Sligo, the classification of bare rock as "settlement" shows up in the western mountainous regions. The confusion of suburban areas with "peatland" is another issue, which can be seen in larger urban areas like Dublin and Cork. It should be noted that these are only provisional results, and have not been quantitatively assessed for their accuracy.

From a technical point of view, upscaling to a national level increased the requirement for disk space and processing time on a linear scale. By way of comparison, the national dataset accounts for an area approximately 30-times larger than the size of the study area of Longford. The raw 13-year time-series data have a size of approximately 14 GB and took about 3 hours to be redistributed to a usable dataset on a standard PC. The processing time for the classification depended on the classifier used and the pre-processing steps required, but was estimated to be approximately 10 hours, whereas this was approximately 20 minutes for the Longford dataset. The software was designed to be able to handle larger datasets and only small optimisation steps are needed to enable the processing of much larger datasets.

2.3.7 Data fusion

The spatial resolution of MODIS proved to be insufficient for the monitoring of land cover and its changes in the fragmented Irish landscape;

however, different methodologies exist to combine the advantages of sensors with a high spatial resolution, but a low temporal resolution, and those with a high temporal, but low spatial, resolution. The most popular fusion algorithm is STARFM (Gao *et al.*, 2006), which combines Landsat and MODIS reflectance data. The algorithm requires a Landsat image as well as one MODIS image from the same date to form the template image pair. The use of these two sensors is ideal because of the presence of spectral bands in the same region of the electromagnetic spectrum (blue, green, red, NIR and middle infrared).

Prior to inputting the data to STARFM, both data sources have to be pre-processed. Based on the variance of the reflectance in this image pair, a MODIS image from a later date is converted to a Landsat-like resolution. The algorithm, which was provided by its developer Feng Gao, was tested on the Longford area using two Landsat 8 images and daily MODIS reflectance data from 2013. The year 2013 was chosen specifically because of the relatively good availability of Landsat data as a result of the cloud-free conditions experienced in the early part of the summer. Initiated by an image pair from 9 June, the MODIS data for 11 July, for which another Landsat–MODIS image pair was available, were modelled using the STARFM algorithm. The difference between the modelled and the observed data was assessed.

This process resulted in quite large differences between the modelled and the observed data (Figure 2.12). Changes in the landscape, such as grass cutting or grass growth, were not sufficiently detected, which is particularly apparent in the reflectance difference of the NIR band. The modelled image showed a much stronger correlation with the template image (9 June) than the target image (11 July). The same analysis

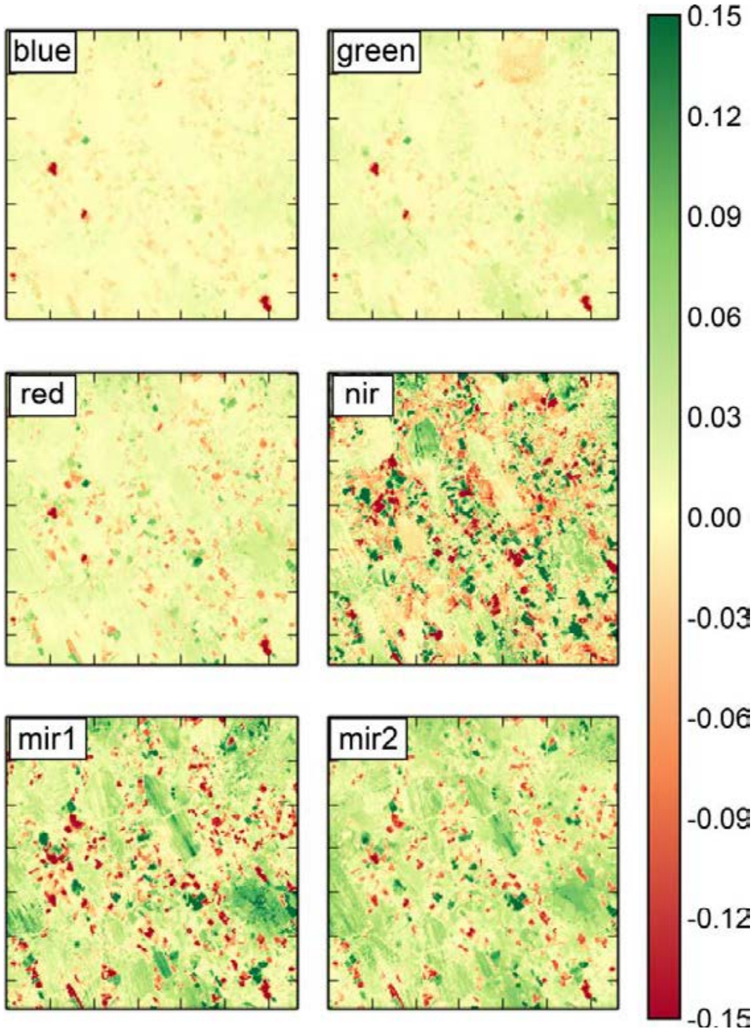

Figure 2.12. Differences in reflectance between modelled and observed results for 11 July 2013. MIR, middle infrared.

later in the year produced similar results, with a strong bias towards the spatial and spectral properties of the template image pair. The pre-requisite of cloud-free imagery for both sensors proved to be a severe obstacle in the study area.

2.4 Discussion

2.4.1 Spatial resolution

The issue of insufficient spatial resolution did not become obvious until the results were viewed in more detail, or compared with a map of the same information but with a higher spatial resolution. In Figure 2.13, a comparison is shown of the MODIS-based classification (cf. Figure 2.4) with a classification performed using the same methodology and land cover classes derived from three images acquired on 26 March, 30 April and 4 November 2011 from the UK Disaster Monitoring Constellation (DMC) satellite with a spatial resolution of 22 m. These sample data, and one further image from 2013, were provided by DMC International Imaging free of charge, but would normally cost £0.01/km^2 for archived imagery (Ireland is covered by two 650 x 650 km images). The multi-temporal classification accuracies associated with these data were generally very high (>95%), but lacked accuracy if mono-temporal classification was conducted. A comparison with Landsat data highlighted the benefits of both sensors, with advantages in temporal resolution and spatial coverage from the DMC constellation, but a more systematic acquisition and superior spectral resolution from the Landsat instrument.

At the 22 to 30 m scale, smaller features, such as stands of trees, large farms or single fields, can be uniquely detected. Furthermore, transitional areas, such as lake shores or small islands, which are subject to the mixed-pixel problem (described in more detail in Chapters 3 and 4) and are therefore prone to misclassification within the MODIS imagery, can be distinguished. However, the use of higher resolution optical data is strongly limited in Ireland by the prevailing climatic conditions. Thus, although there are usable images each year, the timing and number of acquisitions is highly uncertain and not necessarily present during periods of optimal phenological discrimination (cf. section 2.3.4).

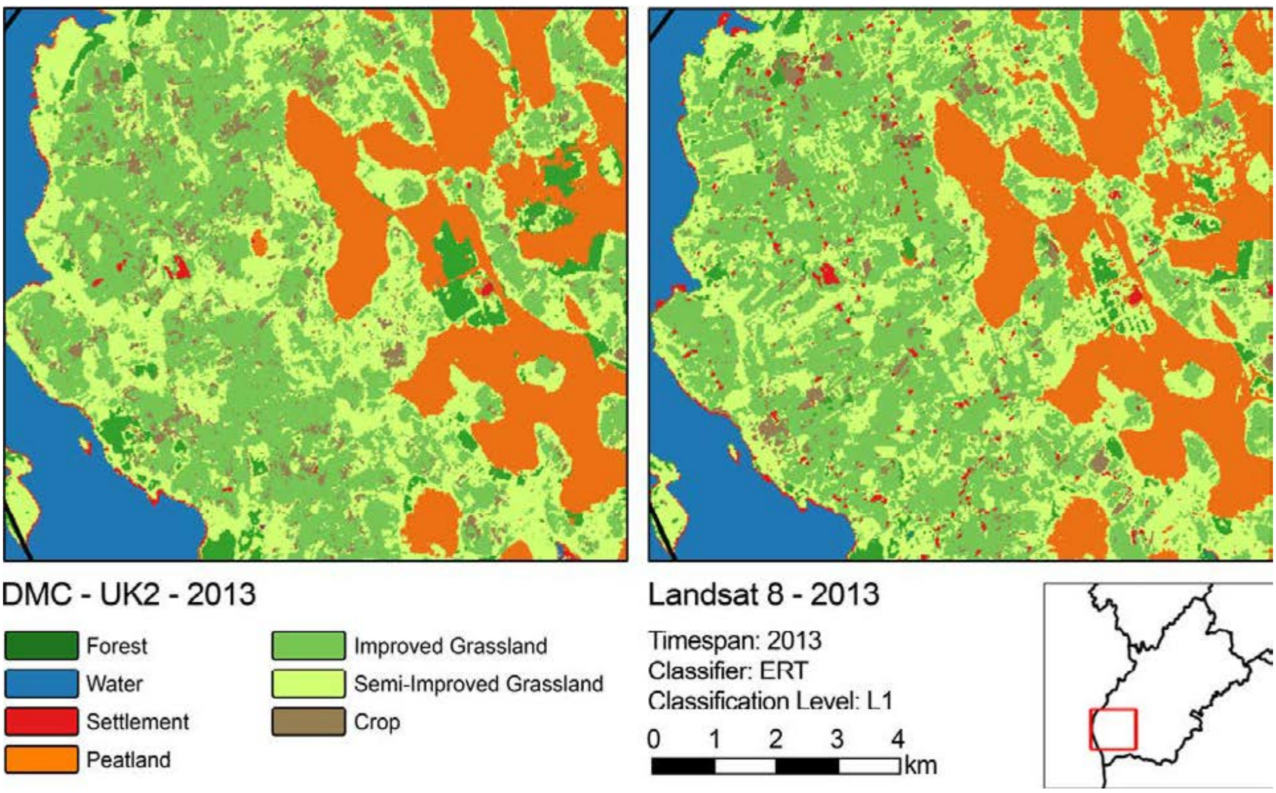

Figure 2.13. Comparison of results of classification using DMC and Landsat data for a small subset of County Longford in 2008.

The resolution of the sensor not only limited the spatial detail of the analysis, but also the thematic detail of the classification scheme. A distinction beyond category L1 of the Irish Land Mapping Observatory (ILMO) grassland classification scheme (see Table 1.2) could not be accomplished because of the lack of reference data for a scale of 250 m.

The use of optical data for land cover classification proved to be a compromise between temporal and spatial resolution. Hyper-/multi-temporal data were beneficial in terms of classification accuracies in homogeneous areas and the retrieval of large-scale vegetation dynamics, but were lacking in spatial detail. High-resolution imagery was successfully classified according to the ILMO classification scheme for a small study area, but the necessary data required could not be relied upon for systematic annual land cover monitoring on a national scale.

Data fusion techniques could not bridge the gap between spatial and temporal resolutions because of the requirement for multiple cloud-free high-resolution acquisitions and the inability of the algorithm to model short-term rapid changes correctly. More work on the implications of spatial resolution and the fragmentation of the Irish landscape is presented in Chapter 3.

2.4.2 Timing of image acquisition

The timing of image acquisition can have a strong influence on the accuracy of classification. Each classification task is different and may result in different temporal separability, depending on the land cover classes and natural conditions. However, as the ILMO classification scheme is consistent over the entire country and the natural conditions do not differ strongly, the findings of the study should be transferrable. Tests of the same methodology in Sligo produced similar results to those produced in Longford.

The timing of image acquisition is not critical for the low-resolution data, as the repetition cycle is very short and the number of acquisitions is very high. However, for expensive high-resolution data, only a limited number of images are potentially available and, because of financial and atmospheric implications, the optimal timing of image acquisition is highly critical.

2.4.3 Use of ancillary data

The use of ancillary data, such as topography and the NPWS Semi-Improved Grasslands Survey data, did not have a significant impact on the classification results; however, such data supported the reference data collection process. The NPWS survey data assisted with the interpretation of the aerial imagery and enabled the identification of suitable reference sites for both grassland classes.

2.4.4 Land cover changes

The analysis of land cover changes showed an interesting trend of intensification in grassland management. Forest cover seems to have decreased steadily, which probably shows the issues arising in change analysis. Only short-term changes, as can occur in grassland management from year to year, or the clearance of forest can be easily detected. Slow and gradual changes are much harder to detect and are, therefore, probably underestimated in the results.

3 The Implication of Small Fields in the Irish Landscape

Research highlights

- Small fields present an insurmountable problem with regard to resolving sub-pixel land cover signals from coarse resolution satellite data because of inherent noise and geo-location issues
- It is likely that the compound effect of shadow in land cover studies from landscape elements such as hedgerows have been under estimated.

3.1 Introduction

The issue of scale in the context of addressing land use and land cover is complicated. At large scales, the landscape of Ireland is a mosaic of farms, forests and natural features. At a local level, much more variation within each farm can be seen, e.g. in terms of buildings, farm yards, different crops and grass paddocks at different stages of grazing or cutting. Within fields, a wide variation in habitats can often be seen, including sub-paddock grassland management ("strip grazing"), degrees of erosion and individual trees, scrub and even archaeological features. The choice of the scale at which to study change in land cover is often determined by need or by capability (Atkinson and Aplin, 2004). For this project, the question to be resolved is: "Can coarse spatial resolution optical data meaningfully map land cover change at the field scale in Ireland?" In Figure 3.1, this issue is illustrated by the MODIS pixel framework (blue) laid across the PRIME2 field boundaries (orange) with an orthophotograph beneath.

3.2 Sub-pixel Classification

The technique used to identify changes that are smaller than the pixel sample resolution is called "sub-pixel classification". The concept for this technique is related to signal processing, in that the final resultant signal (the value recorded at the pixel) is some function of the independent components sampled. In this case, the value recorded by the satellite at each pixel is the area-weighted average value of each individual landscape element. For example, if a pixel was imaging two targets – each covering 50% of the pixel area – and one target was blue and the other red, then the pixel would be recorded as purple.

The current literature on sub-pixel classification indicates that this can be a successful approach to looking at abrupt changes in vegetation cover (Busetto *et al.*, 2008; Wang *et al.*, 2012), and that the relative sub-pixel abundance of easily distinguishable land cover types (e.g. forestry, built) can be ascribed to pixels (Schwarz and Zimmermann, 2005; Yang and Lunetta, 2011). The use of sub-pixel classification systems for more refined land cover/habitat classes typically provides lower estimates of accuracy (i.e. R^2 values in the 0.5–0.7 range) (Thornton *et al.*, 2006; Clark *et al.*, 2010), and many of these studies were carried out in semi-natural regions. Some studies (e.g. Aplin and Atkinson, 2001) attempt to allocate a sub-pixel signal geographically within the pixel and using a per-field approach; it is this technique that is addressed here.

Figure 3.1. MODIS 250 m pixel framework (blue) laid across the PRIME2 field boundaries (orange) with the ESRI 2012 orthophotograph beneath.

The signal recorded at the sensor from the ground pixel area is not “pure”, but is contaminated principally by atmospheric effects, sensor noise and geo-location instability.

Atmospheric effects are resolved at the image scale through atmospheric correction algorithms. For MODIS data, the apparent success of the correction at the pixel scale is recorded as a quality assurance (QA) flag, with each pixel having a coded value that indicates the validity of the signal recorded after correction. Although only high-quality pixels were used in this analysis, there are sources of error that are not identified by the QA flag. The correction was applied at a pixel scale, but it was calculated at a much coarser scale and the QA flag is only an estimate of how well the atmospheric correction algorithm worked and how much cloud was present. The effect of aerosol scattering is not fully resolved, nor is the presence of sub-pixel clouds (Motohka *et al.*, 2011), an issue of particular importance in Ireland. Pixels with a high QA value may therefore still be significantly corrupted with atmospheric effects.

Sensor noise relates to the sensor’s response to incoming light. This varies with angle, light level and time. Models of sensor performance are incorporated into the MODIS product chain, but noise (from multiple sources) remains. This was solved by filtering the time-series data to fill gaps and eliminate extreme values (see Chapter 2). However, the choice of filter is rarely explored, although it can affect the final results (Atzberger and Eilers, 2011). For the work described in this chapter, unfiltered data were used to examine the information content between acquisitions and the ability to detect real change.

Geo-location instability relates to the level of precision with regard to determining exactly where the image pixel lies on the ground. This geo-location instability introduces its own source of noise, and the quoted inaccuracy for MODIS data (of ±50 m) applies at only the centre of the image and to changes within the image as a result of angular and topographic effects (Wolfe *et al.*, 2002).

3.3 The Field-scale Landscape of Longford

The field-scale landscape of County Longford is captured in the OSi PRIME2 database (see section 1.3.2). However, this database does not contain the label “field”, but rather a series of labels (called “FUNCTIONS”; see Table 3.1). There were a number of issues to be addressed with regard to dealing with the PRIME2 database for this project (some of which are explored further in Chapter 4). A cleaned version of the PRIME2 vegetation layer database has 63,390 polygons, with an average size of 1.1 ha.

Table 3.1. OSi FUNCTION labels from the vegetation polygons in the PRIME2 database with corresponding L1 land cover classifications

PRIME2 “FUNCTIONS”	Land cover
Burial Ground	Amenity Grassland
Cemetery	Amenity Grassland
Field Pasture	Pasture
Field Rough Pasture	Pasture
Firebreak	Bare
Garden	Amenity Grassland
Golf Course	Amenity Grassland
Graveyard	Amenity Grassland
Green Space	Amenity Grassland
Managed Woodland	Woodland
Pitch and Putt	Amenity Grassland
Road Verge	Amenity Grassland
Sports Ground	Amenity Grassland
Tennis Court	Amenity Grassland
Unmanaged Woodland	Woodland

Figure 3.2. Dublin Airport in 2012; the orange squares indicate the location of the MODIS pixels used in the analysis.

3.4 Geo-location Accuracy: Dublin Airport Test Site

Location accuracy and noise can be assessed by observing a fixed target over time. Dublin airport was selected as its large areas of concrete are completely free of vegetation, providing target pixels with values ranging from 0% to 100% vegetation cover (see Figure 3.2). The extent of soil sealing in the airport vicinity was mapped over 14 250 m NDVI MODIS products during the grass-growth season (from March to October) in 2012. The NDVI value for each of the 14 acquisitions was correlated against the soil sealing percentage in that pixel. The average variation over time is shown in Figure 3.3 for the pixels that correspond to being 100% soil sealed and 0% sealed. Although the variation in the pixels with no sealing can be explained by natural seasonal variation, the fluctuation in NDVI score for the 100% sealed pixels is due to geo-location instability and residual noise. From the relationship between vegetation cover and NDVI for each of the MODIS imagery dates (Figure 3.4), it is apparent that the average correlation coefficient in this very controlled environment is –0.85 (excluding outliers) with an R^2 of 0.74, which means that 26% of the variance is unexplained by soil sealing percentage. This gives a good indication of the achievable limits for the reliable absolute detection of ground cover.

3.5 Sub-pixel Change Detection in Image Pairs: Cork Test Site

Many of the land cover changes, such as grazing/cutting rotations, which are typical of land use in grasslands, occur at a similar temporal scale to that of the temporal resolution of the MODIS products (i.e. 2–4 weeks). In order to test the sensitivity to land cover change, as expressed in the NDVI signal between consecutive MODIS composites, higher resolution optical data from the Advanced Land Imager (ALI) sensor on board the experimental EO-1 satellite were used. This sensor has similar performance characteristics to Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) [indeed, it was developed as a precursor to the Operational Land Imager (OLI) instrument carried on Landsat 8, which was used in the fusion work discussed in section 2.3.7]. A pair of consecutive ALI images, exactly matching MODIS product delivery dates, was acquired for days 193 and 201 in 2013. Because of image availability, this experiment had to be conducted for a region of County Cork, rather than for the counties, that formed the basis of much of this research, namely Longford and Sligo. After cleaning and testing, a spatial subset of the full image was defined, and NDVI change images (DOY201–DOY193) were constructed for the MODIS pair and the ALI pair, degraded to the same 250 m resolution as the MODIS images. As PRIME2 coverage was not available for County Cork,

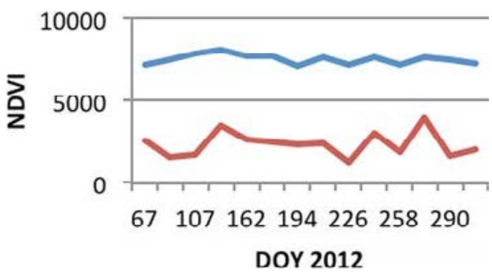

Figure 3.3. Average seasonal variation (in 2012) in the MODIS-scaled NDVI pixel score at Dublin Airport; pixels with 100% vegetation (blue line) show normal seasonal variation and pixels with 0% vegetation (red line) indicate the degree of variation in the reflectance recorded as a result of noise and geo-location issues. DOY, day of year.

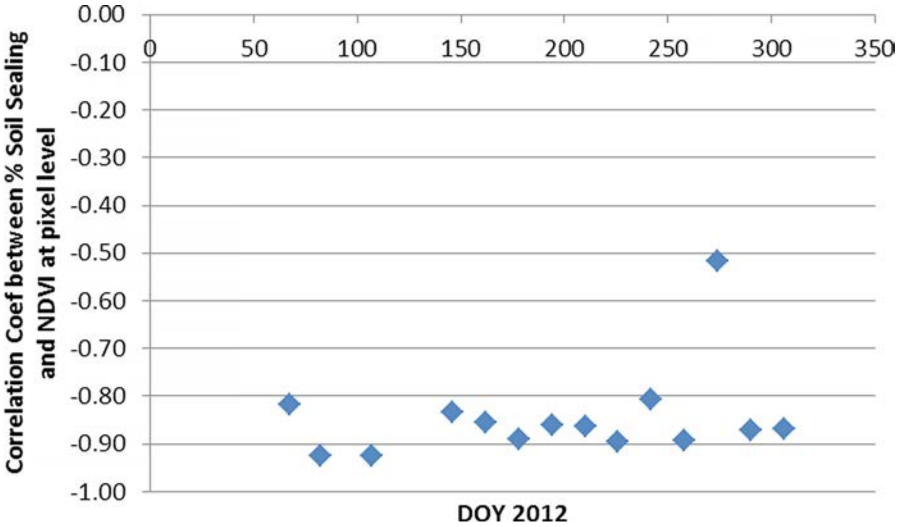

Figure 3.4. Graph illustrating the correlation between NDVI and percentage soil sealing for all 99 pixels in the training area for each acquisition in 2012 (the negative correlation coefficient indicates that as the NDVI decreases, the amount of concrete in a pixel increases). DOY, day of year.

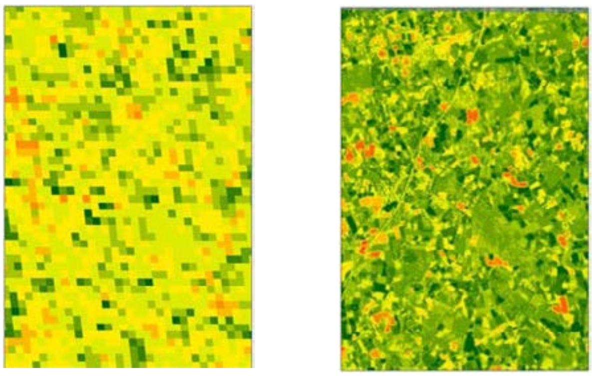

Figure 3.5. Comparison of MODIS (left) and ALI NDVI (right) change images (for NDVI over the 8 days, red indicates decreases, green indicates increases and yellow indicates little change). The differing dynamic ranges of the two sensors and the complexities of VI change, even over 8 days, are self-evident, and an initial examination of the extremes of change indicates that relating sub-pixel events to parcels could be a successful approach.

the LPIS parcel boundaries were used as a proxy for sampling at sub-pixel level.

An initial comparison of the spatial correlation between ALI NDVI change and MODIS NDVI change (see Figure 3.5) produced a pixel-to-pixel correlation coefficient of only 0.14. To examine if relationships existed at the sub-pixel level, both the MODIS change image and the ALI change image were partitioned using LPIS parcels. Only MODIS pixels that were 95% incident with LPIS parcel boundaries (thus precluding any issues of contamination from forestry, built land or water) were selected, and, using intra- and inter-parcel and pixel relationships (Ling *et al*., 2013), each parcel/pixel object was ascribed an ALI NDVI change value and a MODIS NDVI change value. These 8237 objects (sub-parcel polygons formed by intersection of MODIS pixel fishnet and LPIS parcels) were reformed into 1889 MODIS pixels (or 2389 LPIS parcels) (Figure 3.6).

No modelling approaches tried, including generalised linear modelling, could yield a correlation between predicted sub-pixel change (as expressed in the ALI change values) and the MODIS NDVI change value that had a correlation coefficient greater than 0.17.

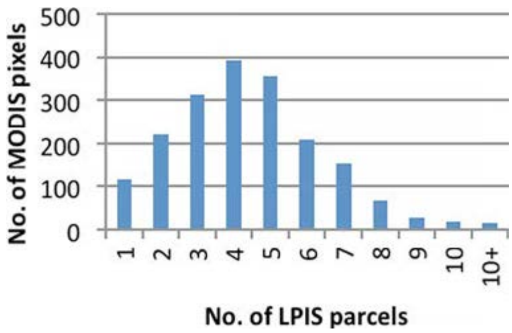

Figure 3.6. Histogram showing the distribution of the number of LPIS parcels that intercept with a given MODIS pixel.

3.6 Sources of Error in Per-field Classification in Ireland

The work discussed in this report (see Chapters 2–4), made it evident that there are considerable sources of error associated with ascribing sub-pixel values to Irish fields. Moreover, these are greater than the inherent noise and geo-location issues would indicate. The sources of these errors relate, once again, to issues of scale and reporting. When reviewing field data or high-resolution aerial photography, it becomes clear that there is considerable intra-field variation, and thus ascribing a single land cover tag to a PRIME2 polygon is problematic. A field nominally classed as "grassland" may contain any amount of scrub, trees, hedgerows, bare earth, etc., and within each individual field these may give rise to a considerable source of confusion. These errors are especially compounded in areas with lots of very small fields (see Figure 3.7).

To explore this issue further, an approach originally developed for classifying hedgerows (Green, 2011) was adapted to capture all small-scale objects, with a sample of aerial photography classified at a 1 m resolution using a texture classifier. Much more intra-field variation in cover is apparent using this approach than is evident using the PRIME2 field approach (Figure 3.8), with the average amount of secondary cover corresponding to 19% of the field area.

The final confounding factor in sub-pixel analysis is perhaps the most important. Shadows cast by landscape objects (trees and hedgerows in particular) have a profound effect on classification accuracy. The combination of small field size, high hedgerows and northerly high latitudes combine to provide a significant source of error. Figure 3.9 illustrates the extent of shadows cast in early autumn in an area of northern Longford.

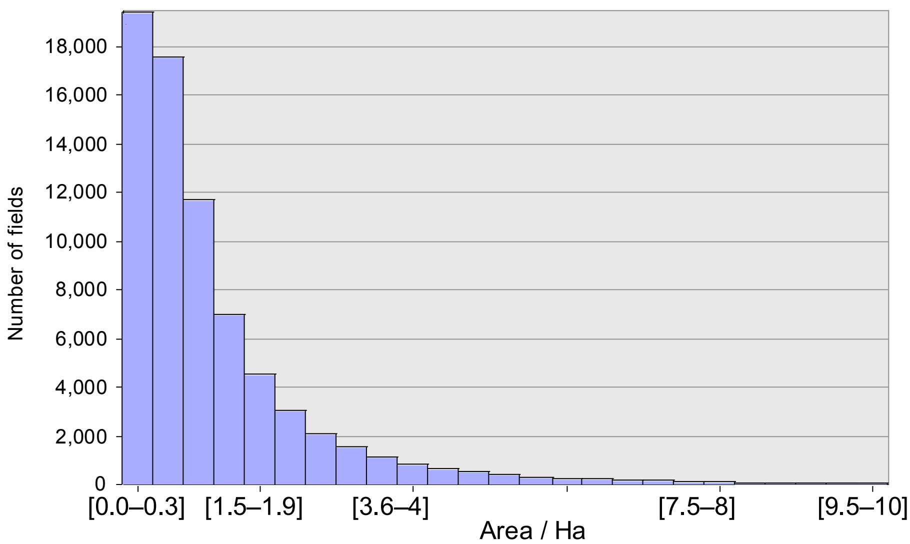

Figure 3.7. Frequency distribution of field sizes (according to the vegetation polygons in PRIME2) in County Longford; the majority of fields are less than 0.5 ha.

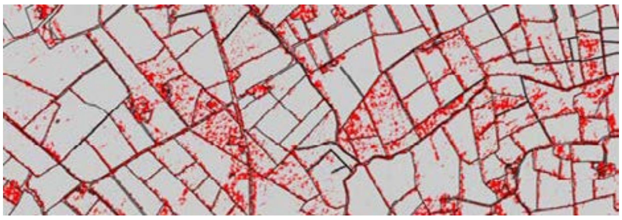

Figure 3.8. Illustration of secondary small-scale land covers (red) in a predominantly "grassland" landscape.

Figure 3.9. Shadows cast in an early autumn aerial photograph of northern Longford.

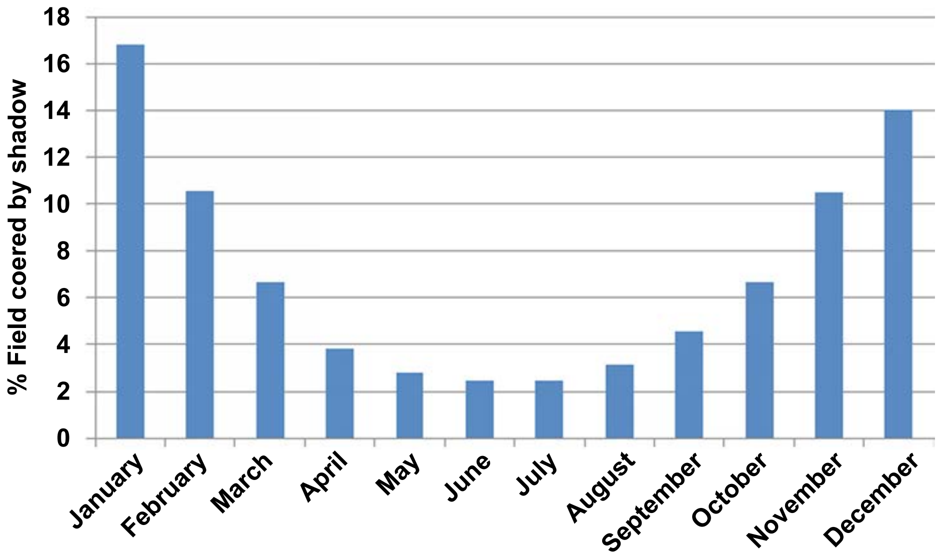

Figure 3.10. Simple model of the area under shadow in an average Longford field.

Using a simple solar illumination model for a site in north Longford at 12:00 (close to the acquisition time for MODIS), the percentage area under shadow can be computed for an average-sized field, with an average hedgerow height of 3.5 m [taken from the Longford Hedgerow Survey Report (Foulkes, 2006)] for 12 months of the year. Although, on average, only 8% of the area is in shadow over a whole year, there is large variation across seasons (Figure 3.10). Sampling on a per-field basis compounds the error. As Figure 3.7 shows, the distribution of fields is not normal but is positively skewed to small-sized fields. If this is taken into account, according to this model, 35% of fields would be in up to 50% shadow for a quarter of the year.

Therefore, shadowing and its seasonal variation, and intra-field variation in small fields, make a significant contribution to error in the context of time-series and sub-pixel methodologies for land cover mapping in Ireland.

4 Allocation of Land Cover to PRIME2 Polygons

Research highlights

- The use of probabilistic classes from coarse-resolution time series can improve the classification of high-resolution mono-temporal images.
- PRIME2 polygons need to be used with caution for analytical purposes, but they are successful containers for viewing land cover.
- Stocking density (SD) at farm level (the best data available) is not a good indicator of grassland intensification at field scale.

4.1 Introduction

PRIME2 is a complex geo-database and mapping system. It can be thought of as a seamless wall-to-wall national cadastre, i.e. it is a national digital map with no holes and with individual objects, such as houses, gardens or fields, mapped. It had been assumed, within the Irish spatial analysis community, that it could be a tool both for creating land cover information and for mapping land cover allocation. Although PRIME2 is too detailed spatially to be used for training boundaries for sub-pixel geo-allocation of land cover, rules can be established to generalise the polygons, based on the likely level of precision that could be established, as outlined in Chapter 3.

4.2 PRIME2 Pre-processing for Analysis

For the purposes of this analysis, the original line work was designated "z0" in PRIME2, and all other z layers (e.g. z1 which identifies old symbols) were eliminated. Themes were generalised to eliminate areas of less than 1.2 ha (compared with a MODIS pixel area of 6.25 ha), and tolerances were adjusted to eliminate narrow (< 2 m width) features. The resulting polygons were merged with adjacent polygons if they shared the same polygon function (vegetation, way, etc.). Thus, built areas and roads became fused, while vegetation areas and very small fields were combined into larger entities, and small polygons within larger polygons of a different function were simply eliminated. It is acknowledged that this approach is rather simplistic, and also serves to compound the effect of intra-field land cover vegetation. Ideally, the process of generalisation of PRIME2 polygons should be an iterative one, with the allocated land cover from high-resolution image classifications being used to fuse polygons rather than the function class, and misclassified polygons being unfused between land cover production runs; however, this approach is outside the scope of this project.

4.3 Medium-Resolution Imagery for MODIS Sub-pixel Partition

The use of medium-resolution imagery, such as Landsat ETM+ data, as an intermediate step in sub-pixel geo-
allocation of land cover data is a technique that has only recently been described in the literature, but does show promise (Busetto *et al.*, 2008). It was developed on the basis of the object-orientated classification paradigm (Blaschke, 2010), wherein classification is based, not on the spectral characteristic of each individual pixel, but on the collective characteristics of a group of pixels, which are either partitioned on the basis of a function of these characteristics (segmentation) or, as in this project, using pre-defined boundaries.

The images used in this analysis were a pair of Landsat 8 OLI images from 11 and 19 July 2013 (Figure 4.1). The imagery was acquired at a number of wavelengths and at different resolutions. For this study, six bands in the visible, NIR and shortwave infrared regions of the electromagnetic spectrum, re-sampled to 30 m spatial resolution, were used. The two dates were stacked together to produce a 12-band image. The polygons in the simplified PRIME2 coverage were populated with the mean value of the pixels within that polygon for each of the 12 bands.

Each polygon also had a mean and standard deviation NDVI value for each of the two acquisition dates.

Figure 4.1. False colour (green, red, NIR) Landsat 8 OLI imagery for Longford.

In this instance, the standard deviation is a simple measure of complexity within the field (smooth featureless fields, such as highly improved grasslands, have a low value, while more complex fields have a higher value).

The *P*-value probability bands from the MODIS time-series classification (discussed in section 2.3) were incorporated into the analysis as a proxy for the sub-pixel allocation that failed in Chapter 3. The probability values can also be interpreted as cover values, thus if a pixel has a 10% chance of being classified as water, this can be interpreted, with some assumptions, as meaning that 10% of the pixel *is* water. The probability values were ascribed to each generalised PRIME2 polygon using a mean area-weighted approach.

Ultimately, therefore, each polygon (field) had a total of 22 attributes [12 spectral bands, 6 probability bands and 4 (2 mean, 2 standard deviation) NDVI values], and these polygons became the objects to be classified.

4.4 Ground Truth Sources: Stocking Density and Orthophotography

The focus of this part of the project was to examine the possibility of defining agricultural enclosed grasslands as improved and semi-improved grassland classes. Visits to each site to assess the grassland status in summer 2013 were not possible, so instead animal stocking density (SD) was considered as a proxy for grazing intensity and thus management. After cleaning, the data provided by DAFM generated 350 fields with an associated SD value ranging from 0.25 livestock units (LU)/ha to 3.1 LU/ha.

Using the SD numbers as ground truth, an attempt was made to classify the generalised PRIME2 objects, based on their spectral properties, into low, medium and high SD. However, conventional statistical image classification techniques, empirical models and simple neural network approaches failed to either robustly classify or produce a reliable model of SD given the spectral properties of the field. This reveals a limitation with using SD, as calculated by the DAFM, as a per-field ground truth source.

The SD is calculated as the total herd size divided by the total farm utilisable agricultural area; this figure is then allocated to each parcel associated with that herd number. But, as highlighted in Chapter 3, issues of scale again present a confounding influence, namely the amount of intra-farm and -parcel variation, and the limits of LPIS as a spatial representation of land use. LPIS is a geo-database used for supporting agricultural grants, and is not a map. Therefore, by default, anything that is claimed as an area that is not a crop is defined as pasture, whether the ground is an upland commonage area or an intensive dairy paddock. Within each LPIS parcel (defined as a contiguous area of management), there is a high degree of variability in land cover and practice. Thus, projecting a single figure for SD onto all the individual PRIME2 fields that make up the farm dilutes the value of SD as an indicator at anything below farm or landscape scale.

In order to resolve this issue, ground truth information for the individual polygons was acquired through the manual inspection of aerial photographs from 2012. Each vegetation polygon was classified as:

- *Improved Grassland* – grassland that shows evidence of intensive management (cutting, sub-paddock grazing, reseeding) and is distinguished by greenness, smoothness and overall level of homogeneity;
- *Semi-Improved Grassland* – enclosed grassland that does not show evidence of intensive management as defined above;
- *Forestry* – managed forest (mature and immature, ground prepared for harvesting, harvested, rejuvenating) and closed canopy woodlands;
- *Natural* – largely uncultivated areas (including mechanically cut bogs).

Water and built land were not included as these are well captured in PRIME2. They are also easily mapped by image classification, and thus their inclusion could have artificially inflated the accuracy values for the final map.

4.5 Processing and Results

The generalised PRIME2 objects were classed into four categories using a conventional minimum-distance-to-means supervised classification (Figure 4.2).

Compared with ground truth data derived from the manual interpretation of orthophotographs, the OA of the County Longford land cover classification was 81% (Table 4.1). This was comparable to the results achieved for single-date acquisitions of MODIS data when considering just homogeneous areas (section 2.3.4).

To test the benefit of the content provided by the MODIS probability layers, an unsupervised classification was performed on the field objects using all data (including probability layers) and then only six OLI spectral layers from a single acquisition. The classes arising from the unsupervised classification were coded using visual inspection, and tested against independently gathered ground truth data (again obtained from manual observation of orthophotographs). The evaluation of the semi-improved and improved grassland classes gave an overall classification accuracy of 49% when only six bands were used, and 88% when all bands were used.

The best comparator map of grassland classes is that of the EPA/Teagasc Soils and Sub-soils (EPA, 2009) project, which produced a land cover map for Longford using the rule-based classification of Landsat imagery and ancillary geographic information system layers. This classification achieved a UA of 70% for “Wet” (akin to semi-improved in the ILMO classification)

Figure 4.2. Subset of the County Longford land cover map.

and 84% for “Dry Grasslands”, compared with 75% and 89%, respectively, in this map. The ILMO classification was also produced without using any ancillary information, such as topography and soil data in particular, which would improve classification. Thus, although an OA for the classified output of 81% was not as good as might be expected from other approaches, the misclassification between semi-improved and improved grasslands was less than with other existing reporting schemes.

Table 4.1. Confusion matrix for Longford land cover map

	GS	GA	P	F	UA
GS	**47**	8	3	1	0.79
GA	14	**110**	3	1	0.86
P	2	0	**12**	1	0.80
F	0	5	0	**14**	0.73
PA	0.75	0.89	0.66	0.82	OA: **0.81**

The numbers in bold refer to correctly classified parcels.
F, forestry; P, peatland.

5 Grassland Classification using Radar Data

Research highlights

- Improved and semi-improved grasslands can be distinguished over large heterogeneous areas using a synergy of synthetic aperture radar (SAR) and ancillary data.
- The ERT classifier consistently outperforms RFs and SVMs.
- Combined C- and L-band classifications outperform single C- or L-band classifications.

5.1 Introduction

Given the difficulty of acquiring multiple usable images throughout a growing season, as optical sensors are limited by frequent cloud cover, the use of synthetic aperture radar (SAR) data can be an important alternative or complementary data source; SAR data can provide the best opportunity to generate a multi-temporal dataset, as they are almost independent of weather and illumination conditions, making their use for operational proposes especially appealing.

In this study, the three machine-learning classifiers already discussed in Chapter 2 (RFs, SVMs, and ERTs) are applied to multi-temporal C- and L-band SAR datasets covering the same areas of Counties Longford and Sligo. This chapter describes the evaluation of their potential for creating grassland inventories over large heterogeneous areas, and makes the key distinction between grasslands that are improved and those that are semi-improved.

5.2 Methodology

The study areas are located in central and north-western Ireland, and encompass the counties of Longford and Sligo, respectively (see Figure 5.1). A total of 12 ENVISAT ASAR Image Mode (IM) scenes, 15 Environmental Resources Satellite-2 (ERS-2) SAR scenes (both C-band with a wavelength of 5.6 cm) and 12 ALOS PALSAR scenes (L-band with a wavelength of 23.6 cm) that covered the study areas in 2008 were analysed (see Table 5.1). The ERS-2 SAR and ENVISAT ASAR scenes were acquired in vertically transmitted–vertically received (VV) polarisation at an incidence angle of ≈23°. PALSAR scenes were acquired in “fine beam single” (FBS) mode, horizontally transmitted–horizontally received (HH) polarisation and “fine beam dual” (FBD) (HH/horizontally transmitted–vertically received polarisation) mode with a ≈38° incidence angle. Ancillary datasets, including OSi Digital Elevation Model (DEM) and orthophotography data, EPA/Teagasc Soils and Sub-soils maps, NPWS Semi-Improved Grassland Surveys, and LPIS and FIPS data, were used for training the classifiers.

The SAR data were co-registered, multi-looked and speckle filtered using a 5 × 5 window size Frost filter, and radiometrically and geometrically calibrated and converted to decibels. All datasets were geo-coded to the Irish Transverse Mercator projection and have a spatial resolution of 20 m. No terrain distortions were present in the Longford dataset as a result of its low-lying topography. Conversely, the scenes for Sligo needed to be masked for certain terrain-induced distortions (e.g. shadow and layover) because of the more varied topography of this county. These areas (ranging between 0.2 and 1.4% of the total county area depending on the acquisition track and frame) were subsequently masked from all the SAR intensity data and SAR-derived texture and multi-temporal measures, and excluded from the classifications. The common grey-level co-occurrence matrix (GLCM) was applied to all SAR data to extract textural information. Four textural parameters (homogeneity, contrast, entropy and second moment) were computed using a 3 × 3 sliding window, and the relationship between neighbouring pixels was considered in the context of four main directions (0°, 45°, 90° and 135°). Multi-temporal features (gradient, standard deviation, median, span ratio, maximum increment, span difference and maximum ratio) were also extracted from the time-series intensity data.

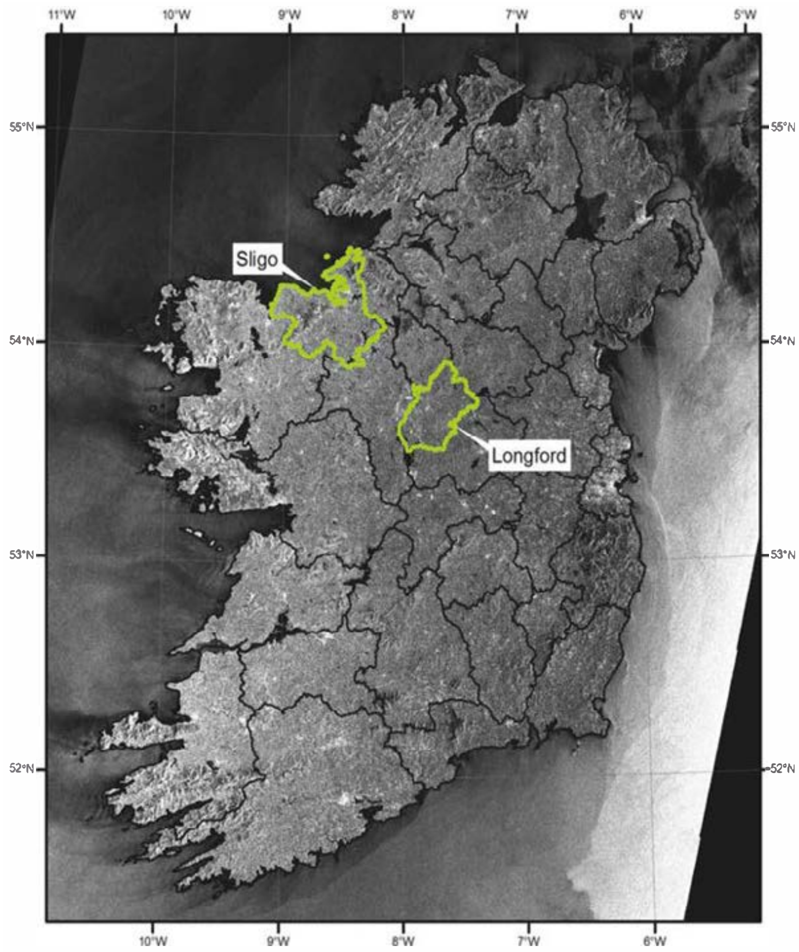

Figure 5.1. ENVISAT ASAR wide swath mode image with county boundaries overlaid; the study counties of Longford and Sligo are highlighted.

A total of 10 land cover classes were considered according to the specific needs of the project [level 3 (L3) of Table 1.2]: dry improved grassland (GAd), reclaimed improved grassland (GAr), wet semi-improved grassland (GSw), humic semi-improved dry grassland (GSdh), calcareous semi-improved dry grassland (GSdc), forest, water, settlement, peatland and cropland. A stratified random sampling approach was adopted for the selection of training and validation data for each class. A total of 5202 samples were selected for Longford and 6442 for Sligo. A five-fold cross-validation was performed to minimise the impact of the training data selection. The five-fold cross-validation partitioned the dataset randomly and used five one folds for training and the remaining one fold for validating the classifier. The main advantage of this is that all of the samples were eventually used for both training and validating the classifier. The OA for each classifier was determined from the accuracy averaged over the five partitions of the training data. The same training and validation sets were used for all classifiers.

The FI scores generated by the RF classifier were used to reduce the dimensionality of the data to include only the variables with the highest scores in the final classification dataset. All SAR derived data and ancillary data features were initially included in the classifications. The GLCM texture measures were found to have no measureable influence on the classification accuracies and were subsequently removed from any further analysis.

5.3 Results

The classification results from the C- and L-band and the combined C- and L-band datasets are shown in Tables 5.2 and 5.3. Several measures derived from the confusion matrix were used to evaluate the classifier performance. These included the OA, UA, PA and the kappa statistic. Training and validation of the classifiers

Table 5.1. SAR data characteristics (data provided by the ESA through Cat-1 ID 11768)

Sensor	Date	Track	Frame
Longford			
ERS-2	23 March 2008	80	2525
ERS-2	27 March 2008	144	1076
ASAR	8 April 2008	309	2526
ERS-2	1 May 2008	144	1076
ASAR	17 June 2008	309	2526
ERS-2	10 July 2008	144	1076
ASAR	22 July 2008	309	2526
ERS-2	10 August 2008	80	2525
ERS-2	14 August 2008	144	1076
ERS-2	26 August 2008	309	2522
ASAR	14 September 2008	80	2524
ERS-2	23 November 2008	80	2525
PALSAR FBS	27 January 2008	1	1060/1070
PALSAR FBD	28 April 2008	1	1060/1070
PALSAR FBD	13 June 2008	1	1060/1070
Sligo			
ERS-2	1 February 2008	352	2512
ERS-2	23 March 2008	80	2514
ASAR	11 April 2008	352	2511
ASAR	9 July 2008	123	2509
ASAR	25 July 2008	352	2511
ERS-2	29 July 2008	416	1086
ERS-2	10 August 2008	80	2514
ERS-2	17 August 2008	187	1084
ERS-2	29 August 2008	352	2512
ASAR	14 September 2008	80	2513
ASAR	17 September 2008	123	2509
ASAR	3 October 2008	352	2511
ASAR	19 October 2008	80	2506
ERS-2	23 November 2008	80	2514
ASAR	31 December 2008	123	2509
PALSAR FBS	1 March 2008	3	1070/1080
PALSAR FBD	1 June 2008	3	1070/1080
PALSAR FBD	17 July 2008	3	1070/1080

were performed on 5202 and 6442 samples from the Longford and Sligo datasets, respectively.

Two different datasets were used for the classifications: “v0” represented classifications that considered all input variables and “v1” represented classifications that considered only the backscatter intensity measurements along with the soils, sub-soils, elevation and slope data. The effect of reducing the number of input features can be seen across both study areas in all classifications and OA increases of between 0.8% and 5.8% were obtained.

From Tables 5.2 and 5.3, it can be seen that the L-band dataset classifications were only marginally outperformed by the C-band dataset (generally by ≈2%). This is significant given the fact that the L-band time series comprises just three separate acquisitions for both study areas while the C-band dataset is made up of 12 and 15 acquisitions for Longford and

Table 5.2. C- and L-band and combined C- and L-band classification results for Longford

Band	Class	Classification results											
		v0_Id[a]						v1_Id[b]					
		RF		SVM		ERT		RF		SVM		ERT	
		PA	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA	UA
C-band	GSdh	0.92	0.96	0.88	0.89	0.93	0.97	0.94	0.99	0.93	0.95	0.96	0.99
	GSdc	0.97	0.97	0.93	0.96	0.93	0.98	1.00	0.98	1.00	0.98	1.00	0.99
	GAd	0.92	0.95	0.89	0.86	0.94	0.93	0.94	0.96	0.95	0.92	0.97	0.97
	GAr	0.90	0.83	0.81	0.77	0.91	0.83	0.93	0.86	0.92	0.89	0.94	0.91
	GSw	0.92	0.82	0.85	0.75	0.91	0.83	0.94	0.88	0.94	0.86	0.96	0.93
	OA	0.96		0.94		0.96		0.97		0.97		0.98	
	Kappa	0.95		0.93		0.95		0.96		0.97		0.98	
L-band	GSdh	0.87	0.74	0.74	0.72	0.90	0.76	0.92	0.90	0.85	0.85	0.93	0.92
	GSdc	0.89	0.95	0.83	0.79	0.85	0.95	0.96	0.98	0.94	0.93	0.97	0.98
	GAd	0.91	0.85	0.79	0.77	0.91	0.87	0.95	0.92	0.93	0.90	0.95	0.94
	GAr	0.86	0.65	0.66	0.50	0.89	0.64	0.87	0.72	0.77	0.70	0.92	0.75
	GSw	0.81	0.70	0.69	0.55	0.82	0.69	0.91	0.82	0.85	0.72	0.91	0.82
	OA	0.92		0.88		0.93		0.95		0.94		0.96	
	Kappa	0.91		0.86		0.91		0.94		0.92		0.95	
C-/L-band	GSdh	0.96	0.94	0.90	0.89	0.98	0.96	0.96	0.97	0.98	0.96	0.97	0.99
	GSdc	0.96	0.98	0.91	0.95	0.98	0.98	1.00	0.99	0.99	0.94	1.00	0.99
	GAd	0.95	0.95	0.92	0.84	0.96	0.96	0.96	0.96	0.98	0.94	0.98	0.97
	GAr	0.91	0.86	0.81	0.80	0.93	0.89	0.95	0.89	0.93	0.93	0.96	0.91
	GSw	0.91	0.87	0.87	0.83	0.94	0.90	0.95	0.92	0.96	0.92	0.96	0.95
	OA	97.20%		95.30%		97.90%		98.00%		97.90%		98.70%	
	Kappa	0.97		0.94		0.97		0.98		0.98		0.98	

[a]"v0" indicates the initial classification in which all input variables were included.

[b]"v1" indicates the classification after the least important variables were excluded.

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Table 5.3. C- and L-band and combined C- and L-band classification results for Sligo

Band	Class	Classification results											
		v0_so[a]						v1_so[b]					
		RF		SVM		ERT		RF		SVM		ERT	
		PA	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA	UA
C-band	GSdh	0.87	0.62	0.70	0.68	0.84	0.68	0.84	0.70	0.70	0.76	0.83	0.73
	GSdc	0.82	0.55	0.70	0.63	0.85	0.63	0.83	0.68	0.68	0.73	0.84	0.75
	GAd	0.80	0.94	0.79	0.87	0.83	0.94	0.85	0.93	0.85	0.85	0.87	0.93
	GAr	0.80	0.78	0.79	0.70	0.83	0.79	0.83	0.86	0.83	0.76	0.86	0.89
	GSw	0.82	0.71	0.74	0.70	0.83	0.75	0.86	0.78	0.80	0.73	0.89	0.81
	OA	0.89								0.89		0.93	
	Kappa	0.87								0.87		0.92	
L-band	GSdh	0.79	0.51	0.60	0.56	0.78	0.52	0.78	0.62	0.70	0.70	0.80	0.66
	GSdc	0.65	0.46	0.50	0.49	0.72	0.43	0.74	0.59	0.68	0.66	0.80	0.63
	GAd	0.79	0.91	0.80	0.83	0.77	0.92	0.83	0.92	0.85	0.85	0.84	0.92
	GAr	0.83	0.80	0.72	0.74	0.82	0.78	0.84	0.85	0.83	0.81	0.85	0.87
	GSw	0.69	0.70	0.64	0.56	0.72	0.71	0.77	0.74	0.76	0.74	0.80	0.79
	OA	0.87		0.84		0.87		0.90		0.89		0.91	
	Kappa	0.85		0.81		0.85		0.88		0.87		0.90	
C-/L-band	GSdh	0.87	0.58	0.72	0.69	0.89	0.67	0.85	0.69	0.76	0.76	0.84	0.73
	GSdc	0.76	0.51	0.57	0.61	0.83	0.59	0.82	0.63	0.77	0.75	0.85	0.73
	GAd	0.80	0.93	0.84	0.84	0.82	0.94	0.84	0.94	0.89	0.89	0.87	0.94
	GAr	0.87	0.79	0.78	0.79	0.88	0.80	0.89	0.86	0.88	0.86	0.92	0.90
	GSw	0.76	0.76	0.73	0.67	0.82	0.82	0.83	0.81	0.83	0.83	0.89	0.85
	OA	89.90%		88.00%		91.60%		92.40%		92.50%		94.10%	
	Kappa	0.88		0.86		0.90		0.91		0.91		0.93	

[a]"v0" indicates the initial classification in which all input variables were included.

[b]"v1" indicates the classification after the least important variables were excluded.

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Sligo, respectively. The positive impact of a synergy between frequencies during classification is clearly demonstrated in Tables 5.2 and 5.3: an increase in OA (average of 1.5%) was observed for each classifier in both study areas. In all three sets of classifications (C-band, L-band and combined C- and L-band), the Longford results outperformed the Sligo results. Notwithstanding this, the final (v1) Sligo classifications have an average OA of 91%. In contrast, the Longford datasets produced average classification accuracies of more than 96%. The UAs and PAs for individual classes for both areas were also high, with Longford having considerably lower class standard deviations than Sligo.

The classification output maps in Figure 5.2 display the distribution of the different land cover categories in the two study counties. These maps were created using only SAR intensity measurements and excluded the ancillary variables. In Sligo, the large-scale effect of the regular rainfall and resulting high humidity is apparent because of the manner in which blanket peat bogs cover the mountainous regions of the Ox (south-west) and Dartry (north) ranges. It can be seen that the majority of improved grassland occurs along the coastline and in a central corridor in the county, in a similar manner to that shown by the optical data discussed in section 2.3.3. The extensive peatlands (raised bogs) in the west of Longford are also clearly distinguished and the majority of improved grassland appears to occur in the southern and north-eastern parts of the county (as discussed in section 2.3.2).

There are some areas of confusion, namely the mixing of settlement and forest classes because of their similar temporal backscatter signal, but nonetheless the distribution of the different classes appears to have been captured reasonably well.

An important output of the ERT (and RF) classifier is the class probability (see Equation 5.1). This is the probability, p, of an observation being classified into class i, k is the total number of trees in the ensemble and k_i is the total number of trees classifying the observation as class i.

$$p(i) = k_i/k \qquad \text{(Equation 5.1)}$$

This can be of particular use as a measure of quantifying the level of uncertainty in the generated classification maps. For example, low probabilities in Figure 5.3 represent pixels that are unlikely to be GAd or GSw, while intermediate probabilities indicate possible confusion between one or more classes. High probabilities indicate pixels that have limited uncertainty about the assigned class. As shown in Figure 5.3, areas along the coastline of Sligo that were classified as improved grasslands have a very high probability of being assigned to the correct class. The semi-improved grasslands with the highest probabilities of being correctly classified are more noticeable to the north-west and south of the Ox Mountains, and towards the east of the county. In Longford, the area dominated by extensive tracts of commercial peatlands interspersed with vegetation is clearly distinguishable in the south-west of the county with corresponding low probabilities. At the same time, the areas of GAd with the highest probabilities are observed in the south-west and east of the county, while areas of GSw in the centre and north-west of the county have the highest probability of being correctly classified.

5.4 Discussion

5.4.1 Multi-frequency and ancillary data, and their impact on classification accuracy

The varying importance of the ancillary data on the different classes is interesting to note. For example, in Longford the soils and sub-soils have a dominant influence on the classification of areas of GSdc (given their usual confinement to limestone areas and alkaline soils). Similarly, elevation is expected to be highly important, as these grasslands are largely confined to the slopes of esker ridges and moraines in the midlands (Fossitt, 2000). As found by Rodriguez-Galiano *et al*. (2012b), elevation is most important for classes whose spatial distribution is conditioned by relief (e.g. GAd is mostly located in lowland areas and GSdh mainly occurs in upland areas). It is not as important for areas of GSw as these are usually found on flat terrain in both upland and lowland areas. The sensitivity of the C-band intensity measurements to phenological differences in terms of the importance scores can be observed for improved grasslands (GAd) in both Longford and Sligo where the spring acquisitions have a higher importance than non-spring acquisitions.

The observed increases in classification accuracy when both frequencies are combined are consistent with the results of Lardeux *et al*. (2009) and Turkar *et al*. (2012). In all three sets of classifications (C-band,

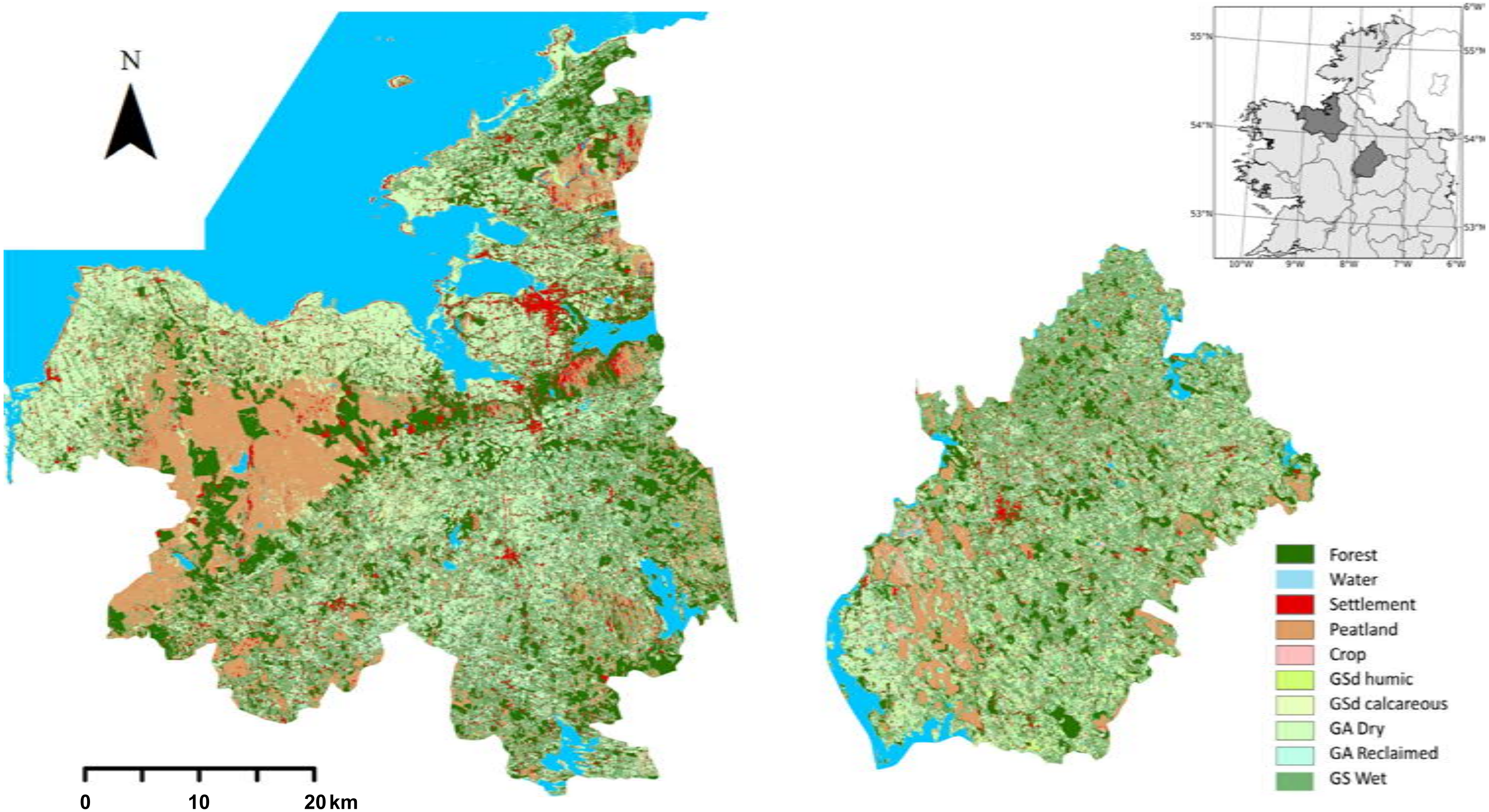

Figure 5.2. ERT classification results as applied to the C- and L-band SAR dataset. Reproduced from Barrett *et al.*, 2014, with permission from Elsevier.

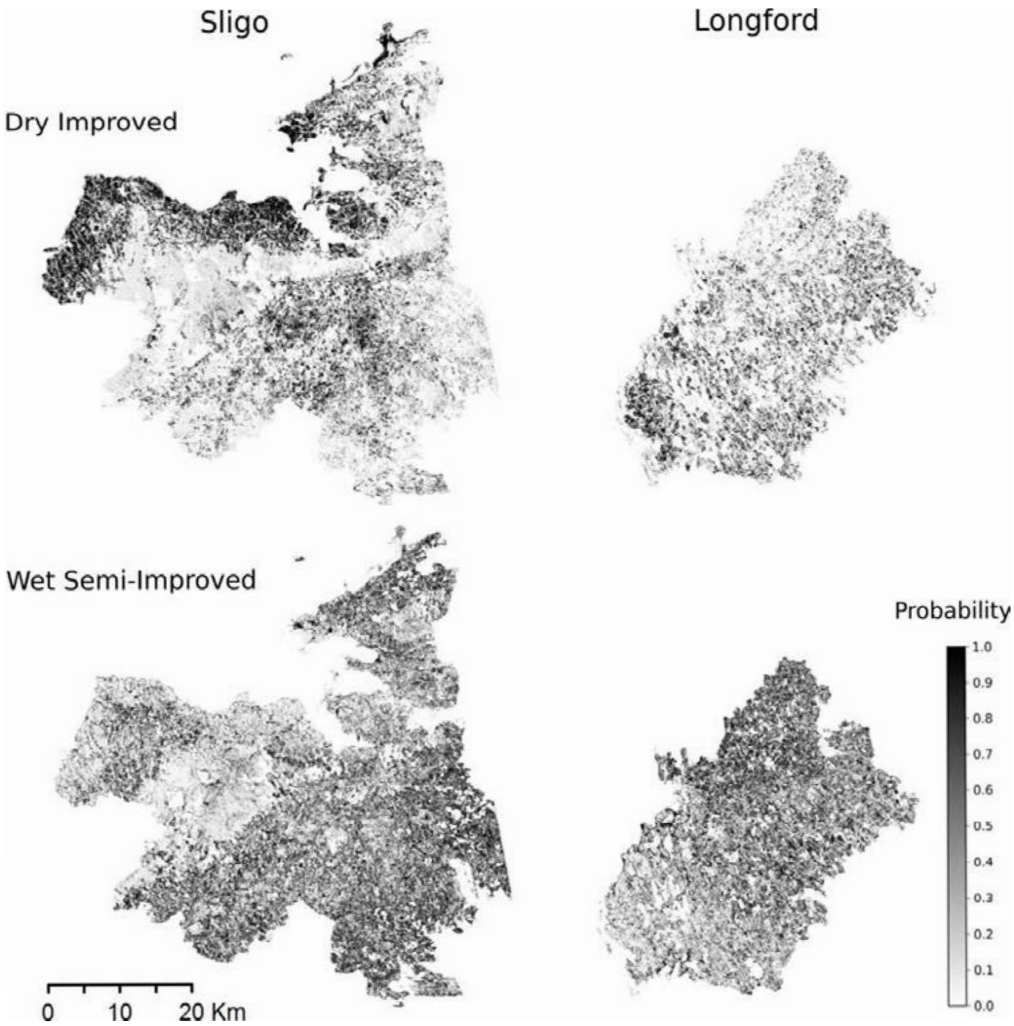

Figure 5.3. ERT classification probabilities of dry improved and wet semi-improved grassland for Sligo and Longford; low probabilities are shown in white and high probabilities are shown in black. Reproduced from Barrett *et al.*, 2014, with permission from Elsevier.

L-band and combined C- and L-band), the Longford results outperformed the Sligo results. This may be as a result of to several factors: Sligo has a much larger area and the landscape has more topographical variation than Longford. In addition, there are some areas with bare rock outcrops and coastal areas that cause some confusion, although these are almost exclusively within the non-grassland classes. In future studies, it may be worthwhile including an additional "other land" class to take these areas into account.

Not surprisingly, the cover types with high intra-class variability (i.e. grasslands) were the most difficult to reliably classify, as grasslands form a continuum of types and, naturally, there is confusion between class boundaries. A similar observation was made by Waske and Braun (2009) using multi-temporal C-band SAR data with a RF classifier.

These misclassifications were expected given their similar backscatter profiles and the heterogeneous nature of the Longford and Sligo landscapes. Clear-cut boundaries between the different classes are not readily apparent and thereby contribute to the confusion between classes. For the Sligo dataset, the majority of misclassifications occurred between the GSdc and GSdh classes; however in Longford, the GAr class was the most difficult to reliably classify. It was observed that the accuracies also varied considerably depending on the classifier used. The increased performance of the ERT classifier was observed across all datasets for both study areas. The OAs for the ERT classifier were 2% and 3% higher for the Longford and Sligo datasets, respectively, if the multi-temporal texture measures were excluded from the classification. The ERT class-specific accuracies

were less variable (lower standard deviations) for the final classifications than the other classifiers. There was also a more discernible increase in SVM accuracy after variable exclusion than the increase in accuracy of the RF and ERT classifiers.

To quantitatively assess the influence of the ancillary datasets on the classification accuracies, a number of classification permutations were carried out (see Table 5.4). Classifications were performed using all radar and ancillary data (a), all data without soils (b), all data without elevation (c) and radar intensities only (d). If the C- and L-band datasets were analysed separately, the differences in accuracies (OA and κ) after the ancillary data were excluded from the classifications were considerably larger than if the frequencies were combined. For Longford, there were small differences (3.6–5%) between the complete dataset and the radar-only dataset for the three classifiers. The differences between the same datasets for Sligo were larger, namely between 7.9% and 9.3%. A much larger decrease was observed for the L-band than the C-band classifications if the ancillary data were excluded. This may be explained by the fact that fewer radar acquisitions make up the L-band dataset than make up the C-band dataset. For all classification scenarios, the ERT classifier outperformed SVM and RF.

These findings showed that combining radar datasets with ancillary data significantly improved the accuracy of distinguishing grasslands. Similar findings were reported for wetlands (Corcoran *et al*., 2013; Marti-Cardona *et al*., 2013). To further improve grassland classifications, the combination of optical datasets with SAR and ancillary datasets may result in increased accuracies (Hill *et al*., 2005; Bagan *et al*., 2012; Smith and Buckley, 2011), although some studies (Price *et al*., 2002; Dusseux *et al*., 2012) have found that a combined approach is unsuccessful at yielding more accurate results. This would have obvious limitations especially from an operational context, as consistent and systematic cloud-free optical imagery may not be available for specific areas on a yearly basis. In addition, the extra effort (in terms of additional optical image processing and analysis) and cost may not be worthwhile in practice, as the findings from this study have shown that both single-frequency and multi-frequency multi-temporal SAR and ancillary data were capable of providing high classification accuracies in the absence of optical data.

5.4.2 SAR change detection

In order to assess the potential of SAR-derived land cover classifications for reporting GHGs (see Chapter 6), changes were calculated on the basis of SAR imagery acquired in 1992 and 2008. ERS-1 was launched on 17 June 1991 and provided data until 10 March 2000. ERS-1 operated in a similar manner to ERS-2 and the I2 IM of the ENVISAT ASAR sensor (C-band, VV polarisation and 23° incidence angle). Tables 5.5 and 5.6 display the acquisition dates and associated data characteristics for the 1992 and 2008 datasets for Longford and Sligo, respectively.

For the 2008 dataset, user interpretation of OSi orthophotography, Bing imagery, and LPIS and FIPS data facilitated the distinction of the non-grassland classes; the grassland classes were distinguished using additional data from the NPWS semi-natural grasslands field survey dataset and LPIS (stocking densities). For the 1992 dataset, Landsat TM imagery from 1989 and 1993 was used to identify different classes. The grassland 2008 training data were also used as the 1992 training data. All samples were selected independently of the SAR data. A five-fold cross-validation was performed to minimise the impact of the training data selection. The RF classifier was used for this analysis; the number of trees was set to 200 and the number of variables to split at each node was set to the square root of the number of predictor variables. Finally, the PRIME2 dataset was populated with the classification outputs using a simple majority rule.

Longford

The 2008 SAR dataset had an OA of 85% (kappa statistic of 0.82), while the 1992 SAR dataset produced an OA of 77% (kappa statistic of 0.73). Tables 5.7 and 5.8 show the classification error matrices and *P*-value error matrices. The highest probability of misclassifications was observed within the grassland and cropland classes. The 2008 dataset displayed the highest number of peatland misclassifications, although the *P*-value was similar to the 1992 dataset *P*-value. The cropland class was the most difficult to correctly classify in the 1992 dataset, which was due in part to the lack of suitable ground reference data for that period.

Table 5.4. Comparison of different classification results with and without ancillary datasets

	Longford						Sligo					
	RF		SVM		ERT		RF		SVM		ERT	
	OA	κ	OA	κ	OA	κ	OA	κ	OA	κ	OA	κ
C-band												
a) All data	96.90%	0.96	97.10%	0.97	97.90%	0.98	91.60%	0.9	88.70%	0.87	93.10%	0.92
b) No soils	94.80%	0.94	91.50%	0.9	95.80%	0.95	87.80%	0.86	84.40%	0.82	89.40%	0.88
c) No elevation	93.50%	0.92	93.90%	0.93	93.90%	0.93	88.30%	0.86	89.90%	0.88	90.30%	0.89
d) Radar only	87.20%	0.85	83.30%	0.8	88.50%	0.87	76.40%	0.73	76.70%	0.73	77.90%	0.74
L-band												
a) All data	95.30%	0.94	93.50%	0.92	95.80%	0.95	90.00%	0.88	89.20%	0.87	91.40%	0.9
b) No soils	89.40%	0.87	80.20%	0.77	89.80%	0.88	82.50%	0.8	69.70%	0.65	83.10%	0.8
c) No elevation	88.30%	0.86	86.10%	0.83	89.00%	0.87	86.00%	83.8	83.30%	0.81	86.80%	0.85
d) Radar only	76.20%	0.72	57.30%	0.49	76.90%	0.73	69.80%	0.65	54.40%	0.46	69.70%	0.64
C- and L-band												
a) All data	98.00%	0.98	97.90%	0.98	98.70%	0.98	92.40%	0.91	92.50%	0.91	94.10%	0.93
b) No soils	96.90%	0.96	96.90%	0.96	97.50%	0.97	89.10%	0.87	88.20%	0.86	91.20%	0.9
c) No elevation	96.70%	0.96	97.00%	0.96	97.40%	0.97	90.70%	0.89	91.80%	0.9	92.70%	0.92
d) Radar only	93.70%	0.93	92.90%	0.92	95.10%	0.94	83.10%	0.8	84.60%	0.82	86.10%	0.84

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Table 5.5. Longford SAR data for 1992 and 2008

Satellite	Date	Pass	Polarisation	θ	Satellite	Date	Pass	Polarisation	θ
ERS-1	23 May 1992	D	VV	23°	ERS-2	27 March 2008	A	VV	23°
ERS-1	1 August 1992	D	VV	23°	ENVISAT	8 April 2008	D	VV	23°
ERS-1	5 September 1992	D	VV	23°	ERS-2	1 May 2008	A	VV	23°
ERS-1	10 October 1992	D	VV	23°	ENVISAT	17 June 2008	D	VV	23°
ERS-1	14 November 1992	D	VV	23°	ERS-2	10 July 2008	A	VV	23°
ERS-1	19 December 1992	D	VV	23°	ENVISAT	22 July 2008	D	VV	23°
					ERS-2	14 August 2008	A	VV	23°
					ERS-2	26 August 2008	D	VV	23°
					ENVISAT	14 September 2008	D	VV	23°

A, Ascending; D, Descending; θ, incidence angle.

Table 5.6. Sligo SAR data for 1992 and 2008

Satellite	Date	Pass	Polarisation	θ	Satellite	Date	Pass	Polarisation	θ
ERS-1	26 May 1992	D	VV	23°	ERS-2	1 February 2008	D	VV	23°
ERS-1	4 August 1992	D	VV	23°	ENVISAT	11 April 2008	D	VV	23°
ERS-1	8 September 1992	D	VV	23°	ENVISAT	25 July 2008	D	VV	23°
ERS-1	13 October 1992	D	VV	23°	ERS-2	17 August 2008	A	VV	23°
ERS-1	17 November 1992	D	VV	23°	ERS-2	29 August 2008	D	VV	23°
					ENVISAT	3 October 2008	D	W	23°

A, Ascending; D, Descending; θ, incidence angle.

Table 5.7. Longford error and *P*-value error matrices for the 2008 C-band SAR dataset

	Error matrix							*P*-value error matrix						
Forest	**753**	0	17	26	3	32	12	**0.784**	0.005	0.057	0.058	0.034	0.035	0.027
Water	1	**778**	0	0	1	5	0	0.008	**0.922**	0.001	0.008	0.013	0.03	0.017
Settlement	40	0	**314**	18	4	1	2	0.127	0.002	**0.717**	0.108	0.028	0.008	0.01
Peatland	18	0	12	**1187**	11	15	37	0.037	0.003	0.03	**0.799**	0.042	0.028	0.061
Cropland	11	1	2	36	**365**	32	12	0.06	0.017	0.023	0.121	**0.603**	0.097	0.08
I-grassland	4	14	0	22	14	**465**	146	0.044	0.035	0.005	0.054	0.068	**0.5**	0.294
SI-grassland	8	7	1	65	12	121	**577**	0.028	0.015	0.005	0.092	0.049	0.242	**0.569**

The figures in bold represent the number of correctly classified pixels.
I-grassland, improved grassland (GA); SI-grassland, semi-improved grassland (GS).

Table 5.8. Longford error and *P*-value error matrices for the 1992 C-band SAR dataset

	Error matrix							*P*-value error matrix						
Forest	**602**	0	8	97	5	13	37	**0.643**	0.005	0.061	0.178	0.026	0.033	0.054
Water	0	**821**	0	0	3	4	9	0.008	**0.945**	0.001	0.002	0.008	0.013	0.024
Settlement	43	0	**242**	80	3	6	13	0.129	0.003	**0.559**	0.218	0.023	0.026	0.043
Peatland	70	0	17	**1066**	2	4	7	0.113	0.001	0.067	**0.792**	0.009	0.007	0.011
Cropland	9	1	0	7	**193**	83	100	0.048	0.014	0.021	0.024	**0.404**	0.258	0.231
I-grassland	11	1	1	4	60	**376**	212	0.038	0.013	0.015	0.014	0.158	**0.463**	0.299
SI-grassland	23	15	6	8	39	133	**567**	0.051	0.027	0.02	0.016	0.12	0.254	**0.513**

The figures in bold represent the number of correctly classified pixels.
I-grassland, improved grassland (GA); SI-grassland, semi-improved grassland (GS).

Table 5.9. Sligo error and *P*-value error matrices for the 2008 C-band SAR dataset

	Error matrix							*P*-values error matrix						
Forest	**775**	1	46	99	6	80	16	**0.594**	0.009	0.114	0.107	0.01	0.101	0.064
Water	4	**552**	0	4	0	49	3	0.016	**0.79**	0.021	0.017	0.003	0.113	0.04
Settlement	113	10	**420**	9	0	65	14	0.19	0.018	**0.579**	0.051	0.01	0.089	0.063
Peatland	62	2	15	**797**	0	148	87	0.094	0.009	0.028	**0.55**	0.007	0.164	0.149
Cropland	5	0	2	5	**135**	17	1	0.056	0.012	0.032	0.042	**0.665**	0.135	0.059
I-grassland	67	22	17	143	8	**1216**	246	0.061	0.038	0.033	0.11	0.012	**0.489**	0.257
SI-grassland	43	8	15	134	1	505	**475**	0.055	0.019	0.03	0.142	0.007	0.367	**0.38**

The figures in bold represent the number of correctly classified pixels.

I-grassland, improved grassland (GA); SI-grassland, semi-improved grassland (GS).

Table 5.10. Sligo error and *P*-value error matrices for the 1992 C-band SAR dataset

	Error matrix							*P*-values error matrix						
Forest	**719**	37	16	164	0	95	92	**0.502**	0.055	0.087	0.175	0.002	0.087	0.092
Water	57	**525**	8	5	0	12	5	0.101	**0.735**	0.049	0.02	0.009	0.05	0.036
Settlement	105	27	**299**	48	2	21	24	0.181	0.055	**0.536**	0.121	0.005	0.049	0.053
Peatland	138	2	26	**762**	0	85	136	0.173	0.01	0.057	**0.533**	0.003	0.098	0.126
Cropland	0	3	0	1	**69**	83	9	0.019	0.028	0.012	0.028	**0.377**	0.424	0.112
I-grassland	53	18	5	50	31	**1191**	324	0.062	0.017	0.017	0.069	0.044	**0.532**	0.258
SI-grassland	65	10	6	91	9	487	**513**	0.09	0.015	0.024	0.124	0.015	0.36	**0.373**

The figures in bold represent the number of correctly classified pixels.

I-grassland, improved grassland (GA); SI-grassland, semi-improved grassland (GS).

Sligo

The 2008 SAR dataset had an OA of 68% (kappa statistic of 0.61), while the 1992 SAR dataset produced an OA of 63% (kappa statistic of 0.55). Tables 5.9 and 5.10 show the classification error matrices and *P*-value error matrices. The Sligo classifications had lower OAs than the Longford results. For both the 1992 and 2008 datasets, the semi-improved class was the most difficult to reliably classify. Similarly to the Longford 1992 dataset, the cropland class also displayed a low *P*-value. As discussed in section 5.4, combining these datasets with ancillary soil and elevation datasets should lead to an improvement in accuracies and a greater capability to distinguish between the grasslands.

6 Greenhouse Gas Emissions and Removal

Research highlights

- High-resolution SAR-derived classification products can be used to estimate GHG emission/reduction profiles for crop and grasslands, based on a pilot study conducted for County Longford and County Sligo.
- The results clearly show that net emissions from croplands in the two study areas, over the period 1992 to 2008, were primarily associated with a loss of soil organic carbon (SOC) following the conversion of grasslands to cropland.
- Transitions between improved grassland, semi-improved grassland and scrub sub-categories within the "grassland remaining grassland" category resulted in a large sink (sequestration) of carbon dioxide (CO_2), equivalent to 0.3 to 1 tCO_2/ha per year.

6.1 Introduction

This chapter outlines the potential use of newly developed land cover classifications for the reporting of GHG emissions/reductions from cropland and grassland transitions. Although the land cover categories used in this project are similar to those used by the National Greenhouse Gas Inventory Report (NGHGIR) (EPA, 2013), a key improvement to the inventory as a result of the project outputs is that spatially explicit data on transitions between grassland categories (see section 1.3.5) can be derived with a high level of accuracy. In addition to deriving suitable land use matrices, this section also describes the development of new methods and activity data used to estimate the carbon stock changes associated with cropland and grazing land management under Article 3.4 of the Kyoto Protocol, and for cropland and grassland reporting under the UNFCCC.

6.2 Methodology

6.2.1 System boundary

The GHG estimates include all CO_2 emissions or removals from biomass, dead organic matter (DOM) and soil pools arising from the transitions listed in Table 6.1. The GHG estimates do not consider the following sources:

- Nitrous oxide (N_2O) emissions from fertiliser application – the national GHG inventory reports this under the agriculture sector based on national fertiliser use data (EPA, 2013).
- N_2O emissions from disturbance associated with land cover conversion to cropland – this is done at the national level, so data were not available at the scale at which this project was undertaken.
- N_2O, CO_2 and methane emissions from biomass burning – this is not currently reported for cropland residues and grasslands because there are no available national data. However, burning of scrublands prior to conversion back to improved grassland is common practice. Emissions from fires are outside the scope of this project.
- CO_2 emissions from the application of lime to soils – this is done at the national level, based on lime sales data.

6.2.2 Deriving land cover change matrices

Land use change matrices were derived from the two different land cover classified map products:

- PRIME2 boundaries populated with the SAR dataset based on data acquired in 1992 and 2008 (Prime-2-SAR_1992–2008);
- PRIME2 boundaries populated with the MODIS dataset based on data acquired in 2008 and 2012 (Prime2-MODIS_2008–2012).

A preliminary assessment of the quality and suitability of the two satellite-derived products, with regard to carbon reporting and accounting requirements,

Table 6.1. Land use transitions in GHG estimates

5B1	**Crop land remaining crop land**	
5B2	**Lands converted to crop land**	
	B2.1	Forest to crop
	B2.2	Grass to crop
	B2.3	Wetland to crop
	B2.4	Settlement to crop
	B2.5	Other land to crop
5C1	**Grass land remaining grass land**	
	C1.1	Improved remaining improved
	C1.2	Semi-improved remaining semi-improved
	C1.3	Rough grazing/scrub remaining rough grazing/scrub
	C1.4	Improved converted to semi-improved
	C1.5	Improved converted to rough grazing/scrub
	C1.6	Semi-improved converted to improved
	C1.7	Semi-improved converted to rough grazing/scrub
	C1.8	Rough grazing/scrub converted to improved
	C1.9	Rough grazing/scrub converted to semi-improved
5C2	**Lands converted to grass land**	
	C2.1	Forest to 3 grass sub-categories
	C2.2	Grass to 3 grass sub-categories
	C2.3	Wetland to 3 grass sub-categories
	C2.4	Settlement to 3 grass categories
	C2.5	Other land to 3 grass categories

was carried out based on data-use guidance and information on QA/quality control requirements in the Intergovernmental Panel on Climate Change (IPCC) good practice guidance (IPCC, 2006). It was determined that the PRIME2-SAR data were the best available data for carbon reporting because:

- the availability of 1992 SAR data provided a good baseline from which net–net accounting of cropland and grassland management activities could be reported under Article 3.4 of the Kyoto Protocol; in contrast, MODIS data were only available from 2000;
- the higher spatial resolution of SAR data was more suitable for reporting LULUCF activities in the Irish context;
- the higher accuracy and *P*-values for the SAR classification of all land use categories, compared with the MODIS data, would result in a lower overall uncertainty with regard to carbon stock changes.

The PRIME2-SAR data were supplied with soil information from the Irish Forest Soils (IFS) project, which indicated the predominant soil type for each PRIME2 polygon, to facilitate calculation of SOC stock changes. The post-classification modification of the SAR datasets was carried out to derive a rough grazing/scrubland category, as the satellite data alone were unable to distinguish between forest land and scrubland (Table 6.2 and 6.3). This was done by spatially selecting all forest areas that occur in the national FIPS data. The remaining SAR-derived forest parcels, which were not classified as forest in the FIPS data, were re-assigned to the category “rough grazing/scrubland”. The rationale for this additional sub-classification was based on various considerations, including the following:

- The current grassland classification system used by the EPA and also within this project (see section 1.3.5) does not accurately describe GHG emission/reduction profiles across the grassland–scrubland continuum.
- The current national inventory land classification system uses a hierarchical classification system (EPA, 2013), in which forest lands are defined using FIPS data.

Table 6.2. Land use change matrix derived from the PRIME2-SAR_1992–2008 data for Longford

		Land use in 2008 (ha)									
	From/to	Scrub	Forest	Other	Settlement	Peatland	Cropland	I-grassland	SI-grassland	Total in 1992	% in 1992
Land use in 1992 (ha)	Scrub	**737.8**	156.6	37.1	46.4	745.4	370.4	1616.3	1627.0	5337.0	5.0
	Forest	0.0	**2554.9**	13.7	144.8	575.0	28.0	414.5	319.1	4050.0	3.8
	Other (0+3)	36.3	12.4	**1715.9**	5.0	15.5	4.7	183.7	106.2	2079.7	2.0
	Settlement	132.2	31.5	18.2	**158.3**	143.6	65.8	264.0	204.9	1018.5	1.0
	Peatland	57.0	40.7	67.7	4.4	**9556.2**	33.9	310.8	349.1	10,419.8	9.8
	Cropland	210.0	102.4	28.3	31.7	282.2	**392.5**	2084.2	1466.7	4598.0	4.3
	I-grassland	1213.5	941.2	418.0	132.6	1459.7	1442.0	**14,660.1**	9767.6	30,034.7	28.3
	SI-grassland	1812.5	2609.9	513.1	217.8	3205.7	1758.7	17,821.8	**20,541.9**	48,481.4	45.7
	Total in 2008	4199.4	6449.6	2812.0	740.9	15,983.3	4096.0	37,355.4	34,382.6	**106,019.2**	
	% in 2008	4.0	6.1	2.7	0.7	15.1	3.9	35.2	32.4		100.0

I-grassland, improved grassland (GA); SI-grassland, semi-improved grassland (GS).
The figures in bold represent the number of correctly classified pixels.

Table 6.3. Land use change matrix derived from the PRIME2-SAR_1992–2008 data for Sligo

		Land use in 2008 (ha)									
	From/To	Scrub	Forest	Other	Settlement	Peatland	Cropland	I-grassland	SI-grassland	Total in 1992	% in 1992
Land use in 1992 (ha)	Scrub	**3234.2**	NO	78.8	380.2	1244.9	34.0	3946.2	411.3	9329.6	5.1
	Forest	NO	**9915.4**	102.3	197.8	2662.6	4.0	1288.4	87.8	14,258.3	7.8
	Other (0+3)	119.3	29.6	**1616.1**	47.5	38.5	2.7	313.5	25.8	2193.0	1.2
	Settlement	115.1	32.4	14.6	**182.6**	38.5	4.8	212.3	14.0	614.3	0.3
	Peatland	1783.6	2556.7	22.7	221.5	**31,013.4**	8.8	3409.0	265.0	39,280.7	21.4
	Cropland	11.2	0.8	0.3	0.3	1.2	**NO**	35.2	0.6	49.6	0.0
	I-grassland	4888.9	4101.6	140.2	602.3	4796.3	45.9	**62,184.1**	4407.0	81,166.3	44.1
	SI-grassland	2770.6	3128.5	39.1	327.3	2913.2	39.4	25,798.2	**2008.0**	37,024.3	20.1
	Total in 2008	12,922.9	19,765.0	2014.1	1959.5	42,708.6	139.6	97,186.9	7219.5	183,916.1	
	% in 2008	7.0	10.7	1.1	1.1	23.2	0.1	52.8	3.9		100.0

I-grassland, improved grassland (GA); SI-grassland, semi-improved grassland (GS).
The figures in bold represent the number of correctly classified pixels.

- Some of the polygons defined as forest in the SAR classification were less than 0.1 ha in size, which was not in line with the current forest definition.
- Some of the polygons defined as forest in the SAR classification were encroaching scrubland or gorse-dominated vegetation cover, which were, by definition, not forest land types.

6.2.3 Greenhouse gas calculations

Biomass

The IPCC good practice guidance for LULUCF (IPCC, 2006) recommends that carbon stock changes should be calculated using either the gain–loss or stock change approach. Selection of the appropriate method depends on country circumstances and the availability of activity data (i.e. biomass estimates in this case). The national GHG inventory for LULUCF currently uses the gain–loss approach with country-specific activity data (EPA, 2013):

$$\Delta C_{LB} = \text{A Conversion} \times (\text{L Conversion} + \Delta\text{C Growth}) \quad \text{Equation 6.1}$$

and

$$\text{L Conversion} = (\text{C After}) - (\text{C Before}) \quad \text{Equation 6.2}$$

where:

- "ΔC_{LB}" is the annual change in carbon stocks in living biomass in land converted to cropland, in tonnes of carbon/year;
- "A Conversion" is the area of land converted to cropland, in ha/year;
- "L Conversion" is the carbon stock change per area for that type of conversion when land use is converted to another land use or management regime (i.e. to grassland or conversions between grassland sub-categories), in tonnes of carbon/ha;
- "ΔC Growth" refers to the changes in carbon stocks from one year of growth following transition, in tonnes of carbon/ha;
- "C After" refers to carbon stocks in biomass immediately after conversion to another land use management regime, in tonnes of carbon/ha; the carbon stock immediately before conversion is always assumed to be zero for grassland and cropland conversions because biomass is harvested (or burned) before conversion;
- "C Before" refers to the carbon stocks in biomass immediately before conversion to another land use, in tonnes of carbon/ha.

The activity data applied to the above biomass equation are shown in Table A1.1 in Appendix 1.

Rough grazing/scrub conversion

There are no current guidelines for the estimation of biomass carbon stock changes following transitions to and from rough grazing/scrubland. The default methods all assume a zero net change. However, a review of the literature suggests that rough grazing/scrubland can contain a significant amount of above-ground biomass, ranging from 21 to 32 t biomass/ha (Woodcock and Stephens, 2012). This would equate to a peak biomass value of approximately 13.5 t carbon/ha over a 25-year period, which could represent a significant emission or carbon gain following transition, and is not currently estimated in the Irish national GHG inventory (EPA, 2013). The gain–loss approach for estimating biomass change following conversion of rough grazing/scrubland to cropland, improved or semi-improved grassland is considered to be reasonable based on the following rationale:

- Reverting from rough grazing/scrubland to semi-improved grassland may involve the removal of biomass and regrowth of natural grass species. This means that biomass change would be (0–13.5 t carbon) × (5 t carbon/ha growth).
- Conversion to crop land or reseeding with *Lolium*/*Trifolium* in the case of improved grasslands would involve the total removal of all biomass, including below-ground biomass, because soils would be cultivated. In this case, a root-to-shoot ratio *R* of 0.2 is applied to obtain a total biomass loss, i.e. 13.5 + (13.5 × 0.2) = 16.2 t carbon/ha.
- The gain–loss approach, as depicted in the equation, considers only biomass stock changes occurring in the year that the land use transition occurs, which is the case for grassland and cropland transition from scrublands. However, because it takes a number of years for rough grazing or scrubland to attain a biomass of 13.5 t carbon/ha after conversion from other land use types, the stock change is the most suitable method to use.

The stock change approach was therefore adopted for transitions between grazing land and rough grazing/ scrubland using the IPCC approach with Tier 2 activity data (Table A1.2 in Appendix 1):

$$\Delta C = \Sigma_{ijk} (C_{t2} - C_{t1})/(t_2 - t_1)_{ijk} \qquad \text{Equation 6.3}$$

Where "ijk" refers to different land use transition categories; "C_{t1}" refers to the carbon stock in the pool at time "t1", in tonnes of carbon; and "C_{t2}" refers to carbon stock in the pool at time "t2", in tonnes of carbon.

Dead organic matter

The Tier 1 approach was adopted for DOM, which assumed that this pool is in steady state (i.e. a net change of zero), as it is only a significant pool for forest land conversions. For forest land conversion to crop and grasslands, a net loss of 13.39 t carbon/ha is assumed based on current methodologies used to report deforestation emissions in the national inventory (EPA, 2013).

Mineral soils

Soil carbon stock changes for mineral soils are based on the currently used NGHGIR approaches, as set out using Equation 3.3.3 of the IPCC good practice guidance on LULUCF (IPCC, 2006):

$$\Delta C_{CC}\text{Mineral}_{ij} = [(SOC_{0ij} - SOC_{(0-T)\,ij}) \times A_{ij}]/T \qquad \text{Equation 6.4}$$

and

$$SOC_{ij} = SOC_{REFij} \times F_{LUij} \times F_{MGij} \times F_{Iij} \qquad \text{Equation 6.5}$$

Where:

- "ΔC_{CC}Mineral" is the annual change in carbon stocks in mineral soils, in tonnes of carbon/year;
- "SOC_0" is the SOC stock in the inventory year, in tonnes of carbon/ha;
- "$SOC_{(0-T)}$" is the SOC stock "T" years prior to the inventory, in tonnes of carbon/ha;
- "T" is the inventory time period, in years (the default is 20 years);
- "A" is the land area of each parcel, in ha;
- "SOC_{REF}" is the reference carbon stock, in tonnes of carbon/ha, based on the IFS soil types (see Table 1.3);
- "F_{LU}" is the stock change factor for land use or land use change type (see Table A1.4 in Appendix 1);
- "F_{MG}" is the stock change factor for management regime (see Table A1.4 in Appendix 1);
- "F_I" is the stock change factor for input of organic matter (see Table A1.4 in Appendix 1);
- "i" and "j" are the different land use and soil type strata.

Organic soils

Grassland and cropland containing histosol soils, such as peats, are assumed to emit 0.25 t carbon/ha per year (the default IPCC value), while peaty mineral soils are assumed to emit 0.125 t carbon/ha per year, since the peat depth is less than 30 cm. This is consistent with other land use methodologies used in the national inventory (EPA, 2013). For forest land conversion to other lands located on peat soils, the emission factor is 0.59 t carbon/ha per year and 0.295 t carbon/ha per year for peaty mineral soils (EPA, 2013).

6.3 Results

6.3.1 Inclusion of scrubland class

Post-classification modification of the SAR data to distinguish between forest and scrubland transitions shows that 4% to 7% of the land cover is scrubland in Counties Sligo and Longford (Tables 6.2 and 6.3). As discussed in section 6.2.2, scrubland areas were previously included in the forest category for the SAR and MODIS classification, as is common for many classifications based on satellite images, such as CORINE. However, research shows that inclusion of scrubland in the forest category results in an overestimation of forest cover (Black *et al*., 2009). The implication of this potential misclassification is that land use carbon flux dynamics are not correctly represented for grassland transitions and grazing land management as scrublands should be reported in the grassland category.

There was an approximately 8% decline is grassland (i.e. improved and semi-improved grassland, and scrub) cover for both Counties Sligo and Longford over the period 1992 to 2008. However, most of the grassland transitions occurred within the "grassland

remaining grassland" category, in which there were large transitions between scrub, and improved and semi-improved grassland (Tables 6.2 and 6.3). In 2008 for example, 38% to 48% of the land remaining grassland underwent a change in management that resulted in transitions within grassland sub-categories.

6.3.2 Cropland

Cropland activities for 2008 were estimated to result in net emissions of 614 and 20,048 t CO_2 for County Sligo and County Longford, respectively (Tables 6.4 and 6.5). These emissions were primarily associated with a loss of SOC resulting from land conversions to cropland over the period 1992 to 2008 (i.e. code 5B.2; see Tables 6.4 and 6.5, and Figure 6.1). Grassland to cropland conversions accounted for 82% and 94% of the total CO_2 emissions from the lands converted to croplands for Counties Sligo and Longford, respectively (see Tables A1.5, A1.6, A1.9 and A1.10 in Appendix 1). Other emissions were associated with biomass and DOM carbon losses due to deforestation to croplands (see Tables A1.5, A1.6, A1.9 and A1.10 in Appendix 1). In the "cropland remaining cropland" category, the reduction in emissions from 1992 to 2008 for County Longford was due to a decline in the cropland area on organic soils (Figure 6.1). Cropland activities in County Sligo were negligible (46 to 139 ha; Table 6.4).

6.3.3 Grasslands

Grasslands are the most dominant land cover in Ireland (EPA, 2013), as was observed for Counties Sligo and Longford. From the 2008 GHG profile for grasslands, a significant net removal (sink), varying from 9001 to 20,439 t CO_2 in the study areas, is apparent (Tables 6.4 and 6.5). This represents an average sequestration rate of 0.12–0.17 t CO_2/ha per year. Only a small percentage of the total grassland area in 2008 was derived from other land transitions to grassland since 1992, but the emission profile from the "land converted to grassland" category is very large (Table 6.4 and 6.5). This was due to large biomass

Table 6.4. Comparison of annual net CO_2 emissions/reductions in 1992 and 2008 for County Longford based on the post-classified SAR data and new activity data

		1992		2008		Net–net change [CO_2 (2008–1992)]
Code	Category	Area (ha)	t CO_2/year	Area (ha)	t CO_2/year[a]	
5B	Croplands	4205.6	3217.6	4095.9	20,048.0	16,830.5
5B.1	Cropland remaining cropland	3974.1	571.2	392.4	37.7	–533.5
5B.2	Land converted to cropland	231.5	2646.4	3703.5	20,010.4	17,364.0
5C	Grasslands	79,023.4	27,372.4	75,937.3	–9001.3	–36,373.7
5C.1	Grassland remaining grassland	78,639.7	11,782.9	69,798.6	–5027.1	–16,810.0
5C.2	Land converted to grassland	383.7	15,589.6	6138.7	–3974.1	–19,563.7

[a]Negative values represent a net removal (sink) of CO_2.

Table 6.5. Comparison of annual net CO_2 emissions/reductions in 1992 and 2008 for County Sligo based on the post-classified SAR data and new activity data

		1992		2008		Net–net change [CO_2 (2008–1992)]
Code	Category	Area (ha)	t CO_2/year	Area (ha)	t CO_2/year[a]	
5B	Croplands	47.1	232.4	139.6	847.0	614.6
5B.1	Cropland remaining cropland	38.4	3.4	NO	NO	–3.4
5B.2	Land converted to cropland	8.7	229.0	139.6	847.0	618.0
5C	Grasslands	126,311.7	27,573.8	117,329.2	–20,439.8	–48,013.6
5C.1	Grassland remaining grassland	125,831.6	3472.18	109,648.5	–33,829.2	–37,301.3
5C.2	Land converted to grassland	480.0	24,101.6	7680.7	13,389.3	–10,712.3

"NO" indicates that the activity is not occurring.

[a]Negative values represent a net removal (sink) of CO_2.

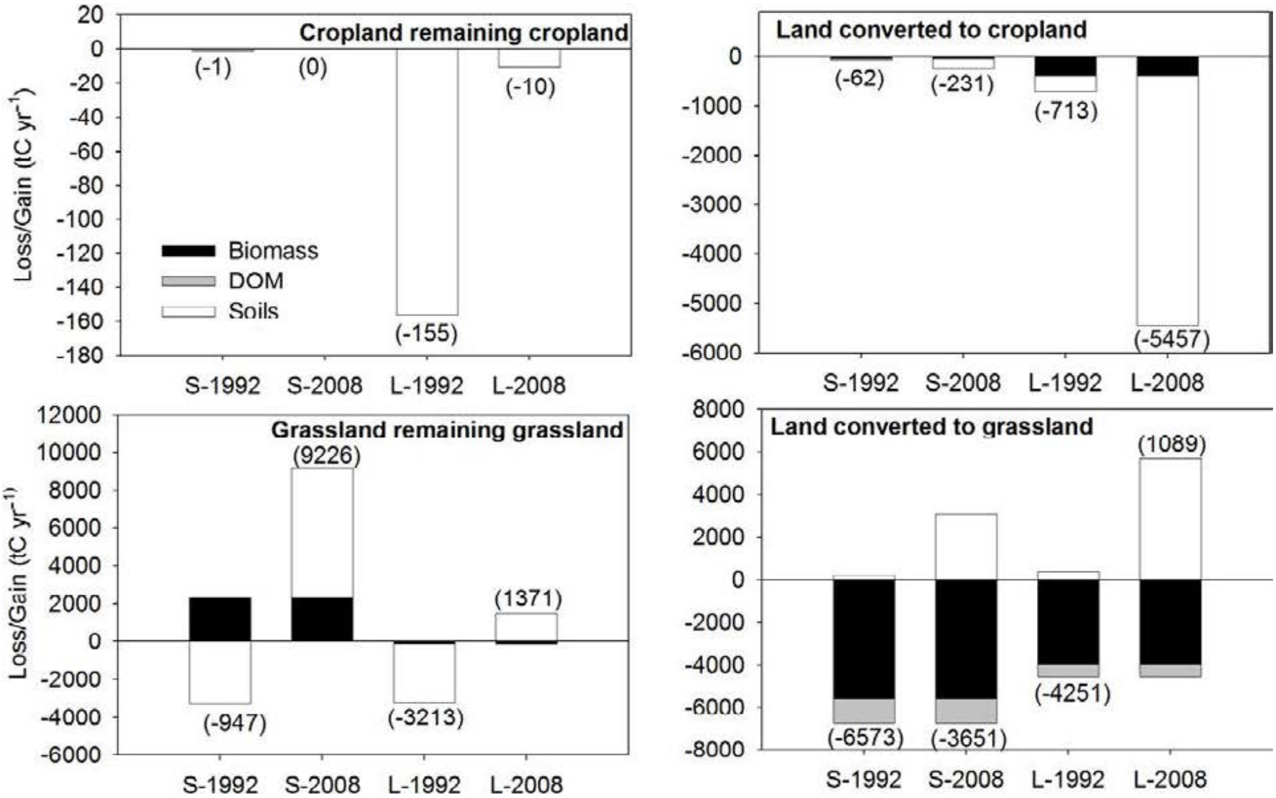

Figure 6.1. Carbon stock changes in the biomass, DOM and soil carbon pools for crop and grassland categories for Counties Sligo (S) and Longford (L) in 1992 and 2008. Negative carbon values indicate a net loss, while positive values indicate a net gain; numbers in parentheses above or below the stacked histograms represent the net total carbon storage value.

losses from deforestation and SOC gains from cropland conversions to grassland (Figure 6.1, see Tables A1.7, A1.8, A1.11 and A1.12 in Appendix 1). For County Longford, most of the conversions to grassland were from cropland (Table 6.2). This is consistent with national trends, which indicate that approximately 78% of land converted to grassland is from croplands (EPA, 2013). However, for County Sligo, most of the conversions to grassland were from wetlands (71%), followed by forest (18%). Therefore, differences between the emission reduction profiles in the lands converted to grassland category for County Sligo and County Longford (see Figure 6.1) are primarily due to the different land use types prior to conversion to grasslands (see Tables A1.7, A1.8, A1.11 and A1.12 in Appendix 1).

A large proportion (51 to 61%) of the "grassland remaining grassland" area did not undergo any management or detectable land cover transition over the study period (Tables A1.7, A1.8, A1.11 and A1.12 in Appendix 1). This means that these land areas, such as "improved remaining improved" grassland, "semi-improved remaining semi-improved" grassland and "scrub remaining scrub" lands, were not subject to a change in management. As a result, there are only potential GHG emissions from organic soils in these sub-categories because biomass and mineral SOC changes are assumed to be in a steady state (i.e. the Tier 1 IPCC default assumption). In 2008, emissions from organic soils were 5741 to 7183 t CO_2 for these sub-categories (i.e. sub-categories 5C.1.1 to 5C.1.3 in Tables A1.8 and A1.12 in Appendix 1).

6.3.4 Land conversions within the grassland remaining grassland category

Land use management within "grassland remaining grassland" (i.e. improved/semi-improved grassland and scrubland transitions; sub-categories 5C.1.4 to 5C.1.9 in Tables A1.8 and A1.12 in Appendix 1) resulted in a net removal of 10,768 and 41,102 t CO_2 in 2008 for Counties Longford and Sligo, respectively. This is equivalent to a net sequestration of 0.3 to 1 t CO_2/ha per year for these sub-categories. Most of the carbon stock changes associated with "grassland

remaining grassland" (Figure 6.1) were associated with land transitions within this category. The increase in the sink capacity of these grasslands is associated with an increase in the biomass carbon stock (for semi-improved to improved grassland transitions, and grassland to scrub conversions) and an increase in mineral SOC, particularly with regard to conversions to improved grassland (Figure 6.1 and Tables A1.8 and A1.12 in Appendix 1).

6.4 Discussion

6.4.1 Greenhouse gas inventory implications

The current methodologies used in national GHG inventory reporting do not estimate emissions/ reductions associated with conversions within the grassland remaining grassland category, such a biomass carbon stock changes. In addition, conversions to and from scrublands were not previously estimated. The remote sensing land cover classification techniques developed in this project, such as those using SAR/PRIME2 and MODIS/ PRIME2 data, together with post-classification techniques, now make it possible to perform a complete carbon balance estimate for these land use transitions. A comparison of implied emission factors (IEFs) derived from the current project and the default national methodology (i.e. NGHGIR) gives an indication of the impact of applying the new methods developed for estimating biomass and SOC in mineral soils (see section 6.2 and Appendix 1) on the national GHG inventory (Table 6.6).

Differences in the IEFs shown in Table 6.6 can be explained by the following findings:

- **Cropland remaining cropland**: The NGHGIR reports on only mineral SOC and suggests that croplands do not occur on organic soils. Based on the data presented from this project, organic cropland soils may represent a significant emission.
- **Land converted to cropland**: The range of IEFs is similar for both methods used, which describe emissions due to the loss of SOC from land that was previously grassland and forest biomass after deforestation.
- **Grassland remaining grassland**: The new methods suggest that this category could be a significant sink because it accounts for all carbon pool changes following transitions within this sub-category (i.e. 5C.1.4 to 5C.1.9). In contrast, the NGHGIR reports only stock changes and emissions from soils.
- **Land converted to grassland**: The NGHGIR does not estimate transitions to and from scrubland. The data in Table 6.3 suggest that there may be significant conversions of wetland to scrub, which would result in an increase in the biomass and soil sink capacity. Cropland to grassland transitions could also result in a significant sink.

6.4.2 Implications for the election of cropland and grassland management under Article 3.4

Ireland has currently elected not to account for cropland and grazing land management under Article 3.4 of the Kyoto Protocol for the second commitment period. The primary reason for this is the lack of historic activity data and uncertainty regarding the estimated emission reductions. The developed methodology presented in this report provides a method to estimate historic, present and future emissions/reductions associated with cropland and grazing land management. The SAR data for 1992 provide reference data from which net–net accounting

Table 6.6. Comparison of IEFs, for the combined biomass, DOM and soil carbon pool, for this project and the current national LULUCF methodology (EPA, 2013)

Code	Category	IEF (t CO_2/ha per year)	
		ILMO	NGHGIR
5B.1	Cropland remaining cropland	0.1 to 0.15	–0.29 to –3.78
5B.2	Land converted to cropland	5.4 to 6.1	2.84 to 5.86
5C.1	Grassland remaining grassland	–0.1 to –0.3	0.06 to 0.08
5C.2	Land converted to grassland	–0.6 to 1.7	–5.8 to –0.01

Negative values represent a net removal of CO_2 (i.e. a sink).

can be estimated with a reasonable degree of accuracy.

If the net–net accounting rule is applied to the data for County Sligo and County Longford, it is estimated that the election of cropland management would have resulted in a net emission of 614–16,830 t CO_2 between 1992 and 2008 for Counties Sligo and Longford (see Tables 6.4 and 6.5). This is equivalent to 0.25–0.28 t CO_2/ha per year. In contrast, the election of grazing land management (i.e. grassland activities) under Article 3.4 would result in Ireland potentially claiming a sink (emission removal unit) of 36,373 to 48,013 t CO_2 between 1992 and 2008 for the two counties (Tables 6.4 and 6.5). This is equivalent to an annual sink of 0.03 t CO_2/ha per year and could equate to a national accountable sink of approximately 1 Mt CO_2 per year, *if the study area is fully representative of all other counties not included in this study.*

Based on these analyses, it would be an advantage for Ireland to elect for grazing land management under Article 3.4, but not for cropland management. The observed trends for land use change to and within the grassland category, in this study, are likely to be consistent with national trends. For example, the NGHGIR suggests that the most prominent land use conversion is from croplands to grasslands (EPA, 2013), which would result in a significant sink. However, the following risks should be considered if grazing land management is elected:

- The new IPCC wetland supplement has revised the current emission factor for organic soil, so emissions under this category are likely to increase.
- Conversions from grassland to other land uses would have a negative impact on the accounted emissions/reductions, particularly if converted back to croplands.

Conversions within the grassland category (i.e. grass–scrub conversions) could result in an emission or a removal depending on the previous land cover/ management (i.e. improved grassland, semi-improved grassland or scrubland). Therefore, any external land use policy that may incentivise the clearing of scrubland for agricultural production may result in an emission from these lands.

7 Conclusions and Recommendations

Research highlights

- Time series of VI composites from MODIS, combined with ancillary ground data, cannot be reliably used to determine intra- and inter-annual variations in land cover and land use given the 250 m spatial resolution of the sensor.
- Microwave imagery proved the most robust of all the data sources explored within this project, and the availability of multi-temporal and multi-configuration C- and L-band data will increase with current and future SAR missions such as Sentinel-1A/B, the Radarsat Constellation and ALOS PALSAR-2.
- The remote sensing techniques developed within this project to generate land cover maps of Longford and Sligo, particularly those using high-resolution SAR data to populate the PRIME2 polygons, together with post-classification techniques, now make it possible to perform a complete carbon balance estimate for grasslands and for transitions into and out of different grassland classes.

7.1 Conclusions

Throughout this project, a number of lessons have been learned with regard to the use of satellite imagery for the mapping of land cover in Ireland, and how the outputs of such land cover maps can be used to inform GHG emissions/removals reporting.

7.1.1 Low-resolution optical time-series data

To capture the dynamics of the vegetation within the Irish landscape, it is necessary to acquire multiple images throughout the year; however, given the challenges of acquiring cloud-free optical images in Ireland, the frequency of data acquisition needs to be high in order to ensure data acquisition under favourable atmospheric conditions. This necessitates the use of daily data, which are acquired at a low spatial resolution and then composited to generate the optimal value within a defined period of time. To meet this goal, 16-day composites of 250 m resolution MODIS VI data were analysed for the period 2001–2013. Automated supervised classification using machine-learning techniques to create annual land cover maps proved to be very accurate in large homogeneous areas. The ERT method proved to be optimal, yielding accuracies exceeding 95%, quick processing times and good usability. However, the use of such low spatial resolution data to generate land cover maps proved to be challenging given the highly fragmented nature of the Irish landscape, and in agricultural and urban areas with small fragmented features and fields, the spatial resolution proved to be insufficient. Nevertheless, the probability values of the classification process were a good indicator of the level of homogeneity within a single pixel. The resolution of the sensor limited not only the spatial detail of the analysis but also the thematic detail of the classification scheme. A distinction beyond level L1 of the ILMO grassland classification scheme could not be accomplished because of the lack of reference data for a 250 m scale. Data fusion techniques proved unable to bridge the gap of spatial–temporal resolutions because of the requirement for multiple cloud-free high-resolution acquisitions, and the inability to model short-term rapid changes, such as silage cutting, correctly.

The optimisation of image acquisition timing and frequency can help to increase the effectiveness of the classification process. Using data from only one optimal acquisition period produced overall classification accuracies of around 80%, which increased to 90% with 8 to 10 images. However, the use of higher resolution optical data is strongly limited in Ireland by the prevailing climatic conditions. Thus, although usable images are acquired by high-resolution sensors each year, the timing and number of acquisitions is highly uncertain and does not necessarily occur during periods of optimal phenological discrimination.

Although there are many benefits of using MODIS data, because of the long time series, high acquisition rate and number of regions within the electromagnetic spectrum where imagery are acquired, there appear to be a number of technical constraints on their use in Ireland. These include an approximately 26% variance in the signal over a time-invariant feature; this cannot be explained, but it is most likely a function of atmospheric effects and geo-location stability.

In summary, time series of VI composites from MODIS, combined with ancillary ground data, cannot be reliably used to determine intra- and inter-annual variations in land cover and land use at the 250 m spatial resolution of the sensor.

7.1.2 Integrating sub-pixel based satellite products into the PRIME2 database

Small fields are a fundamental feature of the Irish landscape and represent a major obstacle to the successful remote sensing of land cover in many parts of the country. As a result, issues caused by multiple intra-field land cover types and shadow effects will always introduce errors and present a seemingly insurmountable barrier to the accurate geo-location of sub-pixel signals at the field scale, even with the use of pre-existing field boundaries. The difficulty of separating the different grassland classes is further compounded by the spectral similarity of the ground components, inherent in the natural continuum that extends from improved to semi-improved to rough grazing lands. Managed grasses are also incredibly dynamic and changeable, and their appearance changes dramatically over a season. Including probability classes from the MODIS time-series analysis improved classification: the differentiation between improved and semi-improved grasslands was about 5% more accurate than it was using the next best available source (which is also nearly 20 years out of date).

In summary, the use of PRIME2 boundaries as objects in classification is a valid approach, but it is clear that there is considerable intra-field variation within many Irish fields and thus ascribing a single land cover tag to a PRIME2 polygon is problematic. A field nominally classed as grassland may contain varying amounts of scrub, trees, hedgerows, bare earth, etc., and within each individual field these may sum to be a considerable source of confusion. These errors are especially compounded in areas with many very small fields and it is highly likely that the intra-field heterogeneity will lead to the whole object being misclassified.

7.1.3 Multi-temporal microwave data

SAR data are less frequently used in land cover classification studies than optical data, yet they can be an important alternative or complementary data source for areas with persistent cloud cover. For the first time, these results have been shown to provide fine spatial resolution land cover classifications for two counties in Ireland, showing the spatial distribution of different grassland classes based on the integration of multi-temporal, multi-sensor C- and L-band SAR and ancillary soils and elevation data. Overall, the high accuracies derived using ERTs, which exceeded 95%, are very encouraging and the presented approach has demonstrated comparable results for two different, large and heterogeneous areas.

The use of ancillary data and more than one wavelength increased the accuracy of the classifications, but, crucially, unlike with the optical data, a much shorter time series of three images can be used successfully, and given the all-weather capabilities of the microwave sensors, the user can be more selective with regard to determining the dates of the imagery to use rather than accepting only those acquired under acquiescent meteorological conditions.

The number of microwave sensors that have been launched is much smaller than the number recording in the optical domain, and very few have a longevity to match the MODIS instruments. Although the focus of this work was on using data from just a single year, a comparative exercise using data from a different instrument demonstrated that it is possible to determine land cover classes from more than 20 years earlier, provided that there is sufficient, good-quality ground data. Although the use of only one, non-optimal wavelength reduced the accuracy with which land cover could be discriminated, the OAs were still acceptable and higher than could be achieved with many optical instruments that were operational during the 1990s.

In summary, it proved possible to reliably classify land cover from microwave data, with the combination of ancillary data and more than one wavelength giving the best results. Microwave imagery proved the most

robust of all the data sources explored within this project, and the availability of multi-temporal and multi-configuration C- and L-band data will increase with current and future SAR missions, such as Sentinel-1A/B, the Radarsat Constellation and ALOS PALSAR-2.

7.1.4 *Calculating greenhouse gas emissions/removals from land cover*

Although the land cover categories used in this project are similar to those used by the NGHGIR (EPA, 2013), a key improvement to the inventory as a result of the project outputs is that spatially explicit data on transitions between grassland categories can be derived with a high level of accuracy. However, significant improvements to satellite-derived classifications, or the post classification of these products, is required to better characterise grassland–scrub–forest transitions. The inclusion of the scrubland category in the land cover classification makes a significant impact on the GHG emission/reduction profile for the LULUCF sector.

For the first time, the 2008 GHG profile for grasslands has been conclusively demonstrated to show a significant net removal (sink), varying from 9001–20,439 t CO_2, in the study areas. This represents an average sequestration rate of 0.12–0.17 t CO_2/ha per year. Only a small percentage of the total grassland area in 2008 was derived from transitions from other land types to grassland since 1992, but the emission profile from the land converted to grassland category is very large. For County Longford, most of the conversions to grasslands were from croplands, which is consistent with national trends, namely that 78% of land converted to grassland was converted from croplands (EPA, 2013). However, for County Sligo, most of the conversions to grassland were from wetlands, followed by forest land. Therefore, differences between emission reduction profiles in the land converted to grassland category for County Sligo and County Longford are primarily due to the different land use types prior to conversion to grasslands. The SAR data for 1992 provide reference data from which net–net accounting can be estimated with a reasonable degree of accuracy. Based on these analyses, it would be advantageous for Ireland to elect for grazing land management under Article 3.4, but not for cropland management.

In summary, the remote sensing techniques developed within this project to generate land cover maps of Longford and Sligo, particularly those using high-resolution SAR data to populate the PRIME2 polygons, together with post classification techniques, now make it possible to perform a complete carbon balance estimate for grasslands, and for transitions into and out of different grassland classes.

7.2 Recommendations

7.2.1 *Investment in Earth observation capabilities*

Radar Earth observation technology will undoubtedly become an integral part of grassland resource management within the next decade, while optical Earth observation technology will continue to be used. SAR approaches offer a better compromise between spatial resolution and cloud-free coverage than optical data; however, this is offset by the higher temporal availability of optical remote data, which is important for capturing annual variation in land use change and associated emissions/reductions. Regardless of the final approach adopted, a land cover product derived from satellite images for the entire country, which goes beyond the existing datasets, is required. This project demonstrated the feasibility of such approaches. With the recent launch of the microwave instrument on the ESA's Sentinel-1A platform, and the promised launches of more microwave and optical instruments in the coming years, this is an opportune time for Ireland to be investing in Earth observation infrastructure and skills.

Earth observation is a very dynamic discipline, and in addition to the Sentinel instruments, the forthcoming availability of S-band data (NovaSAR-S) will present further opportunities, in addition to those already presented by X-band sensors, such as TerraSAR-X and COSMO-SkyMed, which were beyond the scope of this project. The classification of metre-level SAR data could also be considered, with the use of alternative approaches to better define grassland to scrubland conversions based on the pixel-to-pixel variation of backscatter signals within defined boundaries. For example, a more random distribution of biomass within a PRIME2 boundary could be indicative of a transition from pasture land to unmanaged grassland or scrublands. Although this

information is invaluable, it would not be feasible to undertake this at a national scale given the volume of data required.

7.2.2 Development of new processing algorithms

Given the anticipated availability of new data acquisitions, the potential to reduce errors in classification could arise through the continuous ingestion of new images into the processing chain. This would maintain the temporal frequency required to capture the phenological variations in the vegetated landscape, but also allow the machine learning classification algorithms to be constantly improved and refined. For example, the dominance of shadow in some landscapes and its high seasonal variation are possible sources of error in time-series analysis, especially when evaluating phenological phenomena and start-of-season trends. Therefore, consideration could be given to exploring shadow-correction algorithms for optical data as part of any programme of research into time-series analysis.

7.2.3 Access to enhanced computing capabilities

Tests of the potential to upscale the study area from county to national level using MODIS data produced encouraging results. Because of the automation of the image processing chain and the properties of the imagery, it was not necessary to significantly alter the workflow, and if the focus was to be on regional- rather than field-level change this would be a viable annual approach to mapping land cover change. National studies using microwave data were not attempted within the scope of this project because of insufficient data, time and computing resources. The processing of all data within this project was undertaken using Intel Core i3 (dual-core) 4 GB RAM desktop computers. Higher processing power (i.e. quad core) and memory (8 GB) would be required to facilitate the generation of a national scale product efficiently on an operational basis each year. If imagery were to be ingested immediately following acquisition, access to parallel processing computing facilities would be required.

7.2.4 Acquisition of accurate ground reference data

The most significant gap in this, and many other grassland studies, was the absence of high-quality field-scale ground truth data that were exactly contemporaneous with satellite image acquisition. Now that satellite data are widely available for free or at a low cost, the focus for any future grassland classification project is to develop resources to collect ground truth data. Importantly, however, although ecologists may collect the grassland data, this needs to be done in conjunction with Earth observation scientists who have an understanding and appreciation of the limitations of satellite sensors with regard to discriminating discrete vegetation units on the ground. In addition to recording the status and species present within an area of grassland, such field campaigns dedicated to Earth observation could also acquire information on the conditions that impact on the backscatter of SAR pulses (e.g. grass height, moisture content and surface roughness).

In the absence of actual ground truth data, proxy datasets will have to be used; however, this project found that such datasets were limited. New rules on claim criteria for single farm payments will create a LPIS dataset that is more useful for this sort of mapping, but further analyses of these datasets for uses alternative to their originally planned designation are required. This also applies to the OSi PRIME2 dataset, which will need to be updated on a regular, preferably annual, basis, and a history of boundary and function changes also need to be stored, including the ability to roll back to previous iterations.

7.2.5 Policy considerations

The methodology developed by the ILMO project, and presented in this report, provides an approach to estimating historic, present and future emissions/reductions associated with cropland and grazing land management. The observed trends for land use change to and within the grassland category presented in this study are likely to be consistent with national trends; however, national mapping frameworks need to be implemented to assess the implications on a national basis. This is essential for Ireland to fulfil its obligations to the UNFCCC and EU for reporting annual GHG emissions and removals.

7.2.6 Momentum building for product development

Although some of the recommendations may not be fulfilled for some years, it is essential that the momentum and interest developed within the lifetime of ILMO is maintained. It might be preferable to wait for the Sentinel 1 and 2 programmes to be fully operational, thus allowing access to higher resolution microwave and optical data, but it is unlikely that both platforms carrying both instruments will be viable before 2017. As this project has demonstrated, satellite-derived land cover maps will make a valuable contribution to future assessments of Ireland's GHG inventory for the (extended) Kyoto Protocol (2013–2020), EU reporting and other national assessment requirements. If carried out nationally on an annual basis, the lessons learned from this project will stimulate other satellite-derived projects and applications, encourage conversations with researchers and professionals in other disciplines, and continue the growth of and interest in Earth observation in Ireland, which was initiated in 2008.

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Abbreviations

ALI	Advanced Land Imager
ALOS	Advanced Land Observing Satellite
ASAR	Advanced synthetic aperture radar
CO_2	Carbon dioxide
CORINE	Coordination of Information on the Environment
CSO	Central Statistics Office
DAFM	Department of Agriculture, Food and the Marine
DEM	Digital Elevation Model
DMC	Disaster Monitoring Constellation
DOM	Dead organic matter
ERS	Environmental Resources Satellite
ERT	Extremely randomised trees
ESA	European Space Agency
ETM+	Enhanced Thematic Mapper Plus
EU	European Union
EVI	Enhanced Vegetation Index
FBD	Fine beam dual
FBS	Fine beam single
FI	Feature importance
FIPS	Forest Information and Planning System
GA	Improved grassland
GAd	Dry improved grassland
GAr	Reclaimed improved grassland
GHG	Greenhouse gas
GLCM	Grey-level co-occurrence Matrix
GS	Semi-improved grassland
GSdc	Calcareous semi-improved dry grassland
GSdh	Humic semi-improved dry grassland
GSw	Wet semi-improved grassland
HH	Horizontally transmitted–horizontally received
IEF	Implied emission factors
IFS	Irish Forest Soils
ILMO	Irish Land Mapping Observatory
IM	Image mode
IPCC	Intergovernmental Panel on Climate Change
IRS	Indian Remote Sensing
LPIS	Land Parcel Information System
LU	Livestock units
LULUCF	Land use, land use change and forestry
MERIS	Medium resolution imaging spectrometer
ML	Maximum likelihood
MMU	Minimum mapping unit
MODIS	Moderate Resolution Imaging Spectroradiometer
NDVI	Normalised Difference Vegetation Index
NGHGIR	National Greenhouse Gas Inventory Report

NIR	Near-infrared
N_2O	Nitrous oxide
NPWS	National Parks and Wildlife Service
OA	Overall accuracy
OLI	Operational Land Imager
OSi	Ordnance Survey Ireland
PA	Producer’s accuracy
PALSAR	Phased-array L-band synthetic aperture radar
QA	Quality assurance
RF	Random forest
SAR	Synthetic aperture radar
SD	Stocking density
SOC	Soil organic carbon
SPOT	*Satellite Pour l’Observation de la Terre*
SVM	Support vector machine
TM	Thematic Mapper
UA	User’s accuracy
UNFCCC	United Nations Framework Convention on Climate Change
VI	Vegetation index
VV	Vertically transmitted–vertically received

Appendix 1

Table A1.1. Activity data used for different land use categories, based on the gain–loss approach

	AD use in this study			EPA and Tier 1 AD		
Land Use[a]	**C before**	**C after**	**ΔC growth**	**C before**	**C after**	**ΔC growth**
Cropland[b]	5	0	5	5	0	5
Improved grassland[c]	6	0	6	6	0	6
Semi-improved grassland[d]	4[e]	0	2[e]	6	0	6
Rough grazing/scrubland[f]	13.25	0	NA	No AD	No AD	No AD
Settlement[c]	0	0	0	0	0	0
Wetland[c]	3[g]	0	0	3	0	0
Other[c]	0	0	0	0	0	0
Forest[h]	98.25	0	NA	98.25	0	NA

[a]Transitions to rough grazing/scrublands are based on the stock change methodology (see Table A1.2).

[b]Based on IPCC Tier 1 approach. Cropland remaining cropland results in no biomass stock change. The National Inventory Report (EPA, 2013) also assumes all cropland transitions to grassland are assumed to be zero (Tier 1 approach).

[c]Based on country specific activity data used by EPA in current reporting.

[d]Current National Inventory Report method assumes that there is no stock change from conversion of improved to semi-improved grassland.

[e]Tallowin and Jefferson (1999). Note that the ΔC growth value is assumed to be zero for conversion of improved to semi-improved grassland.

[f]The gains loss approach is only used for conversion of rough grazing/scrubland to cropland, improved and semi-improved grassland (see text below for estimation of total biomass change relating to conversion to crop and improved grassland).

[g]The National Inventory Report default, 3 t of carbon/ha accumulate after land use change at a rate of 0.6 t of carbon/ha per year. Wetland to cropland conversion assumed not to occur in the National Inventory Report.

[h]The forestry value is derived from the National Inventory Report. The conversions to settlements, other land and forest land is not considered in this study.

AD, activity data; NA, not applicable.

Table A1.2. The stock change activity data used in this study to calculate biomass stock changes due to land use conversion to rough grazing/scrubland

Land use conversion to rough grazing/scrubland	Stock change in t carbon/ha per year for 25 years
Cropland	(13.25 – 5)/25 = 0.33
Improved grassland	(13.25 – 6)/25 = 0.29
Semi-improved grassland	(13.25 – 4)/25 = 0.37
Settlement	(13.25 – 0)/25 = 0.53
Other	(13.25 – 0)/25 = 0.54
Wetland	(13.25 – 3)/25 = 0.52

Table A1.3. IFS soil types and codes with corresponding world reference soil database definitions and corresponding IPCC SOC_{ref} values used to calculated SOC stock changes in mineral soils

IFS soil description	IFS Code	Included great soil groups	World reference base for soil resources definition	IPCC soil group[a]	SOC_{ref} for wet temperate regions (t C/ha)
Derived from mainly non-calcareous parent materials	11	Acid Brown Earths Brown Podzolics	Protosodic Cambisols	HAC	95
Derived from mainly calcareous parent materials	12	Grey Brown Podzolics Brown Earths	Cambisol, weak Podzolisation	HAC	95
Derived from mainly non-calcareous parent materials	21	Lithosols Regosols	Leptosol and Regosols	HAC	95
Derived from mainly calcareous parent materials	22	Renzinas Lithosols	Redzinic leptosol, Leptosols	HAC	95
Derived from mainly non-calcareous parent materials	31	Surface water Gleys Ground water Gleys	Gleysol	Wetland soils	87
Derived from mainly calcareous parent materials	32	Surface water Gleys Ground water Gleys	Stagnosol	Wetland soils	87
Derived from mainly non-calcareous parent materials	33	Surface water Gleys (Shallow) Ground water Gleys (Shallow)	Gleysol	Wetland soils	87
Derived from mainly calcareous parent materials	34	Surface water Gleys (Shallow) Ground water Gleys (Shallow)	Gleysol	Wetland soils	87
Derived from mainly non-calcareous parent materials	41	Peaty Gleys	Histosol, not defined	Not mineral soils	NA
Derived from mainly calcareous parent materials	42	Peaty Gleys	Histosol, not defined	Not mineral soils	NA
Derived from mainly non-calcareous parent materials	45	Peaty Gleys (Shallow)	Histosol, not defined	Not mineral soils	NA
Derived from mainly calcareous parent materials	44	Peaty Gleys (Shallow)	Histosol, not defined		
Predominantly shallow soils derived from non-calcareous rock or gravels with/without peaty surface horizon	43	Podzols (Peaty) Lithosols Peats	Spodosols	Spodic soils	115
Predominantly shallow soils derived from calcareous rock or gravels with/without peaty surface horizon	46	Lithosols Peats	Dysti-lithic Leptosol	HAC	95
Mineral alluvium	51	Variable	Not defined	LAC	85
Marl type soils	53	Variable	Not defined	LAC	86
Lacustrine–type soils	56	Variable	Not defined	LAC	87
Raised bog	61	Basin Peats	Histozol	Not mineral soils	NA
Blanket peat	63	Blanket Peats	Histozol	Not mineral soils	NA
Cutaway/cutover peat	65	Basin Peats Blanket Peats (some)	Histozol	Not mineral soils Not mineral soils	NA NA
Fen peat	66	Basin Peats	Histozol	Not mineral soils	NA
Scree	70		Not defined	Sandy soils	71
Aeolian undifferentiated	71		Not defined	Sandy soils	71
Beach sand and gravels	72		Not defined	Sandy soils	71
Marine/Estuarine sediments	73		Not defined	Wetland soil	87
Reed Swamp/Marsh	75		Not a soil		

Table A1.3. Continued

IFS soil description	IFS Code	Included great soil groups	World reference base for soil resources definition	IPCC soil group[a]	SOC_{ref} for wet temperate regions (t C/ha)
Made/Built land	74		Not a soil		
Lake (including reservoirs)	76		Not a soil		
Unclassified	77				71

[a]These definitions were derived from IPCC (2006), Chapter 2, Table 2.3.

HAC, high activity clay; LAC, low activity clay; NA, not applicable.

Table A1.4. SOC stock change factors associated with land use types (F_{LU}), management regimes (F_{MG}) and organic carbon inputs (F_I)

Land use	F_{LU}	F_{MG}	F_I
Cropland	0.71	1.09	1.11
Improved grassland	1	1	1.14
Semi-improved grassland[a]	1	0.95	1
Rough grazing/scrubland	1	0.95	NA
Settlement[a]	0.8	1	
Other[a]	0.8	1	
Forest	1	1	1

[a]A total of 20% of SOC is assumed to be lost following land use transition to other land and settlement (EPA, 2013).

NA, not applicable.

Table A1.5. GHG emission/reduction profiles for croplands in County Sligo for inventory year 1992

Category	Description	Area (ha)		Net change in carbon (t)[a]				Total CO_2 (t)[b]
		Total area	Organic area	Biomass	DOM	Soils, mineral	Soils, organic	
5B	Croplands	47.1	8.0	–47.9	–3.3	–11.0	–1.1	232.4
5B.1	Cropland remaining cropland	38.4	6.5	NO	NO	NO	–0.9	3.4
5B.2	Land converted to Cropland	8.7	1.5	–47.9	–3.3	–11.0	–0.2	229.0
5B.2.1	*Forest to cropland*	*0.2*	*1.2×10^{-2}*	*–23.3*	*–3.3*	*–0.4*	*$–1.5 \times 10^{-3}$*	*99.0*
5B.2.2	*Grassland to cropland*	*7.5*	*1.3*	*–28.7*	*NO*	*–9.9*	*–0.2*	*142.5*
5B.2.2.1	Improved grassland to cropland	2.9	0.2	–2.9	NO	–5.8	$–3.4 \times 10^{-2}$	31.9
5B.2.2.2	Semi-improved grassland to cropland	2.5	0.7	–2.1	NO	–2.3	–0.1	16.4
5B.2.2.3	Rough grazing/scrub to cropland	2.1	0.4	–23.8	NO	–1.8	–0.1	94.2
5B.2.3	*Wetland to cropland*	*0.5*	*0.2*	*2.7*	*NO*	*–0.2*	*$–2.0 \times 10^{-2}$*	*–9.2*
5B.2.4	*Settlement to cropland*	*0.3*	*2.1×10^{-2}*	*0.6*	*NO*	*–0.4*	*$–2.6 \times 10^{-3}$*	*–0.7*
5B.2.5	*Other to cropland*	*0.2*	*NO*	*0.8*	*NO*	*–0.1*	*NO*	*–2.7*

"NO" indicates that the activity is not occurring.

Categories in italics are the main classes of conversion to cropland.

[a]The signs used in these tables are based on the UNFCCC common reporting format convention: negative carbon values represent a net loss of carbon and positive values represent a net gain of carbon.

[b]Negative CO_2 values represent a net removal (sink) of CO_2 and positive values represent a net emission of CO_2.

Table A1.6. GHG emission/reduction profiles for cropland in County Sligo for inventory year 2008

Category	Description	Area (ha)		Net change in carbon (t)[a]				Total CO_2 (t)[b]
		Total area	Organic area	Biomass	DOM	Soils, mineral	Soils, organic	
5B	Croplands	139.6	23.7	–47.9	–3.3	–176.4	–3.4	847.0
5B.1	Cropland remaining cropland	NO	NO	NO	NO	NO	NO	NO
5B.2	Land converted to cropland	139.6	23.7	–47.9	–3.3	–176.4	–3.4	847.0
5B.2.1	*Forest to cropland*	*4.0*	*0.2*	*–23.3*	*–3.3*	*–5.7*	*-2.3×10^{-2}*	118.6
5B.2.2	*Grassland to cropland*	*119.3*	*20.6*	*–28.7*	*NO*	*–158.7*	*–3.0*	698.3
5B.2.2.1	Improved grassland to cropland	45.9	3.3	–2.9	NO	–92.9	–0.5	353.2
5B.2.2.2	Semi-improved grassland to cropland	39.4	10.8	–2.1	NO	–36.9	–1.5	148.5
5B.2.2.3	Rough grazing/scrub to cropland	34.0	6.5	–23.8	NO	–28.8	–1.0	196.5
5B.2.3	*Wetland to cropland*	*8.8*	*2.6*	*2.7*	*NO*	*–3.6*	*–0.3*	4.3
5B.2.4	*Settlement to cropland*	*4.8*	*0.3*	*0.6*	*NO*	*–6.8*	*-4.2×10^{-2}*	22.8
5B.2.5	*Other to cropland*	*2.7*	*NO*	*0.8*	*NO*	*–1.7*	*NO*	3.1

“NO” indicates that the activity is not occurring.

Categories in italics are the main classes of conversion to cropland.

[a]The signs used in these tables are based on the UNFCCC common reporting format convention: negative carbon values represent a net loss of carbon and positive values represent a net gain of carbon.

[b]Negative CO_2 values represent a net removal (sink) of CO_2 and positive values represent a net emission of CO_2.

Table A1.7. GHG emission/reduction profiles for grasslands in County Sligo in 1992

Category	Description	Area (ha)		Net change in carbon (t)[a]				Total CO_2 (t)[b]
		Total area	Organic area	Biomass	DOM	Soils, mineral	Soils, organic	
5C	Grasslands	126,311.7	26,959.6	–3307.6	–1149.2	885.6	–3949.0	27,573.8
5C.1	Grassland remaining grassland	125,831.6	26,730.8	2312.0	NO	660.2	–3919.1	3472.2
5C.1.1	Improved remaining improved	97,679.6	18,378.7	NO	NO	NO	–2733.5	10,022.8
5C.1.2	Semi-improved remaining semi-improved	18,199.0	5421.9	NO	NO	NO	–779.3	2857.3
5C.1.3	RG/scrub remaining RG/scrub	7314.2	2174.4	NO	NO	NO	–300.7	1102.7
5C.1.4	Improved to semi-improved	275.4	54.2	–550.9	NO	–187.9	–8.3	2739.3
5C.1.5	Improved to RG/scrub	305.6	69.4	1417.8	NO	–252.2	–10.2	–4236.2
5C.1.6	Semi-improved to improved	1612.4	496.9	3224.8	NO	945.9	–68.0	–15,043.1
5C.1.7	Semi-improved to RG/scrub	173.2	46.1	1025.1	NO	–26.6	–6.5	–3637.4
5C.1.8	RG/scrub to improved	246.6	81.2	–2515.7	NO	177.3	–11.4	8615.8
5C.1.9	RG/scrub to semi-improved	25.7	8.0	–289.2	NO	3.7	–1.2	1051.0
5C.2	Land converted to grassland	480.0	228.8	–5619.5	–1149.2	225.4	–29.9	24,101.6
5C.2.1	*Forest to grassland*	*86.0*	*36.6*	*–7960.2*	*–1149.2*	*29.7*	*–4.9*	*33,310.3*
5C2.1.1	Forest to semi-improved grassland	5.5	3.2	–528.6	–73.3	–0.5	–0.4	2210.6
5C2.1.2	Forest to improved grassland	80.5	33.4	–7431.6	–1075.8	30.2	–4.5	31,099.7
5C2.1.3	Forest to RG/scrub	NO	NO	NO	NO	NO	NO	NO
5C.2.2	*Cropland to grassland*	*2.9*	*0.1*	*14.0*	*NO*	*6.1*	*$–1.6 \times 10^{-2}$*	*–73.5*
5C2.2.1	Cropland to semi-improved grassland	3.5×10^{-2}	NO	–0.1	NO	0.7	NO	–2.3
5C2.2.2	Cropland to improved grassland	2.2	0.1	2.2	NO	4.6	$–1.3 \times 10^{-2}$	–24.9
5C2.2.3	Cropland to RG/scrub	0.7	2.0×10^{-2}	11.9	NO	0.7	$–2.5 \times 10^{-3}$	–46.4
5C.2.3	*Wetland to grassland*	*341.1*	*180.0*	*2042.8*	*NO*	*160.5*	*–23.2*	*–7993.9*
5C2.3.1	Wetland to semi-improved grassland	16.6	8.7	33.1	NO	5.1	–1.2	–135.9
5C2.3.2	Wetland to improved grassland	213.1	125.8	1278.4	NO	127.8	–16.2	–5096.8
5C2.3.3	Wetland to RG/scrub	111.5	45.5	731.3	NO	27.6	–5.8	–2761.2
5C.2.4	*Settlement to grassland*	*21.3*	*4.9*	*99.9*	*NO*	*4.3*	*–0.8*	*–379.2*
5C2.4.1	Settlement to semi-improved grassland	0.9	0.2	–0.9	NO	0.1	$–3.0 \times 10^{-2}$	2.8
5C2.4.2	Settlement to improved grassland	13.3	2.8	39.8	NO	2.3	–0.5	–152.6
5C2.4.3	Settlement to RG/scrub	7.2	1.9	61.0	NO	1.8	–0.3	–229.3
5C.2.5	*Other to grassland*	*28.7*	*7.3*	*184.0*	*NO*	*24.9*	*–1.0*	*–762.1*
5C2.5.1	Other to semi-improved grassland	1.6	0.3	3.2	NO	0.9	$–4.0 \times 10^{-2}$	–14.8
5C2.5.2	Other to improved grassland	19.6	5.5	117.5	NO	21.3	–0.8	–506.4
5C2.5.3	Other to RG/scrub	7.5	1.6	63.2	NO	2.7	–0.2	–240.8

"NO" indicates that the activity is not occurring.

Categories in italics are the main classes of conversion to cropland.

[a]The signs used in these tables are based on the UNFCCC common reporting format convention: negative net carbon values represent a net loss of carbon and positive values represent a net gain of carbon.

[b]Negative CO_2 values represent a net removal (sink) of CO_2 and positive values represent a net emission of CO_2.

RG, rough grazing.

Table A1.8. GHG emission/reduction profiles for grasslands in County Sligo in 2008

Category	Description	Area (ha)		Net change in carbon (t)[a]				Total CO_2 (t)[b]
		Total area	Organic area	Biomass	DOM	Soils, mineral	Soils, organic	
5C	Grasslands	117,329.2	29,013.6	–3307.6	–1149.2	14,159.0	–4128.0	–20,439.8
5C.1	Grassland remaining grassland	109,648.5	25,352.0	2312.0	NO	10,563.4	–3649.2	–33,829.2
5C.1.1	Improved remaining improved	62,184.1	11,700.1	NO	NO	NO	–1740.2	6380.6
5C.1.2	Semi-improved remaining semi-improved	2008.0	598.2	NO	NO	NO	–86.0	315.3
5C.1.3	RG/scrub remaining RG/scrub	3234.2	961.5	NO	NO	NO	–133.0	487.6
5C.1.4	Improved to semi-improved	4407.0	867.3	–550.9	NO	–3007.2	–132.3	13,531.2
5C.1.5	Improved to RG/scrub	4888.9	1110.7	1417.8	NO	–4035.6	–163.6	10,198.7
5C.1.6	Semi-improved to improved	25,798.2	7950.4	3224.8	NO	15,134.8	–1088.5	–63,327.4
5C.1.7	Semi-improved to RG/scrub	2770.6	737.0	1025.1	NO	–425.7	–104.0	–1816.4
5C.1.8	RG/scrub to improved	3946.2	1299.0	–2515.7	NO	2837.6	–182.6	–510.5
5C.1.9	RG/scrub to semi-improved	411.3	127.8	–289.2	NO	59.5	–19.0	911.8
5C.2	Land converted to grassland	7680.7	3661.6	–5619.5	–1149.2	3595.6	–478.8	13,389.3
5C.2.1	*Forest to grassland*	*1376.2*	*585.0*	*–7960.2*	*–1149.2*	*474.7*	*–78.3*	*31,947.7*
5C2.1.1	Forest to semi-improved grassland	87.8	50.4	–528.6	–73.3	–8.1	–6.9	2262.1
5C2.1.2	Forest to improved grassland	1288.4	534.5	–7431.6	–1075.8	482.8	–71.4	29,685.6
5C2.1.3	Forest to RG/scrub	NO	NO	NO	NO	NO	NO	NO
5C.2.2	*Cropland to grassland*	*46.9*	*2.0*	*14.0*	*NO*	*86.2*	*–0.3*	*–367.2*
5C2.2.1	Cropland to semi-improved grassland	0.6	NO	–0.1	NO	0.7	NO	–2.3
5C2.2.2	Cropland to improved grassland	35.2	1.7	2.2	NO	73.6	–0.2	–277.8
5C2.2.3	Cropland to RG/scrub	11.2	0.3	11.9	NO	11.9	-4.0×10^{-2}	–87.2
5C.2.3	*Wetland to grassland*	*5457.6*	*2879.4*	*2042.8*	*NO*	*2568.5*	*–370.7*	*–15,548.7*
5C2.3.1	Wetland to semi-improved grassland	265.0	138.7	33.1	NO	81.9	–19.0	–352.0
5C2.3.2	Wetland to improved grassland	3409.0	2012.3	1278.4	NO	2044.9	–258.4	–11,237.8
5C2.3.3	Wetland to RG/scrub	1783.6	728.4	731.3	NO	441.7	–93.3	–3958.8
5C.2.4	*Settlement to grassland*	*341.4*	*78.6*	*99.9*	*NO*	*68.3*	*–12.8*	*–569.9*
5C2.4.1	Settlement to semi-improved grassland	14.0	2.9	–0.9	NO	2.4	–0.5	–3.7
5C2.4.2	Settlement to improved grassland	212.3	45.2	39.8	NO	36.8	–7.7	–252.6
5C2.4.3	Settlement to RG/scrub	115.1	30.5	61.0	NO	29.1	–4.6	–313.6
5C.2.5	*Other to grassland*	*458.5*	*116.5*	*184.0*	*NO*	*398.0*	*–16.8*	*–2072.6*
5C2.5.1	Other to semi-improved grassland	25.8	4.4	3.2	NO	13.8	–0.6	–60.2
5C2.5.2	Other to improved grassland	313.5	87.3	117.5	NO	341.2	–12.3	–1637.0
5C2.5.3	Other to RG/scrub	119.3	24.8	63.2	NO	43.0	–3.9	–375.4

“NO” indicates that the activity is not occurring.

Categories in italics are the main classes of conversion to cropland.

[a]The signs used in these tables are based on the UNFCCC common reporting format convention: negative net carbon values represent a net loss of carbon and positive values represent a net gain of carbon.

[b]Negative CO_2 values represent a net removal (sink) of CO_2 while positive values represent a net emission of CO_2.

RG, rough grazing.

Table A1.9. GHG emission/reduction profiles for croplands in County Longford for inventory year 1992

Category	Description	Area (ha)		Net change in carbon (t)[a]				Total CO_2 (t)[b]
		Total area	Organic area	Biomass	DOM	Soils, mineral	Soils, organic	
5B	Croplands	4205.6	832.2	–382.6	–23.4	–308.6	–162.9	3217.6
5B.1	Cropland remaining cropland	3974.1	794.8	NO	NO	NO	–155.8	571.2
5B.2	Land converted to cropland	231.5	37.4	–382.6	–23.4	–308.6	–7.1	2646.4
5B.2.1	*Forest to cropland*	*1.8*	*0.6*	*–163.4*	*–23.4*	*–1.8*	*–0.3*	692.6
5B.2.2	*Grassland to cropland*	*223.2*	*35.8*	*–239.5*	*NO*	*–300.5*	*–6.6*	2004.0
5B.2.2.1	Improved grassland to cropland	90.1	11.2	–90.1	NO	–168.1	–2.1	954.4
5B.2.2.2	Semi-improved grassland to cropland	109.9	21.0	109.9	NO	–112.4	–3.8	23.3
5B.2.2.3	RG/scrub to cropland	23.1	3.6	–259.3	NO	–20.0	–0.7	1026.2
5B.2.3	*Wetland to cropland*	4.1	0.5	*8.2*	*NO*	–5.3	*–0.1*	–10.4
5B.2.4	*Settlement to cropland*	2.1	0.5	*10.6*	*NO*	–1.0	*–0.1*	–34.9
5B.2.5	*Other to cropland*	0.3	1.4×10^{-2}	*1.5*	*NO*	–0.1	-1.8×10^{-3}	–4.9

"NO" indicates that the activity is not occurring.

Categories in italics are the main classes of conversion to cropland.

[a]The signs used in these tables are based on the UNFCCC common reporting format convention: negative net carbon values represent a net loss of carbon and positive values represent a net gain of carbon.

[b]Negative CO_2 values represent a net removal (sink) of CO_2 and positive values represent a net emission of CO_2.

RG, rough grazing.

Table A1.10. GHG emission/reduction profiles for croplands in County Longford for inventory year 2008

Category	Description	Area (ha)		Net change in carbon (t)[a]				Total CO_2 (t)[b]
		Total area	Organic area	Biomass	DOM	Soils, mineral	Soils, organic	
5B	Croplands	4095.9	650.8	–382.6	–23.4	–4938.0	–123.7	20,048.0
5B.1	Cropland remaining cropland	392.4	52.3	NO	NO	NO	–10.3	37.7
5B.2	Land converted to cropland	3703.5	598.5	–382.6	–23.4	–4938.0	–113.4	20,010.4
5B.2.1	*Forest to cropland*	*28.0*	*10.3*	*–163.4*	*–23.4*	*–28.0*	*–4.5*	804.5
5B.2.2	*Grassland to cropland*	*3571.0*	*573.0*	–239.5	NO	*807.5*	*–105.5*	18,892.6
5B.2.2.1	Improved grassland to cropland	1442.0	179.2	–90.1	NO	–2689.3	–33.5	10,314.1
5B.2.2.2	Semi-improved grassland to cropland	1758.7	336.2	109.9	NO	–1798.9	–61.4	6418.1
5B.2.2.3	RG/scrub to cropland	370.4	57.6	–259.3	NO	–319.3	–10.6	2160.4
5B.2.3	*Wetland to cropland*	*65.8*	*7.3*	8.2	*NO*	*–84.4*	*–1.8*	285.7
5B.2.4	*Settlement to cropland*	*33.9*	*7.6*	10.6	*NO*	*–15.7*	*–1.5*	24.3
5B.2.5	*Other to cropland*	*4.7*	*0.2*	1.5	*NO*	*–2.3*	-2.8×10^{-2}	3.3

"NO" indicates that the activity is not occurring.

Categories in italics are the main classes of conversion to cropland.

[a]The signs used in these tables are based on the UNFCCC common reporting format convention: negative net carbon values represent a net loss of carbon and positive values represent a net gain of carbon.

[b]Negative CO_2 values represent a net removal (sink) of CO_2 and positive values represent a net emission of CO_2.

RG, rough grazing.

Table A1.11. GHG emission/reduction profiles for grasslands in County Longford in 1992

Category	Description	Area (ha)		Net change in carbon (t)[a]				Total CO_2 (t)[b]
		Total area	Organic area	Biomass	DOM	Soils, mineral	Soils, organic	
5C	Grasslands	79,023.4	20,596.1	–4140.0	–612.5	665.5	–3378.2	27,372.4
5C.1	Grassland remaining grassland	78,639.7	20,489.6	–145.1	NO	284.5	–3352.9	11,782.9
5C.1.1	Improved remaining improved	34,624.2	6514.7	NO	NO	NO	–1166.5	4277.1
5C.1.2	Semi-improved remaining semi-improved	38,917.3	12,546.1	NO	NO	NO	–1974.4	7239.5
5C.1.3	RG/scrub remaining RG/scrub	2982.1	860.2	NO	NO	NO	–120.2	440.6
5C.1.4	Improved to semi-improved	610.5	143.8	–1220.9	NO	–391.9	–25.1	6005.7
5C.1.5	Improved to RG/scrub	75.8	12.9	351.9	NO	–64.9	–2.0	–1044.8
5C.1.6	Semi-improved to improved	1113.9	325.9	2227.7	NO	666.6	–51.9	–10,422.3
5C.1.7	Semi-improved to RG/scrub	113.3	27.6	670.6	NO	–17.8	–4.1	–2378.9
5C.1.8	RG/scrub to improved	101.0	23.6	–1030.4	NO	79.1	–3.7	3501.7
5C.1.9	RG/scrub to semi-improved	101.7	34.7	–1144.0	NO	13.4	–5.1	4164.2
5C.2	Land converted to grassland	383.7	106.5	–3994.9	–612.5	381.0	–25.3	15,589.6
5C.2.1	*Forest to grassland*	*45.8*	*33.2*	*–4311.2*	*–612.5*	*3.5*	*–14.6*	*18,094.3*
5C2.1.1	Forest to semi-improved grassland	19.9	15.0	–1920.5	–266.5	–1.1	–6.6	8047.0
5C2.1.2	Forest to improved grassland	25.9	18.2	–2390.7	–346.1	4.6	–8.0	10,047.3
5C2.1.3	Forest to RG/scrub	NO	NO	NO	NO	NO	NO	NO
5C.2.2	*Cropland to grassland*	*235.1*	*36.2*	*–75.4*	*NO*	*340.6*	*–5.3*	*–952.6*
5C2.2.1	Cropland to semi-improved grassland	91.7	13.5	–275.0	NO	98.2	–2.1	655.8
5C2.2.2	Cropland to improved grassland	130.3	21.7	130.3	NO	229.8	–3.0	–1308.9
5C2.2.3	Cropland to RG/scrub	13.1	1.1	69.3	NO	12.6	–0.2	–299.5
5C.2.3	*Wetland to grassland*	*37.6*	*5.9*	*106.8*	*NO*	*3.2*	*–1.2*	*–398.9*
5C2.3.1	Wetland to semi-improved grassland	12.8	2.3	–12.8	NO	–2.3	–0.5	57.2
5C2.3.2	Wetland to improved grassland	16.5	2.5	49.5	NO	8.6	–0.5	–211.3
5C2.3.3	Wetland to RG/scrub	8.3	1.1	70.1	NO	–3.1	–0.2	–244.8
5C.2.4	*Settlement to grassland*	*44.8*	*27.8*	*183.6*	*NO*	*16.3*	*–3.7*	*–719.1*
5C2.4.1	Settlement to semi-improved grassland	21.8	14.3	43.6	NO	4.6	–1.8	–170.3
5C2.4.2	Settlement to improved grassland	19.4	12.1	116.6	NO	10.7	–1.7	–460.2
5C2.4.3	Settlement to RG/scrub	3.6	1.4	23.4	NO	1.0	–0.2	–88.6
5C.2.5	*Other to grassland*	*20.4*	*3.5*	*101.4*	*NO*	*17.5*	*–0.5*	*–434.1*
5C2.5.1	Other to semi-improved grassland	6.6	1.8	13.3	NO	2.9	–0.2	–58.3
5C2.5.2	Other to improved grassland	11.5	0.6	68.9	NO	14.1	–0.1	–304.1
5C2.5.3	Other to RG/scrub	2.3	1.1	19.2	NO	0.5	–0.1	–71.7

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[b]Negative CO_2 values represent a net removal (sink) of CO_2 while positive values represent a net emission of CO_2.

RG, rough grazing.

Table A1.12. GHG emission/reduction profiles for grasslands in County Longford in 2008

Category	Description	Area (ha)		Net change in carbon (t)[a]				Total CO_2 (t)[b]
		Total area	Organic area	Biomass	DOM	Soils, mineral	Soils, organic	
5C	Grasslands	75,937.3	11,866.6	–4140.0	–612.5	10,647.9	–3440.5	–9001.3
5C.1	Grassland remaining grassland	69,798.6	10,162.0	–145.1	NO	4551.9	–3035.8	–5027.1
5C.1.1	Improved remaining improved	14,660.1	2758.4	NO	NO		–493.9	1810.9
5C.1.2	Semi-improved remaining semi-improved	20,541.9	6622.3	NO	NO		–1042.2	3821.3
5C.1.3	RG/scrub remaining RG/scrub	737.8	212.8	NO	NO		–29.7	109.0
5C.1.4	Improved to semi-improved	9767.6	143.8	–1220.9	NO	–6270.8	–400.9	28,939.7
5C.1.5	Improved to RG/scrub	1213.5	12.9	351.9	NO	–1039.1	–32.7	2639.5
5C.1.6	Semi-improved to improved	17821.8	325.9	2227.7	NO	10,665.9	–830.4	–44,231.6
5C.1.7	Semi-improved to RG/scrub	1812.5	27.6	670.6	NO	–284.1	–65.4	–1177.7
5C.1.8	RG/scrub to improved	1616.3	23.6	–1030.4	NO	1265.2	–58.7	–645.5
5C.1.9	RG/scrub to semi-improved	1627.0	34.7	–1144.0	NO	214.8	–81.8	3707.2
5C.2	Land converted to grassland	6138.7	1704.6	–3994.9	–612.5	6096.0	–404.7	–3974.1
5C.2.1	*Forest to grassland*	*733.6*	*530.8*	*–4311.2*	*–612.5*	*55.8*	*–233.6*	*18,705.4*
5C2.1.1	Forest to semi-improved grassland	319.1	240.1	–1920.5	–266.5	–18.1	–105.7	8472.4
5C2.1.2	Forest to improved grassland	414.5	290.7	–2390.7	–346.1	73.9	–127.9	10,233.0
5C2.1.3	Forest to RG/scrub	NO	NO	NO	NO	NO	NO	NO
5C.2.2	*Cropland to grassland*	*3760.9*	*579.5*	*–75.4*	*NO*	*5449.1*	*–85.3*	*–19,390.8*
5C2.2.1	Crop to semi-improved grassland	1466.7	216.0	–275.0	NO	1571.9	–33.4	–4632.8
5C2.2.2	Crop to improved grassland	2084.2	346.7	130.3	NO	3676.1	–48.6	–13,778.4
5C2.2.3	Crop to RG/scrub	210.0	16.8	69.3	NO	201.2	–3.3	–979.7
5C.2.3	*Wetland to grassland*	*601.1*	*94.0*	*106.8*	*NO*	*50.9*	*–18.6*	*–510.1*
5C2.3.1	Wetland to semi-improved grassland	204.9	36.4	–12.8	NO	–37.3	–7.2	210.2
5C2.3.2	Wetland to improved grassland	264.0	39.6	49.5	NO	137.7	–7.7	–657.9
5C2.3.3	Wetland to RG/scrub	132.2	18.0	70.1	NO	–49.5	–3.6	–62.4
5C.2.4	*Settlement to grassland*	*717.0*	*444.4*	*183.6*	*NO*	*260.4*	*–59.8*	*–1408.5*
5C2.4.1	Settlement to semi-improved grassland	349.1	229.1	43.6	NO	74.2	–29.3	–324.8
5C2.4.2	Settlement to improved grassland	310.8	193.0	116.6	NO	170.8	–27.7	–951.9
5C2.4.3	Settlement to RG/scrub	57.0	22.4	23.4	NO	15.4	–2.8	–131.8
5C.2.5	*Other to grassland*	*326.1*	*55.7*	*101.4*	*NO*	*279.8*	*–7.5*	*–1370.2*
5C2.5.1	Other to semi-improved grassland	106.2	28.5	13.3	NO	45.9	–3.8	–202.9
5C2.5.2	Other to improved grassland	183.7	9.2	68.9	NO	226.4	–1.4	–1077.5
5C2.5.3	Other to RG/scrub	36.3	18.1	19.2	NO	7.6	–2.3	–89.8

"NO" indicates that the activity is not occurring.

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[b]Negative CO_2 values represent a net removal (sink) of CO_2 and positive values represent a net emission of CO_2.

RG, rough grazing.

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

Is féidir obair na Gníomhaireachta a roinnt ina trí phríomhréimse:

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

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

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

Ár bhFreagrachtaí

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

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

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

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

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

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

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

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

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

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

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

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

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The Irish Land Mapping Observatory: Mapping and Monitoring Land Cover, Use and Change

Authors: Fiona Cawkwell, Brian Barrett, Ingmar Nitze, Stuart Green, Kevin Black and Peter Hallahan

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

Background

Advances in remote sensing technologies, data access and processing techniques in recent years have greatly enhanced the resources available to assess land use and land use change at high spatial and temporal resolution. Agriculture is the predominant land use in Ireland. It is estimated that an area of a total of approximately 7.0 million hectares approximately 4.5 million hectares are used for agriculture. Knowledge of other land uses and management practices are not well covered convention data systems, however, this information is critical to understand the long term impact of management on emissions and removals of greenhouse gases in the landscape.

Identifying Pressures

Agriculture, particularly grassland based livestock farming, is the dominant land use in Ireland. There is the potential for removal of carbon dioxide from the atmosphere through good practice in the management of agricultural and other lands. Both the emissions and removal potential need to be quantified at a national level in order to better inform decision making on future land management. Wetlands and drained organic soils are recognised as a potential "hot spot" source of emissions. However, efficient data gathering and analysis tools are required to provide the additional spatial and temporal information required to establish the potential for mitigation of emissions through policies aimed at improved management of these lands.

Informing Policy

Findings from this study indicate that high resolution monitoring of land management using satellite remote sensing is feasible.

The study was also able to identify changes at seasonal and annual timescales, at a spatial resolution which would enable characterisation of regional patterns of grassland management practices.

When combined with existing spatial mapping, it is possible to align vegetative and surface characteristics to field scale, however, this is limited by the highly fragmented nature of the Irish landscape.

The study provides a illustrative example of how one might estimate carbon emissions and removals at a regional scale through the combination the activity data derived from the remote sensing analysis in pilot study areas with the IPCC methodologies.

Developing Solutions

The research investigates identifies the options for advanced analysis of land use and land use management and the impact on emissions and removals of greenhouse gases.

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