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Investigation into the bio-physical constraints on farmer turn-out-date decisions using remote sensing and meteorological data.

Stuart Green

Thesis submitted to the National University of Ireland, Cork, in fulfilment of the requirements for the Degree of Doctor of Philosophy.

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Declaration

I certify that this thesis has not been previously submitted for a degree in this or any other university. This thesis is the result of my own investigations and all secondary sources of information have been acknowledged and references to all literature used have been provided.



_____

Stuart Green

Dedication and Acknowledgements

for Olly

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List of acronyms and abbreviations

AGB, Above-ground biomass

AVHRR, Advanced Very High Resolution Radiometer

BDRF, Bi-Directional Reflectance Factor

CAP, Common Agricultural Policy

CLC2000, Corine Land cover map 2000

CORINE, coordination of information on the environment

CSO, Central Statistics Office

DAFF, Department of Agriculture, Food and Fisheries

DAFM, Department of Agriculture, Food and Marine

DM, Dry matter

DOA, Day of acquisition

DOY, Day of year

DSS, Decision support systems

EAAE, European Association of Agricultural Economists

ED, Electoral district

ENSO, El Niño Southern Oscillation

EM, Electro-magnetic

EO, Earth observation

ESA, European Space Agency

EU, European Union

FADN, Farm Accountancy Data Network

FAO, Food and agriculture organisation

FE, Fixed effects

FH2020, Food Harvest 2020

fPAR, fraction of photosynthetically absorbed radiation

GDD, Growing degree days

GHG, Greenhouse gas

GLAM. Global agricultural monitoring

GMAO, Global Monitoring and Assessment Office

GNSS, global navigation satellite system

GPP, Gross primary production

GPS, Global positioning system

GWR, Geographically Weighted Regression

HISUI, Hyperspectral Imaging Suite

HNV, High nature value

IGBP, International Geosphere-Biosphere Programme

KT, Knowledge transfer

LAI, Leaf Area Index

LSP, Land surface phenology

LSU, Livestock unit

LTA, long term average

LUE, Light Use efficiency

LUT, Look-up table

LULUC, Land Use Land Use Change

LCM2000, Land cover map 2000

LWIR, Long Wave Infra-Red

MERIS, Medium Resolution Imaging Spectrometer

MODIS, Moderate resolution Imaging Spectrometer

MSAVI, Modified Soil Adjusted Vegetation Index

NASA, National Aeronautical and Space Administration

NDII5, Normalised Difference Infrared Index

NDVI, Normalised difference vegetation index

NFS, National farm survey

NIR, Near Infra-Red

NPP, Net primary production

NUTS, Nomenclature of territorial units for statistics

OLS, Ordinary least squares

PA, Precision agriculture

PAR, Photosynthetically Available Radiation

PAV, Photosynthetically-active vegetation

PGSUS, Pasture Growth Simulation Using Smalltalk

PLF, Precision livestock farming

QF, Quality Factor

RAPP, Rangeland and pasture productivity

RE, Random effects

RF, Random forest

RMSE, Root mean square error

RS, Remote sensing

RTE, Radio Telefis Eireann

SAC, Special Area of Conservation

SAR, Synthetic aperture radar

SMD, Soil Moisture Deficit

SPAT, Seasonal progress anomalies in the time domain

SPOT, Satellite Pour l'Observation de la Terre

SR, Stocking Rate

SVI, Standardised vegetation index

SWIR, Short Wave Infra-Red

T, Temperature

TOD, Turn-out date

TVI, Transformed Vegetation Index

UAA, Utilisable agricultural area

UAV, Unmanned aerial vehicle

UK, United Kingdom

USA, United States of Amercia

USDA, United States Department of Agriculture

UN, United Nations

VI, Vegetation index

VLWIR, Very Long Wave Infra-Red

VNIR, Very Near Infra-Red

VP, Vapour pressure

WFD, Water Framework Directive

ABSTRACT

Grass is the most common landcover in Ireland and covers a bigger percentage (52%) of the country than any other in Europe. Grass as fodder is Ireland's most important crop and is the foundation of its most important indigenous industry, agriculture. Yet knowledge of its distribution, performance and yield is scant. How grass is nationally, on a farm by farm, year by year basis managed is not known.

In this thesis the gaps in knowledge about grassland performance across Ireland are presented along with arguments on why these knowledge gaps should be closed. As an example the need for high spatial resolution animal stocking rate data in European temperate grassland systems is shown. The effect of high stocking density on grass management is most apparent early in the growing season, and a 250m scale characterization of early spring vegetation growth from 2003-2012, based on MODIS NDVI time series products, is constructed. The average rate of growth is determined as a simple linear model for each pixel, using only the highest quality data for the period. These decadal spring growth model coefficients, start of season cover and growth rate, are regressed against log of stocking rate ($r^2 = 0.75$, $p<0.001$).

This model stocking rate is used to create a map of grassland use intensity in Ireland, which, when tested against an independent set of stocking data, is shown to be successful with an RMSE of 0.13 Livestock Unit/ha for a range of stocking densities from 0.1 to 3.3 Livestock Unit/ha. This model provides the first validated high resolution approach to mapping stocking rates in intensively managed European grassland systems.

There is a demonstrated a need for a system to estimate current growing conditions. Using the spring growth model constructed for estimating stocking density a new style of grass growth progress anomaly map in the time-domain was

developed. Using the developed satellite dataset and 12 years of ground climate station data in Ireland, NDVI was modelled against time as a proxy for grass growth. This model is the reference for estimating current seasonal progress of grass growth against a ten year average. The model is developed to estimate Seasonal Progress Anomalies in the Time domain (SPAT), giving a result in terms of "days behind" and "days ahead" of the norm. SPAT estimates for 2012 and 2013 are compared to ground based estimates from 30 climate stations and have a correlation coefficient of 0.897 and RMSE of 15days. The method can successfully map current grass growth trends compared to the average and present this information to the farmer in simple everyday language. This is understood by the author to be the first validated growth anomaly service, and the first for intensive European grasslands.

The decisions on when to turn out cattle (the turn out date (TOD)) from winter housing to spring grazing is an important one on Irish dairy farms which has significant impacts on operating costs on the farm. To examine the relationship of TOD to conditions, the National Farm Survey (NFS) of Ireland database was geocoded and the data on turn out dates from 199 farms across Ireland over five years was used.

A fixed effects linear panel data model was employed to explore the association between TOD and conditions, as it allows for unobserved variation between farmers to be ignored in favour of modelling the variance year on year. The environmental variables used in the analysis account for 38% of the variance in the turn out dates on farms nationwide. National seasonal conditions dominate over local variation, and for every week earlier grass grows in spring, farmers gain 3.7 days in grazing season but ignore 3.3 days of growth that could have been used. Every 100mm extra rain in spring means TOD is a day later and every dry day leads to turn out being half a day earlier. A well-drained soil makes TOD 2.5 days earlier compared to a poorly drained soil and TOD gets a day later for every 16km north form the south coast.

This work demonstrates that precision agriculture driven by optical and radar satellite data is closer to being a reality in Europe driven by enormous amounts of free imagery from NASA and the ESA Sentinel programs coupled with open source meteorological data and models and new developments in data analytics.

1. Introduction and overview

1.1 Why Grass?

Grass is fundamental to Ireland. The growing and exploitation of grass has been the bedrock of Irish society and culture since the early Celtic period, when the rearing of cattle was raised to mythological status[1]. This is largely attributed to the fact that Ireland is so favoured for growing grass with a cool temperate western maritime climate with mild, wet winters and warm, moist summers.

Pasture based farming dominates Irish agriculture and its landscape, with 52% of the land mass dedicated to grass growing, comprising 90% of the non-forest agricultural area (O'Mara 2008). Beef and dairy production dominate, with a national herd of approximately 6.5 million cattle. Dairy production is primarily in the south of the country, while beef cattle are concentrated in the west and the north.

Data from the Central Statistics Office of Ireland (CSO) in Table 1.1 show the relative importance of livestock production in the Irish agricultural economy, based on grass as the most important element of the livestock systems (CSO 2015).

Table 1.1: Value at current prices for Irish agriculture, by system and year, CSO 2014

Output (M€)	2007	2008	2009	2010	2011	2012	2013
All Livestock	2378.7	2541.6	2222.8	2282.4	2654.7	3118.6	3169.9
All Livestock Products	1716.1	1681.5	1153.9	1590.9	1894.0	1701.9	2111.8
All Crops	1632.7	1657.1	1377.9	1506.5	1759.5	1896.3	1820.2
Total	5727.5	5880.3	4754.6	5379.8	6308.2	6716.7	7101.9

[1] Táin Bó Cúailnge or The Cattle Raid of Cooley is a pre-Christian legend concerning the attempt by Queen Medb of Connaught to steal the stud bull of ulster protected by the hero Cu Chulainn.

However knowledge, current and historical, of this resource in Ireland, and globally, is fragmentary. There is no detailed nationally complete map of the distribution of grass types (Table 1.2 lists basic grassland communities in Ireland based on Sheridan et al (2011)). These types of grassland are all the result of interplay between agriculture, management and the environment in Ireland and in Section 2 the present lack understanding of the distribution and extent of these communities is explored.

Table 1.2 Dominant grassland types in Ireland from Sheridan et al 2011.

Grass Type	Notes
Intensive	Dominated by *lolilum perenne* (rye grass) & regularly re-seeded
Improved	Dominated by *lolium* but other species found, reseeded perhaps drained
Semi-improved	*Lolilum* and other species, not recently re-seeded
Wet Grassland	*Junctus* (rush) dominated
Species Rich Wet Grassland	Rushes present but with high incidence of herbs/sedges
Transitional	Wholly or partially reverting with scrub
Rough Grazing	Upland natural grasslands kept open/free from scrub through grazing
Meadow	Species rich dry grassland (traditionally used for hay making)
Fen	Ground water fed peat soils, grass/sedge dominant.

There is even less knowledge in Ireland on how these grasslands change and transition on a year on year basis, and there is no map of grass usage or management. How grasslands change and how the dynamics of management influence biodiversity or carbon storage is only now being investigated; for example the CSO provides data on the total amount of land entering and exiting selected categories of grassland use nationally (grazing, rough grazing, silage production and hay making), but the trajectory of land-use change has to be estimated (O'Brien

2007a) and at a parcel[2] level is unknown. Thus the majority of land in Ireland is classed as generic "grass" or "pasture", and the wide variety or landcover, land use and habitat within this class is ignored or not captured. Some information is known on the distribution of farm systems at electoral district (ED) level, and the principal grass based enterprises are shown in Figure 1.1 and Table 1.3, illustrating how areas have changed between 1996 and 2011 (taken from (O'Donoghue et al 2015)).

The values in Table 1.3 are derived from ED level estimates from the CSO national farm census. It appears that there is little change in land use over the period, but these data are designed to record the current conditions in the year of survey so they fail to capture the alternation between pasture and tillage that occurs on some Irish farms. A recent study (in which this author participated) by Zimmermann et al (2016b) demonstrated that areas of cropped land are underestimated by 42% in annual change reports when compared to tracking the entire cropping history of a parcel between the two reporting years.

Table: 1.3: Changes in area covered by major farm land use types between 1996 and 2011 (percentage of area farmed). (Taken from O'Donoghue et al., 2015).

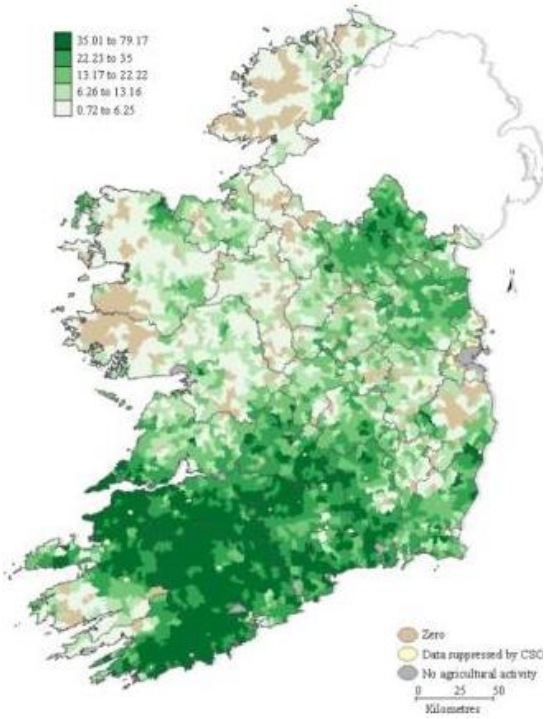
Land Use	Dairy Forage		Cattle Forage		Sheep Forage		Tillage		Forestry	
Year	1996	2011	1996	2011	1996	2011	1996	2011	1996	2011
Soil										
Good	18.5%	17.1%	50.5%	54.5%	10.8%	8.9%	13.2%	14.8%	N/A	1.4%
Medium	16.6%	14.6%	61.7%	64.1%	12.8%	10.8%	2.5%	2.0%	N/A	2.6%
Poor	7.3%	5.4%	44.0%	46.8%	45.8%	32.4%	0.1%	0.0%	N/A	3.8%
Total	16.3%	14.9%	54.2%	57.0%	16.2%	12.3%	7.1%	8.6%	N/A	2.1%

The maps in Figure 1.1 show that dairy production dominates in the south/south-west, beef production in the border, north and north-west, sheep on the coastal uplands and mixed grazing in the midlands. This regionalisation of production

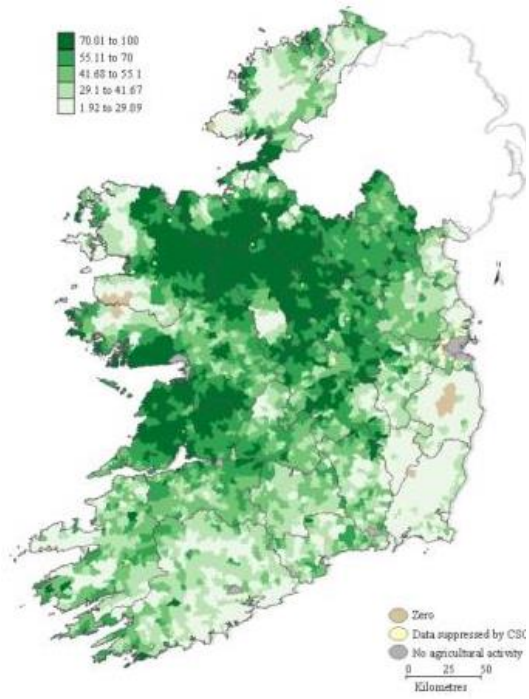
[2] "Parcel" in Ireland is a contiguous area of land under the same management regime, owned by the same farmer; it is not the same as a field or a paddock.

systems is driven mainly by grass season length and soil conditions. Dairy, the most profitable enterprise, dominates in well drained soils (see Table 1.3) in areas with long growing seasons for grass.

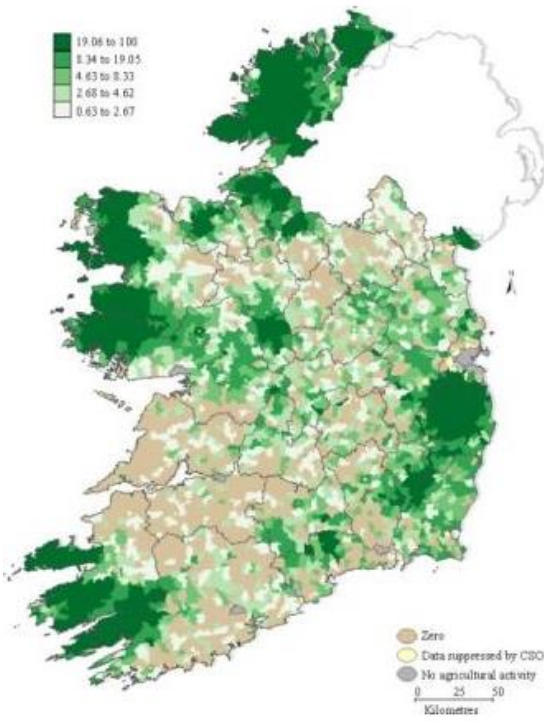
a)Specialist Dairy Farms



b)Specialist Beef Farms



C)Specialist Sheep Farms



d)Mixed Grazing

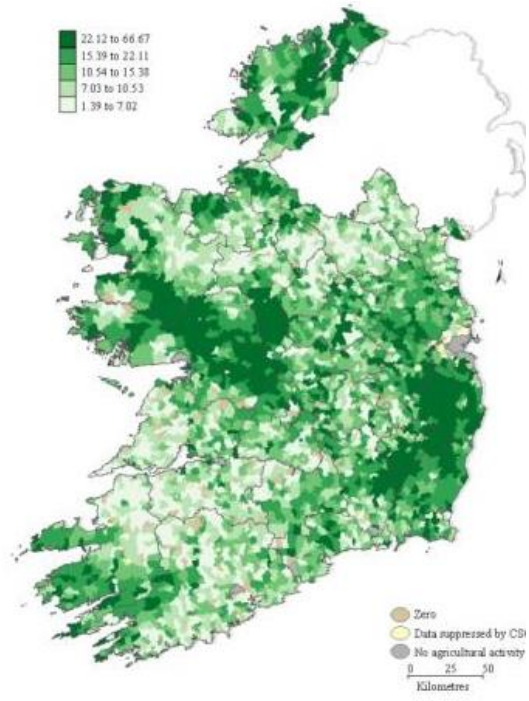


Figure 1.1: Distribution of major grass based farm enterprise types in Ireland.

In more marginal soils where the growing season is shorter, dairy production in these areas cannot compete (milk production is reduced and costs rise as farmers have to provide supplement feed for their animals through a longer winter), and farmers switch to less costly beef production (which is also less risky, if less profitable). It should be noted that Irish dairy production is focused around creamery supplies during the grass growing season with animals dried off (no longer milked) for winter. The production of year round liquid milk for the domestic market is a small percentage (8.5% of total dairy volume annually (National Milk Agency 2014)) of the national dairy output.

In very marginal areas such as uplands, where soils cannot support the traffic of cattle, sheep production dominates. Whereas crop production dominates in the warmer, dryer south-east, with productive well drained soils and a longer autumn than the wetter western region reducing risk around harvest time.

This absence of detailed information on grasslands reflects a general paucity of land cover/use data for Ireland, and as a result it is not possible to state with a high degree of accuracy the detailed spatial distribution of current land use in Ireland. Ireland does not have a national land use database which causes difficulty in correctly estimating areas of crops, monitoring habitats and estimating Greenhouse gas (GHG) emissions. There are a number of projects underway or just completed that attempt to fill in some of the gaps[3].

- Irish Land Mapping Observatory- **ILMO**: This project used optical and radar EO data to produce a hierarchical land-cover classification for grasslands at the field scale driven by a need for better estimates of terrestrial carbon flux. The outputs were land cover maps of grassland within counties Sligo and Longford.

[3] https:\\landmapping.wordpress.com

- Toward Landcover Accounting and Monitoring-**TALAM**: This project used object orientated classification methods to map areas of unenclosed land in Ireland for better land use and change (LULUC) accounting.

These two projects are part of a wider pan-governmental initiative to create a national land cover mapping system, but this aim remains to be formally adopted at a cabinet level. The paucity of detailed knowledge is explored in detail in Sections 2 and 3, but is the compelling reason for this thesis to use remote sensing in the context of managed grasslands to try and fill these knowledge gaps.

Until very recently, knowledge of current conditions of grass growth around the country was very sparse. Weekly records of grass growth, from 6 or 7 sites, are published in the national farming press[4], and the weekly farm weather forecast broadcast on the national broadcaster, RTE, on Sundays would give a "good" or "bad" forecast for grass growth in the coming week.

In 2014 Teagasc, the Irish national agency for agriculture and food research launched PastureBase[5] an online service for recording grass measurements from farms. By recording grass growth covers (as measured by the farmers), feed budgets and other variables (see Section 2.2) can be calculated. Whilst this has the potential to be very useful in understanding grass growth nationally, the figures are self-reported and by 2015 only 150 farmers were using it form a population of 105,000 farmers. Originally the data were captured without a geospatial tag but this is due to change and the farm location will be recorded in the future (the absence of geocoding precludes these data from being used in this research).

However, even if PastureBase becomes a step change in the detail of the understanding of current growing conditions in Ireland, there will always be only a small percentage of Irish farmers contributing their data. As Section 2.2.3 shows,

[4] "Grass Watch", the Irish Farmers Journal

[5] https://pasturebase.teagasc.ie/

the majority of Irish farmers do not measure grass growth or use computer based farm management tools. How to fill the geospatial and temporal gaps and how to find out how grass is growing and being managed is the principal goal of this thesis. The problem can best be addressed by the use of Earth Observation technologies.

1.2 Earth Observation

Remote sensing is the art and science of monitoring targets from a distance, and Earth Observation is the particular branch of remote sensing that attempts to use satellites and airborne sensors to map and monitor earth system processes. It has a long history of over 40 years as a tool for monitoring land use, land cover and agricultural systems.

EO is employed because it provides a holistic, unbiased and repeatable set of observations. Importantly satellites can observe a wide area regardless of access issues making the production of mapped data simple in a county such as Ireland with its very fragmented, diverse land ownership structure, strong rights to property and no right of access.

Section 2 will explore the history of EO of grasslands and Sections 3 and 4 will explain why the system used in this research (the NASA MODIS sensor carried on the Terra and Aqua satellites) was selected.

1.3 Agriculture Context

Applied agricultural research operates within a broad policy framework, encompassing national research agendas but also national policies on the farming industry and food security. Within Ireland, Food Harvest 2020 (FH2020) (DAFF 2011) was an important policy statement from the Department of Agriculture for the 2010-2020 period of Irish Agri-Business. It identifies specific targets, actions needed to achieve these targets, and benchmarks by which success can be

measured. Many of the actions identified and the goals set are dependent on sensor technologies, such as those provided by satellite EO. The broad goals for "*Smart, Green, Growth"* are shown here, with those relevant to this work highlighted in bold:

- **Prioritise R&D**
- **Improve skill levels**
- **Maximise adoption of best practice**
- Foster creativity and entrepreneurship
- Rationalise and collaborate at industry level
- Improve focus on consumer preferences
- Review institutional support and regulatory burden
- **Prioritise environmental protection**
- **Capitalise on natural advantages and resources**
- **Build environmental credibility through research and actions**
- Develop an umbrella 'Brand Ireland'
- Satisfy consumer requirements and preferences
- **Conserve biodiversity**
- **Align sustainability across the supply chain**

The report is presented in the context of the abolition of dairy quotas across the European Union (EU). Dairy quotas were introduced as part of the Common Agricultural Policy (CAP) in 1984 to manage excessive production under the old payment system leading to costly price subvention measurements and creation of "food mountains". Under the quota, each Member State was given a reference quantity, with each farmer in turn having an individual reference quantity (set at 1983 levels for Ireland). Under the quota, dairy prices were maintained above world dairy market prices (Donnellan et al 2015).

However, since April 1st 2015 the quota has been abolished and FH2020 projects milk production in 2020 to be 50% higher than in 2010. This is likely to put stress on

farm systems and sustainability as the static land market in Ireland means more milk is to be produced from a fixed reservoir of land (not with-standing the likelihood of some beef producers converting to dairy). This in turn leads to the question of how food production can be sustainably increased globally to meet the needs and demands of a growing population.

A recent international commission (Beddington et al 2012) looking at global sustainable food production, had, as one of its 7 recommendations :

> *"Create comprehensive, shared, integrated information systems that encompass human and ecological dimensions."*

And it concludes that this should be driven by smart earth observation and geospatial technologies.

1.3.1 The "Fodder Crisis"

Soon after the research on this PhD started, a dramatic agri-climatic event put the aims of the work in focus.

The normal routine in Irish pastoralism (see section 2.2) of animals grazing in open fields from early spring to late autumn, before being brought into cattle sheds to spend a short winter (2-4 months) being fed silage or hay, and then being released the following spring was disrupted.

The summer of 2012 was warm and very wet (Met Eireann 2012b), see Figure 1.2, and there were indications in July that the national fodder harvest (grass cut and put into storage from May as silage to feed cattle over winter) was low. A cold autumn saw grass growth halt and cattle housed early. The spring of 2013 was the wettest and coldest for 70 years meaning that cattle could not be turned out to graze as no grass had grown since the autumn.

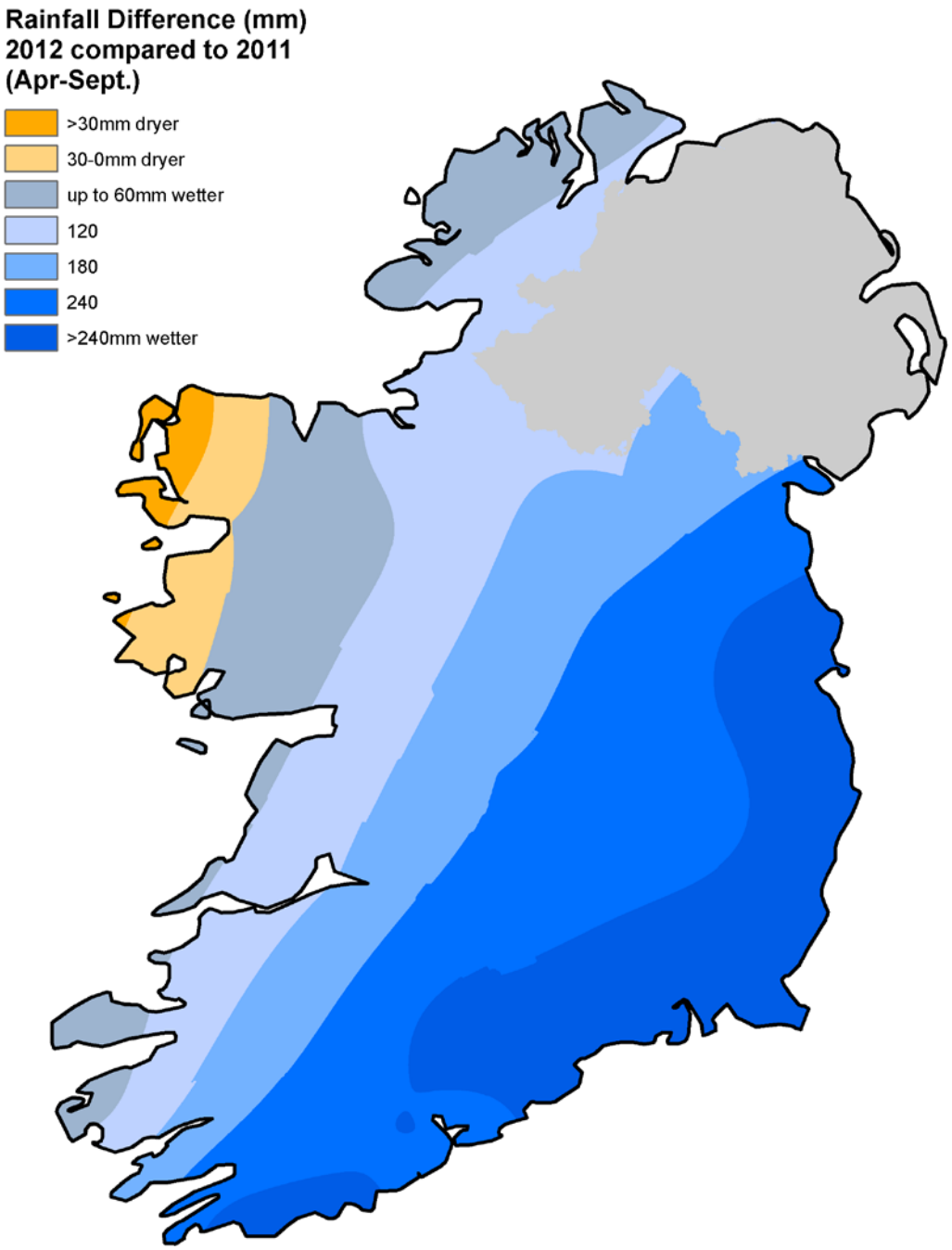


Figure 1.2: Variation in rainfall amounts 2012 compared to 2011. 15 Climate station rainfall records were compared and the results krigged across a simple 2D surface.

What became known as the fodder crisis became public from March 2013 as it became clear many farmers were running out of fodder and animal welfare was an issue. Headlines such as "*Fodder crisis sees cows starve to death*" began to appear in April (Dermody 2013). Government supported schemes to import fodder were

set up and continued into June, with a national effort seeing all available fodder (for example, road side verges, parks, airports) being harvested. An inter-agency task force was established including representatives from Teagasc, the Department of Agriculture, Food and the Marine and other public and private stakeholder bodies.

It became clear that there was no national monitoring of fodder stocks on an official basis and no way of knowing how much fodder had been stored the previous winter. A fodder census was put in place (1000 respondents) in July 2013 to try and develop a national picture for the following winter, revealing that two thirds of farmers at that point had not made up the feed deficit (Kavanagh 2013). Unfortunately, as is often the case once a crisis passes, the fodder census has not continued so there is again no formal measure of the amount of grass in storage each autumn. The full financial and societal impact has yet to be measured (Hanrahan et al 2014b).

The fodder crisis highlighted that, from a national perspective, up to date information on actual grass growing conditions is needed and, as a number of commentators highlighted, increasing weather volatility coupled with increasing stocking density in response to policy changes (the drive to expand milk production in response to the lifting of milk quota) and global food demands make future fodder crises more likely (Flood 2013).

1.4 Research Questions

In north-western Europe there are specific challenges in how best to manage grasslands for supporting likely increases in European production of dairy, beef and food-products to sustainably feed a growing world population. Grassland farmers face daily challenges in trying to manage best practice in measurement of grass, calculating feed demand, grass-budgeting and forward planning. In part to address this, the three questions to be answered in the research are:

- Can the effects of grass management be observed using medium resolution (250m) optical satellite imagery, for example can intra-class variation in the "grassland" category be refined?
- Can current intensive grass growing conditions be assessed by satellite, for example how well is the grass growing now compared to previous years?
- Can management decisions be predicted from observed conditions, for example how efficiently are farmers using the grass that's growing?

1.5 Thesis structure

The answers to the questions in section 1.4 form a set of solutions that begin to explain how Irish pasture management can be integrated into the Precision Agriculture (PA) paradigm to provide useful information directly to the farmers on the ground, enabling them to make better decisions in a more timely manner for managing their grassland based enterprise.

In Chapter 2 the literature is reviewed in order to place the remote sensing of managed grasslands in the context of the much wider literature of environmental Earth Observation. The section aims to show that enclosed grasslands[6] as a managed agronomic resource has been relatively ignored by the EO and PA communities. The section goes on to highlight global information gaps on managed grasslands and the consequences for understanding of biodiversity loss and carbon dynamics that this has entailed. The section shows that temperate managed grass landscapes are an extremely complex system to observe. Finally it suggests that grassland being outside of the existing PA paradigm has put the continuation of open grazing systems for the production of dairy and meat at risk and this should be addressed.

[6] Simply grass lands that are divided and managed as fields or paddocks, enclosed within fences or hedgerows, as opposed to open rangeland grasses where animals are free to graze

Chapter 3 looks at the satellite data used and explains the extensive data processing needed to produce a 10 year data set that can be used for EO of grassland in spring in Ireland given the prevailing cloudy conditions. This data set is used to produce a national spring growth model for Irish grasslands. It is hypothesised that highly stocked farms (with lots of animals per hectare) will be managed to produce good spring grass covers. This hypothesis is successfully tested to produce a national map of stocking density, validated against farm level stocking data. This is the first time such a map has been produced in Europe and goes some way to answer data gaps identified internationally in Section 2.

In Chapter 4 the spring grass growth model is further exploited to answer issues raised by the fodder crisis. The spring growth model allows for a growth anomaly map to be produced comparing current conditions to the 10 year average. This form of anomaly mapping is common in crop growth models but is usually presented as a percentage difference from the norm and is not validated. Here, for the first time, a growth anomaly map is validated (against temperature data from meteorological stations in Ireland) and the data are presented in a farmer friendly manner. A beta level public online service was trialled in 2015 and is presented here.

In Chapter 5 the extent to which current growing conditions inform farmer behaviour is examined to understand the implications of a service such as that developed in Section 4. The key factors determining the date when cattle should be "turned out" (released from their winter housing to graze for the first time in spring) are examined. Five years of turned out dates from 199 geocoded farms along with satellite data on grass growth and rainfall data from the national rain-gauge network are used within an econometric panel data model to see how responsive farmers currently are to changing conditions (both changes between years and current condition in each spring).

Finally Chapter 6 brings these separate analyses together, examines the implications of the results, and suggests a research plan to develop national scale

PA tools for the Irish dairy industry that can be scaled across temperate Atlantic Europe.

1.5.1 Publications

Chapter 3 is an expanded version of a paper published as: Green, Stuart, Fiona Cawkwell, and Edward Dwyer. "*Cattle stocking rates estimated in temperate intensive grasslands with a spring growth model derived from MODIS NDVI time-series*." **International Journal of Applied Earth Observation and Geoinformation** 52 (2016): 166-174. (Green et al 2016)

Chapter 4 is an expanded version of a paper published as: Green, Stuart, Fiona Cawkwell, and Edward Dwyer. "*A time-domain NDVI anomaly service for intensively managed grassland agriculture*." **Remote Sensing Applications: Society and Environment** 11 (2018): 282-290.

Chapter 5 is and expanded version of a paper published as: Green, Stuart, Fiona Cawkwell, and Edward Dwyer. "*How current environmental and weather conditions affect time critical decision making on Irish dairy farms*." **International Journal of Agricultural Management** 7.1 (2018): 1-9.

These three outputs where authored by Green S., Cawkwell F. and E Dwyer. All design, analysis and writing was done by S. Green, and the papers were all initiated and conceived by S. Green. F Cawkwell and E Dwyer provided oversight and copy editing.

2. Literature Review

This review examines the actual and potential role of earth observation (EO) technologies in the management of enclosed improved grasslands; fenced fields or paddocks. The review first places EO of grass management in the wider context of EO of grassland ecosystems and rangelands. It then brings the focus down to paddock grassland management by defining terms and looking at what it means to manage paddocks on the ground. Subsequent sections examine research in EO for each management issue in turn: Herd management and grazing, fodder production and quality monitoring, and sustainability. Finally current operational systems are reviewed and future operational systems identified. The aim of the review is to place the research presented here into context by identifying a need for better remotely sensed information regarding improved grasslands, and demonstrate a gap in the literature regarding mapping in improved enclosed temperate agricultural grassland landscapes as found in Northern Atlantic Europe, Ireland and the UK in particular.

2.1 Earth Observation and Grasslands

2.1.1 Introduction to Earth Observation

Remote sensing is the art and science of monitoring targets from a distance and the work presented here exploits optical based systems.

Light is a form of electromagnetic (EM) energy that radiates from the sun. The energy propagates as electromagnetic waves and these waves are made up of magnetic and electric components. They have a wavelength (λ) and a frequency (ν) that are inversely related and measured in Hertz (Hz):

$$c = \lambda.\nu \qquad \text{eq. 2.1}$$

Where **c** is the *speed of light* (which is constant in any given medium). The energy contained in EM is proportional to the inverse of wavelength. At 400nm, blue light has the shortest wavelength of visible light and thus has the highest energy, and at 700nm red light has the longest wavelength and the lowest energy. Just beyond red light lies the Near Infra-Red (NIR) region which is important in the detection of vegetation from EO (Figure 2.1) and beyond that the Shortwave Infra-Red (SWIR), Medium Wave Infra-Red (MWIR) and the Long wave Infra-Red (LWIR).

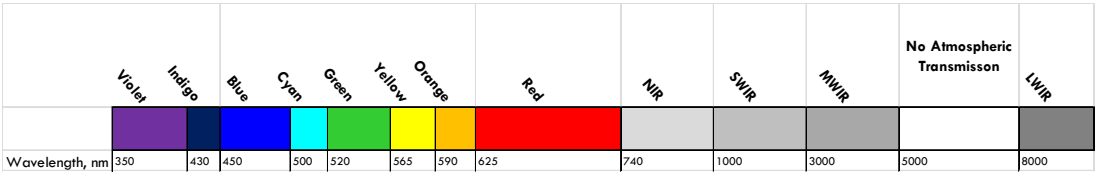


Figure 2.1: The optical Earth Observation electromagnetic spectrum (beyond 1000nm, not to scale)

The light used in EO is, in the main, sunlight, which passes through the atmosphere and reflects off the surface back to the sensor (mounted on aerial or space platforms). In passing through the atmosphere the transmission, absorption and scattering of the light introduces distortion that is countered by atmospheric correction algorithms. In the case of the MODIS sensor data, as shown in Section 3, this is performed automatically by the data providers. These processes are wavelength dependent, with some wavelengths absorbed more than others, some transmitted better than others, and some scattered more than others due to the quantised nature of the processes crudely sketched here.

At the ground the light is either absorbed or reflected (the total amount of reflection is the object's brightness or albedo, and the selective reflection of different wavelengths is the object's colour). Instruments on orbiting satellites are able to record this reflected light as images across several bands, or ranges of wavelength, capturing the spectral absorption characteristics of the target. The image is recorded and stored as pixels, each pixel recording the amount of energy reflected back to the satellite from the area of ground imaged by that pixel, across the wavelength range of the system.

Figure 2.2 shows the reflectance spectra of grass, soil and forest in the visible to NIR spectrum, with the reflectance (the percentage of downwelling energy reflected in a given wavelength) in the NIR much higher than the visible, meaning vegetation is bright in this part of the spectrum. Data from high resolution satellites such as QuickBird are able to capture detail at 2.4m resolution allowing for a greater degree of refinement when looking at vegetation reflection variation across or between images (see Figure 2.3).

As well as spatial resolution (the smallest resolvable separation between objects) and spectral resolution (the number and width of bands in the sensor recording ranges of wavelengths), temporal resolution, how frequently the system revisits a given location, needs to be considered, as well as the image size or swath width, which determine how many images will be needed to cover the area of interest.

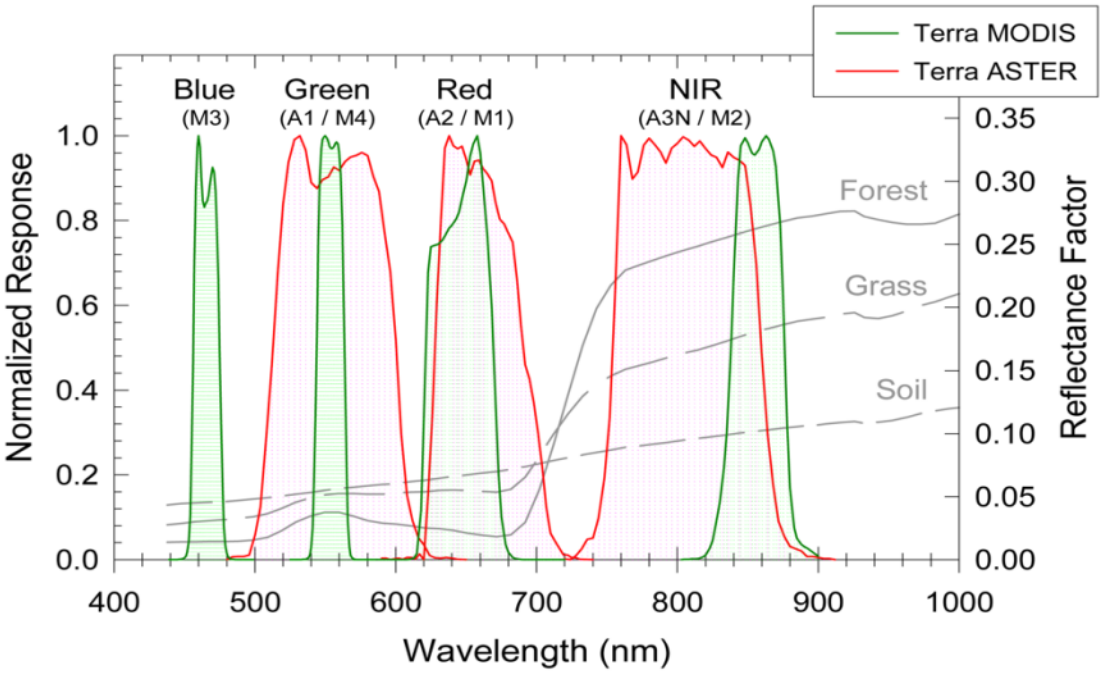


Figure 2.2:The wavelength regions recorded by the MODIS instrument (in Green) across the visible and NIR spectra (from (Miura et al 2008). Also shown are idealised reflectance curves for forest, grass and bare soil targets.

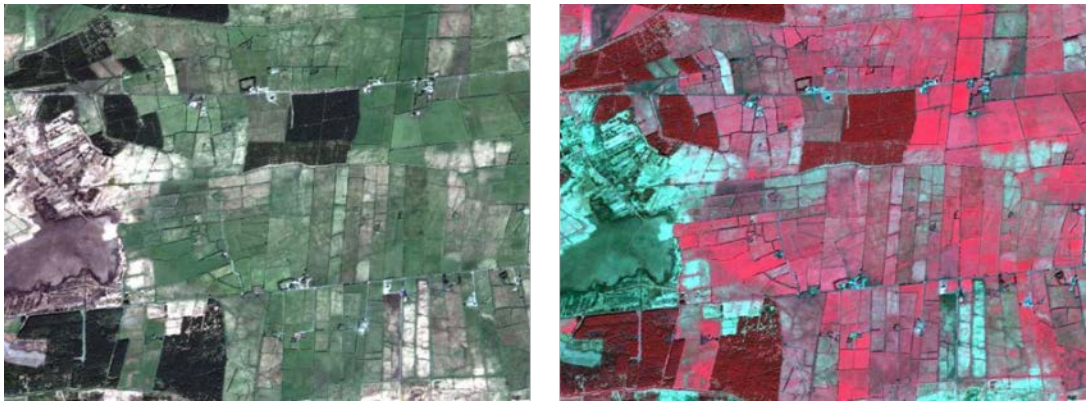


Figure 2.3: A QuickBird Image from County Roscommon (NW Ireland) shown in natural colour (blue, green and red wavelengths) and false colour infra-red (green, red and NIR wavelengths).

2.1.2 Vegetation Indices

One of the products generated using EO data are vegetation indices (VI), the ratio of the reflected red and near infra-red energy. Healthy vegetation strongly absorbs red light, and thus only weakly reflects it, but NIR light is reflected strongly by vegetation. The absorption of red light is due to chlorophyll pigments in the leaf which play an important role in photosynthesis therefore strong red absorption indicates active plant growth. The strong NIR reflection is a function of the structure of the leaf surface, thus a high degree of NIR reflectance indicates a lot of leaves and is also influenced by leaf and canopy structure and the process of evapotranspiration. Thus the simple ratio of red and NIR radiation is closely linked to most of the fundamental biophysical processes in living vegetation.

The normalised difference vegetation index (NDVI) is an adapted version of the simple ratio, with spectral reflectance in the red (around 650nm) and NIR (around 900nm) radiation normalising the output from -1 to 1.

$$NDVI = \frac{NIR-RED}{NIR+RED} \qquad \text{eq. 2.2}$$

No vegetation (e.g. bare rock, soil, man-made surfaces) has an NDVI value typically around 0 or less, but lush, well growing vegetation (Figure 2.4), like grass in Ireland in May, has a high value approaching 1 (values approaching -1 are typically open water). NDVI is just one of scores of indices developed over the last 30 years for analysis of environmental conditions from satellite sensors, and nearly all the

papers in this review rely on measuring reflected light from plants and most will use some form of vegetation index (see Viña et al (2011) for a current overview).

However it should be noted that each satellite sensor or hand held device records over different wavelength ranges, even if they might be labelled as the same radiation type, so NDVI values are not strictly comparable across systems (see Glenn et al (2008) for a more critical overview of VI and their application).

VI have long been exploited operationally from a variety of sources, for example the Climate Change Initiative (CCI) service from ESA[7], provides global VI profiles representing typical growth from 2003-2012 (the operational period of the Medium Resolution Imaging System, MERIS system providing the data) for every 300m pixel indicating the likely land cover.

2.1.3 Introduction to grasslands

Grasslands, defined broadly as "*ground covered by vegetation dominated by grasses, with little or no tree cover*" cover up to 40% of the terrestrial area of the planet (excluding areas of permanent snow/ice cover) (Suttie et al 2005).

This study is primarily concerned with managed, enclosed agricultural grasslands (*c.f.* "*cultural grassland*" (Dixon et al 2014)), but this review will begin with a more expansive definition focusing on land-use: namely grasslands as grazing lands for managed herds of animals. Grassland use typologies can be split into different, often overlapping, categories (this discussion on typologies is a distillation from Suttie (2005) and (Semple 1956)). On extensive, largely natural, systems the level of management can be minimal with nomadic herders following the seasonal progression of natural vegetation. The herds are composed of animals best suited to the climatic conditions; from reindeer in the extreme north to camels near the equator. This can be thought of as a managed exploitation of a natural resource, a land use. Much of the literature on EO of grasslands is related to monitoring this land use, its impact on the grassland ecosystem, and land use change as more

[7] http://maps.elie.ucl.ac.be/CCI/viewer/

intensive grassland management is introduced or land is converted to arable production.

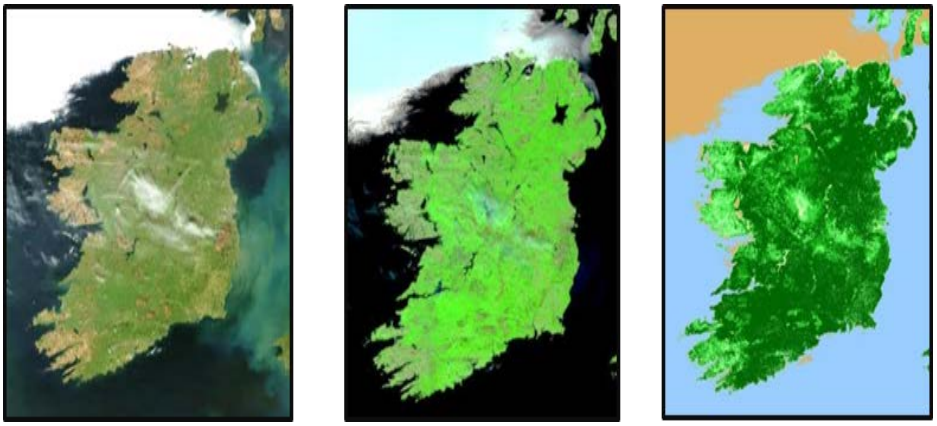


Figure 2.4: MODIS data for the same acquisitions (May, 2007) presented as natural colour (left), false colour and vegetation index.(higher VI represented as darker green).

Transhumance, the movement of animals between winter and summer pasture, can be thought of as a hybrid of extensive natural grazing and more intensive pasture management. Once common throughout the world, it remains now principally in alpine regions[8]. In the summer animals would be moved from lowland farms to take advantage of fresh mountain grass, whilst the smaller lowland/valley homestead would produce hay and fodder for the winter. This allowed small farms to support a much larger herd than their size would suggest.

As herders attempt to control more of the grassland environment, grassland management becomes an issue of agronomy. In extensive systems, the level of management principally revolves around controlling of grazing pressure on the natural system, and even large ranch type operations in rangelands would fall at this end of the spectrum. Once attempts are made to control more than this, then the herder increasingly becomes the farmer, until intensive grassland dairy production systems are reached, with tightly controlled paddocks of highly improved mono-cultural planted swards. Table 2.1 , adapted from Pearson and Ison

[8] In Ireland the seasonal movement of cattle was known as *booleying:* common before WWII it is now no longer practiced (Mitchell F, Ryan M. 2001. *Reading the Irish Landscape*. Ranelagh, Dublin: TownHouse)

(1997), shows the environmental factors, from the grass perspective (not the herd), to be considered in an agronomic approach to grasslands. EO technologies can play a role in the management of all the factors identified, including climate where EO is an essential tool in weather forecasting, allowing the farmer to manage risk associated with weather events.

Large scale studies of grassland ecosystems form the entry point into the literature on EO of grasslands. Extensive grazing systems exploiting large areas of natural grasslands such as the South American pampas, North American prairie and the Eurasian steppes have been the focus of many of the studies in EO of grasslands. The principal drivers of monitoring have been to measure land use change (grassland to cropland or forestry), to measure ecosystem impacts (erosion, habitat loss, desertification) and to examine grasslands' role in global carbon budgets.

Table 2.1: Levels of control of different environmental factors in extensive and intensive grassland systems, adapted from Pearson and Ison (1997).

Environmental Factor	Control in Extensive system	Control in Intensive system	Method
Grazing Pressure	Good	Good	Restrict Stocking
Sward Composition	Poor	Good	Reseeding in intensive systems, some over seeding in extensive
Erosion	Good	Good	Stock management
Pests/Diseases of the sward	Poor	Variable	Re-seeding, pesticides
Drainage	None	Good	Artificial drainage-surface and subsurface
Soil	None	Variable	Liming, fertilization
Climate	None	Poor	Agri-climatically suitable in-sward species selection

2.1.4 Grassland Use and Global Landcover Monitoring

In land cover mapping the themes are often presented as a set of nested levels with increasing complexity, for example level 0 is *vegetation*, level 1 *croplands,* level 2 *wheat* (Ben-Asher 2013). Grassland is identified as a basic level 1 land cover in most global land cover monitoring systems (Figure 2.5 gives an example). However the definitions and the mapped extents differ as shown in Table 2.2. The European Union, through Copernicus (the European Programme for EO exploitation) produce maps of land use in Europe every 6 years, CORINE, and within this programme there was an non-validated high resolution map of "permanent" grassland produced [9] (the author validated an a draft version of this map of Ireland for the Irish Environmental Protection Agency, producing the official verification report as the national contact point[10]; the validation results were poor with an omission error of 61% and the concluding observation "*A poor product, with little utility as it stands".* There have been no re-issues).

The variation in global estimates of percentage grassland cover, as illustrated in Table 2.2, is supported by regional validation and comparison exercises (such as in China (Ran et al 2010)) where the difference in estimates between the global and local product is attributed to remote sensing error, temporal mismatch and differing classification schema.

Grasslands for land cover and land use are monitored globally, principally to explore their roles in global carbon sequestration and to protect their distribution as a global ecosystem. Grasslands have come under increasing pressure from other land uses, principally crops and urbanization and their exploitation has played a role in the global growth of desertification and soil erosion.

[9] http://land.copernicus.eu/pan-european/high-resolution-layers/grassland
[10] Unpublished report

Table 2.2: List of some global land cover mapping services and their estimates of global grass cover (sorted by spatial resolution)

Product[11]	Year	Grass cover	Definition of grassland used	Method	Resolution
GLC2000	2000	9.3%	Unknown	Unsupervised classification on multiple sources	1km
Global Land cover-SARE	2014	13%	Area dominated by natural herbaceous plants, >10% cover regardless of use	Integration of existing datasets	1km
IGBPDiscover	1992-93	8.3%	Herbaceous grasses, >10% ground cover	Unsupervised classification of AVHRR	1km
UMD	1992-93	8.7%	Herbaceous grasses, >10% ground cover	Supervised-Decision tree AVHRR	1km
MOD12	2003-	6.8%	Herbaceous grasses, >10% ground cover	MODIS classification	500m
GlobCover (see Figure 2.4)	2005-09	5.4%	Herbaceous vegetation, sparse (<10% grass cover), Open (10-40%), Closed (>40%)		300m
CCI Landcover	2010	3.2%	Grassland >70%	Reclassification of MERIS	300m
FROM-GLC	2006	13.7%	Pasture and natural grassland	Landsat TM	30m

[11] A list of web addresses for online resources and services is given in the appendix



Figure 2.5: Map of global landcover GLOBCover (credit ESA/ESA GlobCover Project, led by MEDIAS France/Postel.)

2.1.5 Grassland ecosystem monitoring

The over-exploitation of grasslands by animal herds leads to loss of habitat, soil erosion and desertification, and is a principal concern driving EO of grassland ecosystems. The idea of monitoring grasslands (and other globally important ecosystems) by EO was stimulated with the paper by Justice et al (1985), building on earlier work on vegetation indices to present a well-developed methodology for the global monitoring of vegetation change using Advanced Very High Resolution Radiometer (AVHRR) data. From an ecological perspective, remote sensing for rangeland monitoring was promoted by Tueller (1989). This influential paper saw Tueller predicting a, as yet only partially realised, future of remote sensing specialist rangeland managers.

Geographically much of the research covers the North American prairies, South American pampas and China (in a review of grassland degradation in China, Akiyama and Kawamura (2007) concluded, in explicit agreement with Tueller that EO technologies are ideally suited and well developed for grassland monitoring in China). In semi-arid grasslands satellites are used to look at land degradation, in other grasslands habitat loss and carrying capacity seem to be the principal concerns.

The techniques for mapping land use change typically use conventional classification techniques or more up-to-date machine learning methods, or the local correlation of biomass levels with medium scale resolution NDVI time series. In Nepal, Paudel and Andersen (2010) used multi-sensor long term time series of NDVI data, local stocking data and weather data to assess the causes of land degradation, to conclude that grazing pressure and drought were the main drivers.

In the Brazilian state of Rondônia, complex land covers were interpreted as within pixel fractions of green vegetation, non-photosynthetic vegetation and soil to estimate the effect of grazing on the changing of these fractions, the NDII5 index (the Normalised Difference Infrared Index, where bands 4 and 5, replace bands 3 and 4 respectively in a conventional NDVI using Landsat TM data) was found to be

more closely correlated with ground conditions than the conventional NDVI and that this, in turn, correlated with cattle density to explain a significant proportion of degradation (Numata et al 2007). Fraction based, or end-member approaches to un-mixing complex covers, especially in semi-arid grasslands, are an increasingly utilised tool to attempt to overcome the relatively coarse spatial resolution of sensors like MODIS, in order to explain the important sub-pixel changes in the proportion of different vegetation components. Thorp et al (2013) use this approach when looking at scrub encroachment in rangelands, a subtly different approach to the monitoring of grasslands with an emphasis on loss of grazing grounds.

Recent studies on grazing pressure have looked at local effects using very high resolution data. Carmona et al (2013) study on rangeland recovery post grazing used time series of high resolution QuickBird satellite data to estimate both rangeland habitats and grazing impacts in central Spain. Using regression trees to examine persistent vegetation loss as a function of grazing pressure and environment, tested against vegetation mapped from the imagery, they found that habitat was the key determinant in predicting changes in vegetation.

Hunt and Miyake (2006) attempted to estimate the impact of stocking rate on grazing pressure on American rangelands. In this study, NDVI images from 12 years of AVHRR data were used to calculate a monthly productivity, and thus the carrying capacity, and from this a stocking rate. This modelled stocking rate had only a weak correlation with stocking rates inferred from official statistics. However this study relies upon herds utilising all available fodder for the estimate to be correct. Much of the work on relating stock density to NDVI has effectively correlated herds with biomass removal through grazing (Zongyao et al 2012).

Using Geographically Weighted Regression (GWR) to model known grazing intensities and regional growing season trends derived from MODIS time-series data Li et al. (Li et al 2013) found that stocking density was not significant in accounting for variability in NDVI trends in Canadian rangelands. In contrast, Oesterheld et al (1998) used accumulated monthly averages of 1km AVHRR data

over 7 years (1982-88) to build a relationship at county level between NDVI and stocking density. Using 66 counties in Argentina they found a strong relationship (log-log) between NDVI and stocking density ($r^2 = 0.9$). This is best interpreted as a regional scale model of carrying capacity of a semi-natural habitat.

Closer to home, concern about over-grazing in upland areas of Ireland have some common themes with the types of study discussed in this section. The application of remote sensing to these issues has been limited largely to visual inspection of aerial photography (Cooper & Loftus 1998) with some attempts at mapping habitat change using Landsat TM time series (Loftus et al 2002), although the threat of over-grazing has receded as a result of a shift away from farm income supports based on the number of animals grazed. More recent approaches using high resolution imagery and object orientated classification schema have attempted to detect change in upland areas (O'Connell et al 2014).

2.1.6 Loss of Rangelands

Most of the research in this area is concerned with detecting, delimiting and measuring biomass on rangelands, defined as[12]:

"…. predominantly grasses, grass-like plants, forbs[13] or shrubs that are grazed or have the potential to be grazed, and which is used as a natural ecosystem for the production of grazing livestock and wildlife"

As noted in 2.1.5, in Ireland, there is concern now about under grazing in some upland areas (due to EU policy shifts) and the effects this may have on landscape. Globally, a loss of rangelands is becoming an increasing concern, associated in some cases with previous over-grazing, but also with increasing land use change to crops and urbanization (rising commodity prices have led to an increased conversion rate to crop lands (Rashford et al 2011)). Whilst in most parts of the world the loss of

[12] For the purposes of this review the recently agreed definitions of grassland nomenclature are used (Allen VG, Batello C, Berretta EJ, Hodgson J, Kothmann M, et al. 2011. An international terminology for grazing lands and grazing animals. *Grass and Forage Science* 66: 2-28)

[13] "Forbs" are non-grass herbaceous flowering plants

grasslands is associated with ecological change, in Europe losses are associated with urbanization, policy changes and demographic shifts in farming (Wittig et al 2010). As an example Stefanski et al (2014) used Synthetic Aperture Radar (SAR) data and Landsat data in a random forest classifier to map a complex series of changes over 20 years in the Ukraine involving first retreat from agriculture ("land abandonment") and then conversion of grasslands to croplands in response to global food prices. The loss of rangelands due to degradation is a principal concern in Australia (Pickup et al 1998). Early work by Pickup and colleagues (Pickup et al 1994), using measures of vegetation cover from satellite, has led in turn to more complex paddock management systems being monitored via satellite which will be discussed in Section 4. Monitoring ecological impact and rangeland loss naturally leads to the concept of rangeland management.

2.1.7 Rangeland Management

Tueller (1989) identified the potential of remote sensing for rangeland management, and its use has been reinforced since then (Hunt et al 2003). Rangeland management by satellite image analysis principally involves estimating fodder quality, fodder availability and protecting against invasive species. Estimates of biomass for extensive grazing lands, for assessment of fodder availability and quality with the aim of incorporating them into management tools, have until relatively recently concentrated on management at the scale of the rangeland as a common resource, rather than at the scale of the farmer or herd, with available biomass estimated, for example, with Landsat Thematic Mapper data in South African rangelands (Bastin et al 1998) and Argentina (Blanco et al 2009); AVHRR data in the USA (Thoma et al 2002)and Australia (Hill et al 2004) and, MODIS data in China (Cui et al 2012). These studies effectively measured the impact of cattle on the biomass of extensive, relatively homogeneous landscapes, quite different to the paddock systems that are the focus of this study.

At a larger scale Bastin et al (2012) successfully disentangled seasonal effects in long term satellite data series to distinguish the effects of management changes (changes in stocking density) in Australian rangelands. The method establishes a

baseline of minimally changing pixels and then references changing pixels to these references year on year, thus separating seasonal change and inter-annual change from management effects, however although this method identifies areas of change it does not classify them by the nature of the change.

2.1.8 Grasslands and carbon

Another driver for understanding grassland management and intensification is the aim to decouple human activity from longer term climate driven trends in grassland cover and productivity. Two early, heavily cited papers, by Tucker et al (1985) and Prince (1991) both used AVHRR data to estimate productivity in semi-arid Sahel region savannah. They demonstrated how regional biomass production in such environments could be estimated with satellite derived VI using a relatively small number of ground control sites. This had important implications for global climate modelling and the understanding of the sink/source role of grasslands globally through Net Primary Production (NPP) and Gross Primary Production (GPP). Whilst the necessity for caution on application of global algorithms relating accumulation of NDVI with GPP and NPP across different biomes was understood (Schloss et al 1999), routine estimates of global NPP were provided from low spatial resolution satellites like AVHRR (Sala et al 2000).

The production of global NPP and GPP estimates were built into the MODIS processing chain from the beginning. GPP is a function of atmospheric/terrestrial carbon exchange, and the MODIS GPP product is intended to provide a global estimate to complement the international flux tower network (FLUXNET) of site specific measurements**.** The algorithms have developed from simple sums of NDVI to complex, land cover specific, calculations involving estimates of fraction of Photosynthetically Absorbed Radiation (fPAR), Photosynthetically Available Radiation (PAR), Light Use Efficiency (LUE), temperature (T) and vapour pressure (VP). The parameters PAR, T and VP are supplied by the NASA Global Monitoring and Assessment Office (GMAO), whereas fPAR is generated from MODIS based on Bi-Directional Reflectance Factor (BDRF) estimates and a land cover look up table (LUT) from the MODIS annual land cover product (MOD12Q1). Sources of error in

the MODIS GPP include uncertainties in meteorological data provided by the global GMAO data, and quoted errors in the MODIS land cover of up to 30% (Zhao et al 2011).

Specific issues in GPP over grassland have been investigated by a number of authors, with the principal findings being that GPP is underestimated in croplands and grasslands. Zhang et al (2008) found that GPP was underestimated on a daily, seasonal and annual basis in croplands and alpine grasslands in China, with the source of error primarily in estimation of LUE due to errors in allocating the correct land cover labels to the pixels, with the recommendation that GPP estimates could be improved using local higher resolution land cover data sets. Turner et al (2006), report no bias on estimates of GPP over 9 biomes, including prairie grasses, with under-estimation of GPP for low production sites and over-estimation at highly productive sites, however the work was carried out over large (25Km^2), relatively homogenous semi-natural areas.Quaife et al (2008) found variation of up to 25% in calculated GPP depending on the resolution of the land cover dataset used (LCM2000, GLC2000, MODIS products) because of spatial and thematic uncertainty in the United Kingdom (UK). There are no International Geosphere-Biosphere Programme (IGBP) control points in the British Isles and no attempt has been made to validate the MODIS land cover product in Ireland (Kanniah et al 2009) however as parts of the UK have a similar fragmented landscape to Ireland it is likely that Quaife et al.'s UK results are equally valid in Ireland.

The use of EO in studying global carbon budgets is largely constrained to Above Ground Biomass (AGB) and land use change, and whilst the role of AGB and carbon is largely understood on rangelands , the issue of soil organic carbon is less well known, with studies suggesting that typically management decreases storage over time but that some types of management can cause an increase in soil carbon compared to others (Schuman et al 2002).

2.1.9 Rangeland biomass

Many studies have looked at biomass on rangelands using satellites, but this section will be limited to studies that have attempted to build empirical models to estimate

standing biomass in DM/kg/ha. The early work of Tucker et al. (1985) (see Section 2.1.8), cited more than 700 times, has given rise to hundreds of papers estimating biomass from optical sensors, mostly using one or more vegetation indices. It is necessary here only to give a few examples.

Early work in China by Jianlong et al (1998) found that NOAA/AVHRR NDVI time series images could be correlated with total seasonal biomass yield (simple green yield in kg) field measurements across different grassland types (from "mountain meadow" to "desert steppe"). Log-Lin models proved most successful with $p<0.01$. Although the result was based on only 20 sites of $1m^2$ quadrats measured over a season, related to accumulated NDVI score at the 1.1km scale, it did indicate yield measurements for different grassland systems were achievable.Xu et al (2008) tested linear, power and exponential regression models between NDVI and ground measurements of grass yield in China's rangelands, finding an exponential model the most successful ($r^2=0.802$). Grant et al (2013) found a relationship between a number of VI and field measurements of green above ground biomass ($r^2=0.68$, using the Transformed Vegetation Index, TVI) in Canadian rangelands. NDVI performed as well as the other indices tested, and the degree of success of different VI was a function of eco-region. A much earlier study came to an identical conclusion; Todd et al (1998) found that there was a significant relationship ($r^2=0.7$) between NDVI (and other VI) and biomass in rangelands in Colorado, USA (using 6 trial plots) for grazed plots, but no significant relationship with un-grazed plots.

Yu et al (2010) related NDVI from MODIS to grass biomass in Chinese rangelands (modelling against log of biomass which is common in the literature) and linked these observations to potential and actual carrying capacity. In Europe, studies of natural grasslands and estimation of biomass from optical satellites have reached the same conclusion, e.g. Schino et al (2003) in the Italian Alps. A recent study in the French Alps (Barrachina et al 2015) achieved an $r^2=0.76$ relating pasture biomass field measurements with Landsat derived NDVI values.

The difficulties of accurately measuring biomass in rangelands by optical systems, arising due to the complexity of vegetative cover, has led to an increase in studies

using active systems such as LIDAR, commonly through the estimation of AGB based on canopy height (Radtke et al 2010, Streutker & Glenn 2006) although LIDAR is more commonly used for estimating the AGB of the woody component of rangeland vegetation (Ku et al 2012).

There are few examples to date of using radar to measure rangeland grass biomass (Kumar et al 2015). This may be because grassland biomass was considered below the detection threshold of earlier systems, or the canopy height was typically less than the radar band wavelength which presented difficulties in untangling sward effects from soil moisture conditions.

Early work by Hill et al (1999) showed that site specific relationships could be established between backscatter (dB) and sward height from airborne SAR data, but that soil moisture was a considerable source of error. Hill et al (2005) went on to develop the idea of combining radar and optical data, and improved classification of vegetation types in Australian pastures, however these classifications had to be validated against biophysical properties (canopy and surface measurements) rather than the conventional, larger scale, observational habitat type data, and thus ground truth collection was considerably more complex.Wang et al (2013) also combined PALSAR, ENVISAT and COSMO-SkyMED radar data to estimate Australian grassland biomass, but they calibrated only against optical VI, not against ground measurements, which demonstrated that the correlation between the radar backscatter and VI was heavily influenced by rainfall. One element holding back the development of radar based analysis of grassland has been the cost of imagery. Hill et al (2000) stated that the cost of imagery at the time could not be justified on the basis of the results of an experiment classifying Canadian and Australian grassland types with multi-date radarSAT data.

Higher spatial resolution radar data better matches the scale of the pasture target, and a number of studies linking pasture biomass to polarised backscatter of TerraSAR-X imagery (with its' sub-meter scale resolution) have been completed with varying results. McNeill et al (2008) in New Zealand found HH/VV pairs could model grass biomass, but Voormansik et al (2013) in Estonia could not detect even

gross changes in sward height with the same combination. Schuster et al (2015) found that a TerraSAR-X time series in conjunction with Rapid Eye high resolution optical data could classify, with accuracies greater than 90%, small scale grassland habitats.

Early work using airborne SAR (Smith et al 1994) showed promise in detecting habitat variation across rangelands. But radar does not seem to have been adopted widely as a tool for rangeland vegetation monitoring (although rangeland soil properties have been a target of interest). Some work has looked at fusing radar with optical data; for example Huang et al (2010) used airborne SAR data to correct for soil brightness in a Landsat classification of USA rangeland, achieving accuracies of 75%.

Whilst the advent of high resolution radar data and free data from the European SENTINEL programme will drive further research, radar data currently seems to occupy a supporting role in grassland biomass estimation, although as discussed in section 2.8, there is some potential offered by this technique given newer sensor developments.

2.1.10 Commonages: Ireland´s Rangelands?

Whilst Ireland has no real rangelands, the upland commonages (Figure 2.6[14]) present similar issues for remote sensing. These extensive grazed systems in upland hill country, held in common ownership by a cooperative of farmers, present as a complex of shrubs (mostly heather), woody scrub and natural grasslands. These have been mapped as habitats (Cawkwell et al 2010, Fealy & Green 2009) and work is currently underway in designing remote sensing systems for monitoring change in these areas (Raab et al 2015), as was previously done for peatlands, another grazed resource in Ireland (Connell et al 2012).

[14] Figures 2.6, 2.7 and 2.8 from www.high-nature-value-farmland.ie by agreement.



Figure 2.6: Commonages are large unenclosed typically upland areas, characterised by semi-natural and natural habitats used for common grazing.

No work has been done on estimating carrying capacity or grazing pressures in Irish uplands and commonages using remote sensing, though field evidence suggests there are issues to be addressed (O'Rourke & Kramm 2009).

2.1.11 EO and Extensive Grassland summary

The key points from the overview of the EO and rangeland literature presented here are:

- Grasslands are a globally important biome.
- There are widely divergent estimates of their extent, principally due to differing definitions.
- Vegetation indices derived from low resolution optical satellite observations have successfully been interpreted to monitor grassland health and exploitation, with NDVI the most commonly used VI.

- On a large scale, biomass for primary production and fodder are estimated with varying levels of precision (typical r^2 values of 0.65-0.75).
- Estimates of stocking density on rangeland have been made with varying degrees of success.

The challenges of using some of the techniques developed for natural rangelands on intensively managed enclosed grasslands can be best appreciated with an understanding of paddock management on the ground, and here Ireland is used as an example.

2.2 Conventional paddock management on the farm

2.2.1 Introduction to Irish pastoralism

Ireland, with its temperate maritime climate possesses some of the best grass growing conditions in the world, with a long, almost year round growing season in some parts of the south of the island (Fischer et al 2000). Agriculture occupies approximately 62% of the terrestrial area of the Republic of Ireland (ROI), with grass as the foundation of Irish agriculture occupying 90% of that agricultural area (O'Mara 2008). Grass as a resource is typically broken down into four main uses:

- **Pasture** - Land (and the vegetation growing on it) devoted to the production of forage for harvest by grazing, cutting, or both. Usually managed to arrest successional processes (the natural cycle of flowering and seeding).
- **Silage production –** Grass forage harvested and preserved at high moisture contents by organic acids produced during partial anaerobic fermentation.
- **Grazing -** Any vegetated land that is grazed or has the potential to be grazed by animals (domestic and wild). This term is all-inclusive and covers all kinds and types of land that can be grazed.
- **Hay Making -** Harvested grass forage preserved by drying.

Grass supports principally three enterprises (in order of economic value)

- **Dairy**
- **Beef**
- **Sheep**

Some farms employ a mixed system of livestock and tillage, and hybrid dairy/beef systems do occur. There are strong geographic trends in farming systems (see figure 1.1), with dairy concentrated in the south/south-west, sheep on the coastal upland fringes, and beef predominating in the north and west. In 2010 there were 139,829 farms in Ireland with a total utilisable agricultural area (UAA) of 4.75MHa, and an average farm size of 32.7Ha. In 2011 there were 6.5 million cattle in Ireland (DAFM 2012).

Finneran et al (2010) showed that grazed perennial rye grass is the most cost effective feed in Irish systems, and this has been supported by other studies in Ireland (Dillon et al 2005). Increasingly, as compound feed (cereals processed for animal feed) costs increase due to increasing human demand for grain, countries such as USA where feedlot dairy systems are the norm (systems where animals are housed or corralled and the food, in the form of grain, is brought to the animals) are identifying a return to grazed pasture as a path to increased sustainability and profit (Hanson et al 2013).

Grassland in Ireland is managed in a variety of ways determined by farm system, environment and farmer choice (O'Rourke & Kramm 2009). At its most basic, upland grazing on semi-natural or natural grasslands by sheep (and, to a lesser extent, goats and cattle) is managed as an exploited ecosystem (Figure 2.6 & 2.7). Management revolves mainly around the control of animal numbers (low stocking density), although clearing and, more so in the past, burning of encroaching plants also occurs. These upland areas are typically held in common ownership amongst a group of farmers as commonage; they are never reseeded or limed (to adjust soil pH to optimal value of 6.3 for grassland production) and they receive no chemical

fertilizer or mechanically applied organic fertilizer, with their utilisation controlled through a formal commonage framework plan (Van Rensburg et al 2009).



Figure 2.7: A species rich semi natural grassland.

Over-grazing is a declining threat to commonages as a grassland resource, whilst under-grazing or dormancy is a growing problem, up to 34% of the 410KHa of commonage is unclaimed and may be at threat of scrub encroachment through under-grazing (Bleasdale 2013). In contrast to the upland areas, in enclosed lowland areas grass based farms are managed to provide grazing and fodder.

2.2.2 Grass as a crop

Intensive grassland farmers will try to maximise growth of grass on their farm and its exploitation by their herds (Figure 2.8). Grass growth can be optimised by promoting early growth, maximising peak growth and extending the period of maximum growth. Exploitation can be maximised by ensuring grown grass is not

wasted and that sward conditions are such that cattle can graze for an extended season[15]. Grass growth is influenced by:

- Cover density (very low and very high covers can slow growth)
- Temperature
- Moisture
- Soil type
- Nutrients
- Plant damage
- Radiation

In Ireland grass growth rates typically increase sharply in March with a peak around May. A sudden drop in June is followed by a slight recovery in July and then a gradual decline to October (see Figure 2.9). It must be noted that, strictly speaking, this is the sward growth performance, not that of individual grass plants. In grasses new leaves are growing as old leaves die, and the cumulative effect is measured as sward growth rate.



Figure 2.8: An improved grassland.

[15] This section owes much to Turley T, Aylmer M, Fitzgerald L, Heneghan B. 2008. *Forage prodcution*. Kildalton, Kilkenny, Ireland: Teagasc

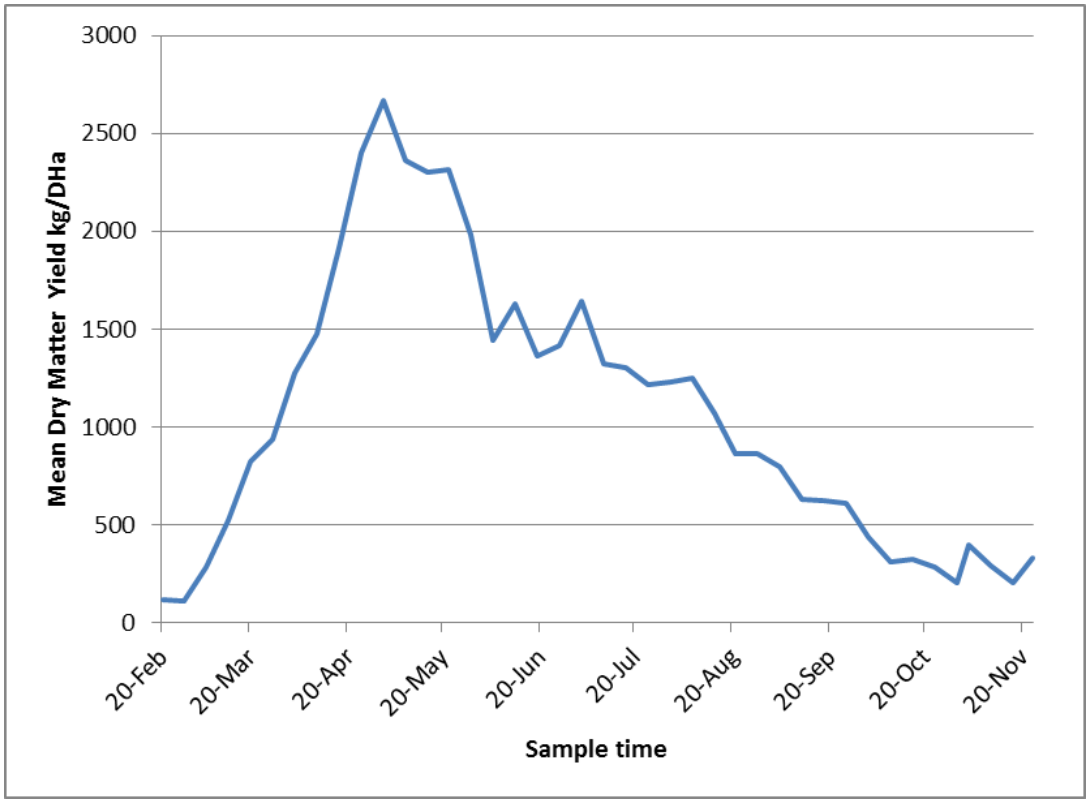


Figure 2.9: Mean grass biomass measurements across a 6 year period, 2003-8, derived from field observations at an experimental farm in the north-east of Ireland (Grange, Co. Meath).

Rye grass plants (*lolilum perenes* is the dominant grass species in improved pastures in Ireland) consist of up to 25 small growing units called tillers. Each tiller is constantly growing but only ever has 3 formed leaves (which the animal eats); as new leaves appear at the growing point at the base of the tiller the mature leaves at the top of the plant begin to die off. At the height of the growing season this cycle can take only 21 days, so if plants are not utilized within three weeks, as grazed grass or fodder, then the grown biomass is lost. To maximise the use of this biomass a system of rotational grazing is employed. The farm is divided up into small paddocks and each is grazed to a residual 3 cm height, or cut for silage, in rotation. To ensure that there is enough fodder ahead of the grazing herds a grass management system known as the grass wedge is employed. The grass wedge involves matching animal needs with current cover and likely growth, and involves calculations of demand and cover with weekly farm walks and sward measurement.

2.2.3 Grass measurement

Grass in the field can be measured in a number of ways. The "gold standard" is a hand clipped sample from each paddock. A 0.5m x 0.5m quadrat, representative of the amount of grass in the paddock, is used and grass within is clipped down to a height of 3.5cm above the ground, the clipped sample is shaken to get rid of excess water and dry matter can be calculated as:

$$DM = w \times 0.16 \times 40000 \qquad \text{eq.2.3}$$

Where *w*, weight in kg is multiplied by *0.16* (representing the average value of 16% Dry Matter (DM) in an un-dried grass sample) and *40,000* (the number of quadrats in 1 ha) to generate an answer in terms of kg DM/ha in the paddock.

Mechanical methods include the rising plate meter, the sward stick and the pasture ruler, all of which essentially measure the height of the sward and then estimate DM from equations, and although they do not perform as well as the cutting technique outlined above they are much faster. Sanderson et al (2001) showed that these mechanical systems had an average error of 30% compared to hand clipped samples, and that this error in measurements reduced the effectiveness of grass budgeting on the farm and lowered the returns per ha compared to correctly budgeted farms. They recommended that errors of no more than 10% in grass cover measurements when compared to hand clipped samples are acceptable.

It is clearly a very time consuming practice to do this sampling in every paddock every week, so the majority of farmers who are recording grass growth (which is a minority of all Irish farmers) will generally "eyeball" the paddock and studies in Teagasc have shown this compares well with mechanical methods. O'Donovan and Dillon (1999) found:

- The most reliable efficient method of measuring grass supply was by visual observation.
- Farmers improved grassland management when they frequently measured grass covers.

- Frequent measurement helped them to promptly identify surpluses and deficits throughout the grazing season.
- The critical grass measurements identified were pre-grazing yield, post-grazing grass height, farm grass cover and the percentage live leaf in the sward.
- The last rotation before closing off the farm is the most critical as it affects spring turnout date.
- When good grassland management techniques were employed through the use of grassland measurement, spring calving herds produced up to 80% of milk from grass.

As with O'Donovan and Dillon's finding of the accuracy of visual assessment of biomass, a trial of visual cover estimates of sward *composition* with other botanical survey methods in grasslands also found visual estimates were well correlated with other more time consuming survey methods across a wide range of grassland use intensities (Pavl et al 2009).

A meta-analysis of measurement technique studies reported in the literature by López Díaz and González-Rodríguez (2003) found a wide range of accuracies and correlations reported for each techniques compared to a cut and measure standard. Table 2.3 presents a distillation of the results presented and they all present a degree of difference from the standard.

More technologically complex systems have been examined, such as field spectroscopy (Flynn et al 2008)where sensors are used to measure NDVI and correlated with field measurements of biomass (r^2=0.68). Sensors developed for use in crops and mounted on quad bikes have been successfully employed to measure grass DM variability across paddocks (Trotter et al 2010). This case study in New Zealand found the use of an on farm grass measuring technology (C-DAX Pasturemeter, a small instrument towed behind a quad-bike) increased fodder production from 12.9 t DM/ha to 18.6 t DM/ha at the cost of spending more time budgeting feed requirements and paddock rotation.

Table 2.3: Data taken from López Díaz and González-Rodríguez's (2003) meta analysis of non-destructive grass measurement methods and their comparison to cut and dried measurement of dry matter.

Method	No. of Studies	Mean significant r^2 reported
Canopy analyser	2	0.50
Capacitance meter	18	0.68
Pasture ruler	8	0.72
Plate meter	37	0.74
Sward stick	11	0.68
Visual obstruction	4	0.78

Measuring grass is a complex but worthwhile task but is in fact employed by only a small percentage of the most progressive farmers (see section 5.1), with the majority employing "rules of thumb" and simplified calculations. In spring the management is somewhat simplified as the first rotation involves ensuring that 100% of the grass is grazed before the second rotation begins, this is achieved through paddock management.

An issue of concern in paddock management in spring is soil trafficability. As the soil can be wet in the spring and compaction from animal traffic is to be avoided to reduce soil compaction and thus limit future grass growth (Herbin et al 2011), paddocks are managed so that they are not trafficked once grazed. In the second rotation, when growth rates are higher and silage production begins, the grass wedge is constructed:

1. Cover estimates of each paddock are made.
2. Cover estimates are converted to dry matter using simple percentage rules of thumb.
3. Daily grass demand is calculated as kg/DM/cow as a function of cow breed and size.
4. Target yield and target residual (the amount of grass left after grazing) are calculated.

5. The farmer must also calculate average growth rates based on the previous weeks´ measurements

These measurements and observations are then plotted on a “grass wedge” graph sheet (Figure 2.10) with the paddocks with highest cover (those next to be grazed) on the left and then in order down to the lowest cover. The diagonal line is the demand line for the herd; if the columns are below the line it means too little grass is being produced and if above then too much is being produced. This complex set of calculations is to be repeated weekly.

Studies show that uptake of management technologies like the grass wedge is small, often due to complexity and time constraints in carrying them out (Creighton et al 2011). Gray et al (2003) in New Zealand observed that data on actual farm planning on the ground was sparse, but in their study they found that even high performance expert dairy farmers only produced formal feed budgets at critical periods in the year, relying for the rest of the season on memory of past performance and planning.

These complex sets of interacting factors are further complicated with issues of fodder quality and the fast response of grass growth to weather changes. These make grassland management the most highly dynamic farming system in which to operate, and are the reasons why most farms do not reach the maximum grazing season length potential.

In the winter animals are housed when grass growth is no longer sufficient to support the herd, and soil conditions are such that animals would damage the soil (through poaching and compaction) and so reduce grass growth the following spring. The decision on when to house in the autumn is driven by weather and planning for the spring. Paddocks that will be the first to be grazed in the spring need to be closed to grazing earlier in the autumn to allow for adequate recovery and to ensure sufficient grass cover in the spring.

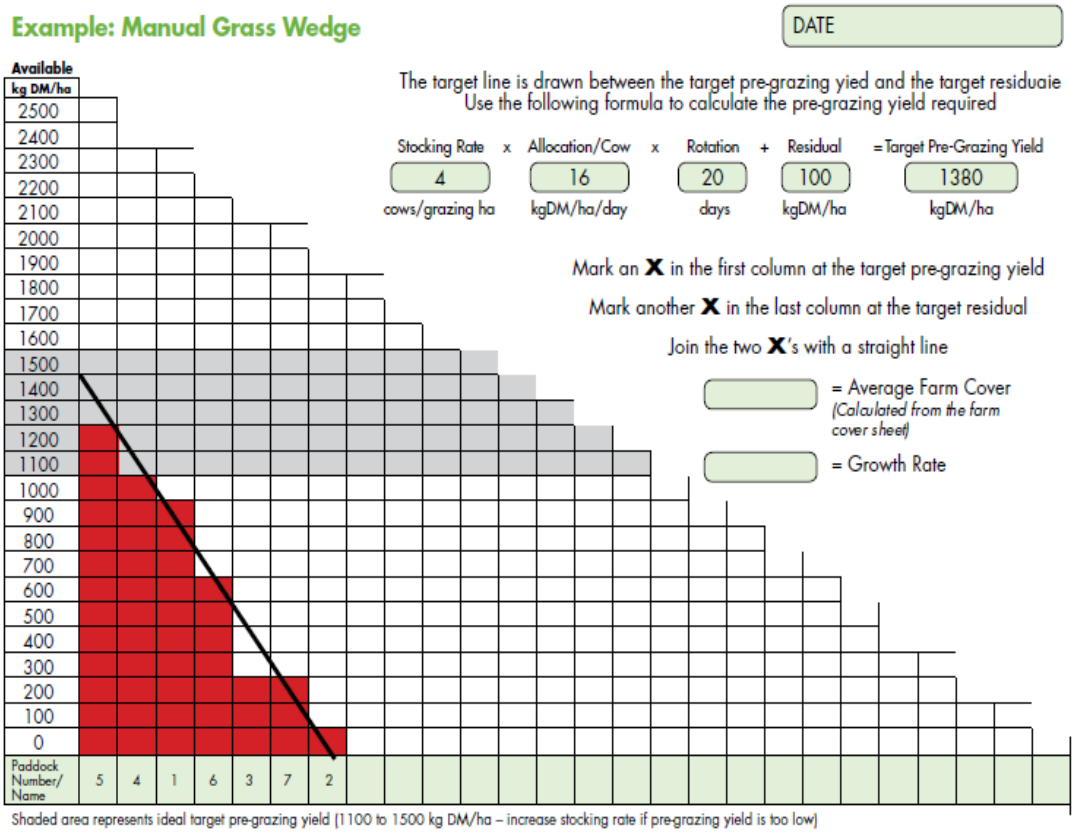


Figure 2.10: Example grass wedge (taken from the Teagasc and IFJ (2009) pg. 33)

As shown in section 5.1 the decision on when to turn out cattle the following spring (first for day time only grazing and then day and night) is a function of the farm management plan, available grass, soil conditions and available alternative feeds (silage and made up rations) available to the farmer.

All these planning decisions are ultimately mediated by the local grass growing season. Grazing season length in Ireland is a multifaceted issue, but an initial attempt to create a map of grazing season start date for the country based primarily on annual temperature data was made by Brereton (1995). Whilst the broad geographic features of Brereton's work remain true, the reality of farm practice means that most of the dates have moved forward by up to a month (see section 3.1). A map of potential grazing season length (not just start of season date) using temperature thresholds and meteorological data was created by Barry (1986) and updated by Fealy and Creamer (Figure 2.11) with up-to-date climate data (Fealy & Creamer 2015).

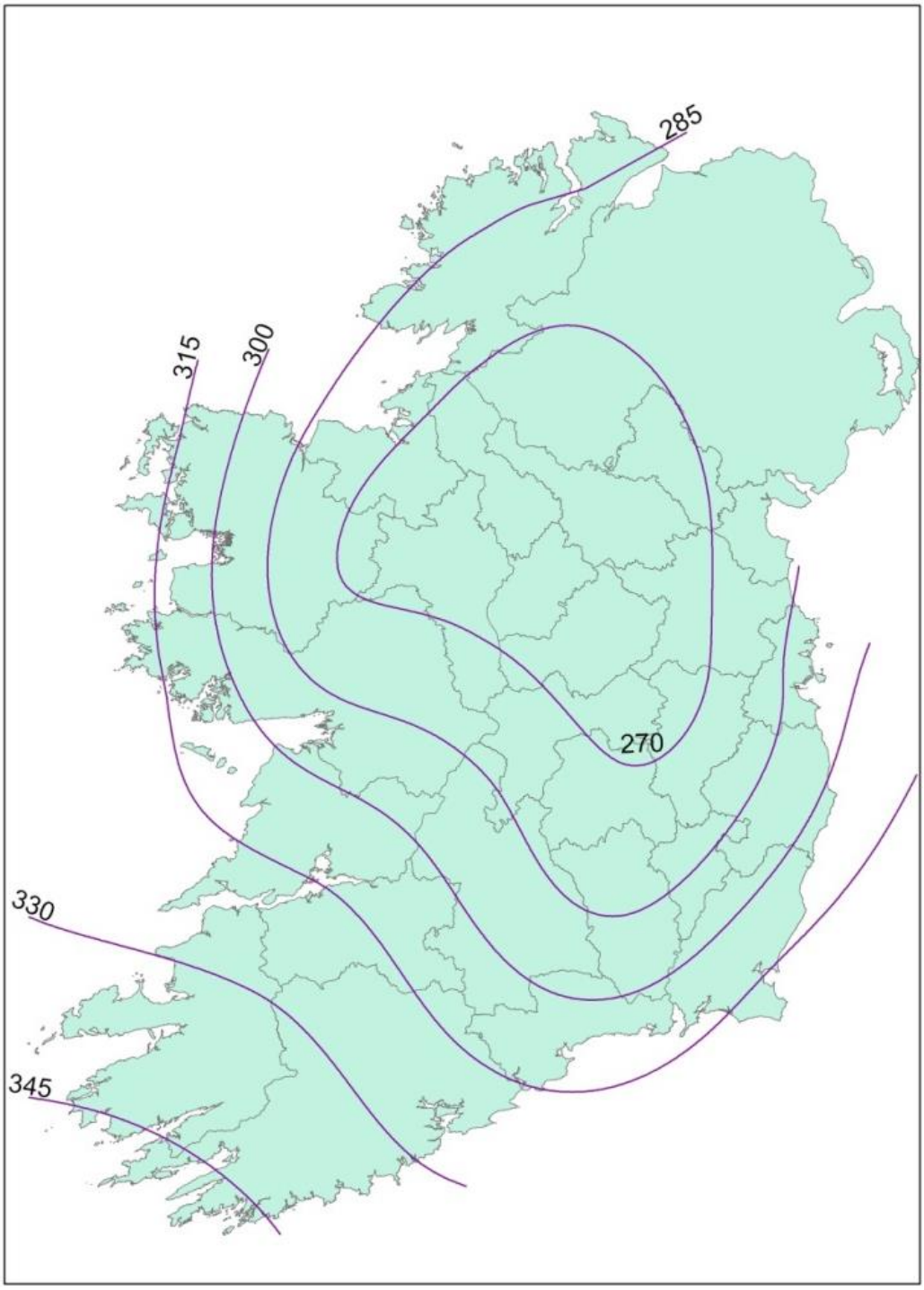


Figure 2.11: Grass growing season length in days (purple isoclines), from Fealy and Creamer (2015, pg. 23).

2.3 EO and herd monitoring

2.3.1 Precision Livestock Farming

A recent report (Zarco-Tejada et al 2014) on support for precision agriculture (PA) from the EU and the CAP, defines precision livestock farming (PLF) as:

" the automatic monitoring of each individual animal, recording data for the growth, detailed milk and egg production, early detection of diseases, and to understand the animal behaviour and monitor its environment."

Summarising from Laca (2009) it can be broken down into:

- **Controlling** - training animals through aversion and preference to behave in a certain way (such as preferentially grazing one plant over another), or operant conditioning, training cows to respond to set commands and stimuli (possibly within an integrated robotic milking scenario).
- **Sensing** - remote devices to monitor animal health and reproductive status.
- **Managing -** virtual fencing, robotic milking etc.

PLF, virtual fencing, and GNSS tracking for herd management is now so commonplace there are demands for standardization to take place (Anderson et al 2013). In intensive systems, PLF is centred around in-situ sensing systems on the cow, detailed record keeping and data analysis in the milking parlour and computer aided feed budgeting. There are some EO approaches to PLF from rangeland farming that can be applied and these are discussed more fully in section 2.4.

2.3.2 Use of EO at herd level

Space borne EO data are used indirectly in herd management, principally in rangelands to ensure adequate feed is available to grazing animals. Estimating carrying capacity in rangeland paddocks has been examined by a number of researchers. Phillips et al (2009) exploited satellite based estimates of vegetation cover and fodder quality to predict grazing capacity of prairie paddocks. This built on earlier work relating photosynthetically-active vegetation (PAV) with a soil

adjusted VI (MSAVI) using a model locally calibrated from field samples (Phillips et al 2006). The model estimated carrying capacity on an 11ha paddock as 24 days in a 28 day cycle (4 day under-estimate). This thoroughly ground-truthed field experiment points toward estimating both carrying capacity and feed quality, but the demand for local calibration limits its potential operationally. It is worth noting that the carrying capacity is only estimated at the start of the 28 days and not updated through-out, an approach that would not be successful in Ireland as grassland production can vary enormously during any 28 day period in the peak growing season. This work is important in the context of demonstrating that biomass estimates are possible, that integrating these estimates into animal management is desirable, and it is applicable at a midway scale between rangeland studies and Irish intensive grassland paddocks. Other examples of EO to estimate carrying capacity include mapping fodder availability in extensive Mediterranean grazing lands (Smith et al 2011). Work by Shakhane et al (2013), linking animal weight gain with forage amounts and grazing, bridges the gap between conventional models of animal feed demands and the use of satellites to estimate the feed available and the biomass consumed at paddock scale. Handcock et al (2009b) successfully combine a number of technologies by relating rangeland use, as revealed through a SPOT 5 image, with movement patterns of GPS tagged cattle.

Furthermore, remote sensing in its strict definition is used in herd management through automatic processing of video imagery and the use of Unmanned Aerial Vehicles (UAV). UAVs are being used as a research tool in rangeland studies (José A. Barasona et al 2014, Rango et al 2006) and their use on the farm, especially in animal husbandry is increasing (Hofmeyr 2015). Image processing and video imaging on the farm with CCTV or from a UAV platform has been investigated to automatically monitor animal health (Song et al 2008) and the use of thermal imaging for monitoring lactation and fertility is being investigated (Kunc & Knizkova 2012). Finally remote sensing is used to track cattle/herd movements through GPS and wireless sensor networks (Mukhopadhyay et al 2013).

2.4 EO and monitoring fodder production and quality at paddock scale

Paddock systems differ across the globe in terms of grass management within the paddock. In Irish and continental European systems, reseeding, fertilizing and managing is common. In paddock systems on rangelands and prairie grasses the level of grass management is reduced and paddocks are used as a herd/grazing control system, allowing grasses to naturally recover in a rotational grazing system. Globally it is a common concern to ensure that there is enough grass available to feed the cattle.

New Zealand is a location for world leading research in the application of EO to managed grasslands and paddocks. Gao (2006) published a review of EO applications for grasslands and many of the conclusions reached still hold true in 2016. Collection of quantifiable ground truth data for remote sensing of grasslands (both bio-physical and spectral) is still an issue, with few campaigns carried out solely for the use of EO calibration and the majority of studies relying on sub-optimum ground truth collected for other agronomic goals. Regression models dominate over biophysical models with non-linear models identified as more successful in measuring biomass. The review identified cover, biomass and degradation as dominant themes in the literature and it looked forward to an increasing use of time series data, all relying on VI.

Some countries, New Zealand included, produce regional estimates of grass growth predictions from simple climate models, driven by meteorological data, instead of from EO models and observations. The Agrifax bulletin is one example giving a regional scale two-week forecast of grass growth[16]

2.4.1 Fodder production monitoring

The relative success of EO in observing grazing pressure in managed rangelands has led to an increased interest in grassland management at paddock scale from satellite observations. An example is the estimation of grass biomass from high

[16] https://agrihq.co.nz/shop/product/18

resolution systems such as SPOT in Australian paddocks (Edirisinghe et al 2012). Field trials have demonstrated that NDVI can successfully estimate paddock biomass in a variety of settings such as alpine meadows (Boschetti et al 2007) and intensive New Zealand paddocks (Edirisinghe et al 2011), with degrees of success. Edirrisinghe et al. (ibid) quote a standard error in estimating biomass of 315kg/Ha across a range from 500-4000kg/Ha using high resolution satellite imagery, whilst field spectroscopy experiments quoted in Boschetti et al., (2007) produced somewhat poorer results.

Time series of high resolution data such as IKONOS imagery have demonstrated that NDVI data can be used to detect post-grazing regrowth within a paddock (Handcock et al 2009a), and that integrating NDVI derived data on stocking levels and grazing pressure into conventional agricultural system models can bring benefits (Donald et al 2010, Phillips et al 2009) in developing decision support systems for herd management. Lower resolution MODIS data have also been incorporated into paddock level management regimes, all be it in large Australian paddock systems. Donald et al. (2012) linked daily MODIS acquisitions with field level sensors in an attempt to create automatic feed budgets for cattle, with success. The use of these time series of satellite data to provide long term benchmarks of vegetation performance for climate studies and agricultural monitoring is well established. AVHRR and MODIS data have been used for long term studies of agricultural land use change at country level (de Beurs & Henebry 2004, Propastin et al 2007, Wardlow et al 2007) and globally (Friedl et al 2002, Ganguly et al 2010).

Local long term averages of NDVI values have been used to characterize agricultural land use (Baldi et al 2008) and deviations from means (NDVI anomaly, see Section 4) are used to alert authorities to potential drought or food shortage, such as the GLAM project (Becker-Reshef et al 2010) and to monitor land use change (Rigge et al 2013). The only Irish studies, relating grassland production yield to EO, used time series of MODIS data over two Irish test sites with longitudinal dry matter yield

records. In Ireland machine learning algorithms accurately modelled standing AGB with an r^2 of 0.86 (Ali et al 2014).

Commercial handheld optical sensors used in crops have been evaluated for estimating biomass in pasture and were found to be successful, with Lim et al (2015) relating AGB to NDVI from the sensor with r^2=0.76.Hyperspectral studies have shown that an analysis of the whole spectrum can successfully estimate parameters beyond biomass such as protein and digestibility (Pullanagari et al 2012a). These sensors are significantly more sophisticated than the simple one or two channel handheld or tractor mounted commercial devices currently deployed in crop evaluation, but show the potential of space-borne hyperspectral systems (such as Hyperion on the NASA EO-1 satellite) and tractor mounted sensors should they become available.

2.4.2 Fodder quality monitoring

Spectral analysis of foliage to estimate nutrient composition (especially Nitrogen, N) is becoming more common. In fresh grasses, Ullah et al (2012) suggested that band depth analysis was better than an array of VIs to estimate biomass of grasslands using MERIS data, but neither band depth or VI could successfully estimate Nitrogen content. Ramoelo et al (2013) successfully linked field spectroscopy measurements with in-situ vegetative Nitrogen and Phosphorus concentration, and a least square regression of spectra proved more successful than individual bands or ratios. This technique was also deployed by Biewer et al (2009) in hyperspectral field studies for estimating biomass in a grass legume sward. Results with a least squares model across the spectra were successful (r^2 = 0.7-0.92), but unsuccessful results with VI were reported.

Adjorlolo et al (2014) recently exploited the coastal blue and yellow bands of the Worldview-2 satellite to create a VI correlated with canopy Nitrogen concentration in grasslands, and through Random Forest (RF) modelling were able to account for 71% of the variation in N.

In a review of non-destructive N testing methods Muñoz-Huerta et al (2013) give some examples of satellite based NDVI studies linked to canopy N concentrations. However, although they question the practical use of systems like this due to issues of timeliness, spatial resolution, data acquisition and accuracy, they suggest that planned hyperspectral satellites such as HISUI (formerly Hyper-X) hold promise of more accurate estimates (see Matsunaga et al (2013) for an overview of HISUI).

Si et al (2012) attempted to model canopy and leaf chlorophyll content using MERIS data and the PROSAIL canopy reflectance model in the Netherlands over a range of biomes. They could not model leaf chlorophyll content due to frequent saturation issues, but canopy chlorophyll content was correlated with leaf area index (LAI). When calibrated against single biome types, canopy chlorophyll content could be better estimated (r^2= 0.61) than for complex biomes (r^2 =0.36).

Proximal multispectral sensing has been deployed to measure pasture quality. Pullanagari et al (2012b) used a 16 band crop scan instrument to link reflectance to quality criteria such as crude protein levels in New Zealand pasture with moderate results (using a least squares model on the 1st principal components of the collected spectra).

2.5 EO and grass farm management

Grass production varies widely within paddocks, between paddocks on the same farm, between farms in the same agro-climatic zone and between years. A study in New Zealand by Clark et al (2010) found within farm variation of 12 tonnes/ha in grass dry matter yields between the highest and lowest yielding paddock, a between farm variation of 17 tonnes/ha, and no correlation between average yield in consecutive years across 9 years.

2.5.1 Detecting management

Dusseux and colleagues have published a number of recent papers on EO and management of paddocks in France. Dusseux et al (2014a) compared the use of

optical and radar satellite image time series to distinguish between grass and crops over 200+ sites in France. Radar derived products performed better than SPOT derived optical parameters in distinguishing between the two types of cover, with 100% success reported for one suite of combined SAR/Optical derived indices. Although an impressive success, the spectral difference of maize and grass across a growing season is expected to be very high and the experiment was very well ground truthed against 256 field observations (64 of which were kept for validation) with biophysical and spectral data collected.

This fusion approach has also been used by (Barrett et al 2014) to map grassland types in Ireland, although here the approach also used ancillary data to provide a more refined classification of grassland (improved, semi-improved and wet grasslands) as well as distinguishing it from crops, with accuracies reported of up to 94%.

Dusseux et al (2014b) used time series of LAI derived indices to highlight the importance of monitoring grasslands across a season to capture the very dynamic nature of these targets. Management (grazing and cutting) is successfully mapped though the use of kernel functions tailored to rapidly changing systems, as opposed to conventional time series analysis of crops with a single phenological profile. The field investigations linking management practice to spectral response are detailed in another paper (Dusseux et al 2014c) ably demonstrating that management is primarily observed in the *temporal* domain and not the *spectral*.

North et al (2014) in New Zealand have had some success in delineating paddocks by segmentation of high resolution satellite time series. This is an important development as the extent and location of paddocks are rarely captured in any official database. In the case of Ireland, grazing methods such as strip grazing or cell grazing mean that the management unit is no longer the field; the smallest mapped entity in official agriculture databases. This has particular implications in the management of field margins and biodiversity on the farm. It also complicates estimates of total biomass growth and removal if the observation unit (the field visible on the image or in cadastral data) is not the same as the management unit.

Donald et al (2013), building on earlier work (see section 2.4.1), examined the response of paddocks to management regimes as recorded by the Landsat satellite. This work illustrates how different farm structure and farm size are in Australia compared to Ireland. Three farmlets[17] observed were of approximately 54Ha, in size compared with an average *farm* size in Ireland of 37Ha (likewise, the average dairy herd in Australia is three times the average Irish herd of 50 cows (Donnellan et al 2011)). Thus data sources and scales applicable in Australia may not work in Ireland.

Though not an issue in Ireland, pastures in Australia and New Zealand are often irrigated, either though surface water supplies or ground water extraction with efforts made to map irrigated paddocks from space to help quantify extraction rates from groundwater. Pairman et al (2011) successfully used NDVI anomaly mapping and rainfall data to identify irrigated pastures with an 89% accuracy in New Zealand, and McAllister et al (2015) used Landsat and ASTER data to find irrigated paddocks in Australia with similar success (88% correct).

2.6 EO and Environmental Sustainability - intensive grassland systems

2. 6. 1 EO and intensification

Herd and grassland management are closely interlinked, with grass supplying the main nutrient inputs for the herd through fresh grazed grass in summer, and silage during winter housing (supplemented by feed in the form of grain). The environment effectively places limits on grass growth in a given locality, through climatic constraints on the length of growing season (temperature) and maximum growth rate (sunshine and moisture), and soil constrains grass performance as a result of different moisture regimes and nutrient contents. The combination of soil and climate obviously affect herd management with respect to turn-out date, but the availability of spring grass can also alter planned breeding cycles. The maximum size of the herd, expressed as stocking density, is controlled through the Water

[17] An Australian colloquial term for a small farm usually run as a part-time or hobby enterprise

Framework Directive (WFD) legislation but also local soil conditions (Bellamy et al 1996).

Franke et al (2012) examined grassland use intensity from high resolution multi-temporal Rapid Eye imagery for the purposes of grassland biodiversity conservation at a plot level. This work was carried out under the wider umbrella of the German land use mapping programme D-COVER, and the focus on intensity came as a result of meetings with conservation stakeholders. They note that monitoring managed grassland cover requires *daily* image acquisition during the peak production period which is unlikely to be achieved in northern Europe due to cloud cover. As well as looking at time-series change of NDVI to classify plots into grass use categories, a parameter that describes the amount of variation over time was created. The results allowed the characterisation of plots into use classes with up to 85% accuracy using 5 observation dates over a season. As such the work classifies grassland into *types* of use (intensive, mixed, extensive, semi-natural) and not the *amount* of intensification.

2.6.2 EO, managed grasslands & carbon

Section 2.1.6 showed how monitoring of rangelands by EO has played an important role in understanding global carbon dynamics; however its use in managed enclosed grasslands has been less well investigated. The emerging results are still a little confused on the overall carbon budget in farm systems, but studies on rangelands (which have 10-30% of global soil organic carbon) show that the amount of soil carbon they store can increase under certain management systems (Dean et al 2012).

Scenario models of Irish dairy farms show that higher stocking rates are linked to higher GHG emissions, and that grazing dairy systems have 10% higher emissions per Ha land area than housed systems (when the off-farm area of land used to grow fodder for the closed system is included) (O'Brien et al 2012). Beef farms have been shown to have higher GHG emissions due to their higher stocking densities (Foley et al 2011). However, actual field flux measurements of grazing systems show that typically the whole farm is a net sink of carbon (~2 t C Ha^{-1})(Byrne et al

2007). This apparent contradiction shows the difficulty in applying theoretical factors to real world situations. A similar complexity emerges in New Zealand with dairy grazing on flat lands associated with soil C loss, but upland grazing associated with soil C gain, depending on soil type, with the authors speculating that past drainage of poorly drained soils may be a significant factor in soil C loss (Schipper et al 2014).

Work has shown that grass re-seeding (a management practice on improved grasslands) is associated with increased GHG emissions (due to ploughing and temporary post re-seeding drop in biomass) (Willems et al 2011). This shows that being able to monitor grassland intensification (of which re-seeding is a necessary function) is important for correctly allocating GHG emissions to land use.

EO plays a role in detecting land use change and particularly soil sealing, drainage and wetland/peat impacts (Houghton et al 2012). Peats represent 20% of Irish soils, but 35% of soil organic carbon stocks (Eaton et al 2008), and are a considerable source of carbon loss when exploited, either mined as fuel or drained for pasture production (O'Brien 2007b). In Ireland land use change is monitored though the European 6 yearly CORINE programme (Kevin Lydon & Smith 2014), an EO derived product based on hybrid classification of SPOT imagery, but this is considered inadequate to properly capture Irish land use change dynamics (Black et al 2008). There is no national programme dedicated to monitoring land use by EO or other means, and Ireland currently amalgamates statistics from a number of national bodies for LULUC reporting. The only national land cover map developed explicitly for Ireland was created by Teagasc as part of the soils and sub-soils programme (Fealy & Green 2009), with some land cover maps for dedicated purposes, for example for peatlands (Cawkwell et al 2010).

When addressing GHG and carbon storage on Irish pasture, the wider agricultural landscape, supported by grass based enterprises, needs to be assessed. Ireland has the lowest cover of forestry in the EU at 13% of the land area (O'Brien, 2012), but hedgerows, planted and maintained by farmers, represent a significant reservoir of woody biomass. Classification of colour aerial photography was used to produce a

national map of hedgerow and scrub, showing the Republic of Ireland has 6% of the land area under hedgerow/scrub cover (Green 2011). Lidar scans were then used to estimate aboveground biomass in hedgerows and the results combined to give a national estimate of carbon stored in AGB of hedges (Black et al 2014).

2.6.3 Nutrient management

Nutrients in the form of organic and inorganic fertilizers have to be managed to ensure the grass grows as well as possible whilst at the same time ensuring no excess nutrients are lost primarily to water(Peukert et al 2014). Nutrient runoff is seen as the biggest environmental externality (next to GHG emissions) of intensive grassland management. The use of EO in managing the application of nutrients is only developing, and is very much a PA issue focused around in-situ sensors (Hedley 2015). There are no examples of the use EO in, for example, developing decision support systems, (DSS) on the ideal time for farmers to apply nutrients (especially slurry), so as to minimise losses and leaching (though weather data are used), although work has begun on the use of EO to monitor application of slurry within closed calendar periods (Donnelly-Swift & Holden 2014). EO has been used however to map and monitor the negative consequences of nutrient runoff. The principal concern is eutrophication, excess algal growth (algal bloom) responding to nutrient increases in the water and impacting negatively on the aquatic biome. The literature on the use of EO to quantify chlorophyll concentration in inland waters is extensive (Matthews (2011)), but in an Irish context eutrophication status in 200 lakes was successfully measured through the use of airborne spectrometry (O'Mongain et al 1999), generally however water quality in Ireland is monitored through *in-situ* networks.

2.6.4 EO and grassland biodiversity

Grassland habitat monitoring in farmed landscapes is most developed in Europe as a result of significant policy drivers. The concept of High Nature Value farming (HNV) is well developed (Lomba et al 2014), and it is within the framework of HNV that farmed grassland habitats, associated with different systems, geographies and levels of intensification are explored. HNV farmland has been defined as "those

areas in Europe where agriculture is a major (usually the dominant) land use and where agriculture sustains or is associated with either a high species and habitat diversity, or the presence of species of European conservation concern, or both" (EEA 2004).The methodology and processes for monitoring routinely are still under development and largely in control of member states. Most studies accept that EO systems cannot recreate the process of field acquisition at the species level that an ecologist would map (Pettorelli et al 2014) and instead they focus on the ability of EO to map large areas repeatedly and reliably. In designing a system for Canada to map biodiversity, Duro et al (2007) emphasise the ability of EO to map productivity, disturbance, topography, and land cover and thus infer biodiversity.

Most attention in Europe is focused on grassland habitats within protected sites such as Natura2000, and there is a growing understanding of the use of EO for monitoring these sites (Vanden Borre et al 2011). However a recent review of EO and conservation site monitoring highlights that methods are far from standardised and these sites are often complex, and this complexity confounds monitoring when different sensors and scales are used (Nagendra et al 2013). As an example Hazeu et al (2014) used SPOT imagery with other spatial data sets to propose an indicative map of HNV farmland in Holland. This approach is used within the Irish IdealHNV project[18], to create an indicative map of HNV presence at a 1km tetrad scale (Matin et al 2016)

In Germany Buck et al (2015) used high-resolution RapidEYE imagery and an expert rule base on landscape scale habitats associated with grassland types to successfully map high value grasslands outside of Natura 2000 sites. The biodiversity status of grasslands is closely linked to intensification and management and these are more directly detectable by EO than species mix. In Ireland the detection of farmland habitats outside of protected areas has relied on field work or simple GIS based generalised additive models of indicative information such as soil maps and stocking density (Sullivan et al 2011). As part of the Teagasc/EPA soils

[18] https://idealhnv.wordpress.com/

project habitat map, referenced in section 2.10, grasslands were mapped at 1Ha resolution in a classification of Landsat-5 imagery, identifying wet and dry grasslands and karst grasslands. Farmland habitats, including grassland types, were also successfully mapped in the Burren Special Area of Conservation (SAC) using field data and Landsat imagery (Parr et al 2006).

2.7 Currently Operational Services

2.7.1 Grassland precision agriculture services

An early review of precision agriculture, PA, in grassland (Schellberg et al 2008) identified a number of issues to be addressed with reference to heterogeneity in grassland management, with species and utilization being the principal concerns. The review outlined a number of broad areas of current PA including robotic machine vision systems for weed detection and species recognition and EO for pasture and livestock management, concluding that heterogeneity and issues with spectral and temporal resolution limit the use of EO in PA for grasses, even if it is tailored to specific localities and production methods. The implications of the review are that decision support systems (DSS) that convert data on grasslands to information to action are under-developed and the economic argument still needs to be made in a convincing manner at the individual farm scale. These issues remain largely true in 2016, as recognised by the UK Office of Science and Technology which also identified PA in grasslands (which, as in Ireland, constitute the largest component of UK agriculture) to be under developed (POST 2015), and suggest central government support, with industry partners, for grassland PA development and adoption.

Table 2.4 gives a list of the EO driven grassland PA services commercially available that the author could discover. The services generally provide up-to date estimates of grassland biomass yield at hectare scale at best.

Table 2.4: Currently available EO driven PA services in grassland (not including crop focused services, imagery suppliers, and local resellers).

Name	Scale	Company	Service Type	Notes
AgImage	Paddock	Land gate (AUS)	Grass yield Estimates	Beta service not fully operational
Pasture From Space	1km	Land gate (AUS)	Pasture Growth Rate	
NRMHub	Unknown	Rangeland Natural Resource Management Alliance (AUS)	Grass cover	Beta service not fully operational
VegMachine	Rangeland	CSIRO (AUS)	Resource change detection	Designed to help rangeland manager observe landscape scale changes of grazing resources in response to management regime change
PiMap	250m	eLeaf, (NL)	Biomass (kgDM /ha)	Claims to estimate biomass and other parameters (c3 plants only) from satellite driven energy balance model.

2.7.2 Farmer Acceptance of PA in pasture management

A pasture growth rate model, PGSUS, was incorporated into pasture management software which estimates paddock scale biomass from local weather conditions, provided some regular local measurements are entered by the farmer, and its use and acceptance to Australian farmers evaluated. Romera et al (2013) found farmers were happy with the idea of PA in dairy farms, but found repeated data entry to be undesirable and stated that any new software had to fit with existing management strategies. The authors conclude that data entry needs to be simplified and made quicker to increase acceptance and results should be made available to farmers instantly. Similarly, a study by Eastwood (2008) in Australia concluded that PA

adoption is slow because of a focus on technology, and not on the farmer and the farm system. A detailed formation of the learning and adoption strategies of the 6 farm case studies showed that engagement is only partial because at some point farmer needs and expectation of the technology deviate from the design principles embedded by the manufacturer.

A recent EU report (Zarco-Tejada et al 2014) on PA adoption concentrates almost exclusively on crops and horticulture (with a small mention of PLF but nothing on grazing or grass), but its general points regarding adoption hold true:

- PA profitability is critical
- Current PA adoption is machinery led
- PA profitability is farm size dependent

Grazed grass is the cheapest feed available, therefore any technologies that increase the amount of grazed grass in a herd diet reduce costs and is a clue to where adoption may evolve in pasture based enterprises is the observation (*ibid*, pg.12):

"*In an agriculture market where gross margin and profitability are getting tighter, farmers are looking for technologies that reduce costs without decreasing production.*"

In a review of PA by Zhang et al. (2002) the following barriers to acceptance were identified:

- Data overflow for farm management has to be overcome by developing data integration tools, expert systems, and DSS.
- Lack of rational procedures and strategies for determining application requirements on a localized basis and a parallel lack of scientifically validated evidence for the benefits claimed for the PA concept.
- Labour-intensive and costly data collection with the development of rapid sensing systems needed before PA can be widely practiced.

- Lack of technology-transfer channels and personnel with educational programmes involving researchers, industry, extension specialists, and consultants urgently needed.

Finally a review of the literature (Pierpaoli et al 2013) on the drivers of adoption found that education and age were frequently cited as important factors in farmer adoption of this technology. As demographic shifts in farm population lead to more formally educated farmers in Ireland (McDonald et al 2013) PA adoption is likely to increase.

2.8 Future Developments

In a detailed and considered review of new technologies in grassland management and research Schellberg and Verbruggen (2014) cover EO in grassland management with their conclusions regarding its use in observing management, cover, composition and biomass echo the literature outlined here. Their observations on the spatial and temporal limitations of EO for grasslands, especially in small scale enclosed intensive systems like Ireland, are clear and the authors conclude that more research on in situ sensors will be the focus of future research (especially with the dramatic increase in drone deployment on farms). In their conclusions they rightly highlight the need for more cross-disciplinary research between agronomists and EO experts, but their conclusions on technology in grasslands in comparison to arable needs a more critical response.

The authors conclude that technology is less critical on grass farms than arable because:

I) there is a limitation of management options in cutting, grazing etc.
II) there is less need for technologies used in arable systems such as weed and pest control
III) only one crop, grass, is grown

This conclusion reflects a common idea in PA for grassland, that grass is a crop and can be treated as such within the PA paradigm. Instead, in dairy and beef systems it is more beneficial to think of grass as a means to an end and management of it as only one part of a multi-functional decision space. The number of management options in grassland systems may be limited, but their potential application and interaction is manifold (refer back to Table 2.1). A tillage field is treated as one management unit with a single goal, maximising yield of the crop, whereas a grass paddock has multiple uses throughout the season (grazing, silage, hay). Tillage fields can be treated as independent objects in a farm management system, where paddocks are part of more complex inter-locking farm systems, attempting to feed animals now and in the future, where decisions on one paddock can have impacts on other paddocks.

PA literature often has a bias toward yield maximisation and reduction in spatial heterogeneity, but formal definitions of PA do emphasise the importance of timing of events, and in grass management in intensive farms it is timing and interaction of events i.e. dealing with temporal heterogeneity where PA can have the biggest impact. Within the PA paradigm of crops and horticulture the drivers have been agronomic (yield maximisation, crop protection, etc.), but with paddock management the drivers are economic and are principally concerned with reducing costs for the whole farm system. As a result it is evident that the application of PA techniques has only begun for paddock management, but that it needs to be considered independently from PA for croplands.

As grass is the cheapest feed available, poor paddock management is money lost, but paddock management is time consuming and thus increases labour costs on the farm. Much of the current PA development is concentrated on automation and reducing labour costs, for example in sensor deployment, robotics and data management. Gobbett et al (2013) are developing proximal sensor systems for deployment in paddock management, but their work highlights the many operational hurdles to be overcome in integrating an automated system reliably into a farm workflow. Reddersen et al (2014) shows how ultrasonic measurements

of sward height is a successful method and compares as well as, or better than, proximal optical sensors, and Fricke and Wachendorf (2013) combined ultrasonic with multispectral sensors to measure biomass in grass-legume swards[19].

As discussed in section 2.1.9, a number of studies have begun to look at SAR as a tool for observing grasslands and pasture, driven by its all-weather capabilities, ability to detect some soil properties and availability of new higher resolution data. Dusseux *et al* (2012) suggest that there is no increased accuracy in distinguishing grassland management between optical and optical plus radar, therefore in cloudy countries such as Ireland where a time series of optical data may be limited the combination of sources is appealing.

Spatial resolution will further improve for EO platforms, and combining local sensors with satellite models will enhance performance of pasture monitoring systems (Rahman et al 2014). The use of UAV mounted sensors is likely to be a significant factor in grassland management at a local scale in the near future (von Bueren et al 2015) in light of very rapid developments in technology (currently hampered somewhat by flight regulations that have failed to keep up with the technology), however this will not be feasible at a large scale.

2.9 Conclusion

Grasslands have long been a target of interest in the remote sensing literature. Within this literature they are principally understood as a land cover but in the absence of an accepted definition of grasslands within the EO community there are widely divergent estimates of what seem to be the same cover.

Beyond land cover, extensive grasslands, or rangelands, are largely treated as an exploited natural resource, more akin to an exploited natural forest than a crop. Satellites have been used to map and monitor degradation of rangelands associated with overgrazing, climate change and land use change. When addressed as a more

[19] Ultra-sonics have been developed into a field sensor for farmers to measure grass biomass by an Irish company http://www.grassometer.com/

sustainable resource, managed rangelands have been studied to estimate carrying capacity and the response of the grassland biome to weather shocks. The role of rangelands in global carbon stocks and sequestration has grown but there is work needed to refine our understanding of carbon sequestration of grasslands in response to different management methods and the net carbon sequestration of the rangeland farm systems.

All of these approaches exploit the same fundamental relation of vegetation cover to Vegetation Index, and the multi-collinearity of different vegetation parameters (LAI, NPP, LUE etc.) is largely unaddressed. By far the most common VI used is NDVI and more recent studies, whilst exploiting newer indices, generally report NDVI as performing adequately in comparison.

As the studies change in focus and scale to look at more intensive pasture production the geographic interest moves from China and the Americas to Australia, New Zealand and North Atlantic Europe, home to large-scale, rain fed, grazing based dairy industries. Australia has the most developed EO for pasture production research, with large dry-land paddocks on ranges providing good targets for estimating feed on offer, grass ecotypes, growth rate estimates and drought effects. As with the studies with less managed rangelands, these services largely rely on NDVI relationships being established with the vegetation parameter under investigation, but models combining satellite data (mostly AVHRR and Landsat) and meteorological data have begun to reach operational standards. By contrast, in enclosed highly managed temperate grassland landscapes such as New Zealand, Ireland and the UK, EO is only beginning to be employed. The early studies (in the last five years) have successfully linked VI with biomass, biomass removal and management on experimental sites but it is clear that the dynamic multifunctional nature of grassland management, with farmers managing multiple paddocks under multiple regimes in ways that adapt to demand on a weekly basis, is a major confounding factor in operationalizing EO in the farm landscapes (made more difficult, as many authors acknowledge, by frequent cloud cover). To be successful, EO applications on these farms need to be able to observe farm structure (e.g. farm

heterogeneity and stocking density), farm management (especially rotation cycle and herd management), feed on offer/feed demand (standing biomass Kg/DM/ha) and yield (silage and hay harvest totals). Stocking density is estimated on rangelands but not in intensive temperate enclosed grasslands, small scale estimates of silage and hay making have been made, as have standing biomass estimates, but there is little literature on herd management decisions in these landscapes.

The use of PA on grassland farms is expanding, especially with the growth of precision dairy farming. The range in performance of grassland farms compared to the range in tillage farms suggests there is a large reservoir of untapped potential. However barriers still exist with a lack of understanding in the PA industry of what grassland farmers need (grass is not just another crop) and existing barriers to PA adoption generally related to cost, relevance and applicability. The growing literature on knowledge transfer (KT) and PA suggests that systems need to fit into existing management paradigms on farms, be easily understood or taught, use a common language and, especially for grassland farmers, concentrate on systems that reduce cost rather than increase yield.

In short, most of the issues raised in this literature review could be resolved with field-scale estimates of biomass, weekly estimates of grass management and performance, and long term monitoring of grassland intensification.

3 Cattle stocking rates estimated in temperate intensive grasslands with a spring growth model derived from MODIS NDVI time-series.

3.1. Introduction

Globally, grasslands are exploited as a feed resource for livestock and broadly can be divided into natural rangelands, which are common in the Americas, China and Australia, and highly managed enclosed paddock/field systems that are common in Atlantic Europe. Managed grasslands for the production of meat and dairy produce are a significant agricultural land use globally (Bouwman et al 2005), and an important factor in global greenhouse gas (GHG) emissions (Suttie et al 2005).

The level of exploitation is largely dependent on the number of animals an area is to support, in rangelands this is the carrying capacity and in pastures it is the stocking density. Open natural grasslands used for grazing, otherwise known as rangelands, have attracted considerable interest from the EO community with studies at global and regional scales as highlighted in Section 2. An example of a global scale study is the work of Zhang et al (2009) in estimating NPP/GPP of grassland biomass using MODIS data (this follows from earlier 2008 work by Zhang discussed in 2.1.8. Regional studies include evaluation of grassland production with Landsat Thematic Mapper data in the South African Rangelands (Bastin et al 1998), use of AVHRR data in Australia (Hill et al 2004), and MODIS data in China (Cui et al 2012) as discussed in section 2.1.7. The literature on EO of rangelands is extensive with Tueller (1989) providing an early review of its potential. Booth and Tueller (2003) assessed EO utility from the perspective of the rangeland manager, and Svoray et al (2013) highlighted developments in methods and technologies during the early years of the 21st century. In contrast, the EO literature on intensively managed paddocks (highly managed enclosed systems, wherein grass is grown as a crop for grazing and fodder) is much smaller and there is no published review

concentrating just on the use of imagery for paddock management (although Schellberg et al (2008) include EO in a review of precision agricultural techniques for grassland management). Recently Ali et al (2016) published a review of grass biomass estimation by RS technologies. Studies that have been done looking at the use of EO for paddocks have focused around decision support systems for farmers and as a precision agriculture tool to maximize grassland production through efficient use of inputs.

As shown in section 2.4 many of the EO studies on monitoring the effect of grazing on grasslands use measurements of a vegetation index (VI). Time series of high resolution data such as IKONOS have demonstrated that NDVI data can detect post-grazing regrowth within a paddock (Handcock et al 2009a), and also that NDVI can be used to measure pasture growth (Donald et al 2010, Phillips et al 2009). Lower resolution MODIS data have been incorporated into paddock level management regimes, all be it in large Australian paddock systems where the average paddock is 25ha compared to the average Irish field size of 4ha, with daily MODIS acquisitions combined with field level sensors in an attempt to create automatic feed budgets for cattle with some success (Donald et al 2012).

In the land cover mapping literature "grassland" is often a default class, ignoring the different land uses that grassland can be put to and the very great variance in habitat value of grassland. In the last few years a number of researchers have highlighted the need for better discrimination in grassland mapping, most especially around grassland habitats and grassland exploitation/management, and most of the reviews identify remote sensing as the mechanism by which this can be achieved. For example a recent overview of the sector by many of the leading researchers in European and agricultural land use modelling (Kuemmerle et al 2013) noted that:

"*Global data on grazing systems are particularly scarce…Likewise information on other* [Grazing] *input indicators are missing*" (pg. 488).

The key recommendation from this paper is that:

"*Future research should focus on improving existing land use intensity metrics…"(*pg.490)

A recent study on Irish grassland/cropland dynamics by Zimmermann et al (2016b) showed an absence of detailed data on permanent grassland, and using grassland as a default "other" class can lead to underestimating emissions in LULUCF reporting under the Kyoto protocol.

Another shortfall in information around grassland exploitation is stocking rate (SR), the number of livestock units per unit area (LSU/ha) which is a basic measure of grassland use. European habitat projects such as ENVIEVAL (Schwarz et al 2014) and others (Elbersen et al 2014) identify the absence of high resolution SR data as a significant barrier to identifying and protecting species rich grasslands. Mapping grassland utilization at high spatial resolution is a necessary pre-requisite to effective agri-environmental planning, with Vinther et al (2011) identifying livestock patterns, SR, intensification, and farmland abandonment as key agri-environment indicators that need to be recorded at scales better than the NUTS-2 level (a regional scale defined under the Nomenclature of Units for Territorial Statistics (Eurostat 2003)) to adequately capture trends.

There have been attempts to model stocking rate as Chang et al (2015) did for Europe, but generally at a coarse scale (e.g. 25km) and with very broad assumptions regarding farmer behaviour and stocking rate. Chang et al.'s adaptation of the ORCHIDEE ecosystem model assumes that farmers in Europe maximise stocking density to the limit imposed by soil and climate conditions, however there is no evidence presented that this is so, and the management options for addressing environmental, especially soil, constraints are not addressed. The global model of animal stocking density produced for the Food and Agricultural Organisation (FAO) for 2010 (Robinson et al 2014) is discussed in detail in section 3.5.1.

3.1.1 Remote sensing and stocking rate.

In rangelands it is common for *a priori* knowledge of stocking rate to be used in spatial ecological models that examine the effect of grazing on grasslands. These mechanistic models can be combined with remote sensing to monitor rangeland degradation, as demonstrated by Paudel and Anderson (2010) with a study on grazing pressure in Nepalese rangelands. Oesterheld et al. (1998) used accumulated monthly averages of 1km AVHRR data over 7 years (1982-88) to build a relationship between NDVI and stocking rate at county level in Argentina. Using MODIS data, Numata et al. (2007) analysed the complex interactions of stocking rate, bio-physical parameters and satellite derived vegetation indices in Amazonian pastures, linking NDVI to grazing intensity via the bio-physical parameters observed. Much of the work on estimating stock rate in rangelands from NDVI has effectively correlated herd numbers with biomass removal through grazing (Zongyao et al 2012). Hunt and Miyake (2006) compared SR derived from 12 years of AVHRR data on Wyoming rangelands with official USDA stocking figures, but found only a weak correlation. In this case the NDVI stocking rate was derived as a function of available forage calculated from accumulated NPP estimates, with the assumption that the animals follow available fodder.

The use of time series of satellite data to provide benchmarks of vegetation performance for climate studies and agricultural monitoring is well established. AVHRR and MODIS data have been used for long term studies of agricultural land use change at country level (de Beurs & Henebry 2004, Propastin et al 2007, Wardlow et al 2007) and globally (Friedl et al 2002, Ganguly et al 2010). Local long term averages of NDVI values have been used to characterize agricultural land use (Baldi et al 2008), and deviations from means (NDVI anomaly) are used to alert authorities to potential drought or food shortages.

In intensively managed temperate grasslands there is less concern in the EO literature with estimating SR as it is often assumed the data are available as a national statistic. However the absence of adequate statistics, even in the European

Union (EU), for validating stocking rate estimates has been identified in a number of studies. Temme and Verburg (2011), in a well cited paper, used statistical downscaling methods to produce maps of agricultural land use intensity across Europe at a 1km^2 scale, however for grasslands they were unable to fully validate the outcome because of a lack of official stocking rate data. The unwillingness of agencies to release detailed stock statistics is identified by the authors as a significant hindrance to development of grassland intensification maps in Europe.

3.1.2 Aim of the section.

An important gap in the generation of agricultural information, namely validated high resolution SR maps for intensively managed enclosed grassland systems has been identified by researchers. Intensive pasture-based farming naturally occurs in climatically favourable areas, but with a high degree of spatial and temporal variability due to farm management practices. The amount of grass in the field in spring can be controlled to some extent by farmers, but it is also influenced by seasonal weather effects with this variability between farms and across seasons evident in a time series of satellite observations.

This section evaluates an approach to estimating stocking rate (SR) of cattle in Ireland through modelling spring grass growth using a MODIS NDVI time series averaged over a decade to produce validated maps of SR. The section first describes the various datasets used to construct the spring growth map, and then goes on to outline the decisions behind the choice of stocking rate model, its construction and testing. The successful NDVI model is used to build a national stocking rate map for Ireland which is tested against independent ground truth data and compared to a simple agri-climatic driven model of SR. The output is compared to a recently released global animal numbers database.

3.2 Materials

3.2.1 Satellite data

The use of a time series of data with a high temporal resolution and a deep historical archive that is freely available limited the choice to MODIS, AVHRR, SPOT-Veg or MERIS data. NDVI imagery (Huete et al 2002) were selected as these have a higher spatial resolution than AVHRR and SPOT-Veg (1km), and are available from 2000 to the present day, unlike ENVISAT-MERIS which has been non-operational since 2012. The principal concerns in this study were frequent observations (both to overcome cloud contamination and to capture grassland dynamics), a long time series and observations in the red and Near Infra-Red, NIR in order to exploit VI, techniques. NDVI is, as outlined in sections 1.1.2, 2.1.2 and3.1.1, the most commonly used VI for grassland studies, and although it exhibits well documented saturation at high biomass levels (Fontana et al 2008) this does not present a significant issue for this study which focuses on spring growth, prior to the peak summer biomass levels.

MODIS is flown on the NASA Terra and Aqua satellites (Figure 3.1 shows an atypical cloud free MODIS image of Ireland). This is a low spatial resolution (1km to 250m), medium spectral resolution (up to 36 bands), and high temporal resolution system (1-2 days between images). The outputs are pre-processed to a high degree with derived products as well as spectral bands readily available.

The Terra and Aqua satellites, like most EO platforms, are polar orbiting at an altitude of 650km above the surface completing an orbit every 87 minutes, passing over each pole in doing so. The satellite is in a sun synchronous orbit, therefore the angular relationship between satellite and sun is constant. The MODIS sensor continuously records observations across its 36 bands, relaying the data in its memory to a network of base stations around the world. The particular combination of orbit and large swath width of 2330km is such that Ireland is observed nearly every day, always at 11.50 am local time.

Many data products derived from MODIS are available; the three products considered are composite products that guarantee an observation at some level of confidence. Compositing is a process to gap fill cloudy or contaminated pixels to ensure a seamless time series. The process is complex but in essence each pixel across the compositing period (8 or 16 days) is the best quality pixel with the maximum value, either band by band or for computed vegetation index (this is done using daily pixel values for 8 and 16 day composites in the collection 5 data used here but from 2016 onward the 16 day composite is itself derived from pre-composited 8-day data (Solano et al, 2010)). However, importantly, if no cloud free pixel value of sufficient quality is available the pixel is filled with a lower quality composite estimate based on historical averages. Earlier work in Ireland (O'Connor et al., 2013) has shown that the frequency of cloud contamination is such that in spring that the composite product represents the only cloud free daily product (i.e. no information is lost in using the composite product over the daily data in composting period).

The MOD09A1 product has surface reflectance in 7 bands with resolution of 500-m. MOD09Q1 provides reflectance values for bands 1 and 2 (band 1 = 620–670 nm; band 2 = 841–876 nm). MOD13Q1 has data for NDVI and EVI, and surface reflectance from bands 1, 2, 3, and 7 with 250-m along with quality flag bands (Table 3.1). The day of year during the composite period when the best observation is recorded is called the day of pixel composite which is included in the MOD09A1 and MOD13Q1 products but not in the MOD09Q1 product.

Table 3.1: Pixel reliability codes for the MODIS products. Only Code, 0 were used in this analysis

Product	Resolution (m)	Composition Day	Composition Period	Band 1	Band 2	NDVI	EVI	QI	Usability Index
MOD13 Q1	250	Yes	16 days	Y	Y	Y	Y	Y	Y
MOD09 Q1	250	N	8days	Y	Y	N	N	Y	N
MOD09 A1	500	Yes	8days	Y	Y	N	N	Y	Y



Figure 3.1: A MODIS image of Ireland (acquired October 11th, 2010)

The selection of MODIS product is a compromise therefor between spatial and temporal resolution and pre-processing requirements. The compositing process guarantee's a pixel value but use of "historical averages" would be in appropriate when attempting to characterise real current conditions, so only pixels using the highest quality real data can be used. In order to build a model representing actual

events the real date of the composite pixel value represents has to be known. As the MOD09A1 8 day product has no day of composition data this could be eliminated.

Previous studies have shown that the highly fragmented heterogeneous Irish landscape presents a considerable challenge at courser scales when studying change over time, the highest possible resolution is preferable (Cawkwell et al, 2018). Therefore the product MOD13Q1, 16day 250m resolution, was selected.

The selected MOD13Q1 16 day composite product provides detailed pixel reliability and quality codes (listed in Table 3.2), and Day of Year (DOY) acquisition code for each 250m pixel (García-Mora et al 2011). In this analysis only those pixels coded 0, use with confidence, were used.

Table 3.2: Pixel reliability codes for the MODIS products. Only Code, 0 were used in this analysis

Code	Pixel Reliability	Description
-1	Fill/No Data	Not Processed
0	Good Data	Use with confidence
1	Marginal data	Useful, but look at other QA information
2	Snow/Ice	Target covered with snow/ice
3	Cloudy	Target not visible, covered with cloud

The use of time composited imagery is essential in Ireland where cloud cover frequently precludes use of daily data, with all 16-day composites for the period February 1- April 30 2003-2012 downloaded from the NASA ftp service. As an example, Figure 3.2 shows how few days are cloud free in March and April over this 10 year period. If data were acquired every day by MODIS over Ireland and every day were cloud free then the number of high quality days, in this period, would be 60, however the average is 8. Figure 3.3 shows the total number of high quality pixels on February 1st, March 1st and April 1st across the ten years. This low number of day/pixels with high quality data is a significant driver in the choice of a simple linear model (needing only a few points to define) over a more complex sigmoidal function, see section 3.3.2.

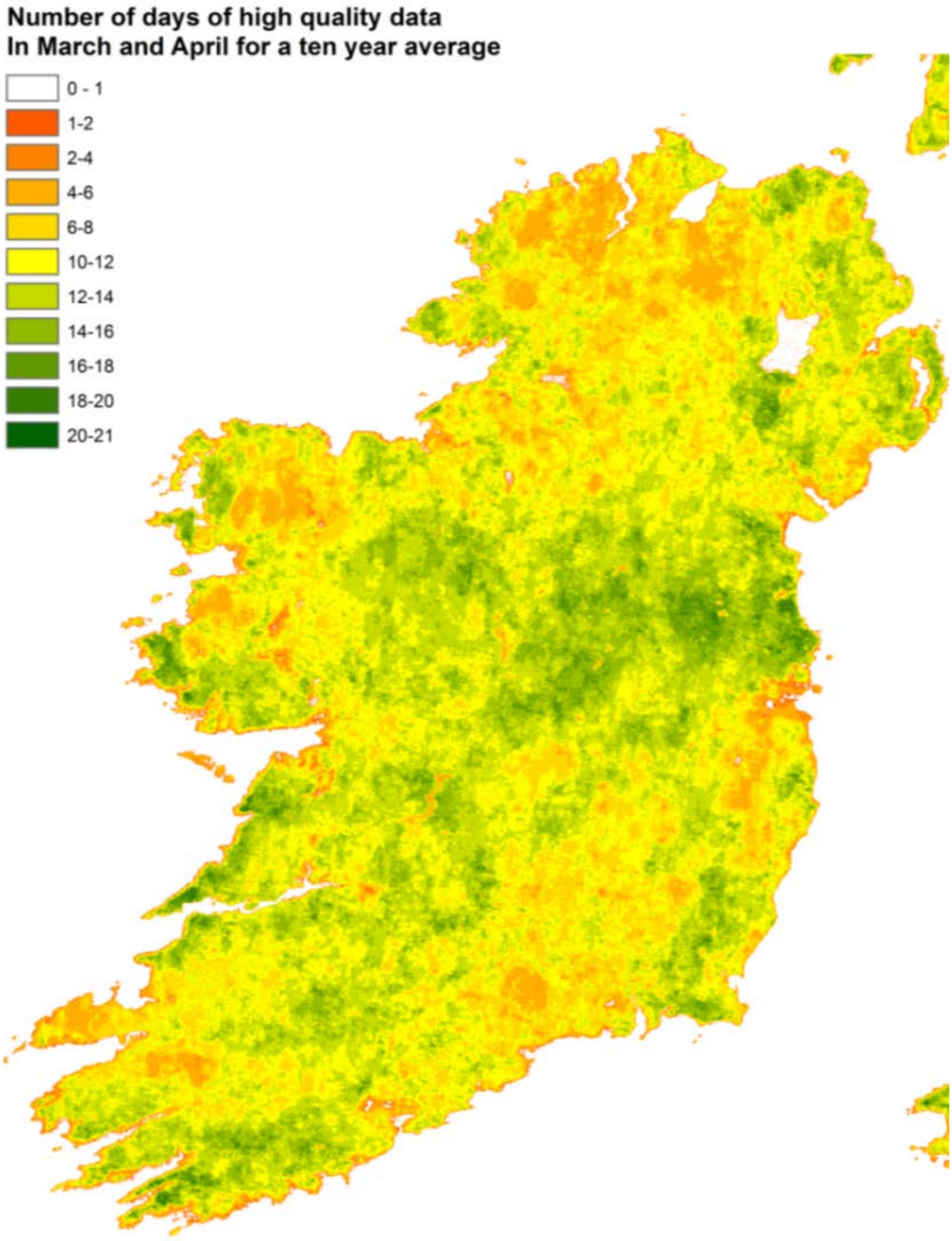


Figure 3.2: Average number of good quality MODIS pixels (QF 0 or 1) in March and April (theoretical maximum 60).

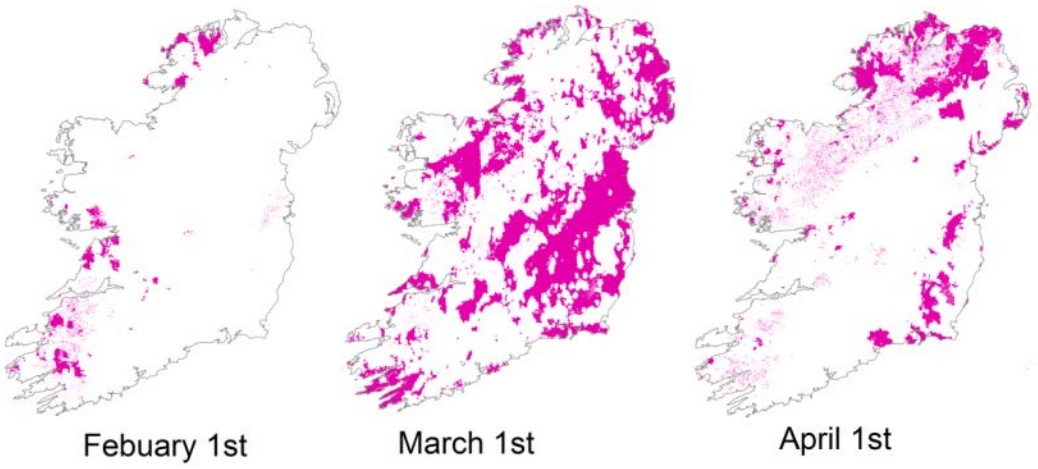


Figure 3.3: For three days of the year, high quality pixels from 10 years of data are shown in purple.

3.2.2 Stocking Data

Data on stocking levels are contained in the confidential Land Parcel Identification Scheme (LPIS), the national inventory of agricultural parcels, used in the payment of EU subsidies (Zimmermann et al 2016a). Stocking rate was calculated as the number of animals (Livestock Units, LSU) per hectare, with animals given a weighting (e.g. a dairy cow=1, a calf=0.4) as per the standard LSU calculation under EU accounting rules (see (FADN 2010) for all definitions).The livestock data were supplied as average stocking rate per townland, the smallest scale address locator in rural Ireland, each being typically 2 or 3 km^2 in size and containing on average 5 or 6 farms (Green & Donoghue 2013) as shown in Figure 3.4. The set of townlands used in this study had a range of stocking densities of between 0.1 LSU/Ha to 3.3 LSU/Ha.

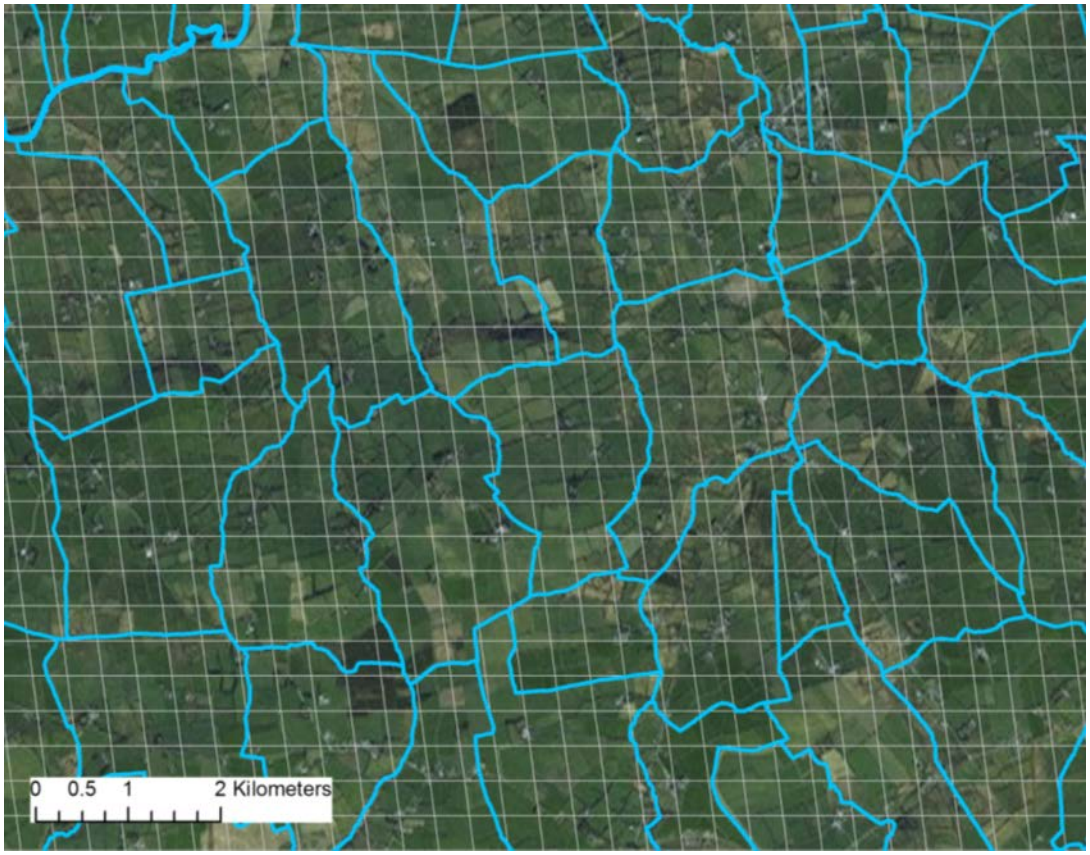


Figure 3.4: Typical agricultural landscape (Co. Kerry in the Southwest of Ireland) with townlands in blue and the MODIS 250m pixels outlined in grey.

The stocking data were only available for 2007 (see Figure 3.5 for distribution map), however policy implementation and the imposition of milk production quotas have kept the Irish cattle population stable through the period 2003-2012, as shown by the CSO data in Table 3.2 (Figure 3.6 shows the regions used in Table 3.3).

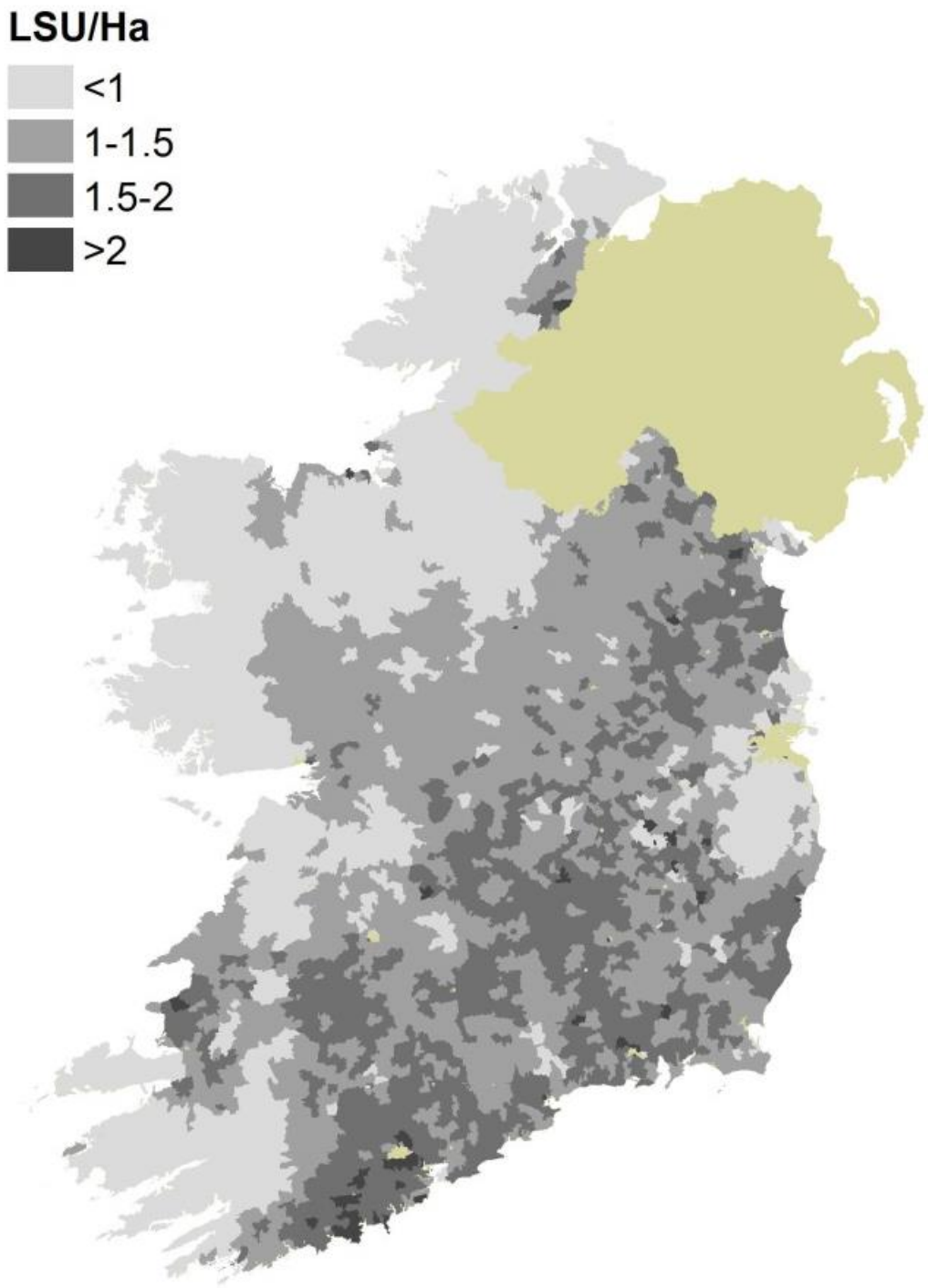


Figure 3.5: Distribution map of LSU data for 2007, with no data for urban areas and Northern Ireland.



Figure 3.6: Regions of Ireland (including Northern Ireland)

There are 46,702 townlands in rural Ireland, but only those larger than 1km^2 were used to allow for a sufficiently large sample size of MODIS pixels. Within that subset only townlands that were, in terms of area, at least 95% grazing and at least 95% grass (grazing can also occur on upland moorlands and peat bogs) were selected. This remaining set of 2180 townlands acted as ground truth in the subsequent analysis (Figure 3.7).

Table 3.3: Regional and national herd figures in thousands for Ireland broken down regionally, taken from the CSO. The average regional and total figures over this period are very similar to the 2007 values.

Cattle(LSU) '000	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	Mean	2007 % diff from mean
Border	962	955	934	925	921	918	909	876	856	884	914	0.8
Midland	793	782	802	814	801	799	799	768	748	783	789	1.5
West	995	990	979	979	981	985	968	908	886	915	959	2.4
Mid-West	1049	1061	1049	1042	1017	1025	1017	959	942	989	1015	0.2
South-East	1202	1241	1243	1253	1243	1242	1257	1218	1207	1265	1237	0.5
South-West	1411	1404	1390	1372	1346	1359	1365	1315	1308	1358	1363	-1.2
Dublin/Mid East	588	583	597	593	582	575	576	563	547	561	576	1.0
Total (LSU)	7000	7016	6992	6978	6891	6902	6891	6607	6493	6754	6852	0.6

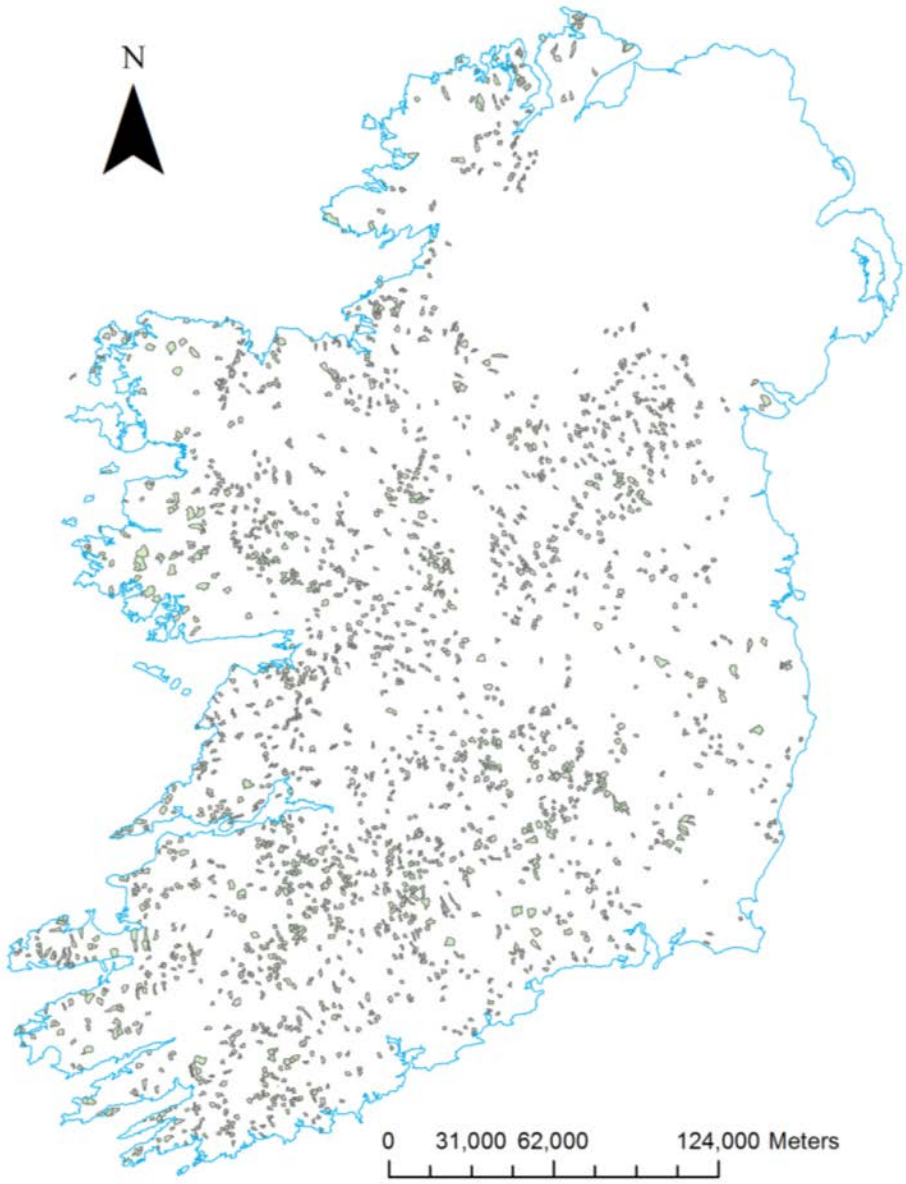


Figure 3.7: Distribution of townlands used in study.

3.2.3 Agri-climatic data

In order to demonstrate that the NDVI time-series data do contain information regarding farm management, and are not merely reflective of general agri-climatic growing conditions, the NDVI model is compared to a simple agri-climatic model of growing conditions against stocking rate. The components of this model are:

- x,y, and z coordinates of the 2180 townlands ground truth set

- Majority soil type in the townland, taken from the General Soil Map of Ireland (Gardiner & Ryan 1969)
- 30 year mean temperatures for February, March and April (rainfall is not a limiting factor in spring grass growth in Ireland) (Met Éireann 2012b).

3.2.4 Grassland in Ireland

In both beef and dairy systems, the animals are grazed throughout most of the year in open fields and are housed over winter for between 2 and 6 months depending on location. A wide variety of herd sizes and levels of intensification exist across Ireland. The SR on the farm is a simple expression of intensification and is a consequence of a number of factors, including location, farm system, farmer age, soil type and grassland production potential (Läpple et al 2012, O'Donnell et al 2008). Irish managed grasslands are complex land functions incorporating multiple land uses in a season in a highly heterogeneous landscape.

High SR can only be supported by the provision of grass fodder, higher stocked farms will put considerable resources into ensuring high growth rates and early spring covers.

3.3 Methodology

3.3.1 Processing satellite data

Phenological analysis has been utilized to find both spatial and temporal trends in important climate indices such as start of season (Jonsson & Eklundh 2002). Phenological approaches often involve statistical smoothing techniques (Chen J et al 2004) to fill in data gaps, and assumptions have to be made about signal to noise ratio in eliminating errant data (Bradley et al 2007). Work in Ireland by (O'Connor et al 2012) used smoothed time series MERIS data to link start of season events with land cover, and highlighted the difficulties posed by Ireland's highly fragmented landscape when attempting to extract a spatio-temporal signal. Much of the literature for crops makes assumptions about the idealized nature of the growth

curve in order to fit a smooth curve, i.e. that there is a single crop in a season, that grows to maturity and is then harvested with a single cropping. It has been shown that these assumptions begin to break down in areas of complex multi-cropping (as discussed by Atzberger (2013)), and in grasslands that experience 2 or 3 silage cuts per year.

These problems can be partly overcome by examining only a short part of the growth cycle where assumptions of seasonal growth curves and single/multiple cropping do not have to be made. Whilst linear and log-linear models are simplistic, a recent review of plant growth modelling by Paine et al (2012) states that linear models are appropriate over small sections of the growing cycle. Growth rates in the early part of the season in Ireland can be represented as a simple linear function with time (Han et al 2003), as can be seen from the rising limb of Figure 3.8, with field data from an experimental farm in the north-east of Ireland illustrating typical grass growth in the country.

The advantage of this approach is that modelling growth over the early spring period as linear functions of time means that only a few good quality observations across the period are needed to define the relationship and characterize the vegetation growth at a locality. This allows for very rigorous quality assessment to be carried out, using only the data that have the highest quality flag in the MODIS product, which is important under conditions of extensive cloud cover. The data were processed to extract only high quality pixels, and for each DOY across the 90 days of the 10 year period, the average NDVI value of just these high quality pixels was found. If the pixel was represented by low quality values in the quality flag (QF) layer the output was set to “No Data”. This process is illustrated in Table 3.4 and the results for a single pixel are shown in Figure 3.9.

Using the 16 day composite product simplifies the process as the production process identifies the high quality pixels in the construction. An analysis of the period in question showed the number good quality days lost were insignificant using the 16 day product over the 8 day or individual daily acquisitions.

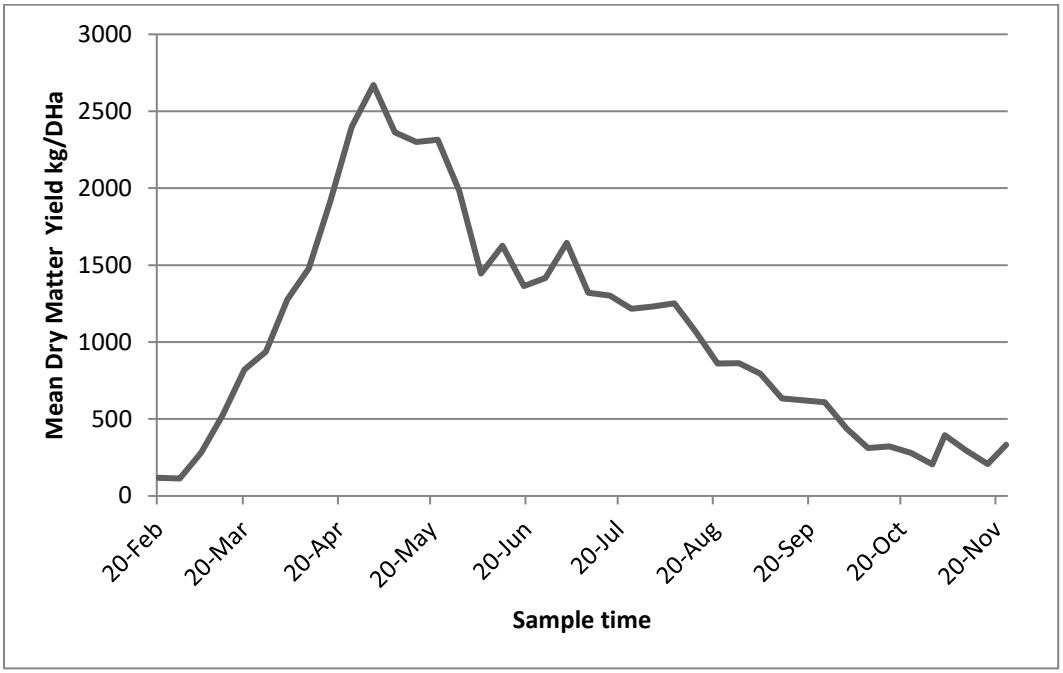


Figure 3.8: Mean grass biomass measurements across a 6 year period, 2003-8, derived from field observations at an experimental farm in the NE of Ireland (Grange, Co. Meath).

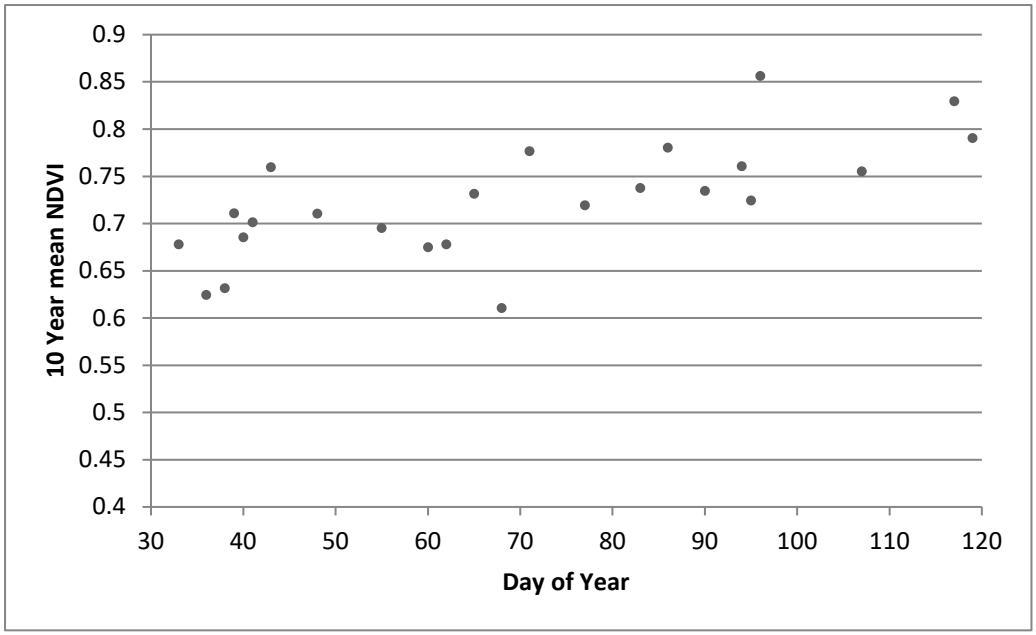


Figure 3.9: Data for a single 'typical' pixel. For the 90 days in the period February 1st to April 30, 66 days had no observations or poor quality pixels across the 10 years, leaving 24 days for which an average value could be calculated on which to fit a trend.

Table 3.4: Quality processing for a single pixel: For each DOY there are 10 potential NDVI scores for years 2003-2012, ND indicates no data available due to cloud. Instead of just taking an average of all available values, only those values with the highest quality flag (shown as bold) are used. This is done for all DOY between 1st February and 30th April, thus each pixel is represented by up to 90 values, representing each average daily NDVI score across the decade

Pixel X	DOY	31	32	33	…..	118	119	120
Year	$^{Year}V_X{}^{DOY}$							
2003		$\mathbf{^{2003}V_X{}^{31}}$	ND	$^{2003}V_X{}^{33}$	…..	ND	$^{2003}V_X{}^{119}$	$^{2003}V_X{}^{120}$
2004		ND	ND	ND	…..	$^{2004}V_X{}^{118}$	ND	$^{2004}V_X{}^{120}$
2005		$^{2005}V_X{}^{31}$	$^{2005}V_X{}^{32}$	ND	…..	$^{2005}V_X{}^{118}$	$\mathbf{^{2005}V_X{}^{119}}$	$^{2005}V_X{}^{120}$
2006		ND	$^{2006}V_X{}^{32}$	$^{2006}V_X{}^{33}$	…..	$\mathbf{^{2006}V_X{}^{118}}$	$^{2006}V_X{}^{119}$	ND
2007		$\mathbf{^{2007}V_X{}^{31}}$	ND	$^{2007}V_X{}^{33}$	…..	$^{2007}V_X{}^{118}$	$\mathbf{^{2007}V_X{}^{11}}$9	$^{2007}V_X{}^{120}$
2008		$^{2008}V_X{}^{31}$	ND	$^{2008}V_X{}^{33}$	…..	ND	$^{2008}V_X{}^{119}$	$^{2008}V_X{}^{120}$
2009		$^{2009}V_X{}^{31}$	ND	ND	…..	$\mathbf{^{2009}V_X{}^{11}}$8	$^{2009}V_X{}^{119}$	$^{2009}V_X{}^{120}$
2010		ND	$\mathbf{^{2010}V_X{}^{32}}$	$^{2010}V_X{}^{33}$	…..	$^{2010}V_X{}^{118}$	ND	$^{2010}V_X{}^{120}$
2011		$^{2011}V_X{}^{31}$	$^{2011}V_X{}^{32}$	ND	…..	$^{2011}V_X{}^{118}$	$^{2011}V_X{}^{119}$	$^{2011}V_X{}^{120}$
2012		$\mathbf{^{2012}V_X{}^{31}}$	ND	$\mathbf{^{2012}V_X{}^{33}}$	…..	ND	$\mathbf{^{2012}V_X{}^{119}}$	$\mathbf{^{2012}V_X{}^{12}}$0
Mean		$V_X{}^{31}$	$V_X{}^{32}$	ND	…..	$V_X{}^{118}$	$V_X{}^{119}$	$V_X{}^{120}$

3.3.2 Spatial Model Development of Early Spring Growth

Taking this stack of high quality NDVI observations and assuming that $NDVI_{DOY}$ is a proxy for biomass, a linear model of mean NDVI against DOY for each pixel was generated using a least squares approach implemented in ArcGIS:

$$NDVI_{DOY} = gr.DOY + c \qquad \text{Eq3.1}$$

where *gr*, is the gradient representing rate of growth and *c*, the intercept, being the theoretical amount of cover at the start of year. The resultant coefficients, *gr* and *c* are plotted in Figures 3.10a and 3.10b at pixel level. For the construction of the stocking rate, SR, model, the average value within the townlands was used.

3.3.3 Simple agri-climatic model

In order to demonstrate that the spring model is responding to more than agri-climatic growing conditions, a simple agri-climatic model with respect to stocking rate was created. Location was described with x, y, z coordinates for the townland centroid, and the mean temperatures in February, March and April were ascribed to each townland from the national gridded climate sets available from the national meteorological agency for the 1981-2010 period.

Soil type in the townland from the General Soil Map of Ireland (Gardiner & Radford 1980) was interpreted as a dummy variable by classifying soils as Poorly or Well Drained. Soils in Ireland are extremely complex and very variable even over small scales, so townlands that didn't have a majority soil type greater than 50% of the area of the townland were excluded. This left 1943 townlands, from the original 2180, for analysis. The model technique applied was a simple stepwise multiple log-linear regression against SR.

3.3.4 Relationship between spring growth model and SR

To create and test a relationship that links the NDVI decadal spring growth model with SR, the 2180 townlands with stock data were randomly split into two samples, 70% of townlands were used to build a model (1700 townlands) and 30% (480 townlands) to validate it. Generalized linear models, including interactions, were created in R and constructed and tested for *gr, c and gr*c* (averaged at townland scale) with respect to the SR and log of SR. The created model was implemented at a pixel level within ArcGIS

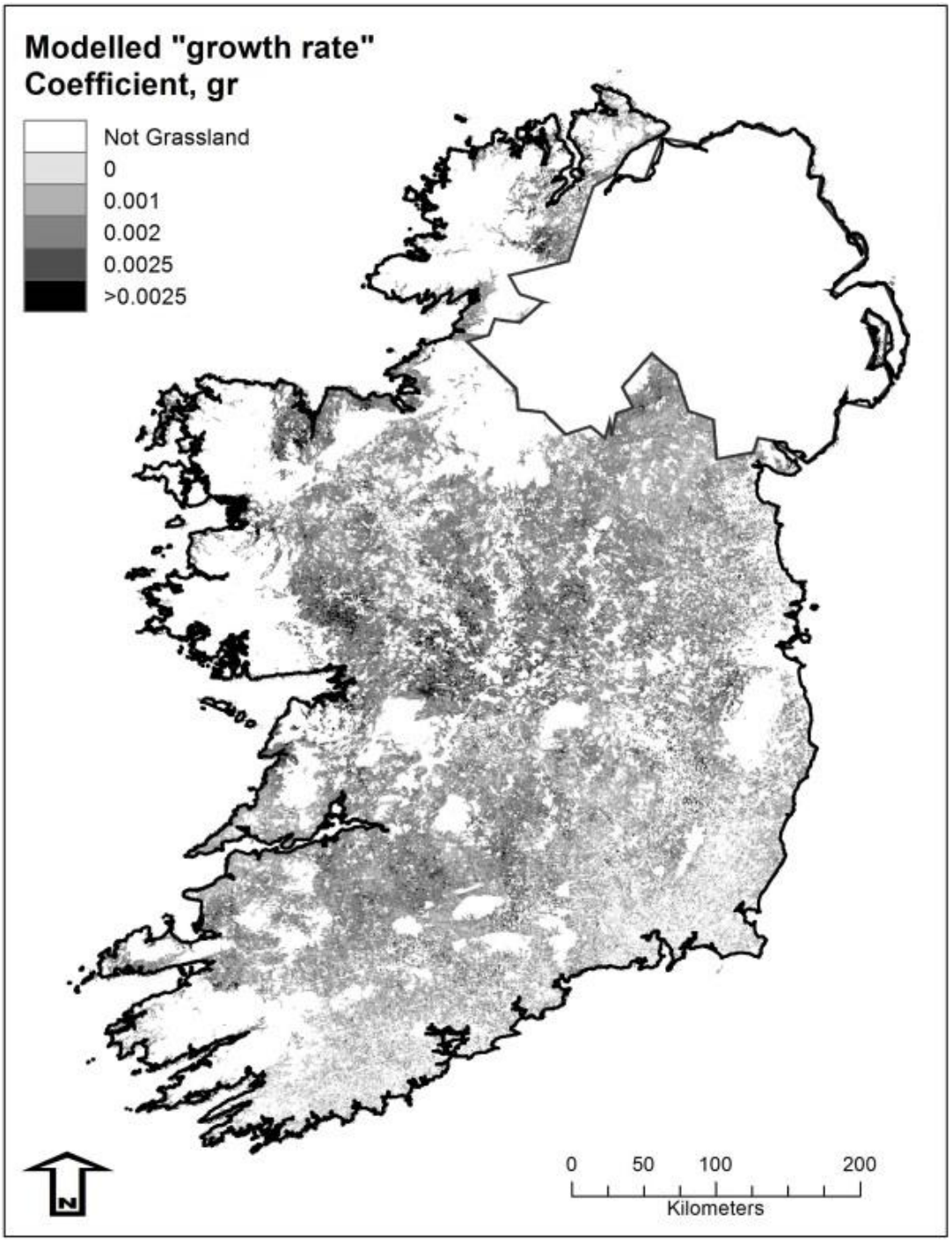


Figure 3.10a: A map of the grass growth rate term. Uplands, croplands, water and settlement have been masked out using the CORINE 2012 land cover map for Ireland. As no training or validation data were available for Northern Ireland, only the results for the Republic of Ireland are shown.

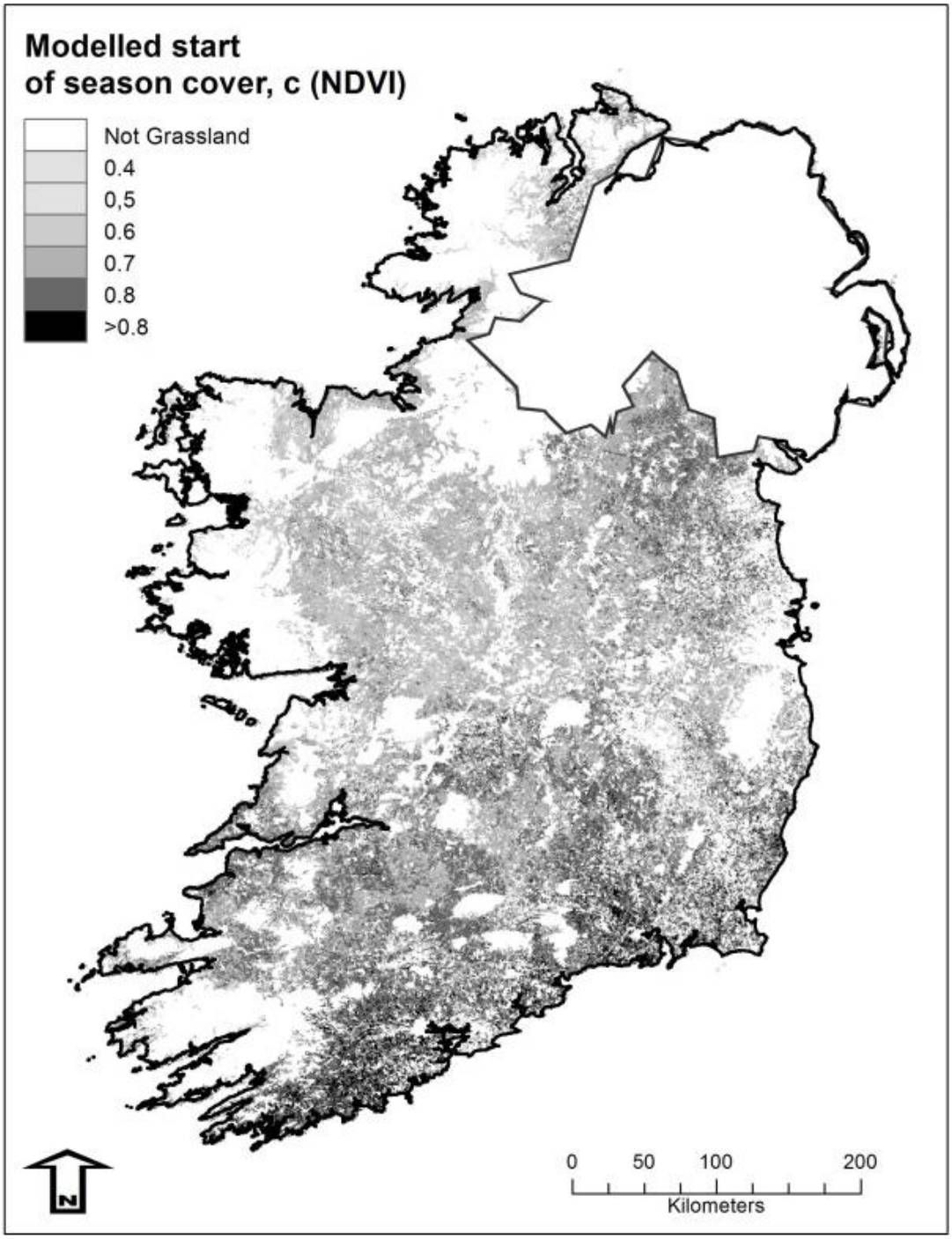


Figure 3.10b: A map of the Start of Season cover term from the national spring grass growth model. Uplands, croplands, water and settlement have been masked out using the CORINE 2012 land cover map for Ireland. As no training or validation data were available for Northern Ireland, only the results for the Republic of Ireland are shown.

3.3.5 Relationship between spring growth model and stocking rate.

A stepwise linear regression of the agri-climatic variables against SR, using all 1943 townlands in the agri-climatic data set was conducted with significance for the variables set at <0.001.

3.4. Results.

The generalized linear model created for SR with respect to the spring model coefficients is shown in Eq. 3.2, with x denoting any given pixel. Each term had a significance greater than 0.0001, and the resultant model had an RMSE = 0.128 with an r^2 value of 0.75.

$$Log(SR_x) = \mathrm{c}_x.(0.041) + gr_x.(0.00032) - (c.gr)_x.(0.0000027) - 2.22 \qquad \text{Eq. 3.2}$$

When this model is applied at townland scale to the validation set of observations (n=480), and compared to the actual SR, we obtain an RMSE of 0.13 with an r^2 value of 0.75 for observed values against predicted as shown in Figure 3.11.

This is a large sample set for both training and testing, so to test for sensitivity to sample selection a bagging approach was implemented in R. Bagging, or Bootstrap Aggregation, is a simple method for testing model ensembles. To test this model multiple random sets of testing observations and training observations (2/3 training, 1/3 testing) were iteratively selected, with the RMSE determined for the resultant model. Over a number of iterations it was found that sample selection had very little effect; with 10 iterations giving an RMSE error of 0.1344 and 1000 giving 0.1340. Changing test/training ratios from 1/8, 1/4 to 1/2 similarly had little effect on the RMSE of the estimated SR values. Therefore it can be concluded that the sample selection upon which the model was initially developed is robust.

The model described in Equation 3.2 was applied with the NDVI-based coefficients shown in figures 3.9a and 3.9b to create a national stocking rate map for Ireland, illustrated in figure 3.12.

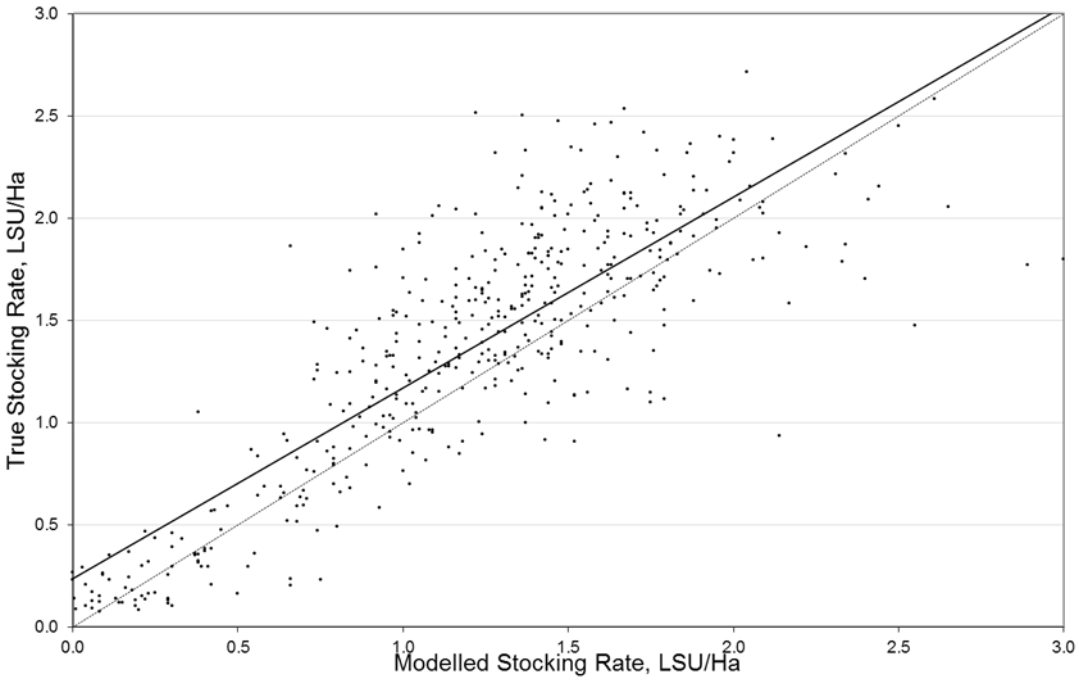


Figure 3.11: The relationship of actual stocking rate to predicted stocking rate (LSU/Ha) at townland scale for the test set (n=480), for the NDVI model. A "best fit" line is shown as solid and a 1:1 fit line is shown as dotted for comparison.

3.4.1 Comparison to agri-climatic model

The results of the linear regression between SR and agri-climatic variables are shown in Table 3.5a), using agri-climatic variables alone has an r^2 value of 0.47 with an RMSE of 0.64, making it far less reliable than the SR-NDVI model outlined and with a much higher error, although the location, elevation, mean February temperature and soil drainage dummy terms are all significant at the 0.001 level.

If the terms from the SR-NDVI model (c, gr, c*gr) are included with the agri-climatic variables the r^2 value increases to 0.78 and the RMSE is 0.13 (Table 3.5b). The performance of the three models is compared in Table 3.6.

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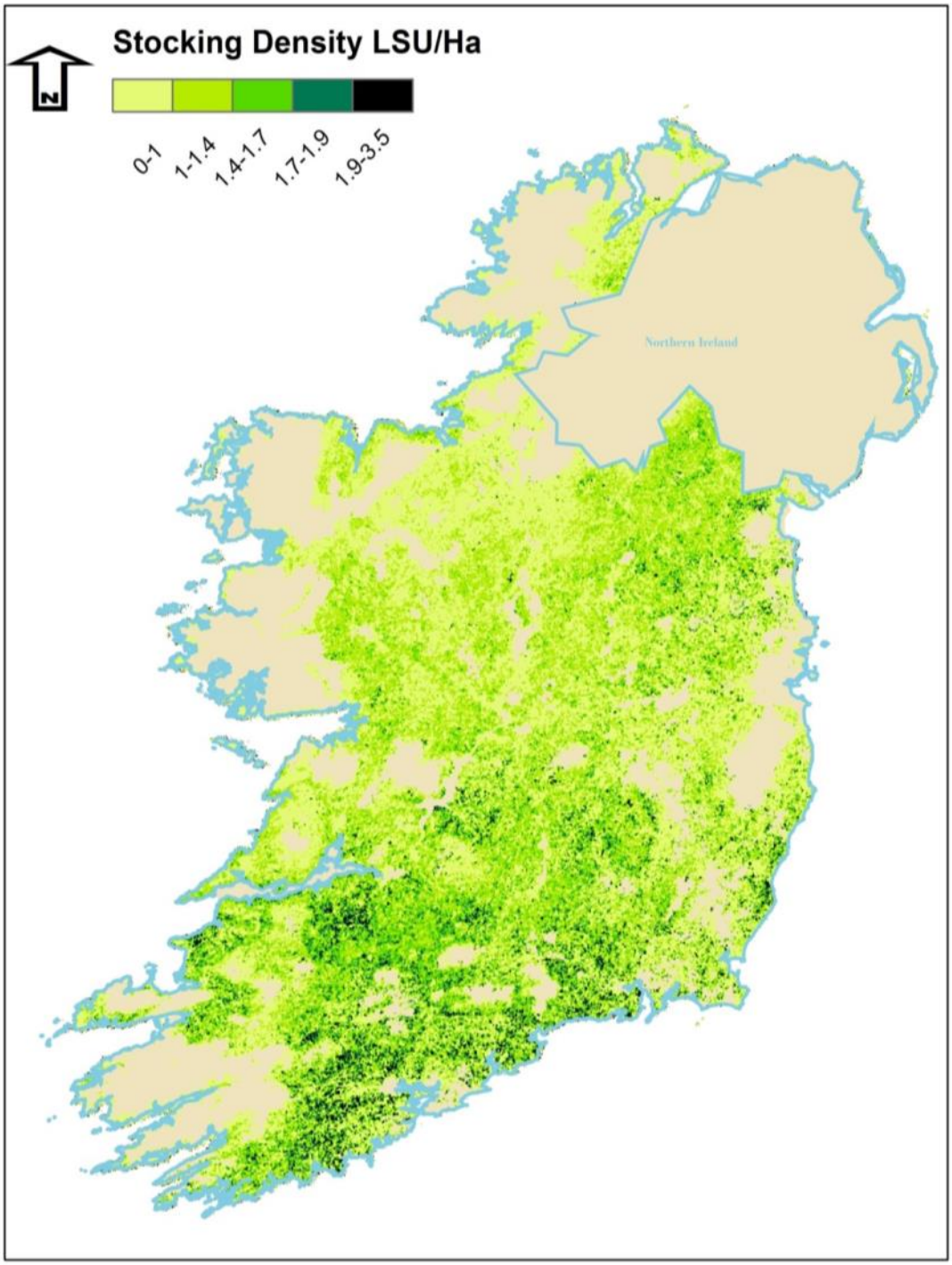


Figure 3.12: Modelled national grassland cattle stocking rate map for the Republic of Ireland, 250m resolution.

Table 3.5: Model coefficients for a) agri-climatic model and b) agri-climatic plus NDVI model with n=1944; * significant at <0.001 level, * significant at 0.1 level**

a)	Estimate	Std. Error	t value	Pr(>|t|)	Significance
(Intercept)	2.965e+00	4.609e-01	6.434	1.57e-10	***
X	6.015e-06	3.064e-07	19.629	<2e-16	***
Y	-5.963e-06	2.200e-07	-27.098	<2e-16	***
Z	-7.581e-03	3.582e-04	-21.163	<2e-16	***
Mean Feb T	-3.006e-01	4.070e-02	-7.387	2.22e-13	***
Wet or Dry Soil	1.534e-01	3.139e-02	4.888	1.10e-06	***

b)	Estimate	Std. Error	t value	Pr(>|t|)	Significance
(Intercept)	-4.853e+00	3.448e-01	-14.072	<2e-16	***
X	1.316e-06	2.350e-07	5.599	2.46e-08	***
Y	-1.954e-06	1.760e-07	-11.100	<2e-16	***
Z	-2.167e-03	2.673e-04	-8.107	9.08e-16	***
Mean Feb T	-1.186e-01	2.771e-02	-4.280	1.96e-05	***
Wet or Dry Soil	4.691e-02	2.119e-02	2.213	0.027	*
C	8.795e-04	2.209e-05	39.813	<2e-16	***
Gr	1.242e-01	1.342e-02	9.258	<2e-16	***
c*gr	-8.593e-06	2.136e-06	-4.023	5.97e-05	***

Table 3.6: Comparison of the three models, in each case n=1944

Model	r-squared	RMSE
Agri-climatic	0.47	0.64
NDVI	0.75	0.13
Agri-climatic+NDVI	0.78	0.13

3.5 Discussion

In the SR map (Figure 3.12) the high stocking densities in the south and south-west of Ireland that are associated with intensive dairy production, and relatively high values in the north-east associated with beef production, are evident. The low stocking densities in the west and the north-west reflect these regions' status as less favoured areas under the EU support scheme of that name. The broad geographic distribution is in agreement with that discussed in section 1.1.

The modelled spring growth coefficients, *c* and *gr,* derived from MODIS NDVI show a strong relationship with stocking rate. As discussed above, this is partly due to geographic determinism of highly stocked intensive farms developing in climatically favourable areas. However the NDVI-only model performs better than the simple agri-climatic model in explaining the variation in stocking rate, indicating that NDVI is not only capturing agri-climatic conditions but also the effect of management of the grasslands by farmers. The marginal improvement in the NDVI model if agri-climatic factors are included shows that most of the agri-climatic variation is accounted for within the NDVI variation. Thus it is concluded that the farmer has a detectable influence on grassland performance. This is not unexpected; the best performing farmers put considerable resources and management skill into ensuring high levels of grass cover in the spring.

The evident heteroscedasticity in Figure 3.11, where errors increase as a function of increasing SR, demonstrates that the model captures only a part of the story. Table 3.2 indicates that at a regional scale stocking numbers change little, as they have been largely constrained by EU policy on milk production limits, but this can hide inter-farm variation, where production capacity is bought from one farmer to increase production by another farmer. It is also worth noting that farms, in practice, do not have a single stocking rate, but will have a range of SR with highly stocked improved grassland paddocks near the parlour and less improved outfields or rented land.

Importantly, having only one year of stocking data and using NDVI and weather averages largely ignores seasonal impacts on grass production. Whilst weather will not influence stocking decisions (as these are made over the medium term of 4-6 years), it does influence management decisions, for example in a good year, when grass growth begins early in the season, farmers will turn out animals early and this will affect the NDVI signal recorded by the satellite. Higher stocked farms are generally more precisely managed and the farmer responds more readily to signals such as early grass growth, thus seasonal effects are likely to be amplified on these farms.

The trend for the model to underestimate SR above values of 1 LSU/Ha is partly a function of the two error sources discussed above, and also because the use of average SR within a townland suppresses the true range of SR evident on the ground at sub-townland scale.To reduce the heteroscedastic nature of the model, multiple years of stocking rate data with NDVI and weather data in a time dependent cross-sectional (or panel data) analysis could be attempted (See section 6.2 for more detail on panel data analysis). More highly resolved stocking rate ground truth, at least to the scale of the remote sensing sensor would also improve the model, however these are not currently available.

The combined model outlined in section 3.3 can predict stocking rate with an RMSE of 0.13 LSU/Ha, with respect to an average stocking rate of 1.3 LSU/ha. As a grass growth model the work presented here using NDVI is successful, however the use of other VI or derived biophysical measures such as fAPAR or LAI could be explored.

As outlined in the section 3.1 there is an accepted paucity of good data on stocking levels in grassland systems. Official data are often at scales that render them useless and the procedure presented here is an improvement on the available data in Europe and globally, however issues of scale remain. The townland scale data used here are not the stocking rate of the townland (number of cattle/area of townland) but the average stocking rate of farms within the townland. The large

pixel size of MODIS means the response of non-agricultural land is being captured even within the carefully selected townlands, and while this could be partially resolved using higher resolution imagery, such as Landsat or the Sentinel program from ESA, these systems individually do not have the necessary temporal resolution so methods of combining the observations will need to be further developed. Even at the farm scale a simple figure of SR does not express the complexity of SR on the farm, and in Ireland´s highly heterogeneous farm landscape the effective SR is not constant across the farm.

An alternative approach to the one presented here would be through the concept of "carrying capacity" that is common in the rangeland literature. In carrying capacity, NPP of grasslands is calculated on a seasonal basis and a mechanistic model of animal feed demand is used to calculate how may animals could be safely fed from the available biomass per Ha (see Peel et al (1998) for a review). Many of the rangeland studies assume animals move in and out of grazing areas in response to available biomass for grazing (the Oesterheld et al. (1998) study discussed in the introduction is a well cited example), but this is not the case in managed paddock landscapes, and therefore this approach is probably not appropriate for such grazing regimes.

It should also be noted, that while inferring intensification through monitoring of grassland management, is particularly suited to Ireland, the UK and some other northern European regions, elsewhere intensification is likely to occur through continually housed dairy and beef production systems, where animals are confined and feed in the form of grain fodder is brought to them. This form of intensification is only observable through land use change from grassland to cereals.

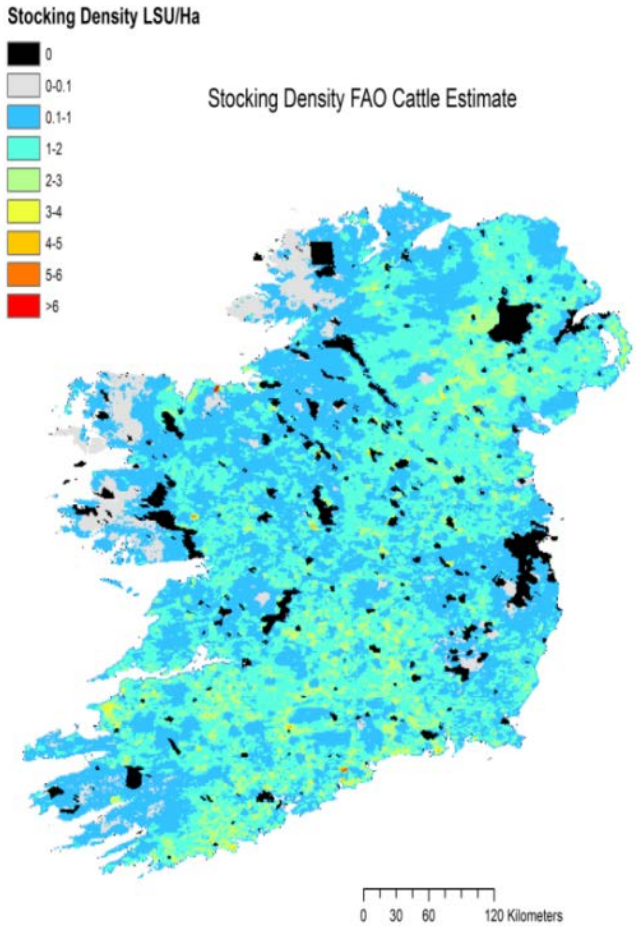
3.5.1 A comparison with the global FAO map

In 2014 (Robinson et al 2014) published a global map of farm animal distribution produced through a spatial downscaling of national estimates using land

cover/animal population models from 2010 data. The map covers all major livestock types and resolves to 1km and a comparison for Ireland with the stocking density map produced here is instructive.The FAO data are presented as the number of cattle per $1km^2$. To compare the two maps visually, the FAO map is recoded to stocking density, cattle/ha (by dividing the cattle numbers in each 1km cell by 100). Figure 3.13 compares the two stocking density maps, and the distributions do appear similar ("no-data" voids not withstanding), with higher stocking densities in the south-west and north-east of Ireland. The difference in spatial resolution is also obvious.

To compare the total animal population estimates, the MODIS Teagasc model must be converted into absolute animal numbers per pixel by multiplying each 250 meter pixel SD value by 6.25 (the area of a 250m pixel in Ha). Comparing the FAO total numbers and the numbers estimated with the model presented here with the corresponding data from the CSO there are considerable differences. Table 3.6 shows that the 2010 FAO map over-estimates the 2010 CSO count by 100% nationally, while the model developed by this work overestimates the 2007 CSO count by only 10%. The FAO data are created using a global allocation model that allocates animals to all land cover types at appropriate rates. As such this global model cannot take into account local relationships between land cover and cattle numbers, for example grazing animals within forests is a common farming practice in some parts of the world but not in Ireland.

To create a more realistic estimate of total cattle numbers from the FAO data, it is reasonable to only count those cattle that are in areas classified as "Pasture" and "Land Principally Occupied by Agriculture" (classes 231 and 243) in the CORINE Landcover Map 2012- i.e. locations where most of the cattle actually are in the country. Doing this, the FAO estimate drops to less than 11 million, and compared to the 6.6 million estimated by the CSO this is a 60% over-estimate. Applying the Teagasc model only in these areas estimates 6.26 million cattle in 2007, compared to the CSO figure of 6.89 million, which is an under-estimate of 10%.



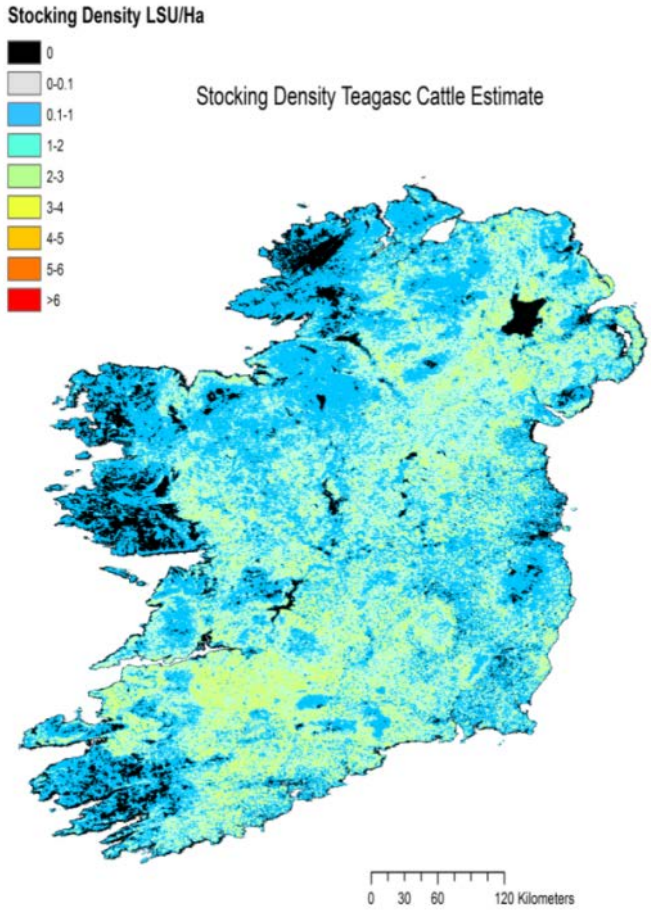


Figure 3.13: Comparison of Stocking Density Map with new FAO cattle d

Table 3.7: Comparison of the total cattle population estimates for Ireland made by the FAO (2010) and the Teagasc model presented here (2007) with CSO data, first for all areas and then for pasture areas only.

CSO-2010	FAO 2010	FAO-Pasture2010	CSO-2007	Teagasc2007	Teagasc-Pasture2007
6,607,000	13,440,232	10,847,024	6,891,000	7,468,214	6,264,102

Therefore, although the FAO map is a considerable achievement and hugely valuable resource at a global scale, the remote sensing approach outlined here produces a more accurate and higher resolution national product.

3.6 Conclusion

Most studies on rangeland vegetation index time series rely on smoothing functions that assume a "natural" single season growth curve. In highly managed grass production regimes, where the same paddock may be used for multiple grazing and silage cuttings in the same season, this is unlikely to hold true. By modelling only one short component of the grass growth cycle in a period when animals are less likely to be present, and as such the grass is responding only to agri-climatic conditions and farmer management, it is possible to couple local agronomic knowledge with remote sensing modelling techniques to successfully estimate SR in complex European managed grassland landscapes using NDVI data alone. This is the first time in Europe that this has been achieved without ancillary geospatial inputs, and is therefore of relevance to the wider community interested in methods to estimate stocking rate across Europe in the absence of official statistics. The model presented here compares very well with the best available global data set covering Ireland and it successfully estimates the total cattle population in Ireland for the reference year. The resultant maps could also play a role in GHG inventories of

farmland landscapes and in monitoring intensification trends in European grasslands as the EU enters the post milk quota era.

4. Time-domain seasonal progression anomaly detection in intensively managed grassland landscapes.

4.1 Introduction

In Irish dairy systems, the animals are grazed throughout most of the year in open fields. They are housed over winter in barns for between 2 to 6 months and the animals are "turned out" (released from barns to graze during the day and brought back inside over-night) in the spring (Figure 4.1). The date chosen to turn out varies across the country, but can have a significant impact on farm performance. Research has demonstrated that extending the grazing season by a few days can increase farm profitability; for example extending the grazing season by only 14 days for a dairy herd of a hundred cows reduces costs by up to €2,300 (Kinsella et al 2010). In many cases the turn out date is set by tradition; for example St. Patrick's Day, March 17th, is a common day for turning out in Ireland largely regardless of current or optimal conditions on the farm (see section 5.2 for more detail).



Figure 4.1: In Ireland cattle are overwintered in barns (left) before being "turned out" in the spring to graze.

Ideally the date should be chosen in response to observed local conditions (temperature, weather, grass growth and soil trafficability) but optimal timing of this event is made harder as farmers, in most cases, do not use feed planning software, farm management support systems or even simple record keeping, preferring to rely on memory and experience (see Creighton et al (2011) for an Irish overview of this phenomena and Gray et al (2003) for a comparative New Zealand perspective). Farmers are not alone in relying on memory in strategic decision making; the use of memory when assessing current conditions against perceived long term trends and planning accordingly, is also a feature of professional agricultural advisors' working practice (Mase & Prokopy 2013). However relying on memory for assessment of time critical grass management decisions, such as when to "turn out" or when to open and close paddocks, is complicated by weather volatility, making these judgment calls against remembered norms more difficult (Loch et al 2012). The increasing likelihood of extreme weather events in Ireland (Matthews et al 2016) will compound this issue in the future.

Farmers are not different from the general population (Goebbert et al 2012) in their capability in assessing current weather conditions in relation to recent trends and averages, as shown for example by surveys of African farmers dealing with extreme weather events (Moyo et al 2012, Simelton et al 2013). Assessments of future conditions are strongly influenced by current conditions and the very recent past, not by averages (an example of the *availability heuristic* (Morewedge et al 2005)), and with increased occurrence of weather extremes, remembering what is normal and what is abnormal becomes harder. Thus being able to plan for the future using only past experience becomes more difficult and this difficulty is amplified by poor record keeping.

Long term time series of satellite data provide a potential benchmark for crop and plant growth in a given location. Time series of data, some of which go back to 1980s allow for the establishment of averages over time across a season, but also for monitoring trends in seasonal events and the timing of events in plant development through the application of phenology.

4.1.1 Global monitoring of crop performance.

The use of time series of EO satellite data to provide long term benchmarks of vegetation performance for climate studies and agricultural monitoring is now well established; for example AVHRR, MODIS and SPOT-VEG satellite sensor data have been used for studies of agricultural land use change at country level (de Beurs & Henebry 2004, Propastin et al 2007, Wardlow et al 2007) and globally (Friedl et al 2002, Ganguly et al 2010). Most of these approaches, as discussed in sections 2.1.5-2.1.9, use some form of vegetation index (VI). Local long term averages of the most common of these VI, the Normalised Difference Vegetation Index (NDVI), have been used to characterize agricultural land use (Baldi et al (2008)). Other indices have been developed relating to crop performance, especially in the context of food security and drought issues. Table 4.1 details some freely available, online vegetation monitoring services, most of which exploit an NDVI anomaly approach to detecting change or deviation from average conditions. These systems generally exploit the concept of land surface phenology, LSP but without any attempt to relate the NDVI signal to timed events on the ground, instead comparing current events with historical averages (see Rodriguez-Galiano et al (2015) which includes a review of European LSP studies).

Most of these services are concerned with monitoring crops and forestry. However a recently established project, Rangelands and Pasture Productivity (RAPP) (CSIRO Australia 2014), is an extension of the GEOGLAM (Whitcraft et al 2015) system for crops into grasslands. GEOGLAM is a global land cover mapping initiative and RAPP is intended as aEO derived equivalent of the annual statistical estimates of cattle density (mapped at 3 arc-seconds) from the FAO (Robinson et al 2014) as discussed in section 3.5.1. The exact details of the proposed RAPP service are not known but the absence of a European pilot site suggests an emphasis on rangelands and not enclosed paddock/pasture systems. In 2016, the service has only just begun a five

year implementation process for a global monitoring system for pastures and rangelands, but a summary document of aims, states:
"*Currently there is no comprehensive global effort for monitoring the status and productivity of pastures and rangelands*."(CSIRO Australia 2014).

Table 4.1: The broad characteristics of the major online crop monitoring services. The services differ in how data are delivered, but most rely on a combination of satellite derived VI scores and local weather data to model crop growth.

Name[20]	Coverage	Cover*	Reporting Period (days)	Resolution	Service**	Data***
Crop Explorer	Global	C	7 /30	25/8/1.1km	N/C/A/W	SV/M
GIEWS	Global	C	8/30	1km	N/A/C/S/W	AV
USA FEWS	Global	C	10/30	1km	N/A/W	M
MARS Agri-Cast	Europe/Africa	C	30	10km	N/C/W	M/AV/SV
Vegscape	USA	C	1/7	0.25km	N/A	M
Veg-Anomaly	Australia	All	8/30	1.1km	N/A	AV
Vega-Pro(free)	Russia	C	8/30	0.25km	N/A/	M/L

*(C)rops, (A)ll. ** (N)DVI, (A)nomaly, (C)rop performance, (S)easonal progression, (W)eather data.*** (M)ODIS, (A)VHRR, (SV)POT-VEG, (L)andsat

4.1.2 NDVI anomaly

By observing NDVI at a given location and time it is possible to compare that observation with the long term average (LTA), and express that comparison as a positive or negative percentage deviation from the LTA. The NDVI deviations from the LTA are assumed to related to vegetation growth changes, with a positive anomaly representing more greenness than the average for that time and place, and a negative anomaly representing the opposite. As an example, the GIEWS service from the FAO uses NDVI anomaly scores derived from AVHRR data, along

[20] Web addresses are given in appendix

with precipitation data for detecting early signs of drought conditions (low levels of green cover associated with plant stress or reduced planting of crops due to political or social instability). An early practical use of NDVI anomaly was in monitoring fire risk (Burgan et al 1996) where a negative anomaly was associated with an increase in area burned, but no statistical relationship was established spatially or temporally.

There seems to be little evidence that these online anomaly services are used by farmers directly. There could be many reasons for this, including lack of access, farmers being unaware of the service, and the service not being designed to be incorporated into farm management. In the literature on technology transfer through extension services (Klerkx et al 2012) and on the development of decisions support systems (Van Meensel et al 2012), the importance of finding a common language between scientists and farmers is emphasized. The seasonal anomaly services highlighted in Table 4.1 show seasonal anomalies as percentages (NDVI is 10% higher or lower than the LTA for example), but this can be difficult to interpret for non-specialist users. Specifically, as shown in section 2.7.2, new data services for farmers have to fit in with existing systems and paradigms for them to be accepted.

In the research literature NDVI anomalies being related to vegetative performance anomalies are accepted as a standard, and are also often used in climate studies to look at the impact on vegetation of global climate change. An early example is Braswell et al (1997) who related AVHRR derived global NDVI anomalies to similar anomalies in the global temperature record. A similar approach has used AVHRR anomaly records in Africa to link drought records to actuarial records to create a more robust livestock insurance market (Vrieling et al 2014). Rembold et al (2013) provide a useful review of the development and application of NDVI anomaly mapping.

However, within this literature on the use of NDVI anomaly mapping it is uncommon for NDVI anomaly studies to be validated spatially, instead more commonly they are validated temporally, with large spatial scale averages of NDVI

anomaly related to local climate conditions. A common approach is typified by the well cited paper from Anyamba et al (2002) which relates NDVI anomaly with Sea Surface Temperature (SST) anomaly in east Africa with respect to ENSO effects, where the relationship between a box average NDVI anomaly for a 300 km^2 area in east Africa with monthly SST anomaly was r=0.06 (n=30).

Steyer et al (2013) used NDVI anomalies from Landsat TM to measure post Hurricane Katrina recovery in natural habitats, and tested these against 253 plots where vegetation was monitored concluding that NDVI anomalies can be used to track post event recovery. Brown et al (2006) tested the compatibility of long term time NDVI series from 5 sensors for interoperability, as well as comparing statistically the products with each other for a total of 21 sites for calibration globally. Peters et al (2002) introduced the concept of a standardised vegetation index (SVI), essentially as a statistical measure of how unlike the average the current reading is with an NDVI anomaly weighted for the SD of the NDVI variation. This anomaly analysis is compared visually to drought maps produced by NOAA but there was no statistical analysis of the spatial or temporal variation.

In this section it is intended to develop a spatial and temporal calibration system for grass growth anomaly measures derived from NDVI.

4.1.3 Grass Growing season in Ireland

In Ireland, once grass growth starts (typically in March, see section 2.2.2) growth rates are high reaching a peak in May of up to 100kgDM/ha/day, growth rates then decline with a secondary peak in August (60kgDM/ha/day) and growth generally ceases around November (O'Mara 2008). In simple empirical grass growth models, growth is seen to be largely controlled by soil type and soil nutrient levels, along with temperature, sun light and rainfall. In Ireland rainfall is rarely a limiting factor, and in the early spring, with a short open grass canopy, sun light levels are adequate in the sward.

Irish and British studies have identified temperature (soil and/or air) as a key constraint of grass growth, with studies establishing different thresholds and initiators for growth. Broad and Hough (1993) found a *mean temperature* of 5°C to be an initiator of grass growth in the UK, and other studies have shown start of growth to be associated with an accumulated temperature threshold, or growing degree days (Hutchinson et al 2000). In Ireland and elsewhere (e.g. Frank (1996) a common rule applied couples both of these approaches; grass is considered to be dormant over winter until growth is initiated by a period of 5 days with a minimum soil temperature of 6°C or an air temperature of 5.6°C (Keane 1986). This is a frequently applied growth indicator used in analysis of grass growing seasons in Ireland, but can also extend elsewhere, as shown by Fealy and Fealy (2008) who used the approach in establishing new agri-climatic zones for Ireland and Europe. This accumulated temperature threshold approach is the indicator used to determine the start of spring grass growth in the research presented here (c.f the concept of Growing Degree Days, GDD).

4.1.4 Section Outline

This section describes the development of a satellite NDVI based tool for assessing spring growth progress in intensively managed agricultural grasslands in Ireland, with a focus on the very early spring growth (January-April), when judgment about condition of available fodder for the release of over wintered animals is most critical. A linear model is fitted to average decadal MODIS NDVI values, as a function of date, at a 250m resolution pixel scale across Ireland. In the model outputs the data are presented in the temporal domain as estimates of how many days early or late the current state of grass growth is compared to the decadal average (rather than the normal percentage). The transformation of the anomaly service into the time domain allows for the use of plain language, e.g. “current growing conditions are two weeks behind normal”, as opposed to giving a percentage difference from the norm, which should improve uptake of any subsequent service by farmers. This model is tested against a weather/temperature

based estimate of the date of grass growth onset, and its subsequent rate of growth, for the spring seasons in 2012 and 2013. This testing of essentially a phenological analysis (albeit estimating relative timing of growing events) is part of a growing body of work in the literature tying ground truth from varying sources to validate satellite time series of LSP (this was explored in a work shop in 2013 reviewed by Dash et al (2013)).

4.2 Materials and methods

4.2.1 Satellite data

The selected MOD13Q1 16-day composite product provided detailed quality flags and Day of Year acquisition stamp for each 250m pixel (García-Mora et al 2011) (see section 3.2 for the rationale behind product selection). All 16-day composites for the period January 21- May 15 2003-2013 were used. As with the stocking density model, only data from high quality, cloud free pixels were used. A grassland/non-grassland mask was produced using ancillary national datasets including the national agricultural parcel database (LPIS). Only pixels that represented managed grasslands were included in the analysis and mapped outputs.

4.2.2 Weather Data

The ground truth weather data are daily maximum and minimum temperatures from the national climate stations maintained by the national meteorological agency, Met Eireann. Climate stations continually operating from 1/1/2002 to 30/12/2013, with no data gaps in the spring were selected - giving a total of 51 station records distributed around the country (Figure 4.2). The spring seasons in 2012 and 2013 prove to be excellent years for testing seasonal progress tools in Ireland given their very different behaviour. The seasons are described in reports issued by Met Eireann:

- 2012 had above average temperatures, around 2-3°C higher than normal from January-March (Met Éireann 2012a).
- 2013 was a very poor spring (following a cold winter) with average temperatures 2°C colder than the 30 year norm and "cold everywhere, dry, dull and windy" providing poor conditions for grass growth (Met Éireann 2013).

To provide viable ground truth for this study, the stations had to be situated in a predominately grassland landscape. Thus those stations in urban, tillage or forested areas, or that were not within 1km of agricultural grasslands (some island and coastal sites) were rejected. This left only 31 stations to act as ground truth sites (indicated by a ring in Figure 4.2).

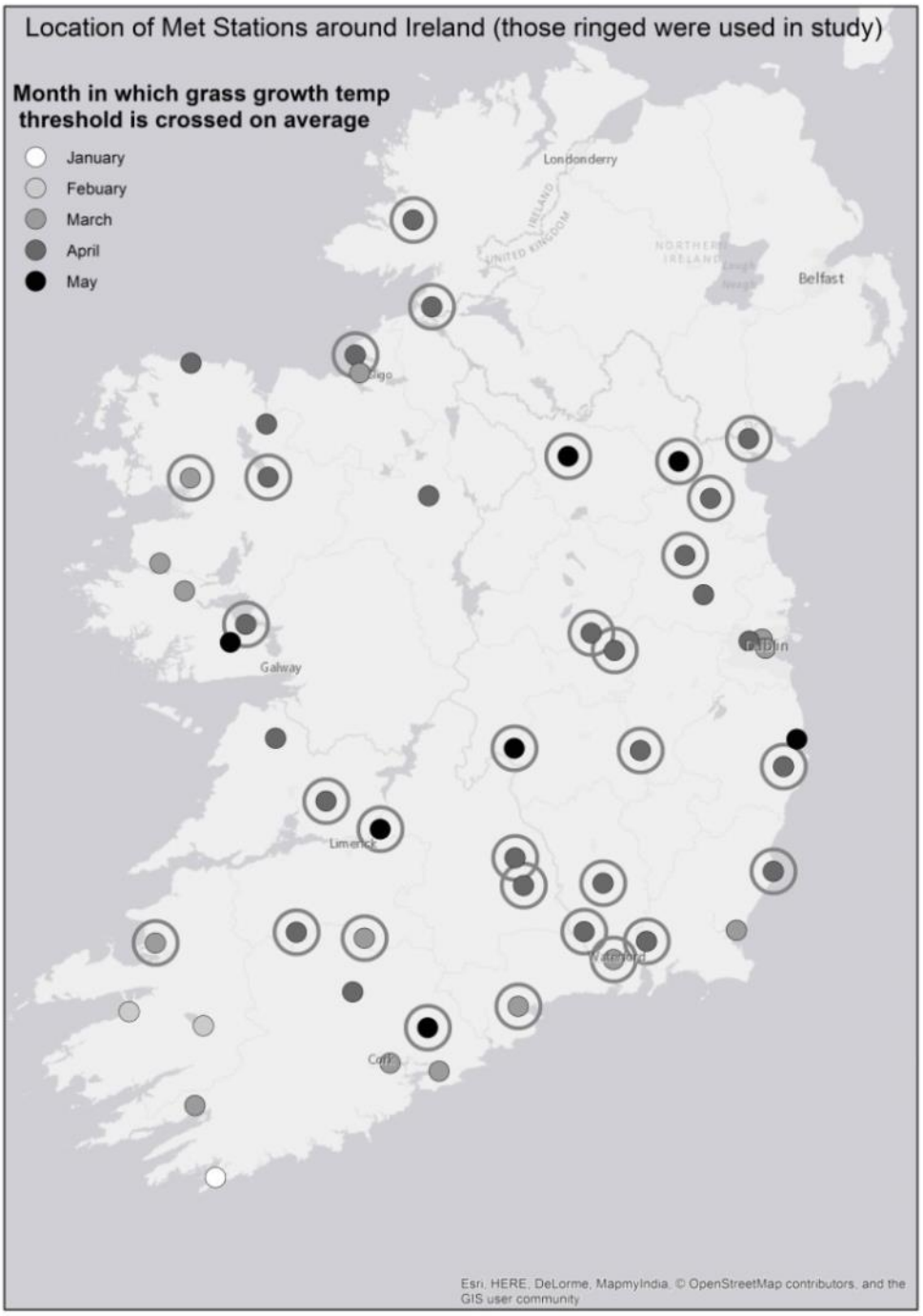


Figure 4.2: Geographical distribution of climate stations in Ireland, shaded to show the average month in which grass starts to grow. Stations used in the final analysis are ringed.

4.3. Methodology

4.3.1 Establishing seasonal progress ground truth

The model does not intend to estimate the specific date of an event, for example the start of spring, but instead shows progress in days ahead or behind a reference norm, namely the decadal average NDVI value for that pixel in that 16-day compositing period. Therefore a ground truth dataset is needed in the same format, with a reliable indicator whose performance against a decadal norm can be measured.

Unfortunately there is only one site in Ireland with 12 years of grass growth measurements, and weekly measurements are only begun once grass is visibly growing. Nevertheless, temperature (as opposed to light levels or rainfall) as a controlling factor in initiating grass growth in Ireland is well understood and serves as a ground truth proxy for grass data. Using the definition of start of grass growth as outlined in section 4.1.3, the first time that five consecutive days occur with a minimum ground temperature of 5.5°C was identified, and the 5th day of that period selected as the start of growing season ground truth indicator. 5.5°C was chosen as it is the middle of the range of temperature thresholds for grass growth defined in the literature, however, the exact temperature threshold used is not so important as the model judges against on a relative performance.

The climate station database was processed (in MS Access) to identify the date when this threshold was achieved, *d,* for each year in the 2002-13 period at each of the 31 stations. Figure 4.3 shows the average date (as DOY) nationally for each year, as well as the earliest and latest for each year. For the reference date for the model, the ten year average date, $\bar{d}$ (expressed as DOY), for each climate station is used. Across the whole country averaged over the 10 years, the mean date on which grass starts growing is DOY 88 or March 27th, with the earliest recorded date at a station being January 7th (in 2007) and the latest July 5th (in 2002).

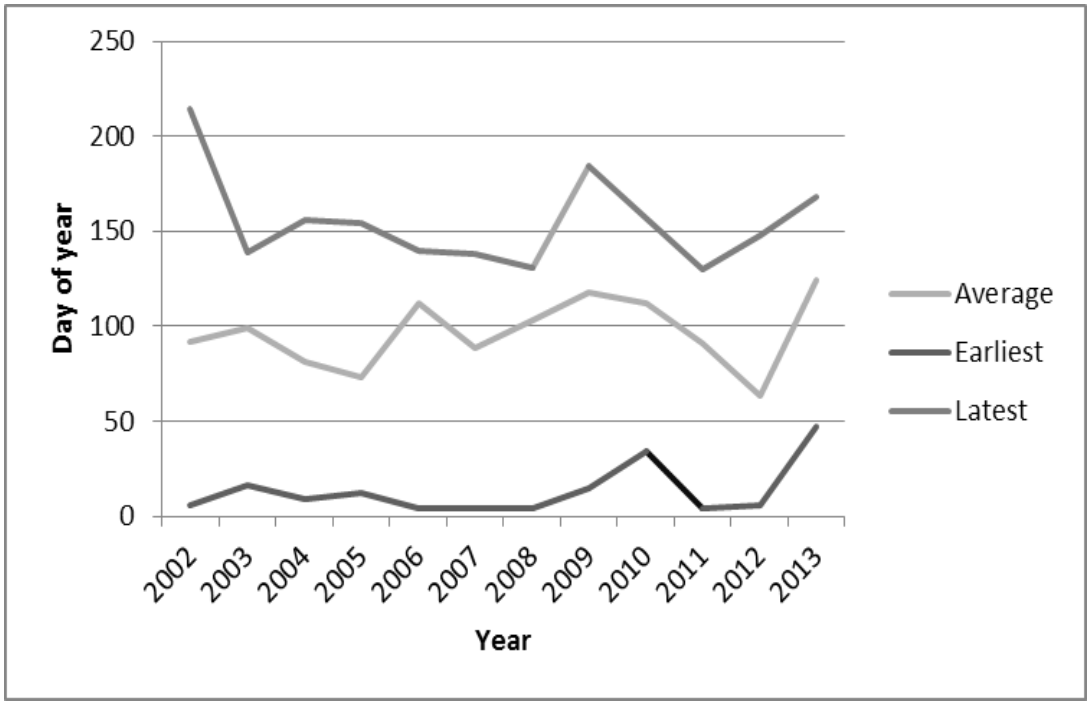


Figure 4.3: The mean national average, earliest and latest date on which grass starts growing in each year 2002-13 for 31 climate stations.

The climate station Seasonal Progress Anomaly in the Time domain, cSPAT, for any subsequent year, y, is calculated (eq. 4.1) as

$$cSPAT_y = d_y - \bar{d} \qquad \text{eq. 4.1}$$

Where d_y is the date on which the temperature threshold is passed, at a climate station, in year y and $\bar{d}$ is the average date on which this occurs. Figure 4.4 shows the cSPAT for the 31 climate stations in 2012 and 2013. In this figure it is evident that in 2012 the sites are generally indicating a much earlier start of spring growth (bars to the left) than normal, with the sites on average being 36 days earlier than normal and with one site 90 days early. In the 2013 “poor” spring by contrast, most of the sites have a late start of spring date (bars to the right), on average 23 days later than normal but with one site 70 days later.

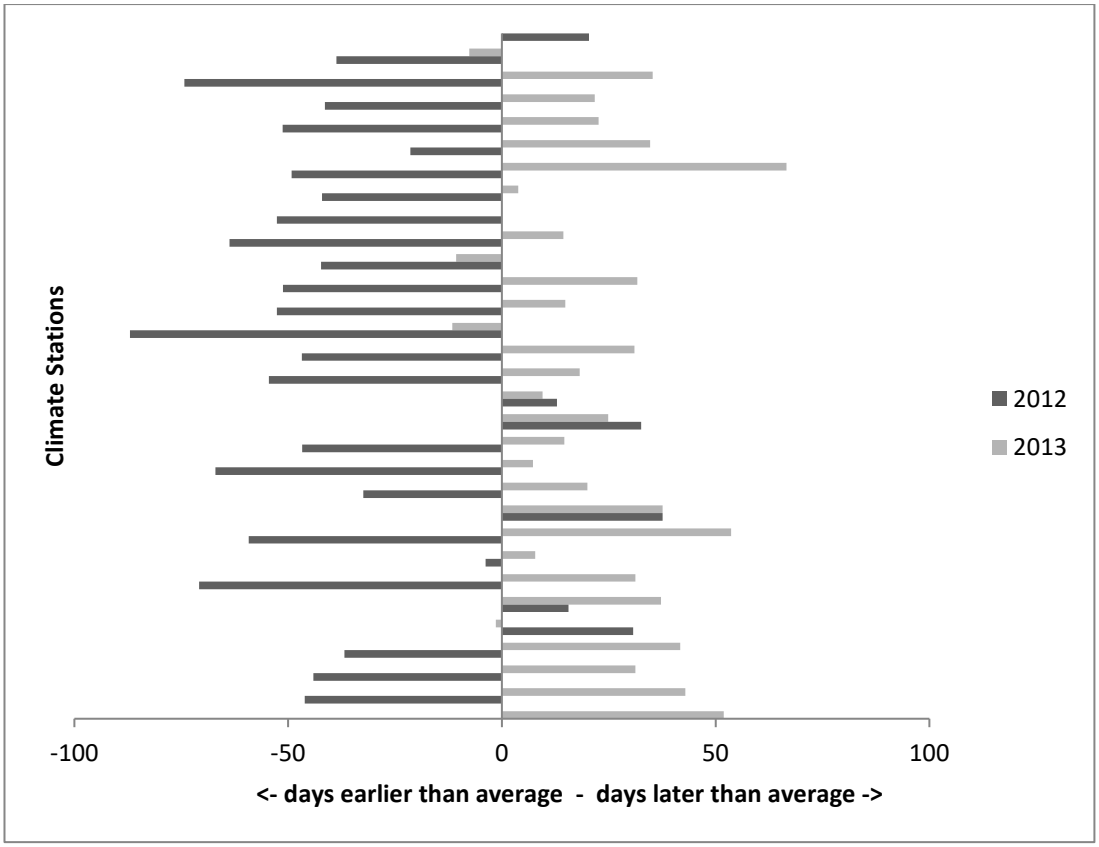


Figure 4.4: The difference from the 2002-11 average grass growth start date for the 31 climate stations used in the analysis in 2012 and 2013, the most northerly station at the top, and southerly at the bottom.

4.3.2 NDVI spring growth model from satellite

Satellite based NDVI phenological analysis has been widely utilized to find both spatial and temporal trends in important climate indices, such as start of season (Jonsson & Eklundh 2002). Conventional methods for observing growth cycles over a season with NDVI data involve first quality checking, filtering and gap-filling the data, then fitting a complex function. This approach is well suited to crops with features such as maximum NDVI and green-up phase corresponding to identifiable phenological stages on the ground. However in managed grasslands in Ireland (and elsewhere) where growth can be almost continual, and with complicated dynamics of grazing, cutting and hay making operating over cycles of up to 21 days, relating the NDVI curve to ground conditions is less straightforward. O'Connor et al (2012) used a smoothed time series of 10-day MERIS composite data to link start of season

events with land cover, and highlighted the difficulties posed by Ireland's highly fragmented landscape when attempting to extract a spatio-temporal signal at a 1.2km scale. Common assumptions concerning inherent inter-annual cyclic behaviors, specific to land cover types and crops (discussed further in Bradley et al. (2007)) used when fitting a curve to NDVI data to represent an annual growth cycle, breakdown in managed grassland when management choices can differ year to year (Dusseux et al (2014c)).

These difficulties in grasslands can be partly overcome by examining only a short part of the growth cycle, where assumptions about management practices can be more easily defined. Early spring growth is one such period in Ireland, when it can be stated with some confidence that only grass growth is observed with no management intervention until animals are released onto paddocks from winter housing. This allows the increase in NDVI over this period to be modeled against time to represent just spring grass growth. Whilst linear and log-linear models are simplistic and do not represent real plant growth over the season, or represent the current state of the art in plant growth modeling, a recent review by Paine et al. (2012) shows that linear fits are acceptable across short sections of the growing cycle. One advantage of a linear approach is that only a few observations across the period are needed to characterize the vegetation growth rates at a locality. This allows for very rigorous quality assessment of the satellite data at a pixel level to be carried out, meaning only the data that have the highest quality flag in the MODIS product are used but this leaves enough data points to fit a line.

The first stage of the model is to generate ten year (2002-11) average NDVI scores for each day in spring using the high quality flagged MODIS values. A linear model is then fitted from January 20th to April 30th defining the rate of increase in NDVI and the initial start of year NDVI for every pixel (using a minimum of 3 data points). In producing this model only data with the highest quality flag (0) were used which meant rejecting >75% of the data across the period, that were lower quality typically due to atmospheric effects. Thus each pixel has two model factors representing average values for the decade 2002-2011; the intercept, interpreted

as an indicator of start of season cover, *s* (a dimensionless NDVI value), and a gradient interpreted as the linear early spring growth rate, *g* (NDVI/day). Therefore, for every 250m pixel (representing 6.25Ha on the ground) across the Republic of Ireland the timing and average rate of spring grass growth can be determined (see section 3).

NDVI seasonal progress anomalies for any year outside of the reference period can be calculated for any day in spring, *d*, from the modelled NDVI ($NDVI_m$) (eq. 4.2). The difference between the modelled value and the observed NDVI ($NDVI_o$) is divided by the growth rate parameter from the model giving the seasonal progression anomaly (SPA) in days (eq. 4.3). A negative anomaly score indicates growth is earlier than would normally be seen at that time and a positive score indicates that growth is late.

$$NDVI_m = g.d + s \qquad \text{eq. 4.2}$$

$$SPA = \frac{NDVI_m - NDVI_o}{g} \qquad \text{eq. 4.3}$$

This calculation is performed on every grassland pixel in each new satellite acquisition to map the NDVI-SPAT. The value *d*, is extracted at the pixel level as the Day of Acquisition (DOA) of the observation within the 16-day composite (band 11 in the MOD13Q1 product). Data in spring are noisy, and even pixels with a good QA rating can be of poor quality. To reduce noise, the model output is processed using a 3x3 median filter that operates only on values that fall within plus or minus 1 standard deviation of the global image mean. This process, outlined in Figure 4.5 was applied to 9 16-day MODIS products (DOY 21 to DOY 137) for both 2012 and 2013.

To assess the accuracy of the NDVI-SPAT, the mapped outputs for the appropriate period were compared to the meteorological estimates of seasonal progression at each of the climate station sites, cSPAT. To overcome no-data pixels (those with a low QA flag for that observation) the NDVI-SPAT used was the average of good

quality observations on grassland pixels within 1km of the station. There were some stations, notably in 2013, where even within 1km of the station no good quality pixels were found, so in all only 54 (from 30 stations) points were used in the accuracy assessment.

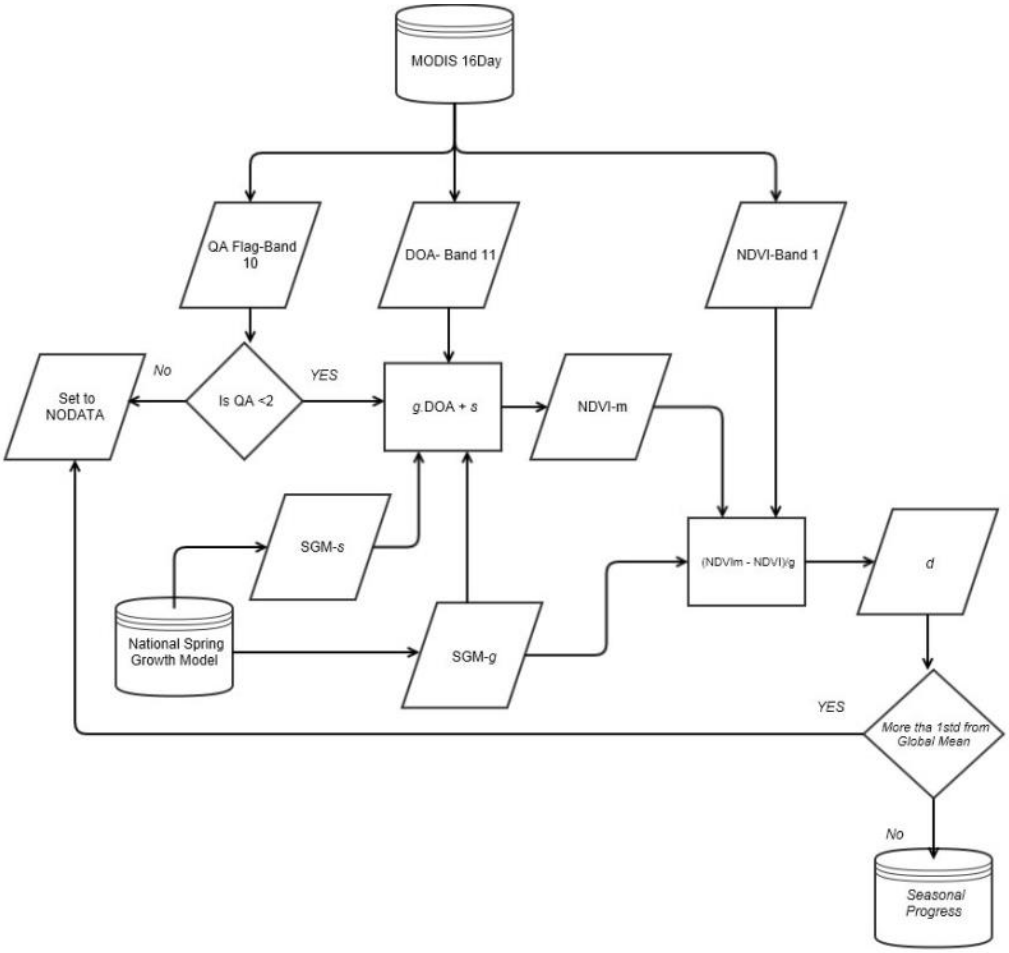


Figure 4.5: Flowchart detailing generation of Seasonal Progress Anomaly estimates for any 16-day image composite outside the reference years.

4.4 Results.

Seasonal progression in agricultural grasslands in Ireland was estimated and mapped for 18 16-day periods (nine each in 2012 and 2013).To illustrate the type of maps that can be produced, the mid-season outputs (16-day composite period 5, end of March) for both years are shown in Figure 4.6. The general national trend is clear in both, with Figure 4.6b (2012) mostly green, indicating growth is ahead of normal, and 4.6a (2013) is mostly blue indicating growth is behind the normal schedule, but some interesting local effects are present especially in 2012. Some

parts of the country in 2012 are blue, such as the Areas in the North West indicating that the locality is behind normal growth, but as Figure 4.4 shows there were some locations with late spring growth in 2012. Interestingly, the apparent lateness of growth in the far south is likely to be an artefact, growth started so early in 2012 that many farmers in this region were able to graze from January and considerable biomass had been consumed by mid–March, such that growth appeared backward when compared to the average. Conversely the 2013 image, whilst mostly blue because of the late spring, there is a fringe of light green along the south coast indicating that conditions are normal there.

Figure 4.7 shows the image mean values (average NDVI-SPAT for the country) for the 9 periods in 2012 and 2013.The accuracy of the model is illustrated in Figure 4.8. The NDVI-SPAT correlates well with the meteorologically derived seasonal progression anomaly cSPAT, with an r^2=0.897 (n=54) and a p value >0.0001. The RMSE is 15 days. Figure 4.9 illustrates the progression in 2012 and 2013 as mapped by the SPAT process for comparison with Figure 4.7. This figure illustrates one of the complexities of mapping managed grassland progression; the April map for 2012 seems to indicate that progress is behind normal that month. In reality the previous month's growth is so far ahead that grazing began earlier than normal (see figure 5.13), leading to removal of biomass and a lower than normal NDVI.

4.5 Discussion

The correspondence between the modeled estimate of seasonal progression and the meteorologically derived climate station estimate is good. This suggests that the approach does successfully begin to estimate deviations in grass growth in the early spring period compared to the average, and that an RMSE of 15 days is within the range at which the information could be of value to farmers.

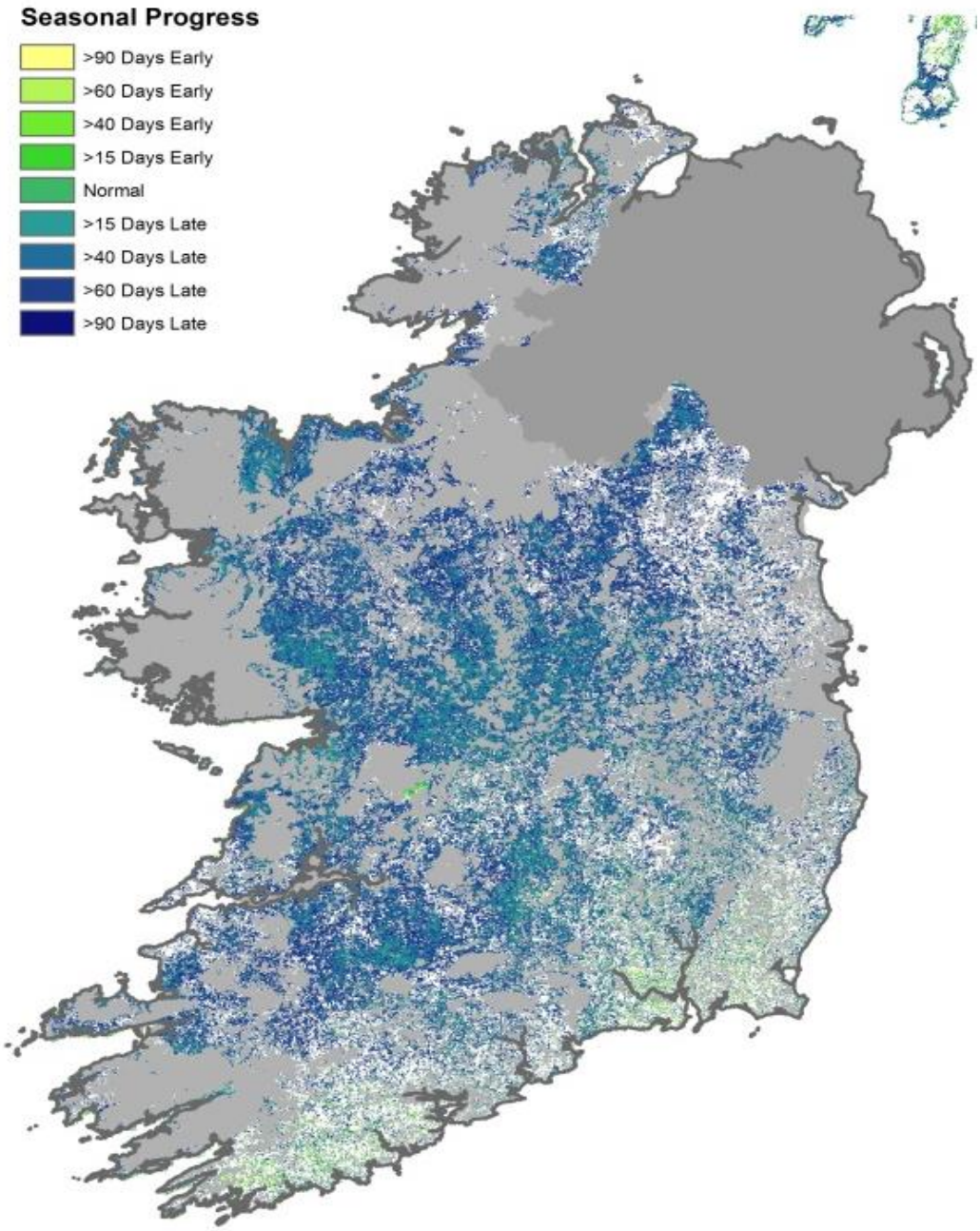


Figure 4.6a: Example of the final output of the SPA system for end of March in 2013. No data are white and non-grassland areas are excluded in light grey.[21]

[21] . As no validation data were available for Northern Ireland it is excluded (Dark Grey) from the published maps, though output was generated and the approach is an all-island one.

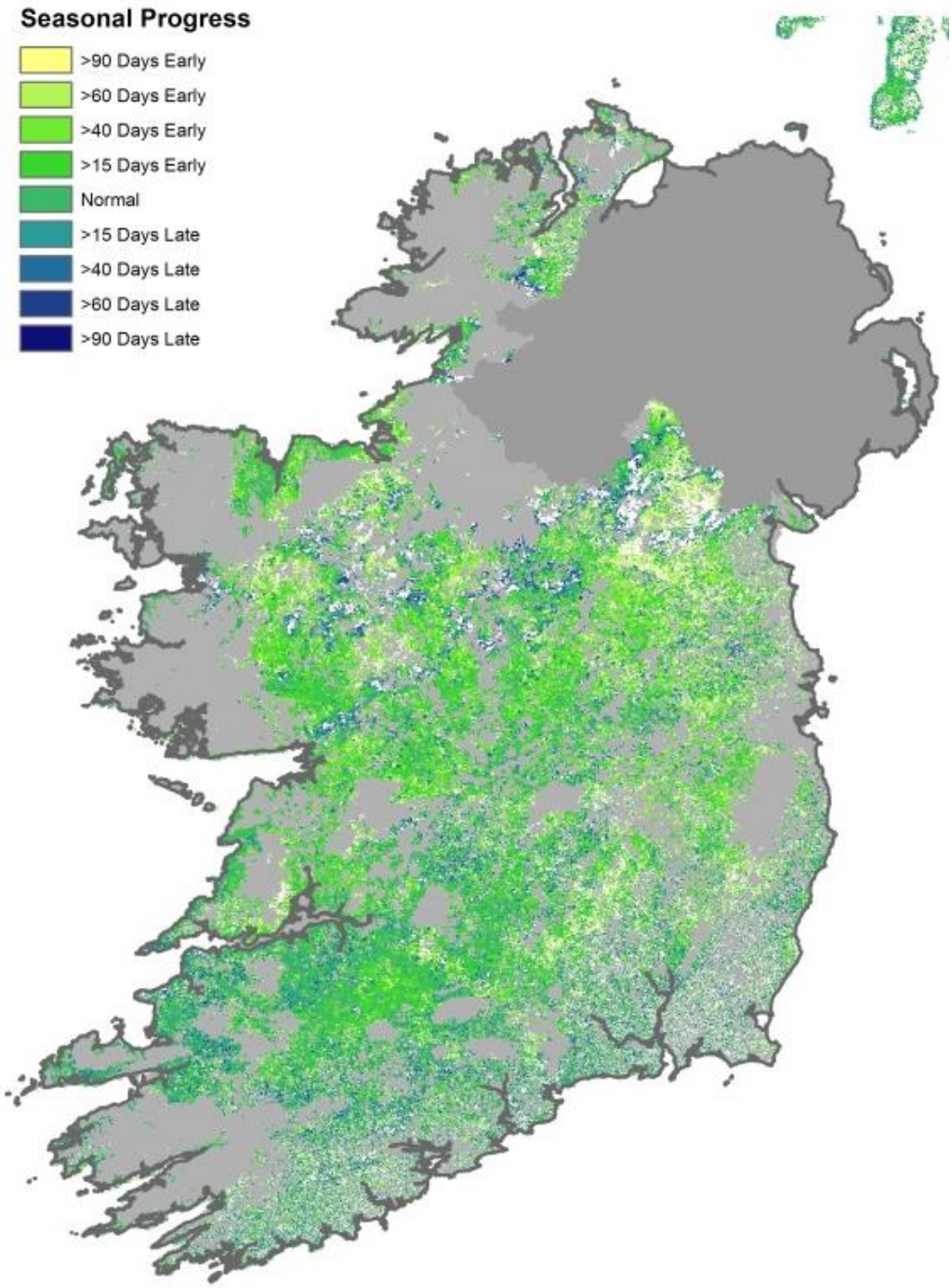


Figure 4.6b: Example of the final output of the SPA system for end of March 2012. No data are white and non-grassland areas are excluded in light grey.[22]

[22] . As no validation data were available for Northern Ireland it is excluded (Dark Grey) from the published maps, though output was generated and the approach is an all-island one.

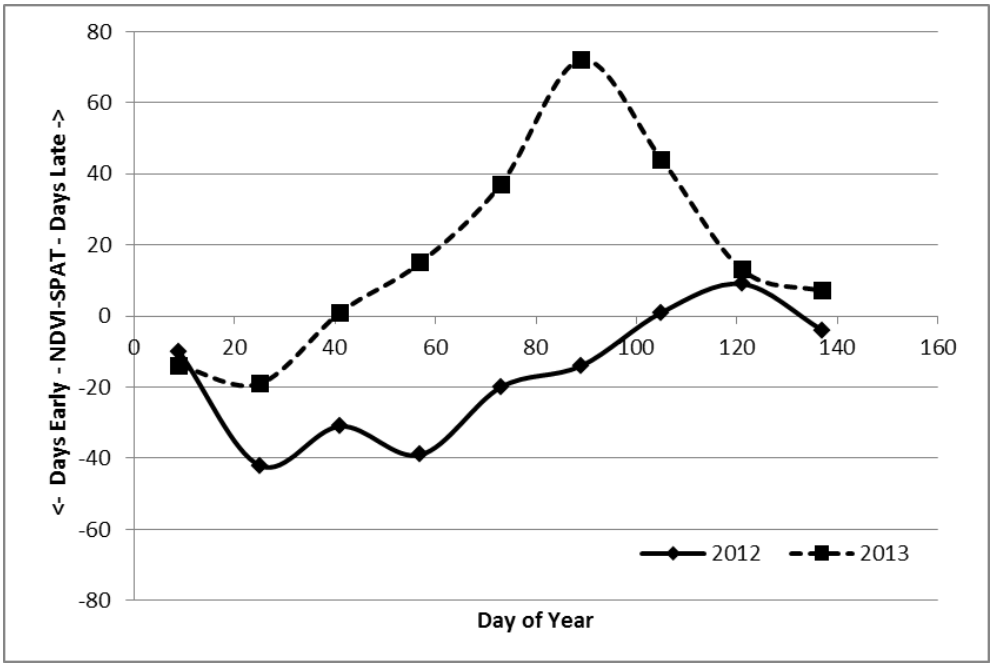


Figure 4.7: The national mean NDVI-SPAT in 2012 and 2013 for each of the nine 16-day composite periods.

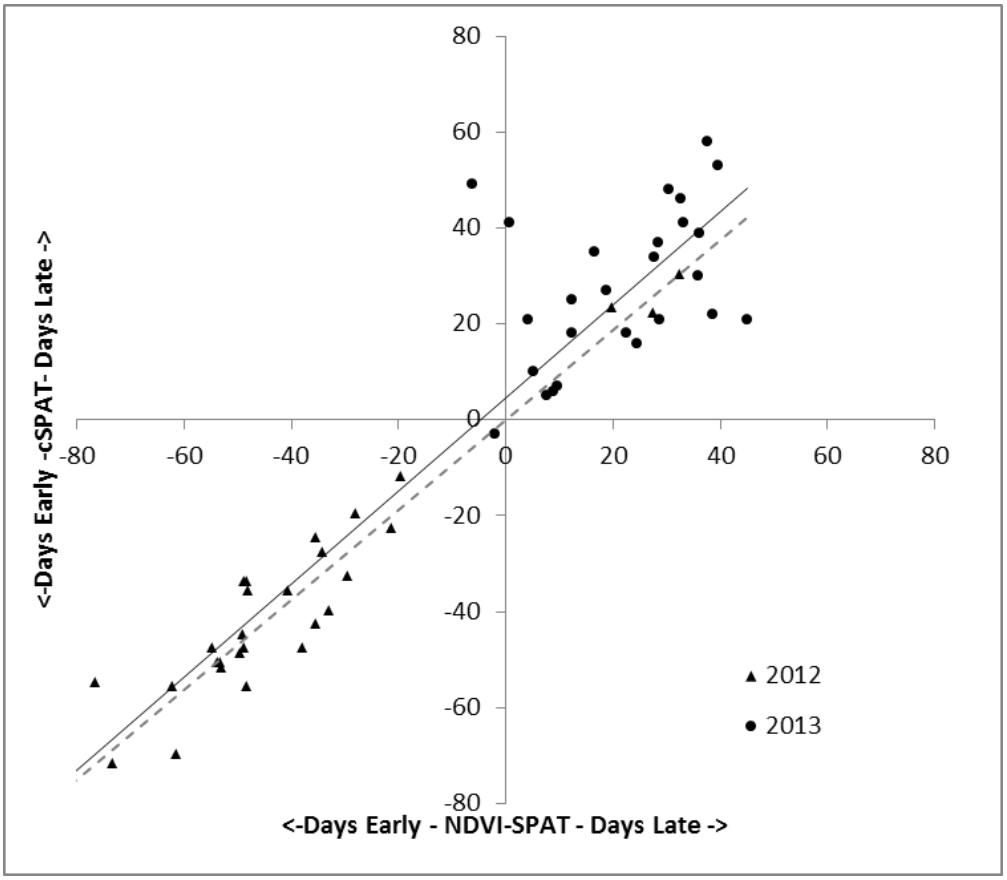


Figure 4.8: The relationship between satellite derived NDVI-SPAT and corresponding meteorological station derived cSPAT estimates for 54 observations from 30 stations across Ireland in 2012 and 2013. The solid black line is the regression between observed and modeled, the dotted line shows the 1:1 relationship.

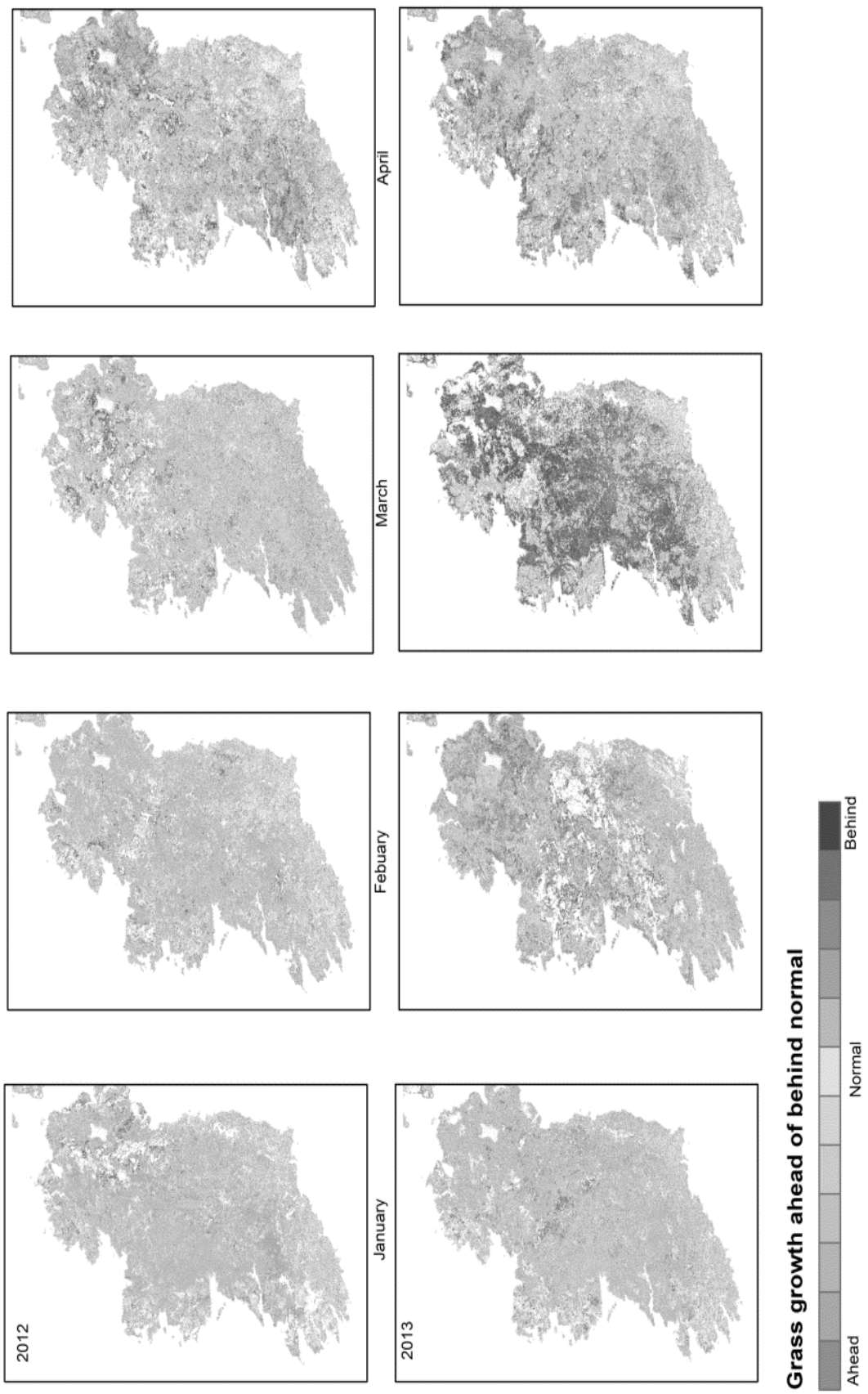


Figure 4.9: Illustration of seasonal progression in 2012 and 2013 as mapped by the SPAT method.

The levels of noise in the early part of the season, as well as the intent to provide a "real-time" online service to Irish farmers in the future, justify the use of a simple linear model of spring growth rather than the more familiar sinusoidal model used to detect "green–up" in the phenological curve. Identifying the actual date of start of season with these familiar techniques is difficult in Ireland because of the noise levels (O'Connor et al., 2012) and can only be done in hindsight as a significant number of data points post green-up are required to satisfactorily fit such a function. This would negate any utility to the farmer as identifying the fact that the season began a month ago is of little value, but being able to say *current* conditions are a month behind normal, is useful.

Figure 4.6 shows the wide variation in seasonal progress across the country in the two years analysed. This wide variety in grass growth behavior across even short distances and between two years is not captured in the established maps and models of national grass growth onset (Brereton (1995). The number of "no data" pixels in 2013 (Figure 4.6b) is much larger than in 2012 (Figure 4.6a) as the conditions that lead to poor grass growth are concomitant with increased cloud cover, and thus reduced observational efficiency of the satellite. This does mean there are challenges in making this a completely reliable operational service in extreme conditions. The apparent "lateness" of growth in the far south in 2012 (fig 4.6a), is likely an artefact of much higher grazing than normal because of the very early spring, leading to an apparent reduction in observable biomass in March compared to average. This will have to be addressed in any subsequent service, probably by comparing consecutive anomaly maps with meteorological data and adjusting accordingly.

Figure 4.7 shows how the spring seasons of 2012 and 2013 progressed as evidenced in the NDVI images. Both start with growth slightly ahead of normal and the good start of 2013 mirrors the meteorological narrative; Met Eireann records report that nationally the first half of January was warmer than average and it was only subsequently that temperatures dropped significantly and persistently for the rest of spring. However, for 2012 the trend remains well ahead of the 2002-11 average.

By the end of March 2013 (day 90) the grass performance is up to several weeks behind what would be expected, and this again is reflected in the anecdotal evidence of the "Fodder Crisis" of that year, where very poor spring growth caused severe hardship on farms (Irish Examiner 2013). In both years the trend returns to normal by the end of April, however this is likely to be the point where grassland management (grazing, and even cutting in 2012) begins to dominate the biomass/NDVI signal.

A comparison of Figure 4.4 and Figure 4.7 shows how effects are cumulative over the season. On average grass started growing 26 days later than average in 2013 at the climate stations (Figure 4.4, but a late start coupled with slow growth meant the impact was amplified until the end of March (Figure 4.7).

Figure 4.8 shows the comparison of the satellite estimated progress, NDVI-SPAT, in comparison to the meteorologically calculated progress from the climate stations, cSPAT. The fit and range of the estimates seem good, with the exception of two stations some distance away from the diagonal in 2013. These two sites are counter to the overall trend of 2013 and show a slightly early start to spring growth compared with the general lateness in 2013. This highlights one of the limitations of using accumulated temperature to indicate start of growing season when temperatures subsequently drop and grass stops growing, indicating that a "false spring" has been identified as seems to be the case at these two sites. When these 2 outliers are removed, the r^2 increases to 0.937. The positive and negative values show that the satellite observations can estimate whether growth is ahead of or behind the ten year average and only one observation (one of the two outliers discussed above), is in the wrong quadrant, however the wide range may overestimate the goodness of fit. If the NDVI-SPAT and cSPAT values are compared irrespective of sign, the r^2 value drops to 0.78, which although a reduced correlation still represents a statistically significant relationship ($p>0.001$).

The relatively coarse resolution (250m) and the high level of noise in optical satellite observations is a source of error. Whilst there is considerable spatial variability in grass performance in Ireland it is apparent that monitoring the national mean of the satellite derived NDVI-SPAT across the season is an indicator of spring conditions. New satellites such as ESA's Sentinel-2 will offer 10m resolution compared to the 250m resolution here allowing for improved registration between meteorological sites and the satellite image and improved spatial and temporal resolutions for EO farm services. By combining Sentinel, Landsat and DMC satellites a revisit time of only a few days will be possible, matching the temporal performance of MODIS, but if they are to be used for long term trend analysis, research needs to be carried out on cross system calibration between these instruments.

4.6 Implementation

The algorithm outlined here was implemented in Python to automate the construction of grassland anomaly maps in ArcMap. As a beta test an online service of fortnightly grassland anomaly maps was hosted on the Teagasc ArcGIS online web server in 2015. The pixel based outputs were remapped as townland averages, the smallest administrative areas in Ireland and in the absence of postcodes addresses in rural Ireland do not resolve below townlands. There are 52,000 townlands in Ireland, each containing approximately 5-7 farms. To speed up loading times the original complex townland boundaries were simplified to polygons with a minimum of vertices.On the online mapping service, farmers can search via townland and the map will locate the appropriate townland and give current growing conditions as the temporal anomaly.. Figure 4.10- shows a screen grab of the data as presented online.

Feedback was sought informally from Teagasc advisory service officers and it was felt that the information was valuable, but that the map presented did not contain sufficient geographical markers and the townland boundaries were too simplified and this reduced recognition. New versions of the will be recoded to 1km tetrads

overlaying current aerial photography and include geographic identifiers like village names, main roads and rivers. The search facility will still utilise townlands but these townland boundaries will not be displayed.

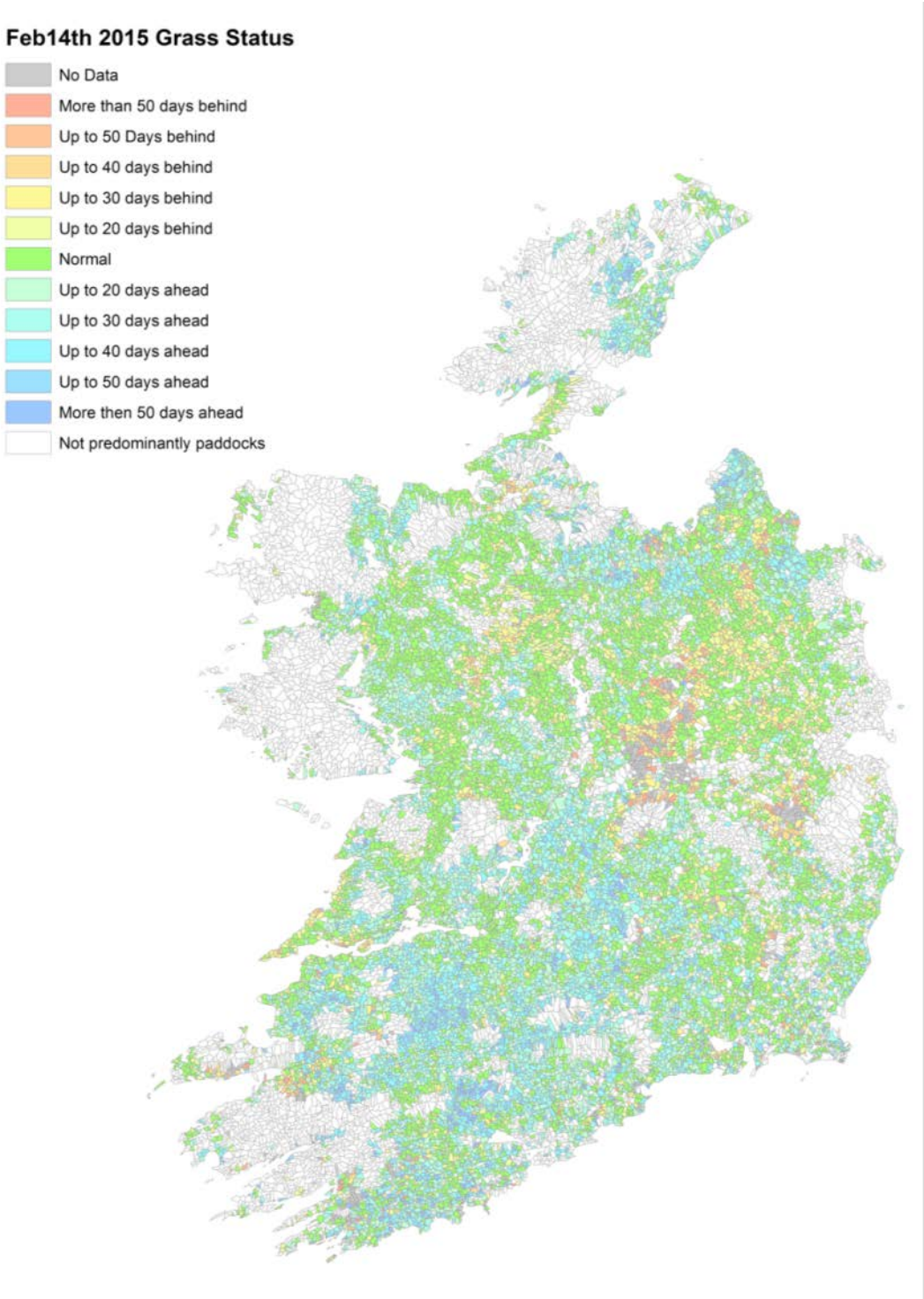


Figure 4.10: Temporal Anomaly Map for Feb 14th 2015 presented at townland scale online.

4.7 Conclusion

Grassland based farmers need to constantly adjust their management strategies to accommodate changing conditions on an almost daily basis and thus, it could be argued, are more in need of the timeliness and spatial coverage of satellite based productivity monitoring systems than conventional tillage farmers. Existing NDVI anomaly services (see section 4.1) typically present the results as a percentage change of NDVI from a ten year mean, but this means very little to the average farmer and interpreting a percentage change is not intuitive.

This research demonstrates a model that estimates in days, how far ahead or behind is grass growth compared to the ten year average. Expressing it in this way provides a system that is easier for a farmer to understand and interpret, and it allows evaluation of its accuracy against other measures of spring growth anomaly that can be expressed in days. The example presented here used ground temperature from meteorological stations, but other indicators such as the date when cattle are first turned out, or day of the first grazing or mowing could also be used to monitor the accuracy of this kind of service. Designing systems that produce simple, easy to understand, outputs such as: “Your current grass growth is 3 weeks behind normal” are essential for the wide acceptance of geospatial data products on farms.

Whilst most global food security systems concentrate on crop monitoring for food security concerns and commodity markets, managed grazing lands are a significant global food resource and should be monitored as assiduously. The availability of fodder is a concern, not just in human food security terms, but is important in ensuring the welfare of over 1billion domesticated grazing animals. Important metrics such as current cover, total grazed biomass and total harvested fodder (hay and silage) should be routinely monitored, in the same way as crop yields are monitored. In this paper we have shown that in managed paddock grazing landscapes the relative progress of early spring cover can be successfully

monitored. This information could act as a valuable prompt to the farmer to ensure maximum use of in field grazing and thus improve farm profitability. Monitoring growth against the average can also act as an indicator of fodder shortages nationally. However this should be coupled with monitoring of use, grazing or silage cutting in order for a fully rounded picture of current conditions and total accumulated biomass. Monitoring needs to be done using optical imagery at a high spatial and temporal resolution, and although new radar methods are showing early promise in grassland management monitoring, there is not the same robust and well understood relationship as between NDVI and biomass.

This work has demonstrated that a time domain anomaly service produces accurate estimates of current growing conditions, but a number of steps are needed before it can become an operational tool, principally field testing with farmers to create the most acceptable delivery mechanism; improving the temporal and spatial resolution of the service (down to weekly estimates at 1ha resolution) and incorporating weather data into the estimate of the anomaly, rather than as a validation of it.

The next chapter explores weather farmers do in fact respond to current environmental conditions.

5. Inter-annual variation in cattle turn-out dates on Irish dairy farms and the relationship with satellite derived grassland performance indices and rainfall.

5.1 Introduction

5.1.1 Importance of early grazing

As previous sections have shown, managing pasture in intensive grazing dairy systems is a complex task that involves matching fodder production to variable feed demands in a changing environment. Many of the decisions a farmer makes are time dependent and interlinked, such as opening and closing paddocks to allow animals to graze, and harvesting silage/hay for the winter. Optimizing these decisions, whilst minimising risk, is one of key drivers in ensuring a profitable farm. For example linking calving with spring growth has a beneficial impact on profitability but requires management skills in husbandry and pasture growth and demands a flexible approach to timing of turn out events (Porqueddu et al 2005). But the risks associated with mismanaging these decisions, such as underperforming animals or feed shortages, has led to a decline in grazing across Europe, in favour of continuously housed herds fed a grain based feed (Reijs et al 2013), despite the economic and environmental benefits of grazing. In Reijs et al.'s conclusion the report highlights that the major perceived weakness in grazing systems is their unpredictability, and the greater managerial difficulties associated with matching feed to demand in an unpredictable system:

"To maintain grazing in the North-West European dairy industry, governments and other stakeholders should invest in knowledge development and technological innovation on grazing issues. Important are the development of tools and systems that simplify grazing management on large farms and assistance of farmers in their management and strategic choices." (pg 10.)

These time critical decisions impact on the length of time a herd is grazing and grazing season length affects farm profits, with Irish research demonstrating that extending the grazing reduces costs (Kinsella et al 2010). In a survey of Irish dairy farmers in 2008, Creighton et al (2011) found the average grazing season length was 245 days. Profitability is increased with better utilisation of pasture but only 18% of farmers use any of the measurement and budgeting methods needed to achieve higher utilisation. With respect to turn out dates, fodder availability and soil condition were the main factors in the timing of the decision. Field trials have shown that early grazing options across a wide range of stocking densities improve animal and sward performance and are to be recommended in dairy systems (O'Donovan et al 2004). However the situation for specialist beef production in Ireland is not as clear, with work suggesting that the effect on profitability is only marginal and only for some types of beef production systems (McGee et al 2014).

These environmental conditions can vary significantly year on year as highlighted in Figure 5.1, which shows mean growth curves at three Teagasc research farms (Moorepark in the South, Ballyhaise in the midlands and Grange in the north-east of Ireland).

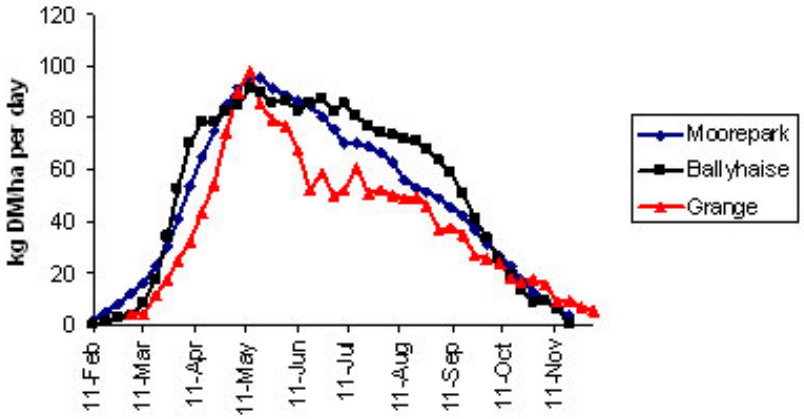


Figure 5.1: Grass growth curves for 3 locations in Ireland (mean of 1982 - 2006 for Moorpark, 1998 - 2006 for Ballyhaise and 2001 - 2007 for Grange).

In order to understand why farmers do not engage in the management practices that would allow for a longer season, the issues around adoption of extended

grazing have been examined by O'Shea et al (2015) within the context of technical adoption theory. The survey results of 207 respondents were analysed as a binary probit model of adoption/non-adoption of extended grazing defined relative to the regional average. Agricultural education and off-farm employment had the most significant positive relationship with an extended grazing season, while past participation in agri-environment schemes had the strongest negative effect on the choice of extended grazing.

An Ordinary Least Squares (OLS) analysis of one year (2009) of turn out data by Läpple et al (2012), found that geographic region and soil status were strongly associated with length of grazing season, but that farm size, stocking density or grazing method had no relationship with grazing season length. The absence of a grazing method link is instructive, as Irish dairy farmers, by and large, treat their herd as a single unit and turn out the whole herd at the same time whereas Irish beef producers release cattle from winter storage in small groups over time in anticipation of the animals´ ultimate fate at market as weanlings (being sold in the spring or kept for another year) or store cattle (due to spend a second winter in houses)(Connor & McGrath 2014).Many of the studies looking at farmer beheivour patterns and choices employ panel analysis techniques.

5.1.2 Panel data and spatial data

Panel data (some-times referred to as longitudinal or cross-sectional data) are data that represent multiple observations of the same sample over time (factory profits over a number of years is a simple example). For reasons outlined in section 5.3.2 these have to be treated differently from true random samples as in conventional statistical analysis).

The use of panel data analysis within a remote sensing context is an emerging field. Whilst spatial econometrics has a broad acceptance within the literature, and a strong conceptual basis from which to develop (see Anselin (2013) for a standard textbook), there is no review of EO explicitly within econometrics or of the use of common econometric statistical techniques within the EO literature.

Broadly, remote sensing and econometrics techniques interact in three ways. The first and most common is the provision of data, derived from remote sensing as an *a-priori* dataset. The most common EO derived data are land use/cover information which is used for building models of economic drivers of change (Irwin & Geoghegan 2001). Analysis of forestry dynamics has been a particular focus of such work, for example Nelson and Hellerstein (1997) with an analysis of new roads and forest clearance.

Secondly, statistical techniques such as logistic regression and Bayesian analysis, common in econometrics, are used to predict and map change in remote sensing datasets, improving second order products such as change detection but not acting upon the "raw" pixel data. This is particularly common in agent based approaches (where complex systems are modelled as the sum effects of individual smaller autonomous agent models) to change prediction/detection in land cover (see Verburg et al (2004)).

Thirdly, and least common, are statistical approaches more usually associated with econometrics that are used directly on EO data to perform analysis and classification. For example logit models have been used to classify image pixels into land use classes with some success (Seto & Kaufmann 2005) instead of traditional clustering techniques familiar in the EO literature.

From an econometric perspective, conventional panel analysis often ignores spatial dimensions and issues of geographic relationships within datasets. Although the issue is beginning to be addressed in the literature; with the special case of spatial heterogeneity being handled with spatially defined lags (Anselin et al 2008) (*cf.* the more familiar time-lags employed in panel analysis). More sophisticated approaches are being developed such as the geographically weighted panel regression approach put forward by Yu (2010).

The use of EO derived data in panel analysis (with or without a spatial component) is increasing as econometrics begins to draw on a new source of independent data

that can, through GIS systems, be incorporated into traditional data models. An example is Wheeler et al (2013) which uses a panel approach to investigate drivers of deforestation in Indonesia, where the deforestation data were taken from a monthly satellite derived inventory.

5.1.3 Overview of Chapter 5

The purpose of this section is to investigate the environmental drivers, if any, that influence the decision when to turn out cattle for spring grazing on Irish farms. Five years of geocoded farm level data recording when animals are first turned out from winter housing along with contemporaneous satellite derived measures of fodder availability and local rainfall data (as a proxy for soil condition) are analysed. First the environmental conditions present when animals are turned out are characterised and then through a panel analysis those indicators that are most strongly associated with the decision to turn out are determined. This model is developed further as a random effects model with time lags to predict when a farmer is likely to have turned out given prevailing spring conditions. The implications from the model regarding farmer decision making are discussed.

5.2. Data Sources

5. 2.1 Dependent variable: Turn out date

The Teagasc National Farm Survey (NFS) (Hanrahan et al 2014a) is collected as part of the EU Farm Accountancy Data Network. It consists of a detailed set of accounts for approximately 900 farms and is statistically sampled to take different farm systems into account. Between 2008 and 2012 specialist dairy farmers in the NFS (~300 farmers in each survey year, with some change each year in the sample) recorded turn out dates. This gave a total of 1536 recorded turn out events, however to avoid issues of an unbalanced panel (incomplete records), only those farms with five complete years of data were selected for the final analysis, leaving a sample population of 199 farmers and 995 turn out dates. The TOD is transformed

to Julian day of year, with January 1st as 1, so an early turn out date is a low number and a late turn out date a high number.

The farms are linked to environmental variables via location, with the NFS geo-coded (Green & Donoghue 2013) using address matching methods. In Ireland this is not a trivial matter as a postcode system has only been in place since July 2015 (and the uptake of postcodes seems slow). Moreover, Irish toponymy is complicated with a history of local place-names surviving against imposition of standards by different authorities meaning there are multiple "official" versions possible for each address. Furthermore the absence of street names or numbers in rural Ireland, outside of towns and villages, means that most rural addresses are not unique, and instead are resolved to a single location through the addressee's name.

The addresses were matched using SQL in MS Access to location via the An Post database of delivery addresses called the Geo-directory. This database is supplied with tables and fields allocating every address to a building and every building to a geographic 6-figure position in Irish National Grid (ING) coordinates (Fahey & Finch 2008). Figure 5.2[23] shows the percentage of NFS addresses that automatically match with a given number of buildings in the Geo-directory. Only 6% of NFS addresses match one-to-one with a Geo-directory entry, the rest matching with a range of numbers of buildings and on average an NFS address matches to 10 Geodirectory buildings. It is important to note that this is not an "error", all ten buildings in the Geo-directory have exactly the same address, and this *one-to-many* matching is common in rural Ireland and cannot be eliminated unless the actual location from another source, such as parcel ID or postcode[24], is known.

[23] Figures 5.2 and 5.3 are taken, with permission, from Green and Donoghue (2013)

[24] This problem has technically been eliminated since 2015 with the introduction of a national postcode scheme, Eircode, where every address in Ireland has been allocated a unique 7 figure ID. However access to the full database is very expensive.

In order to allocate a single point for each farm the geographic centre of the cluster of buildings with the NFS address is used. Figure 5.3 shows the relationship between the geographic size of the cluster (defined at 1 standard deviation distance from the centre) with the number of addresses within the cluster. This ambiguity around location however does help preserve NFS respondent anonymity and the true locations of the farms are not specified in this thesis. The geo-coding used in this analysis was a six figure coordinate, to the nearest meter, in the Irish Transverse Mercator projection.

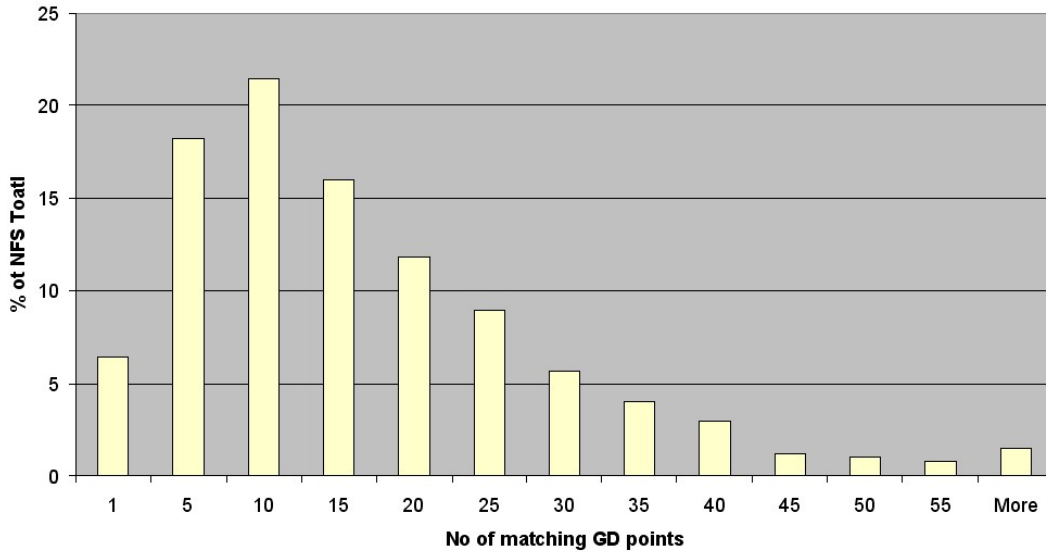


Figure 5.2: Frequency histogram showing the percentage of the NFS addresses that match to a cluster of buildings of a given size.

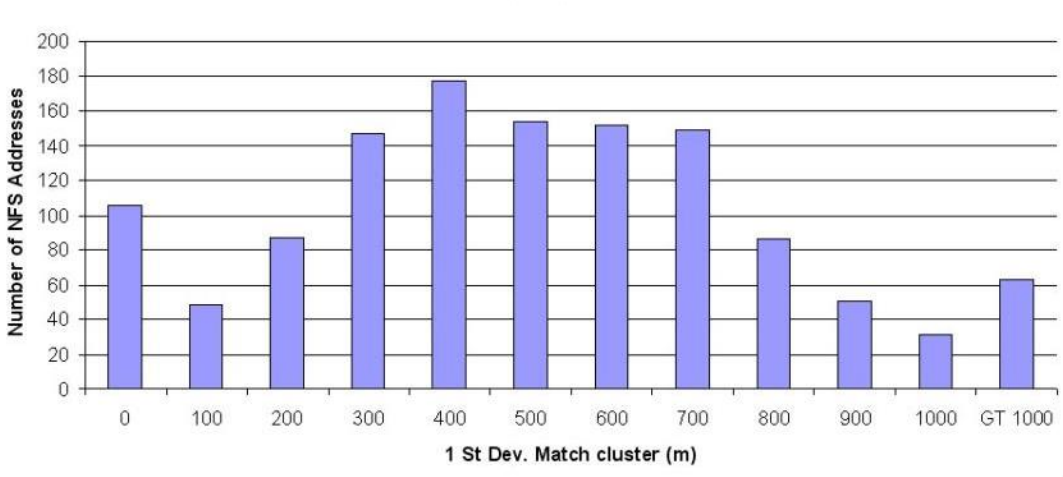


Figure 5.3: Frequency histogram showing the number of NFS addresses found within a range of 1 standard deviation from the geographic mean of each building cluster.

To illustrate the geographic distribution, the average turn out month over the five years for the farms in this analysis is mapped in 10km tetrads in Figure 5.4a and the range of dates (difference in days between the earliest and latest turn out date on each farm) is shown in 5.4b. It is evident that farms in the south generally turn out up to three months earlier than farms in the north but there seem little geographic trend in the range of dates.

Looking at the turn out date data graphically it is apparent that some trends and habits persist. If we look at all recorded turn out dates between 2008-2012 and not just those farmers who recorded a TOD for all five years (as this is not a panel analysis, we can use all the data)) gives a total of 1536 turn out events and these are plotted to look at day of the week when turn out occurs (Figure 5.5), the day of the month (Figure 5.6) and day of the year (Figure 5.7).

There seems to be little bias in day of the week, Figure 5.5, with perhaps a small drop at the weekend, but as dairy farmers run a 7 day week operation, it is unsurprising that there is no preference by day of the week for when turn out occurs.

However, there is a clear bias toward the 1st of the month when turning out (Figure 5.6) which may be farmers responding to advice or defaulting to a habitual day (it may also be casual recording, a *post hoc* record of turn out being "around the start" of March being noted as March 1st). Clearly there is no agronomic reason for the start of the month turn out but it must be acknowledged that this decision does not occur in a vacuum and having a fixed date, set in advance, may have personal advantages within a farm household that faces the myriad of competing demands of any other family home. Also the 10th, 15th and 20th of the month stand out, the 15th and 20th may reflect activity around traditional turn out days such as valentine's day and St Patricks day, the reason for a spike around the 10th of the month is less obvious.

We can see clearly in Figure 5.7 that March 1st is the most favoured turn out day, with February 15th next (which may reflect response to Teagasc advice of considering the period around Valentine's day as a TOD target. It is this apparent tendency for inertia around set calendar days that advice around extending the grazing season according to actual conditions seeks to overcome.

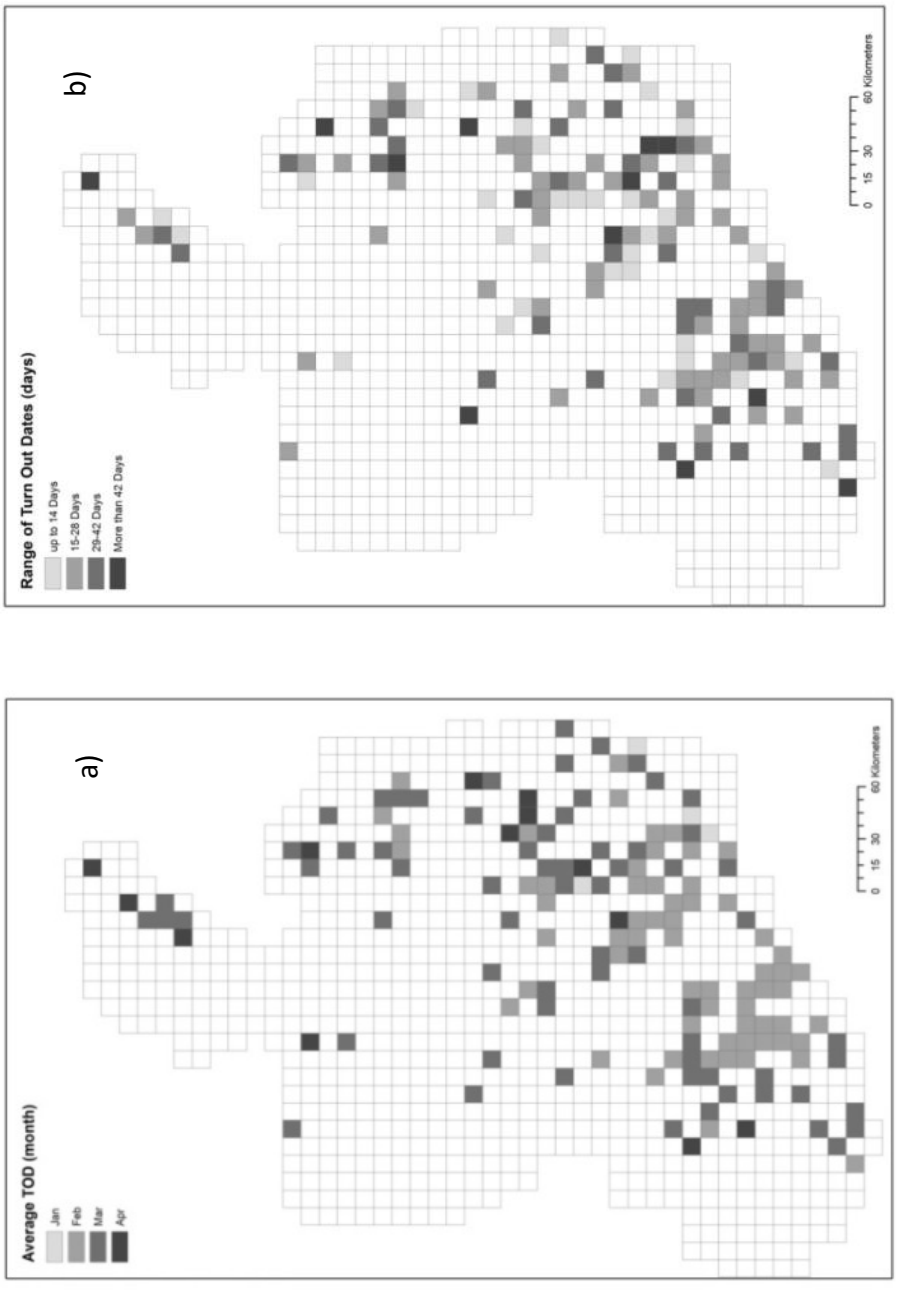


Figure 5.4: 10km tetrad distribution map of a) average turn out dates (TOD) of the dairy farms in the sample and TOD range over the period 2008-2012

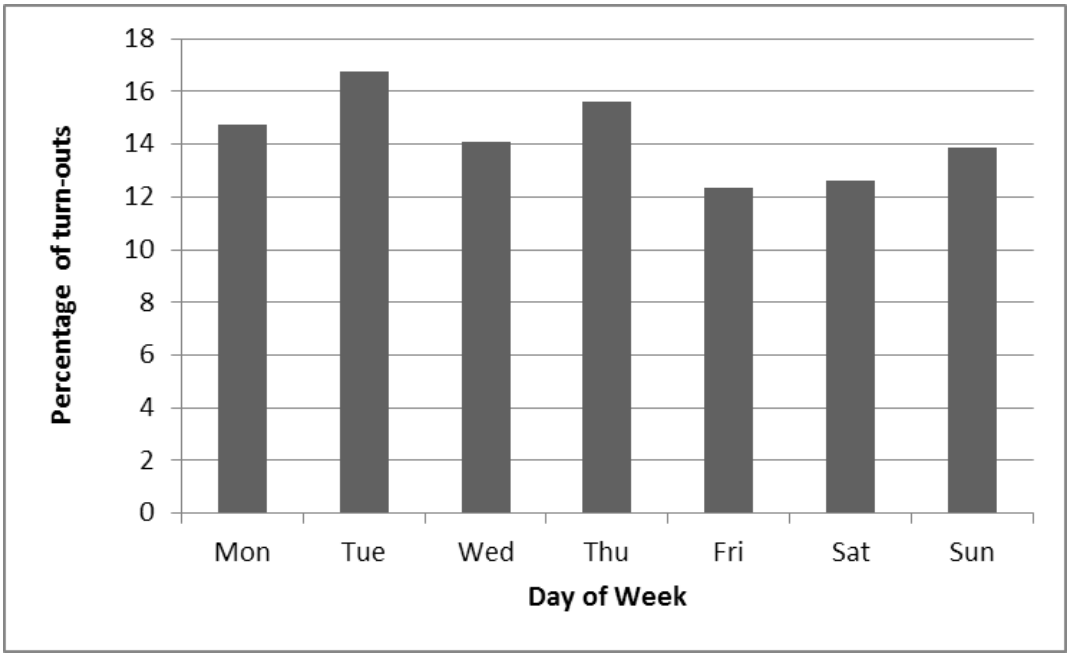


Figure 5.5: Day of the week on which turn-out first occurs, 1536 turn out events, 2008-2012

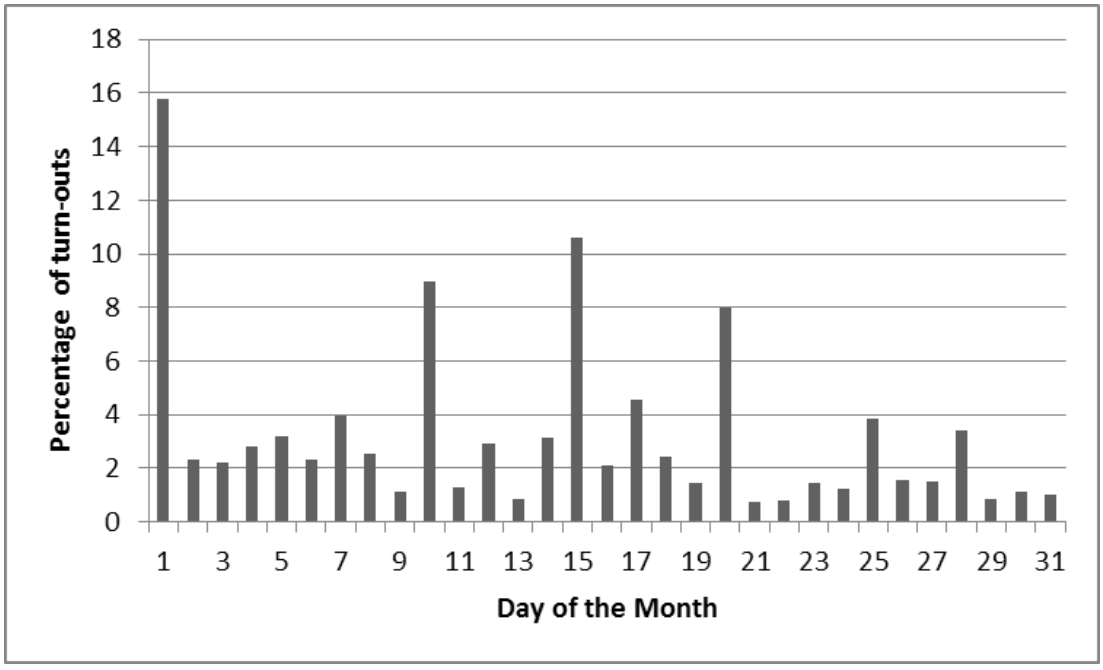


Figure 5.6: Day of the month on which turn-out first occurs, 1536 turn out events, 2008-2012

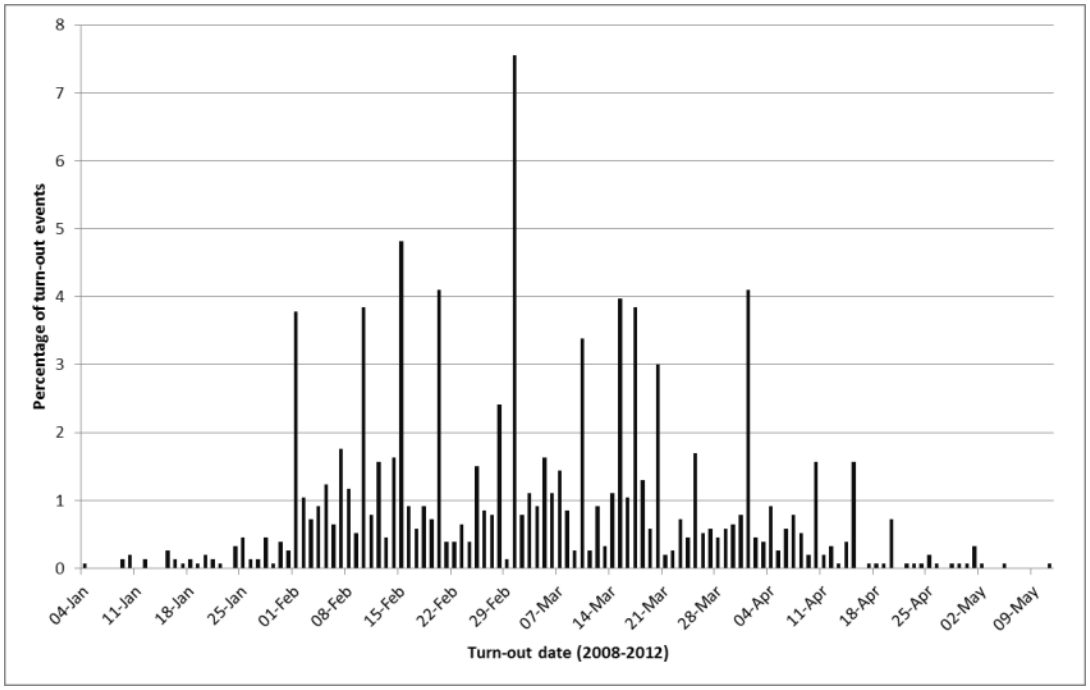


Figure 5.7: Day of the year on which turn-out first occurs, 1536 turn out events, 2008-2012

5.2.2 Explanatory variables: Satellite observation of grass growth

The satellite data used were 16-day composites of Normalised Difference Vegetation Index (NDVI) imagery from the MODIS sensor on the Terra satellite (Huete et al 2002) as discussed in section 3.2 in detail. The selected MOD13Q1 product provided detailed quality flags and a Day of Year acquisition stamp for each 250m pixel (García-Mora et al 2011). All 16-day composites for the period January 1- May 15 2003-2012 were used with 9 images each year. The farm locations in the study were overlaid on the images and the corresponding NDVI pixel value extracted so that each farm has 9 NDVI scores each year.

The average NDVI score for each year for each farm and the actual 16-day composite NDVI score at turn out for each farm was also recorded. It is important to note that the NDVI score is uncalibrated, it is related to grass cover amounts but is not a direct estimate of such.

]

5.2.3 Explanatory data: Rainfall

Daily rainfall data from the national rain gauge network from Met Eireann was used (Walsh 2012). The exact number of stations in the network varies from year to year but in this analysis (2008-2012) there were approximately 550 stations of which 301 had complete records and were used in this analysis, Figure 5.8. Each farm in the sample set was ascribed the average of the daily rainfall recorded at the 3 stations closest to it (mean distance, farm to rain gauge, was 7.5km).

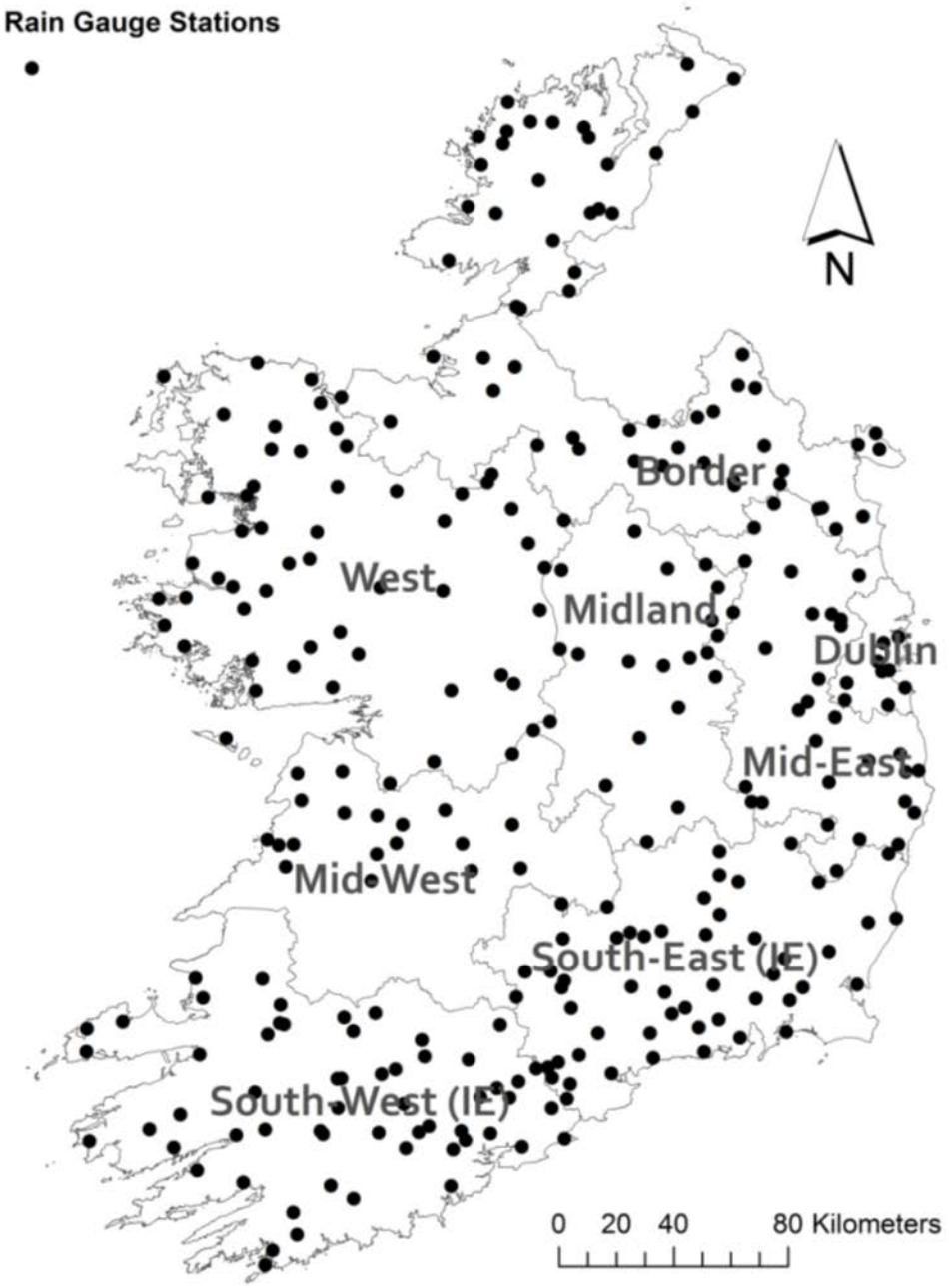


Figure 5.8: Distribution of rain gauge stations used in analysis.

Field experiments in Ireland have shown that Soil Moisture Deficit, SMD, the amount of rain needed to bring the soil moisture content back to field capacity, is a predictor of potential soil damage through poaching (Piwowarczyk et al 2011). SMD is often negative in Ireland indicating excessive water (a SMD <-10mm is considered saturation).

SMD is the interaction of weather and soil. As the soil remains the same over time it was assumed that SMD and thus trafficability would be strongly influenced by recent rainfall volume. Therefore total rainfall (in mm) in the 16 day period before each satellite acquisition and the number of dry days in the period was calculated for each farm as proxies for SMD and trafficability conditions. The total rainfall in spring and the total number of dry days in spring were also calculated each for year for each farm. Table 5.1 list summarizes the variables used.

Table 5.1: Summary of variables used in analysis

Variable	Obs	Mean	Std. Dev.	Min	Max	Description
TOD	995	60.871	21.686	4	121	Turn Out Day
meanvi	995	0.762	0.059	0.467	0.866	Average NDVI Jan 1-May8
totrain	995	358.972	111.772	123.4	880	Total Rain Jan1-May8 (mm)
totdry	995	63.537	16.622	11	119	Total Number of Dry Days Jan1-May8
truevi	995	0.757	0.066	0.440	0.882	Actual NDVI at TOD
trurain	995	40.962	28.521	0	184.2	Total Rain 16days prior to TOD (mm)
trudry	995	6.587	3.399	0	16	Total number of Dry Days 16 days prior to TOD
totr_1	995	45.966	43.066	0	269.7	Total Rain Jan1-Jan16 (mm)
totr_17	995	69.835	37.070	0	246.9	Total Rain Jan17-Feb1 (mm)
totr_33	995	43.053	25.347	0	152.1	Total Rain Feb2-Feb17 (mm)
totr_49	995	37.082	29.960	0	170.8	Total Rain Feb18-Mar5 (mm)
totr_65	995	38.850	21.606	0	139	Total Rain Mar6-Mar21 (mm)
totr_81	995	23.681	16.327	0.2	84.3	Total Rain Mar22-Apr6 (mm)

Table 5.1

cont.

totr_97	995	40.621	35.635	0	168.5	Total Rain Apr7-Apr22 (mm)
totr_113	995	28.035	24.724	0	99.3	Total Rain Apr23-May8 (mm)
totr_129	995	31.850	22.151	0	140.6	Total Rain May9-May25 (mm)
ndvi_1	995	0.731	0.065	0.463	0.864	NDVI Jan1-Jan16
ndvi_17	995	0.731	0.067	0.448	0.859	NDVI Jan17-Feb1
ndvi_33	995	0.737	0.069	0.440	0.879	NDVI Feb2-Feb17
ndvi4_49	995	0.748	0.069	0.444	0.882	NDVI Feb18-Mar5
ndvi_65	995	0.763	0.067	0.459	0.885	NDVI Mar6-Mar21
ndvi_81	995	0.780	0.062	0.477	0.893	NDVI Mar22-Apr6
ndvi_97	995	0.796	0.056	0.493	0.895	NDVI Apr7-Apr22
ndvi_113	995	0.810	0.049	0.512	0.895	NDVI Apr23-May8
ndvi_129	995	0.755	0.066	0.440	0.879	NDVI May9-May25
dry_1	995	7.006	3.964	0	16	No. Dry Day Jan1-Jan16
dry_17	995	4.716	3.127	0	16	No. Dry Day Jan17-Feb1
dry_33	995	6.778	3.087	0	16	No. Dry Day Feb2-Feb17
dry_49	995	7.401	3.403	0	16	No. Dry Day Feb18-Mar5
dry_65	995	5.371	3.453	0	15	No. Dry Day Mar6-Mar21
dry_81	995	8.232	3.221	0	15	No. Dry Day Mar22-Apr6
dry_97	995	7.426	3.532	0	14	No. Dry Day Apr7-Apr22
dry_113	995	8.963	4.538	0	16	No. Dry Day Apr23-May8
dry_129	995	7.644	3.990	0	16	No. Dry Day May9-May25

5.3. Methodology

5.3.1 GIS and spatial analysis

This study is primarily concerned with farm inter-annual variation in turn out date than with between farm spatial variation in turn out date. However a spatial analysis technique to identify geographic trends was applied to test if location influences the size of the within farm inter-annual variation i.e. does the turn out date vary more in some locations than others.

The technique chosen is well suited to the analysis of geographic trends in point data (whilst the farms are not points on the ground, their attributes are associated with a single point, the location of the farmhouse in this analysis). Moran's I test is a test of spatial autocorrelation, and provides information on whether a spatial characteristic is random (a value of zero in the test) with respect to location, perfectly dispersed (-1) or entirely dependent on location (1). For ease of interpretation these values are transformed into a Z-score with 5% significance (Anselin 1992).

The test is a two dimensional (x and y coordinate) extension of the standard measure of autocorrelation with variance. The extension to two dimensions is achieved via a matrix of site to site distances between points; in practice maximum calculation distances are often imposed in order to rationalise any hypothesized spatial relationship. The calculation was performed in ArcGIS. A range of maximum distances for calculations were selected to observe any scale effects. The spatial effects on average turn dates and intra-farm range (difference between earliest and latest date at each farm) were examined. As the sample of farms in the NFS is not selected to represent a random or representative *geographic* sample, row standardisation was employed to counter any clustering in the sample.

5.3.2 Panel data analysis

Our sample of farms is not a random one and was not designed to model the distribution of farm response to environmental conditions. The repeated measurements are not equivalent to treatments and are not controlled. So simple general linear modelling of response would be inappropriate.
Here recall the assumptions for standard multivariate OLS fits (or many of the clustering approaches used in EO):

- Random sample
- No complete co-linearity between regressors; none of the x terms can be written as a linear combination of the others.

- The average error value is zero; E(e)=0
- None of the x's are correlated with the error; Cov(x,e) = 0. (no endogeneity)
- Homoscedasticity; the variance in the y term is not a function of the x term (or the error term when analysing results)

These do not always hold for time-series data and especially "natural experiment" ground truth data. Data points recorded in time t+1 at the same location as at time, t, are not independent and should not be treated as such. This issue is of principal concern in growth studies and phenological studies. It´s unlikely our sample and variables capture all effects and that any omitted covariate will cause a bias in estimating the effects of the covariates we have included.

However our data is presented as a panel. A data set is said to be a "cross-sectional panel" when we have repeated observations of the same variable over time from the same target. Examples might be pollution samples from a fixed point over a number of years or a set of production figures from the same set of factories over a number of years. In an EO context – then the pixels in a time series of images of the same target are in fact a panel data. Using a fixed effects model allows us to control for all fixed differences between farms (location, size of farm, farmer education , soil type, etc) within the panel.

This is illustrated in figure 5.9 where ignoring between and within farm effects on the relationship between NDVI and TOD is shown to lead to erroneous conclusions about the trend. In figure 5.9a data from 6 farms over the five years are shown and a linear trend fitted demonstrating an apparent positive relationship between NDVI and TOD. However when individual trends are fitted to each farm, as in 5.9b, then the trend between TOD and NDVI is negative. By using a Fixed effect model on this panel we eliminate the problems caused by omitted variables in our analysis.

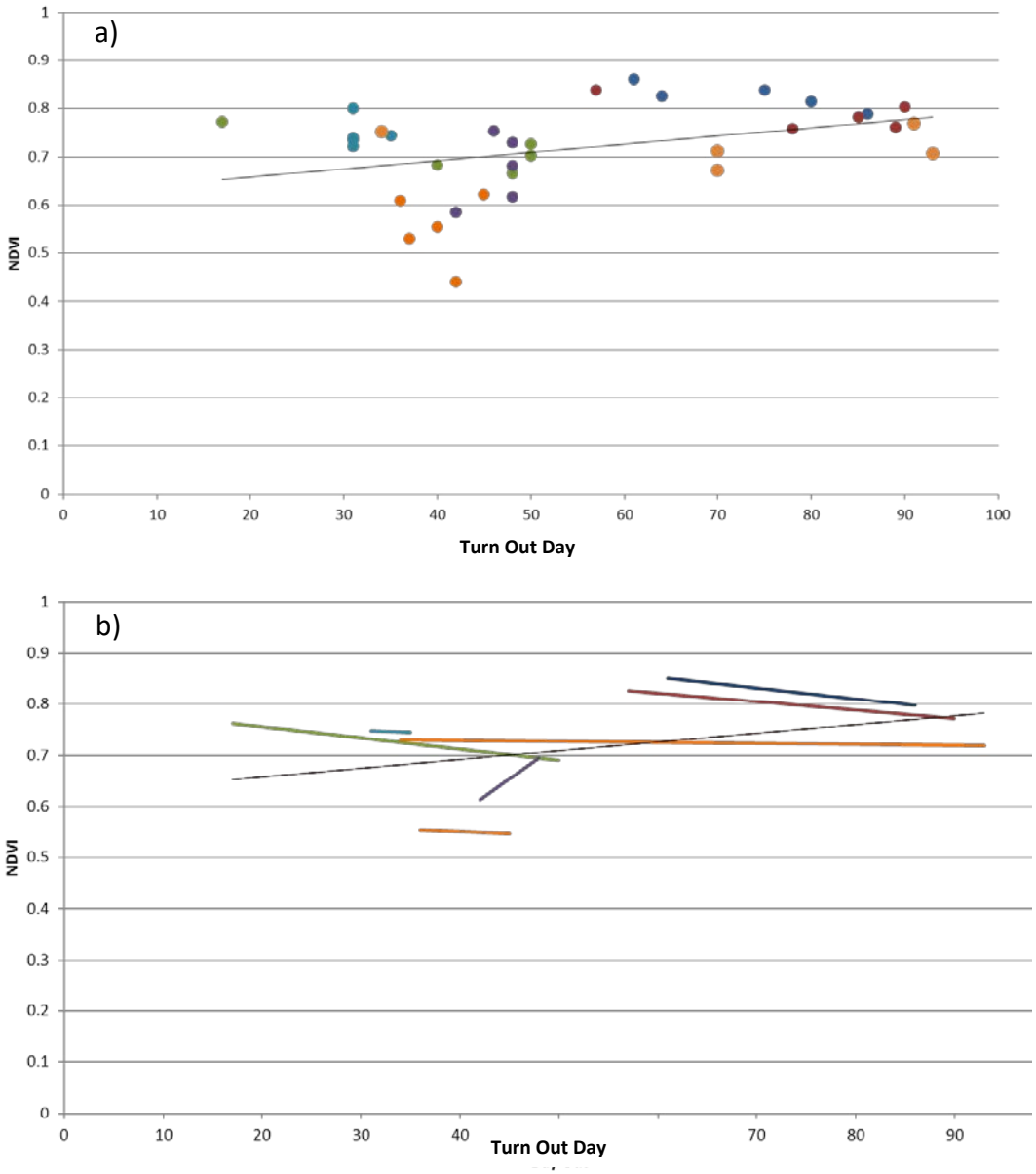


Figure 5.9: The relationship of NDVI at turn out and TOD for 7 farms over 5 years. A) shows the trend fitted against all data treated as independent observations, as NDVI increases so does TOD B) shows trends of individual farms, and that the relationship on the farm is the opposite, later TOD associated with lower NDVI.

The fixed model then essentially looks at how variation in TOD (around the mean) changes in response to variation in NDVI and rainfall. In the fixed effect model the intercept is allowed to change between farms but the slope of the response is considered the same across each farm and is formulated as:

$$\boldsymbol{Y_{it} = \alpha_i + \beta_1 X_{it} + U_{it}} \quad \text{eq. 5.1}$$

- Y_{it} is the dependent variable (TOD) where i = farm (i=1….199) and t = time (t=2008…2012).
- α_i is the intercept for each farm.
- X^{it} represents one independent variable (NDVI or Rainfall),
- β_1 is the coefficient for that variable,
- U_{it} is the error term

It should be noted that this model assumes there are unobserved factors that influence TOD that are time invariant. A possible source of non-time-invariant factors could be severe weather in an autumn or policy/advice changes nationally – neither are considered to have occurred during 2008 -2012.

A fixed effect linear panel analysis of the variation between years of TOD and environmental variables was carried out. The panel of 199 farms with 5 years of observations (995 observations in total) is balanced (there are no data gaps, each farm is represented all five years). The panel ID variable is Farm ID and the time variable is year (2008-2012) and the panel is structured as shown in Table 5.2. When examining the presence of a seasonal effect, then a year dummy is included.

Table 5.2: Structure of the panel

Farm ID	Year	NDVI_1… NDVI129	TOTR1… TOTR129	DRY1… …DRY129	TOTRAIN	TOTDRY	MEANVI	TRUVI	TRURain	TRUDRY
1	2008									
1	2009									
1	2010									
1	2011									
1	2012									
2	2008									
2	2009									
2	2010									
⋮	⋮									
199	2010									
199	2011									
199	2012									

As explained above the focus on inter-annual variation in TOD in response to changing environmental variables, as opposed to the causes of variation between

farmers, indicated the use of a fixed effect model, as did the results of the spatial analysis (see 4.1). This was confirmed by the application of a Hausmann test strongly suggesting the rejection of a random effects model (F test results strongly indicated fixed effects over pooled approaches). All non-spatial statistical analyses were conducted in the statistical package Stata 11 (StataCorp, 2009). The relationship is illustrated in Figure 5.10, where the NDVI in each 16 day period is plotted against the rainfall in the period for each farm for each year (199*9*5= 8955 points) and colour coded for whether the cattle are turned out ("no" if the period is before the turn out date that year, "yes" if after). The relationship is complex but in general the black dots (yes) cluster around low rain, high NDVI.

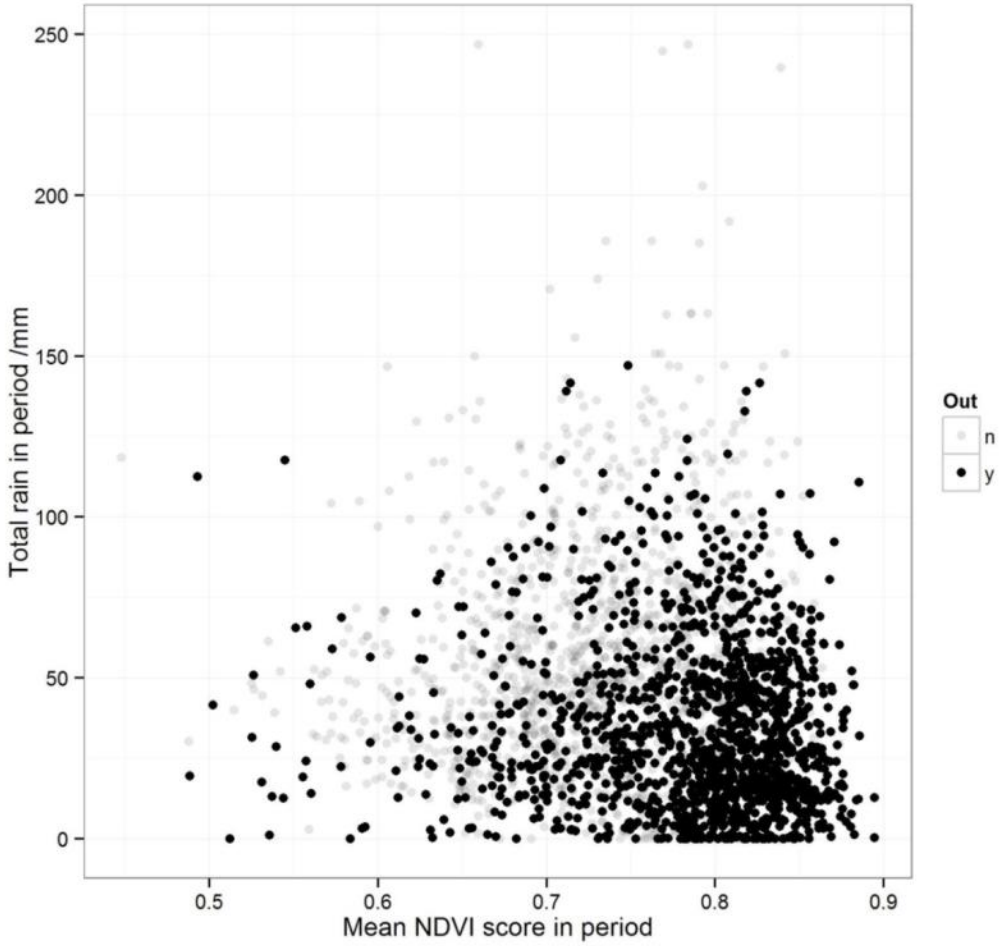


Figure 5.10: NDVI against rainfall for all observed periods, coded for whether the cattle are turned out (yes or no)

5.4. Results

5.4.1 Spatial Analysis

The Moran's I index score was calculated for average TOD and the range of TOD of each farm. The analysis was calculated over a number of distances from 50km to 400km. As well as the Moran's score, the corresponding z value was calculated (with reference to the null hypothesis of no spatial co-dependency, a Moran's score of zero). The results are plotted in Figure 5.11.

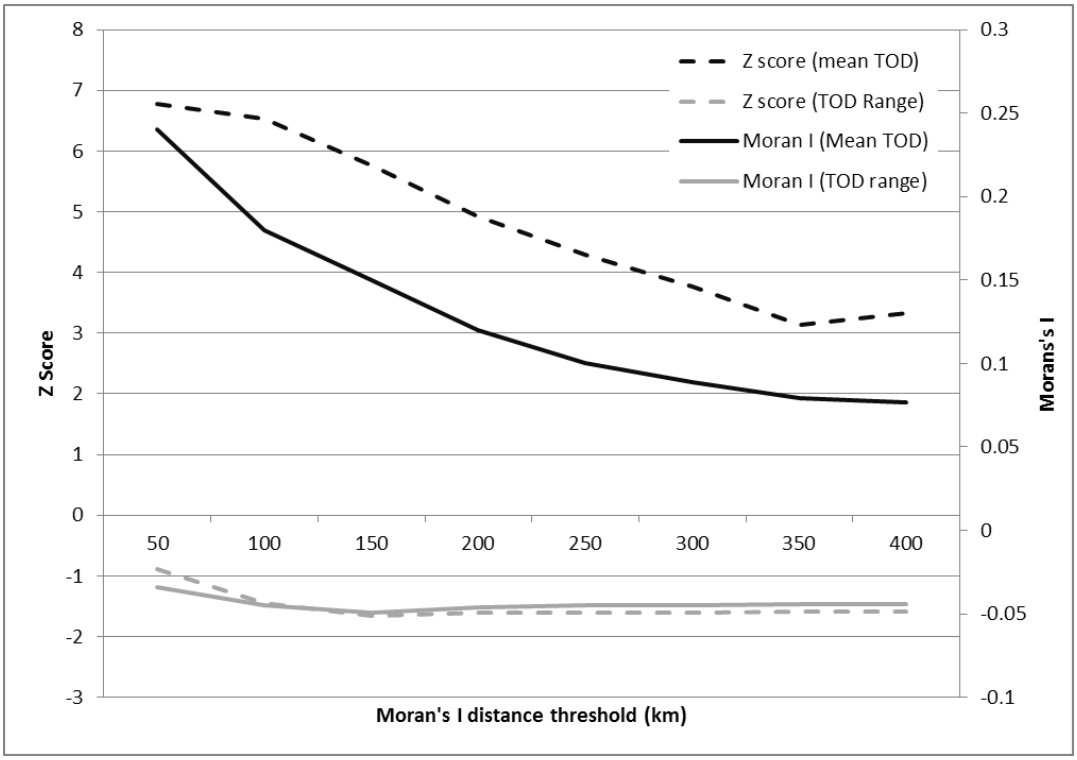


Figure 5.11: results of a spatial analysis of the distribution of average TOD and on farm variation (latest day of year minus earliest day of year) 199 farms over 5 years.

There is a relationship between location and *average* TOD, a positive Moran's I score (with relatively a high Z positive score at distances less than 100km) that weakens as distance increases (your TOD is likely to be similar to your near neighbour but not to someone at the other end of the county) but there is no relationship between inter-annual variation in TOD and location (Moran's I score near 0, with an insignificant Z score). So whilst some locations in Ireland will always

be able to turn out animals earlier than other locations, no place in Ireland suffers more unpredictability in turn out dates than any other.

5.4.2 NDVI panel analysis

Table 5.3 shows the result of the fixed effect panel analysis examining how amounts of grass and rainfall during the spring season relates to the decision of the farmer to turn out. The within variation r^2= 0.387 (199 farms, 5 years a total of 995 observations) shows the overall fit of the model is good but many of the variables have a low significance. Note that when interpreting the variables the TOD variable is a Julian day , with January 1st as 1, January 2nd as 2 etc., so a low value TOD indicates an early turn out of cattle and this is generally desirable; this means negative coefficients will decrease TOD as the variable increases.

Rainfall at End of March is significant, with every extra 10.1 mm of rain in the period delaying the TOD by 1 day. This seems logical, farmers may delay turn out if rainfall is heavy, even if enough grass is present. However rainfall at the end of April is also significant but this time the increasing rain leads to a decrease in TOD; this is difficult to interpret but nearly all farmers will have already turned out by then and we may be capturing a seasonal effect in that a wet April may indicate a wet spring and farmers have waited as long as possible and thus turn out earlier than is advisable given the prevailing conditions.

Grass growth as indicated by NDVI has less of an apparent influence, nonetheless NDVI at the end of February, when many farmers will be considering turning out, is related such that an early turn out date is more likely with higher grass growth. The NDVI score for Mid-May is significantly related to turnout and this is a seasonal effect, the significance disappears when year dummies are included. The coefficient seems to indicate that more grass in Mid-May is associated with a later turn out date, this is because in a “good year”, significant biomass is removed by mid-May through grazing and even silage cutting, so high NDVI in May indicates that perhaps

spring began slowly. The “number of dry days” is not influencing, individually, the TOD. Rainfall and number of dry days were both included to attempt to account for intensity of rainfall. Interaction terms for these variables were investigated and show no significance in the model performance or make up.

It is clear that multi-collinearity between variables must be high in this scenario- the grass growth in March is strongly related to grass growth in February and so on. Even rainfall shows a relative pattern of decrease across the spring. To attempt to reduce this effect, the bi-weekly variables were reduced to three single metrics to describe the overall spring: Mean NDVI score Jan 1st to May 25th (a high mean NDVI score across spring implies good grass growth), the total rainfall Jan 1st to May 25th and the total number of dry days in the same period. We also included 3 metrics to characterise TOD: the NDVI score at actual turn out date, the rainfall in the 16 days preceding and the number of dry days in the same period.

Table 5.4 shows the results of a fixed effect panel analysis on TOD using these variables with and without a year dummy. Without year dummies all the variables are significant with average NDVI strongly influencing TOD. If grass growth over spring is high then turn out dates are early, if spring is wet then TOD is late (3.5 days later for every 100mm of rain). But the number of dry days seems to affect TOD contrary to expectation with TOD later if the number of dry days increases.

Around the time of making the TOD decision an increase in the number of recent dry days makes the TOD earlier (0.46 days earlier for every extra dry day) but so does an increase in rainfall and higher grass growth at turn out is associated with a later date. Some of these contrary results are partially explained when a year dummy is included in the result. We can see that, in comparison with 2008, 2010 is associated with TOD being 4.94 days later and 2012 with TOD being 5.96 days earlier. As a result of including the year dummies total dry days are no longer significant and total rainfall is only just significant at the 5% level.

Table 5.3: Factors associated with turn out date.

Variable associated with Turn Out Day (Julian Day of Year)	Coefficient (t)	Variable associated with Turn Out Day (Julian Day of Year)	Coefficient (t)
Total Rain Jan1st-Jan16 (mm)	-0.001(0.05)	No. Dry Day Jan1st-Jan16	0.238(1.26)
Total Rain Jan17-Feb1 (mm)	0.025(1.71)	No. Dry Day Jan17-Feb1	0.156(0.60)
Total Rain Feb2-Feb17 (mm)	0.008(0.37)	No. Dry Day Feb2-Feb17	0.236(1.33)
Total Rain Feb18-Mar5 (mm)	-0.019(0.78)	No. Dry Day Feb18-Mar5	-0.022(0.10)
Total Rain Mar6-Mar21 (mm)	0.009(0.38)	No. Dry Day Mar6-Mar21	-0.395(1.88)
Total Rain Mar22-Apr6 (mm)	0.109(2.76)**	No. Dry Day Mar22-Apr6	0.217(0.87)
Total Rain Apr7-Apr22 (mm)	0.023(0.73)	No. Dry Day Apr7-Apr22	-0.311(1.37)
Total Rain Apr23-May8 (mm)	-0.088(2.64)**	No. Dry Day Apr23-May8	-0.279(1.33)
Total Rain May9-May25 (mm)	0.015(0.54)	No. Dry Day May9-May25	0.045(0.29)
NDVI Jan1st-Jan16	-42.132(1.14)	Constant	81.505(5.76)**
NDVI Jan17-Feb1	2.005(0.03)		
NDVI Feb2-Feb17	-94.435(1.61)		
NDVI Feb18-Mar5	-111.586(2.03)*		
NDVI Mar6-Mar21	-91.843(1.70)		
NDVI Mar22-Apr6	-144.295(1.81)		
NDVI Apr7-Apr22	174.002(1.37)		
NDVI Apr23-May8	-103.291(1.42)		
NDVI May9-May25	380.257(11.54)**		

Observations= 995. Panel ID FARM_CODE=199.Time ID Years=5

Within r^2=0.387 (F=9.57***).Absolute value of t-statistics in parentheses

* p<0.05; ** p<0.01

Table 5.4: Seasonal and local factors associated with TOD

Variables associated with		*with year dummies*
Turn Out Day (Julian Day of Year)	Coefficient (t)	Coefficient (t)
Average NDVI Jan 1-May8	-399.312(11.74)**	-357.209(10.70)**
Total rain Jan1-May8 (mm)	0.036(6.77)**	0.015(1.96)*
Total number of Dry Days Jan1-May8	0.245(4.54)**	0.093(1.60)
Actual NDVI at TOD	323.206(11.26)**	323.439(11.37)**
Total rain 16days prior to TOD (mm)	-0.079(4.68)**	-0.082(4.84)**
Total number of dry days in 16 days prior to TOD	-0.464(2.84)**	-0.518(3.19)**
Year Dummy		
2009		0.322(0.703)
2010		4.94(2.83)**
2011		1.2(0.83)
2012		-5.962(-4.13)**
Constant	98.246(8.70)**	83.273(6.54)**

Observations=995. Panel ID FARM_CODE=199.Time ID Years=5

Within r^2=0.323 (F=35.59***), with Year Dummies r^2=0.363 (F=24.91***)

Absolute value of t-statistics in parentheses

* p<0.05; ** p<0.01

If the assumption of a farmer having a target date is true then this could be picked up with a lagged variable- the previous year´s TOD. If farmers have a preference for a TOD regardless of conditions and only change in extremis, using the previous year´s TOD allows us to capture this. One impact of using a lagged variable is that 2008 cannot be used as we do not have 2007 TOD.

The inclusion of the lagged variable in the FE model above has little impact. The lagged variable itself is not significant, although the overall model r^2 marginally increases and the RMSE goes from 15.3 to 14.3 (see table 5.5). Note that the year dummy now references 2009 as 2008 data not included in analysis.

Table 5.5: Seasonal and local factors associated with TOD in a fixed effects model with a lagged TOD variable added

Variables associated with	*with year dummies*
Turn Out Day (Julian Day of Year)	Coefficient (t)
Average NDVI Jan 1-May8	-344.342(9.55)**
Total rain Jan1-May8 (mm)	0.012(1.34)
Total number of Dry Days Jan1-May8	0.037(0.54)
Actual NDVI at TOD	301.930(10.34)**
Total rain 16days prior to TOD (mm)	-0.072(3.82)**
Total number of dry days in 16 days prior to TOD	-0.227(1.16)
TOD_lag	0.017(0.5)
Year Dummy	
2010	4.57(2.77)**
2011	0.930(0.63)
2012	-6.475(-3.75)**
Constant	83.841(6.13)**

Observations=796. Panel ID FARM_CODE=199.Time ID Years=4
Year Dummies r^2=0.382 (F=22.51)
Absolute value of t-statistics in parentheses
* p<0.05; ** p<0.01

5.4.3 A predictive model

The explanatory approach in the previous section can be expanded to look at prediction of TOD knowing current conditions. For the predictive model we can move beyond the fixed effects into a random effects model that incorporates

variance between farms. This is important as formally the fixed effects model can only be used to infer relationships within the sample whereas a random effects model allows for inference and thus prediction from the larger population from which the sample was drawn (due to the assumption of a normal distribution to the residual term). This allows us to include x and y location and soil type (dummy variable for well drained or poorly drained recorded in the NFS) in our model as a between farm effect. The result of the random effects models (maximum likelihood) also shows the much bigger impact of using the lagged TOD variable , table 5.6.

Table 5.6: Seasonal and local factors associated with TOD in a random effects model with a lagged TOD variable added

Variables associated with Turn Out Day (Julian Day of Year)	*i)* Coefficient (t)	*ii) with lag* Coefficient (t)
X Coor	-0.0000141(-1.03)	-0.00000677(0.77)
Y Coor	0.0000627(7.00)**	0.00000924 (1.56)
Dry Soil Dummy	-4.230995 (2.97)**	-2.581223(3.02)**
Average NDVI Jan 1-May8	-503.589(23.22)**	-375.260(17.86)**
Total rain Jan1-May8 (mm)	0.038(7.4)**	0.0313 (6.37)**
Total number of Dry Days Jan1-May8	0.250(6.56)**	0.130(3.92)**
Actual NDVI at TOD	427.206(22.73)**	313.487(16.84)**
Total rain 16days prior to TOD (mm)	-0.102(-5.95)**	-0.097(5.53)**
Total number of dry days in 16 days prior to TOD	-0.489(3.01)**	-0.199(1.18)
TOD_Lag		0.4868 (20.9)**
Constant	94.168(10.83)**	66.239(9.63)**

Observations=995. Panel ID FARM_CODE=199.Time ID Years=5
Overall r^2=0.589, with TOD lag
Observations=796. Panel ID FARM_CODE=199.Time ID Years=4
r^2=0.745
Absolute value of t-statistics in parentheses
* p<0.05; ** p<0.01

This random effects model, shows the influence of location and soil drainage as found in other studies (see 5.1), with dry soil associated with TOD being 4.5 days earlier and northerliness (y coordinate) leading to TOD being 1 day later for every 16km north. The other terms are similar to the FE coefficients. If the TOD_lag is introduced we can see the r^2 fit of the model increase significantly but the x and y coordinates are no longer significant as the TOD variation is captured in the lagged variable. This model allows us to predict a TOD for the NFS farmers using the equation:

$$\boldsymbol{TOD} = \mathbf{66.236} + \boldsymbol{DSM}.(\mathbf{-2.581}) + \boldsymbol{meanndvi}.(\mathbf{-375.260}) + \boldsymbol{totr}.(\mathbf{0.0313}) + \boldsymbol{totdry}.(\mathbf{0.13}) + \boldsymbol{truendvi}.(\mathbf{313.487}) + \boldsymbol{trurain}.(\mathbf{-0.097}) + \boldsymbol{TOD_lag}.(\mathbf{0.487}) \quad \text{eq. 5.2}$$

To tease out the interpretation of equation 5.2, the First coefficient tells us we have a baseline turn out day 66.236 DOY, ie March 6th or 7th (depending on leap year). The negative dry soil dummy variable tells us that farm TOD is 2.581 days earlier on a farm with well drained soils compared to poorly drained soils, the negative *meanndvi* term tells us that for every 0.01 increase in average NDVI score for the spring, TOD is 3.75 days earlier (where an NDVI change of 0.001 is approximately a weeks' worth of growth when we look at the growth rates calculated in section 3). Every mm of extra rain from the average in spring delays TOD by 0.03 days but every extra dry day also delays TOD by 0.13 days.

The coefficient of NDVI actually at TOD (*truendvi*) shows that higher NDVI scores are associated with later TOD, a 0.01NDVI increase at TOD means TOD is 3.13 days later and rain at TOD is higher for earlier dates. The lag term shows strong the influence of inertia, for very day the previous years TOD was later than March 6 the current TOD is 0.487 days later.

Predicted TOD and actual TOD for the period are shown in figure 5.12. Note that in the TOD_lag model the constant value (66.2) is 28 days earlier than the model without the lagged variable (94.2). The lagged coefficent is 0.487. If we apply the

coefficient to the mean TOD we get 29.7 days, this is not a coincidence as the lagged variable within the random effects model is moving variation from the alpha term fixed in time into a time variant variable. It would be preferable to have an independent test set to test this predictive power fully.

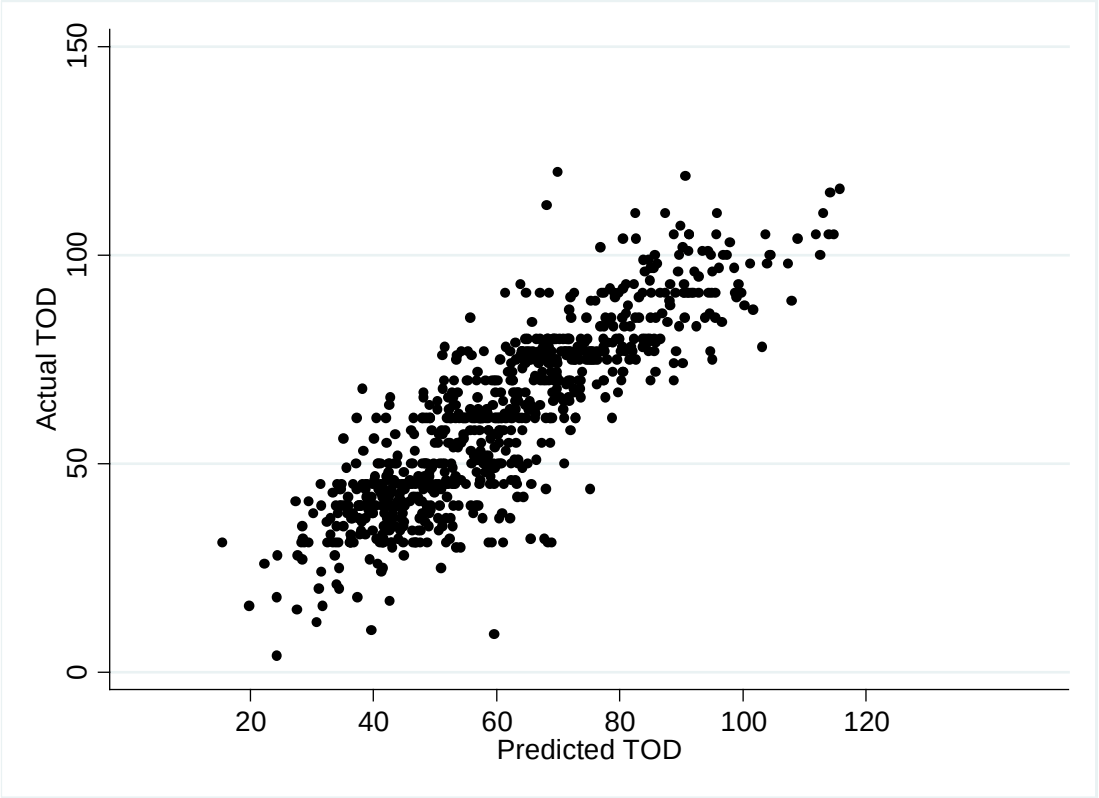


Figure 5.12: Predicted TOD against actual TOD (Julian days) for the model data.

5.5. Discussion

Better overall grass growth in spring seems to be related to earlier turn out dates but an opposite, equal effect is present locally at turn out, more grass on the farm at turn out is related to a later turn out. It is important to remember the strong seasonal effects; grass grows over time, all things being equal, the longer you wait the more grass there will be and less rain will fall as spring turns to summer. However we have hypothesised that farmers have a target grass level at their farm they want to achieve before turn out.

A simple plot helps us to understand some of the apparently contrary results. Figure 5.13 shows the average national turn out date for all 199 farms and the

average national NDVI value at time of turn out for each of the five years. If it were true that farmers have an ideal target of grass growth that they want to reach and they always wait for that target then the line would be horizontal but we can see that the later the average national TOD the less grass there is when cattle are turned out; so farmers wait as long as they can but eventually turn out cattle at less than ideal grass cover in bad years and contrary to that are not turning out as early as they could in good.

This allows us to interpret the results in table 5.10. Farmers respond to overall conditions, to a "bad" spring, like 2010, or to a "good" spring like 2012 and adjust their turn out dates but they do not do so optimally, there is a lag in the response, shown by the positive relationship between NDVI at turn out and TOD. In a good year they are letting the grass grow too far before responding.

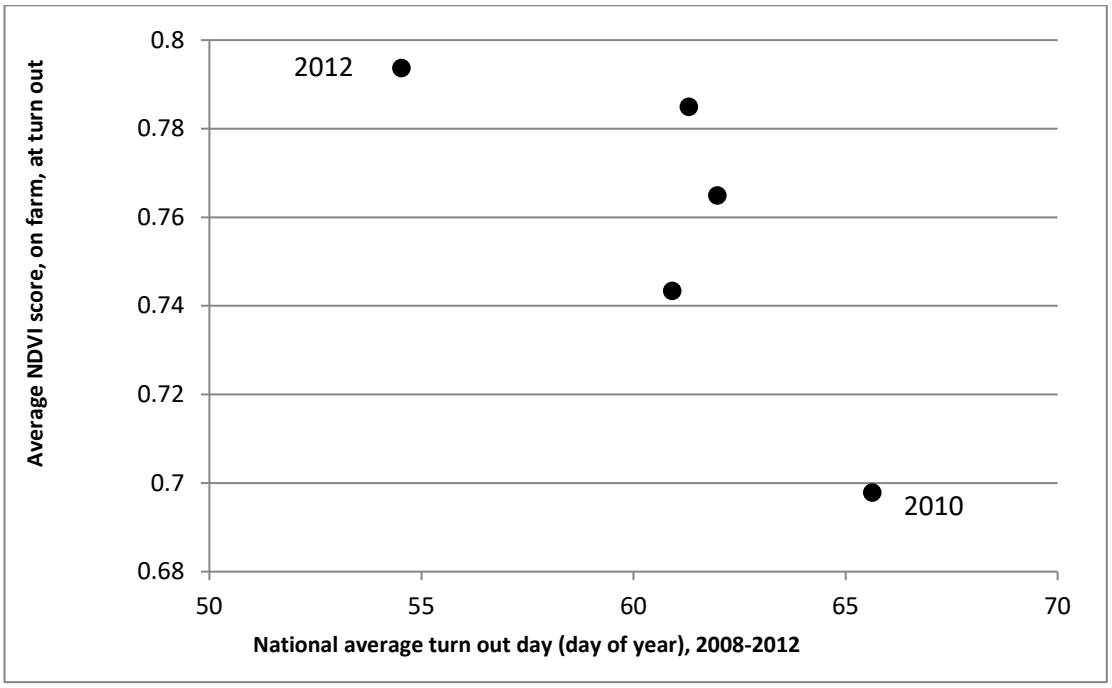


Figure 5.13: Relationship between national average turn out day and the NDVI score on the farm at TOD. Five years are shown and the "good" spring of 2012 and the "bad" spring of 2010 are labelled.

If the response of farmers to good conditions was optimal then the coefficient of NDVI at turn out date would be zero in equation 5.2, all else being equal the amount of grass at turn out on the farm should always be the same. The size of the coefficient is an indicator of how far from optimal the group of farmers are.

The increased rainfall at turn out being related to early TOD could be a seasonal effect, there is more rainfall early in the season and could indicate that farmers are more driven by available grass growth than soil conditions when considering an early turn out. A soil drainage dummy was included in earlier analysis and did not prove significant. The increase in the number of dry days at turn out being associated with earlier turn out is however an indicator that farmers are responding to local weather conditions when deciding to turn out. An interaction term between rainfall and dry days at turn out was investigated and not found significant.

It is likely that better knowledge of soils and drainage on the NFS farms would add considerable nuance to the picture of weather conditions and turn out date as would a more sophisticated handling of the rainfall data (the number of days over which to sum rain to get a picture of soil trafficability would vary considerably by soil type). However such farm level soil profiles are not available and would have to collected at considerable expense. It should be noted soils in Irish farms are often quite heterogeneous, with wet and dry soils on the same farm.

Our picture of NDVI and growth is also crude but better resolution satellite imagery form Landsat and Sentinel programs, and better geolocation of the NFS farms (mapped parcels rather than location of farmhouse) will allow us in the near future to be able to characterise the grass growth at field scale rather than in the generally location of the farm. Better temporal resolution of the satellite imagery will also help in resolving the decision making process but this has to be considered in the context of the prevailing cloudy conditions.

The predictive capabilities of the model seem good, at least for the NFS sample, in the absence of previous TOD for all farms then any national TOD prediction will depend upon the random effects coefficients in table 5.6. A comparison of the predictive capabilities is shown in table 5.7. The RMSE of 10.8 days when compared to an intra-farm average TOD variation of 25 days suggests this model could provide useful high resolution measurements of impact on TOD of current spring conditions on the farms in the NFS and wider.

Table 5.7: Comparison of the internal predictive capabilities of the four models

	r2 predict	Rmse on prediction (days)
Fixed Effects (FE)	0.501	15.32
FE+ TOD lag	0.549	14.3
Random Effects(RE)	0.581	14
RE+TOD lag	0.7419	10.8

5.6. Conclusion

Farmers are responding to general springtime grass growth conditions and measurements of NDVI over spring by satellite can quantify the effect on turn out dates at the farm, and nationally, of changes in grass growth year on year. Farmers seem to have a lag in their response to good conditions, waiting until there is more grass than is normal at their farm before turning out and turning out early in poor years to lower levels of grass cover. The number of dry days in the run up to turning out and the total amount of rainfall are associated with changes in TOD.

In the future we will be able to characterise generally growing conditions and give an estimate at the end of April of the turn-out dates across the NFS farms. New methods are being developed to directly estimate the amount of grass biomass in fields (Kg DM/Ha) from satellite, so rather than a relative score like NDVI we would have the actual amounts of grass cover on the farm. Incorporating a spatial dimension using newly developed spatial panel analysis techniques will allow for

national maps of TOD to be produced. This will allow for geographically tailored advice and turn out date targets. Having a more realistic target for turn out (as opposed to the promoted national target of the start of February) could help to increase up take of extended grazing.

Remote sensing data can add a considerable dimension to conventional agri-economic analysis providing the independent “real-time” data that is sometimes lacking; allowing for evaluation of current conditions rather than analysis of past performance. It is possible to use current observations of spring conditions and deduce national and local impacts on TOD.

6 Summary and conclusion.

6.1 Summary

In this work we attempted to answer three research questions:

- Can the effects of grass management be observed using medium resolution (250m) optical satellite imagery?
- Can current intensive grass growing conditions be assessed by satellite?
- Can management decisions be predicted from observed conditions?

6.1.1 Can the effects of grass management be observed using medium resolution (250m) optical satellite imagery?

Yes by coupling an understanding of farm systems with available time series satellite data it is possible to map LSU/ha, an important grassland classification that had been identified in the literature as a significant gap.

Stocking density or stocking rate is the number of animals per unit area on a farm. This simple figure (measured as Livestock Units per hectare, LSU/ha) is hugely important in ecological studies, GHG inventories and socio-economic modelling of the agricultural geography and yet, as demonstrated in section 3.1, the information is not readily available across the EU. Authors repeatedly bemoan a lack of such data or that data supplied at a very coarse spatial resolution.

In Chapter 3 it is shown how the growth rate and cover of grass in the early spring is related to the stocking density of the farm and this relationship can be modelled to produce a 250m resolution national map of stocking density in Irish grasslands.

Many of the studies examined in chapter 3 used a phenological approach, tracking growth over time and fitting a theoretically driven “growth curve”; often a sigmoidal function. This approach is fine in a natural or semi natural ecosystem where growth is driven by climate but in a highly managed grassland landscape where individual fields are grazed, mowed or cut repeatedly throughout the season

this “growth curve” fails as has been shown in earlier French and Irish studies referenced. Thus the decision was made to look only at a limited time period (1st January to 31st April) and assume that growth, once it starts, is linear (an assumption borne out by the literature and the data). By using a linear model this allows for only the very highest quality data to be used to characterise spring growth (only a few data points are needed to fit a straight line).

Within this linear model, 10 years of MODIS satellite data, using the 16 day NDVI composite, over the spring period was used to fit a linear model to the high quality pixels on the days available to create a decadal average growth rate and start of season cover values for every 250m pixel.

Using a database of stocking figures a simple relationship between the log of stocking density and these parameters was developed based on the assumption that in spring, before animals are put out to graze, the amount of grass is a function not only of water and soil but of management practices put in place by a farmer to support the level of intensification on the farm.

This model predicts stocking density with an RMSE= 0.13 LSU/ha (compared to a national average stocking density of 1.8 LSU/ha) and explains more of the variation in national stocking rate than the simple meteorological model presented in the section (an r^2 of 0.74 compared to 0.47 for agro-climatic model).

So for the first time, an accurate estimate of stocking density, at high spatial resolution has been made in the complex heterogeneous managed grassland landscapes common in northern Europe.

6.1.3 Can current intensive grass growing conditions be assessed by satellite?

Yes, taking the well-established idea of NDVI anomaly but re-figuring in the context of pastoral farming allows for the creation of a tool that satisfies adoption criteria in

the literature and also means it can be meaningfully compared to an independent measure of likely performance in the meteorological record.

The fodder crisis of 2012/13 demonstrated the need for regular updates of current grass growing conditions. In chapter 4 the spring growth models from chapter 3 was repurposed to create a growth anomaly map of current grass growing conditions.
Whilst anomaly maps based on NDVI data are common monitoring tools, they are presented as percentage deviations from a normal value, something that farmers can find difficult to interpret. Using a decadal average spring growth model means that the deviation from the norm can be expressed in days or weeks difference for normal, using language the farmer can understand.

Anomaly services are usually presented as *caveat emptor* with little interpretation and no validation. Here, for the first time, an anomaly map is validated against a temperature driven start of season index derived at meteorological stations. The accuracy of the model is that NDVI-SPAT correlates well with the meteorologically derived seasonal progression anomaly cSPAT, with an r^2=0.897 (n=54) and a p value >0.0001 (when the 2 outliers are removed, see discussion, the r^2 = 0.937). The RMSE is 15 days. This means we can, accurately and repeatedly, estimate local and national growing conditions compared to the 10 year average. In the face of increasing weather extremes and variability this should prove useful for national policy makers looking to predict likelihood of a fodder shortage and for farmers looking to plan their spring grazing. As section 5 shows, the average variation, year on year, of turn out date on a farm is 25 days, so this RMSE value shows the output accurate enough to be potentially useful.

To further demonstrate usefulness a beta version of a SPAT service was trialled on the Teagasc/ArcGIS online mapping platform, with a growth anomaly map produced for every 16 day MODIS acquisition period in the spring of 2015, where Teagasc advisors could enter their address and get the current SPAT value for their locale. As a result of feedback the design of the online service was altered post

2016. The simplified Townland boundaries used (simplified to speed up loading times) was not liked. Instead the SPAT data will be delivered as 1km tetrads (equivalent to 16 MODIS pixels). Static national and regional maps will also be created and hosted by Teagasc on the client website for those advisors who do not want to interact with the data.

6.1.4 Can management decisions be predicted from observed conditions?

For the first time we have linked direct observation of growing conditions with contemporaneous records of a management over 5 years and showed, within a panel analysis how these two are related. The potential is then of improving responses by showing missed opportunities or targeting advice when it is likely decisions are being made is huge.

Understanding how farmers respond to conditions when making farm management decisions is important when designing decision support systems. In section 5 how grass growth and soil conditions influence the decision on when to turn cattle out from winter housing to spring grazing is discussed. Five years of NDVI MODIS data was used along with daily rainfall data from more than 300 rain-gauges and turn out dates from 199 participants in the NFS. Using a statistical technique known as panel data analysis that a review of the remote sensing literature indicates is not widely used, it was possible to link conditions at the time of turn out with the actual date.

Seasonal effects dominate over local and for every extra 0.01 in the average spring NDVI score at the farm location turnout was 3.7 days earlier. However this early turnout was associated with a higher actual NDVI on the day, that showed effectively the turn-out was 3.3 days later than it could have been. As 0.01 NDVI equates to a week's growth typically it showed that farmers do respond to good conditions but not as quickly as they could. Outputs from the model based on use of the rainfall data implied that soil condition was of secondary importance to grass

levels, especially in poor springs and year dummies showed that seasonal effects are national- 2010 was a cold spring and caused turn out dates to be 4.6 days later, whereas the warm spring of 2012 allowed cattle to be turned out 5.6 days earlier.

The inertia in decision making around a preferred date was shown by using the previous year´s TOD in the model. The model accurately predicts when turn out occurs with a RMSE of 10 days. Compared with the average difference between the earliest and latest dates (25days) on a farm a 10 day RMSE on the estimated TOD can be considered accurate. The model presented here can be used to predict TOD for any spring, this could be coupled with economic models on the costs associated with, for example, a late spring and allow Teagasc to make forecasts of cost impact of weather on farming as it happens.

6.2 Conclusion

The work presented here is part of a wider movement toward “smart” agriculture in Irish dairying and as such will continue to be developed. It also points towards gaps in understanding of the role that EO technologies may play in grazing systems; how managed grasslands cannot be treated as a crop in the EO community and specific issues regarding developing of EO services in Ireland.

6.2.1 Implementing EO solutions in managed grasslands farms.

By supporting Irish Dairy through new PA technologies in which EO will play a big role it will be demonstrated to European policy makers that grazing grass is a sustainable and resilient farming model. Surveys show that European consumers want produce from animals that graze at least some of the year and the PA approaches developed here will support farmers across Europe in doing so.

This will mean overcoming technical challenges in designing EO tools that deliver what the farmer wants and deliver it reliably when it is needed. The literature

review in section 2 showed that farmers resist PA technologies that do not integrate with their normal management modes and they do not want to spend a great deal of time inputting data in DSS.

The accepted paradigm of EO driven PA, that of passive data production and presentation "*this is the crop yield today*" needs to change. EO scientists need to go beyond interrogating the pixel and no further, to see how the information within the pixel matches the understanding of the person managing the land imaged by the pixel. Grassland farmers need information regarding the whole farm every day, they also need forecasts of future conditions and growth rates. It is possible to see a near future in Ireland where this is possible but certain infrastructure and algorithmic developments are needed.

6.2.2 Improving EO methods for monitoring managed grasslands

Cloud is the most serious handicap to fully integrating EO data into day to day management within Ireland. However with frequent enough acquisitions, the sort of gap filling/compositing systems developed in the MODIS program could maximise the cloud free viewing opportunities. However the gap filling algorithm must be tailored to the particular dynamics of grassland management in Ireland.

Sentinel 2 and Landsat 8 are designed to be compatible and have complementary acquisition programs, meaning Ireland will be imaged every 8 days. This may provide an opportunity for spring time monitoring of grass growth at a <30m resolution, allowing for sub-farm level characterisation. Using commercial services like DMC and SPOT by themselves would be too expensive but using them to gap fill a Landsat/Sentinel 2 series would be more cost effective. These approaches however will demand a more robust and open infrastructure for handling large volumes of data.

Cloud can be overcome using radar data from space but the current literature of trying to derive grass biomass or soil moisture from the complex Irish farming and pedological landscape is only just beginning. However it may be possible to use the back-scatter coefficient of the Sentinel 1a & 1b satellites directly as an input into a model similar to the one presented in section 5. Rather than trying to untangle the contributing factors of moisture, roughness, cover etc., use the total backscatter as a simple index of the combination of soil and grass condition. Because the panel analysis can ignore variation between farms then a backscatter value particular to each farm or field may be related to the conditions when that farmer turns out cattle at that farm.

Farmers may choose to bypass EO systems and move directly to RPAS or drones. There has been a huge growth in a very short space of time in the provision of drone based services for Irish farmers. For now the focus is on farm mapping and farm design and regulation form the IAA has stymied the use of the autonomous systems. Technical issues still need to be overcome regarding flight time and stability in windy conditions but it is easy to see a time in the next decade when lightweight (<5kg) systems are autonomously flying Irish farms with 4 band NIR cameras. A new European project, GrassQ, lead by Teagasc and Maynooth university is looking at these issues, with a particular focus on estimating grass quality.

The challenge in the EO community is to ensure that the systems are fully autonomous and provide robust estimates of grass biomass which feed directly into the farm grass budget plan. One possible way to continually test for robustness is compare drone acquired observations with satellite driven models, comparing and refining results with each acquisition.

A national repository/ hub for all acquisitions over Ireland, combined with a big data analytics sandbox is critical. Also important is the construction of a ground segment in Ireland allowing for the ad hoc acquisition of data form EO satellites not

normally tasked with observing Ireland. This ground segment could play a role beyond Ireland, especially in the area of ocean remote sensing.

A recent paper (to which this author contributed) by O'Donoghue et al (2016) proposed a national spatial analytical platform for combining agronomic, meteorological and remote sensing data to characterise in near real time farm performance across Ireland. The driver for this is the understanding of the need to move from passive advice to active service delivery- providing farm services (such as annual accounts, feed budgets, nutrient management plans) directly to the farmer, freeing the farmer to farm.

6.2.3 Fusing EO and other approaches

Another solution to over-come data gaps due to cloud is to model the grass growth between clear observations. Weather data driven bio-physical models allow for accurate biomass estimates. On-going work in Teagasc has lead to development of the Moorepark Grass Growth Model that can successfully simulate grass growth using data on weather and soil conditions, future grass growth using weather forecast data (Paillette et al 2015).

These mechanistic models can interact with EO data models in two ways, they can bridge data gaps by modelling grass growth during the period when EO data is not available. More usefully EO data can tie mechanistic simulations of grass growth to the real world. By coupling local weather and soil data to drive the mechanistic model with an EO observation of actual conditions the EO data acts as an empirical term in the model correcting for local conditions (management, drainage, grass variant, etc.) and improving accuracy. The EO data can also capture management, grazing and cutting, that of course a synthetic grass growth model cannot.

New meteorological weather prediction products from Met Eireann and IBM are moving weekly forecasts of weather down to 5km cells or less and using EO

observations of current conditions means that field scale forecasts of grass growth up to one week ahead are very close to being realised.

Ideally a system that reliably gives weekly 1 ha scale data on the following is needed:

- Current grass cover in kgDM/ha
- Current grass growth in kgDM/ha/day
- Soil Moisture
- Comparison with average (SPAT)
- Current usage (grazing, cutting, hay making)
- Forecast of likely growth in the next week/fortnight
- Farm level feed demand

All these can be feasibly achieved based on the work presented here and by others in the last few years.

The results presented here are a basis for a set of tools at both national and farm levels to allow Irish farmers fully exploit their managed grasslands, improving profitability and helping to ensure long term sustainability and animal welfare as the Irish Dairy Industry grows.

Managed European grasslands as a farm system have been largely ignored in the EO literature. It is hoped that the work here prompts a deeper interest in these systems. These are incredibly valuable and complex systems and our limited understanding across Europe of the dynamics of these farm landscapes hampers everything from rural development to GHG reporting and only EO can help provide the answers.

Appendix

Global vegetation monitoring services referenced in section 4.1.1

Links live, December 2018

USDA, Crop Explorer - http://www.pecad.fas.usda.gov/cropexplorer/Default.aspx

Australian NDVI Maps- http://www.bom.gov.au/jsp/awap/ndvi/index.jsp#

USA, Food Early Warning System (FEWS): http://www.fews.net/

MARS/JRC Agri4Cast: http://mars.jrc.ec.europa.eu/mars/About-us/AGRI4CAST

GIEWS: http://www.fao.org/giews/

VegScape: http://nassgeodata.gmu.edu/VegScape/

GeoGlam: http://www.earthobservations.org/geoglam_me.php

Vega-Pro: http://pro-vega.ru/eng/

Bibliography

Adjorlolo C, Mutanga O, Cho MA. 2014. Estimation of Canopy Nitrogen Concentration Across C3 and C4 Grasslands Using WorldView-2 Multispectral Data. *Selected Topics in Applied Earth Observations and Remote Sensing, IEEE Journal of* 7: 4385-92

Akiyama T, Kawamura K. 2007. Grassland degradation in China: Methods of monitoring, management and restoration. *Grassland Science* 53: 1-17

*Ali I, Cawkwell F, Dwyer E, Barrett B, Green S. 2016. Satellite remote sensing of grasslands: from observation to management—a review. *Journal of Plant Ecology*: rtw005

*Ali I, Cawkwell F, Green S, Dwyer N. 2014. *Application of statistical and machine learning models for grassland yield estimation based on a hypertemporal satellite remote sensing time series*. Presented at Geoscience and Remote Sensing Symposium (IGARSS), 2014 IEEE International

Allen VG, Batello C, Berretta EJ, Hodgson J, Kothmann M, et al. 2011. An international terminology for grazing lands and grazing animals. *Grass and Forage Science* 66: 2-28

Anderson DM, Estell RE, Cibils AF. 2013. Spatiotemporal Cattle Data—A Plea for Protocol Standardization. *Positioning* 4: 115-36

Anselin L. 1992. *Spatial data analysis with GIS: an introduction to application in the social sciences*, University of California, Santa Barbara

Anselin L. 2013. *Spatial econometrics: methods and models*: Springer Science & Business Media

Anselin L, Le Gallo J, H. J. 2008. Spatial panel econometrics. In *The Econometrics of Panel Data: Fundamentals and Recent Developments in Theory and Practice (3rd ed.)*, ed. L Matyas, P Sevestre: Springer, New York

Anyamba A, Tucker CJ, Mahoney R. 2002. From El Niño to La Niña: Vegetation Response Patterns over East and Southern Africa during the 1997–2000 Period. In *Journal of Climate*, pp. 3096-103: American Meteorological Society

Atzberger C. 2013. Advances in Remote Sensing of Agriculture: Context Description, Existing Operational Monitoring Systems and Major Information Needs. *Remote Sensing* 5: 949-81

Baldi G, Nosetto MD, Aragón R, Aversa F, Paruelo JM, Jobbágy EG. 2008. Long-term satellite NDVI data sets: evaluating their ability to detect ecosystem functional changes in South America. *Sensors* 8: 5397-425

Barrachina M, Cristóbal J, Tulla AF. 2015. Estimating above-ground biomass on mountain meadows and pastures through remote sensing. *International Journal of Applied Earth Observation and Geoinformation* 38: 184-92

*Barrett B, Nitze I, Green S, Cawkwell F. 2014. Assessment of multi-temporal, multi-sensor radar and ancillary spatial data for grasslands monitoring in Ireland using machine learning approaches. *Remote sensing of environment* 152: 109-24

Barry P. 1986. Potential of Irish climate for agriculture In *Climate, weather and Irish agriculture*, ed. T Keane. Glasnevin, Dublin: Agmet

Bastin G, Scarth P, Chewings V, Sparrow A, Denham R, et al. 2012. Separating grazing and rainfall effects at regional scale using remote sensing imagery: A dynamic reference-cover method. *Remote Sensing of Environment* 121: 443-57

Bastin GN, Tynan RW, Chewings VH. 1998. Implementing satellite-based grazing gradient methods for rangeland assessment in South Australia. *The Rangeland Journal* 20: 61-76

Becker-Reshef I, Justice C, Sullivan M, Vermote E, Tucker C, et al. 2010. Monitoring Global Croplands with Coarse Resolution Earth Observations: The Global Agriculture Monitoring (GLAM) Project. *Remote Sensing* 2: 1589-609

Beddington J, Asaduzzaman M, Clark M. 2012. Achieving food security in the face of climate change: Final report from the Commission on Sustainable Agriculture and Climate Change.

Bellamy JA, Lowes D, Ash AJ, McIvor JG, Macleod ND. 1996. A Decision Support Approach to Sustainable Grazing Management for Spatially Heterogeneous Rangeland Paddocks. *The Rangeland Journal* 18: 370-91

Ben-Asher Z. 2013. HELM-Harmonised European Land Monitoring: Findings and Recommendations of the HELM Project. Tel-Aviv, Israel

Biewer S, Fricke T, Wachendorf M. 2009. Determination of Dry Matter Yield from Legume-Grass Swards by Field Spectroscopy. *Crop Sci* 49: 1927-36

Black K, Gallagher G, Brien PO, Redmond J, Barrett F, Twomey M. 2008. *Dispelling myths: the true extent of recent peatland afforestation in Ireland*, COFORD, Dublin

*Black K, Green S, Mullooly G, Povida A. 2014. *Towards a national hedgerow biomass inventory for the LULUCF sector using LiDAR remote sensing (2010-CCRP-DS-1.1): Final report*, EPA, Dublin

Blanco LJ, Ferrando CA, Biurrun FN. 2009. Remote Sensing of Spatial and Temporal Vegetation Patterns in Two Grazing Systems. In *Rangeland Ecology & Management*, pp. 445-51: Society for Range Management

Bleasdale A. 2013. Managing Ireland's Commonages (and Uplands). In *Teagasc AE Conference 2013*. Tullamore: Teagasc

Booth DT, Tueller PT. 2003. Rangeland monitoring using remote sensing. *Arid Land Research and Management* 17: 455-67

Boschetti M, Bocchi S, Brivi PA. 2007. Assessment of pasture production in the Italian Alps using spectrometric and remote sensing information. *Agriculture, Ecosystems and Environment* 118: 267-72

Bouwman AF, Van der Hoek KW, Eickhout B, Soenario I. 2005. Exploring changes in world ruminant production systems. *Agricultural Systems* 84: 121-53

Bradley BA, Jacob RW, Hermance JF, Mustard JF. 2007. A curve fitting procedure to derive inter-annual phenologies from time series of noisy satellite NDVI data. *Remote Sensing of Environment* 106: 137-45

Braswell BH, Schimel DS, Linder E, Moore B. 1997. The response of global terrestrial ecosystems to interannual temperature variability. *Science* 278: 870-3

Brereton AJ. 1995. Regional and year-to-year variation in production. *Jeffrey, DW, Jones, MB & JH McAdam (eds)*: 12-22

Broad HJ, Hough MN. 1993. The growing and grazing season in the United Kingdom. *Grass and Forage Science* 48: 26-37

Brown ME, Pinzon JE, Didan K, Morisette JT, Tucker CJ. 2006. Evaluation of the consistency of long-term NDVI time series derived from AVHRR,SPOT-vegetation, SeaWiFS, MODIS, and Landsat ETM+ sensors. *Geoscience and Remote Sensing, IEEE Transactions on* 44: 1787-93

Buck O, Millán VEG, Klink A, Pakzad K. 2015. Using information layers for mapping grassland habitat distribution at local to regional scales. *International Journal of Applied Earth Observation and Geoinformation* 37: 83-9

Burgan RE, Hartford RA, Eidenshink JC. 1996. Using NDVI to AssessDeparture From Average Greenness and its Relation to Fire Business-General Technical Report INT-GTR-333. ed. USDoAF Service. Intermountain Research Station

Byrne KA, Kiely G, Leahy P. 2007. Carbon sequestration determined using farm scale carbon balance and eddy covariance. *Agriculture, Ecosystems & Environment* 121: 357-64

Carmona CP, Röder A, Azcárate FM, Peco B. 2013. Grazing management or physiography? Factors controlling vegetation recovery in Mediterranean grasslands. *Ecological Modelling* 251: 73-84

Cawkwell F, Dwyer N, Scarrott R. 2010. *The use of Remote Sensing to evaluate the potential of identifying exposed and vegetated peatlands in the Republic of Ireland (final report)*, UCC, Cork

*Cawkwell, F., Raab, C., Barrett, B., Green, S., & Finn, J. (2018). TaLAM: mapping land cover in lowlands and uplands with satellite imagery. EPA, Wexford

Chang J, Viovy N, Vuichard N, Ciais P, Campioli M, et al. 2015. Modeled Changes in Potential Grassland Productivity and in Grass-Fed Ruminant Livestock Density in Europe over 1961–2010. *PLoS ONE* 10

Chen J, Jönsson P, Tamura M, Gu Z, Matsushita B, Eklundh L. 2004. A simple method for reconstructing a high-quality NDVI time-series data set based on the Savitzky–Golay filter. *Remote Sensing of Environment* 91: 332-44

Clark CEF, Romera AJ, Macdonald KA, Clark DA. 2010. Inter-paddock annual dry matter yield variability for dairy farms in the Waikato region of New Zealand. *New Zealand Journal of Agricultural Research* 53: 187-91

Connell JO, Connolly J, Holden N. 2012. Calibration and validation of multispectral multiplatform based change detection on irish peatlands. *Biosystems engineering research review* 17: 68

Connor AO, McGrath O. 2014. Feeding Weanlings and Store Cattle this Winter. In *http://www.teagasc.ie/publications/view_publication.aspx?PublicationID=3375*, ed. Advisory: Teagasc

Cooper A, Loftus M. 1998. The application of multivariate land classification to vegetation survey in the Wicklow Mountains, Ireland. *Plant Ecology* 135: 229-41

Creighton P, Kennedy E, Shalloo L, Boland TM, O' Donovan M. 2011. A survey analysis of grassland dairy farming in Ireland, investigating grassland management, technology adoption and sward renewal. *Grass and Forage Science* 66: 251-64

CSIRO Australia. 2014. *Summary Brief:Establishment of GEO Global Rangelands and Pasture Productivity (RAPP)*, Group on Earth Observations

CSO. 2015. Crops and Livestock Survey June Final Results, June 2014. ed. CSO, pp. 2. Central Statistics Office, Dublin: Central Statistics Office, Dublin

Cui X, Guo ZG, Liang TG, Shen YY, Liu XY, Liu Y. 2012. Classification management for grassland using MODIS data: a case study in the Gannan region, China. *International Journal of Remote Sensing* 33: 3156-75

DAFF. 2011. *Food Harvest 2020: Milestones for sucess*, Department of Agriculture, Fisheries and Food, Ireland, Dublin

DAFM. 2012. *Factsheet on Irish Agriculture 2012*, Dept. Agriculture Food and Marine, Dublin

Dash J, Jones M, Nightingale J. 2013. Validating Satellite-Derived Vegetation Phenology Products. *Eos, Transactions American Geophysical Union* 94: 127-

de Beurs KM, Henebry GM. 2004. Land surface phenology, climatic variation, and institutional change: Analyzing agricultural land cover change in Kazakhstan. *Remote sensing of environment* 89: 497-509

Dean C, Wardell-Johnson GW, Harper RJ. 2012. Carbon management of commercial rangelands in Australia: Major pools and fluxes. *Agriculture, Ecosystems & Environment* 148: 44-64

Dermody J. 2013. Fodder crisis sees cows starve to death. In *Irish Examiner*. Cork: Irish Examiner

Di Bella CM, Negri IJ, Posse G, Jaimes FR, Jobbágy EG, et al. 2009. Forage Production of the Argentine Pampa Region Based on Land Use and Long-Term Normalized Difference Vegetation Index Data. *Rangeland Ecology & Management* 62: 163-70

Dillon P, Roche JR, Shalloo L, Horan B. 2005. Optimising financial return from grazing in temperate pastures. *Utilisation of grazed grass in temporal animal systems*: 131-47

Dixon AP, Faber-Langendoen D, Josse C, Morrison J, Loucks CJ. 2014. Distribution mapping of world grassland types. *Journal of Biogeography*: n/a-n/a

Donald G, Ahmad W, Hulm E, Trotter M, Lamb D. 2012. *Integrating MODIS satellite imagery and proximal vegetation sensors to enable precision livestock management*. Presented at Agro-Geoinformatics (Agro-Geoinformatics), 2012 First International Conference on

Donald GE, Gherardi SG, Edirisinghe A, Gittins SP, Henry DA, Mata G. 2010. Using MODIS imagery, climate and soil data to estimate pasture growth rates on farms in the south-west of Western Australia. *Animal Production Science* 50: 611-5

Donald GE, Scott JM, Vickery PJ. 2013. Satellite derived evidence of whole farmlet and paddock responses to management and climate. *Animal Production Science* 53: 699-710

Donnellan T, Hennessy T, Keane M, Thorne F. 2011. *Study of the international competitiveness of the Irish dairy sector at farm level.*, Teagasc, Carlow, Ireland

Donnellan T, Hennessy T, Thorne F. 2015. *The End of the Quota Era: A History of the Irish Dairy Sector and Its Future Prospects*, Teagasc, Athenry, Ireland

Donnelly-Swift R, Holden N. 2014. MONITORING OF SLURRY APPLICATION USING REMOTE SENSING. *BIOSYSTEMS ENGINEERING RESEARCH REVIEW 19*: 169

Duro DC, Coops NC, Wulder MA, Han T. 2007. Development of a large area biodiversity monitoring system driven by remote sensing. *Progress in Physical Geography* 31: 235-60

Dusseux P, Corpetti T, Hubert-Moy L, Corgne S. 2014a. Combined Use of Multi-Temporal Optical and Radar Satellite Images for Grassland Monitoring. *Remote Sensing* 6: 6163-82

Dusseux P, Gong X, Corpetti T, Hubert-Moy L, Corgne S. 2012. *Contribution of radar images for grassland management identification*

Dusseux P, Gong X, Hubert-Moy L, Corpetti T. 2014b. Identification of grassland management practices from leaf area index time series. *Journal of Applied Remote Sensing* 8: 083559-

Dusseux P, Vertès F, Corpetti T, Corgne S, Hubert-Moy L. 2014c. Agricultural practices in grasslands detected by spatial remote sensing. *Environmental monitoring and assessment*: 1-17

Eastwood CR. 2008. *Innovative precision dairy systems: a case study of farmer learning and technology co-development*

Eaton JM, McGoff NM, Byrne KA, Leahy P, Kiely G. 2008. Land cover change and soil organic carbon stocks in the Republic of Ireland 1851–2000. *Climatic change* 91: 317-34

Edirisinghe A, Clark D, Waugh D. 2012. Spatio-temporal modelling of biomass of intensively grazed perennial dairy pastures using multispectral remote sensing. *International Journal of Applied Earth Observation and Geoinformation* 16: 5-16

Edirisinghe A, Hill MJ, Donald GE, Hyder M. 2011. Quantitative mapping of pasture biomass using satellite imagery. *International Journal of Remote Sensing* 32: 2699-724

EEA. 2004. *High nature value farmland. Characteristics, trends and policy challenges*, European Environment Agency, Copenhagen

Elbersen B, Beaufoy G, Jones G, Noij G, Doorn A, et al. 2014. *Aspects of data on diverse relationships between agriculture and the environment. Report for DG-Environment*, Alterra. Wageningen

Eurostat. 2003. *Regions: Nomenclature of territorial units for statistics NUTS — 2003*, Eurostat, Luxembourg

FADN. 2010. *Farm Accounting Data Network : An A to Z of methodology*, FADN

Fahey D, Finch F. 2008. *GeoDirectory Technical Guide*, An Post/OSI

Fealy R, Creamer RE. 2015. Agronomic and environmental drivers of landuse change. In *Drivers of agricultural land use change in Ireland to 2025*, ed. C O'Donoghue. Carlow, Ireland: Teagasc

Fealy R, Fealy RM. 2008. The spatial variation in degree days derived from locational attributes for the 1961 to 1990 period. *Irish Journal of Agricultural and Food Research*: 1-11

*Fealy R, Green S. 2009. *Teagasc\EPA Soils and Subsoils mapping project: Final report*, EPA, Dublin

Finneran E, Crosson P, O'Kiely P, Shalloo L, Forristal D, Wallace M. 2010. Simulation Modelling of the Cost of Producing and Utilising Feeds for Ruminants on Irish Farms. *Journal of Farm Management* 14: 95-116

Fischer G, van Velthuizen HT, FO N. 2000. *Global Agro-Ecological Zones Assessment: Methodology and Results*, FAO

Flood S. 2013. *Projected economic impacts of climate change on Irish agriculture*, Stop Climate Chaos, Dublin, Ireland

Flynn ES, Dougherty CT, Wendroth O. 2008. Assessment of pasture biomass with the Normalized Difference Vegetation Index from active ground-based sensors. *Agronomy Journal* 100: 114-21

Foley PA, Crosson P, Lovett DK, Boland TM, O'Mara FP, Kenny DA. 2011. Whole-farm systems modelling of greenhouse gas emissions from pastoral suckler beef cow production systems. *Agriculture, ecosystems & environment* 142: 222-30

Fontana F, Rixen C, Jonas T, Aberegg G, StefanWunderle. 2008. Alpine grassland phenology as seen in AVHRR, VEGETATION, and MODIS NDVI Time Series - a comparison with in situ measurements. *Sensors* 8: 2833-53

Frank AB. 1996. Evaluating grass development for grazing management. *Rangelands Archives* 18: 106-9

Franke J, Keuck V, Siegert F. 2012. Assessment of grassland use intensity by remote sensing to support conservation schemes. *Journal for Nature Conservation* 20: 125-34

Fricke T, Wachendorf M. 2013. Combining ultrasonic sward height and spectral signatures to assess the biomass of legume–grass swards. *Computers and Electronics in Agriculture* 99: 236-47

Friedl MA, McIver DK, Hodges JCF, Zhang XY, Muchoney D, et al. 2002. Global land cover mapping from MODIS: algorithms and early results. *Remote sensing of environment* 83: 287-302

Ganguly S, Friedl MA, Tan B, Zhang X, Verma M. 2010. Land surface phenology from MODIS: Characterization of the Collection 5 global land cover dynamics product. *Remote sensing of environment* 114: 1805-16

Gao J. 2006. Quantification of grassland properties: how it can benefit from geoinformatic technologies? *International Journal of Remote Sensing* 27

García-Mora TJ, Mas J-F, Hinkley EA. 2011. Land cover mapping applications with MODIS: a literature review. In *International Journal of Digital Earth*, pp. 63-87: Taylor & Francis

Gardiner MJ, Radford T. 1980. *Soil associations of Ireland and their landuse potential*, An Foras Taluntais, Dublin

Gardiner MJ, Ryan P. 1969. A new generalised soil map of Ireland and its land-use interpretation. *Irish Journal of Agricultural Research*: 95-109

Glenn E, Huete A, Nagler P, Nelson S. 2008. Relationship Between Remotely-sensed Vegetation Indices, Canopy Attributes and Plant Physiological Processes: What Vegetation Indices Can and Cannot Tell Us About the Landscape. *Sensors* 8: 2136-60

Gobbett DL, Handcock RN, Zerger A, Crossman C, Valencia P, et al. 2013. Prototyping an operational system with multiple sensors for pasture monitoring. *Journal of Sensor and Actuator Networks* 2: 388-408

Goebbert K, Jenkins-Smith HC, Klockow K, Nowlin MC, Silva CL. 2012. Weather, Climate, and Worldviews: The Sources and Consequences of Public Perceptions of Changes in Local Weather Patterns*. In *Weather, Climate, and Society*, pp. 132-44: American Meteorological Society

Grant KM, Johnson DL, Hildebrand DV, Peddle DR. 2013. Quantifying biomass production on rangeland in southern Alberta using SPOT imagery. *Canadian Journal of Remote Sensing* 38: 695-708

Gray DI, Parker WJ, Kemp EA, Kemp PD, Brookes IM, et al. 2003. *Feed planning–alternative approaches used by farmers*. Presented at Proceedings of the New Zealand Grassland Association

*Green S. 2011. *The Irish Hedge Map version 1.0*, Teagasc

*Green S, Cawkwell F, Dwyer E. 2016. Cattle stocking rates estimated in temperate intensive grasslands with a spring growth model derived from MODIS NDVI time-series. *International Journal of Applied Earth Observation and Geoinformation* 52: 166-74

*Green S, Donoghue C. 2013. Assessing the Geographic Representativity of Farm Accountancy Data. *ISPRS International Journal of Geo-Information* 2: 50-66

Han D, O'Kiely P, Sun DW. 2003. Linear models for the dry matter yield of the primary growth of a permanent grassland pasture. *Irish Journal of Agricultural and Food Research* 42: 17-38

Handcock RN, Mata G, Donald GE, Edirisinghe A, Henry D, Gherardi SG. 2009a. The spectral response of pastures in an intensively managed dairy system. In *Innovations in Remote Sensing and Photogrammetry*, ed. S Jones, K Reinke, pp. 309-21: Springer Berlin Heidelberg

Handcock RN, Swain DL, Bishop-Hurley GJ, Patison KP, Wark T, et al. 2009b. Monitoring Animal Behaviour and Environmental Interactions Using Wireless Sensor Networks, GPS Collars and Satellite Remote Sensing. *Sensors* 9: 3586-603

Hanrahan K, Hennessy T, Kinsella A, Moran B. 2014a. *National Farm Survey 2013*, Agricultural Economics & Farm Surveys Department, REDP, Teagasc

Hanrahan K, Hennessy T, Kinsella A, Moran B. 2014b. Teagasc National Farm Survey 2013. *Teagasc: Agricultural Economics & Farm Surveys Department, Athenry, Co. Galway, Ireland*

Hanson JC, Johnson DM, Lichtenberg E, Minegishi K. 2013. Competitiveness of management-intensive grazing dairies in the mid-Atlantic region from 1995 to 2009. *Journal of Dairy Science* 96: 1894-904

Hazeu G, Milenov P, Pedroli B, Samoungi V, Van Eupen M, Vassilev V. 2014. High Nature Value farmland identification from satellite imagery, a comparison of two methodological approaches. *International Journal of Applied Earth Observation and Geoinformation* 30: 98-112

Hedley C. 2015. The role of precision agriculture for improved nutrient management on farms. *Journal of the Science of Food and Agriculture* 95: 12-9

Herbin T, Hennessy D, Richards KG, Piwowarczyk A, Murphy JJ, Holden NM. 2011. The effects of dairy cow weight on selected soil physical properties indicative of compaction. *Soil Use and Management* 27: 36-44

Hill MJ, Donald GE, Hyder MW, Smith RCG. 2004. Estimation of pasture growth rate in the south west of Western Australia from AVHRR NDVI and climate data. *Remote sensing of environment* 93: 528-45

Hill MJ, Donald GE, Vickery PJ. 1999. Relating Radar Backscatter to Biophysical Properties of Temperate Perennial Grassland. *Remote Sensing of Environment* 67: 15-31

Hill MJ, Smith AM, Foster TC. 2000. Remote Sensing of Grassland with RADARSAT; Case Studies from Australia and Canada. *Canadian Journal of Remote Sensing* 26: 285-96

Hill MJ, Ticehurst CJ, Jong-Sen L, Grunes MR, Donald GE, Henry D. 2005. Integration of optical and radar classifications for mapping pasture type in Western Australia. *Geoscience and Remote Sensing, IEEE Transactions on* 43: 1665-81

Hofmeyr I. 2015. A bird's eye view to counting our herds : the leading edge technology. In *FarmBiz* pp. 48-9: SA ePublications

Houghton RA, House JI, Pongratz J, Van der Werf GR, DeFries RS, et al. 2012. Carbon emissions from land use and land-cover change. *Biogeosciences* 9: 5125-42

Huang S, Potter C, Crabtree RL, Hager S, Gross P. 2010. Fusing optical and radar data to estimate sagebrush, herbaceous, and bare ground cover in Yellowstone. *Remote Sensing of Environment* 114: 251-64

Huete A, Didan K, Miura T, Rodriguez EP, Gao X, Ferreira LG. 2002. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote sensing of environment* 83: 195-213

Hunt ER, Miyake BA. 2006. Comparison of stocking rates From remote sensing and geospatial data. In *Rangeland Ecology & Management*, pp. 11-8: Society for Range Management

Hunt JER, Everitt JH, Ritchie JC, Moran MS, Booth DT, et al. 2003. Applications and Research Using Remote Sensing for Rangeland Management. *Photogrammetric Engineering & Remote Sensing* 69: 675-93

Hutchinson GK, Richards K, Risk WH. 2000. *Aspects of accumulated heat patterns (growing degree-days) and pasture growth in Southland*. Presented at PROCEEDINGS OF THE CONFERENCE-NEW ZEALAND GRASSLAND ASSOCIATION

Irish Examiner. 2013. Fodder crisis sees cows starve to death. In *Irish Examiner*. Cork, Ireland

Irwin EG, Geoghegan J. 2001. Theory, data, methods: developing spatially explicit economic models of land use change. *Agriculture, Ecosystems & Environment* 85: 7-24

Jianlong L, Tiangang L, Quangong C. 1998. Estimating grassland yields using remote sensing and GIS technologies in China. *New Zealand Journal of Agricultural Research* 41: 31-8

Jonsson P, Eklundh L. 2002. Seasonality extraction by function fitting to time-series of satellite sensor data. *Geoscience and Remote Sensing, IEEE Transactions on* 40: 1824-32

José A. Barasona , Margarita Mulero-Pázmány, Pelayo Acevedo, Juan J. Negro, María J. Torres, et al. 2014. Unmanned Aircraft Systems for Studying Spatial Abundance of Ungulates: Relevance to Spatial Epidemiology. *PLoS One* 9(12)

Justice CO, Townshend JRG, Holben BN, Tucker CJ. 1985. Analysis of the phenology of global vegetation using meteorological satellite data. *International Journal of Remote Sensing* 6: 1271-318

Kanniah KD, Beringer J, Hutley LB, Tapper NJ, Zhu X. 2009. Evaluation of Collections 4 and 5 of the MODIS Gross Primary Productivity product and algorithm improvement at a tropical savanna site in northern Australia. *Remote sensing of environment* 113: 1808-22

Kavanagh S. 2013. Current Fodder Situation & Lessons Learnt. In *Future Weather Future Farming*, ed. G Lanigan. Teagasc, Ashtown: Teagasc

Keane T. 1986. Meteorological parameters in Ireland. In *Climate, Weather and Irish Agriculture*, ed. T Keane, pp. 30-9. Dublin: AGMET

Kevin Lydon, Smith G. 2014. *CORINE 2012 Ireland final report*, ENVIRONMENTAL PROTECTION AGENCY, Johnstown Castle, Co.Wexford, Ireland

Kinsella A, Laepple D, Moran B, Hennessy T. 2010. Benefits of extending the grazing season. *TResearch* 5: 30-1

Klerkx L, Schut M, Leeuwis C, Kilelu C. 2012. Advances in Knowledge Brokering in the Agricultural Sector: Towards Innovation System Facilitation. *IDS Bulletin* 43: 53-60

Ku N-W, Popescu SC, Ansley RJ, Perotto-Baldivieso HL, Filippi AM. 2012. Assessment of Available Rangeland Woody Plant Biomass with a Terrestrial Lidar System. *Photogrammetric Engineering & Remote Sensing* 78: 349-61

Kuemmerle T, Erb K, Meyfroidt P, Müller D, Verburg PH, et al. 2013. Challenges and opportunities in mapping land use intensity globally. *Current Opinion in Environmental Sustainability* 5: 484-93

Kumar L, Sinha P, Taylor S, Alqurashi AF. 2015. Review of the use of remote sensing for biomass estimation to support renewable energy generation. *Journal of Applied Remote Sensing* 9: 097696-

Kunc P, Knizkova I. 2012. The Use of Infrared Thermography in Livestock Production and Veterinary Field. In *Infrared Thermography Recent Advances and Future Trends*, ed. C Meola, pp. 85-101: Bentham Books

Laca EA. 2009. Precision livestock production: tools and concepts. *Revista Brasileira de Zootecnia* 38: 123-32

Läpple D, Hennessy T, O'Donovan M. 2012. Extended grazing: A detailed analysis of Irish dairy farms. *Journal of Dairy Science* 95: 188-95

Li Z, Huffman T, McConkey B, Townley-Smith L. 2013. Monitoring and modeling spatial and temporal patterns of grassland dynamics using time-series MODIS NDVI with climate and stocking data. pp. 232-44

Lim J, Kawamura K, Lee H-J, Yoshitoshi R, Kurokawa Y, et al. 2015. Evaluating a hand-held crop-measuring device for estimating the herbage biomass, leaf area index and crude protein content in an Italian ryegrass field. *Grassland Science* 61: 101-8

Loch A, Hatt M, Mamun E, Xu J, Bruce S, et al. 2012. *Farm risk management in a changing climate*. Presented at Paper presented at the 42nd ABARES Outlook conference

*Loftus M, Bulfin M, Farrelly N, Fealy R, Green S, et al. 2002. The Irish Forest Soils Project and its Potential Contribution to the Assessment of Biodiversity. *BIOLOGY AND ENVIRONMENT: PROCEEDINGS OF THE ROYAL IRISH ACADEMY,* 102b: 151-64

Lomba A, Guerra C, Alonso J, Honrado JP, Jongman R, McCracken D. 2014. Mapping and monitoring High Nature Value farmlands: Challenges in European landscapes. *Journal of Environmental Management* 143: 140-50

López Díaz JE, González-Rodríguez A. 2003. *Measuring grass yield by non-destructive methods*. Presented at Optimal forage systems for animal production and the environment. Proceedings of the 12th Symposium of the European Grassland Federation'. Pleven, Bulgaria

Mase AS, Prokopy LS. 2013. Unrealized Potential: A Review of Perceptions and Use of Weather and Climate Information in Agricultural Decision Making. In *Weather, Climate, and Society*, pp. 47-61: American Meteorological Society

Matin S, Sullivan CA, Ó hUallacháin D, Meredith D, Moran J, et al. 2016. Predicted distribution of High Nature Value farmland in the Republic of Ireland. In *Journal of Maps*, pp. 1-4: Taylor & Francis

Matsunaga T, Iwasaki A, Tsuchida S, Tanii J, Kashimura O, et al. 2013. *Current status of Hyperspectral Imager Suite (HISUI)*. Presented at IGARSS

Matthews MW. 2011. A current review of empirical procedures of remote sensing in inland and near-coastal transitional waters. *International Journal of Remote Sensing* 32: 6855-99

Matthews T, Mullan D, Wilby RL, Broderick C, Murphy C. 2016. Past and future climate change in the context of memorable seasonal extremes. *Climate Risk Management* In Press

McAllister A, Whitfield D, Abuzar M. 2015. Mapping Irrigated Farmlands Using Vegetation and Thermal Thresholds Derived from Landsat and ASTER Data in an Irrigation District of Australia. *Photogrammetric Engineering & Remote Sensing* 81: 229-38

McDonald R, Pierce K, Fealy R, Horan B. 2013. Characteristics, intentions and expectations of new entrant dairy farmers entering the Irish dairy industry through the New Entrant Scheme. *International Journal of Agricultural Management* 2: 189-98

McGee M, Drennan MJ, Crosson P. 2014. Effect of concentrate feeding level in winter and turnout date to pasture in spring on biological and economical performance of weanling cattle in suckler beef production systems. *Irish Journal of Agricultural and Food Research* 53: 1-9

McNeill SJ, Pairman D, Belliss SE, Dalley D, Dynes R. 2008. *Estimation of pasture biomass using dual-polarisation radar imagery; a preliminary study*. Presented at Image and Vision Computing New Zealand, 2008. IVCNZ 2008. 23rd International Conference

Met Éireann. 2012a. *Spring 2012 Bulletin*, Climatology and Observations Division of Met Éireann, Dublin

Met Éireann. 2012b. *A summary of climate averages for ireland 1981-2010*, Met Éireann, Glasnevin Hill, Dublin

Met Éireann. 2013. *Spring 2013 Bulletin*, Climatology and Observations Division of Met Éireann, Dublin

Mitchell F, Ryan M. 2001. *Reading the Irish Landscape*. Ranelagh, Dublin: TownHouse

Miura T, Yoshioka H, Fujiwara K, Yamamoto H. 2008. Inter-comparison of ASTER and MODIS surface reflectance and vegetation index products for synergistic applications to natural resource monitoring. *Sensors* 8: 2480-99

Morewedge CK, Gilbert DT, Wilson TD. 2005. The least likely of times how remembering the past biases forecasts of the future. *Psychological Science* 16: 626-30

Moyo M, Mvumi BM, Kunzekweguta M, Mazvimavi K, Craufurd P, Dorward P. 2012. Farmer perceptions on climate change and variability in semi-arid Zimbabwe in relation to climatology evidence. *African Crop Science Journal* 20: 317-35

Mukhopadhyay SC, Jiang J-A, Stephen B, Michie C, Andonovic I. 2013. Remote Sensing in Agricultural Livestock Welfare Monitoring: Practical Considerations. In *Wireless Sensor Networks and Ecological Monitoring*, pp. 179-93: Springer Berlin Heidelberg

Muñoz-Huerta RF, Guevara-Gonzalez RG, Contreras-Medina LM, Torres-Pacheco I, Prado-Olivarez J, Ocampo-Velazquez RV. 2013. A review of methods for sensing the nitrogen status in plants: Advantages, disadvantages and recent advances. *Sensors* 13: 10823-43

Nagendra H, Lucas R, Honrado JP, Jongman RHG, Tarantino C, et al. 2013. Remote sensing for conservation monitoring: Assessing protected areas, habitat extent, habitat condition, species diversity, and threats. *Ecological Indicators* 33: 45-59

National Milk Agency. 2014. National Milk Agency Annual Report and Accounts 2014. IPC House, Dublin 4, Ireland: National Milk Agency

Nelson GC, Hellerstein D. 1997. Do Roads Cause Deforestation? Using Satellite Images in Econometric Analysis of Land Use. *American Journal of Agricultural Economics* 79: 80-8

North HC, Pairman D, Belliss SE. 2014. *Paddock segmentation using multi-temporal satellite imagery*. Presented at Geoscience and Remote Sensing Symposium (IGARSS), 2014 IEEE International

Numata I, Roberts DA, Chadwick OA, Schimel J, Sampaio FR, et al. 2007. Characterization of pasture biophysical properties and the impact of grazing intensity using remotely sensed data. *Remote sensing of environment* 109: 314-27

O'Brien P. 2007a. *Data analysis and estimation of greenhouse gas emissions and removal for the IPCC sector land-use, land-use change and forestry sectors in Ireland*, Environmental Protection Agency Johnstown Castle, Ireland

O'Brien P. 2007b. *Data analysis and estimation of greenhouse gas emissions and removal for the IPCC sector land use, land-use change and forestry sectors in Ireland*: Environmental Protection Agency Johnstown Castle, Co. Wexford

O'Donnell S, Shalloo L, Butler AM, Horan B. 2008. A survey analysis of opportunities and limitations of Irish dairy farmers. *Journal of Farm Management* 13: 419-34

O'Mara F. 2008. Country Pasture/Forage Resource Profile/Ireland. FAO

O'Rourke E, Kramm N. 2009. Changes in the Management of the Irish Uplands: A Case-Study from the Iveragh Peninsula. In *European Countryside*, pp. 53

O'Brien D, Shalloo L, Patton J, Buckley F, Grainger C, Wallace M. 2012. A life cycle assessment of seasonal grass-based and confinement dairy farms. *Agricultural Systems* 107: 33-46

O'Connell J, Connolly J, Holden NM. 2014. A monitoring protocol for vegetation change on Irish peatland and heath. *International Journal of Applied Earth Observation and Geoinformation* 31: 130-42

O'Connor B, Dwyer E, Cawkwell F, Eklundh L. 2012. Spatio-temporal patterns in vegetation start of season across the island of Ireland using the MERIS Global Vegetation Index. *ISPRS Journal of Photogrammetry and Remote Sensing* 68: 79-94

O'Connor, B., Dwyer, E., & Cawkwell, F. (2013). The implications of cloud cover for vegetation seasonality monitoring across the island of Ireland using the MERIS Global Vegetation Index (MGVI). *Irish Geography, 46*(1-2), 25-49.

O'Donoghue C, Creamer R, Crosson P, Curran T, Donnellan T, et al. 2015. DRIVERS OF AGRICULTURAL LAND USE CHANGE IN IRELAND TO 2025. ed. Teagasac. Carlow, Ireland

*O'Donoghue C, McKinstry A, Green S, Fealy R, Heanue K, et al. 2016. A Blueprint for a Big Data Analytical Solution to Low Farmer Engagement with Financial Management. *International Food and Agribusiness Management Review* 19

O'Donovan M, Delaby L, Peyraud JL. 2004. Effect of time of initial grazing date and subsequent stocking rate on pasture production and dairy cow performance. *Animal research* 53: 489-502

O'Donovan M, Dillon P. 1999. *Measurement of Grassland Management Practice on Commercial Dairy Farms*, Teagasc

*O'Mongain E, Collins A, Green S, O'Ríain G, Caffrey J. 1999. *Remote sensing of lakes – Improved chlorophyll calibration and data processing. Final report.*, EPA, Wexford, Ireland

O'Shea R, Bougard M, Breen J, O'Donoghue C, Ryan M. 2015. Greenhouse gas (GHG) Mitigation and Technology Adoption Theory: Extended Grazing as a Case Study. In *89th Annual Conference of the Agricultural Economics Society*. University of Warwick, England

Oesterheld M, DiBella CM, Kerdiles H. 1998. Relation between NOAA-AVHRR satellite data and stocking rate of rangelands. *Ecological Applications* 8: 207-12

Paillette CA, Delaby L, Shalloo L, O'Connor D, Hennessy D, et al. 2015. *Developing a predictive model for grass growth in grass-based milk production systems*. Presented at Grassland and forages in high output dairy farming systems.

Proceedings of the 18th Symposium of the European Grassland Federation, Wageningen, The Netherlands, 15-17 June 2015.

Paine CET, Marthews TR, Vogt DR, Purves D, Rees M, et al. 2012. How to fit nonlinear plant growth models and calculate growth rates: an update for ecologists. *Methods in Ecology and Evolution* 3: 245-56

Pairman D, Belliss SE, Cuff J, McNeill SJ. 2011. *Detection and mapping of irrigated farmland in Canterbury, New Zealand*. Presented at Geoscience and Remote Sensing Symposium (IGARSS), 2011 IEEE International

Parr S, O'Donovan G, Finn JA. 2006. Mapping the broad habitats of the Burren using satellite imagery. *End of Project Report 5190c. Carlow. Teagasc*

Paudel KP, Andersen P. 2010. Assessing rangeland degradation using multi temporal satellite images and grazing pressure surface model in Upper Mustang, Trans Himalaya, Nepal. *Remote sensing of environment* 114: 1845-55

Pavl VV, Hejcman M, Mikulka J. 2009. Cover estimation versus density counting in species-rich pasture under different grazing intensities. *Environ Monit Assess*: 156:419–24

Pearson CJ, Ison RL. 1997. Chapter 1: Perspectives on grassalnd systems. In *Agronomy of Grassland Systems (2nd Ed.)*: Cambridge Academic Press

Peel MJS, Biggs H, Zacharias PJK. 1998. Perspective article: The evolving use of stocking rate indices currently based on animal number and type in semi-arid heterogeneous landscapes and complex land-use systems. *African Journal of Range & Forage Science* 15: 117-27

Peters AJ, Walter-Shea EA, Ji L, Vina A, Hayes M, Svoboda MD. 2002. Drought monitoring with NDVI-based standardized vegetation index. *Photogrammetric engineering and remote sensing* 68: 71-5

Pettorelli N, Laurance WF, O'Brien TG, Wegmann M, Nagendra H, Turner W. 2014. Satellite remote sensing for applied ecologists: opportunities and challenges. *Journal of Applied Ecology* 51: 839-48

Peukert S, Griffith BA, Murray PJ, Macleod CJA, Brazier RE. 2014. Intensive Management in Grasslands Causes Diffuse Water Pollution at the Farm Scale. *Journal of Environmental Quality* 43: 2009-23

Phillips R, Beeri O, Scholljegerdes E, Bjergaard D, Hendrickson J. 2009. Integration of geospatial and cattle nutrition information to estimate paddock grazing capacity in Northern US prairie. *Agricultural Systems* 100: 72-9

Phillips RL, Beeri O, Liebig M. 2006. Landscape estimation of canopy C:N ratios under variable drought stress in Northern Great Plains rangelands. *Journal of Geophysical Research* 111

Pickup G, Bastin GN, Chewings VH. 1994. Remote-Sensing-Based Condition Assessment for Nonequilibrium Rangelands Under Large-Scale Commercial Grazing. *Ecological Applications* 4: 497-517

Pickup G, Bastin GN, Chewings VH. 1998. Identifying trends in land degradation in non-equilibrium rangelands. *Journal of Applied Ecology* 35: 365-77

Pierpaoli E, Carli G, Pignatti E, Canavari M. 2013. Drivers of Precision Agriculture Technologies Adoption: A Literature Review. In *6th International Conference on Information and Communication Technologies in Agriculture, Food and Environment (HAICTA 2013)*, pp. 61-9

Piwowarczyk A, Giuliani G, Holden NM. 2011. Can soil moisture deficit be used to forecast when soils are at high risk of damage owing to grazing animals? *Soil Use and Management* 27: 255-63

Porqueddu C, Maltoni S, McIvor JG, McGilloway DA. 2005. Strategies to mitigate seasonality of production in grassland-based systems. In *Grassland: A Global Resource*, ed. DA McGilloway, pp. 111-22: Wageningen Academic Publisher

POST. 2015. Post Note: Precsion Farming. ed. POoSa Technology, pp. 5. London: Parliamentary Office of Science and Technology

Prince SD. 1991. Satellite remote sensing of primary production: comparison of results for Sahelian grasslands 1981-1988. *International Journal of Remote Sensing* 12: 1301-11

Propastin PA, Kappas M, Erasmi S, Muratova NR. 2007. Remote Sensing based study on intra-annual dynamics of vegetation and climate in drylands of Kazakhstan. *Basic and Applied Dryland Research* 1: 138-54

Pullanagari RR, Yule IJ, Tuohy MP, Hedley MJ, Dynes RA, King WM. 2012a. In-field hyperspectral proximal sensing for estimating quality parameters of mixed pasture. *Precision Agriculture* 13: 351-69

Pullanagari RR, Yule IJ, Tuohy MP, Hedley MJ, Dynes RA, King WM. 2012b. Proximal sensing of the seasonal variability of pasture nutritive value using multispectral radiometry. *Grass and Forage Science* 64: 110-9

Quaife T, Quegan S, Disney M, Lewis P, Lomas M, Woodward FI. 2008. Impact of land cover uncertainties on estimates of biospheric carbon fluxes. *GLOBAL BIOGEOCHEMICAL CYCLES* 22

*Raab C, Barrett B, Cawkwell F, Green S. 2015. Evaluation of multi-temporal and multi-sensor atmospheric correction strategies for land-cover accounting and monitoring in Ireland. *Remote Sensing Letters* 6: 784-93

Radtke PJ, Boland HT, Scaglia G. 2010. An evaluation of overhead laser scanning to estimate herbage removals in pasture quadrats. *Agricultural and Forest Meteorology* 150: 1523-8

Rahman MM, Lamb DW, Stanley JN, Trotter MG. 2014. Use of proximal sensors to evaluate at the sub-paddock scale a pasture growth-rate model based on light-use efficiency. *Crop and Pasture Science* 65: 400-9

Ramoelo A, Skidmore AK, Cho MA, Mathieu R, Heitkönig IMA, et al. 2013. Non-linear partial least square regression increases the estimation accuracy of grass nitrogen and phosphorus using in situ hyperspectral and environmental data. *ISPRS Journal of Photogrammetry and Remote Sensing* 82: 27-40

Ran Y, Li X, Lu L. 2010. Evaluation of four remote sensing based land cover products over China. *International Journal of Remote Sensing* 31: 391–401

Rango A, Laliberte A, Steele C, Herrick JE, Bestelmeyer B, et al. 2006. Using unmanned aerial vehicles for rangelands: current applications and future potentials. *Environmental Practice* 8: 159-68

Rashford BS, Walker JA, Bastian CT. 2011. Economics of Grassland Conversion to Cropland in the Prairie Pothole Region. Economía de la Conversión de Pastizales a Tierras Agrícolas en la Región Prairie Pothole. *Conservation Biology* 25: 276-84

Reddersen B, Fricke T, Wachendorf M. 2014. A multi-sensor approach for predicting biomass of extensively managed grassland. *Computers and Electronics in Agriculture* 109: 247-60

Reijs JW, Daatselaar CHG, Helming JFM, Jager J, Beldman ACG. 2013. Grazing dairy cows in north-west Europe. *LEI Report 2013* 1

Rembold F, Atzberger C, Savin I, Rojas O. 2013. Using low resolution satellite imagery for yield prediction and yield anomaly detection. *Remote Sensing* 5: 1704-33

Rigge M, Wylie B, Gu Y, Belnap J, Phuyal K, Tieszen L. 2013. Monitoring the status of forests and rangelands in the Western United States using ecosystem performance anomalies. *International Journal of Remote Sensing* 34: 4049-68

Robinson TP, Wint GRW, Conchedda G, Van Boeckel TP, Ercoli V, et al. 2014. Mapping the global distribution of livestock. *PloS one* 9: e96084

Rodriguez-Galiano VF, Dash J, Atkinson PM. 2015. Characterising the land surface phenology of Europe using decadal MERIS data. *Remote Sensing* 7: 9390-409

Romera A, Beukes P, Clark D, Clark C, Tait A. 2013. Pasture growth model to assist management on dairy farms: Testing the concept with farmers. *Grassland Science* 59: 20-9

Sala O, Jackson R, Mooney H, Howarth R, Running S, et al. 2000. Global Terrestrial Gross and Net Primary Productivity from the Earth Observing System. In *Methods in Ecosystem Science*, pp. 44-57: Springer New York

Sanderson MA, Rotz CA, Fultz SW, Rayburn EB. 2001. Estimating Forage Mass with a Commercial Capacitance Meter, Rising Plate Meter, and Pasture Ruler. *Agronomy Journal* 93: 1281-6

Schellberg J, Hill MJ, Gerhards R, Rothmund M, Braun M. 2008. Precision agriculture on grassland: Applications, perspectives and constraints. *European Journal of Agronomy* 29: 59-71

Schellberg J, Verbruggen E. 2014. Frontiers and perspectives on research strategies in grassland technology. *Crop and Pasture Science* 65: 508-23

Schino G, Borfecchia F, De Cecco L, Dibari C, Iannetta M, et al. 2003. Satellite estimate of grass biomass in a mountainous range in central Italy. *Agroforestry Systems* 59: 157-62

Schipper LA, Parfitt RL, Fraser S, Littler RA, Baisden WT, Ross C. 2014. Soil order and grazing management effects on changes in soil C and N in New Zealand pastures. *Agriculture, Ecosystems & Environment* 184: 67-75

Schloss AL, Kicklighter DW, Kaduk J, Wittenberg U, Intercomparison TPOFTPNM. 1999. Comparing global models of terrestrial net primary productivity (NPP): comparison of NPP to climate and the Normalized Difference Vegetation Index (NDVI). *Global Change Biology* 5: 25-34

Schuman GE, Janzen HH, Herrick JE. 2002. Soil carbon dynamics and potential carbon sequestration by rangelands. *Environmental Pollution* 116: 391-6

Schuster C, Schmidt T, Conrad C, Kleinschmit B, Förster M. 2015. Grassland habitat mapping by intra-annual time series analysis – Comparison of RapidEye and TerraSAR-X satellite data. *International Journal of Applied Earth Observation and Geoinformation* 34: 25-34

Schwarz G, Wolff A, Offermann F, Osterburg B, Aalders I, et al. 2014. ENVIEVAL Development and application of new methodological frameworks for the evaluation of environmental impacts of EU rural development programmes.

Semple AT. 1956. *Improving the World's Grasslands*, FAO

Seto KC, Kaufmann RK. 2005. Using logit models to classify land cover and land-cover change from Landsat Thematic Mapper. *International Journal of Remote Sensing* 26: 563-77

Shakhane LM, Scott JM, Hinch GN, Mackay DF, Lord C. 2013. Estimating the balance between pasture feed supply and demand of grazing livestock in a farmlet experiment. *Animal Production Science* 53: 711-26

Sheridan H, McMahon BJ, Carnus T, Finn JA, Anderson A, et al. 2011. Pastoral farmland habitat diversity in south-east Ireland. *Agriculture Ecosystems & Environment* 144: 130-5

Si Y, Schlerf M, Zurita-Milla R, Skidmore A, Wang T. 2012. Mapping spatio-temporal variation of grassland quantity and quality using MERIS data and the PROSAIL model. *Remote Sensing of Environment* 121: 415-25

Simelton E, Quinn CH, Batisani N, Dougill AJ, Dyer JC, et al. 2013. Is rainfall really changing? Farmers' perceptions, meteorological data, and policy implications. *Climate and Development* 5: 123-38

Smith AM, Major DJ, Hill MJ, Willms WD, Brisco B, et al. 1994. Airborne Synthetic Aperture Radar Analysis of Rangeland Revegetation of a Mixed Prairie. *Journal of Range Management* 47: 385-91

Smith RCG, Adams M, Gittins S, Gherardi S, Wood D, et al. 2011. Near real-time Feed On Offer (FOO) from MODIS for early season grazing management of Mediterranean annual pastures. *International Journal of Remote Sensing* 32: 4445-60

Solano, R., Didan, K., Jacobson, A., & Huete, A. (2010). *MODIS Vegetation Index User's Guide (MOD13 Series)*. Vegetation Index and Phenology Lab: University of Arizona.

Song X, Leroy T, Vranken E, Maertens W, Sonck B, Berckmans D. 2008. Automatic detection of lameness in dairy cattle—Vision-based trackway analysis in cow's locomotion. *Computers and Electronics in Agriculture* 64: 39-44

Stefanski J, Chaskovskyy O, Waske B. 2014. Mapping and monitoring of land use changes in post-Soviet western Ukraine using remote sensing data. *Applied Geography* 55: 155-64

Steyer GD, Couvillion BR, Barras JA. 2013. Monitoring Vegetation Response to Episodic Disturbance Events by using Multitemporal Vegetation Indices. In *Journal of Coastal Research*, pp. 118-30: Coastal Education and Research Foundation

Streutker DR, Glenn NF. 2006. LiDAR measurement of sagebrush steppe vegetation heights. *Remote Sensing of Environment* 102: 135-45

*Sullivan CA, Bourke D, Skeffington MS, Finn JA, Green S, et al. 2011. Modelling semi-natural habitat area on lowland farms in western Ireland. *Biological Conservation* 144: 1089-99

Suttie JM, Reynolds SG, Batello C. 2005. *Grasslands of the World*. ROME: FAO

Svoray T, Perevolotsky A, Atkinson PM. 2013. Ecological sustainability in rangelands: the contribution of remote sensing. *International Journal of Remote Sensing* 34: 6216-42

Teagasc, IFJ. 2009. Grazing Notebook. In *Teagasc & Irish Farmers Journal,*, ed. Teagasc & Irish Farmers Journal

Temme AJAM, Verburg PH. 2011. Mapping and modelling of changes in agricultural intensity in Europe. *Agriculture, Ecosystems & Environment* 140: 46-56

Thoma DP, Bailey DW, Long DS, Nielsen GA, Henry MP, et al. 2002. Short-Term Monitoring of Rangeland Forage Conditions with AVHRR Imagery. *Journal of Range Management* 55: 383-9

Thorp KR, French AN, Rango A. 2013. Effect of image spatial and spectral characteristics on mapping semi-arid rangeland vegetation using multiple endmember spectral mixture analysis (MESMA). *Remote sensing of environment* 132: 120-30

Todd SW, Hoffer RM, Milchunas DG. 1998. Biomass estimation on grazed and ungrazed rangelands using spectral indices. *International Journal of Remote Sensing* 19: 427-38

Trotter MG, Lamb DW, Donald GE, Schneider DA. 2010. Evaluating an active optical sensor for quantifying and mapping green herbage mass and growth in a perennial grass pasture. *Crop and Pasture Science* 61: 389-98

Tucker CJ, Vanpraet CL, Sharman MJ, Van Ittersum G. 1985. Satellite remote sensing of total herbaceous biomass production in the senegalese sahel: 1980–1984. *Remote Sensing of Environment* 17: 233-49

Tueller PT. 1989. Remote sensing technology for rangeland management applications. *Journal of Range Management* 42: 442-53

Turley T, Aylmer M, Fitzgerald L, Heneghan B. 2008. *Forage prodcution*. Kildalton, Kilkenny, Ireland: Teagasc

Turner DP, Ritts WD, Cohen WB, Gower ST, Running SW, et al. 2006. Evaluation of MODIS NPP and GPP products across multiple biomes. *Remote sensing of environment* 102: 282-92

Ullah S, Si Y, Schlerf M, Skidmore AK, Shafique M, Iqbal IA. 2012. Estimation of grassland biomass and nitrogen using MERIS data. *International Journal of Applied Earth Observation and Geoinformation* 19: 196-204

Van Meensel J, Lauwers L, Kempen I, Dessein J, Van Huylenbroeck G. 2012. Effect of a participatory approach on the successful development of agricultural

decision support systems: The case of Pigs2win. *Decision Support Systems* 54: 164-72

Van Rensburg TM, Murphy E, Rocks P. 2009. Commonage land and farmer uptake of the rural environment protection scheme in Ireland. *Land Use Policy* 26: 345-55

Vanden Borre J, Haest B, Lang S, Spanhove T, Forster M, Sifakis NI. 2011. *Towards a wider uptake of remote sensing in Natura 2000 monitoring: Streamlining remote sensing products with users' needs and expectations*. Presented at Space Technology (ICST), 2011 2nd International Conference on

Verburg PH, de Nijs TCM, Ritsema van Eck J, Visser H, de Jong K. 2004. A method to analyse neighbourhood characteristics of land use patterns. *Computers, Environment and Urban Systems* 28: 667-90

Viña A, Gitelson AA, Nguy-Robertson AL, Peng Y. 2011. Comparison of different vegetation indices for the remote assessment of green leaf area index of crops. *Remote Sensing of Environment* 115: 3468-78

Vinther FP, Oenema O, Wilson L. 2011. *Data requirements, availability and gaps in Agri-environment indicators (AEIs) in Europe*, Eurostat, Luxembourg: Publications Office of the European Union,

von Bueren SK, Burkart A, Hueni A, Rascher U, Tuohy MP, Yule IJ. 2015. Deploying four optical UAV-based sensors over grassland: challenges and limitations. *Biogeosciences* 12: 163-75

Voormansik K, Jagdhuber T, Olesk A, Hajnsek I, Papathanassiou KP. 2013. Towards a detection of grassland cutting practices with dual polarimetric TerraSAR-X data. *International Journal of Remote Sensing* 34: 8081-103

Vrieling A, Meroni M, Shee A, Mude AG, Woodard J, et al. 2014. Historical extension of operational NDVI products for livestock insurance in Kenya. *International Journal of Applied Earth Observation and Geoinformation* 28: 238-51

Walsh S. 2012. NEW LONG-TERM RAINFALL AVERAGES FOR IRELAND. In *National Hydrology Conference*. Athlone, ireland: OPW, Dublin

Wang X, Ge L, Li X. 2013. Pasture Monitoring Using SAR with COSMO-SkyMed, ENVISAT ASAR, and ALOS PALSAR in Otway, Australia. *Remote Sensing* 2013: 3611-36

Wardlow BD, Egbert SL, Kastens JH. 2007. Analysis of time-series MODIS 250 m vegetation index data for crop classification in the U.S. Central Great Plains. *Remote sensing of environment* 108: 290-310

Wheeler D, Hammer D, Kraft R, Dasgupta S, Blankespoor B. 2013. Economic dynamics and forest clearing: A spatial econometric analysis for Indonesia. *Ecological Economics* 85: 85-96

Whitcraft AK, Becker-Reshef I, Justice CO. 2015. A Framework for Defining Spatially Explicit Earth Observation Requirements for a Global Agricultural Monitoring Initiative (GEOGLAM). *Remote Sensing* 7: 1461-81

Willems AB, Augustenborg CA, Hepp S, Lanigan G, Hochstrasser T, et al. 2011. Carbon dioxide emissions from spring ploughing of grassland in Ireland. *Agriculture, Ecosystems & Environment* 144: 347-51

Wittig R, Becker U, Nawrath S. 2010. Grassland loss in the vicinity of a highly prospering metropolitan area from 1867/68 to 2000—The example of the Taunus (Hesse, Germany) and its Vorland. *Landscape and Urban Planning* 95: 175-80

Xu B, Yang XC, Tao WG, Qin ZH, Liu HQ, et al. 2008. MODIS-based remote sensing monitoring of grass production in China. *International Journal of Remote Sensing* 29: 5313-27

Yu D. 2010. *Exploring spatiotemporally varying regressed relationships: the geographically weighted panel regression analysis*. Presented at Joint International Conference on Theory, Data Handling and Modelling in GeoSpatial Information Science. Hong Kong

Yu L, Zhou L, Liu W, Zhou H-K. 2010. Using Remote Sensing and GIS Technologies to Estimate Grass Yield and Livestock Carrying Capacity of Alpine Grasslands in Golog Prefecture, China. *Pedosphere* 20: 342-51

Zarco-Tejada PJ, Hubbard N, Loudjani P. 2014. *Precision agriculture: an opportunity for eu farmers -potential support with the cap 2014-2020*, Directorate-general for internal policies policy department B: structural and cohesion policies agriculture and rural development, Brussels

Zhang N, Wang M, Wang N. 2002. Precision agriculture—a worldwide overview. *Computers and Electronics in Agriculture* 36: 113-32

Zhang Y, Xu M, Chen H, Adams J. 2009. Global pattern of NPP to GPP ratio derived from MODIS data: effects of ecosystem type, geographical location and climate. *Global Ecology and Biogeography* 18: 280-90

Zhang Y, Yu Q, Jiang JIE, Tang Y. 2008. Calibration of Terra/MODIS gross primary production over an irrigated cropland on the North China Plain and an alpine meadow on the Tibetan Plateau. *Global Change Biology* 14: 757-67

Zhao M, Running S, Heinsch FA, Nemani R. 2011. MODIS-derived terrestrial primary production In *Land Remote Sensing and Global Environmental Change: NASA's Earth Observing System and the Science of ASTER and MODIS.*

Remote Sensing and Digital Image Processing, vol. 11., ed. B Ramachandran, CO Justice, MJ Abrams, pp. 635-60: Springer

*Zimmermann J, Fealy RM, Lydon K, Mockler EM, O'Brien P, et al. 2016a. *THE IRISH LAND-PARCELS IDENTIFICATION SYSTEM (LPIS) Á EXPERIENCES IN ONGOING AND RECENT ENVIRONMENTAL RESEARCH AND LAND COVER MAPPING*. Presented at Biology and Environment: Proceedings of the Royal Irish Academy

*Zimmermann J, González A, Jones MB, O'Brien P, Stout JC, Green S. 2016b. Assessing land-use history for reporting on cropland dynamics—A comparison between the Land-Parcel Identification System and traditional inter-annual approaches. *Land Use Policy* 52: 30-40

Zongyao S, Brown DG, Xie Y, Welsh WF. 2012. *Discriminating stocking rates in a typical grassland using in situ spectral reflectance data*. Presented at Earth Observation and Remote Sensing Applications (EORSA), 2012 Second International Workshop on

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