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RETRIEVAL OF GRASSLAND BIOPHYSICAL PARAMETERS USING MULTITEMPORAL OPTICAL AND RADAR SATELLITE DATA

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Dissertation submitted to the
University College Cork for the degree of
Doctor of Philosophy



NATIONAL UNIVERSITY OF IRELAND, CORK
DEPARTMENT OF GEOGRAPHY

February, 2016

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Seek knowledge from the cradle to the grave.

— Prophet Muhammad (PBUH)



I–Iftikhar Ali–dedicate my PhD thesis to all the victims of terrorism and specially to the martyred[1] and injured school childern of Army Public School in Peshawar (KPK, Pakistan) on 16th **Dec. 2014**.

1 **#RIP dear fellow countrymen.**

ABSTRACT

The amount and quality of available biomass is a key factor for the sustainable livestock industry and agricultural management related decision making. Globally 31.5% of land cover is grassland while 80% of Ireland's agricultural land is grassland. In Ireland, grasslands are intensively managed and provide the cheapest feed source for animals. This dissertation presents a detailed state of the art review of satellite remote sensing of grasslands, and the potential application of optical (Moderate–resolution Imaging Spectroradiometer (MODIS)) and radar (TerraSAR-X) time series imagery to estimate the grassland biomass at two study sites (Moorepark and Grange) in the Republic of Ireland using both statistical and state of the art machine learning algorithms. High quality weather data available from the on-site weather station was also used to calculate the Growing Degree Days (GDD) for Grange to determine the impact of ancillary data on biomass estimation.

In situ and satellite data covering 12 years for the Moorepark and 6 years for the Grange study sites were used to predict grassland biomass using multiple linear regression, Artificial Neural Networks (ANN) and Adaptive Neuro Fuzzy Inference Systems (ANFIS) models. The results demonstrate that a dense (8-day composite) MODIS image time series, along with high quality in situ data, can be used to retrieve grassland biomass with high performance ($R^2 = 0.86$, $p < 0.05$, RMSE = 11.07 for Moorepark). The model for Grange was modified to evaluate the synergistic use of vegeta-

tion indices derived from remote sensing time series and accumulated GDD information. As GDD is strongly linked to the plant development, or phenological stage, an improvement in biomass estimation would be expected. It was observed that using the ANFIS model the biomass estimation accuracy increased from $R^2 = 0.76$ ($p < 0.05$) to $R^2 = 0.81$ ($p < 0.05$) and the root mean square error was reduced by 2.72%.

The work on the application of optical remote sensing was further developed using a TerraSAR-X Staring Spotlight mode time series over the Moorepark study site to explore the extent to which very high resolution Synthetic Aperture Radar (SAR) data of interferometrically coherent paddocks can be exploited to retrieve grassland biophysical parameters. After filtering out the non-coherent plots it is demonstrated that interferometric coherence can be used to retrieve grassland biophysical parameters (i. e., height, biomass), and that it is possible to detect changes due to the grass growth, and grazing and mowing events, when the temporal baseline is short (11 days). However, it not possible to automatically uniquely identify the cause of these changes based only on the SAR backscatter and coherence, due to the ambiguity caused by tall grass laid down due to the wind.

Overall, the work presented in this dissertation has demonstrated the potential of dense remote sensing and weather data time series to predict grassland biomass using machine-learning algorithms, where high quality ground data were used for training. At present a major limitation for national scale biomass retrieval is the lack of spatial and temporal ground samples, which can be partially resolved by minor modifications in the existing PastureBaseIreland database by adding the location and extent of

each grassland paddock in the database. As far as remote sensing data requirements are concerned, MODIS is useful for large scale evaluation but due to its coarse resolution it is not possible to detect the variations within the fields and between the fields at the farm scale. However, this issue will be resolved in terms of spatial resolution by the Sentinel-2 mission, and when both satellites (Sentinel-2A and Sentinel-2B) are operational the revisit time will reduce to 5 days, which together with Landsat-8, should enable sufficient cloud-free data for operational biomass estimation at a national scale.

The Synthetic Aperture Radar Interferometry (InSAR) approach is feasible if there are enough coherent interferometric pairs available, however this is difficult to achieve due to the temporal decorrelation of the signal. For repeat-pass InSAR over a vegetated area even an 11 days temporal baseline is too large. In order to achieve better coherence a very high resolution is required at the cost of spatial coverage, which limits its scope for use in an operational context at a national scale. Future InSAR missions with pair acquisition in Tandem mode will minimize the temporal decorrelation over vegetation areas for more focused studies.

The proposed approach complements the current paradigm of Big Data in Earth Observation, and illustrates the feasibility of integrating data from multiple sources. In future, this framework can be used to build an operational decision support system for retrieval of grassland biophysical parameters based on data from long term planned optical missions (e. g., Landsat, Sentinel) that will ensure the continuity of data acquisition. Similarly,

Spanish X-band PAZ and TerraSAR-X2 missions will ensure the continuity of TerraSAR-X and COSMO-SkyMed.

PUBLICATIONS

Peer Reviewed Journal Articles:

[1] **Ali, I.;** Cawkwell, F.; Dwyer, E.; Barrett, B.; and Green, S.; **2016**, *"Satellite remote sensing of grasslands: from observation to management—a review"*, *Journal of Plant Ecology*, doi: 10.1093/jpe/rtw005[2]. [IF: 2.646]

[2] **Ali, I.;** Cawkwell, F.; Dwyer, E.; and Green, S.; **2016**, *"Modelling managed grassland biomass estimation by using multitemporal remote sensing data—a machine learning approach"*, Journal of Selected Topics in Applied Earth Observations and Remote Sensing, IEEE. [Accepted, (IF: 3.026)]

[3] **Ali, I.;** Cawkwell, F.; Dwyer, E.; and Green, S.; **2016**, *"Synergetic use of remote sensing and weather data to retrieve grassland biomass and growth rate"*, International Journal of Applied Earth Observation and Geoinformation. [Submitted, (IF: 3.470)]

[4] [3] **Ali, I.;** Barrett, B.; Cawkwell, F.; Green, S.; Dwyer, E.; Neumann, M.: **2016**, *"Limitations Of Repeat-Pass TerraSAR-X (Staring Spotlight Mode) InSAR Coherence To Monitor Pasture Biophysical Parameters"*, Journal of Selected Topics in Applied Earth Observations and Remote Sensing, IEEE. [Accepted (IF: 3.026)]

[5] **Ali, I.;** Greifeneder, F.; Stamenkovic, J.; Neumann, N.; Notarnicola, C.: **2015**, *"Review of biomass and soil moisture retrievals by using machine learning methods and remote sensing data"*, Remote Sens. 2015, 7, 16398-16421. [F: 3.180]

Non–Peer Reviewed Articles:

[1] Green, S.; **Ali, I.;** Cawkwell, F.; **2013**, *"Monitoring grass from space, using satellite imaging to observe and predict grass growth rates"*. Teagasc Research, volume 8 number 4, ISSN 1649-8917: pp. 34-35, 2013.

Conference Poster/Proceedings:

[1] **Ali, I.;** Cawkwell, F.; Green, S.; and Dwyer, E.; **2016**, *"Grassland biomass retrieval using multitemporal optical satellite remote sensing time series"*, Living Planet Symposium, 09–13 May, 2016 in Prague, Czech Republic. [Submitted]

[2] Barrett, B.; Raab, C.; **Ali, I.;** Green, S.; and Cawkwell, F.; **2016**, *"Grassland management and biomass retrieval in an intensive dairy farm in Ireland using a combination of RADARSAT-2 and TerraSAR-X data"*, Living Planet Symposium, 09–13 May, 2016 in Prague, Czech Republic. [Submitted]

[3] **Ali, I.;** Cawkwell, F.; Green, S.; and Dwyer, E.; **2014**, *"Application of statistical and machine learning modelds for grassland yield estimation based on a hypertemporal satellite remote sensing time series"*, IEEE IGARSS, 13–18 July, 2014 in Quebec, Canada.

[4] **Ali, I.;** Cawkwell, F.; Green, S.; and Dwyer, E.; **2014**, *"Grassland biomass estimation using satellite data"*. Agricultural Research Forum 2014, 10^{th} & 11^{th} March, Tullamore, Co. Offaly, Ireland.

[5] **Ali, I.;** Cawkwell, F.; Green, S.; and Dwyer, E.; **2013**, *"Grassland yield estimation based on satellite data: A machine Learning Approach"*. 7^{th} *Irish Earth Observation Symposium* $24 - 25^{th}$ *October 2013 Teagasc Ashtown Research Centre, Dublin.* [Best presentation award]

[6] Green, S.; Cawkwell, F.; **Ali, I.;** **2013**, *"New remote sensing tools to monitor grass growth"*, A Conference on Agriculture and Future Weather Patterns. 5^{th} December 2013, Teagasc Ashtown Research Centre, Dublin.

2 Online available at: http://jpe.oxfordjournals.org/content/early/2016/02/02/jpe.rtw005.abstract?sid=37fbd6ed-e24a-4ce7-9992-8c7457cbced6

3 This research was conducted during my stay at JPL/NASA.

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There are no limitations to the mind except those we acknowledge.

—Napoleon Hill [1883—1970]

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ACRONYMS

ALOS Advanced Land Observing Satellite

ANPP Aboveground Net Primary Production

ANN Artificial Neural Networks

ANFIS Adaptive Neuro Fuzzy Inference Systems

APAR Absorbed Photosynthetically Active Radiation

ASTER Advanced Space borne Thermal Emission and Reflection Radiometer

ATSAVI Adjusted Transformed Soil Adjusted Vegetation Index

AVHRR Advanced Very High Resolution Radiometer

AVIRIS Airborne Visible/Infrared Imaging Spectrometer

CTA Classification Tree Analysis

DM Dry Matter

COP Conference of Parties

DT Decision Tree

ERM Exponential Regression Model

ERS European Remote Sensing Satellite

ESA European Space Agency

ETM+ Enhanced Thematic Mapper plus

EVI Enhanced Vegetation Index

fAPAR fraction of Absorbed Photosynthetically Active Radiation

FLVQ Fuzzy Learning Vector Quantization

GIS Geographic Information System

GDD Growing Degree Days

GHG greenhouse gas

IFAD International Fund for Agricultural Development

InSAR Synthetic Aperture Radar Interferometry

IRS Indian Remote Sensing Satellite

iRVI Integrated Ratio Vegetation Index

LAI Leaf Area Index

LRM Linear Regression Model

LogRM Logrithmic Regression Model

LPDAAC Land Process Distributed Active Archive Center

LPAA Lima-Paris Action Agenda

LUE Light Use Efficiency

LVE Lichen Volume Estimation

MIR Mid Infrared

MLC Maximum Likelihood Classification

MLR Multiple Linear Regression

MODIS Moderate–resolution Imaging Spectroradiometer

MSS Multispectral Scanners

MSAVI Modified Soil Adjusted Vegetation Index

NEPAD New Partnership for African's Development

NGOs non-governmental organizations

NDLI Normalized Difference Lichen Index

NDMI Normalized Difference Moisture Index

NDVI Normalized Difference Vegetation Index

NIR Near Infrared

NPP Net Primary Production

OBC Object Based Classification

OBIA Object Based Image Analysis

OCIM Object Based Crop Identification and Mapping

OSAVI Optimized Soil Adjusted Vegetation Index

PCA Principal Component Analysis

PRM Power Regression Model

RDVI Renormalized Difference Vegetation Index

RVI Ratio Vegetation Index

SAR Synthetic Aperture Radar

SAVI Soil Adjusted Vegetation Index

SGB Stochastic Gradient Boosting

SSURGO Soil Survey Geographic

SVM Support Vector Machine

SWVI Short Wave Vegetation Index

TM Thematic Mapper

TSAVI Transformed Soil Adjusted Vegetation Index

UAV Unmanned Aerial Vehicles

VI Vegetation Indices

UNFCCC United Nations Framework Convention on Climate Change

Part I

PROJECT BACKGROUND AND LITERATURE REVIEW

1

INTRODUCTION

Sitting quietly, doing nothing, spring comes, and the grass grows by itself.

— a Zenrin poem

The biosphere is known as the life zone on the Earth's surface, and without this Earth is no different from lifeless planets like Mars and Venus. The biosphere is responsible for food production and the air that we breathe. Grasslands cover the major proportion of the terrestrial land cover and are broadly defined as *"ground cover by vegetation dominated by grasses, with little or no tree cover"* (Suttie et al., 2005). Due to their role in food security and climate change (O'Mara, 2012), precise

assessment of grassland biomass at both regional and global scales is very important. Understanding of vegetation health, status (see Table 1) and the changes caused by climate and humans (Barnosky et al., 2012) is required. Globally, grasslands are one of the biggest terrestrial ecosystems. With 181 Mg/ha, they are the second highest carbon stock after forests (210 Mg/ha), and together, forests, croplands, and grasslands play a crucial role in the regulation of the global carbon cycle (see Table 1 for details). Land cover transformations caused by biomass burning and agricultural intensification contribute significantly to greenhouse gas emissions (Chuvieco, 2008).

Table 1: Grasslands, forests and croplands global coverage and carbon stocks.

		Carbon stocks (Mg/ha) (Franzluebbers, 2010)		
Biome	Coverage (%) (Latham et al., 2014)	Above ground	Soil	Total
Grasslands/Herbaceous	31.5	21	160	181
Forests	27.7	97	113	210
Croplands	12.6	2	80	82

In relation to global greenhouse gas emissions it is very important to monitor the biosphere at a large scale in order to fully understand the impact caused by change in vegetation area and hence biomass amount. Conventional ground-based methods (e. g., rising plate meter, cut and dry, visual assessment) have been used for decades for field or farm scale monitoring of grassland biomass. All these methods are very time consuming, laborious and are applicable to a very small scale. A possible solution to these limitations is the use of remote sensing technologies. Remote sensing

technologies can be used to monitor ground targets at a regional to global scale on a regular basis. The use of such technologies for biomass estimation of different vegetation types (grasslands, forests, croplands) has been on-going for many years, and many studies have contributed to the development of remote sensing methodologies and implementation schemes. Scientists (e. g., Gordon (1974)) have demonstrated an interest in satellite-based biomass quantification from the time of the launch of Landsat-1 (originally called "Earth Resource Technology Satellite 1") in 1972.

1.1 IMPORTANCE OF GRASSLANDS

Grasslands are not only important for their wide spread coverage (see Table 2) but they also play a substantial role in food security and other ecosystem services. Below are highlighted some of the key roles grasslands are playing in our life and environment :

I dairy products constitute a major proportion of our daily intake. In order to meet the global demand for food, especially milk and meat, a sustainable dairy farming system is very important. Globally grasslands cover a major proportion ($\approx$ 31.5%) of the terrestrial land cover of the Earth's surface (Latham et al., 2014), as shown in Table 2 and their adaptation to climate changes will be variable (O'Mara, 2012). Statistics show that the area of permanent pasture cover at a global scale is decreasing except in Africa and America, however, in Europe the area

(179 Millions of hectares) is quite stable and has been consistent for the last three decades (FAOSTAT, 2014).

II soil covered by grass has more potential to store carbon than forests and crops as shown in Table 1.

III grasslands are helpful in the struggle against erosion (their leaves intercept rainfall and their roots bind the soil) and for the regularizing of water regimes (Carlier et al., 2009).

IV Borer et al. (2014) has reported that biodiversity across grasslands can be maintained by fertilizing and controlled grazing.

Grassland/pasture is the only crop able to fulfil so many tasks and to fit so many requirements (e. g., environmental, development of the countryside) (Carlier et al., 2009)

Table 2: Global status of permanent pastures (in millions of hectares) [Statistics source: (FAOSTAT, 2014)]. Overall globally pasture cover has decreased in the last two decades, however, at a continental scale the trends vary for different regions e. g., consistent increase in pasture cover in Africa and America, continuous decrease in Asia and Oceania. For the last three decades pasture cover in Europe is quite stable.

	Time period		
Region	1994	2004	2012
Africa	881	898	904
Asia	1102	1099	1080
Europe	179	180	178
Oceania	435	404	369
America	797	811	827
World	3395	3395	3359

1.2 AGRICULTURE AND CLIMATE CHANGE

1.2.1 *Global context*

"Human influence on the climate system is clear, and recent anthropogenic emissions of greenhouse gases are the highest in history. Recent climate changes have had widespread impacts on human and natural systems" (IPCC, 2014). Maintaining the carbon budget–the estimated amount of carbon dioxide the world can emit while still having a likely chance of limiting global temperature rise to 2°C above pre-industrial levels (IPCC, 2014)–is crucial for the sustainable future of planet Earth. 52% of the available estimated global CO_2 budget has already been burnt, and if the greenhouse gas (GHG) emissions continue at the current rate the remaining 48% will be used by 2045 (IPCC, 2014). After consuming half of the carbon budget, the world is already experiencing catastrophic events due to more extreme weather events and climate changes, for example:

- global sea level rise
- forest fires
- heavy precipitation events
- longer and more intense droughts

Carbon dioxide constitutes the major proportion of total annual anthropogenic GHG emissions by gases, as compared to methane, nitrous oxide and other gases as shown in Figure 1.

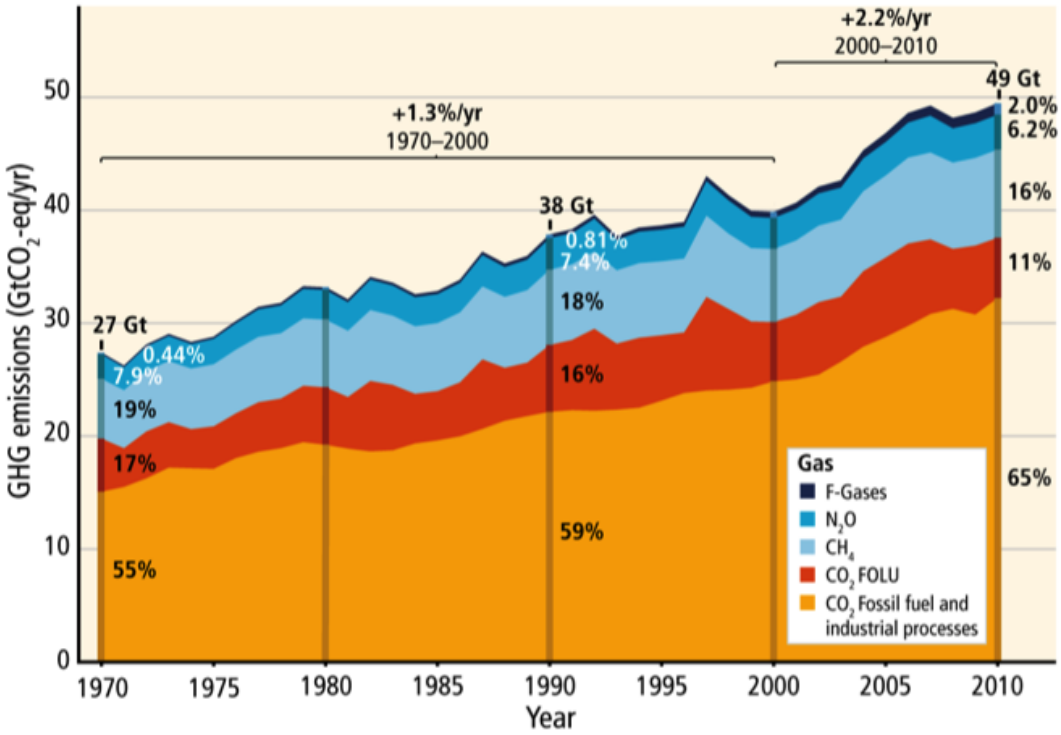


Figure 1: Total annual anthropogenic GHG emissions by gases 1970–2010 (IPCC, 2014).

With the increase of every degree of warming above 2°C, modelling demonstrates that the situation will not improve and that disastrous events will be more frequent in future. For example, if the GHG emissions continue unabated, global sea levels could be nearly 1 meter higher by 2100 (IPCC, 2014). To address these issues policy and decision makers have been attempting to reach a consensus on the global climate change policy framework. Finally, after 20 years of hard work, discussions and negotiations, on December 12th 2015 the participants from 195 countries signed the global

climate change pact, the Paris Agreement[1], to reduce greenhouse gas emissions. The aim of the Agreement is described in Article 2, "enhancing the implementation" of the United Nations Framework Convention on Climate Change (UNFCCC) through[2]

(a) "Holding the increase in the global average temperature to well below 2°C above pre-industrial levels and to pursue efforts to limit the temperature increase to 1.5°C above pre-industrial levels, recognizing that this would significantly reduce the risks and impacts of climate change;

(b) Increasing the ability to adapt to the adverse impacts of climate change and foster climate resilience and low greenhouse gas emissions development, in a manner that does not threaten food production;

(c) Making finance flows consistent with a pathway towards low greenhouse gas emissions and climate-resilient development."

Countries furthermore aim to reach the global peak of greenhouse gas emissions as soon as possible.

Efforts to reduce the emissions are of relevance to the agriculture sector, as the world population is set to increase from 7.4 billion (2016) to 8.9 billion by 2050, and meeting the food requirements for the growing population will result in emissions of additional greenhouse gases (particularly methane and nitrous oxide). Growing populations and wealth will increase the global demand for meat and dairy products, and in return the agriculture sector will also be impacted by climate change. Events (e. g., flood,

1 http://newsroom.unfccc.int/unfccc-newsroom/finale-cop21/
2 http://unfccc.int/resource/docs/2015/cop21/eng/l09r01.pdf

drought and changes in precipitation patterns) caused by extreme weather and climate will challenge the worldwide capacity to produce food. In order to avoid future humanitarian food crises there is a need to stabilise the concentration of GHG in the atmosphere.

During the Conference of Parties (COP) 21 meeting of the United Nations Framework Convention on Climate Change (UNFCCC) in Paris, governments and food and agriculture organizations joined at the Lima-Paris Action Agenda (LPAA) focus on agriculture to respond to urgent climate challenges facing agriculture with cooperative initiatives that will protect the long-term livelihood of millions of farmers and reduce greenhouse gas emissions[3]. Globally agriculture is contributing 24% of the greenhouse gas emissions[4] and in return it is seriously affected by extreme climates. The following four initiatives were on the agenda list:

i soils in agriculture sector,

ii the livestock sector,

iii food losses and waste, and

iv sustainable production methods and resilience of farmers.

The UN Secretary General's special representative for food security and nutrition Mr. David Nabarro highlighted the potential of these initiatives for sustainable agricultural development in future: *"The time has come to reshape agriculture but it must be of the right type: regenerative, smallholder centered, focused on food loss and waste, adaptation, soils management, oceans and*

3 http://newsroom.unfccc.int/lpaa/agriculture/
4 http://www3.epa.gov/climatechange/ghgemissions/global.html

livestock". At the Action Agenda, the following six major initiatives supporting farmers included:

1. *The "4/1000[5] Initiative: Soils for Food Security and Climate":* Officially launched by a hundred partners, including both developed and developing states, international organizations, private foundations, non-governmental organizations (NGOs) and farmers' organizations. By knowing that soil can store huge amounts of carbon, the aim of the 4/1000 initiative is to protect and increase carbon stocks in soils.

2. *Live Beef Carbon:* Farmers from four European countries took the initiative to reduce the carbon footprint of the livestock sector. Initially launched in October 2015, the "Live Beef Carbon" initiative aims at developing innovative livestock farming systems for sustainable beef farming in order to reduce the contribution of livestock production to GHG emissions. The end target is to reduce the beef carbon footprint by 15% over 10 years in France, Ireland, Italy and Spain.

3. *Adaptation for Smallholder Agriculture Programme (ASAP):* In order to increase the agricultural production and to reduce agriculture's carbon footprint, the International Fund for Agricultural Development (IFAD) committed to invest in poor smallholder farmers in developing countries.

4. *15 West-African Countries Transitioning to Agro-ecology:* With the support of the World Bank, European Union, and the New Partnership

5 What does "4 per 1000" mean? A "4%" annual growth rate of the soil carbon stock would make it possible to stop the present increase in atmospheric CO2. For more details: http://4p1000.org/understand

for African's Development (NEPAD) of the African Union, this initiative is aimed to deliver both adaptation and emission mitigation benefits. It will allow the adoption of agro-ecological practices by 25 million householders by 2025.

5. *The "Global Initiative on Food Loss and Waste Reduction – SAVE FOOD":* In order to reduce the global food waste and loss which accounts for 3.3 Gt of CO_2 equivalent per year, this initiative aims to drive innovations and promote interdisciplinary dialogue to reduce food loss and waste.

Approximately 24% of our greenhouse gas emissions come from agriculture (Gilbert, 2012), for example, globally rice crops accounts for 19% of anthropogenic methane emissions (Chen and Prinn, 2006). Similarly the agriculture (or grass crop) based dairy sector is also contributing significantly (2.2 CO_2 eq/kg Fat and Protein Corrected Milk (FPCM) at farm gate) to greenhouse gas emissions. Regions like East Asia, West Asia & North Africa, Central & South America and Sub Saharan Africa are producing less milk (compared to the developed countries) but generate high GHG emissions due to the poor management (e. g., poor nitrogen fertiliser management) as shown in Figure 2 (the complete report is available at http://www.fao.org/docrep/012/k7930e/k7930e00.pdf).

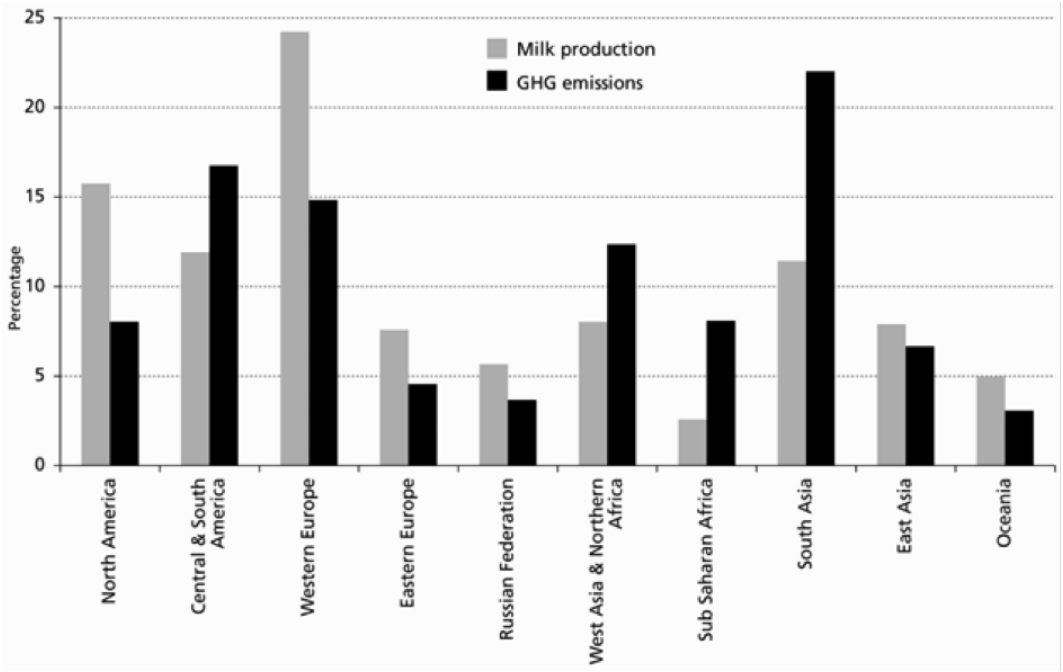


Figure 2: Relative contribution of world regions to milk production and GHG emissions associated with milk production, processing and transportation (source: http://www.fao.org/docrep/012/k7930e/k7930e00.pdf).

1.2.2 *Irish context*

In the Irish economy agriculture plays a very important role, as agriculture and the Irish food industry provide 230,000 jobs and contribute approximately €25 billion to the Irish economy (2016 report)[6]. Most of the revenue (€10 billion) is generated through the exports of dairy products and ingredients. Grasslands in Ireland are intensively managed–receiving artificial fertiliser and other treatments such as liming and re-seeding to optimise grass productivity–and are the backbone of the Irish livestock industry (O'Brien, 2007).

6 http://www.irishexaminer.com/business/growing-potential-of-the-food-industry-\in-ireland-374226.html

EU member states, including Ireland, are working on short, medium and long term plans to mitigate the effects of climate change by minimizing the emissions of greenhouse gases (see Figure 3 for GHG emissions by sector in Ireland). In Ireland the agriculture sector is a major source of greenhouse gas emissions. From 1990 (20.83 Mt CO_2eq/annum) to 2013 (19.04 Mt CO_2eq/annum) a significant decrease (8.59%) in emissions is reported in the agriculture sector[7], while in the case of the transport sector the percentage has increased from 9.0% to 19.5% during this period. Historically it has been established that there is a strong connection between local climate and local vegetation, and therefore gross changes to local ecosystems are expected (Prentice et al., 1992). In the case of Ireland, climate change will result in changes in land use, potentially agricultural land abandonment in some places and changes from livestock to crops or vice versa (Lennon, 2015).

1.2.2.1 *GHG emissions from the agriculture sector*

In the Irish agriculture sector the emissions of greenhouse gases are mainly from natural processes but are also due to land cover change. The main gases are[8]:

- Methane from ruminants from the breakdown of plant material
- Methane from stored manure

7 Ireland's GHG Emission Projections (May 2015 report): https://www.epa.ie/pubs/reports/air/airemissions/irelandsghgemissions2014-2035.html#.Vrc0HzaLTGI

8 http://www.agriculture.gov.ie/ruralenvironment/climatechangebioenergybiodiversity/agricultureclimatechange/

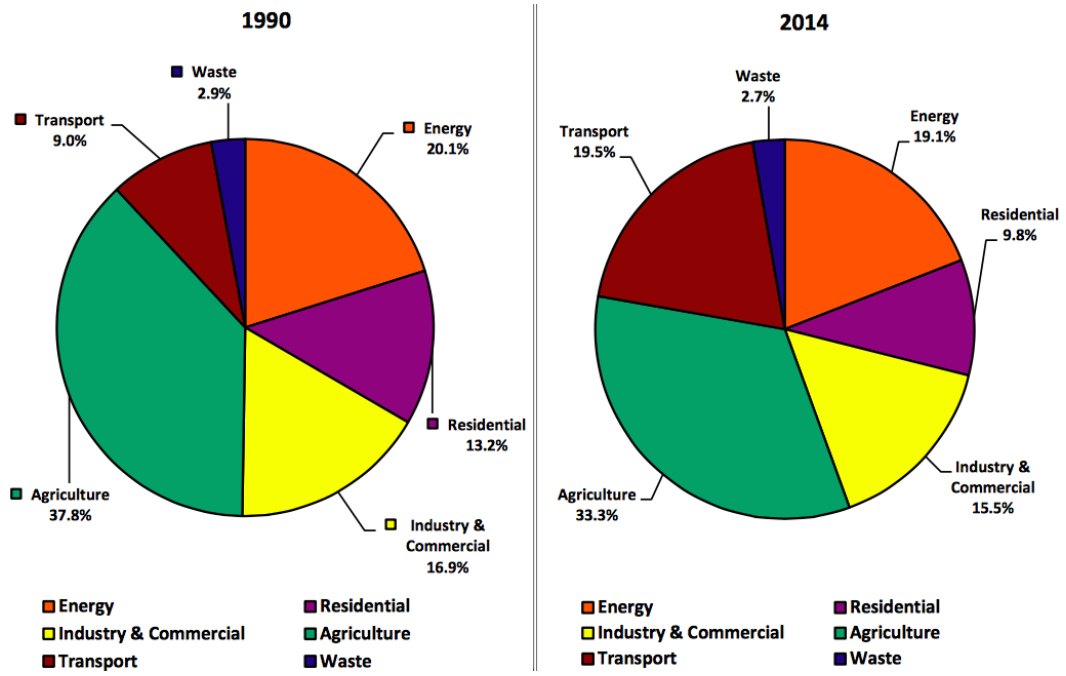


Figure 3: Ireland: greenhouse gas emissions in 1990 and 2014 by sector (EPA, 2014).

- Nitrous oxide from soils

In addition to this, 5% of CO_2 emission from the agriculture sector is due to the farm combustion of fuels. From the management perspective, grassland re-seeding or land-use change requires ploughing, which may enhance carbon dioxide emissions from soil (Willems et al., 2011).

1.2.2.2 *Trends in GHG emissions from agriculture sector*

Due to the small industrial base and large dairy exports, Ireland's major proportion of total national emissions is from the agricultural sector, Figure 3 shows a reduction in GHG emissions in agriculture sector. This reduction in emissions was mainly due the improvement in efficiency without compromising the production scale and quality.

1.2.2.3 *Mitigating GHG emissions from the agriculture sector*

Overall the target is to reduce global GHG emissions by 50% by 2050. Due the increasing population of the world, and increasing demand for dairy and meat products, it is very difficult to reduce or maintain the level of global agricultural emissions. Ireland's agriculture system is very well developed and is one of the most technologically advanced and carbon efficient systems in the world. However, reforms in greenhouse gas accounting methods are required for better assessment of agricultural greenhouse gas emissions (O'Brien et al., 2014). Styles and Jones (2008) have reported that energy-crop heat production has greater potential to reduce greenhouse emission compared to agricultural de-stocking. Nitrous oxide (N_2O) emissions from grassland-based agriculture is an important component of greenhouse gases and legume based grasslands have lower N_2O emissions than fertilizer-based systems. N_2O emissions can be mitigated by reducing manure nitrogen inputs according to need and by restricting grazing by reducing grazing time (Li et al., 2013).

1.3 IRISH AGRICULTURAL TRENDS

Due to its temperate climate Ireland has suitable grass growing conditions, including regions (southern part) with a year round growing season (Fischer et al., 2000). Agricultural land makes up about 62% of Ireland's terrestrial area, and 80% of this area is grassland. Over time there have been substantial and inexorable changes in Irish agricultural structure. Some of

the significant changes in Irish agricultural trends are listed below (Kearney, 2010):

FARM SIZE AND STRUCTURE: In the mid 1960s, before joining the EU, the number of farms in Ireland was about 239,000 and by the mid 1970s this number decreased by 4.6% to 228,000. According to the Census of Agriculture, in 1991 there were 170,600 farms in Ireland and by end of 2007 the number declined to 128,200 (24.8% decrease). A similar trend was observed across the European Union. The trend of increasing farm size is also very consistent, in 1991 an average farm size was about 26 hectares which was increased by 24.2% to 32.3 hectares in 2007.

LAND RENTING: An increasing trend in renting agricultural land/farms is evident in the Irish agricultural system. In 1991 21% of total farms were rented and this percentage was increased to 33% in 2007.

LAND FRAGMENTATION: Over the period of time (1991–2007) a significant change in number of parcels–an individual piece of land that can be sold separately–per farm has been reported. The average number of parcels per farm was 3.5 in 2007 as compared to 1.9 parcels in 1991.

PART-TIME FARMING: The trend of part-time farming is increasing in smaller farming systems (e.g., cattle and sheep farming) due to the increasing trend of getting off-farm jobs. The percentage of part-time farmers was increased from 33% to 42% from 1990 to 2000.

LAND USE: Since 1970 agricultural/crop land has reduced by about 24.8% and most of this land has been diverted to forestry.

LAND PRICES: Before joining the EU in 1973, the average agricultural land price in Ireland was €524 per hectare but subsequently there was a rapid increase in land prices, for example €4292 per hectare in 1980, €12665 per hectare in 2000 and €50508 per hectare in 2007.

1.4 MILK QUOTA – ECONOMIC VALUE

A milk quota was one of the measures used by governments in the European Union to intervene in agriculture to bring rising milk production under control. Milk quotas were attached to land holdings, and they represented a cap on the amount of milk that a farmer could sell every year without paying a levy. The introduction of the milk quota in 1984 was a major setback for both the dairy sector and Irish economy, and that was a difficult time for the Irish agriculture sector. After more than 30 years European Union milk quotas were lifted in March 2015. A study by the Irish Farmers Association (IFA) estimated the ending of quotas would create 9500 extra jobs in Ireland, and upwards of 1.3 billion Euro annual additional export revenue (www.independent.ie, 2015). But at the same time, optimization of the carbon footprint of milk and economic output of dairy farms is also very important for mitigating GHG emissions. O'Brien et al. (2015) performed a detailed analysis by using 221 nationally representative samples of grass-based Irish dairy farms in order to relate the carbon footprint of

milk to farms' economic performance. It was concluded that extending the length of the grazing season and increasing milk production per hectare or per cow reduced the carbon footprint and increased farm profit. However, the use of concentrate feeding affected the carbon footprint of milk and economic performance by increasing both costs and off-farm emissions.

1.5 CURRENT SITUATION

Food Wise 2025, the Report of the 2025 Agri Food Strategy Committee in Ireland sets out a cohesive, strategic plan for the development of an agri-food sector over the next decade. The report emphasizes the development of a sustainable export-led, smart economy. On the basis of available data, the Committee believes that the following growth projections are achievable by 2025 (FoodWise-2025, 2015)

- Increasing the value of agri-food exports by 85% to €19 billion.
- Increasing the value added in the agri-food, fisheries and wood products sector by 70% to in excess of €13 billion.
- Increasing the value of primary production by 65% to almost €10 billion.
- The creation of an additional 23,000 direct jobs in the agri-food sector all along the supply chain from primary production to high value added product development.

Apart from maximizing the economic output from the farms, at the same time it is also important to protect the ecological aspects of these grassland farms. One of the European Rural Development policy's objectives is to identify and protect the High Nature Values (HNV) farmland. However, in grass-based farmland (e. g., in Ireland) it is difficult to distinguished between fine-scale biodiversity features of different grassland types. For these type of investigations, field-scale survey work is required along with very high resolution remote sensing and information from Corine Landcover Classification Sullivan et al. (2010).

1.6 MOTIVATION FOR THIS WORK

Almost two-thirds of Ireland's land cover is grassland, consistent monitoring of which is of utmost importance in the context of national agriculture initiatives. For proper management and monitoring more efficient and scientifically reliable models are required for grass growth estimation. Grass-based intensive systems demand constant intervention on a daily and weekly basis by the farmer, and estimation of pasture cover (biomass) is the most important variable in these decisions which play a vital role in paddock and herd management (Edirisinghe et al., 2012; Clark et al., 2013; Boschetti et al., 2007).

In addition, EU member states are required to adhere to a growing number of environmental and agricultural directives, and it is essential that individual member states have the independent capacity to provide input

to these. No Earth Observation studies of grasslands have been undertaken in Ireland for grassland biomass estimation. As such, little is known about the spatial, temporal and spectral requirements necessary to develop a national monitoring strategy based on Remote Sensing. Moreover, as agricultural environments respond to changing climate conditions (e. g., an earlier start and later finish to the growing season) it is imperative to develop robust approaches which will permit both contemporary and historic capture of the grassland condition.

Currently in Ireland, mostly the farmers are using visual (eye ball), rising plate meter and cut and dry methods[9] to evaluate grass stocks. This is clearly a very time consuming approach and the estimates are also not very accurate as shown by O'Donovan and Dillon (1999) who compared visual and mechanical methods. Both visual and rising plate meter methods do not perform as well as the cutting technique (Pavlu et al., 2009). Grassland biomass estimations available in the *"PastureBaseIreland"* database from Teagasc's[10] farms (e. g., Moorepark, Curtins, Grange) are determined using the cut and dry method, a strip of approximately three meters long and one meter wide is clipped and dried to calculate the Dry Matter (DM) kg/ha as shown in Figure 4. *"PastureBaseIreland"* has very high quality, long term in-situ measurements of grassland biophysical parameters for some Teagasc farms (e. g., Moorepark, Grange, Curtins), but now more farms are being added to the database (with georeferenced information of geo-referencing)

9 The details of these methods is given in next chapter.

10 Teagasc is the agriculture and food development authority in Ireland. Its mission is to support science-based innovation in the agri-food sector and the broader bioeconomy that will underpin profitability, competitiveness and sustainability.

in order to increase the number and country wide spatial distribution of these farms.

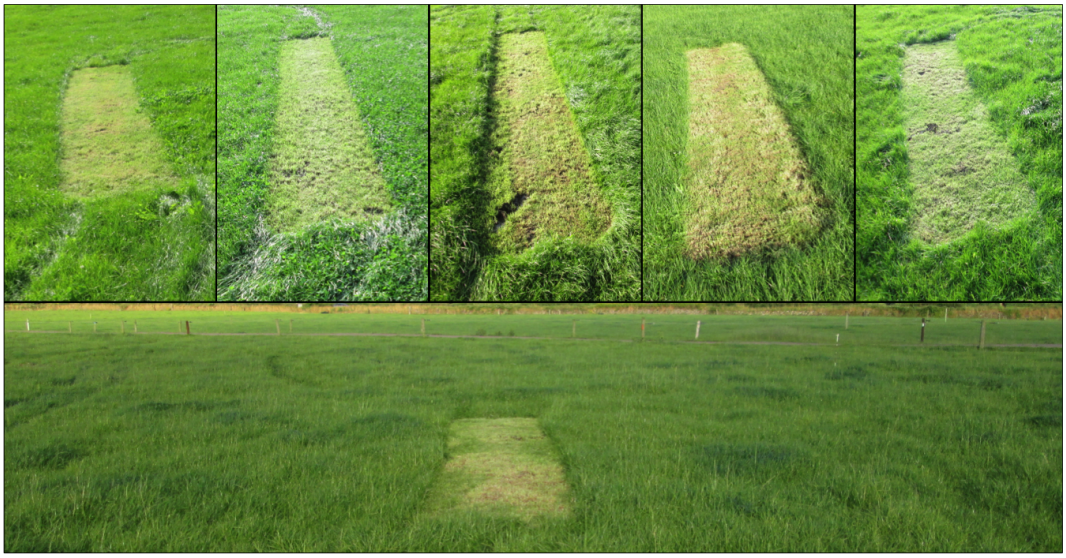


Figure 4: Teagasc grassland biomass estimation method (Photographs were taken during the Curtins (Teagasc farm) field campaign).

1.7 REMOTE SENSING TECHNOLOGY – SCOPE AND POTENTIAL

To feed the growing population of the planet and to avoid food shortage related humanitarian crises, it is very important to monitor crops and agricultural activities on a consistent basis. At a global scale, this type of monitoring is important for understanding the influence of climate change on vegetation health. At the same time, it is equally important to monitor agricultural fields at the farm and paddock scale in order to assess their production and performance-related biophysical parameters.

Optical satellite imagery is currently being used in the field of agriculture for the discrimination of crop types (e. g., Löw and Duveiller (2014)) and to address more challenging tasks such as calculation of Net Primary Production (NPP) (Rossini et al., 2012). Knowledge of the spatial distribution of different agricultural land covers and their annual growth cycle is important, not only for predicting annual yields, but also for accurately calculating carbon reserves which are key inputs for international greenhouse gas accounting tools (Lin et al., 2012).

At present, the remote sensing community is benefiting from advances in technology that are allowing for the acquisition of data with higher spatial, temporal, and spectral resolutions. This influx of big-data from satellites is giving birth to many new research fields and application domains (Cavallaro et al., 2015; Ma et al., 2015). In the context of agricultural monitoring, satellite remote sensing has been employed since the launch of Landsat-1 in 1972. Classification of the land cover types is a typical application of remote sensing datasets. There is a common consensus that space borne optical remote sensing is a more feasible approach for vegetation monitoring than microwave radar remote sensing. This may be due to (1) the fact that there exists a long history of dedicated investigations, and, therefore a wider appreciation of the optical approach; (2) the availability of the high number of spectral bands, with spectral responses linked to well understood phenological stages; and (3) the rapid improvement in spatial resolution. However, with the increasing availability of very high resolution spaceborne SAR data the trend is now changing. TerraSAR-X Staring Spotlight mode (Mittermayer et al., 2014) can acquire data with 0.25m spatial

resolution which may revolutionize the monitoring of ground targets from space (Gutjahr et al., 2015).

Since the dawn of satellite remote sensing, significant advances in technological development have occurred and new applications are continuously being identified. Within the last decade alone (2005-2015), many new sensors (e. g., SAR: Sentinel-1, ALOS, COSMO-SkyMed, TerraSAR-X, Radarsat-2, Tandem-X. Optical: Landsat-8, RapidEye, SPOT-7, Sentinel-2, WorldView) with high spatial, temporal and spectral resolution have been developed and launched. At the same time, a paradigm shift has occurred, whereby we have moved on from simple land cover classification and mapping to the retrieval of more complex essential biophysical parameters. The rapid and revolutionary development in spatial, temporal and spectral resolution has triggered this shift. For example, currently available high spatial resolution spaceborne optical (e. g., WorldView-3 with a spatial resolution of 1.24m; panchromatic band at 0.31m) and SAR (e. g., TerraSAR-X Staring Spotlight mode has 0.25m spatial resolution) data has great potential to track inter and intra field variations. With these developments, new state of the art operational decision support systems for various ecosystems have been, and need to be, developed.

Despite the fact that optical remote sensing has great potential in the monitoring and retrieval of vegetation/crop biophysical parameters, a major drawback of this approach is that it is limited by cloud cover. The microwave radar remote sensing data acquisition technique, on the other hand, is advantageous in that it is possible to acquire data at any time due to the ability of microwaves to penetrate through cloud cover, haze and

dust. While optical sensors can acquire cloud-free data in different regions of the world throughout the year, microwave sensors may be useful in areas with consistent cloud cover (e. g., Northern Europe) where it is not possible to acquire high spatial resolution cloud-free optical data on a regular basis. This is important for precision agriculture or crop monitoring because it is crucial to have a dense and temporally consistent time series in order to trace the plant's phenological developments.

Studies (Immerzeel et al., 2009; Rocchini, 2015) have shown that the satellite remote sensing approach is the most feasible and economical way of monitoring large ecosystems from the local to global scale. This approach has significantly helped scientists to understand the functionality and dynamics of terrestrial ecosystems. Monitoring and estimation of grassland production are of great importance for animal feed production and calculating the national contribution of land cover types to carbon budgets, including the utilization of space borne satellite data-driven VI for the estimation of grassland's biomass.

The techniques of monitoring grasslands and nature conservation sites from space are now quite mature and widely used. The VI (e. g., NDVI, Enhanced Vegetation Index (EVI) and Soil Adjusted Vegetation Index (SAVI)) are being effectively used for agricultural monitoring and crop discrimination in a number of countries, but still their integration with machine learning algorithms/models for grassland biomass estimation is very limited. Climate variables and features extracted from climate data also have a very strong relationship with the growth dynamics of vegetation or plant phenology. Similarly, synergistic use of remote sensing derived parameters

(e. g., NDVI, EVI, SAVI) and features such as GDD derived from climate data have never been tested for grassland biomass retrieval. Work has been done on the fusion of VI and GDD for surface temperature (Hassan and Rahman, 2013) or wetness estimation using linear methods but to the best of our knowledge the fusion of VI and GDD for grassland biomass retrieval using a machine learning approach has not yet been reported in the literature.

1.8 OBJECTIVES

There is a critical need for quantitative spatial and temporal information on agricultural land use at a national scale within Ireland to assist with agricultural monitoring, as an input to national carbon budget reporting requirements, and to inform agri-environmental policy development. The aim of this study is to investigate the capability of retrieving grassland biomass in an intensively[11] managed environment using multi-temporal space borne optical (2001 – 2012) and radar (July, 2014 – July, 2015) remote sensing time series. Specifically, the objectives are to:

1. undertake a detailed state of the art review of published literature in order to determine the current status of grassland monitoring globally based on satellite remote sensing data

11 The term *"intensive"* is meant to describe livestock and grass management practices that focus on increased levels of manager involvement, increased forage quality, increased meat production per unit area, and more uniform forage utilization.

2. explore the potential application of satellite–driven VI for grassland biomass estimation for selected Irish sites using a machine learning approach

3. investigate the fusion of VI and GDD in order to analyse the contribution of climate variables for grassland biomass and growth rate estimation at a selected Irish site

4. evaluate the potential and limitations of using repeat-pass InSAR to retrieve grassland biophysical parameters at an Irish site using X-band TerraSAR-X time series

5. make recommendations for the development of a nation wide operational decision support system

1.9 CHAPTER OVERVIEW

CHAPTER—2: This chapter[12] gives a detailed state of the art review of satellite remote sensing of grasslands. The first part provides a comprehensive overview of the global presence of grassland and describes the most commonly employed applications of remotely sensed data for classification and mapping. The second part covers the monitoring of managed grasslands' properties such as growth rate, biomass, pasture quality and grazing intensity. Finally, research gaps are identified and potential solutions to these issues suggested.

12 Chapter—2 title: *"Satellite remote sensing of grasslands"*

CHAPTER—3: In this chapter[13] the development of machine learning models (ANN and ANFIS) for grassland biomass estimation is described. Their performance is compared with the conventional and most commonly used statistical approach, Multiple Linear Regression (MLR). The chapter also describes how the developed methodology was tested on two different test sites (Moorepark and Grange) using 12 years and 6 years time series of MODIS remote sensing data.

CHAPTER—4: This chapter[14] presents the inclusion of weather data into the developed model (ANFIS) as a proxy to predict and improve biomass estimation. The relationship between NDVI and the minimum/maximum temperature is explained. Our results, which show that fusion of remote sensing VI and accumulated growing degree-days temperature has improved the biomass rate and yield estimation performance for the Grange site, are presented.

CHAPTER—5: This chapter[15] investigates the potential of repeat-pass synthetic aperture radar interferometry (InSAR) to retrieve biophysical parameters over intensively managed pastures. It describes initial findings based on the highest resolution space borne TerraSAR- X Staring Spotlight time series for Moorepark, which demonstrate the possibility, under certain conditions, of detecting changes due to grass growth, grazing and mowing by using interferometric coherence information.

13 Chapter–3 title: *"Modelling biomass estimation of managed grasslands"*
14 Chapter–4 title: *"Fusion of remote sensing and weather data to retrieve grassland biomass and growth rate"*
15 Chapter–5 title: *"Retrieval of grassland biophysical parameters using SAR interferometry"*

CHAPTER—6: The final chapter[16] summarizes the general findings of the present work, and outlines directions for future research.

16 Chapter–6 title: *"Conclusion and future research"*

2

SATELLITE REMOTE SENSING OF GRASSLANDS

Literature is air, and I'm suffocating in mediocrity.

— Armand Assante

CHAPTER PUBLICATION:

This chapter has been published as a review article in Journal of Plant Ecology:

Ali, I.; Cawkwell, F.; Dwyer, E.; Barrett, B.; and Green, S.; **2016**, *"Satellite remote sensing of grasslands: from observation to management—a review"*, *Journal of Plant Ecology*, doi: 10.1093/jpe/rtw005[1]. [IF: 2.646]

1 Online available at: http://jpe.oxfordjournals.org/content/early/2016/02/02/jpe.rtw005.abstract?sid=37fbd6ed-e24a-4ce7-9992-8c7457cbced6

2.1 PAPER—1

2.1.1 ***Ali, I.;*** *Cawkwell, F.; Dwyer, E.; Barrett, B.; and Green, S.;* ***2016****, "Satellite remote sensing of grasslands: from observation to management—a review", Journal of Plant Ecology, doi: 10.1093/jpe/rtw005. [IF: 2.646]*

This state of the art review paper covers the different aspects of the application of remote sensing technology for retrieval of biophysical parameters which are used for grassland management related decision making (for graphical abstract see Figure 5). This review starts with conventional field methods (e. g., clipping, Rising Plate Meter) used for grassland monitoring (e. g., biomass, height and status) and their limitations. In order to overcome these limitations, the use of optical and radar remote sensing approaches are discussed. Due to the widespread presence of grasslands on the terrestrial land cover of the Earth, the global context of grasslands and the applications of remote sensing technologies for large scale monitoring of grasslands are discussed in this review. The classical application of remote sensing data (i. e., mapping, classification) is discussed and critically analysed. The next part of the review is focused on the application of remote sensing methods to retrieve grassland biomass and management strategies (e. g., grazing impacts, grazing capacity, pasture quality, growth rate and status). Grasslands in Ireland are mainly intensively managed, therefore it is very important to critically evaluate the potential of remote sensing technologies in this context. Operational and technical challenges

of the remote sensing approach to monitoring grasslands are discussed and examples are also given in this context. At the end, this review concludes with some suggestions on current challenges and future directions.

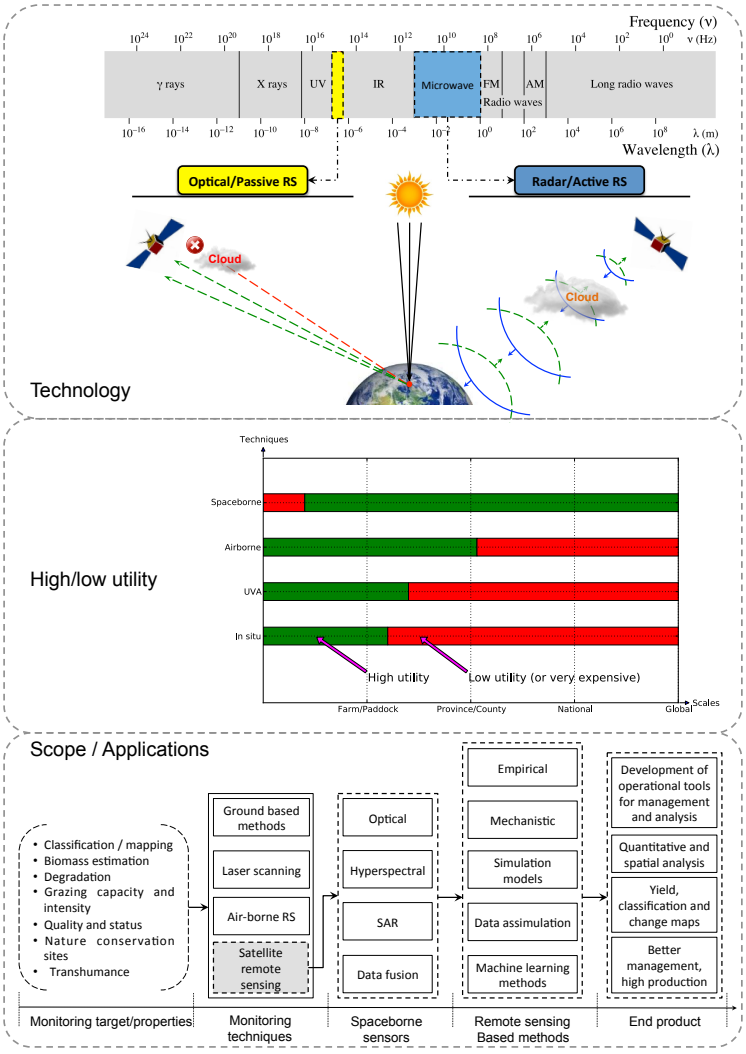


Figure 5: Graphical abstract of this review: **Ali, I.;** Cawkwell, F.; Dwyer, E.; Barrett, B.; and Green, S.; **2016**, *"Satellite remote sensing of grasslands: from observation to management—a review"*, *Journal of Plant Ecology*, doi: 10.1093/jpe/rtw005. [IF: 2.646]

CONTRIBUTION STATEMENT

Declaration of own contribution to the published (or intended for publication) scientific papers within my dissertation.

DISSERTATION TITLE: Retrieval of grassland biophysical parameters using multitemporal optical and radar satellite data.

PAPER–1: **Ali, I.;** Cawkwell, F.; Dwyer, E.; Barrett, B.; and Green, S.; **2016**, *"Satellite remote sensing of grasslands: from observation to management—a review"*, *Journal of Plant Ecology*, doi: 10.1093/jpe/rtw005. [IF: 2.646]

OWN CONTRIBUTION IN THIS WORK: Concept development (fully), Literature search (fully), Methods development (fully), Research design (fully), Data collection (mainly), Data pre-processing (fully), Data analysis (fully), Construction of the manuscript (fully), Argumentation (fully), Critical revision of the article (mainly).

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Satellite remote sensing of grasslands: from observation to management–a review

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Abstract

Aims

Grasslands are the world's most extensive terrestrial ecosystem, and are a major feed source for livestock. Meeting increasing demand for meat and other dairy products in a sustainable manner is a big challenge. At a field scale, GPS and ground based sensor technologies provide promising tools for grassland and herd management with high precision. With the growth in availability of spaceborne remote sensing data it is therefore important to revisit the relevant methods and applications that can exploit this imagery. In this article we have reviewed the (1) current status of grassland monitoring/observation methods and applications based on satellite remote sensing data, (2) the technological and methodological developments to retrieve different grassland biophysical parameters and management characteristics (i.e., degradation, grazing intensity), and (3) identified the key remaining challenges and some new upcoming trends for future development.

Important Findings

The retrieval of grassland biophysical parameters have evolved in recent years from classical regression analysis to more complex, efficient and robust modelling approaches, driven by satellite data, and are likely to continue to be the most robust method for deriving

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grassland information, however these require more high quality calibration and validation data.We found that the hypertemporal satellite data are widely used for time series generation, and particularly to overcome cloud contamination issues, but the current low spatial resolution of these instruments precludes their use for field-scale application in many countries. This trend may change with the current rise in launch of satellite constellations, such as RapidEye, Sentinel-2 and even the microsatellites such as those operated by Skybox Imaging. Microwave imagery has not been widely used for grassland applications, and a better understanding of the backscatter behaviour from different phenological stages is needed for more reliable products in cloudy regions. The development of hyperspectral satellite instrumentation and analytical methods will help for more detailed discrimination of habitat types, and the development of tools for greater end-user operation.

Keywords:remote sensing; agricultural grassland; grassland biomass; pasture management; grazing intensity

BACKGROUND

Global grasslands

Grasslands are one of the most prevalent and widespread land cover vegetation types, covering 31.5% of the global landmass (Latham et al., 2014). After forests, grasslands are the largest terrestrial carbon sink (Anderson, 1991; Derner and Schuman, 2007) and, as such, they play a vital role in regulating the global carbon cycle(Franzluebbers, 2010; Scurlock and Hall, 1998), as well as supporting plant and animal biodiversity(Bergman et al., 2008; Pokluda et al., 2012; Punjabi et al., 2013; van Swaay, 2002). From an agricultural perspective, grasslands provide the cheapest feed source for the livestock industry, however they contribute both directly and indirectly to climate change through the emission of greenhouse gases (FAO, 2014). As a result, a restriction on a maximum level of grassland intensification (animal stocking) is required in order to minimize the environmental risks

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(Soussana and Lemaire, 2014). During the period of 1994to2012,global permanent pasture cover declined by approximately 1% from 3395x10^6ha to 3359 x10^6ha (FAOSTAT, 2014), as a result of urbanization, overgrazing (Piñeiro et al., 2006b; Han et al., 2008), industrial development (Wang et al., 2008), intensive management practices and climate change (Thorvaldsson et al., 2004). Grassland degradation results in increased carbon emissions, has serious repercussions for society (Cardinale et al., 2012), and leads to more complex interactions between grassland ecosystems, management practices and climate change. These human activities, coupled with unfavorable environmental conditions, are major causes of changes in the productivity of grasslands (Xu et al., 2008).

Definition and distribution of managed grasslands

Three distinct categories of managed grasslands are recognised:

Human–generated pastures/meadows/grasslands or improved grasslands: These grasslands are typically created by the conversion of natural landscapes (e.g.forests) into pastures or grassland paddocks (Foley et al., 2005; Hill, 2004).These grasslands areintensively managed in order to maximize production (dairying, meat, wool), for example through regular application of fertilizer, intensive grazing, cutting of silage for winter–feeding and reseeding every few years. Improved grasslands arewidely found in parts ofNorthern Europe, New Zealand and Australia.

Highly managed natural grasslands: In this category natural grasslands are modified and managed to support intensive grazing for thelivestock industry e.g. the semi–improved natural grasslands of eastern Australia, and fescue prairie of Alberta, Canada (Breymeyer, 1990; Hill, 2004).

Rangelands: Based on their species composition, rangelands are different from pastures due to the presence of native herbaceous/shrubby vegetation which are a feed source for

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both domestic and wild herbivores e.g. tallgrass prairies (e.g.North American Great Plains), steppes, desert shrublands, shrub woodlands and savanas. Management of rangelands is solely through controlling the number of grazing units and length of the grazing season.

Figure 1 gives an overview of grasslands as a proportion of land cover, with the major managed pastures, grasslands and rangelands areas (Hill, 2004) of the world highlighted.

Grassland monitoring and feasibility of remote sensing technologies

Grassland monitoring, either through in-situ field observation or remote sensing, requires data on the current status of the grass and of the potential offered by the immediate environment, such as soil, weather and human activities. The current status of the grass includes aspects such as sward height, biomass,quality, phenological stage, productivity level, species composition and change in each of these since a previous recording stage (earlier in the same season or in a previous season). In situ methods, from visual analysis to techniques such as a rising plate meter, to cutting and laboratory analysis, can be extremely informative at a local scale, but they are labour intensive and not feasible for large-scale coverage. Remote sensingand modelling approachesallow for large scale monitoring, quantification and prediction(Gao, 2006) of different phenomena (e.g. land use and land cover, biodiversity, impacts of climate change) occurring on the surface of the Earth at varying spatial and temporal resolutions(Nordberg and Evertson, 2003).The integration of multispectral and multi-temporal remote sensing data with local knowledge and simulation models has been successfully demonstrated as a valuable approach to identifying and monitoring a wide variety of agriculturally related characteristics (Yiran et al., 2012; Oliver et al., 2010). In the context of global food security and to avoid food shortages, estimated yield production prior to harvest is needed for planners and decision makers, and remote

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sensing platforms are increasingly recognized as essential tools for this task(Boschetti et al., 2007). An early and accurate indication of a decrease in fodder production is especially important for agriculture-dependent developing economies, however, to date, little work has been undertaken on grass–based food security. Recently Svoray et al. (2013) has published a detailed review on remote sensing of rangelands, so this review focused on managed grasslands and pastures for their greater relevance to agriculture, livestock and the concept of precision farming from space (precision agriculture).

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Objectives and scope of the review

This article will review the application of satellite remote sensing for grassland and its transition from grassland mapping to grassland/pasturemonitoring and management. The aims of this review are to examine the extent of satellite remote sensing applications in the field of grasslands and pastures, and to identify the contemporary trends and future potential of these data and methods. The main objectives of this paper are:

to provide an overview of satellite remote sensing (optical andmicrowave) technological and methodological developmentsto retrieve different grassland biophysical parameters and management characteristics

to identify trends and gaps in the work done to date resulting in recommendations for future research and operational systems.

APPROACHES TO GRASSLAND MONITORING

Grassland monitoring approaches are broadly categorized into two groups: (i) ground-based, and (ii) remote sensing methods. The term “grassland management” in the context of this research includes weed control, removing dead plants, mowing, clipping, assessment of

biomass and growth rate, extent, grazing length, and utilization of grassland (incorporating elements of herd management)(Hybu Cig Cymru, 2008).

Ground based measurements for validation of remotely sensed data

Ground-based grass monitoring techniques heavily depend on an infrastructure which includes in situ data collection stations, measurement devices and frequent field surveys (del Pozo et al., 2006). Current methods used for the retrieval of grassland biophysical parameters and other management related information include:

Visual: visual assessment by human eye (expert or farmer), this method is spatially sparse with limited performance for different management strategies (Newnham, 2010).

Cut and dry (clipping): grass harvested from the paddock is dried and weighed to get the dry matter (DM) yield, as well as a laboratory assessment of grass quality and nutrient status(Xie et al., 2009).

Rising plate meter (RPM): both mechanical and electronic plate meters work on the principle of a plate rising up and down the shaft taking measurements of grass height (Castle, 1976; Hakl et al., 2012; Hejcman et al., 2014). This method is most commonly used for accurate biomass and grass height estimation at a point but is very time intensive.

Field spectrometry:reflectance spectra are collected using a spectrometer held at waistheight and are calibrated against in situ samples, with species discriminatedusing local field data or spectral libraries. Based on the reflectance at red and near infrared wavelengths, vegetation indices (VIs) are calculated, from which biophysical parameters such as above ground biomass and leaf area index can be retrieved (Flynn et al., 2008; Psomas et al., 2011a). Flynn et al. (2008) used a ground-based sensor to calculate the Normalized Difference Vegetation Index (NDVI) in order to investigate the within-field

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variability in biomass and assess the potential for the application of NDVI for pasture management activities. They found that NDVI showed a good correlation with biomass ($r^2 = 0.68$) and with the results from the rising plate meter ($r^2 = 0.54$), however as noted by Todd et al. (1998), possible relationships between such indices and the vegetation biomass are influenced by the ground-based sampling methods, for example biomass can be underestimated due to the presence of non–photosynthetically active plant material.

Table 1 gives the summary comparison of different ground-based methods.

While these ground–based methods are very useful for grassland monitoring on a local scale, and for providing values for model development and calibration of ex situ data, they are subjective, time consuming and are only feasible (or applicable) for small scale assessment (Xu et al., 2008).

For remote sensing studies, high quality ground truth data are of great importance for cross validation and algorithm training. All these ground-based methods are equally applicable for this purpose, and data collected using these methods have proven very useful. For example forest inventory, crop yield and grassland (Xu et al., 2008)data collected in past is currently being used by the remote sensing scientists for forest change detection and development of yield estimation models.

Remote sensing methods

As highlighted in the field spectrometry discussion of section 2.1, measurement of the reflectance at visible and infrared wavelengths can enable discrimination of different grassland species and status.These principles are equally applicable forlocal scale mapping and monitoringfrom optical sensors mounted on eddy covariance towers, unmanned aerial vehicles,aircraft and spaceborne platforms. It is these spaceborne platforms that can collect

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data at spatial scales from 25cm to 1km, for regional, national and global studies, that are the focus of this review. The last 20-30 years have seen many technological developments that enable economically cost effective, statistically reliable and consistent, and operationally robust tools for remote monitoring of grassland sites and acquisition of data on their behavior.

Optical remote sensing

Discrimination of different terrestrial ecosystem types andmeasurement of their productivity primarily relies on vegetation indices (VI) that combine reflectance values at two or more wavelengths, selected to accentuate particular features of the spectral signature, such as greenness, water content or light use efficiency(Song et al., 2013). Given the similar composition, and therefore spectral signature, of many grassland sites, data at multiple wavelengths allows more robust characterization of grassland speciesand their biophysical parameters. This has been facilitated by the trend in recent years for satellite sensors to record a higher number of carefully selected wavelengths, e.g. the yellow band of Worldview-3is designed to detect ripening or dying plants. The red–edge, where there is a rapid increase in reflectance from the red to NIR reflectance (around 680-730nm), has been shown to have a strong correlation with the grass chlorophyll content of the canopy ($r = 0.93$) and the leaves ($r = 0.86$) (Pinar and Curran, 1996). Inclusion of measurements made in a red-edge channel are thus a reliable indicator of foliar chlorophyll content and vegetation stress (Dawson and Curran, 1998), and are also useful for assessment of plant chlorophyll concentration, leaf area index and therefore nutritional status (Filella and Penuelas, 1994). With the launch of RapidEye, the first high-resolution multispectral satellite system that operationally provides a red edge channel, Schuster et al. (2012) reported a higher classification accuracy for managed grassland typesthan could be achieved without inclusion of measurements at this

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wavelength.Hyperspectral remote sensing data, which record a larger number of wavelength bands, therefore offer the opportunity of defining new vegetation indices that can be tailored to a particular species and/or parameter application(Clevers et al., 2007).

Although increased spectral resolution offers significant benefits to resolving species composition at a single point in time, it is recognised that a time series of imagery acquired through the growing season provides maximum information on yields and management. Phenological stages of grasslands can progress rapidly during the growing season as a function of factors including weather, germination, management strategies, grazing pressure/intensity, hydrological processes and nutrient input.Huang and Geiger (2008)demonstrated that inclusion of grass phenological stages increased the accuracy of mapping grass cover, andButterfield and Malmström (2009)showed that understanding of grassland dynamics could be improved through looking at biomass-NDVI relationships at different phenological stages. An increased temporal frequency of image acquisition is advantageous in countries with cloud-dominated climates where multiple overpasses fail to generate an image of the ground.O'Connor et al. (2012)highlighted the benefits offered by a dense time series of 10-day compositesfor mapping spatial variability in vegetation seasonality in Ireland, with landcover classes separated on the basis of their start of season greening. The benefits of timely imagery are recognised for yield estimation from crops (Morel et al., 2014),and with an increased number of spaceborne sensors available in a constellation, there is an increased potential to acquire more frequent, cloud-free imagery coincident with key stages in the grass growth season.

There is typically an inverse relationship between the frequency of image acquisition and the swath width of the sensor and its spatial resolution, which results in the sensors that acquire daily images doing so at resolutions of 300-1000m. While this may be sufficient for large rangeland areas, it is often too coarse for imaging intensively managed grasslands, and where

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the pasture paddock size is smaller than the sensor resolution cell, inconsistency and discrepancies with in situ data validation arise in averaging and aggregation during up and down scaling for multi sensor data integration (Hill, 2004). Due to the small size of many managed agricultural grassland paddocks, access to high spatial resolution imagery is essential in determining inter- and intra-field variations. Figure 2shows the false color composite of a managed grassland areawhere small-scale differences in growth are more evident in the 2.4m Quickbird image than the 6.5m RapidEye image, and almost impossible to detect in the 30m Landsat–8 scene.

A number of high and very high-resolution sensors have been launched in the last 10 years which enable such intra-field variations to be detected, and when multiple identical instruments are in a constellation a time series of cloud-free imagery can be maintained. However thescale of imaging remains a very complex and dynamic topic in the context of remote sensing, with Wu and Li (2009) and Quattrochi and Goodchild (1997) providing more detailed discussion on this topic.

Microwave remote sensing

The use of optical instruments for vegetation mappingis common practice, with a good understanding of the relationship between reflectance and biophysical information, however it is limited to periods when the target is illuminated by the sun under cloud-free conditions. In recent years there has been a growing interest in the potential offered by microwave spaceborne instruments which measure the strength of the backscattered signal from the surface under almost all weather and light conditions, allowing frequent repeat measurements throughout the growing season. While the number of wavelengths utilized by active microwave instruments is relatively limited, synthetic aperture radar (SAR) instruments offer a number of different acquisition modes, with different polarizations, incidence angles and

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orbital directions (ascending/descending). The backscatter signal from vegetated surfaces is a function of the soil surface, the radar system, and the biophysical parameters of the scatterers in the vegetation that can influence the depth to which the radar wave penetrates. Different theoretical approaches have been developed to interpret the backscatter signal, for example the water cloud model in which the total backscatter signal comprises components from the soil, vegetation and attenuation(Attema and Ulaby, 1978).A number of SAR instruments have been launched during the 21st century that have allowed advancement of microwave remote sensing of vegetation phenology, for example TerraSAR-X, with a very high resolution (up to 1m) X-band sensor, and the COSMO–SkyMed constellation of four X-band platforms which were used by Hajj et al. (2014) to investigate the sensitivity of radar signals to soil moisture and vegetation within irrigated grassland plots. The Japanese ALOS and ALOS-2 L-band instruments, and European Space Agency ASAR and Sentinel–1 C–band platforms have a lower spatial resolution but the longer wavelength can be more sensitive to vegetation volume, as shown by Barrett et al. (2014) in discriminating between grassland types in Ireland. A number of studies have been undertaken to compare the sensitivity of the different wavelengths to vegetation conditions (e.g.Gao et al., 2013; Inoue et al., 2002), with Metz et al. (2012) demonstrating how the most accurate discrimination of European Natura 2000 protected sites and high nature value habitats could be achieved with combined use of a TerraSAR–X and Radarsat–2 time series.In addition to using different wavelengths for different applications, the different polarimetric acquisition capabilities can be exploited e.g. Voormansik et al. (2013) used a TerraSAR–X dual polarimetric SAR time series to detect grassland cutting practices, and Buckley and Smith (2010) used a combination of multi angle Radarsat–2 quad-polarisation images, demonstrating improved grassland classification results when compared to the individual incidence angles.

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However, a number of limitations have constrained the work done in the microwave domain, predominantly the difficulty of distinguishing the signal response associated with vegetation cover from moisture and acquisition conditions. The inherent speckle of SAR imagery also requires processing that reduces the spatial resolution, and thus can lose some of the detail that may be present at the scale at which the image is acquired. To overcome these limitations and derive conclusive results has typically required intensive ground-based measurements (Moran et al., 1997).

Several studies have been carried out to compare the outputs from optical and microwave instruments. Smith and Buckley (2011) did a comparative analysis of Radarsat–2 and Landsat–5 TM for the classification of cultivated crops, summer fallow, improved and native grassland. Even though the classification accuracy for Radarsat–2 (kappa: 0.65) was less than that for Landsat–5 TM (kappa: 0.81), due to the backscattering similarities between native and improved grasslands, it was able to successfully discriminate between the cultivated crops and grasslands. By contrast, in a recent study Dusseux et al. (2014) reported classification results of fully polarimetric Radarsat–2 (98% accuracy) that outperformed the optical imagery (SPOT–5 and Landsat–5 TM, 81% accuracy).

It is apparent that there have been many developments in the use of remote sensing for vegetation monitoring, mapping and management in recent years, with a number of reviews dedicated to specific aspects of agricultural and ecosystem practices (e.g., Atzberger, 2013; Shoshany et al., 2013).In an early review paper, Tappan (1982) highlighted some topics for future research using remote sensing for grassland applications e.g., biomass estimation, instrument calibration and use of high spatial and temporal resolution satellite platforms. To date however, available reviews on grasslands have focused either on a site-specific approach (e.g. Trotter, 2013), or on just classification and mapping of grasslands (Booth and Tueller, 2003; Svoray et al., 2013; Xie et al., 2008). The following review broadens this focus to

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address some of the issues raised by Tappan (1982) on spaceborne remote sensing within grassland environments, and the transition from grassland classification/mapping to grassland management.

REMOTE SENSING OF MANAGED GRASSLANDS AND PASTURES

Classification

The motivation for grassland mapping includes distinguishing different grassland ecologies that may reflect management practices, grassland degradation and estimation of grassland productivity trends over time. Data (and/or derived products) from Landsat TM/MSS, SPOT, AVHRR, MODIS and RapidEye sensors amongst others have been most commonly used for the purpose of land cover classification and land cover change mapping, including grass–based habitats such as rangelands, pastures and meadows. Many of the studies have been undertaken using optical rather than SAR sensors, which reflects their longer history of operation, the importance of the red and NIR bands for vegetation discrimination, and the availability of data at a range of resolutions, including sub–meter for field scale work and 1km for global mapping.

Discriminating between grassland types is usually achieved using either statistical, object-oriented or machine learning classification approaches. The maximum likelihood classification approach was widely used until the 1990s, with typical overall classification accuracies in the range 70–90%.For exampleToivonen and Luoto (2003) mapped grasslands in Finland from Landsat data with an overall accuracy of 89%, although the classification accuracy was as low as 63% for the semi–natural grassland class. Similarly, Jadhav et al. (1993) achieved an overall accuracy for grassland mapping in India of 82%, and Baldi et al. (2006) distinguished South American grasslands with accuracies of 90–95%. While some studies using these statistical classifiers performed very well, in general the complexity of

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grasslands and the spectral similarity of different grassland types limits the value of these approaches. Furthermore, these statistical approaches have a limited capability to determine boundaries between different natural grassland ecologies. Brenner et al. (2012) compared object and pixel classification approaches for classifying Buffel grass in Mexico from satellite imagery, and found that determining objects on the basis of their contiguity allowed for more accurate results. Decision trees permit data from different sources to be included to aid distinguishing between grassland classes and also to preclude some misclassification opportunities, as Dubinin et al. (2010) showed with a multi–sensor approach to assess annual burned areas in the grasslands of southern Russia, and Wang et al. (2010) discriminated between warm and cold season grasslands in the USA from ASTER data with an overall accuracy of 80%. Peña-Barragán et al. (2011) developed a hybrid classification strategy, combining object based image analysis with a decision tree (DT) including information on textural features and phenology, to classify ASTER imagery of California. While some of the 13 classes were very reliably classified with accuracies of 95%, others remained problematic with only a 50% chance of being correctly labelled. A hybrid classification approach was also adopted by Masocha and Skidmore (2011) to map an invasive species in part of southern Zimbabwe. Artificial Neural Network (ANN) and Support Vector Machine (SVM) approaches gave accuracies of 71% and 64% respectively, but after incorporating the information from a GIS expert system the accuracies increased to 83% and 76% respectively. In addition to mapping different grassland ecologies or species, classification approaches have also been used to assess grassland use intensity and to monitor changes over time. Tovar et al. (2013) used object-based classification of Landsat imagery of Peru to analyse trends in land use and land cover from 1987–2007, with an overall accuracy of 80.3%, showing an annual decrease in the spatial extent of the Jalca grasslands of 1.5%.

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Many grassland studies have been conducted at a local scale using high spatial resolution imagery, but the same methods can be applied to a national or regional scale using coarser spaceborne imagery (e.g. MODIS).In a recent study, Nitze et al. (2015) established the value and consistency of a machine learning algorithm for the classification of improved and semi-improved grasslands in Irelandfrom a 9 year MODIS time series of NDVI and enhanced vegetation index(EVI) vegetation indices. In order to optimize the data acquisition period, the importance of different features was considered in this study, with the authors concluding that to achieve an accuracy of more than 90%, only 6-10 images are required per year.

In general, optical sensors have been preferred to SAR sensors for classification of grasslands, exploiting the multispectral information acquired at the shorter wavelengths. For example, Price et al. (2002) conducted a comprehensive study to compare the use of Landsat TM and ERS-2 C–band SAR data in order to discriminate different grassland types under different treatments in eastern Kansas. In this study, Landsat TM and ERS-2 were used to discriminate between the cold and warm season grass species, with discriminant analysis showing that both types can be distinguished, with an accuracy of 90.1% using Landsat TM data, but only 73.2%using ERS-2 SAR data. Three management strategies were also classified, with an accuracy of 70.4% (Landsat TM) and 39.4% (ERS-2 SAR). The last step in this study was the combined use of Landsat TM and ERS-2 SAR data, and it was found that the SAR contribution to the discrimination of the grassland types was statistically significant. In another study,Smith and Buckley (2011) used Radarsat-2 C–band polarimetric SAR data in order to discriminate improved grasslands, native grasslands and agriculture crops, and again Radarsat-2 classification results were less accurate than the Landsat TM (Kappa coefficient: Radarsat-2 = 0.65, Landsat TM = 0.81). Interestingly however, the latest generation of high resolution SAR sensors, such as TerraSAR-Xand ALOS–2, show greater potentialfor information retrieval from grassland pastures at smaller scales, allowing changes

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in surface roughness and moisture, typical of different grassland regimes, to be better detected. Wang et al. (2013) compared satellite imagery from three different SAR (X, C and L-band) sensors and showed that X-band SAR data has the highest correlation with the vegetation indices. Barrett et al. (2014)highlighted the value of machine learning classifiers for discriminating different grassland types using multi–sensor C and L–band SAR data.

In summary, classification of grassland types and formations using satellite remote sensing data has been successfully applied using different classifiers and sensors in different regions of the world.Table 2highlights a number of studies that have been done since 2000 using spaceborne remote sensing data for mapping different aspects of grasslands around the world. The majority of these studies are from optical sensors, emphasising their suitability for vegetation mapping and the availability of high resolution optical data (Franke et al., 2012), as well as a good understanding of the relationships between the data and biophysical plant parameters.

Biomass estimation

Gao (2006) addressed the difficulties and importance of remote sensing based quantification of grassland properties. For example, *(i)*the date of image acquisition and ground truth collection must be the same or very close to each other, *(ii)*samples must be selected randomly, *(iii)*a sufficient number of samples(at least 30) is needed, *(iv)*the use of GPS during ground truth collection so that in situ measurements and corresponding pixels correctly overlie each other, and *(v)* if the grassland is highly dynamic then high temporal resolution satellite time series should be used instead of a single image. Methods for remote sensing of grass yield estimation can be broadly grouped into three strategies: development of yield estimation regression models based on different satellite driven VIs, use of different machine

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learning algorithms (e.g. ANN, SVM), and combined use of remote sensing driven vegetation parameters and biophysical simulation models (e.g. WOFOST, Lingra).

Vegetation index based regression models

Remote sensing of biomass estimation has been undertaken for many years, and numerous studies show a good correlation between in situ measurements and VIs derived from satellite data(e.g. Wylie et al., 1991; Anderson et al., 1993). Boschetti et al. (2007) assessed pasture production in an alpine region using field spectrometry and Landsat-7 imagery, with integration of these data, via regression analysis, supporting assessment of pasture production. Ullah et al. (2012) used MERIS data and analysed different VIs for the estimation of grassland biomass in the northern Netherlands, where NBDI (normalized band depth index (Mutanga and Skidmore, 2004)) produced better results than the more conventional VIs (NDVI, soil—adjusted vegetation index SAVI, and Transformed SAVI (TSAVI)). Xu et al. (2008)tested three different regression modelsusing MODIS derived NDVI and ground measurements of grass yield for the estimation of grass production in China, where more than 8000 samples were collected from 17 grassland dominant provinces and regions, with the best correlation shown for an exponential relationship (linear$r^2 = 0.671$, power$r^2 = 0.794$ and exponential$r^2 = 0.805$). In the north-eastern province of China, Zha et al. (2003) found a high correlation($r^2 = 0.74$) between NDVI, derived from Landsat TM and field spectrometer measurements, and the percentage of grass cover. By contrast, An et al. (2013) used biweekly AVHRR NDVI values to predict above ground net primary production (ANPP) in a tall grass prairie system, but their model, validated by in situ measurements, was less able to predict year-to-year ANPP variations ($r^2 = 0.54$), with the coarse resolution (1 km), and thus the influence of mixed pixels, a possible explanation for this low value of coefficient of determination. As plant phenology is highly influenced by inter-annual changes

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in temperature and precipitation, Lee et al. (2002) investigated the influence of climatic variation on plant phenology in Inner Mongolia by analysing a 9-year (1982-1990) AVHRR NDVI time series and monthly mean temperature and precipitation. However they reported little or no change in phenological response during this period, which could again be attributed to the low spatial resolution of the imagery.

A major challenge in the use of VIs to assess vegetation parameters is to minimize the influence of external factors and to maximize the sensitivity of the relationship between VIs and biophysical parameters. Many authors have tried to find the most suitable subset of VIs (e.g. those for best estimation of biomass for a particular type of vegetation), with some advocating a move away from the index-based approach. Even though many researchers have established significant relationships between VIs and vegetation parameters in the context of a single study, many such models are site or season specific, and the successful transferability from one site to another is variable. Based on the combined use of field spectroradiometer data and satellite driven indices, Boschetti et al. (2007) concluded that log-transformed regression analysis between soil-adjusted VIs and fresh biomass show higher correlation than aratio vegetation index or NDVI. Likewise,Ullah et al. (2012) showed that band depth analysis outperformed the use of traditional VIs when they modelled vegetation parameters and spectral values by simple linear regression and stepwise multiple linear regression (MLR), and continuum removed spectra—normalized reflectance spectra used to compare individual absorption features—were used to calculate band depth parameters.

Table 3 presents a summary of several studies conducted since 1990 on grass yield estimation derived using vegetation index based approaches, with many of the better results achieved at a local to regional scale.

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Machine learning models

ArtificialNeural Network (ANN) models belong to a powerful class of empirical modelling with the capability of computing, predicting and classifying data, and are more versatile than linear regression models. The use of machine learning algorithms for estimating crop yields e.g. corn (Panda et al., 2010; Serele et al., 2000) and rice (Ji et al., 2007) has been widely reported, however only a limited number of studies have been described for their application to estimation of grassland above-ground biomass (dry matter)(Ali et al., 2015, 2014). Xie et al. (2009) compared the performance of ANN and MLR for above-ground grassland biomass in the Xilingol River Basin, Inner Mongolia. Topographic, vegetation index and spectral information from Landsat ETM+ were used as input data, with ANN generating a better yield estimation than the MLR ($r^2 = 0.817$, $RMSE = 42.36\%$ compared to $r^2 = 0.591$, $RMSE = 53.20\%$). In another study,Yang et al. (2012) used a back propagation ANN algorithm for grassland yield estimation based on five VIs derived from MODIS satellite data, with NDVI and SAVI showing the best fit with the in situ sample biomass. Once again, the ANN models were more accurate ($R^2 = 0.56–0.71$) than the statistical models ($R^2 = 0.54–0.68$).

Mountrakis et al. (2011) comprehensively reviewed the application of SVM in satellite remote sensingapplications but itsuse for biomass estimation is not discussed. A limited number ofstudies have applied SVM to biomass assessment from satellite imagery (e.g. Jachowski et al. (2013), for mangrove ecosystems), but there is no reference to it being used for grassland biomass. Thepotential of SVM forgrassland biomass estimation was established by Clevers et al. (2007) with a band shaving algorithm to identify highly correlated bands inairborne hyperspectral data and thus develop the most predictive band ratio. With the development of new hyperspectral satellite instruments, the potential for powerful species and site specific indices will be enhanced.

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Simulation models

For indirect vegetation biomass estimation, simulation modelling techniques are used, whereby remote sensing data are used as an input variable or substitute for vegetation parameters. In order to better understand the growth mechanism and spatial variability of grasslands, meteorological data driven models have been used to simulate and predict the grassgrowth rates (Barrett et al., 2005; Bouman et al., 1996; Moore et al., 1997; Woodward, 2001). The precision of these models heavily depends on their ability to incorporate multisource data over different spatial scales for yield estimation(Hansen and Jones, 2000). Some authors (Brilli et al., 2013; Maselli et al., 2013, 2006)have explored the potential application of the parametric model C-Fix, a Monteith type parametric model driven by temperature, radiation and fraction of Absorbed Photosynthetically Active Radiation (fAPAR), for the estimation of gross primary productivity of grasslands, olive groves and forests in Italy. Parameters derived from satellite data and ground measurements are combined in order to simulate the total production. Maselli et al. (2013) compared the efficiency of C-Fix and the BIOME-BGC biogeochemical model for grassland productivity, demonstrating that the parametric model performed better, with a root mean square error of 49.7 gDM $m^{-2}y^{-1}$ compared to 85.4 gDM $m^{-2}y^{-1}$for the BIOME-BGC model.

In summary, regression models based on VIs have predominantly been used for grass yield estimation. Machine learning algorithms are proving to be powerful tools for grassland classification, but still need to be further developed for grass yield estimation (Mountrakis et al., 2011).The fusion of multi-source data into biophysical simulation models also requires further research in order to better exploit their suitability and transferability.

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Grazing management

Grazing impacts

Degradation in grasslands and rangelands is a very complex and dynamic phenomenon caused by natural and anthropogenic activities (Paudel and Andersen, 2010) which can be assessed at a small scale by an expert opinion or visual evaluation, however, for national or global scale evaluationthe use of remote sensing technology is a more feasible approach.Tueller (1989) first described the application of aerial photography and satellite imageryto support management of rangeland resources, but the quality and quantity of satellite imagery available at the time proved a limiting factor. Tueller did however predict that within 20 years the majority of required management information would be available from satellite imagery, a prediction realised by Munyati and Makgale (2009) who used a time series of Landsat TM imagery to map and quantify degraded rangeland in South African communal grazing lands.Pickup et al. (1994) first used satellite data for the assessment of land degradation by combining image derived vegetation cover index values and spatial models of grazing density determined as a function of distance from a watering point.Trends in rangeland degradation (Pickup et al., 1998) were also identified from imagery,with a vegetation cover model built from multi-temporal remote sensing data in order to distinguish between natural and human impacts on degradation. With a longer time series of Landsat data to derive locations of persistent ground cover, Bastin et al. (2012) demonstrated that it is also possible to discriminate between natural and human induced grazing effects on ground cover in Queensland. Other studies have also exploitedmulti-temporal datasets for degradation assessment (Paudel and Andersen, 2010),mapping and quantification of degraded areas at different scales (Alves Aguiar et al., 2010), and in combination with GIS technologiesto investigate changes in grassland cover(Zheng et al., 2011).

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Remote sensing technology is not only useful for the identification of degraded areas, but also for mapping, monitoring and quantifying restoration of such degraded land after the implementation of corrective measures. A ban on grazing was imposed in Ningxia province of China in 2003 to decrease degradation, and in a recent studyLi et al. (2013) used Landsat imagesto map the positive outcomes of this ban, with 59.41% restoration reported between 1993 and 2011. Huang et al. (2013) also successfully demonstrated how such techniques could be used to effectively evaluate trends in degradation after the implementation of restoration programs using AVHRR (1982–2003) and MODIS (2000–2008) remote sensing images.

In summary, remotely sensed imagery has been successfully used for detecting degradation and recovery of grassland areas. More research is needed to fully explore the data from newly launched high resolution SAR sensors because in degraded areas grass cover is sparse with open soil, and more work is required in order to better understand the backscatter response from such sites.

Assessment of grazing capacity and intensity

Grazing management strategies are directly linked to factors including grazing intensity, length of grazing period, grazing regimes, stocking rate and elevation(Bradley and O'Sullivan, 2011; Vermeire et al., 2008; Volesky et al., 2004), and vary from area to area in order to meet livestock grazing management goals. Grazing intensity has the most influence on grassland productivity, and overgrazing can cause grassland degradation (Boddey et al., 2004) with some studies showing that light to moderate grazing intensity practices can enhance grassland productivity under certain environmental conditions (Luo et al., 2012). Remote sensing approaches can be used to monitor livestock grazing (Feng and Zhao, 2011) at light to moderate intensity(Xiaohui Yang et al., 2012; Yang and Guo, 2011).Kawamura et

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al. (2005b) used NDVI derived from remote sensingdata for the quantification($R^2 = 0.77-0.83$) of grazing distribution in Inner Mongolian grasslands. In another study, Numata et al. (2007) used Landsat TM data in order to analyse the impact of grazing intensity on a pasture's biophysical features, with remotely sensed non–photosynthetic vegetation showing the highest correlation with grazing intensity ($r^2 = 0.70$) compared to the other measured biophysical features e.g.above ground biomass, canopy height and water content.

Consistent and frequent monitoring ofthe effects of grazingintensity is crucial in arid, semi–arid and commercial grazing pasture areas, as grazing intensity influences the grassland ecosystem(Röder et al., 2008) both in a positive and a negative manner. An example of apositive influence is given by Cohen et al. (2013) for a high latitude, intensively grazed area, where late snow melt means the surface is protected from heating for longer, and, as snow has a high albedo, it can easily be analysed from image data. Studies show that at high latitudes where the vegetation is tall, dense snow melts earlier (Loranty et al., 2011; Marsh et al., 2010) compared to the short vegetation. In response to Hein's (2006), findings Retzer (2006) reported that high resilience after drought may be due to the precipitation dynamics not because of high intensity grazing as suggested by Hein (2006).

Careful consideration of sampling scale is very important in remote sensing studies, and needs to be determined according to the application. Yang et al. (2011)tested the significance of measured biophysical parameters (canopy cover, height and LAI) to find the difference between grazed and ungrazed sites,where for canopy height, and ratio of photosynthetically active and non-active vegetation cover,the difference was significant. Among the various spectral vegetation indices,red and NIR based measures showed the most significant correlation with canopy height. This analysis was based on single dates and suggests the use of multitemporal remote sensingdata for evaluating pre and post-grazing vegetation

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conditions. A combination of remote sensingand GIS models can be used for the evaluation and classification of study sites based on their suitabilityfor grazing (Bozkurt et al., 2011).

In grassland management and the livestock business, grazing capacity and intensity are the key factors that need to be monitored consistently in order to optimize the feeding resources. Information extracted from satellite remote sensing has been shown to be useful forestimatinggrazing capacity—the maximum number of animals that can be sustained in a given area of pasture in a year—and intensity, which is required for nutritional planning of livestock. For the assessment of short–term grazing capacity at paddock level, Phillips et al. (2009) developed a model based on remote sensing and ground-based data on cattle nutrition. They observed the underestimation of grazing capacity by the model and suggest additional testing of the model and at multiple sites. Along with additional testing at multiple sites, use of very high resolution data (e.g.GeoEye–2: 1.35m, WorldView–3: 1.24m) might be valuable to correct this anomaly. Wu et al. (1996) proposed a physical model for simulating productivity in grazing ecosystems, withBénié et al. (2005)developing the model further to include remote sensing and socio-economic parameters in order to simulate the available biomass or carrying capacitywith an accuracy of 80%. The use of remote sensing data becomes a challenge in applications where the underlying target area is composed of sparse vegetation and highly reflective soil. In order to overcome this problem,Edwards et al. (1999) proposed a geometric optical model based on low resolution satellite imagery whose output is a series of change maps that can be used to estimate the final vegetation cover. A very high correlation between observed and estimated vegetation cover was reported ($r^2 = 0.837$), but even though the approach was quite useful no further applications of this approach can be found. Similarly, no reference to SAR data for assessment of grazing capacity and intensity is evident in the literature.

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In summary, identification of grazing capacity and intensity is required in order to avoid overgrazing and degradation, but there is a very fine distinction between normal grazing and overgrazing, and in order to better understand this transition the use of very high resolution optical data, SAR data, and a combination of both needs further investigation.

Pasture quality and status

Grazing capacity depends not only on the grassland spatial extent but also on the quality of grass, which is directly linked to livestock feeding. While the potential of remote sensing based classification and mapping of grassland quality has been long recognized (Giraed et al., 1990), only a limited number of studies have been done on grassland quality assessment using this approach. The range of data used varies between coarse (Kawamura et al., 2005b; Si et al., 2012), medium (Kawamura et al., 2005b) and high (Guo et al., 2005; Si et al., 2012) spatial resolution. Studies show that the leaf area index (LAI) is considered as more appropriate for the assessment of grassland health, biomass and plant water content than the satellite derived NDVI (Guo et al., 2005). In a recent study, Falldorf et al. (2014) developed a remote sensing based tool called the Lichen Volume Estimator (LVE) to assess winter pasture quality (in terms of volume) by using a 2D Gaussian regression model based on a Normalized Difference Lichen Index (NDLI = MIR-NIR/MIR+NIR) and Normalized Difference Moisture Index (NDMI = NIR-MIR/NIR+MIR). The authors concluded that LVE could become an important tool to assist in prediction of winter grazing areas for reindeer and caribou herds at one location, and with further field studies it could become more widely applicable. Multispectral remote sensing data has also been used in combination with in situ data (Zerger et al., 2011) and models such as the radiative transfer model PROSAIL(Quan et al., 2015; Si et al., 2012) for the assessment of vegetation/grassland condition and quality. The inversion(Si et al., 2012) of the PROSAIL model and MERIS reflectance data (single

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biome approach) has great potential to estimate the grassland LAI ($R^2 = 0.70$) and canopy chlorophyll content ($R^2 = 0.61$). Hill (2013) simulated ESA Sentinel-2 (high resolution optical sensor) data and showed that VIs based on these bands can be used for the identification of vegetation states in grassland and savannas.

In summary, pasture quality and status are directly related to grassland management. Detailed investigations on the use of hyperspectral remote sensing data are required, and to exploit the large number of bands different VIs at different wavelengths can be calculated in order to retrieve multiple vegetation parameters.

Pasture growth rate assessment

To meet the increasing demand for food, optimisation of agricultural production and effective resource management are critical. Precision agriculture involves real or near real-time data collection about the physical and/or chemical properties of the target vegetation in order to assist decision making through the use of predictive tools and forecasting models. For satellite based precision agriculture, the spatial resolution, satellite revisit frequency and number of spectral bands are the key factors that are related to the acquisition of a dense time series for consistent monitoring at a farm or paddock scale. Much of the work done to date on this subject has been focused on croplands using field spectrometry (Gutiérrez et al., 2008; Prabhakar et al., 2011; Zhang et al., 2003), airborne imagery(Epinat et al., 2001; Erives and Fitzgerald, 2005) and satellite data (De Benedetto et al., 2013; López-Lozano et al., 2010; Nahry et al., 2011; Thenkabail, 2003), and it is only very recently that grassland management and precision farming has been considered. The "*Pastures From Space*[1]"project in Australia is one of the most prominent, and has developed a dedicated grassland/pastures tool to deliver near real-time information (e.g. biomass, growth rate) at the farm and paddock level using

[1]http://www.pasturesfromspace.csiro.au

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high and medium resolution satellite remote sensing(Donald et al., 2004; Edirisinghe et al., 2011; Henry et al., 2004). The techniques were developed and validated in Western Australia over a five year period, and then transferred and verified in Southern Australia, and the project is providing online (web and also software based) pasture growth rate at weekly regional and paddock scales. Schellberg et al. (2008) wrote a detailed review focusing on precision agriculture of grasslands, in which they discuss the applications of different remote sensingtechniques for the monitoring of physical, chemical and area-based grassland properties for farm related decision-making.

Pasture growth rate is a biophysical property (monitored as kg dry matter/ha per day) which is related to how much grass grows on a daily basis and is an important driving factor for feed budgeting related decisions. Apart from management practices, climatic factors also influence the growth rate of grasses (Thorvaldsson et al., 2004). There is no precipitation component in the C-Fix model (as discussed in section 3.2.3) but the Australian *"Pastures From Space"* model differs by including precipitation as well aslight use efficiency (LUE) models (Hill et al., 2004; Piñeiro et al., 2006a), data integration (Hill et al., 1996; Moore et al., 1999) and classification (Vickery et al., 1997)tools for growth rate prediction (Donald et al., 2010), monitoring and mapping.Multisource (e.g., Landsat, SPOT, MODIS, AVHRR, Hyperion) remote sensing data with different spatial resolutions were used to successfully assess the growth rate at different spatial scales(Donald et al., 2004; Henry et al., 2004).

"Pastures From Space" is an effective tool for near real–time monitoring at farm and paddock level in order to better manage the feed resources for livestock industries, but currently represents the only operational system designed specifically for pastures. Schellberg and Verbruggen (2014) discuss the delay in transferring techniques developed for arable land to grassland,although there is scope for the successful implementation of emerging technologies such as precision agriculture in a variety of environments. After the successful

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implementation and validation of the*"Pastures From Space"* project, in2003 Fonterra[2] formed a partnership with CSIRO in order to explore its potential in New Zealand dairy farming and pasture monitoring, and various studies have been done since then (Ausseil et al., 2011; Dymond et al., 2006; Edirisinghe et al., 2012; Mata et al., 2010).

In summary, both airborne and spaceborne remote sensing data are being used to collect real time (or near real time) information on pasture yields and growth rates. Based on satellite remote sensing data, decision support systems can be developed for farm related management decisions.

Transhumance

In mountainous regions there is an annual cycle of livestock migration to the higher elevation pastures in warm seasons and return to lower altitudes for the rest of the year, with a concurrent cycle of high grazing intensity and pressure. Such transhumance, or herd mobility, is one of the key components for sustainable use of these upland resources (Sitters et al., 2009) that are highly sensitive to environmental changes, and for that reason it is essential to monitor their land cover dynamics (Morán-Ordóñez et al., 2011). Satellite imagery has considerable potential to detect and map land use,their corresponding effects on livestock feed resources and feed deficit management strategies (Mekasha et al., 2014). Butt et al. (2011) used a MODIS NDVI time series from 2000–2010 in order to evaluate the gradient of rangeland phenology with respect to the changing latitude and its effects on the direction and timing of livestock movement in the Sudano–Sahelian region in West Africa. A double logistic function was adapted to fit the NDVI trajectories drived from 1Km resolution MODIS data, and a strong dependency of vegetation phenology on altitude was found. In another study Sulieman and Elagib (2012) used multitemporal remote sensingdata to map the

[2]http://www.fonterra.com/global/en

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effects of climate, land use and land cover changes along three different livestock seasonal migration routes in eastern Sudan. A major conversion from natural vegetation cover to agricultural land is reported along with the significant increase in climate warming (based on 68 years (1941–2009) of climate date e.g., temperature, rainfall and aridity index). Dedicated efforts are being made to fully detect and map the transhumance corridors using both remote sensing and geospatial analysis approaches (Trans, 2014).

In summary, the potential of remote sensing to trace corridors of seasonal movement of herds has been established. More work needs to be done in order to exploit the use of high resolution optical and radar imagery in order to fully uncover the impact of these seasonal movements on vegetation phenology.

Remote sensing of nature conservation grassland sites

For the maintenance of biodiversity in Europe, the European Union has legislated a legal policy framework that includes the Habitats and Birds Directives (EEC, 1997, 1979) which describe the types of habitat (e.g. grassland, forest or meadow types) whose existence is in danger (Natura 2000) and needs to be preserved by the member states (Ali et al., 2013). Since the implementation of these directives,mapping, reporting and monitoring on the status of nature conservation sites has been a key research topic. Over time remote sensingmethodologies and techniques have become more sophisticated, especially for synoptic data acquisition, and are now being successfully used for fast, reliable and consistent mappingof habitats and species(Nagendra, 2001; Nagendra and Gadgil, 1999). Most conservation sites, including grasslands, are small in size, therefore very high-resolution imagery is required to monitor them, and some of the very high-resolution spaceborne instruments with a short revisit time of a few days, launched within the last decade have been proven suitable for this application(Schuster et al., 2015).

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The nature conservation sites are monitored using both multispectral optical and SAR imagery, and increasingly a combination of both. Optical sensors have a long legacy of use in identification of location and changes in habitats (Velazquez et al., 2008), knowledge and object based classification mapping of Natura 2000 species (Förster et al., 2008, 2012) and for assessingclimatic influences on Natura 2000 habitats (Förster et al., 2014). Multi-temporal high resolution RapidEye data have proven particularly useful in deriving phenological vegetation dynamics from time series imagery, where at least three acquisition dates within a year are available (Franke et al., 2012). Since the launch of the very high-resolution TerraSAR-X and COSMO-SkyMed SAR sensors, protected sites can also be monitored using radar imagery, with recent studies by Ali et al. (2013) and Schuster et al. (2011) demonstrating the potential of both sensors for successfully identifying grassland management practices in protected sites. Although the combined use of SAR and optical data has not yet been explored in detail, Ali et al. (2013) highlighted the potential use of both data sources for cross validation.

Vanden Borre et al. (2011a, 2011b) conducted a detailed review of the legal requirements for Natura 2000 habitat monitoring requirements and practices, and how remote sensingis being used to fulfil this task. In order to enhance the utilization of remote sensing technology, field experts and conservation site managers suggested that the prime focus must be on data standardisation, development of user-friendly products, method validation and knowledge sharing. Since their review, work has been ongoing to resolve these issues, for example, Schröder et al. (2013) stress the need for pre-validation of Earth observation products for Natura 2000 sites before delivery. On the other hand, Nieland et al. (2012) are working on an ontological approach for the integration of classification methodologies in order to overcome the issues of scale and the transferability of methodologies. While these studies address all conservation sites, the challenges raised apply equally to grasslands, and the need for

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common data standards and methods, and accessible products for a range of end-users are of relevance to all aspects of grassland management.

In summary, the applicability of multispectral and multitemporal remote sensing data for both monitoring and mapping of grassland conservation sites has been demonstrated. More research is required to overcome the limitations of site specific methodologies (Schuster et al., 2011) in order to make them more robust and standardised. These sites are typically small in size, so high resolution hyperspectral remote sensing data can be used to better explore species compositions. Application of SAR data in cloudy conditions is equally feasible as demonstrated by Ali et al. (2013).

OPERATIONAL AND TECHNICAL CHALLENGES

Overall in the domain of remote sensing the research focus for classification and retrieval of biophysical parameters is now shifting towards the application of machine learning algorithms.Object-based image classification presents a paradigm shift to gain a new perspective on image classification and better follow the boundaries of natural vegetation elements. In object-based classification, segmentation scale and classification accuracy are strongly linked(Liu and Xia, 2010), and careful selection of segmentation scale is required. Machine learning strategies are becoming more widely used within the remote sensing community, and methods like random forest and extremely randomized treesare now widely evident in the literature(Barrett et al., 2014). In future,approachessuch as deep learning and data assimilation will provide more insight into the integration of multisource remote sensing data for complex and dynamic environmental systems. These methods are based on supervised learning, and thus training data are required for classification and parameter retrieval applications. Machine learning algorithms are data driven and their performance is highly influenced by the number of features, sample size and data pre-processing steps. Until

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recently it was a challenge to build a sufficiently long time series for machine learning applications,especially for multi-temporal analysis. For example remote sensing data from Landsat and MODIS are available for longer periods of time, but in situ or inventory data are available only for selected sites, which limits the national or global scale evaluation using these methods.

Until recently, optical sensors were considered the best data source for mapping and monitoring small-scale variations within and among the fields due to their high spatial and spectral resolution.However, following the launch of high-resolution microwave radar remote sensing satellites (e.g., TerraSAR-X, COSMO-SkyMed, Radarsat, Sentinel-1) the application domain of radar sensors has widened. For example the TerraSAR-X Staring Spotlight acquisition mode can acquire images with a spatial resolution of up to 0.25m every 11 days. Achieving this high resolution from space can further support precision agriculture developments, especially for areas under persistent cloud cover.

High-resolution radar remote sensing data with an improved temporal resolution will help to monitor crop health and will provide a mechanism for timely crop yield estimation, while in case of grasslands it can be used for monitoring grassland management practices as shown in Figure 3. Spatial resolution is a crucial component in remote sensing applications, especially for quantitative scientific analysis, and as Figure 3 demonstrates inter and intra paddock/field variations can be detected using radar data, highlighting different agricultural states. Using high-resolution sensors(e.g., TerraSAR-X, Radarsat, COSMO-SkyMed) it is possible to detect many management related activities for example grazing herds, hedges and cultivation. It is also possible to trace the identify poorly performing patches of the field using multi-temporal acquisitions,but the major challenge and limitation remains inthe high data acquisition cost of the highest spatial resolution sensors, and their small area coverage. Currently most of the radar remote sensing sensors (with some exceptions) are single or dual

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channel, and polarisation limited to two directions, but as the technology matures further future radar sensors will potentially provide additional information for more reliable methods for agricultural monitoring.

Thus, for both optical and radar remote sensing the major limitation is the compromise between spatial resolution and spatial coverage. For example TerraSAR-X Staring Spotlight mode has the highest illumination time and spatial resolution (up to 0.25m) but the smallest swath size (4Km (width) x 3.7Km (length)), compared to the Spotlight mode (spatial resolution up to 2m: 10km (width) x 10km (length)),Asimilar comparison is true for WorldView and MODIS, where high spatial resolution is achieved at the cost of swath size.

Farmers in every region follow different management strategies i.e., amount of fertilizer, use of pesticides, grazing season length, and measuring units (kg/tonne dry matter per hectare, kg/tonne dry matter per acre). With this diversification in management practices there are challenges in building a robust and transferable classification and reporting scheme (Figure 4 gives an over of different remote sensing techniques their potential scope and limitations). In future, as more sensors are launched it is important for the community to develop a uniform standardized and transferable approach for monitoring farms at different geographical scales. For the transferability of methods it is very important to have a uniform input dataset, and one potential solution for this could be the development of a new ontology based data collection and standardization framework asundertaken by the biology community(Bard and Rhee, 2004).Additionally, the remote sensing community must continue to advocate the launch of follow-up missions of imaging satellites in order to ensure long term consistent monitoring.

There is a need to train and educate the end users (farmers, land manages and policy makers) about the potential applications of satellite remote sensing, and with standardised methods this is more achievable. Current technical and scientific deliverables (e.g. project reports,

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scientific publications) output from many research projects further discourage communication between the data providers and end users. One option could be forscientiststo develop more portable (i.e., WebGIS) and accessible (mobile apps) solutions, which are readily available to the end users (e.g., PastureFromSpace Australian project). The benefits offered by remote sensing scientists working with those in the agricultural community will not only help to generate more business, but also to widen the scope and application domain that can be achieved through the use of imaging satellites.

DISCUSSION AND FUTURE PROSPECTS

In conclusion, grasslands are one of the most widespread landcover types found globally, and they need to be monitored at multiple scales (gobal, regional, national, paddock) depending on the nature of the information required.Given the small–scale coverage of traditional ground–based methods of grassland monitoring, satellite remote sensing approaches are likely to be a significant contributor to future operational studies. Different sensor specifications are required depending on the application scale, for example, for global scale applications a sensor with large spatial coverage and coarse resolution (i.e., MODIS, AVHRR) would be sufficient.In the case of managed grassland related applications (at paddock scale) sensorswith high spatial and temporal (GeoEye: 1.35m, 3 days; RapidEye: 6.5m, 5.5 days; QuickBird: 2.4m, 1–3.5 days) resolution are the preferred choice. During the growing season temporal resolution is very important and plays a critical role in near real-time monitoringof phenological stages, and when combined with very high spatial resolution imagery,inter- and intra-field variations can be detected.Thus, despite some instrument biases (Yang et al., 2013) satellite sensors currently present the best option for long term, large scale, objective and repeatable studies.

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Optical sensors are more appropriate for grass monitoring and mapping compared to radar data (Price et al., 2002; Smith and Buckley, 2011) at present, given the difficulty in relating radar backscatter to grassland properties(Hajj et al., 2014), but this may change with the advent of very high resolution fully polarimetric SAR sensors. Different VIs derived from optical remote sensing data correlate well with different vegetation biophysical parameters, but the biggest challenge to the use of optical imagery is cloud contamination and atmospheric noise. Data cleaning, by filtering or use of a cloud mask to remove noisy pixels is widely undertaken, but is very sensor specific and location dependent. The conservation of image information and removal of noisy signals is complex, and in order to construct a long time series of reliable values the most commonly used approaches are time-series composites and the integration of multi-sensor data. However, this latter approach is hindered by variable instrument biases, spectral response signals and spatial resolutions. Poorly designed data fusion algorithms that assimilate different datasets might also result in high uncertainty in the final output. On the other hand, modelling approaches driven by satellite remote sensing have proven to be a robust method for deriving grassland information, but the availability of high quality validation data to accurately calibrate the model can be a limiting factor as it requires a collection of sufficient high quality validation samples at large scales both expensive and laborious. Careful selection of sensors (especially in terms of spatial and temporal resolution) for data acquisition is also very important, for example frequently acquired and freely available hypertemporal remote sensing data (e.g. MODIS) are widely used to generate time composites and thus overcome cloud contamination issues, but they cannot be applied for field level mapping and monitoring in many countries due to the coarse resolution whereby the pixel size is greater than field size.

To achieve the maximum benefit from satellite remote sensing for grassland related activities a number of issues have been identified.

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Classification is a classical application of satellite images, and currently the focus is shifting from statistical to machine learning approaches, due to their ability to better identify the relative importance of different inputs as well as learn from repeated use. Classification of grassland types and formations using satellite remote sensing data has been tested by using different classifiers and sensors in different regions of the world. In addition to local, regional and national scales, an acceptable classification accuracy using medium resolution (Landsat TM/ETM+) data has been achieved at the global scale (Gong et al., 2013), however such an approach is very data and computationally intensive. Individually machine learning and object based classification methods perform very well but, in future, these two approaches may be further integrated to exploit the benefits of each, for example a random forest random field $(RF)^2$classifier (Payet and Todorovic, 2010).The literature suggests that random forest and extremely randomized trees classifiers have the best potential and offer improved classification results for grassland identification, but further work on these methods is needed to validate new high resolution optical and SAR data and explore the transferability of these methods.

Maximum separabilityofspectrally similar classes, such as different grassland types, can be achieved with a larger number of narrowband images,but currently the scope of spaceborne hyperspectral remote sensing is very limited due the fact that Hyperion is the only operational satellite. More detailed analysis is still to be done on the potential for grassland mapping and monitoring from spaceborne hyperspectral data, but this is unlikely to progress prior to the launch of EnMAP which has 244 spectral bands (scheduled for 2017). The use of hyperspectral data for grassland classification using machine learning classifiers has not been fully explored but studies using airborne hyperspectral remote sensing data (Chan and Paelinckx, 2008; Yang and Everitt, 2010; Darvishzadeh et al., 2011) suggest the potential and feasibility of the application of spaceborne hyperspectral remote sensing data for grassland

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mapping. In future this might result in a paradigm shift in sensor development from multispectral to hyperspectral constellations.

The advantage of using fully polarimetric SAR data over dual and single polarizations in terms of improvement in classification performance is well established (Lee et al., 2001). The inconsistencies reported in the literature (Dusseux et al., 2014; Smith and Buckley, 2011) indicate that SAR polarimetry applications to grasslands still require more detailed investigation as an understanding of SAR polarimetry theory matures and the availability of spaceborne fully polarimetric data increases. In coming years, especially after the launch of SAOCOM–1/2 (an Argentinian constellation of two L-band SAR sensors scheduled for launch in 2015) and the RADARSATConstellation mission (three Canadian C-band SAR sensors, scheduled for launch in 2018), a better understanding of the potential for fully polarimetric SAR data to analyse the back scattering behaviour of different habitat types at different polarizations will be possible.As a result, a more reliable delivery of grassland products in cloudy regions should be possible.

The application of very high resolution data for remote sensing based precision agriculture approaches to grassland is now evolving to the same level of maturity as experienced by arable agriculture. As more very high-resolution sensors are launchedand work is done on data standarisation more reliable operational satellite based grassland management tools are expected. Furthermore, operational tools that are simple to understand and operate for non–experts, such as websites or mobile applications that retrieve information from a dedicated data center server could become a more common practice across precision agriculture for all land cover types.

Much of the research that has been done on grasslands has exploited multi-temporal datasets, with relatively few long term studies done except those which could exploit information content from Landsat or MODIS datasets. Additionally, hypertemporal time series that are

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optimised to minimise the computational load,can enhance grassland classification, especially where there are rapid or distinctive phenological changes through the growing season. To have a consistent time series of data over many years to track long term changes in land cover, and especially for operational purposes, a commitment to continuity missions is required.MODIS is providing free data at different spatial scales for more than a decade. Suomi National Polar-orbiting Partnership (NPP) equipped with five sensors including Visible Infrared Imaging Radiometer Suite (VIIRS) was launched in 2011. Spacecraft orbits the Earth 14 times a day. VIIRS has the spatial resolution of 375m and 750m for Imagery and Moderate resolution bands respectively. NPP VIIRS data will be used to expand upon the MODIS applications to land, ocean and air quality. The VIIRS data will also be freely available to the public unlike Rapideye and Quickbird hyper-spatial data, which is not easily accessible and are expensive for developing countries and large scale applications. Sentinel-2 will also provide a comparable dataset to the Landsat and SPOT missions in the optical part of the spectrum, and at radar wavelengths Sentinel–1 will provide C–band SAR data following ERS1/2 and ENVISAT ASAR, and a TerraSAR-X2 launch is planned in 2016 as a follow–up mission of TerraSAR-X (Janoth et al., 2012).

Despite the complexity of grassland ecosystems, this review has demonstrated that satellite remote sensing technologies have been proven as effective tools for monitoring, mapping and quantifying different grassland types and biophysical parameters. Use of optical remote sensing data is the most prevalent in the literature, while the use of SAR or a combination of SAR and optical data has been less widely reported, although this will increase as more SAR missions become operational in the coming years.

SUMMARY

To conclude this review paper:

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Satellite remote sensing can be used for the retrieval of grassland biophysical parameters, including biomass, quality, growth, land cover, degradation, grazing capacity, as well as mapping and monitoring for conservation and management.

Optical sensors have been most widely used given the good understanding between reflectance and vegetation properties and the difficulty in relating radar backscatter to grassland biophysical properties, but this may change with the advent of very high-resolution fully polarimetric SAR sensors.

The use of hyperspectral data for grassland classification using machine learning classifiers has not been fully explored but studies using airborne hyperspectral remote sensing data suggest the potential and feasibility of the application of spaceborne hyperspectral remote sensing data for grassland mapping, and with future hyperspectral sensors this potential may be realised.

The application of very high-resolution data for remote sensing based precision agriculture approaches to grassland is now evolving to the same level of maturity as experienced by arable agriculture, but more work needs to be done on communicating the benefits and opportunities of space to the farming community.

Hypertemporal time series that are optimized to minimize the computational load, can enhance grassland classification, especially where there are rapid or distinctive phenological changes through the growing season

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Reference:

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, in: Geoscience and Remote Sensing Symposium (IGARSS), 2014 IEEE International. Presented at the Geoscience and Remote Sensing Symposium (IGARSS), 2014 IEEE International, pp. 5060–5063. doi:10.1109/IGARSS.2014.6947634

Ali, I., Greifeneder, F., Stamenkovic, J., Neumann, M., Notarnicola, C., 2015. Review of Machine Learning Approaches for Biomass and Soil Moisture Retrievals from Remote Sensing Data. Remote Sens. 7, 16398–16421. doi:10.3390/rs71215841

Ali, I., Schuster, C., Zebisch, M., Forster, M., Kleinschmit, B., Notarnicola, C., 2013. First Results of Monitoring Nature Conservation Sites in Alpine Region by Using Very High Resolution (VHR) X-Band SAR Data. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 6, 2265–2274. doi:10.1109/JSTARS.2013.2241735

Alves Aguiar, D., Adami, M., Fernando Silva, W., Rudorff, B.F.T., Mello, M.P., dos Santos Vila da Silva, J., 2010. Modis time series to assess pasture land, in: Geoscience and Remote Sensing Symposium (IGARSS), 2010 IEEE International. Presented at the Geoscience and Remote Sensing Symposium (IGARSS), 2010 IEEE International, pp. 2123–2126. doi:10.1109/IGARSS.2010.5649388

Anderson, G.., Hanson, J.., Haas, R.., 1993. Evaluating landsat thematic mapper derived vegetation indices for estimating above-ground biomass on semiarid rangelands. Remote Sens. Environ. 45, 165–175. doi:10.1016/0034-4257(93)90040-5

Anderson, J.M., 1991. The Effects of Climate Change on Decomposition Processes in Grassland and Coniferous Forests. Ecol. Appl. 1, 326–347. doi:10.2307/1941761

Downloaded from http://jpe.oxfordjournals.org/ at University College Cork on April 9, 2016

An, N., Price, K.P., Blair, J.M., 2013. Estimating above-ground net primary productivity of the tallgrass prairie ecosystem of the Central Great Plains using AVHRR NDVI. Int. J. Remote Sens. 34, 3717–3735. doi:10.1080/01431161.2012.757376

Attema, E.P.W., Ulaby, F.T., 1978. Vegetation modeled as a water cloud. Radio Sci. 13, 357–364. doi:10.1029/RS013i002p00357

Atzberger, C., 2013. Advances in Remote Sensing of Agriculture: Context Description, Existing Operational Monitoring Systems and Major Information Needs. Remote Sens. 5, 949–981. doi:10.3390/rs5020949

Ausseil, A.-G., Dymond, J., Dynes, R., Shepherd, R., DeVantier, B., Sutherland, A., 2011. Estimating pasture quality using Landsat ETM+: application for the greenhouse gas inventory of New Zealand. Presented at the International Symposium on Remote Sensing for the Environment, Sydney, Australia.

Baldi, G., Guerschman, J.P., Paruelo, J.M., 2006. Characterizing fragmentation in temperate South America grasslands. Agric. Ecosyst. Environ. 116, 197–208. doi:10.1016/j.agee.2006.02.009

Bard, J.B.L., Rhee, S.Y., 2004. Ontologies in biology: design, applications and future challenges. Nat. Rev. Genet. 5, 213–222. doi:10.1038/nrg1295

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 Sens. Environ. 152, 109–124. doi:10.1016/j.rse.2014.05.018

Barrett, P.D., Laidlaw, A.S., Mayne, C.S., 2005. GrazeGro: a European herbage growth model to predict pasture production in perennial ryegrass swards for decision support. Eur. J. Agron. 23, 37–56. doi:10.1016/j.eja.2004.09.006

Downloaded from http://jpe.oxfordjournals.org/ at University College Cork on April 9, 2016

Bastin, G., Scarth, P., Chewings, V., Sparrow, A., Denham, R., Schmidt, M., O'Reagain, P., Shepherd, R., Abbott, B., 2012. Separating grazing and rainfall effects at regional scale using remote sensing imagery: A dynamic reference-cover method. Remote Sens. Environ. 121, 443–457. doi:10.1016/j.rse.2012.02.021

Belsky, A.J., 1986. Does herbivory benefit plants? A review of the evidence. Am. Nat. 127, 870–892. doi:10.1086/284531

Bénié, G.B., Kaboré, S.S., Goïta, K., Courel, M.-F., 2005. Remote sensing-based spatio-temporal modeling to predict biomass in Sahelian grazing ecosystem. Ecol. Model. 184, 341–354. doi:10.1016/j.ecolmodel.2004.10.012

Bergman, K.-O., Ask, L., Askling, J., Ignell, H., Wahlman, H., Milberg, P., 2008. Importance of boreal grasslands in Sweden for butterfly diversity and effects of local and landscape habitat factors. Biodivers. Conserv. 17, 139–153. doi:10.1007/s10531-007-9235-x

Boddey, R.M., Macedo, R., Tarré, R.M., Ferreira, E., de Oliveira, O.C., de P. Rezende, C., Cantarutti, R.B., Pereira, J.M., Alves, B.J.R., Urquiaga, S., 2004. Nitrogen cycling in Brachiaria pastures: the key to understanding the process of pasture decline. Agric. Ecosyst. Environ. 103, 389–403. doi:10.1016/j.agee.2003.12.010

Booth, D.T., Tueller, P.T., 2003. Rangeland Monitoring Using Remote Sensing. Arid Land Res. Manag. 17, 455–467. doi:10.1080/713936105

Boschetti, M., Bocchi, S., Brivio, P.A., 2007. Assessment of pasture production in the Italian Alps using spectrometric and remote sensing information. Agric. Ecosyst. Environ. 118, 267–272. doi:10.1016/j.agee.2006.05.024

Bouman, B.A.M., Schapendonk, A.H.C.M., Stol, W., 1996. Description of the growth model LINGRA as implemented in CGMS, Quantitative approaches in systems analysis;no. 7. AB-DLO [etc.], Wageningen.

Downloaded from http://jpe.oxfordjournals.org/ at University College Cork on April 9, 2016

Bozkurt, Y., Uzun, N., Dogan, C., Pötsch, E.M., Krautzer, B., Hopkins, A., 2011. Grassland evaluation based on GIS model and Remote Sensing data for beef cattle grazing., in: Grassland Farming and Land Management Systems in Mountainous Regions. Proceedings of the 16th Symposium of the European Grassland Federation, Gumpenstein, Austria, 29th-31st August, 2011. Agricultural Research and Education Center (AREC) Raumberg-Gumpenstein, pp. 181–183.

Bradford, J.B., Hicke, J.A., Lauenroth, W.K., 2005. The relative importance of light-use efficiency modifications from environmental conditions and cultivation for estimation of large-scale net primary productivity. Remote Sens. Environ. 96, 246–255. doi:10.1016/j.rse.2005.02.013

Bradley, B.A., O'Sullivan, M.T., 2011. Assessing the short-term impacts of changing grazing regime at the landscape scale with remote sensing. Int. J. Remote Sens. 32, 5797–5813. doi:10.1080/01431161.2010.507680

Brenner, J.C., Christman, Z., Rogan, J., 2012. Segmentation of Landsat Thematic Mapper imagery improves buffelgrass (Pennisetum ciliare) pasture mapping in the Sonoran Desert of Mexico. Appl. Geogr. 34, 569–575. doi:10.1016/j.apgeog.2012.02.008

Breymeyer, A.I. (Ed.), 1990. Managed Grasslands: Regional Studies, 1 edition. ed. Elsevier Science, Amsterdam ; New York.

Brilli, L., Chiesi, M., Maselli, F., Moriondo, M., Gioli, B., Toscano, P., Zaldei, A., Bindi, M., 2013. Simulation of olive grove gross primary production by the combination of ground and multi-sensor satellite data. Int. J. Appl. Earth Obs. Geoinformation 23, 29–36. doi:10.1016/j.jag.2012.11.006

Buckley, J.R., Smith, A.M., 2010. Monitoring grasslands with radarsat 2 quad-pol imagery, in: Geoscience and Remote Sensing Symposium (IGARSS), 2010 IEEE International.

Downloaded from http://jpe.oxfordjournals.org/ at University College Cork on April 9, 2016

Presented at the Geoscience and Remote Sensing Symposium (IGARSS), 2010 IEEE International, pp. 3090–3093. doi:10.1109/IGARSS.2010.5652367

Butt, B., Turner, M.D., Singh, A., Brottem, L., 2011. Use of MODIS NDVI to evaluate changing latitudinal gradients of rangeland phenology in Sudano-Sahelian West Africa. Remote Sens. Environ. 115, 3367–3376. doi:10.1016/j.rse.2011.08.001

Butterfield, H.S., Malmström, C.M., 2009. The effects of phenology on indirect measures of aboveground biomass in annual grasses. Int. J. Remote Sens. 30, 3133–3146. doi:10.1080/01431160802558774

Cardinale, B.J., Duffy, J.E., Gonzalez, A., Hooper, D.U., Perrings, C., Venail, P., Narwani, A., Mace, G.M., Tilman, D., Wardle, D.A., Kinzig, A.P., Daily, G.C., Loreau, M., Grace, J.B., Larigauderie, A., Srivastava, D.S., Naeem, S., 2012. Biodiversity loss and its impact on humanity. Nature 486, 59–67. doi:10.1038/nature11148

Castle, M.E., 1976. A simple disc instrument for estimating herbage yield. J. Br. Grassl. Soc. 31.

Chan, J.C.-W., Paelinckx, D., 2008. Evaluation of Random Forest and Adaboost tree-based ensemble classification and spectral band selection for ecotope mapping using airborne hyperspectral imagery. Remote Sens. Environ. 112, 2999–3011. doi:10.1016/j.rse.2008.02.011

Clevers, J., Van Der Heijden, G., Verzakov, S., Schaepman, M., 2007. Estimating grassland biomass using SVM band shaving of hyperspectral data. Photogramm. Eng. Remote Sens. 73, 1141.

Cohen, J., Pulliainen, J., Ménard, C.B., Johansen, B., Oksanen, L., Luojus, K., Ikonen, J., 2013. Effect of reindeer grazing on snowmelt, albedo and energy balance based on satellite data analyses. Remote Sens. Environ. 135, 107–117. doi:10.1016/j.rse.2013.03.029

Downloaded from http://jpe.oxfordjournals.org/ at University College Cork on April 9, 2016

Darvishzadeh, R., Atzberger, C., Skidmore, A., Schlerf, M., 2011. Mapping grassland leaf area index with airborne hyperspectral imagery: A comparison study of statistical approaches and inversion of radiative transfer models. ISPRS J. Photogramm. Remote Sens. 66, 894–906. doi:10.1016/j.isprsjprs.2011.09.013

Dawson, T.P., Curran, P.J., 1998. Technical note A new technique for interpolating the reflectance red edge position. Int. J. Remote Sens. 19, 2133–2139. doi:10.1080/014311698214910

De Benedetto, D., Castrignano, A., Diacono, M., Rinaldi, M., Ruggieri, S., Tamborrino, R., 2013. Field partition by proximal and remote sensing data fusion. Biosyst. Eng. 114, 372–383. doi:10.1016/j.biosystemseng.2012.12.001

Del Pozo, A., Ovalle, C., Casado, M.A., Acosta, B., de Miguel, J.M., 2006. Effects of grazing intensity in grasslands of the Espinal of central Chile. J. Veg. Sci. 17, 791–798. doi:10.1111/j.1654-1103.2006.tb02502.x

Derner, J.D., Schuman, G.E., 2007. Carbon sequestration and rangelands: A synthesis of land management and precipitation effects. J. Soil Water Conserv. 62, 77–85.

Donald, G.E., Edirisinghe, A., Henry, D.A., Mata, G., Gherardi, S.G., Oldham, C.M., Gittins, S.P., Smith, R.C.G., 2004. Pastures from space : validation of predictions of pasture growth rates. http://www.publish.csiro.au/?act=view_file&file_id=SA0401077.pdf.

Donald, G., Gherardi, S., Edirisinghe, A., Gittins, S., Henry, D., Mata, G., 2010. Pasture growth rate for individual paddocks can be accurately predicted real-time from MODIS imagery, climate and soil data. Presented at the Australian Society of Animal Production, Armidale, July 2010, pp. 611–615.

Dubinin, M., Potapov, P., Lushchekina, A., Radeloff, V.C., 2010. Reconstructing long time series of burned areas in arid grasslands of southern Russia by satellite remote sensing. Remote Sens. Environ. 114, 1638–1648. doi:10.1016/j.rse.2010.02.010

Downloaded from http://jpe.oxfordjournals.org/ at University College Cork on April 9, 2016

Dusseux, P., Corpetti, T., Hubert-Moy, L., Corgne, S., 2014. Combined Use of Multi-Temporal Optical and Radar Satellite Images for Grassland Monitoring. Remote Sens. 6, 6163–6182. doi:10.3390/rs6076163

Dymond, J.R., Shepherd, J.D., Clark, H., Litherland, A., 2006. Use of VEGETATION satellite imagery to map pasture quality for input to a methane budget of New Zealand. Int. J. Remote Sens. 27, 1261–1268. doi:10.1080/01431160500212070

Edirisinghe, A., Clark, D., Waugh, D., 2012. Spatio-temporal modelling of biomass of intensively grazed perennial dairy pastures using multispectral remote sensing. Int. J. Appl. Earth Obs. Geoinformation 16, 5–16. doi:10.1016/j.jag.2011.11.006

Edirisinghe, A., Hill, M.J., Donald, G.E., Hyder, M., 2011. Quantitative mapping of pasture biomass using satellite imagery. Int. J. Remote Sens. 32, 2699–2724. doi:10.1080/01431161003743181

Edwards, M.C., Wellens, J., Al-Eisawi, D., 1999. Monitoring the grazing resources of the Badia region, Jordan, using remote sensing. Appl. Geogr. 19, 385–398. doi:10.1016/S0143-6228(99)00007-7

EEC, 1997. The Council of the European Communities, "Council Directive 97/62/EC of 27 October 1997 adapting to technical and scientific progrss directive 92/43/EEC on the conservation of natural habitats and of wild fauna and flora,." Off. J. Novemb. 1997.

EEC, 1979. The Council of the European Communities, "Council Directive 79/403/EEC of 2 April 1979 on the conservation of wild birds." Off. J. Eur. Communities 0001–0018.

Epinat, V., Stein, A., de Jong, S.M., Bouma, J., 2001. A wavelet characterization of high-resolution NDVI patterns for precision agriculture. Int. J. Appl. Earth Obs. Geoinformation 3, 121–132. doi:10.1016/S0303-2434(01)85003-0

Downloaded from http://jpe.oxfordjournals.org/ at University College Cork on April 9, 2016

Erives, H., Fitzgerald, G.J., 2005. Automated registration of hyperspectral images for precision agriculture. Comput. Electron. Agric. 47, 103–119. doi:10.1016/j.compag.2004.11.016

Falldorf, T., Strand, O., Panzacchi, M., Tømmervik, H., 2014. Estimating lichen volume and reindeer winter pasture quality from Landsat imagery. Remote Sens. Environ. 140, 573–579. doi:10.1016/j.rse.2013.09.027

FAO, 2014. The role of livestock in climate change [WWW Document]. Food Agric. Organ. URL http://www.fao.org/agriculture/lead/themes0/climate/en/

FAOSTAT, 2014. Food and Agriculture Organization Of The United Nations: STATISTICS DIVISION [WWW Document]. URL http://faostat.fao.org/site/377/DesktopDefault.aspx?PageID=377#ancor

Feng, X.M., Zhao, Y.S., 2011. Grazing intensity monitoring in Northern China steppe: Integrating CENTURY model and MODIS data. Ecol. Indic. 11, 175–182. doi:10.1016/j.ecolind.2009.07.002

Filella, I., Penuelas, J., 1994. The red edge position and shape as indicators of plant chlorophyll content, biomass and hydric status. Int. J. Remote Sens. 15, 1459–1470. doi:10.1080/01431169408954177

Filippi, A.M., Jensen, J.R., 2006. Fuzzy learning vector quantization for hyperspectral coastal vegetation classification. Remote Sens. Environ. 100, 512–530. doi:10.1016/j.rse.2005.11.007

Flynn, E.S., Dougherty, C.T., Wendroth, O., 2008. Assessment of Pasture Biomass with the Normalized Difference Vegetation Index from Active Ground-Based Sensors. Agron. J. 100, 114. doi:10.2134/agrojnl2006.0363

Foley, J.A., DeFries, R., Asner, G.P., Barford, C., Bonan, G., Carpenter, S.R., Chapin, F.S., Coe, M.T., Daily, G.C., Gibbs, H.K., Helkowski, J.H., Holloway, T., Howard, E.A.,

Downloaded from http://jpe.oxfordjournals.org/ at University College Cork on April 9, 2016

Kucharik, C.J., Monfreda, C., Patz, J.A., Prentice, I.C., Ramankutty, N., Snyder, P.K., 2005. Global Consequences of Land Use. Science 309, 570–574. doi:10.1126/science.1111772

Förster, M., Frick, A., Walentowski, H., Kleinschmit, B., 2008. Approaches to utilising QuickBird data for the monitoring of NATURA 2000 habitats. Community Ecol. 9, 155–168. doi:10.1556/ComEc.9.2008.2.4

Förster, M., Schmidt, T., Schuster, C., Kleinschmit, B., 2012. Multi-temporal detection of grassland vegetation with RapidEye imagery and a spectral-temporal library, in: Geoscience and Remote Sensing Symposium (IGARSS), 2012 IEEE International. Presented at the Geoscience and Remote Sensing Symposium (IGARSS), 2012 IEEE International, pp. 4930–4933. doi:10.1109/IGARSS.2012.6352506

Förster, M., Zebisch, M., Wagner-Lücker, I., Schmidt, T., Renner, K., Neubert, M., 2014. Remote Sensing-Based Monitoring of Potential Climate-Induced Impacts on Habitats, in: Rannow, S., Neubert, M. (Eds.), Managing Protected Areas in Central and Eastern Europe Under Climate Change, Advances in Global Change Research. Springer Netherlands, pp. 95–113.

Franke, J., Keuck, V., Siegert, F., 2012. Assessment of grassland use intensity by remote sensing to support conservation schemes. J. Nat. Conserv. 20, 125–134. doi:10.1016/j.jnc.2012.02.001

Franzluebbers, A.J., 2010. Soil organic carbon in managed pastures of the southeastern United States of America, in: Integrated Crop Management. Presented at the Proceedings of the workshop on the role of grassland carbon sequestration in the mitigation of climate change, p. Chapetr VIII.

Gao, J., 2006. Quantification of grassland properties: how it can benefit from geoinformatic technologies? Int. J. Remote Sens. 27, 1351–1365. doi:10.1080/01431160500474357

Downloaded from http://jpe.oxfordjournals.org/ at University College Cork on April 9, 2016

Gao, T., Xu, B., Yang, X., Jin, Y., Ma, H., Li, J., Yu, H., 2013. Using MODIS time series data to estimate aboveground biomass and its spatio-temporal variation in Inner Mongolia's grassland between 2001 and 2011. Int. J. Remote Sens. 34, 7796–7810. doi:10.1080/01431161.2013.823000

Giraed, C.M., Benoit, M., Vaubernier, E.D., Curran, P.J., 1990. SPOT HRV data to discriminate grassland quality. Int. J. Remote Sens. 11, 2253–2267. doi:10.1080/01431169008955173

Gong, P., Wang, J., Yu, L., Zhao, Y., Zhao, Y., Liang, L., Niu, Z., Huang, X., Fu, H., Liu, S., Li, C., Li, X., Fu, W., Liu, C., Xu, Y., Wang, X., Cheng, Q., Hu, L., Yao, W., Zhang, H., Zhu, P., Zhao, Z., Zhang, H., Zheng, Y., Ji, L., Zhang, Y., Chen, H., Yan, A., Guo, J., Yu, L., Wang, L., Liu, X., Shi, T., Zhu, M., Chen, Y., Yang, G., Tang, P., Xu, B., Giri, C., Clinton, N., Zhu, Z., Chen, J., Chen, J., 2013. Finer resolution observation and monitoring of global land cover: first mapping results with Landsat TM and ETM+ data. Int. J. Remote Sens. 34, 2607–2654. doi:10.1080/01431161.2012.748992

Guo, X., Zhang, C., Wilmshurst, J.F., Sissons, R., 2005. Monitoring grassland health with remote sensing approaches. Prairie Perspect. 8, 11–22.

Gutiérrez, P.A., López-Granados, F., Peña-Barragán, J.M., Jurado-Expósito, M., Hervás-Martínez, C., 2008. Logistic regression product-unit neural networks for mapping Ridolfia segetum infestations in sunflower crop using multitemporal remote sensed data. Comput. Electron. Agric. 64, 293–306. doi:10.1016/j.compag.2008.06.001

Gu, Y., Wylie, B.K., Bliss, N.B., 2013. Mapping grassland productivity with 250-m eMODIS NDVI and SSURGO database over the Greater Platte River Basin, USA. Ecol. Indic. 24, 31–36. doi:10.1016/j.ecolind.2012.05.024

Hajj, M.E., Baghdadi, N., Belaud, G., Zribi, M., Cheviron, B., Courault, D., Hagolle, O., Charron, F., 2014. Irrigated Grassland Monitoring Using a Time Series of TerraSAR-

Downloaded from http://jpe.oxfordjournals.org/ at University College Cork on April 9, 2016

X and COSMO-SkyMed X-Band SAR Data. Remote Sens. 6, 10002–10032. doi:10.3390/rs61010002

Hakl, J., Hrevušová, Z., Hejcman, M., Fuksa, P., 2012. The use of a rising plate meter to evaluate lucerne (Medicago sativa L.) height as an important agronomic trait enabling yield estimation. Grass Forage Sci. 67, 589–596. doi:10.1111/j.1365-2494.2012.00886.x

Han, G., Hao, X., Zhao, M., Wang, M., Ellert, B.H., Willms, W., Wang, M., 2008. Effect of grazing intensity on carbon and nitrogen in soil and vegetation in a meadow steppe in Inner Mongolia. Agric. Ecosyst. Environ. 125, 21–32. doi:10.1016/j.agee.2007.11.009

Han, L.-C., 2001. A method of modifying error for non-synchronicity of grass yield remote sensing estimation and measurement. Int. J. Remote Sens. 22, 3363–3372. doi:10.1080/01431160010006421

Hansen, J.W., Jones, J.W., 2000. Scaling-up crop models for climate variability applications. Agric. Syst. 65, 43–72. doi:10.1016/S0308-521X(00)00025-1

Hein, L., 2006. The impacts of grazing and rainfall variability on the dynamics of a Sahelian rangeland. J. Arid Environ. 64, 488–504. doi:10.1016/j.jaridenv.2005.06.014

Hejcman, M., Sochorová, L., Pavlů, V., Štrobach, J., Diepolder, M., Schellberg, J., 2014. The Steinach Grassland Experiment: Soil chemical properties, sward height and plant species composition in three cut alluvial meadow after decades-long fertilizer application. Agric. Ecosyst. Environ. 184, 76–87. doi:10.1016/j.agee.2013.11.021

Henry, D.A., Edirisinghe, A., Donald, G.E., Mata, G., 2004. “Pastures from Space” - quantitative estimation of pasture biomass and growth rate using satellite remote sensing. Precision Agriculture Center, University of Minnesota, Department of Soil, Water and Climate, pp. 1246–1254.

Downloaded from http://jpe.oxfordjournals.org/ at University College Cork on April 9, 2016

He, Y., Guo, X., Wilmshurst, J.F., 2009. Reflectance measures of grassland biophysical structure. Int. J. Remote Sens. 30, 2509–2521. doi:10.1080/01431160802552751

Hill, M.J., 2013. Vegetation index suites as indicators of vegetation state in grassland and savanna: An analysis with simulated SENTINEL 2 data for a North American transect. Remote Sens. Environ. 137, 94–111. doi:10.1016/j.rse.2013.06.004

Hill, M.J., 2004. Grazing agriculture - Managed Pasture, Grassland and Rangeland, in: Manual of Remote Sensing, Remote Sensing for Natural Resource Management and Environmental Monitoring (Ed. S. L. Ustin). Wiley International, New York, pp. 449–530.

Hill, M.J., Donald, G.E., Hyder, M.W., Smith, R.C.G., 2004. Estimation of pasture growth rate in the south west of Western Australia from AVHRR NDVI and climate data. Remote Sens. Environ. 93, 528–545. doi:10.1016/j.rse.2004.08.006

Hill, M.J., Donald, G.E., Vickery, P.J., Furnival, E.P., 1996. Integration of satellite remote sensing, simple bioclimatic models and GIS for assessment of pastoral development for a commercial grazing enterprise. Aust. J. Exp. Agric. 36, 309–321.

Hill, M.J., Ticehurst, C.J., Lee, J.-S., Grunes, M.R., Donald, G.E., Henry, D., 2005. Integration of optical and radar classifications for mapping pasture type in Western Australia. IEEE Trans. Geosci. Remote Sens. 43, 1665–1681. doi:10.1109/TGRS.2005.846868

Hill, M.J., Vickery, P.J., Furnival, E.P., Donald, G.E., 1999. Pasture Land Cover in Eastern Australia from NOAA-AVHRR NDVI and Classified Landsat TM. Remote Sens. Environ. 67, 32–50. doi:10.1016/S0034-4257(98)00075-3

Huang, C., Geiger, E.L., 2008. Climate anomalies provide opportunities for large-scale mapping of non-native plant abundance in desert grasslands. Divers. Distrib. 14, 875–884. doi:10.1111/j.1472-4642.2008.00500.x

Downloaded from http://jpe.oxfordjournals.org/ at University College Cork on April 9, 2016

Huang, L., Xiao, T., Zhao, Z., Sun, C., Liu, J., Shao, Q., Fan, J., Wang, J., 2013. Effects of grassland restoration programs on ecosystems in arid and semiarid China. J. Environ. Manage. 117, 268–275. doi:10.1016/j.jenvman.2012.12.040

Huang, N., He, J.-S., Niu, Z., 2013. Estimating the spatial pattern of soil respiration in Tibetan alpine grasslands using Landsat TM images and MODIS data. Ecol. Indic. 26, 117–125. doi:10.1016/j.ecolind.2012.10.027

Hybu Cig Cymru, M.P.W., 2008. Grassland management: http://hccmpw.org.uk/publications/farming_and_industry_development/grassland_management/.

Inoue, Y., Kurosu, T., Maeno, H., Uratsuka, S., Kozu, T., Dabrowska-Zielinska, K., Qi, J., 2002. Season-long daily measurements of multifrequency (Ka, Ku, X, C, and L) and full-polarization backscatter signatures over paddy rice field and their relationship with biological variables. Remote Sens. Environ. 81, 194–204. doi:10.1016/S0034-4257(01)00343-1

Jachowski, N.R.A., Quak, M.S.Y., Friess, D.A., Duangnamon, D., Webb, E.L., Ziegler, A.D., 2013. Mangrove biomass estimation in Southwest Thailand using machine learning. Appl. Geogr. 45, 311–321. doi:10.1016/j.apgeog.2013.09.024

Jadhav, R.N., Kimothi, M.M., Kandya, A.K., 1993. Grassland mapping/monitoring of Banni, Kachchh (Gujarat) using remotely-sensed data. Int. J. Remote Sens. 14, 3093–3103. doi:10.1080/01431169308904422

Janoth, J., Gantert, S., Koppe, W., Kaptein, A., Fischer, C., 2012. TerraSAR-X2 - Mission overview, in: Geoscience and Remote Sensing Symposium (IGARSS), 2012 IEEE International. Presented at the Geoscience and Remote Sensing Symposium (IGARSS), 2012 IEEE International, pp. 217–220. doi:10.1109/IGARSS.2012.6351599

Downloaded from http://jpe.oxfordjournals.org/ at University College Cork on April 9, 2016

Jianlong, L., Tiangang, L., Quangong, C., 1998. Estimating grassland yields using remote sensing and GIS technologies in China. N. Z. J. Agric. Res. 41, 31–38. doi:10.1080/00288233.1998.9513285

Ji, B., Sun, Y., Yang, S., Wan, J., 2007. Artificial neural networks for rice yield prediction in mountainous regions. J. Agric. Sci. 145, 249–261. doi:10.1017/S0021859606006691

Kawamura, K., Akiyama, T., Yokota, H., Tsutsumi, M., Yasuda, T., Watanabe, O., Wang, S., 2005a. Quantifying grazing intensities using geographic information systems and satellite remote sensing in the Xilingol steppe region, Inner Mongolia, China. Agric. Ecosyst. Environ. 107, 83–93. doi:10.1016/j.agee.2004.09.008

Kawamura, K., Akiyama, T., Yokota, H., Tsutsumi, M., Yasuda, T., Watanabe, O., Wang, S., 2005b. Comparing MODIS vegetation indices with AVHRR NDVI for monitoring the forage quantity and quality in Inner Mongolia grassland, China. Grassl. Sci. 51, 33–40. doi:10.1111/j.1744-697X.2005.00006.x

Kurtz, D.B., Schellberg, J., Braun, M., 2010. Ground and satellite based assessment of rangeland management in sub-tropical Argentina. Appl. Geogr. 30, 210–220. doi:10.1016/j.apgeog.2009.01.006

Latham, J., Cumani, R., Rosati, I., Bloise, M., 2014. Global Land Cover SHARE (GLC-SHARE): database Beta-Release Version 1.0-2014.

Lawrence, R., Bunn, A., Powell, S., Zambon, M., 2004. Classification of remotely sensed imagery using stochastic gradient boosting as a refinement of classification tree analysis. Remote Sens. Environ. 90, 331–336. doi:10.1016/j.rse.2004.01.007

Lee, J.-S., Grunes, M.R., Pottier, E., 2001. Quantitative comparison of classification capability: fully polarimetric versus dual and single-polarization SAR. IEEE Trans. Geosci. Remote Sens. 39, 2343–2351. doi:10.1109/36.964970

Downloaded from http://jpe.oxfordjournals.org/ at University College Cork on April 9, 2016

Lee, R., Yu, F., Price, K.P., Ellis, J., Shi, P., 2002. Evaluating vegetation phenological patterns in Inner Mongolia using NDVI time-series analysis. Int. J. Remote Sens. 23, 2505–2512. doi:10.1080/01431160110106087

Li, J., Yang, X., Jin, Y., Yang, Z., Huang, W., Zhao, L., Gao, T., Yu, H., Ma, H., Qin, Z., Xu, B., 2013. Monitoring and analysis of grassland desertification dynamics using Landsat images in Ningxia, China. Remote Sens. Environ. 138, 19–26. doi:10.1016/j.rse.2013.07.010

Liu, D., Xia, F., 2010. Assessing object-based classification: advantages and limitations. Remote Sens. Lett. 1, 187–194. doi:10.1080/01431161003743173

López-Lozano, R., Casterad, M.A., Herrero, J., 2010. Site-specific management units in a commercial maize plot delineated using very high resolution remote sensing and soil properties mapping. Comput. Electron. Agric. 73, 219–229. doi:10.1016/j.compag.2010.04.011

Loranty, M.M., Goetz, S.J., Beck, P.S.A., 2011. Tundra vegetation effects on pan-Arctic albedo. Environ. Res. Lett. 6, 024014. doi:10.1088/1748-9326/6/2/024014

Loris, V., Damiano, G., 2006. Mapping the green herbage ratio of grasslands using both aerial and satellite-derived spectral reflectance. Agric. Ecosyst. Environ. 115, 141–149. doi:10.1016/j.agee.2005.12.018

Luo, G., Han, Q., Zhou, D., Li, L., Chen, X., Li, Y., Hu, Y., Li, B.L., 2012. Moderate grazing can promote aboveground primary production of grassland under water stress. Ecol. Complex. 11, 126–136. doi:10.1016/j.ecocom.2012.04.004

MARS BULLETIN, 2011. Pasture monitoring in Europe - Report 1 (No. Vol. 19, NO. 9).

Marsh, P., Bartlett, P., MacKay, M., Pohl, S., Lantz, T., 2010. Snowmelt energetics at a shrub tundra site in the western Canadian Arctic. Hydrol. Process. 24, 3603–3620. doi:10.1002/hyp.7786

Downloaded from http://jpe.oxfordjournals.org/ at University College Cork on April 9, 2016

Maselli, F., Argenti, G., Chiesi, M., Angeli, L., Papale, D., 2013. Simulation of grassland productivity by the combination of ground and satellite data. Agric. Ecosyst. Environ. 165, 163–172. doi:10.1016/j.agee.2012.11.006

Maselli, F., Barbati, A., Chiesi, M., Chirici, G., Corona, P., 2006. Use of remotely sensed and ancillary data for estimating forest gross primary productivity in Italy. Remote Sens. Environ. 100, 563–575. doi:10.1016/j.rse.2005.11.010

Masocha, M., Skidmore, A.K., 2011. Integrating conventional classifiers with a GIS expert system to increase the accuracy of invasive species mapping. Int. J. Appl. Earth Obs. Geoinformation 13, 487–494. doi:10.1016/j.jag.2010.10.004

Mata, G., Edirisinghe, A., Waugh, D., Petch, S., Clark, D., 2010. Algorithm improvements to deliver higher accuracy of prediction of pasture cover from satellite data in Waikato Dairy Farms. Presented at the Australasian Dairy Symposium, Lincoln, New Zealand, pp. 225–229.

Mekasha, A., Gerard, B., Tesfaye, K., Nigatu, L., Duncan, A.J., 2014. Inter-connection between land use/land cover change and herders'/farmers' livestock feed resource management strategies: a case study from three Ethiopian eco-environments. Agric. Ecosyst. Environ. 188, 150–162. doi:10.1016/j.agee.2014.02.022

Metz, A., Schmitt, A., Esch, T., Reinartz, P., Klonus, S., Ehlers, M., 2012. Synergetic use of TerraSAR-X and Radarsat-2 time series data for identification and characterization of grassland types - a case study in Southern Bavaria, Germany, in: Geoscience and Remote Sensing Symposium (IGARSS), 2012 IEEE International. Presented at the Geoscience and Remote Sensing Symposium (IGARSS), 2012 IEEE International, pp. 3560–3563. doi:10.1109/IGARSS.2012.6350649

Miehe, G., Miehe, S., Bach, K., Nölling, J., Hanspach, J., Reudenbach, C., Kaiser, K., Wesche, K., Mosbrugger, V., Yang, Y.P., Ma, Y.M., 2011. Plant communities of

Downloaded from http://jpe.oxfordjournals.org/ at University College Cork on April 9, 2016

central Tibetan pastures in the Alpine Steppe/Kobresia pygmaea ecotone. J. Arid Environ. 75, 711–723. doi:10.1016/j.jaridenv.2011.03.001

Moore, A.D., Donnelly, J.R., Freer, M., 1997. GRAZPLAN: Decision support systems for Australian grazing enterprises. III. Pasture growth and soil moisture submodels, and the GrassGro DSS. Agric. Syst. 55, 535–582. doi:10.1016/S0308-521X(97)00023-1

Moore, A.D., Vickery, P.J., Hill, M.J., Donnelly, J.R., Donald, G.E., 1999. Combining satellite data with a simulation model to describe spatial variability in pasture growth at a farm scale. Aust. J. Exp. Agric. 39, 285–300.

Moran, M.S., Inoue, Y., Barnes, E.M., 1997. Opportunities and limitations for image-based remote sensing in precision crop management. Remote Sens. Environ. 61, 319–346. doi:10.1016/S0034-4257(97)00045-X

Morán-Ordóñez, A., Suárez-Seoane, S., Calvo, L., de Luis, E., 2011. Using predictive models as a spatially explicit support tool for managing cultural landscapes. Appl. Geogr. 31, 839–848. doi:10.1016/j.apgeog.2010.09.002

Moreau, S., Le Toan, T., 2003. Biomass quantification of Andean wetland forages using ERS satellite SAR data for optimizing livestock management. Remote Sens. Environ. 84, 477–492. doi:10.1016/S0034-4257(02)00111-6

Morel, J., Todoroff, P., Bégué, A., Bury, A., Martiné, J.-F., Petit, M., 2014. Toward a Satellite-Based System of Sugarcane Yield Estimation and Forecasting in Smallholder Farming Conditions: A Case Study on Reunion Island. Remote Sens. 6, 6620–6635. doi:10.3390/rs6076620

Mountrakis, G., Im, J., Ogole, C., 2011. Support vector machines in remote sensing: A review. ISPRS J. Photogramm. Remote Sens. 66, 247–259. doi:10.1016/j.isprsjprs.2010.11.001

Downloaded from http://jpe.oxfordjournals.org/ at University College Cork on April 9, 2016

Munyati, C., Makgale, D., 2009. Multitemporal Landsat TM imagery analysis for mapping and quantifying degraded rangeland in the Bahurutshe communal grazing lands, South Africa. Int. J. Remote Sens. 30, 3649–3668. doi:10.1080/01431160802592534

Mutanga, O., Skidmore, A.K., 2004. Hyperspectral band depth analysis for a better estimation of grass biomass (Cenchrus ciliaris) measured under controlled laboratory conditions. Int. J. Appl. Earth Obs. Geoinformation 5, 87–96. doi:10.1016/j.jag.2004.01.001

Nagendra, H., 2001. Using remote sensing to assess biodiversity. Int. J. Remote Sens. 22, 2377–2400. doi:10.1080/01431160117096

Nagendra, H., Gadgil, M., 1999. Satellite imagery as a tool for monitoring species diversity: an assessment. J. Appl. Ecol. 36, 388–397. doi:10.1046/j.1365-2664.1999.00406.x

Nahry, A.H.E., Ali, R.R., Baroudy, A.A.E., 2011. An approach for precision farming under pivot irrigation system using remote sensing and GIS techniques. Agric. Water Manag. 98, 517–531. doi:10.1016/j.agwat.2010.09.012

Newnham, G., 2010. Improved Methods for Assessment and Prediction of Grassland Curing Satellite Based Curing Methods and Mapping - final report [WWW Document].

Nieland, S., Förster, M., Kleinschmit, B., 2012. A Remote Sensing Biodiversity Monitoring Ontology, in: Proceedings of the AGILE'2012 International Conference on Geographic Information Science. Presented at the Multidisciplinary Research on Geographical Information in Europe and Beyond, Springer, Avignon, France, pp. 312–315.

Nitze, I., Barrett, B., Cawkwell, F., 2015. Temporal optimisation of image acquisition for land cover classification with Random Forest and MODIS time-series. Int. J. Appl. Earth Obs. Geoinformation 34, 136–146. doi:10.1016/j.jag.2014.08.001

Downloaded from http://jpe.oxfordjournals.org/ at University College Cork on April 9, 2016

Nordberg, M.-L., Evertson, J., 2003. Monitoring Change in Mountainous Dry-Heath Vegetation at a Regional Scale Using Multitemporal Landsat TM Data. Ambio 32, 502–509. doi:10.2307/4315433

Numata, I., Roberts, D.A., Chadwick, O.A., Schimel, J., Sampaio, F.R., Leonidas, F.C., Soares, J.V., 2007. Characterization of pasture biophysical properties and the impact of grazing intensity using remotely sensed data. Remote Sens. Environ. 109, 314–327. doi:10.1016/j.rse.2007.01.013

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 J. Photogramm. Remote Sens. 68, 79–94. doi:10.1016/j.isprsjprs.2012.01.004

Oliver, Y.M., Robertson, M.J., Wong, M.T.F., 2010. Integrating farmer knowledge, precision agriculture tools, and crop simulation modelling to evaluate management options for poor-performing patches in cropping fields. Eur. J. Agron. 32, 40–50. doi:10.1016/j.eja.2009.05.002

Painter, E.L., Belsky, A.J., 1993. Application of Herbivore Optimization Theory to Rangelands of the Western United States. Ecol. Appl. 3, 2. doi:10.2307/1941780

Panda, S.S., Ames, D.P., Panigrahi, S., 2010. Application of Vegetation Indices for Agricultural Crop Yield Prediction Using Neural Network Techniques. Remote Sens. 2, 673–696. doi:10.3390/rs2030673

Paudel, K.P., Andersen, P., 2010. Assessing rangeland degradation using multi temporal satellite images and grazing pressure surface model in Upper Mustang, Trans Himalaya, Nepal. Remote Sens. Environ. 114, 1845–1855. doi:10.1016/j.rse.2010.03.011

Downloaded from http://jpe.oxfordjournals.org/ at University College Cork on April 9, 2016

Payet, N., Todorovic, S., 2010. (RF)^2 – Random Forest Random Field, in: Lafferty, J.D., Williams, C.K.I., Shawe-Taylor, J., Zemel, R.S., Culotta, A. (Eds.), Advances in Neural Information Processing Systems 23. Curran Associates, Inc., pp. 1885–1893.

Peña-Barragán, J.M., Ngugi, M.K., Plant, R.E., Six, J., 2011. Object-based crop identification using multiple vegetation indices, textural features and crop phenology. Remote Sens. Environ. 115, 1301–1316. doi:10.1016/j.rse.2011.01.009

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. Agric. Syst. 100, 72–79. doi:10.1016/j.agsy.2009.01.002

Pickup, G., Bastin, G.N., Chewings, V.H., 1998. Identifying trends in land degradation in non-equilibrium rangelands. J. Appl. Ecol. 35, 365–377. doi:10.1046/j.1365-2664.1998.00319.x

Pickup, G., Bastin, G.N., Chewings, V.H., 1994. Remote-Sensing-Based Condition Assessment for Nonequilibrium Rangelands Under Large-Scale Commercial Grazing. Ecol. Appl. 4, 497–517. doi:10.2307/1941952

Pinar, A., Curran, P.J., 1996. Technical Note Grass chlorophyll and the reflectance red edge. Int. J. Remote Sens. 17, 351–357. doi:10.1080/01431169608949010

Piñeiro, G., Oesterheld, M., Paruelo, J.M., 2006a. Seasonal Variation in Aboveground Production and Radiation-use Efficiency of Temperate rangelands Estimated through Remote Sensing. Ecosystems 9, 357–373. doi:10.1007/s10021-005-0013-x

Piñeiro, G., Paruelo, J.M., Oesterheld, M., 2006b. Potential long-term impacts of livestock introduction on carbon and nitrogen cycling in grasslands of Southern South America. Glob. Change Biol. 12, 1267–1284. doi:10.1111/j.1365-2486.2006.01173.x

Pokluda, P., Hauck, D., Cizek, L., 2012. Importance of marginal habitats for grassland diversity: fallows and overgrown tall-grass steppe as key habitats of endangered

Downloaded from http://jpe.oxfordjournals.org/ at University College Cork on April 9, 2016

ground-beetle Carabus hungaricus. Insect Conserv. Divers. 5, 27–36. doi:10.1111/j.1752-4598.2011.00146.x

Prabhakar, M., Prasad, Y.G., Thirupathi, M., Sreedevi, G., Dharajothi, B., Venkateswarlu, B., 2011. Use of ground based hyperspectral remote sensing for detection of stress in cotton caused by leafhopper (Hemiptera: Cicadellidae). Comput. Electron. Agric. 79, 189–198. doi:10.1016/j.compag.2011.09.012

Price, K.P., Guo, X., Stiles, J.M., 2002. Comparison of Landsat TM and ERS-2 SAR data for discriminating among grassland types and treatments in eastern Kansas. Comput. Electron. Agric. 37, 157–171. doi:10.1016/S0168-1699(02)00110-2

Prince, S.D., 1991. Satellite remote sensing of primary production: comparison of results for Sahelian grasslands 1981-1988. Int. J. Remote Sens. 12, 1301–1311. doi:10.1080/01431169108929727

Psomas, A., Kneubühler, M., Huber, S., Itten, K., Zimmermann, N.E., 2011a. Hyperspectral remote sensing for estimating aboveground biomass and for exploring species richness patterns of grassland habitats. Int. J. Remote Sens. 32, 9007–9031. doi:10.1080/01431161.2010.532172

Psomas, A., Kneubühler, M., Huber, S., Itten, K., Zimmermann, N.E., 2011b. Hyperspectral remote sensing for estimating aboveground biomass and for exploring species richness patterns of grassland habitats. Int. J. Remote Sens. 32, 9007–9031. doi:10.1080/01431161.2010.532172

Punjabi, G.A., Chellam, R., Vanak, A.T., 2013. Importance of Native Grassland Habitat for Den-Site Selection of Indian Foxes in a Fragmented Landscape. PLoS ONE 8, e76410. doi:10.1371/journal.pone.0076410

Downloaded from http://jpe.oxfordjournals.org/ at University College Cork on April 9, 2016

Quan, X., He, B., Li, X., Tang, Z., 2015. Estimation of Grassland Live Fuel Moisture Content From Ratio of Canopy Water Content and Foliage Dry Biomass. IEEE Geosci. Remote Sens. Lett. 12, 1903–1907. doi:10.1109/LGRS.2015.2437391

Quattrochi, D.A., Goodchild, M.F., 1997. Scale in Remote Sensing and GIS. CRC Press.

R&D Brief, 2008. Measuring pasture growth rate [WWW Document]. URL http://www.beeflambnz.com/farm/research-development/research-findings/?pg=3&dsrt=date&ds=ForageAndPasture (accessed 1.12.13).

Reiche, M., Funk, R., Zhang, Z., Hoffmann, C., Reiche, J., Wehrhan, M., Li, Y., Sommer, M., 2012. Application of satellite remote sensing for mapping wind erosion risk and dust emission-deposition in Inner Mongolia grassland, China. Grassl. Sci. 58, 8–19. doi:10.1111/j.1744-697X.2011.00235.x

Retzer, V., 2006. Impacts of grazing and rainfall variability on the dynamics of a Sahelian rangeland revisited (Hein, 2006))—new insights from old data. J. Arid Environ. 67, 157–164. doi:10.1016/j.jaridenv.2006.01.002

Röder, A., Udelhoven, T., Hill, J., del Barrio, G., Tsiourlis, G., 2008. Trend analysis of Landsat-TM and -ETM+ imagery to monitor grazing impact in a rangeland ecosystem in Northern Greece. Remote Sens. Environ. 112, 2863–2875. doi:10.1016/j.rse.2008.01.018

Schellberg, J., Hill, M.J., Gerhards, R., Rothmund, M., Braun, M., 2008. Precision agriculture on grassland: Applications, perspectives and constraints. Eur. J. Agron. 29, 59–71. doi:10.1016/j.eja.2008.05.005

Schellberg, J., Verbruggen, E., 2014. Frontiers and perspectives on research strategies in grassland technology. Crop Pasture Sci. 65, 508–523.

Schröder, C., Garcia, F., Buck, O., Corbane, C., Deshayes, M., Förster, M., García-Millán, V., Gil-Jimenez, Y., Lang, S., Ramos-Losada, B., Simón-Colina, A., Vanden Borre,

Downloaded from http://jpe.oxfordjournals.org/ at University College Cork on April 9, 2016

J., 2013. Validation of Habitat Assessment Services in Natura 2000 Sites: Streamlining the Role of Stakeholders from User Needs to Conservation Status Evaluation, in: Jekel, T., Car, A., Strobl, J., Griesebner, G. (Eds.), GI_Forum 2013 - Creating the GI Society - Conference Proceedings. Wichmann, Salzburg, pp. 548–551. doi:10.1553/giscience2013s548

Schuster, C., Ali, I., Lohmann, P., Frick, A., Förster, M., Kleinschmit, B., 2011. Towards Detecting Swath Events in TerraSAR-X Time Series to Establish NATURA 2000 Grassland Habitat Swath Management as Monitoring Parameter. Remote Sens. 3, 1308–1322. doi:10.3390/rs3071308

Schuster, C., Förster, M., Kleinschmit, B., 2012. Testing the red edge channel for improving land-use classifications based on high-resolution multi-spectral satellite data. Int. J. Remote Sens. 33, 5583–5599. doi:10.1080/01431161.2012.666812

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. Int. J. Appl. Earth Obs. Geoinformation 34, 25–34. doi:10.1016/j.jag.2014.06.004

Scurlock, J.M.O., Hall, D.O., 1998. The global carbon sink: a grassland perspective. Glob. Change Biol. 4, 229–233. doi:10.1046/j.1365-2486.1998.00151.x

Serele, C.Z., Gwyn, Q.H.J., Boisvert, J.B., Pattey, E., McLaughlin, N., Daoust, G., 2000. Corn yield prediction with artificial neural network trained using airborne remote sensing and topographic data, in: Geoscience and Remote Sensing Symposium, 2000. Proceedings. IGARSS 2000. IEEE 2000 International. Presented at the Geoscience and Remote Sensing Symposium, 2000. Proceedings. IGARSS 2000. IEEE 2000 International, pp. 384–386 vol.1. doi:10.1109/IGARSS.2000.860527

Downloaded from http://jpe.oxfordjournals.org/ at University College Cork on April 9, 2016

Shoshany, M., Long, D., Bonfil, D., 2013. Remote Sensing for sustainable agriculture. Int. J. Remote Sens. 34, 6021–6023. doi:10.1080/01431161.2013.795004

Sitters, J., Heitkönig, I.M.A., Holmgren, M., Ojwang', G.S.O., 2009. Herded cattle and wild grazers partition water but share forage resources during dry years in East African savannas. Biol. Conserv. 142, 738–750. doi:10.1016/j.biocon.2008.12.001

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 Sens. Environ. 121, 415–425. doi:10.1016/j.rse.2012.02.011

Smith, A.M., Buckley, J.R., 2011. Investigating RADARSAT-2 as a tool for monitoring grassland in western Canada. Can. J. Remote Sens. 37, 93–102. doi:10.5589/m11-027

Song, C., Dannenberg, M.P., Hwang, T., 2013. Optical remote sensing of terrestrial ecosystem primary productivity. Prog. Phys. Geogr. 37, 834–854. doi:10.1177/0309133313507944

Soussana, J.-F., Lemaire, G., 2014. Coupling carbon and nitrogen cycles for environmentally sustainable intensification of grasslands and crop-livestock systems. Agric. Ecosyst. Environ., Integrated Crop-Livestock System Impacts on Environmental Processes 190, 9–17. doi:10.1016/j.agee.2013.10.012

Sulieman, H.M., Elagib, N.A., 2012. Implications of climate, land-use and land-cover changes for pastoralism in eastern Sudan. J. Arid Environ. 85, 132–141. doi:10.1016/j.jaridenv.2012.05.001

Svoray, T., Perevolotsky, A., Atkinson, P.M., 2013. Ecological sustainability in rangelands: the contribution of remote sensing. Int. J. Remote Sens. 34, 6216–6242. doi:10.1080/01431161.2013.793867

Tappan, G., 1982. A review of remote sensing and grasslands literature. Available from NTIS.

Downloaded from http://jpe.oxfordjournals.org/ at University College Cork on April 9, 2016

Thenkabail, P.S., 2003. Biophysical and yield information for precision farming from near-real-time and historical Landsat TM images. Int. J. Remote Sens. 24, 2879–2904. doi:10.1080/01431160710155974

Thorvaldsson, G., Bjornsson, H., Hermannsson, J., 2004. The influence of weather on early growth rate of grasses. Icel. Agric. Sci. 65–73.

Todd, S.W., Hoffer, R.M., Milchunas, D.G., 1998. Biomass estimation on grazed and ungrazed rangelands using spectral indices. Int. J. Remote Sens. 19, 427–438. doi:10.1080/014311698216071

Toivonen, T., Luoto, M., 2003. Landsat TM images in mapping of semi-natural grasslands and analysing of habitat pattern in an agricultural landscape in south-west Finland. Fenn. - Int. J. Geogr. 181, 49–67.

Tovar, C., Seijmonsbergen, A.C., Duivenvoorden, J.F., 2013. Monitoring land use and land cover change in mountain regions: An example in the Jalca grasslands of the Peruvian Andes. Landsc. Urban Plan. 112, 40–49. doi:10.1016/j.landurbplan.2012.12.003

Trans, 2014. TRANS: Transhumance, natural resources, and conflict in the Sahel [WWW Document]. URL http://lcccrsp.org/focusregions/west-africa/trans/ (accessed 3.25.14).

Trotter, M., 2013. PA Innovations in livestock, grazing systems and rangeland management to improve landscape productivity and sustainability [WWW Document]. URL http://search.informit.com.au/documentSummary;dn=410039721522825;res=IELHSS (accessed 2.3.15).

Tueller, P.T., 1989. Remote sensing technology for rangeland management applications. J. Range Manag. 42.

Ullah, S., Si, Y., Schlerf, M., Skidmore, A.K., Shafique, M., Iqbal, I.A., 2012. Estimation of grassland biomass and nitrogen using MERIS data. Int. J. Appl. Earth Obs. Geoinformation 19, 196–204. doi:10.1016/j.jag.2012.05.008

Downloaded from http://jpe.oxfordjournals.org/ at University College Cork on April 9, 2016

Vanden Borre, J., Haest, B., Lang, S., Spanhove, T., Forster, M., Sifakis, N.I., 2011a. Towards a wider uptake of remote sensing in Natura 2000 monitoring: Streamlining remote sensing products with users' needs and expectations, in: 2011 2nd International Conference on Space Technology (ICST). Presented at the 2011 2nd International Conference on Space Technology (ICST), pp. 1–4. doi:10.1109/ICSpT.2011.6064686

Vanden Borre, J., Paelinckx, D., Mücher, C.A., Kooistra, L., Haest, B., De Blust, G., Schmidt, A.M., 2011b. Integrating remote sensing in Natura 2000 habitat monitoring: Prospects on the way forward. J. Nat. Conserv. 19, 116–125. doi:10.1016/j.jnc.2010.07.003

Van Swaay, C.A.M., 2002. The importance of calcareous grasslands for butterflies in Europe. Biol. Conserv. 104, 315–318. doi:10.1016/S0006-3207(01)00196-3

Velazquez, J., Förster, M., Kleinschmit, B., 2008. GIS and Remote Sensing for Natura 2000 Monitoring in Mediterranean Biogeographic Region, in: Car, A., Griesebner, G., Strobl, J. (Eds.), Proceedings of the Geoinformatics Forum Salzburg. Wichmann, Heidelberg, pp. 268–275.

Verbesselt, J., Somers, B., van Aardt, J., Jonckheere, I., Coppin, P., 2006. Monitoring herbaceous biomass and water content with SPOT VEGETATION time-series to improve fire risk assessment in savanna ecosystems. Remote Sens. Environ. 101, 399–414. doi:10.1016/j.rse.2006.01.005

Vermeire, L.T., Heitschmidt, R.K., Haferkamp, M.R., 2008. Vegetation response to seven grazing treatments in the Northern Great Plains. Agric. Ecosyst. Environ. 125, 111–119. doi:10.1016/j.agee.2007.12.003

Vescovo, L., Gianelle, D., 2008. Using the MIR bands in vegetation indices for the estimation of grassland biophysical parameters from satellite remote sensing in the

Downloaded from http://jpe.oxfordjournals.org/ at University College Cork on April 9, 2016

Alps region of Trentino (Italy). Adv. Space Res. 41, 1764–1772. doi:10.1016/j.asr.2007.07.043

Vickery, P.J., Hill, M.J., Donald, G.E., 1997. Satellite derived maps of pasture growth status: association of classification with botanical composition. Aust. J. Exp. Agric. 37, 547–562.

Volesky, J.D., Schacht, W.H., Richardson, D.M., 2004. Stocking Rate and Grazing Frequency Effects on Nebraska Sandhills Meadows. J. Range Manag. 57, 553. doi:10.2307/4003987

Voormansik, K., Jagdhuber, T., Olesk, A., Hajnsek, I., Papathanassiou, K.P., 2013. Towards a detection of grassland cutting practices with dual polarimetric TerraSAR-X data. Int. J. Remote Sens. 34, 8081–8103. doi:10.1080/01431161.2013.829593

Wang, C., Jamison, B.E., Spicci, A.A., 2010. Trajectory-based warm season grassland mapping in Missouri prairies with multi-temporal ASTER imagery. Remote Sens. Environ. 114, 531–539. doi:10.1016/j.rse.2009.10.010

Wang, X., Ge, L., Li, X., 2013. Pasture Monitoring Using SAR with COSMO-SkyMed, ENVISAT ASAR, and ALOS PALSAR in Otway, Australia. Remote Sens. 5, 3611–3636. doi:10.3390/rs5073611

Wang, Y., Zhou, G., Jia, B., 2008. Modeling SOC and NPP responses of meadow steppe to different grazing intensities in Northeast China. Ecol. Model. 217, 72–78. doi:10.1016/j.ecolmodel.2008.05.010

Weiers, S., Bock, M., Wissen, M., Rossner, G., 2004. Mapping and indicator approaches for the assessment of habitats at different scales using remote sensing and GIS methods. Landsc. Urban Plan. 67, 43–65. doi:10.1016/S0169-2046(03)00028-8

Downloaded from http://jpe.oxfordjournals.org/ at University College Cork on April 9, 2016

Wen, Q., Zhang, Z., Liu, S., Wang, X., Wang, C., 2010. Classification of Grassland Types by MODIS Time-Series Images in Tibet, China. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 3, 404–409. doi:10.1109/JSTARS.2010.2049001

Williamson, H.D., Eldridge, D.J., 1993. Pasture status in a semi-arid grassland. Int. J. Remote Sens. 14, 2535–2546. doi:10.1080/01431169308904291

Woodward, S.J.R., 2001. Validating a model that predicts daily growth and feed quality of New Zealand dairy pastures. Environ. Int. 27, 133–137. doi:10.1016/S0160-4120(01)00073-3

Wu, H., Li, B.-L., Stoker, R., Li, Y., 1996. A semi-arid grazing ecosystem simulation model with probabilistic and fuzzy parameters. Ecol. Model. 90, 147–160. doi:10.1016/0304-3800(95)00162-X

Wu, H., Li, Z.-L., 2009. Scale Issues in Remote Sensing: A Review on Analysis, Processing and Modeling. Sensors 9, 1768–1793. doi:10.3390/s90301768

Wylie, B.K., Harrington, J.A., Prince, S.D., Denda, I., 1991. Satellite and ground-based pasture production assessment in Niger: 1986-1988. Int. J. Remote Sens. 12, 1281–1300. doi:10.1080/01431169108929726

Wylie, B.., Meyer, D.., Tieszen, L.., Mannel, S., 2002. Satellite mapping of surface biophysical parameters at the biome scale over the North American grasslands: A case study. Remote Sens. Environ. 79, 266–278. doi:10.1016/S0034-4257(01)00278-4

Xie, Y., Sha, Z., Yu, M., 2008. Remote sensing imagery in vegetation mapping: a review. J. Plant Ecol. 1, 9–23. doi:10.1093/jpe/rtm005

Xie, Y., Sha, Z., Yu, M., Bai, Y., Zhang, L., 2009. A comparison of two models with Landsat data for estimating above ground grassland biomass in Inner Mongolia, China. Ecol. Model. 220, 1810–1818. doi:10.1016/j.ecolmodel.2009.04.025

Downloaded from http://jpe.oxfordjournals.org/ at University College Cork on April 9, 2016

Xu, B., Yang, X.C., Tao, W.G., Qin, Z.H., Liu, H.Q., Miao, J.M., Bi, Y.Y., 2008. MODIS-based remote sensing monitoring of grass production in China. Int. J. Remote Sens. 29, 5313–5327. doi:10.1080/01431160802036276

Xu, B., Yang, X., Tao, W., Qin, Z., Liu, H., Miao, J., 2007. Remote sensing monitoring upon the grass production in China. Acta Ecol. Sin. 27, 405–413. doi:10.1016/S1872-2032(07)60012-2

Yang, C., Everitt, J.H., 2010. Mapping three invasive weeds using airborne hyperspectral imagery. Ecol. Inform., Special Issue on Advances of Ecological Remote Sensing Under Global Change 5, 429–439. doi:10.1016/j.ecoinf.2010.03.002

Yang, J., Gong, P., Fu, R., Zhang, M., Chen, J., Liang, S., Xu, B., Shi, J., Dickinson, R., 2013. The role of satellite remote sensing in climate change studies. Nat. Clim. Change 3, 875–883. doi:10.1038/nclimate1908

Yang, X., Guo, X., 2011. Investigating vegetation biophysical and spectral parameters for detecting light to moderate grazing effects: a case study in mixed grass prairie. Cent. Eur. J. Geosci. 3, 336–348. doi:10.2478/s13533-011-0032-4

Yang, X., Guo, X., Fitzsimmons, M., 2012. Assessing light to moderate grazing effects on grassland production using satellite imagery. Int. J. Remote Sens. 33, 5087–5104. doi:10.1080/01431161.2012.657372

Yang, X., Wilmshurst, J.F., Fitzsimmons, M., Guo, X., 2011. Can satellite imagery evaluate the pre-condition of a grazing experiment? Prairie Perspect. Geogr. Essays 14.

Yang, X., Xu, B., Yunxiang, J., Jinya, L., Zhu, X., 2012. On Grass Yield Remote Sensing Estimation Models of China's Northern Farming-Pastoral Ecotone, in: Lee, G. (Ed.), Advances in Computational Environment Science, Advances in Intelligent and Soft Computing. Springer Berlin Heidelberg, pp. 281–291.

Downloaded from http://jpe.oxfordjournals.org/ at University College Cork on April 9, 2016

Yiran, G.A.B., Kusimi, J.M., Kufogbe, S.K., 2012. A synthesis of remote sensing and local knowledge approaches in land degradation assessment in the Bawku East District, Ghana. Int. J. Appl. Earth Obs. Geoinformation 14, 204–213. doi:10.1016/j.jag.2011.09.016

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, 342–351. doi:10.1016/S1002-0160(10)60023-9

Zerger, A., Mcintyre, S., Gobbett, D., Stol, J., 2011. Remote detection of grassland nutrient status for assessing ground layer vegetation condition and restoration potential of eucalypt grassy woodlands. Landsc. Urban Plan. 102, 226–233. doi:10.1016/j.landurbplan.2011.05.001

Zhang, M., Qin, Z., Liu, X., Ustin, S.L., 2003. Detection of stress in tomatoes induced by late blight disease in California, USA, using hyperspectral remote sensing. Int. J. Appl. Earth Obs. Geoinformation 4, 295–310. doi:10.1016/S0303-2434(03)00008-4

Zha, Y., Gao, J., Ni, S., Liu, Y., Jiang, J., Wei, Y., 2003. A spectral reflectance-based approach to quantification of grassland cover from Landsat TM imagery. Remote Sens. Environ. 87, 371–375. doi:10.1016/j.rse.2003.05.001

Zheng, S., Meng, K., Sun, Y., 2011. Grassland degradation in the Western of Songnen plain, in: 2011 19th International Conference on Geoinformatics. Presented at the 2011 19th International Conference on Geoinformatics, pp. 1–5. doi:10.1109/GeoInformatics.2011.5980808

Downloaded from http://jpe.oxfordjournals.org/ at University College Cork on April 9, 2016

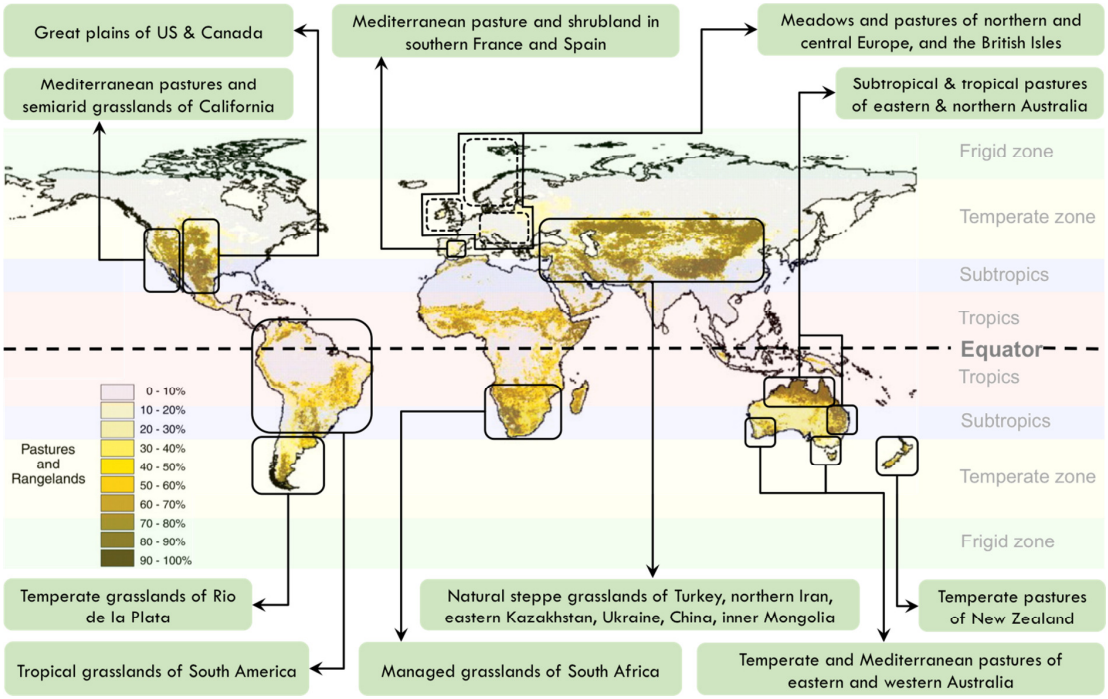


Figure 1. Overview of the global extent of pastures/grasslands [Modified fromFoley et al. (2005), grey boxes are themajor managed pastures, grasslands and rangelands areas (Hill, 2004)].

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Figure 2. Spatial resolution comparison (false colour composite: R = NIR, G = RED, B = GREEN) among QuickBird (A), RapidEye (B) and Landsat–8 (C) covering a managednatural grassland conservation site west of Berlin, Germany (Courtesy: Dr. Michael Förster).

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Figure 3 TerraSAR-X Staring Spotlight color composite (R: 08-06-2014, G: 19-06-2014, B: 11-07-2014) of Teagasc Curtin Farm. Potential of very high-resolution microwave radar (TerraSAR-X) data: (A) Monitoring of hedges and individual tree count, (B) furrow/plough lanes, (C) possibility to detect the location of grazing herds if they are standing close to each other, and (D) inter and intra paddock variation.

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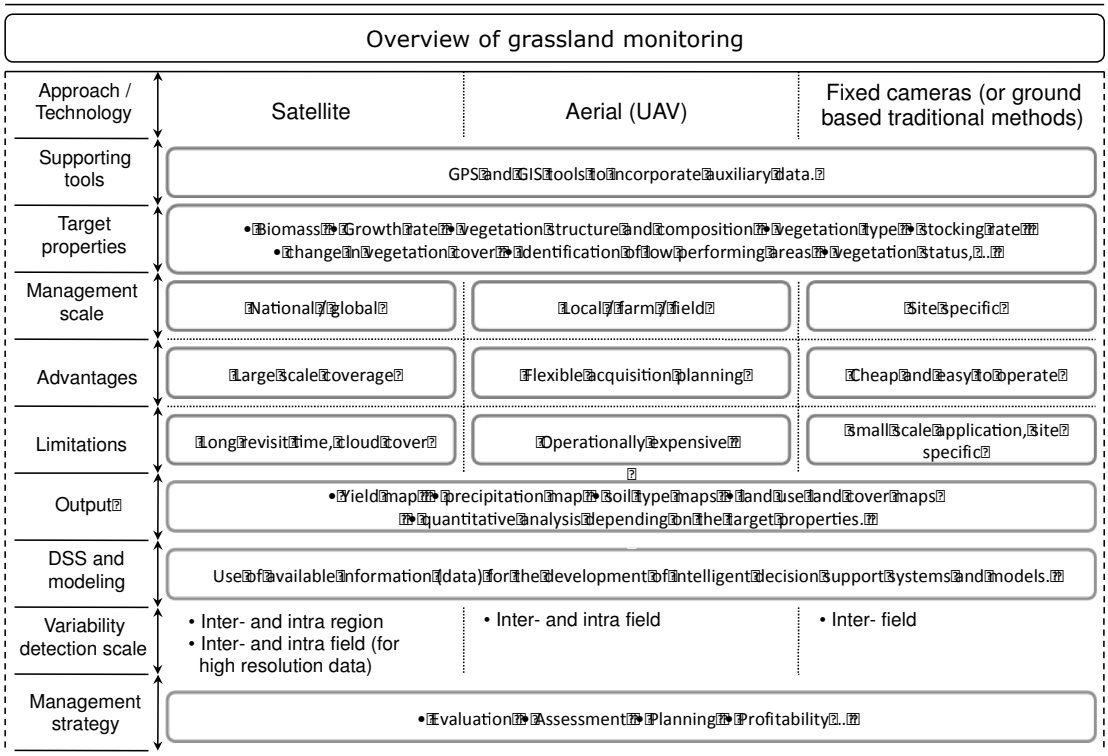


Figure 4 An overview of grassland monitoring technologies with their limitations and scope.

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Table 1 Comparison among ground-based methods.

Methods	Scale	Benefits	Limitations	Category
Visual	Field/paddock–farm	Fast and cheap.	Need specific expertise, vague estimation.	Non-destructive
Clipping		More accurate than visual assessment.	Time consuming if large number of samples are required.	Destructive
RPM		Esay to operate and cheap.	Time consuming.	Non-destructive
Field spectrometry		Information on other biophysical parameters can also be retrieved.	Trained operator and post processing is required.	Non-destructive

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Table 2 Grassland mapping/classification using satellite remote sensing data (examples from literature are grouped according to the classifiers used)

Classifiers	Examples	Advantages	Disadvantages
Unsupervised	Gu et al., (2013); Wen et al., (2010)	It is simple and easy to implement. Training (prior knowledge) data is not required for classification. It is unbiased, as clustering is purely based on pixel values.	Does not consider the spatial relationships in the data and spectral classes do not represent the on ground features. Post classification interpretation can be very time consuming.
Maximum likelihood	Baldi et al., (2006); Miehe et al., (2011); Reiche et al., (2012); Toivonen and Luoto, (2003); Weiers et al., (2004)	Until recently it was the most popular and widely used supervised classification approach. The pixels are classified based on their probability of belonging to a class and if the probabilities are not same for each class 'weight factors' can be specified. It is accurate for normally distributed datasets and considers variability in the data.	In the case of large data sets classification is extremely slow. Classification results can be biased for small training samples. Normally distributed data assumption is not always true, and this might result in misclassification.
Object based classification	Brenner et al., (2012); Franke et al., (2012); Peña-Barragán et al., (2011); Tovar et al., (2013)	It can utilize the spatial information (i.e., shape, size, color, compactness) of high resolution data, and provide high accuracy.	High computational cost. Accuracy depends on segmentation process for example scale selection, which is not well defined
Principal component analysis	Hill et al., (2005, 1999)	Reduces the data dimensionality and enhances the key features in the data. The new 'components' might detect the variations/changes.	Assumes multi-temporal data are highly correlated, and makes very strong assumptions that the directions with the largest variance contain most of the information.
Decision tree	Dubinin et al., 2010; Peña-Barragán et al., 2011; Wang et al., 2010; Wen et al., 2010)	Simple to understand and to interpret. Trees can be visualized. Requires little data preparation. Fast and able to handle both numerical and categorical data.	Decision-tree learners can create over-complex trees that do not generalize the data well and trees can be biased if some classes dominate.
Machine learning	Filippi and Jensen, (2006); Lawrence et al., (2004); Masocha and Skidmore, (2011)	Often much more accurate than human-crafted rules as they are data driven. Automatic method to search for hypotheses explaining data. Flexible and can be applied to any learning task. Rich interplay between theory and practice, with improved results as datasets increase.	Data–driven methods need a lot of labeled data, requiring extensive ground truth datasets. Typically require some programming knowledge.

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Table 3 Grassland yield estimation using satellite remote sensing data (examples from literature are grouped according to the models/methods applied)

Models/methods	Sensor	Examples
Linear regression	Landsat TM/MSS/ETM+, IRS, SPOT VEGETATION, SPOT 4/5, Hyperion, NOAA/AVHRR,	(Bradford et al., 2005; Han, 2001; He et al., 2009; Kurtz et al., 2010; Loris and Damiano, 2006; Prince, 1991; Psomas et al., 2011b; Verbesselt et al., 2006; Williamson and Eldridge, 1993; Wylie et al., 2002)
Exponential regresssion	Landsat TM, MODIS	(Xu et al., 2008, 2007), Huang et al. (2013)
Optimal regression model	MODIS, Landsat TM, NOAA/AVHRR	Yu et al. (2010), Jianlong et al. (1998)
Power regression	MODIS	(Xu et al., 2008, 2007)
Logrithmic regression	ERS-SAR, IRS, SPOT-5	Vescovo and Gianelle. (2008), Moreau and Le Toan. (2003)
Advantages:	The principal advantage of empirical modelling is its simplicity, availability, interpretability and acceptance among the scientific community.	
Disadvantages:	In nonlinear dynamic environment, the data from chaotic systems do not corrspond to the strong assumptions of a linear model. These models do not havea physical basis and mostly used for site specific analysis or model development.	

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The literature review suggests that the domain of spaceborne remote sensing of the biosphere is shifting (or expanding) from its classical applications (e. g., classification and mapping) to biophysical parameter's retrieval. With the availability of spaceborne remote sensing data with improved spatial, temporal and spectral resolution the current focus is to develop operational decision support systems for farm management.

Based on the findings of this review, the potential of multi-temporal optical and SAR data to retrieve grassland biophysical parameters and management strategies was explored. In this review an increasing trend of using machine learning approaches for both classification and information retrieval is evident. The comparative analysis of various investigations performed using different methods (or classifiers) shows that the linear statistical models cannot handle the complex and multidimensional dataset. However, machine learning algorithms have the ability to learn the complex patterns in the dataset, for example Barrett et al. (2014) have reported a high performance of state of the art machine learning algorithms for image classification.

For training machine learning algorithms, both the size and the quality of training samples is very important. Machine learning algorithms that are trained by using a high quality dataset with few anomalies (or outliers) and missing values can learn and retrieve complex hidden patterns more efficiently. In this study, high quality field measurements (biomass and growth rate) and weather data were used to train machine learning algorithms.

Part II

REMOTE SENSING AND MACHINE LEARNING BASED GRASSLAND BIOMASS ESTIMATION

3

MODELLING BIOMASS ESTIMATION OF MANAGED GRASSLANDS

A breakthrough in machine learning would be worth ten Microsofts.

— Bill Gates (Chairman, Microsoft)

CHAPTER PUBLICATION:

This chapter has been accepted as a research article for publication in "Journal of Selected Topics in Applied Earth Observations and Remote Sensing, IEEE":

Ali, I.; Cawkwell, F.; Dwyer, E.; and Green, S.; **2016**, *"Modelling managed grassland biomass estimation by using multitemporal remote sensing data—a machine learning approach"*, Journal of Selected Topics in Applied Earth Observations and Remote Sensing, IEEE. [Accepted, (IF: 3.026)]

3.1 PAPER—2

3.1.1 *Ali, I.; Cawkwell, F.; Dwyer, E.; and Green, S.; 2016, "Modelling managed grassland biomass estimation by using multitemporal remote sensing data—a machine learning approach", IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing. [Accepted, (IF: 3.026)]*

Precise assessment of available biomass is a key factor for the management and optimization of resource allocation for the livestock industry, and as well as sustainable agricultural development. In Ireland, grasslands are the primary and cheapest feed source for livestock industry. In order to determine the grazing capacity of a grassland farm a precise assessment of available biomass is crucial, because overgrazing and poor management might lead to a complete degradation.

In the Irish context, grassland management is critical to ensure adequate grass supply, good quality feed, and spring and autumn grass availability– optimizing resource allocation for a sustainable livestock industry. Due to the high level of precipitation in Ireland the potential for soil compaction is greater due to wet soil conditions. In grasslands, surface compaction occurs due to poaching (hooves) of livestock at high stocking densities, this can be managed through lower stocking densities or careful management such as timing and rotation of grazing animals[1].

For the development of machine learning based models to predict the grassland biomass, a 12 (2001 – 2012) and 6 (2001 – 2005, 2007) years of

1 http://www.teagasc.ie/soil/square/compaction.asp

satellites remote sensing (MODIS 8 day composite) time series data were used. For the training of the machine learning algorithms, very high quality weekly biomass in-situ data for this period is available for two different test sites, representative of different meteorological and agricultural regimes. In Ireland such datasets are available for only a few sites where intensive monitoring and management has been undertaken for many years for dairy related research, namely at the Teagasc research farms, with Moorepark in the south of Ireland and Grange in the north-east being selected as suitable for this research. The purpose of this work is to analyse the feasibility of transferring the processing chain and model developed for one site to another site, and thus potentially to a national scale. Figure 14 shows the graphical abstract of this paper.

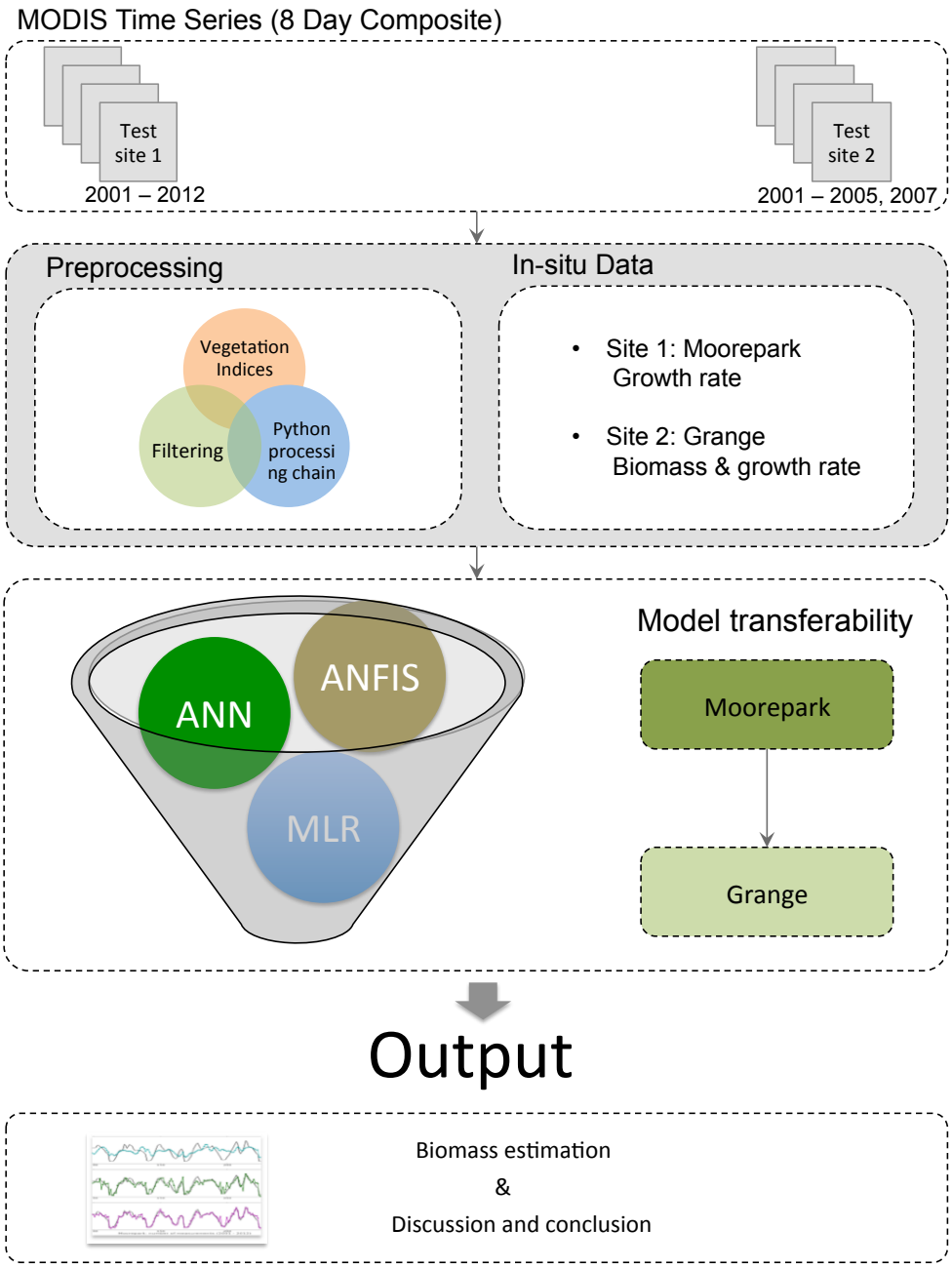


Figure 6: Graphical abstract of this paper: **Ali, I.;** Cawkwell, F.; Dwyer, E.; and Green, S.; **2016**, *"Modelling managed grassland biomass estimation by using multitemporal remote sensing data—a machine learning approach"*, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing. [Accepted, (IF: 3.026)]

CONTRIBUTION STATEMENT

Declaration of own contribution to the published (or intended for publication) scientific papers within my dissertation.

DISSERTATION TITLE: Retrieval of grassland biophysical parameters using multitemporal optical and radar satellite data.

PAPER–2: **Ali, I.;** Cawkwell, F.; Dwyer, E.; and Green, S.; **2016**, *"Modelling managed grassland biomass estimation by using multitemporal remote sensing data—a machine learning approach"*, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing. [Accepted, (IF: 3.026)]

OWN CONTRIBUTION IN THIS WORK: Concept development (fully), Literature search (fully), Methods development (fully), Research design (fully), Data collection (mainly), Data pre-processing (fully), Data analysis (fully), Construction of the manuscript (fully), Argumentation (fully), Critical revision of the article (mainly).

Iftikhar Ali, MSC

April 17, 2016

RE: IEEE JSTARS-2015-00663 Manuscript Decision

1 message

jocelyn.chanussot@gipsa-lab.grenoble-inp.fr <jocelyn.chanussot@gipsa-lab.grenoble-inp.fr> Wed, Dec 2, 2015 at 1:23 AM
To: iffi.math@gmail.com

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Your manuscript JSTARS-2015-00663 Modeling managed grassland biomass estimation by using multitemporal remote sensing data–a machine learning approach has been reviewed by the J-STARS Editorial Review Board and recommended for publication subject to satisfactory response to minor revisions suggested. It is recommended that you resubmit your manuscript as revised in accordance with the Editorial Review Board comments given below.

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Associate Editor Comments:

Associate Editor
Comments to the Author:
This revised version is fine, except for one of the reviewer who is asking for a minor revision. The paper can be accepted after taking those last comments into account.

Reviewer(s) Comments:
Reviewer: 1

Comments to the Author
No comments

Reviewer: 2

Comments to the Author
The revised version has been improved.

Reviewer: 3

Comments to the Author
The responses by the author seems convincing especially the comments about using the SAR data for height estimation. The SAR data for height estimation of grasslands biomass does not work because of the signal penetration through the grass to the water layer below the ground surface. The experimentation and analysis is satisfactory and the big data for 12 years is a very remarkable study here.

Reviewer: 4

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Modeling managed grassland biomass estimation by using multitemporal remote sensing data–a machine learning approach

Journal:	*Journal of Selected Topics in Applied Earth Observations and Remote Sensing*
Manuscript ID	JSTARS-2015-00663.R1
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Keywords:	Remote sensing

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Modeling managed grassland biomass estimation by using multitemporal remote sensing data–a machine learning approach

Abstract

More than 80% of agricultural land in Ireland is grassland, which is a major feed source for the pasture based dairy farming and livestock industry. Many studies have been undertaken globally to estimate grassland biomass by using satellite remote sensing data, but rarely in systems like Ireland's intensively managed, but small-scale pastures, where grass is grazed as well as harvested for winter fodder. Multiple linear regression (MLR), artificial neural network (ANN) and adaptive neuro–fuzzy inference system (ANFIS) models were developed to estimate the grassland biomass (kg DM/ha/day) of two intensively managed grassland farms in Ireland. For the first test site (Moorepark) 12 years (2001–2012) and for second test site (Grange) 6 years (2001–2005, 2007) of in–situ measurements (weekly measured biomass) were used for model development. Five vegetation indices (VIs) plus two raw spectral bands (RED, NIR) derived from an 8–day MODIS product (MOD09Q1) were used as an input for all three models. Model evaluation shows that the ANFIS ($R^2_{Moorepark} = 0.85, RMSE_{Moorepark} = 11.07$; $R^2_{Grange} = 0.76, RMSE_{Grange} = 15.35$) has produced improved estimation of biomass as compared to the ANN and MLR. The proposed methodology will help to better explore the future inflow of remote sensing data from spaceborne sensors for the retrieval of different biophysical parameters, and with the launch of new members of satellite families (ALOS–2, Radarsat–2, Sentinel, TerraSAR–X, TanDEM–X/L) the development of tools to process large volumes of image data will become increasingly important.

Keywords: Managed grassland; biomass estimation; remote sensing; time series; machine learning

1 Introduction

Grasslands are one of the major and crucial components of the terrestrial ecosystem [1] and most prevalent and widespread global land cover types. Grasslands cover about 40.5% of the Earth's surface [2]–[4] and after forests, grasslands are the major source (about 30%) of carbon sink [5], [6] and thus play a very important role in regulating the global carbon cycle [4]. The demand and consumption of

dairy products is increasing globally [7], [8] and in order to meet this demand, an equivalent growth in livestock has to be maintained.

Grasslands are the major feed source for grazing livestock, and the amount of above ground biomass will determine the pasture's carrying capacity–the maximum number of animals that can graze a pasture for a set period without harming it. Grazed grass is the cheapest feed for livestock, and for that reason it is very important to manage grasslands because better management will result in low cost high quality grass. Based on these management approaches, grasslands can be categorized into broader management strategies: (*i*) unmanaged (natural) and (*ii*) managed (agricultural pastures) grasslands. The term "grassland management" in the context of this research includes weed control, removing dead plants, mowing, clipping, assessment of growth rate, grazing length, and utilization of grassland [9].

Grassland biomass can be estimated by using both ground based conventional methods and remote sensing technology. Existing ground-based methods include:

i. *Visual:* the visual assessment by human eye (expert or farmer), this method is spatially sparse with limited performance [10].
ii. *Cut and dry (Clipping):* grass is harvested from the paddock and is dried and weighed to get the dry matter (DM) yield.
iii. *Rising plate meter:* both mechanical and electronic plate meters work on the same principle, where the plate rises up and down the shaft taking measurements of grass height [11]–[13].
iv. *Field spectrometry:* can also be used for above ground biomass estimation where collected spectra are converted into reflectance and calibration is performed from biomass samples [14], [15].

Conventional ground based methods are subjective, time consuming and are feasible (or applicable) only for small scale assessment and monitoring of grasslands [16].

More advanced and spatially extensive grassland monitoring methods include the use of remotely sensed data. Remote sensing data can be acquired from sensors (optical and/or radar) mounted on different platforms [17], for example in the case of airborne remote sensing the sensor is mounted on aircraft, helicopters or unmanned aerial vehicles (UAV) while in case of satellite remote sensing the sensor(s) is mounted on a spacecraft. Airborne remote sensing is good for cloud free data acquisition at a small scale, as the aircraft can fly under the cloud cover at an optimal time for data collection. Airborne remote sensing data have been used for vegetation change detection [18] and discrimination

[19] at a local scale. Similarly, for grassland monitoring, Curran and Williamson [20] have used airborne multispectral scanner data for the mapping of leaf area index, while in another study Darvishzadeh et al [21] used hyperspectral airborne imagery. Despite the advantages (timely and flexible in acquisitions, high spatial resolution) of airborne remote sensing data, the approach is still considered expensive [22] for consistent large scale applications, and impractical for the development of operational tools. At present, in order to overcome these limitations, satellite remote sensing remains the best available alternative, where sensors with different microwave wavelengths (TerraSAR-X, Radarsat), spectral bands (Landsat, QuickBird, Hyperion), resolution and revisit time can be used operationally. Data from both optical and SAR instruments are being used for grassland related investigations [23], [24].

Since the launch of Landsat–1 in 1972, satellite remote sensing data have been used for agricultural activities e.g., biomass estimation [25], soil moisture [26], water consumption [27], discrimination of different crop types [28] and monitoring of agricultural drought [29]. With the development of satellite sensors with high spatio–temporal resolution and wide area coverage, agriculture remote sensing has moved a step further towards “precision agriculture” whereby growth rates can be monitored [30], [31], inter and intra field variability mapped [32], poor/under performing areas identified [33] and decision support systems developed [34]–[37].

Over the past 40 years a number of methods have been developed for grassland biomass estimation based on satellite remote sensing data, and the technology is now mature enough for the monitoring of detailed grassland management activities. Based on a review of past work, satellite driven grassland biomass estimation methodologies can be categorized into three broader groups: (i) using vegetation indices, (ii) biophysical simulation models, and (iii) machine learning algorithms [38].

1.1 Use of vegetation indices for grassland biomass estimation

The use of satellite driven vegetation indices in combination with in–situ measurements [39], [40] for the development of regression models for grassland biomass estimation is the most popular and well-studied approach [41]–[49]. Many researchers have investigated the application of different vegetation indices derived from satellite imagery (e.g., QuickBird, MODIS, Landsat) and developed different regression models (e.g., linear, power, logarithmic, multiple linear) for grassland biomass estimation [16], [50]–[52]. Very high accuracies of the vegetation index based regression models for biomass estimation have been reported in the literature [16], [53]–[59], but their major limitation is that these

models are site specific and do not have the capability to learn the highly non–linear and complex patterns in the data.

1.2 Use of biophysical simulation models for grassland biomass estimation

The LINGRA simulation model has been designed for the prediction of grassland (perennial rye grass) productivity in Europe [60], [61]. In a recent study, Maselli et al. [62] used the C–Fix parametric model for grassland gross primary production in combination with in–situ measurements and remote sensing data. This approach of data assimilation has frequently been used for crop (i.e., wheat, rice, maize) monitoring [63]–[65], but has not been fully explored yet for grassland monitoring.

1.3 Use of machine learning algorithms for grassland biomass estimation

Unlike crops [66]–[69] and forests [70] the number of studies on the use of machine learning algorithms for remote sensing based grassland biomass estimation is limited [71]. Xie et al. [72] and Yang et al. [73] reported the successful application of an artificial neural network approach for grassland yield estimation based on utilization of satellite driven vegetation indices. In another study Clevers et al. [74] used a support vector machine approach for grassland biomass estimation based on airborne remote sensing data.

The objective of this paper is to estimate the biomass of managed grasslands where weekly grass growth (kg DM/ha/day) is recorded on a regular basis. Three different methods were used for grassland biomass estimation, namely: Multiple Linear Regression (MLR), Artificial Neural Networks (ANN) and Adaptive–Neuro Fuzzy Inference Systems (ANFIS). To the best of our knowledge only a few studies [72], [73] have reported on the application of ANN with remote sensing data for grassland biomass estimation; and there has been no work published to date on the application of ANFIS using satellite imagery for grassland biomass estimation. After the publication of Jang [75] research, where the framework of ANFIS was introduced, this modeling approach has been used in various disciplines [76]–[83]; and some studies reported the performance comparison between ANN and ANFIS, but not previously in the context of deriving biophysical parameters from a satellite image. It is evident from a number of previous studies that in some cases ANN performs better than ANFIS [84], but in most of the cases ANFIS performs as well as, or better than the ANN [85]–[93][94], [95]. This trend of model performance varies between application domains, and performance also depends upon a number of factors e.g., the quality and size of datasets and underlying problem formulation. This paper will explore some of these issues in more depth for two Irish sites with differing data inputs.

2 Materials and methods

2.1 Study sites

The Moorepark (soil type: Free-draining acid brown earth of sandy loam to loam in texture, aspect: South facing, 40m above sea level, average paddock size: about 5.0 hectares, management: management practices includes both grazing and silage cut) and Grange (soil type: moderately well drained, aspect: 92m above sea level, average paddock size: about 2.5 hectares, management: management practices includes both grazing and silage cut) study sites are Teagasc (the Irish agriculture and food development authority) research farms located in the south ($50^{\circ}07'$ N, $08^{\circ}16'$ W) and north east ($53^{\circ}30'$ N, $06^{\circ}40'$ W) of Ireland respectively (see Figure 1). Teagasc research farms in Ireland have been closely monitored for many years, providing a valuable source of grassland biomass (intensively managed grassland), meteorological and farm management data. This study uses in-situ data of weekly biomass (kg DM/ha/day) from 2001 to 2012 for Moorepark (area: 100 ha) and from 2001 to 2005 and 2007 for Grange (area: 71.3 ha). For Moorepark, annual mean temperature ranges from 9.4–10.1°C and for Grange it is 8.8–11°C, while the annual average rainfall varies between 854 and 1208 mm for Moorepark and between 601.5 and 1065.8 mm for Grange study site (see Figure 2).

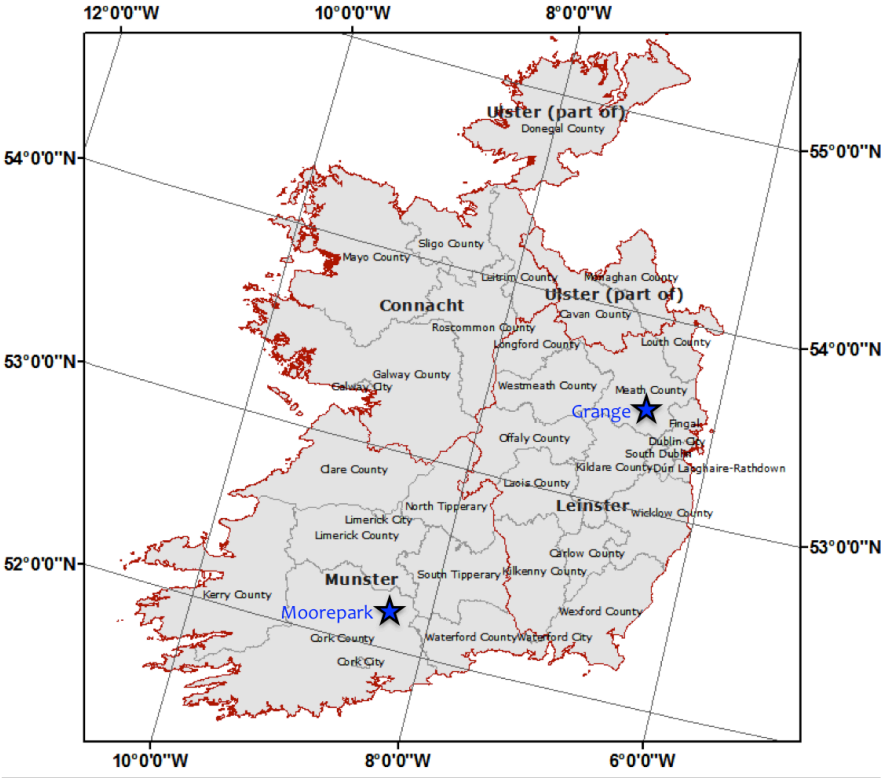


Figure 1 The two Teagasc research farm study sites (Blue stars: Moorepark and Grange) where weekly in situ data are collected.

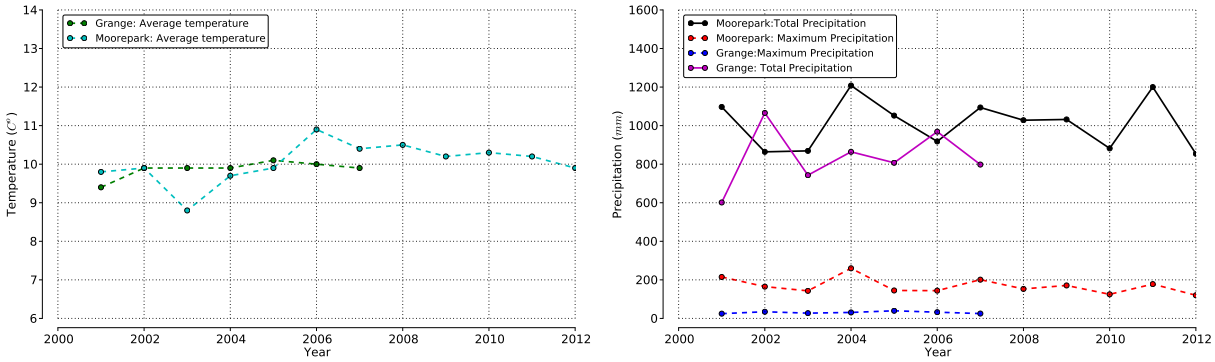


Figure 2 The meteorological profiles of annual average temperature and annual maximum and total precipitation for Moorepark and Grange study sites.

2.2 Data used

2.2.1 Remotely sensed data

A time series (46 images per year) of 250m MODIS Terra surface reflectance 8-day composite (MOD09Q1), and 500m MODIS Terra surface reflectance 8-day composite (MOD09A1) images were freely downloaded from the NASA Land Process Distributed Active Archive Center (LPDAAC) (https://lpdaac.usgs.gov/lpdaac/get_data/glovis) for the Moorepark study site from 2001 to 2012 and for the Grange study site from 2001 to 2007. For accurate estimation of the grass growth index based on satellite data, the date of ground truth data collection and satellite image acquisition are required in order to establish a true correlation between the observed biophysical parameters and satellite driven vegetation indicators. The day of pixel composite information was extracted from the MOD09A1 product as suggested by Guindin-Garcia et al. [96] and applied to the 250m product, which was used for the model development.

2.2.2 Field data

Both the test sites consist of managed grassland pasture fields, and different grassland related biophysical parameters have been recorded for many years. In this study the grassland weekly biomass (kg DM/ha/day) values have been used. For the Moorepark test site, 12 years (2001-2012) of in-situ measurements of grassland biomass are used, while for Grange 6 years (2001-2005 and 2007) of field data are analyzed. Biomass (dry matter) for each paddock is calculated by cutting and drying a grass strip of approximately 1 meter wide and 3 meters long (see Figure 3) from which biomass and growth rate for the whole farm are calculated. Figure 4 shows a summary of ground data collected for both the test sites.

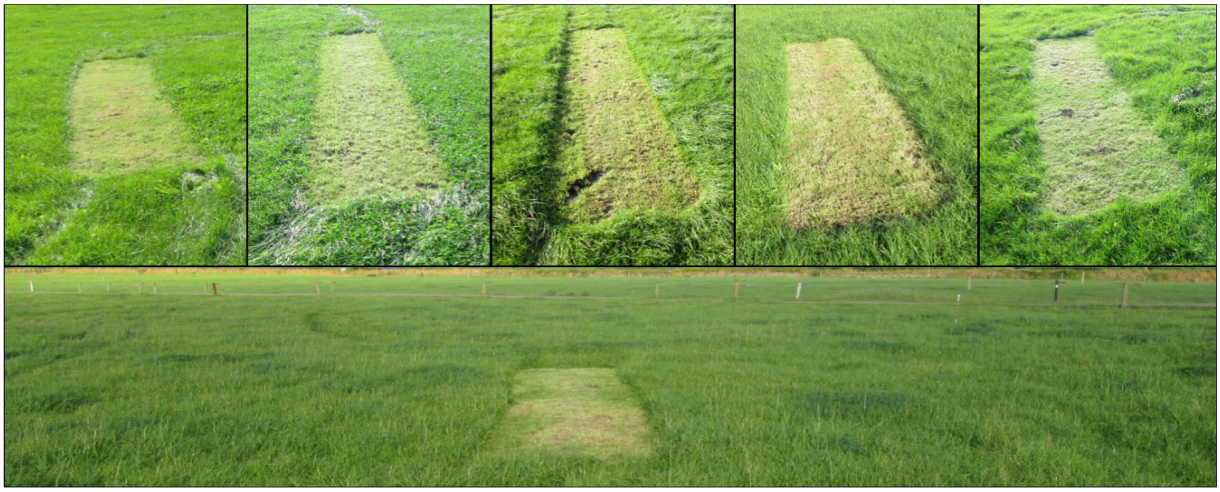


Figure 3 In–situ data collection for each individual paddock using the clipped method, where a strip of grass approximately 1 metre wide and 3 metres long is cut and dried to estimate the biomass (kg DM/ha/day).

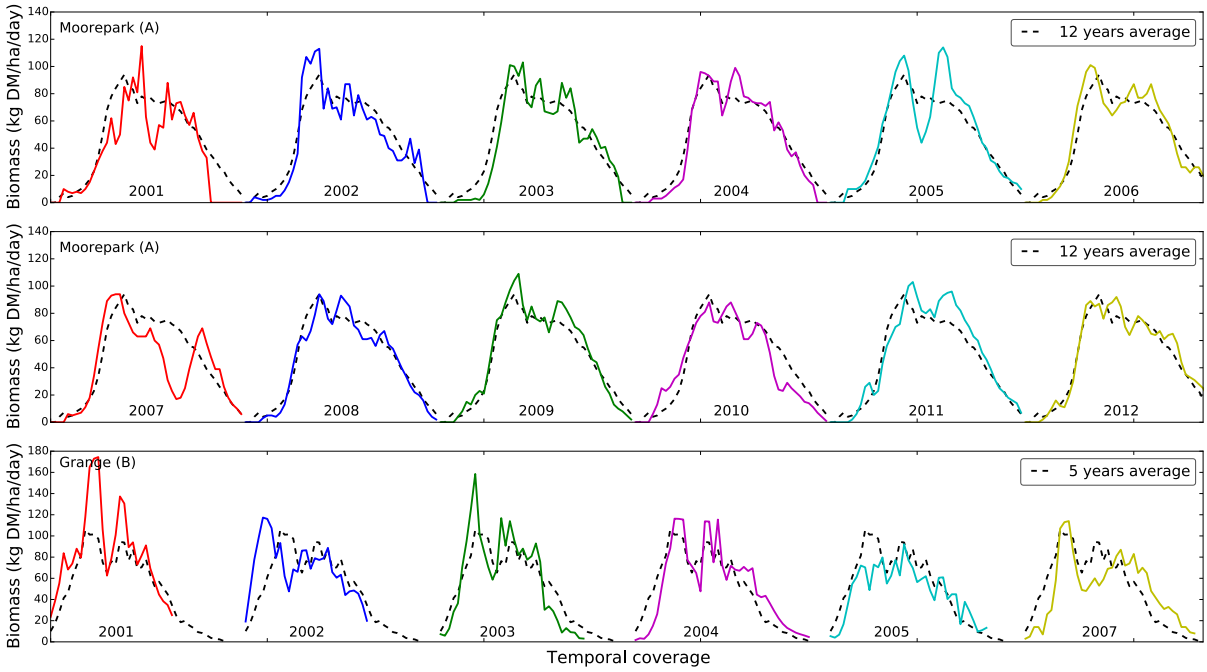


Figure 4 Weekly biomass measurements for (A): Moorepark 12 years in–situ measurements, (B) Grange 6 years in–situ measurements: the black line represents the weekly biomass (kg DM/ha/day) value for each year, and red dotted lines show 12 and 6 years average biomass (kg DM/ha/day)

2.3 Data preprocessing and study design

Both MODIS products were downloaded in HDF file format and a Python script was written to extract the reflectance values five vegetation indices were calculated as shown in Table 1:

Table 1 List of vegetation indices used.

Vegetation Index	Acronyms	Formula	Description	Refference
Normalized Difference Vegetation Index	NDVI	$\frac{NIR - RED}{NIR + RED}$	is widely used for the separation of green vegetation and background soil brightness with values ranging from -1 to +1, where, -1 represents non-vegetative and +1 vegetative area.	[97]
Enhanced Vegetation Index–2	EVI2	$2.5\left(\frac{NIR - RED}{NIR + 2.4RED + 1}\right)$	is a modified form of NDVI—highly sensitive to vegetation, capable of decoupling canopy background signal, and reduces the atmospheric influence.	[98]
Soil Adjusted Vegetation Index	SAVI	$(1 + L)\left(\frac{NIR - RED}{NIR + RED + L}\right)$	in case of low vegetation cover soil noise causes a poor estimation of vegetation biomass. In order to overcome this limitation SAVI is used—to minimize the contribution of soil background signals by using a soil adjustment factor L. Huete (1988) suggested a value of L = 0.5 in most conditions.	[99]
Modified Soil Adjusted Vegetation Index	MSAVI	$\frac{1}{2}\left[(2NIR + 1) - \sqrt{(2NIR + 1)^2 - 8(NIR - RED)}\right]$	is a modification of SAVI which has a modified soil adjustment factor L, pixels with negative values represents non-vegetative area and pixels with positive values represent vegetative area.	[100]
Optimised Soil Adjusted Vegetation Index	OSAVI	$\frac{NIR - RED}{NIR + RED + X}$	also belongs to the SAVI family of vegetation indices, in order to minimize the background soil noise, here the factor X is crucial for the minimization of background soil noise, Rondeaux et al. (1996) found an optimized value of X=0.16.	[101]

Calculated vegetation indices were filtered using the Savitzky-Golay algorithm, which is widely used to smooth high frequency variability, such as the spiky nature of the time series of vegetation indices. This process was implemented in Python in order to smooth out noise in the time series and fill gaps resulting from cloud-induced missing data. Principal Component Analysis (PCA) was then applied to reduce the data dimensionality and variable dependencies. The pixels covering the study sites were used to calculate mean value of each vegetation index. The pixels only partially intersecting the site areas were also included in the region of interest shape file covering the study sites. Figure 5 shows the systematic workflow of this approach.

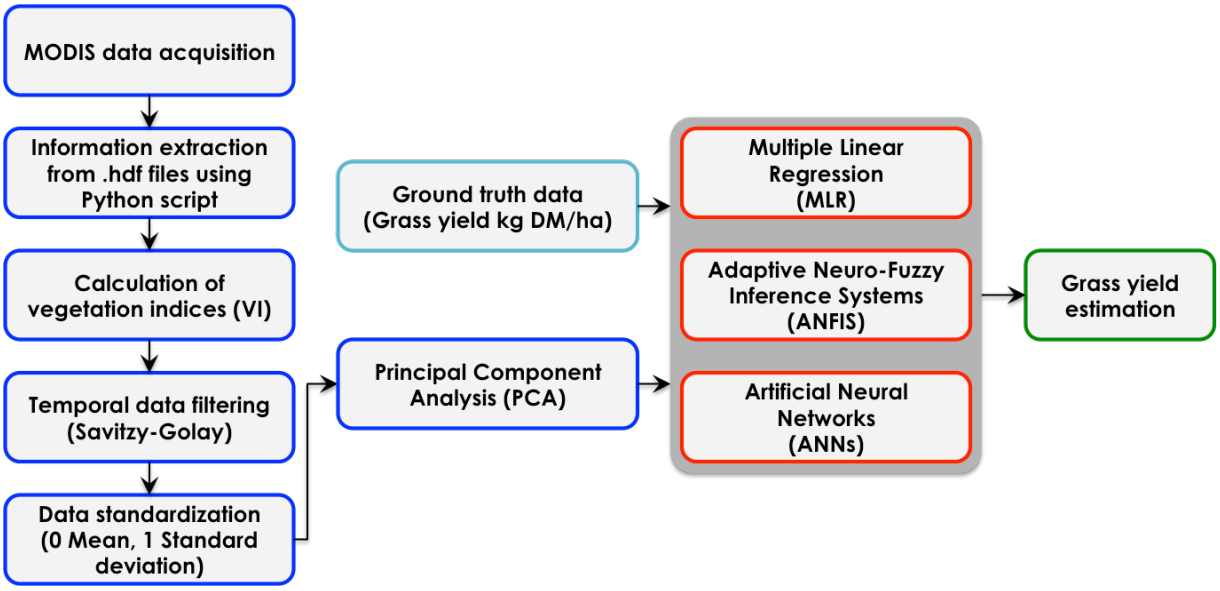


Figure 5 Study design and methodological workflow scheme.

2.4 Model development

2.4.1 Multiple linear regression model

The multiple linear regression (MLR) approach is used where there is more than one predictor variable, and to find linear relationships between the dependent and independent variables [102]. Five vegetation indices and two raw bands (RED, NIR) were used as independent predictor variables for grassland biomass (kg DM/ha/day). The model formulation is as follows (Eq. 1):

$$Y_i = \beta_0 + \beta_1 X_{i1} + \cdots + \beta_k X_{ik} + \varepsilon_i \quad \text{(Eq. 1)}$$

Where,

$Y_i = model\ reponse,$

$\beta_0 = intercept,$

$\beta_1, \cdots, \beta_k = slopes\ or\ regression\ coefficients,$

$X_{i1}, \cdots, X_{ik} = predictor\ variables,$

$\varepsilon_i = independent\ variables\ that\ are\ normally\ distributed\ with\ 0\ mean\ and\ constant\ variance.$

2.4.2 Artificial Neural Networks model

Artificial neural networks (ANNs) belong to the family of machine learning algorithms, where the computational models have a great ability to adapt, learn and generalize the complex and complicated patterns hidden in the data. ANN works like a biological neuron where the information flows in are

processed by the neuron and the results flow out [103]. This gives the neuron an ability to react based on previously learned patterns. Scientists replicate this by creating a structure that processes information like a biological neuron does, except this approach is mathematically driven [104], [105]. Figure 6 shows the example of a single biological (A) and artificial neuron (B).

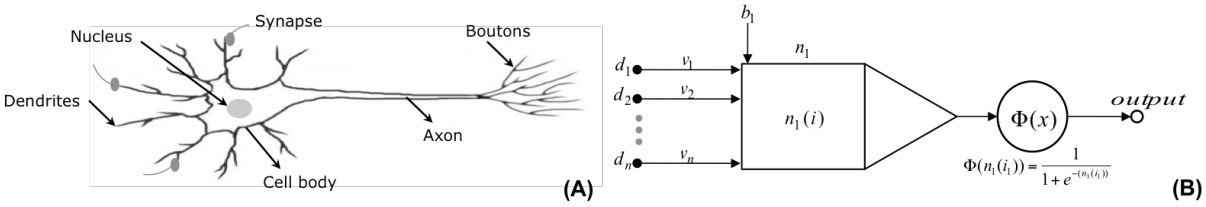


Figure 6 A: Biological neuron, B: unit artificial neuron.

A single processing unit (an artificial neuron) computes the weighted sum of input data sets and there is always an activation function, which gives the output of the unit. The mathematical representation of an artificial neuron (n_1) at an instance (i_1) and its activation function [104] are given by Eq. 2:

$$n_1(i_1) = \sum_{j=1}^{n} v_{j1} d_j + b_1(i_1) \quad \text{(Eq. 2)}$$

where, $d_1, \ldots, d_n$ are inputs, $v_1, \ldots, v_n$ are associated connection weights and b_1 is the bias value, with the activation function sigmoid (Eq. 3);

$$\Phi(x) = \frac{1}{1+e^{-x}} \quad \text{(Eq. 3)}$$

Other possible activation functions could be linear or hyperbolic tangent functions.

For this study, a feed-forward back propagation neural network algorithm [104] was used, where individual neurons (processing units) are arranged in layers where the first layer takes inputs and last layer produces output(s). Neurons in each layer are connected to all the neurons in the next layer and information flows in the forward direction (hence “feed forward”), while there is no connection among the neurons in the same layer. Figure 7 shows the structure of the multilayer feed-forward back propagation algorithm.

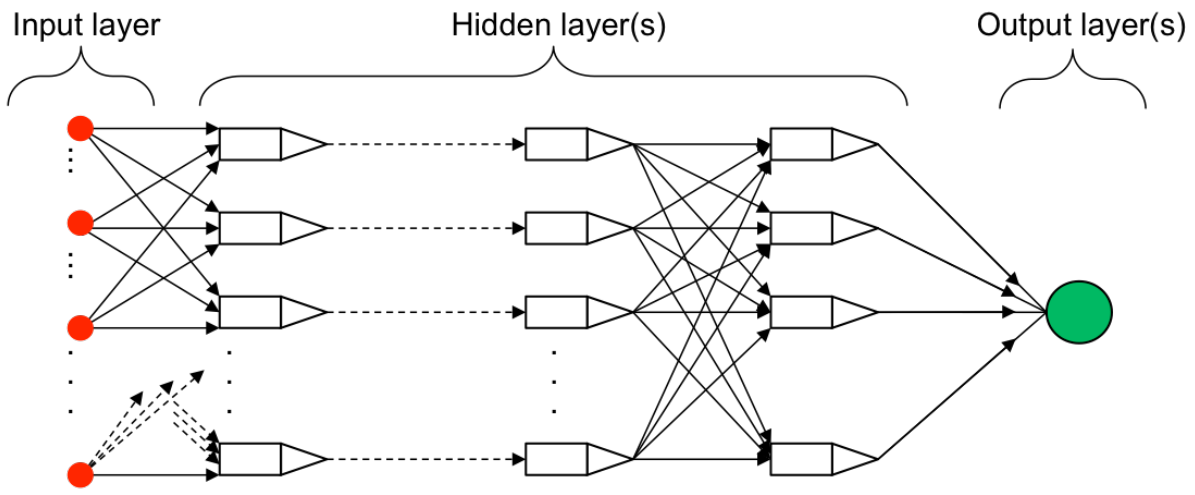


Figure 7 Structure of multilayer feed–forward back propagation algorithm.

Back propagation is a form of supervised learning algorithm where the input dataset consists of training samples and desired outputs. In back propagation, learning occurs every time an input training sample is fed to the net, and the output of this exercise is compared with the desired results and an error (or deviation from original results) is calculated. The value of error is a quantitative measure, which shows how far away the output is from the desired value. Using the calculated errors, the back propagation-training algorithm then follows the backward pass through the layers from output layer to the input layer in order to adjust the weights, with the ultimate objective being to minimize the error.

2.4.3 Adaptive Neuro Fuzzy Inference Systems (ANFIS) model

ANNs have the power of learning patterns, while on the other hand fuzzy logic has the capabilities of reasoning. ANFIS is a fusion or hybrid model that integrates the positive aspects of both ANNs and fuzzy logic in order to construct a robust model that will associate the independent (input values) variables with the dependent (target values) variables with minimum estimation error.

A five layers ANFIS was first introduced by Jang [75], with the capability to incorporate linguistic knowledge (expert opinion) and human like reasoning based on a training data set and a set of IF-THEN fuzzy rules. A unit format for defining fuzzy rules is:

$$\boldsymbol{IF} < Antecedent > \boldsymbol{THEN} < Consequent >$$

For illustration purpose, ANFIS architecture with two inputs (x_1, x_2) and one output (O_f) is shown in Figure 8. The corresponding two fuzzy IF-THEN rules of Takagi and Sugeno's type [106] can be expressed as follows:

Rule 1: $\boldsymbol{IF}\ x_1\ is\ Y_1\ and\ x_2\ is\ Z_1, \boldsymbol{THEN}\ f_1 = p_1x_1 + q_1x_2 + r_1$

Rule 2: $\boldsymbol{IF}\ x_1\ is\ Y_2\ and\ x_2\ is\ Z_2, \boldsymbol{THEN}\ f_2 = p_2x_1 + q_2x_2 + r_2$

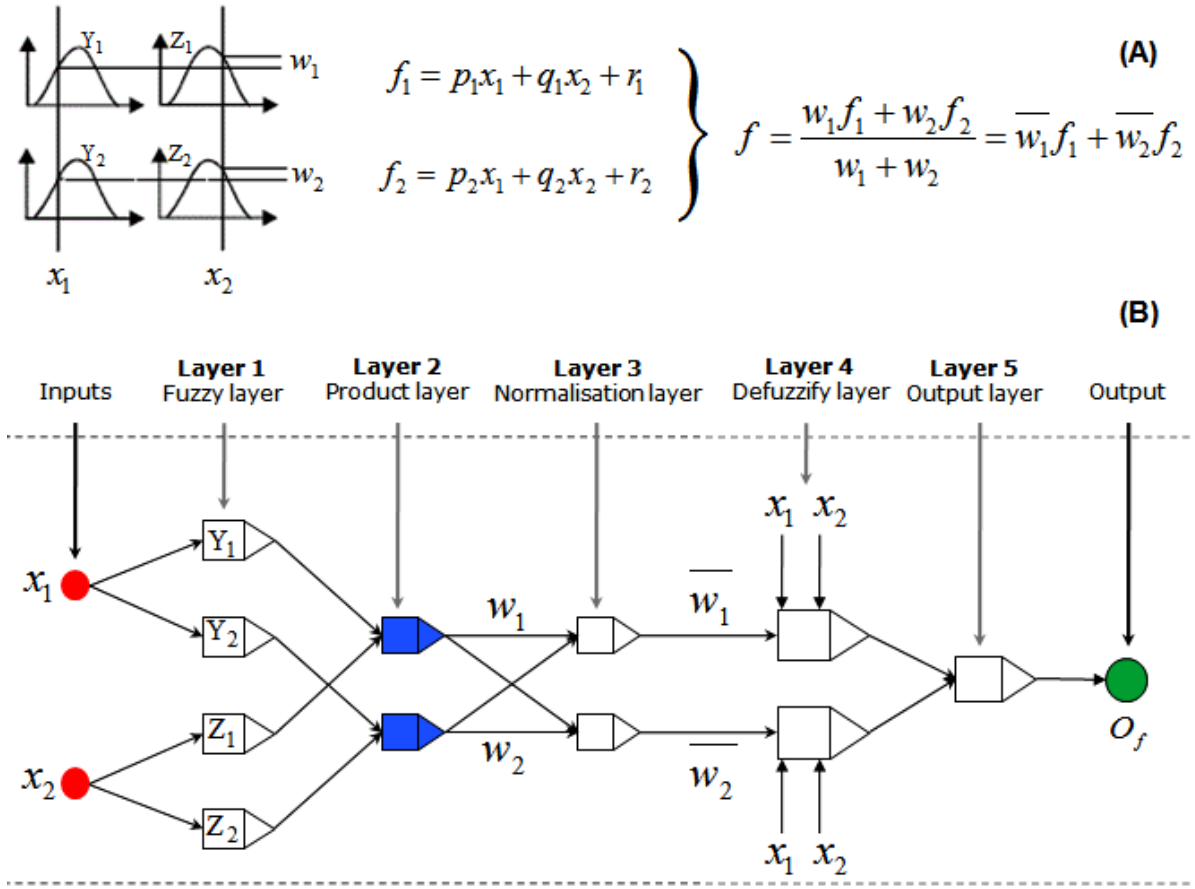


Figure 8 A: Type–3 fuzzy reasoning and, B: equivalent ANFIS.

Figure 8 (A) shows the type-3 (two inputs and one output) fuzzy reasoning and Figure 8 (B) shows the corresponding ANFIS architecture.

The functionality and corresponding mathematical formulation of each layer is as follows [75]:

Layer 1: Fuzzy layer: Every node in this layer is fixed and adaptive and membership $(\mu(\circ))$ of each label (Y_i, Z_i) is calculated by using equation (4) and (5):

$$U_i^1 = \mu_{Y_i}(x_1), for\ \ i = 1, 2 \qquad \text{(Eq. 4)}$$

$$U_i^1 = \mu_{Z_i}(x_2), for\ \ i = 1, 2 \quad \text{(Eq. 5)}$$

where, x_1 and x_2 are inputs and i is the node and Y_i and Z_i are the linguistic labels. $\mu_{Y_i}(x_1)$ is a membership function of Y_i which gives the degree of membership of x_1 to be part of Y_i (Eq. 6). The parameters $\{a_i, b_i, c_i\}$, referred to as premise parameters, determine the shape of the membership function.

$$\mu_{Y_i}(x_1) = \frac{1}{1+\left[\left(\frac{x_1-c_i}{a_i}\right)^2\right]^{b_i}} \quad \text{(Eq. 6)}$$

Layer 2: Product layer: Every node in this layer is labeled N_2, the outcome of this layer is the product of incoming signals and is given by Eq. 7.

$$w_i = \mu_{Y_i}(x_1) \times \mu_{Z_i}(x_2), for\ \ i = 1, 2 \quad \text{(Eq. 7)}$$

where, w_i is the output of layer 2.

Layer 3: Normalization layer: The third layer, labeled as N_3, is called the normalization layer,

$$\overline{w}_i = \frac{w_i}{w_1+w_2}, for\ i = 1, 2 \quad \text{(Eq. 8)}$$

where the ratio of each weight to the total weight is calculated, i.e., i^{th} node calculates the ratio of the i^{th} rule's firing strength (Eq. 8).

Layer 4: Defuzzify layer: Every node in this layer is adaptive and it is called the defuzzification layer (labeled as N_4 (Eq. 9)),

$$D_i^4 = \overline{w}_i f_i = \overline{w}_i(p_i x_1 + q_i x_2 + r_i) \quad \text{(Eq. 9)}$$

where $\overline{w}_i$ is the output of layer 3, and the set of parameters $\{p_i, q_i, r_i\}$ is referred to as consequent parameters.

Layer 5: Output layer: All the incoming signals are summed in order to compute the overall output (Eq. 10), i.e.,

$$O_f = output = \sum_{i=1}^{2} \overline{w}_i f_i = \frac{\sum_{i=1}^{2} w_i f_i}{\sum_{i=0}^{2} w_i} = \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2} \quad \text{(Eq. 10)}$$

Table 2 shows the list of parameters used for in ANN and ANFIS models.

Table 2 Features of input data, performance evaluation criteria and architecture and parameters used in the ANFIS and ANN models.

Data	
Standardization:	0 Mean, 1 Std
Reduction:	PCA
Division:	70%—Training (Moorepark: 235, Grange: 94) 30%—Testing (Moorepark: 101, Grange: 41)
Performance evaluation criteria	
R^2:	Correlation coefficient
RMSE:	Root Mean Square Error
ANN	
Number of layers:	4
Neural net algorithm:	Feed-forward backpropagation
Number of neurons:	Input layer: 7, hidden layer neurons: 15, Output layer: 1
Initialization:	Weights: random, biases: random
Training algorithm:	Levenberg—Marquardt
Activation functions:	Log–sigmoid
ANFIS	
Number of layers:	5
Type:	Sugeno-type
Input membership function type:	Generalized bell-shaped membership function
Learning rule	Hybrid learning algorithm
Implementation	
Both ANN and ANFIS were implemented using Matlab library (2009b version). The number of neurons in the hidden layer were selected based on trial and error approach.	

2.4.4 Performance evaluation criteria

Root mean square error ($RMSE_{Growth\ rate}$ (DM kg/ha/day) and coefficient of determination (R^2) were used as bench marks for the performance assessment of all models (MLR, ANN and ANFIS). The mathematical formulations of these statistical error/performance criteria are as follow (Eq. 11 and 12) [107]:

$$R^2 = \frac{\sum_{i=1}^{n}(O_i - \overline{O}_i)^2 - \sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \overline{O}_i)^2} \quad \text{(Eq. 11)}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2} \quad \text{(Eq. 12)}$$

279 Where, n is the number of observations; P_i is predicted/estimated value; O_i is actual/observed value
280 and $\overline{O_i}$ is the mean of observed values. The ideal performance of the underlying model gives a value of
281 RMSE close to zero and the value of R^2 should be close to 1.

282 3 Results and discussion

283 Three different biomass estimation models, including both statistical (MLR) and machine learning (ANN
284 and ANFIS) approaches, were used to estimate intensively managed grassland biomass. These three
285 models were used for both aforementioned study sites (see section 2.1); and grassland biomass
286 estimation models were developed where five VIs plus two spectral bands (RED, NIR) were used as input
287 features. Firstly, the 12–year time series for Moorepark was used for model (MLR, ANN and ANFIS)
288 development, with the dataset randomly divided into training (70%) and testing (30%) subsets (see
289 Table 2). The evaluation of the models was performed on the entire datasets (see Table 3).

290 **Table 3 Models development and evaluation.**

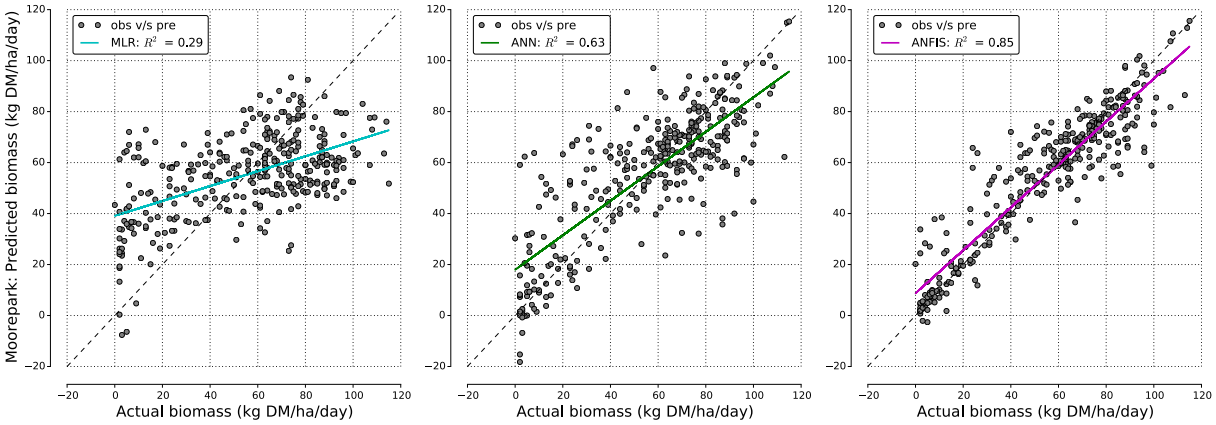
Model development				
	Moorepark (R^2)		Grange (R^2)	
	Training	Testing	Training	Testing
MLR	0.31	0.21	0.39	0.29
ANN	0.65	0.54	0.71	0.54
ANFIS	0.88	0.78	0.80	0.74
Model evaluation on entire data set				
	Moorepark		Grange	
	R^2	$RMSE$ (DM kg/ha/day)	R^2	$RMSE$ (DM kg/ha/day)
MLR	0.29	25.08	0.38	24.02
ANN	0.63	18.05	0.59	20.43
ANFIS	0.85	11.07	0.76	15.35

291

292 Figure 9 shows the results for Moorepark study site. The first approach to estimating grassland biomass
293 in this study was with the MLR, which has been demonstrated to be very robust when the relationship
294 between datasets is linear. However, as shown in Figure 9, the value of coefficient of determination for
295 MLR is very low ($R^2 = 0.29$) and the value of root mean square error ($RMSE = 25.08$ DM kg/ha/day) is
296 high compared to the ANN model ($R^2 = 0.63, RMSE = 18.05$ DM kg/ha/day), suggesting a non-linear
297 relationship between the variables. To date the use of machine learning algorithms for grassland
298 biomass estimation is not very widespread. Two studies [72], [73] have compared the performance of

299 the MLR and ANN, and in every case ANN outperformed the MLR; and the results generated by this
300 study endorsed these findings.

301 The literature review suggests that the application of ANFIS is very powerful for estimation and
302 prediction tasks [76]–[78], [80], but the use of ANFIS for spaceborne earth observation applications is
303 only in its infancy [108], [109] and in these studies a high overall accuracy of ANFIS against ANN was
304 reported. This outcome can also be seen here, as the ANFIS model gave better estimation results
305 ($R^2 = 0.85, RMSE = 11.07$ DM kg/ha/day) than both MLR and ANN (see Figure 9).



306

307 **Figure 9 Scatter plots for the accuracy comparison of MLR, ANN and ANFIS estimated grassland biomass versus in–situ**
308 **biomass for the Moorepark test site.**

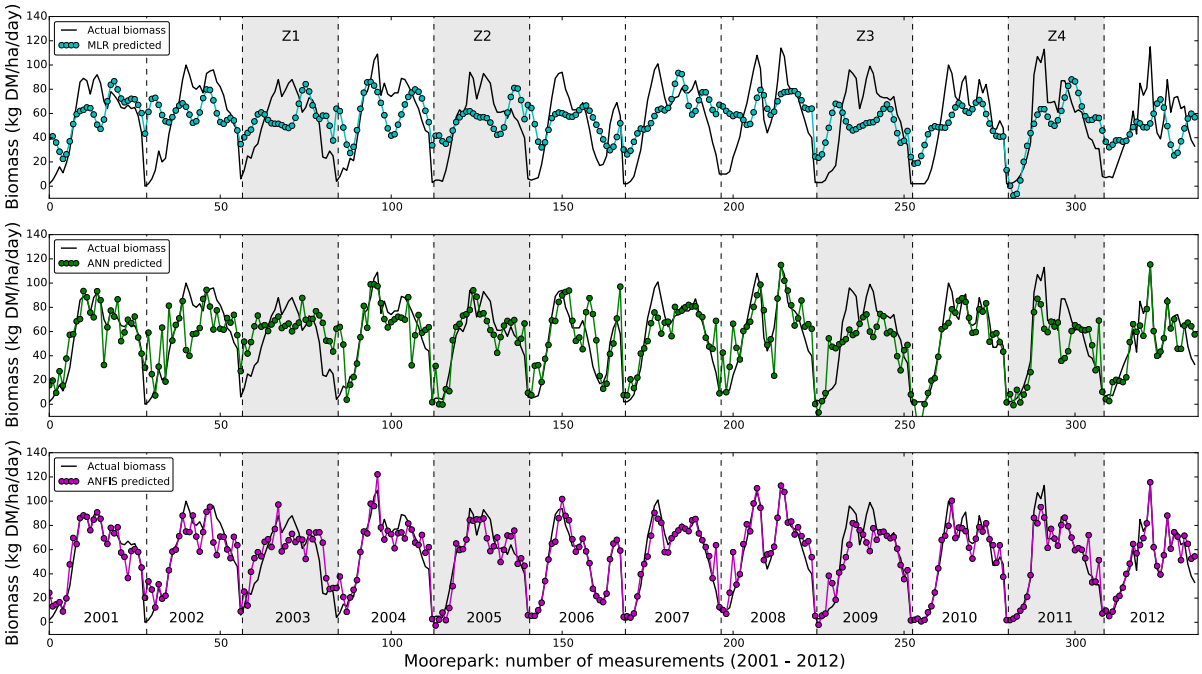


Figure 10 Plots of observed and modeled time series by using MLR, ANN and ANFIS for Moorepark study site. The shaded regions Z1 (2003), Z2 (2005), Z3 (2009) and Z4 (2011) were selected for more detailed analysis (see Figure 11).

Figure 10, which gives an overview of the performance of the three models, shows that the ANN model was able to identify the start of the season more reliably than the MLR, this was further improved by the ANFIS model. The ANFIS also produced a closer seasonal curve fit with minimum residuals compared to the MLR and ANN, but there are still some spurious spikes that are not present in the field data and some features are not replicated.

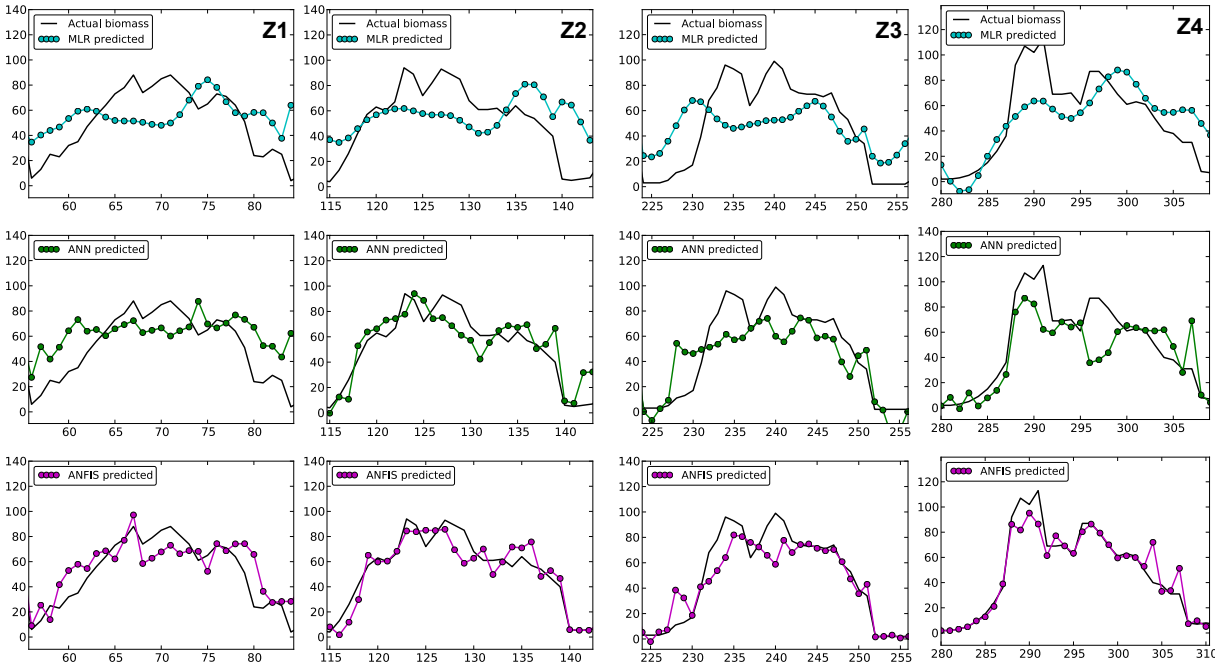


Figure 11 Zoomed view of Fig. 10 highlighted parts (Z1, Z2, Z3 and Z4).

Figure 11 shows examples where peaks (higher biomass values) were not reached and underestimation is observed in four cases (Z1, Z2, Z3 and Z4). The reason for these anomalies is not yet clear, but one potential cause could be saturation of the satellite data, as in all four cases (Z1, Z2, Z3 and Z4) the overall general behavior of the estimated/modeled biomass curve is comparable for the three models (MLR, ANN, ANFIS). For example, in the case of Z1 all three models have over estimated the biomass during the start of the season, underestimated the higher biomass values (during summer) and again at the end of the season over estimation is observed (see Figure 11 (Z1)). A similar trend is shown in Figure 11 (Z2 and Z3) where higher biomass values are under estimated, while at the end of the season ANFIS has improved (reduced) the over estimation as compared to the MLR and ANN. In the case of Z4 the overall trend of the estimated pattern of MLR, ANN and ANFIS is comparable and ANN and ANFIS have identified the start of the season quite well, although ANFIS has minimized the estimation error, but still it has failed to reach the peak (higher biomass values) during the mid of the season, and the anomalies at the end of the season are similar for ANN and ANFIS. Figure 11 shows that ANFIS has produced an improved estimation as compared to the MLR and ANN but still in some cases it has underestimated the high biomass values. Another reason for this could be the bias and variation in measured biomass as reported by Ji et al. [110].

To further explore the functional relationship between the input feature space and the in–situ data, and also to explore the performance of the models, the same approach was applied to the Grange study site. Again the results show that the ANFIS model was the most accurate among the three models, with a higher value of coefficient of determination ($R^2 = 0.76$) and low root mean square error ($RMSE = 15.35$ DM kg/ha/day), followed by ANN ($R^2 = 0.59, RMSE = 20.43$ DM kg/ha/day) and MLR ($R^2 = 0.38, RMSE = 24.02$ DM kg/ha/day) (see Table 3; Figure 12).

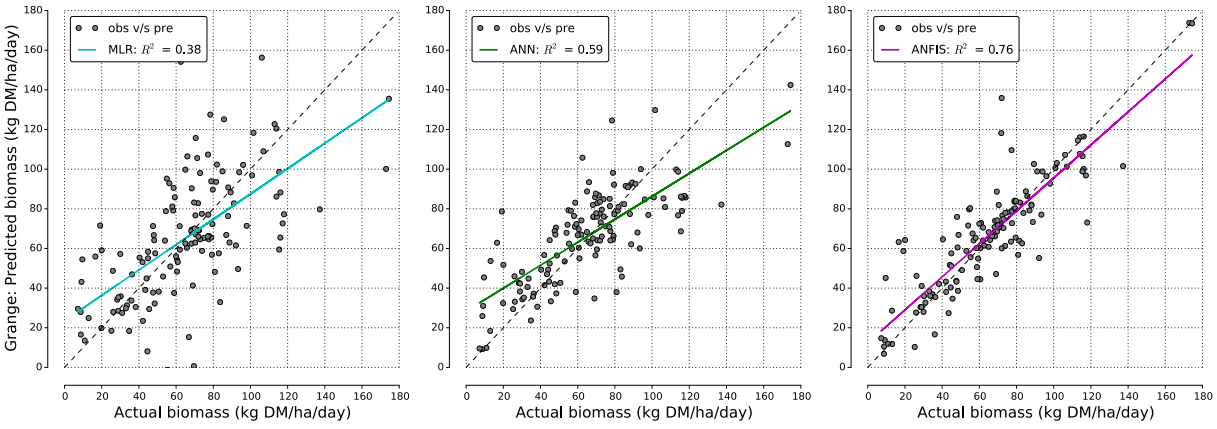


Figure 12 Scatter plots for the accuracy comparison of MLR, ANN and ANFIS estimated grassland biomass verses in–situ biomass for Grange test site.

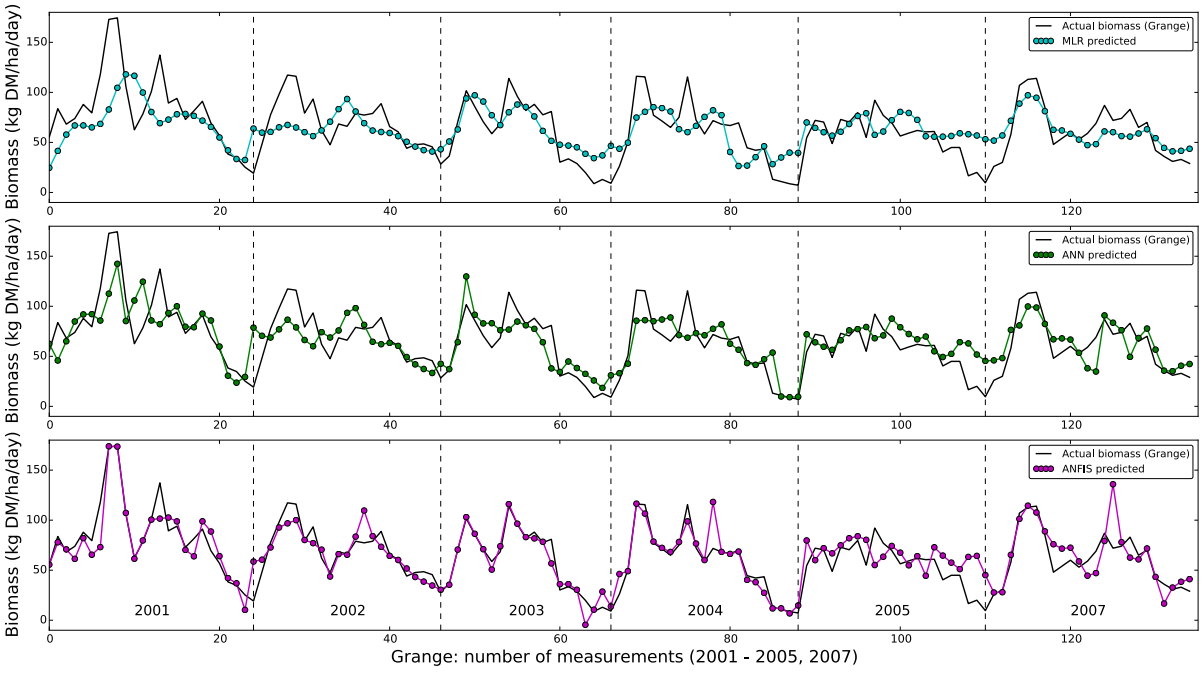


Figure 13 Plots of observed and modeled time series for Grange study site.

Machine learning methods require large data sets in order to better understand the patterns hidden inside the data, which could be a reason for the higher accuracy achieved for the Moorepark study site. Another reason for the lower accuracy at the Grange test site could be that it is under more intense grazing practices, indicated by the biomass curves for Grange (see Figure 4 (B)) being more complex and variable, with considerable inter annual variation compared to the Moorepark in-situ data (see Figure 4 (A)).

The issue of under estimation at higher biomass values was also observed at the Grange study site in some time periods, although better estimation at the start of the season can be seen in Figure 13. In order to further analyze the effect of complexity on the models' performance, residual boxplots for each year were created for the Grange study site as shown in Figure 14. The 2002 and 2005 residual boxplots show the highest variability and wide spread, especially for 2005 which is the most complex and nonlinear part of the Grange time series. By contrast, the Moorepark 12–year average and individual yearly biomass curves are quite consistent and similar in data range (min–max values; see Figure 4 and 15).

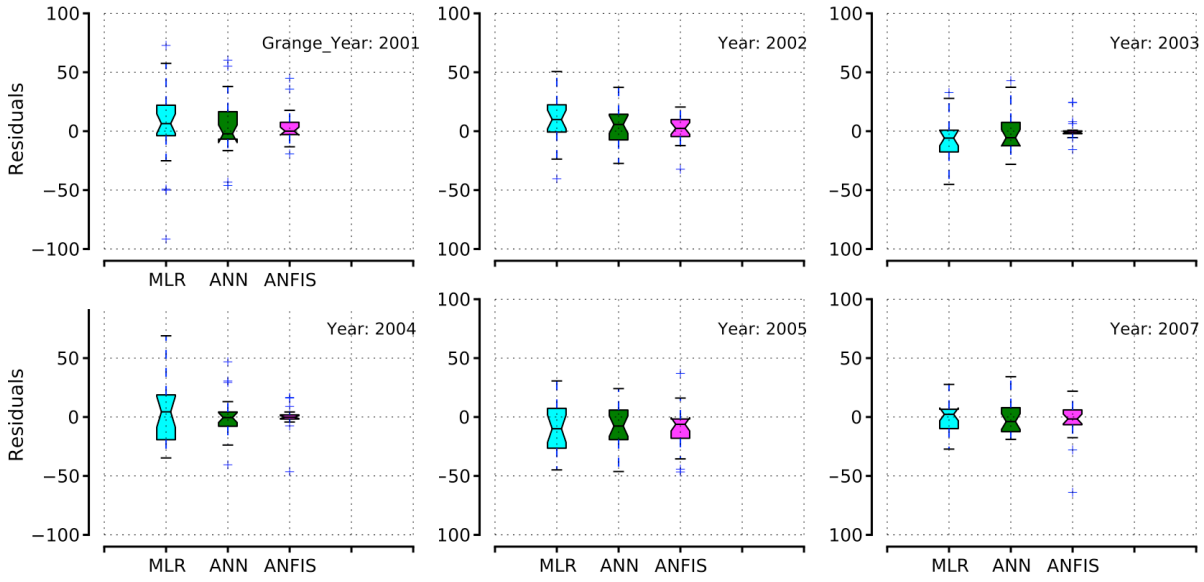


Figure 14 Year wise residual plots for Grange study site.

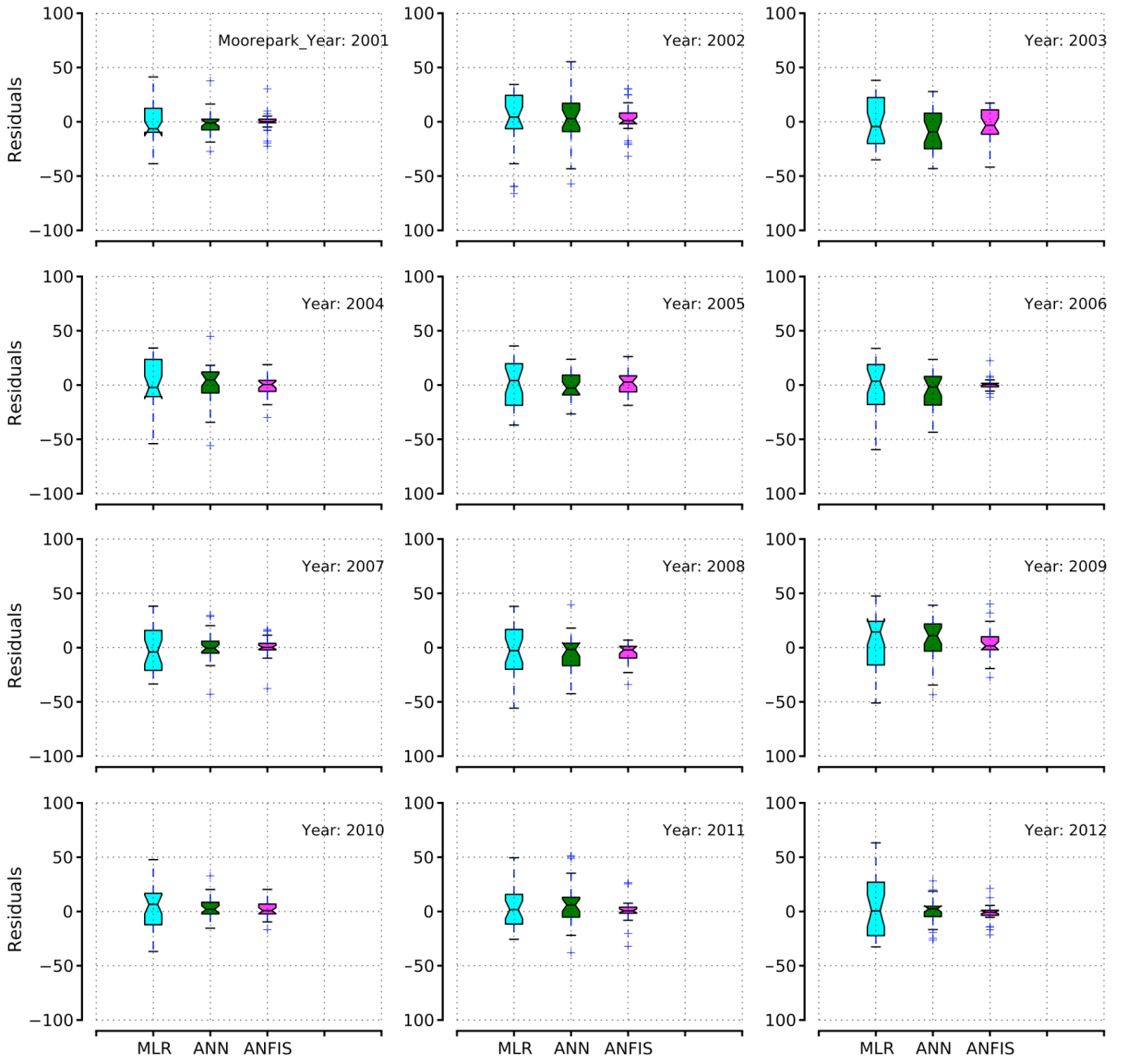


Figure 15 Year wise residual plots for Moorepark study site

3.1 Selection of input variables

As machine-learning models are generally data driven and require a large amount of data for better performance all five vegetation indices along with two spectral bands (RED, NIR) were used as input variables to the PCA, and resulting principal component features were used as an input to the models. Various different combinations of inputs were tested (accuracy (R^2) for these different combinations varies between 0.38 to 0.54) and it was shown that the best accuracy was achieved by using all

vegetation indices as input variables for both statistical and ANN models. In order to remove the high correlation between various input features a dimension reduction approach (PCA) was used.

3.2 Comparison of three models performance on both study sites

In terms of performance evaluation of the three models (see Figure 16), it is evident that the distribution of interquartile range (IQR) of MLR ($IQR_{Moorepark} = 39.98$, $IQR_{Grange} = 26.72$) and ANN ($IQR_{Moorepark} = 17.99$, $IQR_{Grange} = 22.37$) residuals is quite large for both the test sites as compared to the distribution of interquartile range of ANFIS ($IQR_{Moorepark} = 7.78$, $IQR_{Grange} = 10.2$). For both the study sites ANFIS has less variability than the MLR and ANN, and the overall spread (min–max whisker range) of ANFIS for both the sites is small and symmetrical around zero. However the ANFIS scatter plots for both Moorepark (Figure 9) and Grange (Figure 12) are more unreliable for the higher biomass values. For example, for Moorepark under estimation is evident for the values >60 kg DM/ha/day, similarly for Grange, large over and under estimation errors can be seen for the values >100 kg DM/ha/day.

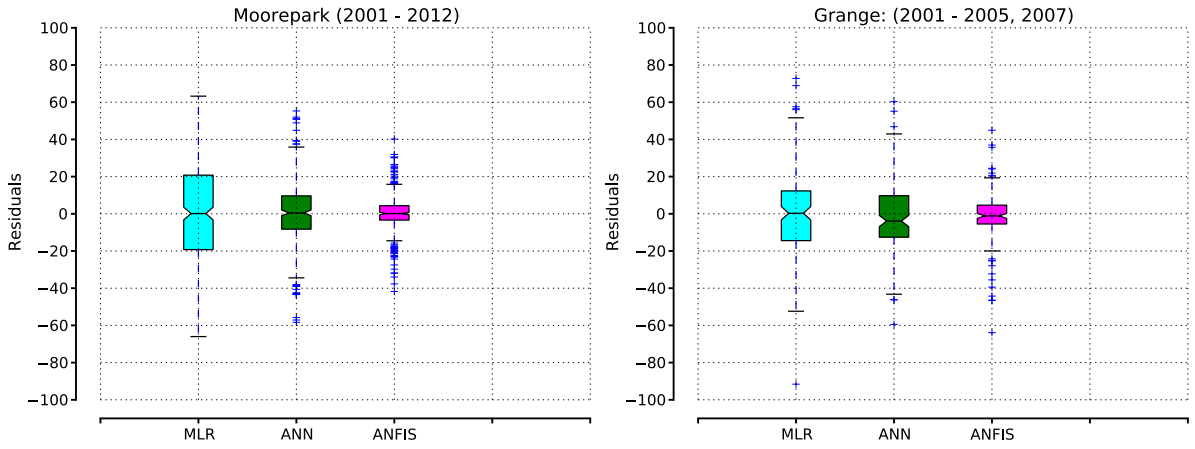


Figure 16 Variations in residual for all three models (MLR, ANN, ANFIS) estimations. The boxplots show the spread, lower quartiles, medians and upper quartiles. The lines are drawn from the box (1.5 times the interquartile range from the nearer quartile).

Studies show that whenever ANN and MLR are used for grassland biomass estimation ANN has always out-performed the traditional statistical approach. For example, Xie et al. (2009) used a single Landsat ETM+ image for above ground grassland biomass estimation and showed the superior performance of ANN ($R^2 = 0.817$) against MLR ($R^2 = 0.591$). Similar findings were reported by Yang et al. [73] where MODIS driven vegetation indices from July–September 2005 were used to model the grass yield estimation, and ANN models were found to be more accurate ($R^2 = 0.56 – 0.71$) compared to the

statistical models ($R^2 = 0.54–0.68$). The results of the current study have endorsed this trend of high performance for ANN against MLR. With respect to ANFIS and ANN, it has also been established in both non–remote sensing and remote sensing applications that the former generates more reliable results e.g., Rajesh et al. [109] indicated the higher classification performance of ANFIS (overall accuracy: 86.01%) compared to the ANN (overall accuracy: 83.62%).

3.3 Advantages and limitations of proposed methodology

ANFIS not only integrates the strengths of ANN and fuzzy logic, but also overcomes some of the disadvantages of each applied separately and produces better results in terms of smoothness and adaptability. The presented framework of ANFIS modelling allows multiple inputs to produce a single output, however to achieve a higher level of accuracy a larger amount of data might be required to drive the model, with the model performance also dependent on the data quality and study design [111], [112].

4 Conclusion

In this paper, the estimation capabilities of the ANFIS approach are compared against the ANN and more commonly used MLR modeling techniques. Although well established in other scientific fields (engineering, expert systems) the potential of ANFIS modelling in remote sensing is not yet fully explored, although as demonstrated by this research it is a technique that holds promise for future studies. Five MODIS derived VIs and two spectral bands (RED, NIR) along with the in–situ measurements were used for model training and testing; and their performance was evaluated using R^2 and $RMSE$. For both the study sites, ANFIS ($R^2_{Moorepark} = 0.85, RMSE_{Moorepark} = 11.07$ DM kg/ha/day; $R^2_{Grange} = 0.76, RMSE_{Grange} = 15.35$ DM kg/ha/day) produced better estimations of biomass compared to the ANN ($R^2_{Moorepark} = 0.63, RMSE_{Moorepark} = 18.05$ DM kg/ha/day; $R^2_{Grange} = 0.59, RMSE_{Grange} = 20.43$ DM kg/ha/day) and MLR ($R^2_{Moorepark} = 0.29, RMSE_{Moorepark} = 25.08$ DM kg/ha/day; $R^2_{Grange} = 0.39, RMSE_{Grange} = 24.02$ DM kg/ha/day). However, there are some occasions when the model data under-estimates the actual biomass peak (a common feature of VI driven biomass models); one potential reason for this underestimation could be the effect of saturation of the satellite signal or vegetation index value and further work is required to understand these anomalies. Nevertheless, these results show significant promise for the use of a hyper–temporal time series of satellite imagery as input to modeling for an effective tool for grassland monitoring and management.

With the launch of members of satellite families (ALOS–2, Radarsat–2, Sentinel, TerraSAR–X, TanDEM–X/L) the volume of data for such modelling studies will increase markedly, and concepts of big data are becoming more relevant in the remote sensing domain. As machine-learning models are considered to be data driven models, more data heralds higher accuracy. To date, grassland-modelling activities over 12 years have not been reported in the literature, but the scope for such long term studies will increase significantly over the coming years. In addition to demonstrating the potential of such long time series studies, this work has also highlighted the potential for complex modelling approaches such as ANFIS in the field of remote sensing. With the passage of time and availability of high quality spectral, spatial and temporal resolution data, these models will get further refined, more robust and applicable to other biophysical parameter retrieval tasks.

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References

[1] J. M. O. Scurlock, K. Johnson, and R. J. Olson, "Estimating net primary productivity from grassland biomass dynamics measurements," *Glob. Change Biol.*, vol. 8, no. 8, pp. 736–753, Aug. 2002.

[2] FAO, "The role of livestock in climate change," *Food and Agriculture Organization*, 21-Nov-2014. [Online]. Available: http://www.fao.org/agriculture/lead/themes0/climate/en/.

[3] H. Lieth, Ed., *Patterns of Primary Production in the Biosphere*. Hutchinson Ross Publishing Company, 1978.

[4] J. M. O. Scurlock and D. O. Hall, "The global carbon sink: a grassland perspective," *Glob. Change Biol.*, vol. 4, no. 2, pp. 229–233, 1998.

[5] J. M. Anderson, "The Effects of Climate Change on Decomposition Processes in Grassland and Coniferous Forests," *Ecol. Appl.*, vol. 1, no. 3, pp. 326–347, Aug. 1991.

[6] J. D. Derner and G. E. Schuman, "Carbon sequestration and rangelands: A synthesis of land management and precipitation effects," *J. Soil Water Conserv.*, vol. 62, no. 2, pp. 77–85, Mar. 2007.

[7] C. Delgado, M. Rosegrant, H. Steinfeld, S. Ehui, and C. Courbois, "Livestock to 2020: The next food revolution," IFPRI, Working Paper, 1999.

[8] J. Kearney, "Food consumption trends and drivers," *Philos. Trans. R. Soc. B Biol. Sci.*, vol. 365, no. 1554, pp. 2793–2807, Sep. 2010.

[9] M. P. W. Hybu Cig Cymru, "Grassland management: http://hccmpw.org.uk/publications/farming_and_industry_development/grassland_managemen t/," 2008.

[10] G. Newnham, "Improved Methods for Assessment and Prediction of Grassland Curing Satellite Based Curing Methods and Mapping - final report," 2010. .

[11] M. E. Castle, "A simple disc instrument for estimating herbage yield.," *J. Br. Grassl. Soc.*, vol. 31, no. 1, 1976.

[12] J. Hakl, Z. Hrevušová, M. Hejcman, and P. Fuksa, "The use of a rising plate meter to evaluate lucerne (Medicago sativa L.) height as an important agronomic trait enabling yield estimation," *Grass Forage Sci.*, vol. 67, no. 4, pp. 589–596, Dec. 2012.

[13] M. Hejcman, L. Sochorová, V. Pavlů, J. Štrobach, M. Diepolder, and J. Schellberg, "The Steinach Grassland Experiment: Soil chemical properties, sward height and plant species composition in three cut alluvial meadow after decades-long fertilizer application," *Agric. Ecosyst. Environ.*, vol. 184, pp. 76–87, Feb. 2014.

[14] E. S. Flynn, C. T. Dougherty, and O. Wendroth, "Assessment of Pasture Biomass with the Normalized Difference Vegetation Index from Active Ground-Based Sensors," *Agron. J.*, vol. 100, no. 1, p. 114, 2008.

[15] A. Psomas, M. Kneubühler, S. Huber, K. Itten, and N. E. Zimmermann, "Hyperspectral remote sensing for estimating aboveground biomass and for exploring species richness patterns of grassland habitats," *Int. J. Remote Sens.*, vol. 32, no. 24, pp. 9007–9031, 2011.

[16] B. Xu, X. C. Yang, W. G. Tao, Z. H. Qin, H. Q. Liu, J. M. Miao, and Y. Y. Bi, "MODIS-based remote sensing monitoring of grass production in China," *Int. J. Remote Sens.*, vol. 29, no. 17–18, pp. 5313–5327, 2008.

[17] G. Joseph, *Fundamentals of Remote Sensing*. Universities Press, 2005.

[18] D. Stow, Y. Hamada, L. Coulter, and Z. Anguelova, "Monitoring shrubland habitat changes through object-based change identification with airborne multispectral imagery," *Remote Sens. Environ.*, vol. 112, no. 3, pp. 1051–1061, Mar. 2008.

[19] M. Lewis, V. Jooste, and A. A. de Gasparis, “Discrimination of arid vegetation with airborne multispectral scanner hyperspectral imagery,” *IEEE Trans. Geosci. Remote Sens.*, vol. 39, no. 7, pp. 1471–1479, Jul. 2001.
[20] P. J. Curran and H. D. Williamson, “Estimating the Green Leaf Area Index of Grassland with Airborne Multispectral Scanner Data,” *Oikos*, vol. 49, no. 2, pp. 141–148, Jun. 1987.
[21] R. Darvishzadeh, C. Atzberger, A. Skidmore, and M. Schlerf, “Mapping grassland leaf area index with airborne hyperspectral imagery: A comparison study of statistical approaches and inversion of radiative transfer models,” *ISPRS J. Photogramm. Remote Sens.*, vol. 66, no. 6, pp. 894–906, Nov. 2011.
[22] L. G. Olmanson, P. L. Brezonik, and M. E. Bauer, “Airborne hyperspectral remote sensing to assess spatial distribution of water quality characteristics in large rivers: The Mississippi River and its tributaries in Minnesota,” *Remote Sens. Environ.*, vol. 130, pp. 254–265, Mar. 2013.
[23] I. Ali, C. Schuster, M. Zebisch, M. Forster, B. Kleinschmit, and C. Notarnicola, “First Results of Monitoring Nature Conservation Sites in Alpine Region by Using Very High Resolution (VHR) X-Band SAR Data,” *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, vol. 6, no. 5, pp. 2265–2274, Oct. 2013.
[24] C. Schuster, I. Ali, P. Lohmann, A. Frick, M. Förster, and B. Kleinschmit, “Towards Detecting Swath Events in TerraSAR-X Time Series to Establish NATURA 2000 Grassland Habitat Swath Management as Monitoring Parameter,” *Remote Sens.*, vol. 3, no. 7, pp. 1308–1322, Jun. 2011.
[25] M. Claverie, V. Demarez, B. Duchemin, O. Hagolle, D. Ducrot, C. Marais-Sicre, J.-F. Dejoux, M. Huc, P. Keravec, P. Béziat, R. Fieuzal, E. Ceschia, and G. Dedieu, “Maize and sunflower biomass estimation in southwest France using high spatial and temporal resolution remote sensing data,” *Remote Sens. Environ.*, vol. 124, pp. 844–857, Sep. 2012.
[26] M. E. Holzman, R. Rivas, and M. C. Piccolo, “Estimating soil moisture and the relationship with crop yield using surface temperature and vegetation index,” *Int. J. Appl. Earth Obs. Geoinformation*, vol. 28, pp. 181–192, May 2014.
[27] D. K. Sari, I. H. Ismullah, W. N. Sulasdi, and A. B. Harto, “Estimation of Water Consumption of Lowland Rice in Tropical Area based on Heterogeneous Cropping Calendar Using Remote Sensing Technology,” *Procedia Environ. Sci.*, vol. 17, pp. 298–307, 2013.
[28] T. G. Van Niel and T. R. McVicar, “Determining temporal windows for crop discrimination with remote sensing: a case study in south-eastern Australia,” *Comput. Electron. Agric.*, vol. 45, no. 1–3, pp. 91–108, Dec. 2004.
[29] J. Rhee, J. Im, and G. J. Carbone, “Monitoring agricultural drought for arid and humid regions using multi-sensor remote sensing data,” *Remote Sens. Environ.*, vol. 114, no. 12, pp. 2875–2887, Dec. 2010.
[30] G. Donald, S. Gherardi, A. Edirisinghe, S. Gittins, D. Henry, and G. Mata, “Pasture growth rate for individual paddocks can be accurately predicted real-time from MODIS imagery, climate and soil data,” presented at the Australian Society of Animal Production, Armidale, July 2010, 2010, vol. 50, pp. 611–615.
[31] M. J. Hill, G. E. Donald, M. W. Hyder, and R. C. G. Smith, “Estimation of pasture growth rate in the south west of Western Australia from AVHRR NDVI and climate data,” *Remote Sens. Environ.*, vol. 93, no. 4, pp. 528–545, Dec. 2004.
[32] Y. P. Dang, M. J. Pringle, M. Schmidt, R. C. Dalal, and A. Apan, “Identifying the spatial variability of soil constraints using multi-year remote sensing,” *Field Crops Res.*, vol. 123, no. 3, pp. 248–258, Sep. 2011.
[33] Y. Gu and B. K. Wylie, “Detecting Ecosystem Performance Anomalies for Land Management in the Upper Colorado River Basin Using Satellite Observations, Climate Data, and Ecosystem Models,” *Remote Sens.*, vol. 2, no. 8, pp. 1880–1891, Jul. 2010.

528 [34] S. Kalluri, P. Gilruth, and R. Bergman, "The potential of remote sensing data for decision makers at
529 the state, local and tribal level: experiences from NASA's Synergy program," *Environ. Sci. Policy*,
530 vol. 6, no. 6, pp. 487–500, Dec. 2003.
531 [35] M. Qingyuan, Z. Chao, C. Zhenghua, and Y. Zhen, "Management decision-making support system of
532 percision agriculture based on CNCS," in *Geoscience and Remote Sensing Symposium, 2007.
533 IGARSS 2007. IEEE International*, 2007, pp. 819–822.
534 [36] S. K. Seelan, S. Laguette, G. M. Casady, and G. A. Seielstad, "Remote sensing applications for
535 precision agriculture: A learning community approach," *Remote Sens. Environ.*, vol. 88, no. 1–2,
536 pp. 157–169, Nov. 2003.
537 [37] M. Turker and E. H. Kok, "Field-based sub-boundary extraction from remote sensing imagery using
538 perceptual grouping," *ISPRS J. Photogramm. Remote Sens.*, vol. 79, pp. 106–121, May 2013.
539 [38] I. Ali, F. Greifeneder, J. Stamenkovic, M. Neumann, and C. Notarnicola, "Review of Machine
540 Learning Approaches for Biomass and Soil Moisture Retrievals from Remote Sensing Data,"
541 *Remote Sens.*, vol. 7, no. 12, pp. 16398–16421, Dec. 2015.
542 [39] G. . Anderson, J. . Hanson, and R. . Haas, "Evaluating landsat thematic mapper derived vegetation
543 indices for estimating above-ground biomass on semiarid rangelands," *Remote Sens. Environ.*,
544 vol. 45, no. 2, pp. 165–175, Aug. 1993.
545 [40] B. K. Wylie, J. A. Harrington, S. D. Prince, and I. Denda, "Satellite and ground-based pasture
546 production assessment in Niger: 1986-1988," *Int. J. Remote Sens.*, vol. 12, no. 6, pp. 1281–1300,
547 1991.
548 [41] P. Dusseux, L. Hubert-Moy, T. Corpetti, and F. Vertès, "Evaluation of SPOT imagery for the
549 estimation of grassland biomass," *Int. J. Appl. Earth Obs. Geoinformation*, vol. 38, pp. 72–77, Jun.
550 2015.
551 [42] N. Huang, J.-S. He, and Z. Niu, "Estimating the spatial pattern of soil respiration in Tibetan alpine
552 grasslands using Landsat TM images and MODIS data," *Ecol. Indic.*, vol. 26, pp. 117–125, Mar.
553 2013.
554 [43] S. Itano and H. Tomimatsu, "Reflectance spectra for monitoring green herbage mass in Zoysia-
555 dominated pastures," *Grassl. Sci.*, vol. 57, no. 1, pp. 9–17, Mar. 2011.
556 [44] L. Jianlong, L. Tiangang, and C. Quangong, "Estimating grassland yields using remote sensing and
557 GIS technologies in China," *N. Z. J. Agric. Res.*, vol. 41, no. 1, pp. 31–38, Jan. 1998.
558 [45] Y. Jin, X. Yang, J. Qiu, J. Li, T. Gao, Q. Wu, F. Zhao, H. Ma, H. Yu, and B. Xu, "Remote Sensing-Based
559 Biomass Estimation and Its Spatio-Temporal Variations in Temperate Grassland, Northern China,"
560 *Remote Sens.*, vol. 6, no. 2, pp. 1496–1513, Feb. 2014.
561 [46] M. Shen, Y. Tang, J. Klein, P. Zhang, S. Gu, A. Shimono, and J. Chen, "Estimation of aboveground
562 biomass using in situ hyperspectral measurements in five major grassland ecosystems on the
563 Tibetan Plateau," *J. Plant Ecol.*, vol. 1, no. 4, pp. 247–257, Dec. 2008.
564 [47] W. Song, H. Jia, S. Liu, S. Liang, Z. Wang, L. Hao, and S. Chai, "A Remote Sensing Based Forage
565 Biomass Yield Inversion Model of Alpine-cold Meadow during Grass-withering Period in
566 Sanjiangyuan Area," *IOP Conf. Ser. Earth Environ. Sci.*, vol. 17, no. 1, p. 012042, Mar. 2014.
567 [48] B. Xu, X. C. Yang, W. G. Tao, Z. H. Qin, H. Q. Liu, J. M. Miao, and Y. Y. Bi, "MODIS-based remote
568 sensing monitoring of grass production in China," *Int. J. Remote Sens.*, vol. 29, no. 17–18, pp.
569 5313–5327, Sep. 2008.
570 [49] F. Zhao, B. Xu, X. Yang, Y. Jin, J. Li, L. Xia, S. Chen, and H. Ma, "Remote Sensing Estimates of
571 Grassland Aboveground Biomass Based on MODIS Net Primary Productivity (NPP): A Case Study
572 in the Xilingol Grassland of Northern China," *Remote Sens.*, vol. 6, no. 6, pp. 5368–5386, Jun.
573 2014.

[50] M. Boschetti, S. Bocchi, and P. A. Brivio, "Assessment of pasture production in the Italian Alps using spectrometric and remote sensing information," *Agric. Ecosyst. Environ.*, vol. 118, no. 1–4, pp. 267–272, Jan. 2007.
[51] S. Ullah, Y. Si, M. Schlerf, A. K. Skidmore, M. Shafique, and I. A. Iqbal, "Estimation of grassland biomass and nitrogen using MERIS data," *Int. J. Appl. Earth Obs. Geoinformation*, vol. 19, pp. 196–204, Oct. 2012.
[52] Y. Zha, J. Gao, S. Ni, Y. Liu, J. Jiang, and Y. Wei, "A spectral reflectance-based approach to quantification of grassland cover from Landsat TM imagery," *Remote Sens. Environ.*, vol. 87, no. 2–3, pp. 371–375, Oct. 2003.
[53] D. Bella, R. Faivre, F. Ruget, B. Seguin, M. Guérif, B. Combal, M. Weiss, and C. Rebella, "Remote sensing capabilities to estimate pasture production in France," *Int. J. Remote Sens.*, vol. 25, no. 23, pp. 5359–5372, 2004.
[54] J. B. Bradford, J. A. Hicke, and W. K. Lauenroth, "The relative importance of light-use efficiency modifications from environmental conditions and cultivation for estimation of large-scale net primary productivity," *Remote Sens. Environ.*, vol. 96, no. 2, pp. 246–255, May 2005.
[55] L.-C. Han, "A method of modifying error for non-synchronicity of grass yield remote sensing estimation and measurement," *Int. J. Remote Sens.*, vol. 22, no. 17, pp. 3363–3372, 2001.
[56] V. Loris and G. Damiano, "Mapping the green herbage ratio of grasslands using both aerial and satellite-derived spectral reflectance," *Agric. Ecosyst. Environ.*, vol. 115, no. 1–4, pp. 141–149, Jul. 2006.
[57] L. Vescovo and D. Gianelle, "Using the MIR bands in vegetation indices for the estimation of grassland biophysical parameters from satellite remote sensing in the Alps region of Trentino (Italy)," *Adv. Space Res.*, vol. 41, no. 11, pp. 1764–1772, 2008.
[58] B. . Wylie, D. . Meyer, L. . Tieszen, and S. Mannel, "Satellite mapping of surface biophysical parameters at the biome scale over the North American grasslands: A case study," *Remote Sens. Environ.*, vol. 79, no. 2–3, pp. 266–278, Feb. 2002.
[59] B. Xu, X. Yang, W. Tao, Z. Qin, H. Liu, and J. Miao, "Remote sensing monitoring upon the grass production in China," *Acta Ecol. Sin.*, vol. 27, no. 2, pp. 405–413, Feb. 2007.
[60] B. A. M. Bouman, A. H. C. M. Schapendonk, and W. Stol, *Description of the growth model LINGRA as implemented in CGMS*. Wageningen: AB-DLO [etc.], 1996.
[61] A. H. C. . Schapendonk, W. Stol, D. W. . van Kraalingen, and B. A. . Bouman, "LINGRA, a sink/source model to simulate grassland productivity in Europe," *Eur. J. Agron.*, vol. 9, no. 2–3, pp. 87–100, Nov. 1998.
[62] F. Maselli, G. Argenti, M. Chiesi, L. Angeli, and D. Papale, "Simulation of grassland productivity by the combination of ground and satellite data," *Agric. Ecosyst. Environ.*, vol. 165, pp. 163–172, Jan. 2013.
[63] A. de Wit, G. Duveiller, and P. Defourny, "Estimating regional winter wheat yield with WOFOST through the assimilation of green area index retrieved from MODIS observations," *Agric. For. Meteorol.*, vol. 164, pp. 39–52, Oct. 2012.
[64] A. V. M. Ines, N. N. Das, J. W. Hansen, and E. G. Njoku, "Assimilation of remotely sensed soil moisture and vegetation with a crop simulation model for maize yield prediction," *Remote Sens. Environ.*, vol. 138, pp. 149–164, Nov. 2013.
[65] R. E. E. Jongschaap, *Integrating Crop Growth Simulation and Remote Sensing to Improve Resource Use Efficiency in Farming Systems*. Wageningen Universiteit, 2006.
[66] B. Ji, Y. Sun, S. Yang, and J. Wan, "Artificial neural networks for rice yield prediction in mountainous regions," *J. Agric. Sci.*, vol. 145, no. 03, pp. 249–261, 2007.

620 [67] S. S. Panda, D. P. Ames, and S. Panigrahi, "Application of Vegetation Indices for Agricultural Crop
621 Yield Prediction Using Neural Network Techniques," *Remote Sens.*, vol. 2, no. 3, pp. 673–696,
622 Mar. 2010.
623 [68] C. Z. Serele, Q. H. J. Gwyn, J. B. Boisvert, E. Pattey, N. McLaughlin, and G. Daoust, "Corn yield
624 prediction with artificial neural network trained using airborne remote sensing and topographic
625 data," in *Geoscience and Remote Sensing Symposium, 2000. Proceedings. IGARSS 2000. IEEE 2000
626 International*, 2000, vol. 1, pp. 384–386 vol.1.
627 [69] Y. Uno, S. O. Prasher, R. Lacroix, P. K. Goel, Y. Karimi, A. Viau, and R. M. Patel, "Artificial neural
628 networks to predict corn yield from Compact Airborne Spectrographic Imager data," *Comput.
629 Electron. Agric.*, vol. 47, no. 2, pp. 149–161, May 2005.
630 [70] M. E. J. Cutler, D. S. Boyd, G. M. Foody, and A. Vetrivel, "Estimating tropical forest biomass with a
631 combination of SAR image texture and Landsat TM data: An assessment of predictions between
632 regions," *ISPRS J. Photogramm. Remote Sens.*, vol. 70, pp. 66–77, Jun. 2012.
633 [71] I. Ali, F. Cawkwell, S. Green, and N. Dwyer, "Application of statistical and machine learning models
634 for grassland yield estimation based on a hypertemporal satellite remote sensing time series," in
635 *Geoscience and Remote Sensing Symposium (IGARSS), 2014 IEEE International*, 2014, pp. 5060–
636 5063.
637 [72] Y. Xie, Z. Sha, M. Yu, Y. Bai, and L. Zhang, "A comparison of two models with Landsat data for
638 estimating above ground grassland biomass in Inner Mongolia, China," *Ecol. Model.*, vol. 220, no.
639 15, pp. 1810–1818, Aug. 2009.
640 [73] X. Yang, B. Xu, J. Yunxiang, L. Jinya, and X. Zhu, "On Grass Yield Remote Sensing Estimation Models
641 of China's Northern Farming-Pastoral Ecotone," in *Advances in Computational Environment
642 Science*, G. Lee, Ed. Springer Berlin Heidelberg, 2012, pp. 281–291.
643 [74] J. Clevers, G. Van Der Heijden, S. Verzakov, and M. Schaepman, "Estimating grassland biomass
644 using SVM band shaving of hyperspectral data," *Photogramm. Eng. Remote Sens.*, vol. 73, no. 10,
645 p. 1141, 2007.
646 [75] J.-S. R. Jang, "ANFIS: adaptive-network-based fuzzy inference system," *IEEE Trans. Syst. Man
647 Cybern.*, vol. 23, no. 3, pp. 665–685, May 1993.
648 [76] M. K. Goyal, B. Bharti, J. Quilty, J. Adamowski, and A. Pandey, "Modeling of daily pan evaporation
649 in sub tropical climates using ANN, LS-SVR, Fuzzy Logic, and ANFIS," *Expert Syst. Appl.*, vol. 41, no.
650 11, pp. 5267–5276, Sep. 2014.
651 [77] M. Hosoz, H. M. Ertunc, M. Karabektas, and G. Ergen, "ANFIS modelling of the performance and
652 emissions of a diesel engine using diesel fuel and biodiesel blends," *Appl. Therm. Eng.*, vol. 60, no.
653 1–2, pp. 24–32, Oct. 2013.
654 [78] H. M. Jiang, C. K. Kwong, W. H. Ip, and T. C. Wong, "Modeling customer satisfaction for new
655 product development using a PSO-based ANFIS approach," *Appl. Soft Comput.*, vol. 12, no. 2, pp.
656 726–734, Feb. 2012.
657 [79] R. K. Kharb, S. L. Shimi, S. Chatterji, and M. F. Ansari, "Modeling of solar PV module and maximum
658 power point tracking using ANFIS," *Renew. Sustain. Energy Rev.*, vol. 33, pp. 602–612, May 2014.
659 [80] A. Mellit and S. A. Kalogirou, "ANFIS-based modelling for photovoltaic power supply system: A case
660 study," *Renew. Energy*, vol. 36, no. 1, pp. 250–258, Jan. 2011.
661 [81] A. Nazari, A. A. Milani, and G. Khalaj, "Modeling ductile to brittle transition temperature of
662 functionally graded steels by ANFIS," *Appl. Math. Model.*, vol. 36, no. 8, pp. 3903–3915, Aug.
663 2012.
664 [82] S. Sabzi, P. Javadikia, H. Rabani, and A. Adelkhani, "Mass modeling of Bam orange with ANFIS and
665 SPSS methods for using in machine vision," *Measurement*, vol. 46, no. 9, pp. 3333–3341, Nov.
666 2013.

[83] A. Sadrmomtazi, J. Sobhani, and M. A. Mirgozar, "Modeling compressive strength of EPS lightweight concrete using regression, neural network and ANFIS," *Constr. Build. Mater.*, vol. 42, pp. 205–216, May 2013.
[84] T. R. Kiran and S. P. S. Rajput, "An effectiveness model for an indirect evaporative cooling (IEC) system: Comparison of artificial neural networks (ANN), adaptive neuro-fuzzy inference system (ANFIS) and fuzzy inference system (FIS) approach," *Appl. Soft Comput.*, vol. 11, no. 4, pp. 3525–3533, Jun. 2011.
[85] D. S. Ali Haghighat Mesbahi, "Performance prediction of a specific wear rate in epoxy nanocomposites with various composition content of polytetrafluoroethylen (PTFE), graphite,short carbon fibers (CF) and nano-TiO2 using adaptive neuro-fuzzy inference," *Compos. Part B*, 2011.
[86] H. Esen and M. Inalli, "ANN and ANFIS models for performance evaluation of a vertical ground source heat pump system," *Expert Syst. Appl.*, vol. 37, no. 12, pp. 8134–8147, Dec. 2010.
[87] M. Iphar, "ANN and ANFIS performance prediction models for hydraulic impact hammers," *Tunn. Undergr. Space Technol.*, vol. 27, no. 1, pp. 23–29, Jan. 2012.
[88] A. Karami and S. Afiuni-Zadeh, "Sizing of rock fragmentation modeling due to bench blasting using adaptive neuro-fuzzy inference system (ANFIS)," *Int. J. Min. Sci. Technol.*, vol. 23, no. 6, pp. 809–813, Nov. 2013.
[89] G. Karimi, S. B. Sedaghat, and R. Banitalebi, "Designing and modeling of ultra low voltage and ultra low power LNA using ANN and ANFIS for Bluetooth applications," *Neurocomputing*, vol. 120, pp. 504–508, Nov. 2013.
[90] B. Rahmanian, M. Pakizeh, S. A. A. Mansoori, M. Esfandyari, D. Jafari, H. Maddah, and A. Maskooki, "Prediction of MEUF process performance using artificial neural networks and ANFIS approaches," *J. Taiwan Inst. Chem. Eng.*, vol. 43, no. 4, pp. 558–565, Jul. 2012.
[91] M. Talebizadeh and A. Moridnejad, "Uncertainty analysis for the forecast of lake level fluctuations using ensembles of ANN and ANFIS models," *Expert Syst. Appl.*, vol. 38, no. 4, pp. 4126–4135, Apr. 2011.
[92] Y. Varol, E. Avci, A. Koca, and H. F. Oztop, "Prediction of flow fields and temperature distributions due to natural convection in a triangular enclosure using Adaptive-Network-Based Fuzzy Inference System (ANFIS) and Artificial Neural Network (ANN)," *Int. Commun. Heat Mass Transf.*, vol. 34, no. 7, pp. 887–896, Aug. 2007.
[93] Z. Yuan, L.-N. Wang, and X. Ji, "Prediction of concrete compressive strength: Research on hybrid models genetic based algorithms and ANFIS," *Adv. Eng. Softw.*, vol. 67, pp. 156–163, Jan. 2014.
[94] J. Sobhani, M. Najimi, A. R. Pourkhorshidi, and T. Parhizkar, "Prediction of the compressive strength of no-slump concrete: A comparative study of regression, neural network and ANFIS models," *Constr. Build. Mater.*, vol. 24, no. 5, pp. 709–718, May 2010.
[95] I. Yilmaz and O. Kaynar, "Multiple regression, ANN (RBF, MLP) and ANFIS models for prediction of swell potential of clayey soils," *Expert Syst. Appl.*, vol. 38, no. 5, pp. 5958–5966, May 2011.
[96] N. Guindin-Garcia, A. A. Gitelson, T. J. Arkebauer, J. Shanahan, and A. Weiss, "An evaluation of MODIS 8- and 16-day composite products for monitoring maize green leaf area index," *Agric. For. Meteorol.*, vol. 161, pp. 15–25, Aug. 2012.
[97] J. Rouse, R. Haas, J. Schell, and D. Deering, "Monitoring vegetation systems in the Great Plains with ERTS.," presented at the Proceedings of the Third ERTS Symposium, 1973, vol. 1, pp. 309–317.
[98] Z. Jiang, A. R. Huete, K. Didan, and T. Miura, "Development of a two-band enhanced vegetation index without a blue band," *Remote Sens. Environ.*, vol. 112, no. 10, pp. 3833–3845, Oct. 2008.
[99] A. . Huete, "A soil-adjusted vegetation index (SAVI)," *Remote Sens. Environ.*, vol. 25, no. 3, pp. 295–309, Aug. 1988.

[100] J. Qi, A. Chehbouni, A. R. Huete, Y. H. Kerr, and S. Sorooshian, "A modified soil adjusted vegetation index," *Remote Sens. Environ.*, vol. 48, no. 2, pp. 119–126, May 1994.
[101] G. Rondeaux, M. Steven, and F. Baret, "Optimization of soil-adjusted vegetation indices," *Remote Sens. Environ.*, vol. 55, no. 2, pp. 95–107, Feb. 1996.
[102] G. Civelekoglu, N. O. Yigit, E. Diamadopoulos, and M. Kitis, "Prediction of Bromate Formation Using Multi-Linear Regression and Artificial Neural Networks," *Ozone Sci. Eng.*, vol. 29, no. 5, pp. 353–362, 2007.
[103] B. Yegnanarayana, *Artificial Neural Networks*. PHI Learning Pvt. Ltd., 2009.
[104] I. A. Basheer and M. Hajmeer, "Artificial neural networks: fundamentals, computing, design, and application," *J. Microbiol. Methods*, vol. 43, no. 1, pp. 3–31, Dec. 2000.
[105] M. H. Hassoun, *Fundamentals of Artificial Neural Networks*. MIT Press, 1995.
[106] T. Takagi and M. Sugeno, "Deviation of Fuzzy Control Rules from Human Operator's Control Actions," presented at the Proceeding of the IFAC Symposium on Fuzzy Information, Knowledge Representation and Decision Analysis, 1983, pp. 55–60.
[107] J. Benesty, M. M. Sondhi, and Y. Huang, *Springer Handbook of Speech Processing*. Springer, 2008.
[108] S. Mojeddifar, H. Ranjbar, and H. Nezamabadipour, "Adaptive Neuro-Fuzzy Inference System application for hydrothermal alteration mapping using ASTER data," *J. Min. Environ.*, vol. 4, no. 2, pp. 83–96, Oct. 2013.
[109] S. Rajesh, S. Arivazhagan, K. P. Moses, and R. Abisekaraj, "ANFIS Based Land Cover/Land Use Mapping of LISS IV Imagery Using Optimized Wavelet Packet Features," *J. Indian Soc. Remote Sens.*, vol. 42, no. 2, pp. 267–277, Jun. 2014.
[110] L. Ji, B. K. Wylie, D. R. Nossov, B. Peterson, M. P. Waldrop, J. W. McFarland, J. Rover, and T. N. Hollingsworth, "Estimating aboveground biomass in interior Alaska with Landsat data and field measurements," *Int. J. Appl. Earth Obs. Geoinformation*, vol. 18, pp. 451 – 461, 2012.
[111] E. Giovanis, "Study of Discrete Choice Models and Adaptive Neuro-Fuzzy Inference System in the Prediction of Economic Crisis Periods in USA," Social Science Research Network, Rochester, NY, SSRN Scholarly Paper ID 2014737, Mar. 2012.
[112] B. Issac and N. Israr, *Case Studies in Intelligent Computing: Achievements and Trends*. CRC Press, 2014.

3.2 ADDITIONAL COMMENTARY

The following section addressed the method of calculating total annual yield from growth rate.

3.2.1 *Total annual yield*

Observed and ANFIS modelled grass growth rate for both the study sites (Moorepark and Grange) were used to calculate the total annual yield (t/ha) for each year as follows:

$$T_{yield} = \left(\sum_{i=1}^{N} [Observed\ or\ Modelled]_{rate}(i) \right) \times 7 \tag{1}$$

In Equation 1 N represents the total number of samples for each year, and the factor 7 represents the seven days in a week. In Equation 1 daily growth rate is multiplied by 7 to get the total weekly yield and finally summed to get the total annual yield. However, this makes a very strong assumption that the growth rate is the same (constant) for all seven days in a week.

For both the study sites, the total annual yields for MLR, ANN and ANFIS were plotted against the observed annual yield as shown in Figure 7 and Figure 8. For both cases, ANFIS gives the better estimate as compared to the MLR and ANN, and it gives the lowest root mean square error and highest correlation for Moorepark (RMSE = 0.584 t/ha, $R^2 = 0.72$, $p < 0.05$) and Grange (RMSE = 0.291 t/ha, $R^2 = 0.92$, $p < 0.05$).

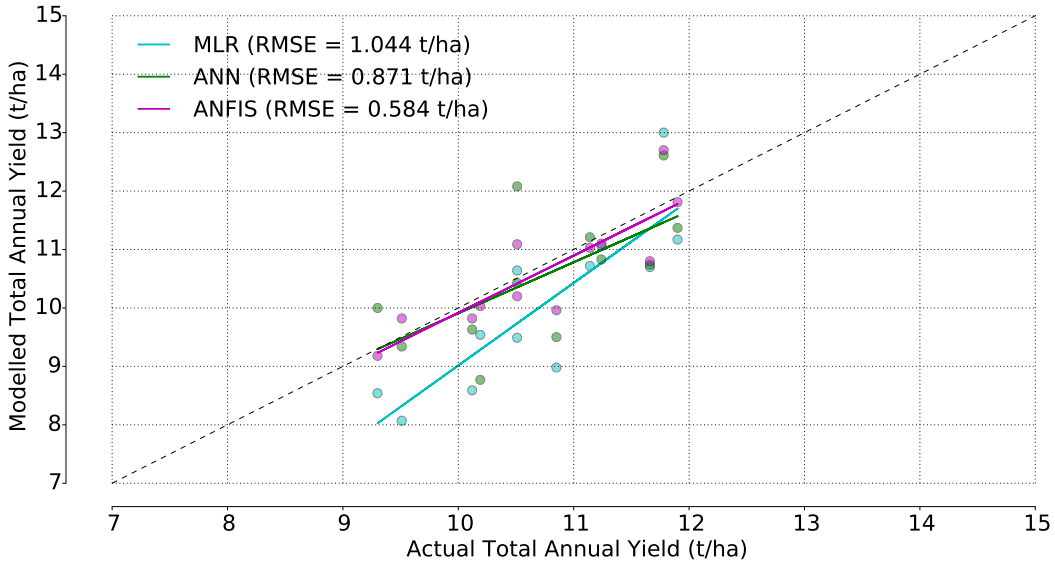


Figure 7: Moorepark total annual yield (t/ha).

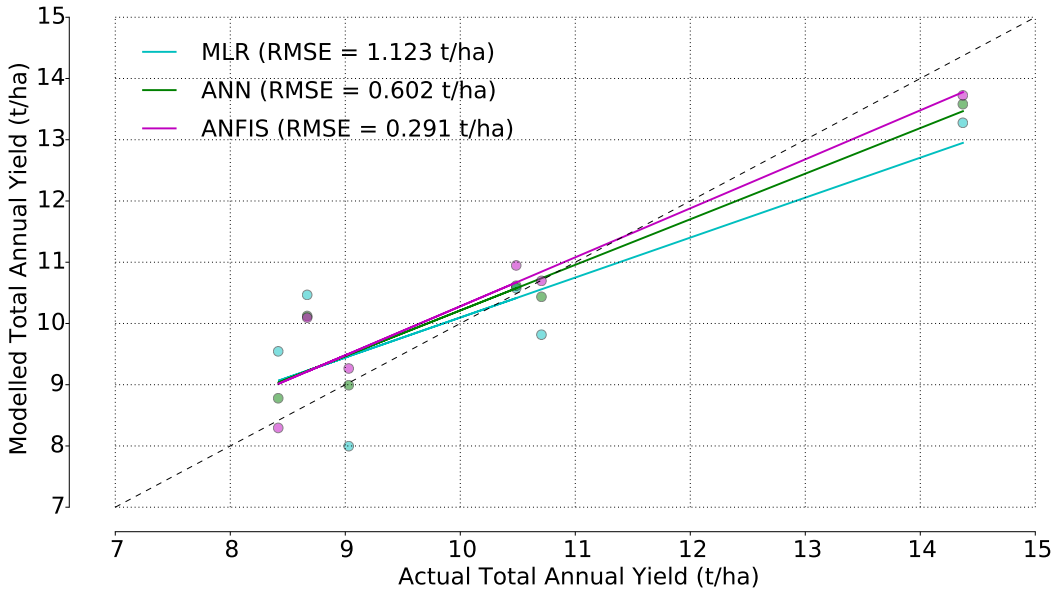


Figure 8: Grange total annual yield (t/ha).

From Figure 7 and Figure 8 it can be concluded that the precise estimation of growth rate can be used to calculate the total weekly and annual yield. However, the assumption of linear growth throughout the week is

not always true. Due to the strong relationship between the growth rate and weather conditions (e. g., daily temperature, precipitation) this issue of linear (or constant) growth rate can be resolved by using GDD information. In the next chapter the GDD information calculated from weather data (daily: minimum, maximum and mean temperature) were combined with the VI in order to analyse the influence of climate variability on the retrieval of grassland biomass and growth rate.

4

FUSION OF REMOTE SENSING AND WEATHER DATA TO RETRIEVE GRASSLAND BIOMASS AND GROWTH RATE

Climate is what we expect, weather is what we get.

— Mark Twain

CHAPTER PUBLICATION:

This chapter has been submitted as a research article for publication in "International Journal of Applied Earth Observation and Geoinformation":

Ali, I.; Cawkwell, F.; Dwyer, E.; and Green, S.; **2016**, *"Synergetic use of remote sensing and weather data to retrieve grassland biomass and growth rate"*, International Journal of Applied Earth Observation and Geoinformation. [Submitted, (IF: 3.470)]

4.1 PAPER—3

4.1.1 ***Ali, I.;*** *Cawkwell, F.; Dwyer, E.; and Green, S.;* ***2016****, "Synergetic use of remote sensing and weather data to retrieve grassland biomass and growth rate", International Journal of Applied Earth Observation and Geoinformation. [Submitted, (IF: 3.470)]*

The main abiotic factors which determine the growth potential of each vegetation type or plant include climate and soil. Therefore, it is important to know the climatic requirements for plant species, and because of their different phenological characteristics, different plant species require a different range of temperature and soil moisture. There is thus a very strong link between the current and future climate and its effects on plant phenology. After analysing the climate data from the past century Khanduri et al. (2008) have reported that the average length of the growing season (in different parts of the world) has extended by 3.3 days per decade.

GDD are a measurement of the growth and development of plants during the growing season. Based on the findings from the previous paper (Chapter 3), this paper presents the inclusion of climate variables (daily minimum, maximum and mean temperature for GDD calculation) into the model development (ANFIS: for details, see chapter 3, section 2.4.3) as a proxy to predict and improve biomass and growth rate estimation.

In the literature, different methods for calculating GDD have been reported which have different interpretations, based on the scenarios of ad-

justing minimum, maximum and average temperature with respect to the selected base temperature. Based on these adjustments each method will produce a different profile of accumulated GDD, therefore it is important to clearly define the criteria and conditions used to calculate the GDD. In this study, three different methods of calculating GDD are used and their performance for predicting both grassland biomass (DM kg/ha) and growth rate (DM kg/ha/day) for the Grange study site is analysed.

Results show that the fusion of remote sensing VI and accumulated growing degree-days temperature has improved the biomass rate and yield estimation performance.

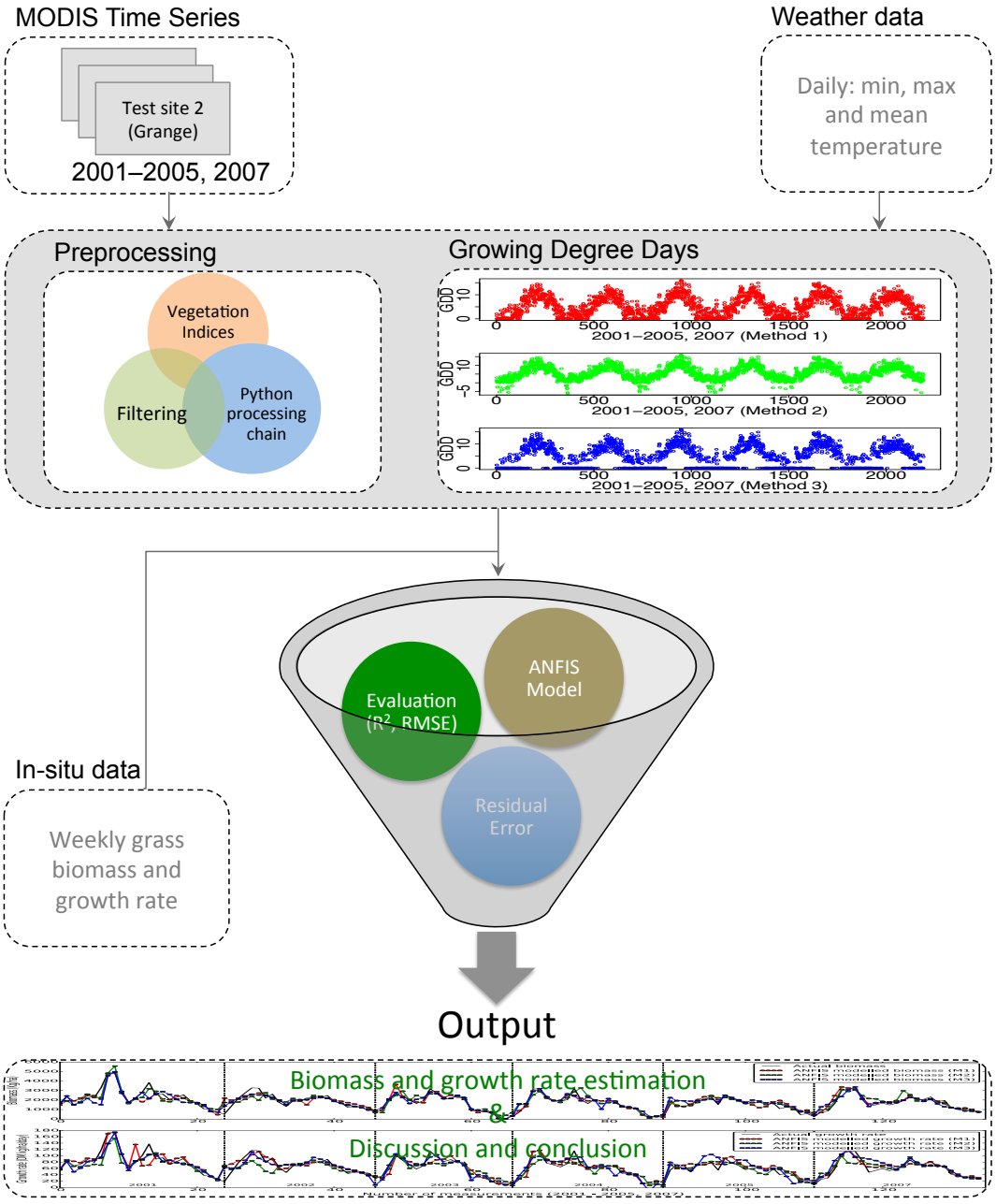


Figure 9: Graphical abstract of this paper: **Ali, I.;** Cawkwell, F.; Dwyer, E.; and Green, S.; **2016**, *"Synergetic use of remote sensing and weather data to retrieve grassland biomass and growth rate"*, International Journal of Applied Earth Observation and Geoinformation. [Submitted, (IF: 3.470)]

CONTRIBUTION STATEMENT

Declaration of own contribution to the published (or intended for publication) scientific papers within my dissertation.

DISSERTATION TITLE: Retrieval of grassland biophysical parameters using multitemporal optical and radar satellite data.

PAPER–3: **Ali, I.;** Cawkwell, F.; Dwyer, E.; and Green, S.; **2016**, *"Synergetic use of remote sensing and weather data to retrieve grassland biomass and growth rate"*, International Journal of Applied Earth Observation and Geoinformation. [Submitted, (IF: 3.470)]

OWN CONTRIBUTION IN THIS WORK: Concept development (fully), Literature search (fully), Methods development (fully), Research design (fully), Data collection (mainly), Data pre-processing (fully), Data analysis (fully), Construction of the manuscript (fully), Argumentation (fully), Critical revision of the article (mainly).

Iftikhar Ali, MSC

April 17, 2016

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Corresponding Author: Mr. Ali Iftikhar,

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First Author: Ali Iftikhar

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Abstract: In this study we have designed an experiment to retrieve grassland biomass (dry matter (DM) kg/ha) and growth rate (DM kg/ha/day) based on satellite (MODIS 8-day composite, six year time series) driven vegetation indices (VI), and the synergetic use of vegetation indices and accumulated growing degree days (GDD) information using an adaptive-neuro fuzzy inference systems (ANFIS) approach. Three different configurations of GDD calculations were compared for grassland biomass and growth rate retrieval. The results show that, with the synergetic use of remote sensing vegetation indices and weather data, the grassland biomass and growth rate estimation performance (R^2) was improved by 12.5% and 3.9% respectively as compared to the results achieved by using VI only.

Opposed Reviewers: Christian Schuster
Co-auther in the past and worked togather.

COVER LETTER

International Journal of Applied Earth Observation and Geoinformation

Date: 29-01-2016

Dear Editor-in-Chief,
I am enclosing herewith a manuscript entitled "Synergetic Use Of Remote Sensing And Weather Data To Retrieve Grassland Biomass and Growth Rate" for publication in International Journal of Applied Earth Observation and Geoinformation for possible evaluation. The Corresponding author of this manuscript is Iftikhar Ali and the complete list (and order) of authors for this paper includes:

Iftikhar Ali,
Fiona Cawkwell,
Edward Dwyer, and
Stuart Green.

With the submission of this manuscript I would like to undertake that:

- All authors of this research paper have directly participated in the planning, execution, or analysis of this study;
- All authors of this paper have read and approved the final version submitted;
- The contents of this manuscript have not been copyrighted or published previously;
- The contents of this manuscript are not now under consideration for publication elsewhere;
- The contents of this manuscript will not be copyrighted, submitted, or published elsewhere, while acceptance by the Journal is under consideration;
- There are no directly related manuscripts or abstracts, published or unpublished, by any authors of this paper;

Submitted manuscript is a Research Article.

Regards,

Iftikhar Ali.

iffi.math@gmail.com

Synergetic Use Of Remote Sensing And Weather Data To Retrieve Grassland Biomass and Growth Rate

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Abstract

In this study we have designed an experiment to retrieve grassland biomass (dry matter (DM) kg/ha) and growth rate (DM kg/ha/day) based on satellite (MODIS 8-day composite, six year time series) driven vegetation indices (VI), and the synergetic use of vegetation indices and accumulated growing degree days (GDD) information using an adaptive-neuro fuzzy inference systems (ANFIS) approach. Three different configurations of GDD calculations were compared for grassland biomass and growth rate retrieval. The results show that, with the synergetic use of remote sensing vegetation indices and weather data, the grassland biomass and growth rate estimation performance (R^2) was improved by 12.5% and 3.9% respectively as compared to the results achieved by using VI only.

Keywords: Biomass, time series, Growing Degree Days, remote sensing, grasslands, biophysical parameters retrieval

1. Introduction

Monitoring grassland and pastures from space using imaging satellites is becoming more feasible due to improved spatial, temporal and spectral resolution of the data. A review of published studies on grassland suggests that the remote

*Corresponding author

sensing community and agronomists are increasingly working together in order to realize the potential of remote sensing technologies, with the aim of developing real time decision support systems. Consistent and regular monitoring of the world's second largest terrestrial ecosystem is not only important for the grazing industry, but also for the environment where grasslands play a crucial role in regularization of the carbon cycle [1].

Ireland is an ideal test location to develop such technologies as more than 80% of agricultural land is grassland, providing the major feed source for the pasture based dairy and livestock industry. Intensive grass based systems demand high levels of intervention by the farmer, with pasture cover (biomass) being the most important variable in land use management decisions, as well as playing a vital role in paddock and herd management. In grassland management and the livestock business, grazing capacity and intensity are the key factors, and for sustainable farming need to be monitored consistently in order to optimize feed resources and to avoid grassland degradation.

At present, the remote sensing community is benefiting from advances in technology that are allowing for the acquisition of spaceborne data with higher spatial, temporal, and spectral resolutions [2]. Optical sensors have a long history and have provided high quality and consistent data since the launch of Landsat-1 in 1972. Both optical [3, 4] and radar [5] remote sensing data are being used for monitoring grassland parameters and management strategies. Vegetation indices derived from optical remote sensing data better explain the on ground phenological developments of plants compared to the indicators derived from radar data. These phenological developments are strongly linked to the climatic variables (e.g., temperature, precipitation) that drive the photosynthesis process.

As growing degree days (GDD)–a measure of heat accumulation used by the farm managers to understand plant development and growth status–are strongly linked to the phenological elements of the growing season, we have explored the synergy of satellite driven vegetation indices–an indicator that describes the greenness–and accumulated GDD to retrieve biomass and growth rate of an

intensively managed grassland farm in Ireland.

Multiple linear regression is one of the most widely adopted modelling approaches to derive biophysical parameters from satellite and in situ data [6, 7, 8, 9], but with growing data volumes new state of the art modelling methods have been developed to better manage the high dimensionality and non-linearity of many of the datasets. In the context of developing robust farm decision support systems, it is very important to explore the strength of state of the art machine learning methods using multi-source datasets. Artificial neural networks (ANN) are one of the most commonly used machine learning algorithms which have the ability to learn from complex patterns in a dataset[10, 11, 12], while fuzzy logic approaches have the power to reason and generate rules from the dataset. Adaptive-neuro fuzzy inference systems (ANFIS) are the integration of both ANN and fuzzy logic, combining the power of both methods to provide an approach with improved predictive or approximation ability. This modelling approach has been used in various disciplines [11, 13, 14] due to its ability to handle very chaotic and complex patterns in the dataset, and is also getting attention for remote sensing related application [3, 15, 16, 17]. Therefore, we have used the ANFIS approach for grassland biomass and growth rate estimation.

The objective of this paper is to investigate the contribution of GDD information to more accurate retrieval of biomass and growth rate of intensively managed grasslands compared to the use of just VI on its own. The following two scenarios were analysed:

I Grassland biomass and growth rate estimation using only satellite driven vegetation indices.

II Grassland biomass and growth rate estimation using both satellite driven vegetation indices and accumulated local GDD profiles.

2. Materials and methods

2.1. Study site

The Grange study site is a Teagasc (the Irish agriculture and food development authority) research farm located in the north east (53° $06^{'}$ N, 06° $40^{'}W$) of Ireland. Teagasc research farms in Ireland have been closely monitored for many years, providing a valuable source of grassland biomass (intensively managed grassland), meteorological and farm management data.

2.2. Remote sensing data

A time series (46 images per year) of 250m MODIS Terra surface reflectance 8-day composite (MOD09Q1), and 500m MODIS Terra surface reflectance 8-day composite (MOD09A1) images were freely downloaded from the NASA LPDAAC[1] for the Grange study site from 2001 to 2007. For accurate estimation of the grass growth index based on satellite data, the date of ground truth data collection and satellite image acquisition are required in order to establish a true correlation between the observed biophysical parameters and satellite driven vegetation indicators. The day of pixel composite information was extracted from the MOD09A1 product as suggested by Guindin-Garcia et al. [18] and applied to the 250m product, which was used for the model development.

2.3. In-situ data

The study site consists of intensively managed grassland pasture fields, and a number of grassland related biophysical parameters have been recorded for many years. Weekly biomass (DM kg/ha) and growth rate (DM kg/ha/day) from six years (2001-2005, 2007) are used. These measurements are calculated by cutting and drying a grass strip of approximately 1 meter wide and 3 meters long for each paddock. The available on farm biomass is calculated by averaging the individual paddock biomass. For the calculation of GDD, daily minimum,

[1] (https://lpdaac.usgs.gov/lpdaac/get_data/glovis)

maximum and mean temperature for these six years were retrieved from the on-site weather station (with hourly logging).

2.4. Growing Degree Days (GDD) calculation

Growing degree days, also called *heat units*, are a measure of heat accumulation used by farm managers to understand plant development and growth status. The concept was first introduced by Reaumer in 1930, and since then it has been successfully used for different applications in agriculture and plant ecology related investigations [19]. It is measured in growing degree-day (GDD, $^{\circ}C$-day). Air temperature is one of the main factors that determines the rate of plant development [20].

The canonical form for calculating GDD is:

$$GDD = \left(\frac{T_{MAX} + T_{MIN}}{2}\right) - T_{BASE} \tag{1}$$

Where T_{MAX} is the maximum daily temperature, T_{MIN} is the daily minimum and T_{BASE} a baseline temperature (all in $^{\circ}C$) In the literature [19] there are three different interpretations of this equation for adjusting the base temperature with respect to the values of minimum, maximum and average temperature. A base temperature of 5 $^{\circ}C$ was selected for grassland [21]. The three different scenarios of equation 1 are [19, 22]:

Method 1:

$$GDD_{M1} = \left(\frac{T_{MAX} + T_{MIN}}{2}\right) - T_{BASE} \tag{2}$$

where if $[(T_{MAX}+T_{MIN})/2] < T_{BASE}$, then $[(T_{MAX}+T_{MIN})/2] = T_{BASE}$

Method 2:

$$GDD_{M2} = \left(\frac{T_{MAX} + T_{MIN}}{2}\right) - T_{BASE} \tag{3}$$

where if $T_{MAX} < T_{BASE}$, then $T_{MAX} = T_{BASE}$, and if $T_{MIN} < T_{BASE}$, then $T_{MIN} = T_{BASE}$

Method 3: If $T_{MIN} > T_{BASE}$, then

$$GDD_{M3} = \left(\frac{T_{MAX} + T_{MIN}}{2}\right) - T_{BASE} \tag{4}$$

If $T_{MAX} < T_{BASE}$, then

$$GDD_{M3} = T_{BASE} - \left(\frac{T_{MAX} + T_{MIN}}{2}\right) \tag{5}$$

If $T_{MAX} > T_{BASE}$ & $T_{MIN} < T_{BASE}$ & $\left(\frac{T_{MAX}+T_{MIN}}{2}\right) > T_{base}$, then,

$$GDD_{M3} = \left[\left(\frac{T_{MAX} - T_{BASE}}{2}\right) - \left(\frac{T_{BASE} - T_{MIN}}{4}\right)\right] \tag{6}$$

If $T_{MAX} > T_{BASE}$ & $T_{MIN} < T_{BASE}$ & $\left(\frac{T_{MAX}+T_{MIN}}{2}\right) < T_{base}$, then,

$$GDD_{M3} = \left[\left(\frac{T_{BASE} - T_{MIN}}{2}\right) - \left(\frac{T_{MAX} - T_{BASE}}{4}\right)\right] \tag{7}$$

Figure 1 shows the weather dataset (Figure 1 (A)) that was used for calculating GDD profiles for these three methods (Figure 1 (B)), and the corresponding profiles of accumulated sum of GDD for each year (Figure 1 (C)). Based on the defined conditions and constraints, the output of each GDD method is different. For example M1 will always produce positive values ($GDD_{M1} \geq 0$), M2 can have negative values as well, while in the case of M3 if the given conditions are not true the values will be set to zero or excluded making it more conservative than the other methods. Therefore based on these conditions the values of accumulated GDD profile for M1 and M2 are higher than the values of M3 due to the elimination of data points that do not satisfy the defined criteria (as shown in Figure 1 (C)).

2.5. Model development

ANN have the ability to learn patterns, while fuzzy logic has the capability of reasoning. ANFIS is a fusion or hybrid model that integrates the positive aspects of both ANN and fuzzy logic in order to construct a robust model that will associate the independent (input values) variables with the dependent (target values) variables with minimum estimation error. A five layer ANFIS was first introduced by Jang [23], with the ability to incorporate linguistic knowledge (expert opinion) and human like reasoning based on a training data set and a set of $IF - THEN$ fuzzy rules (for detailed description of the algorithm see [23]).

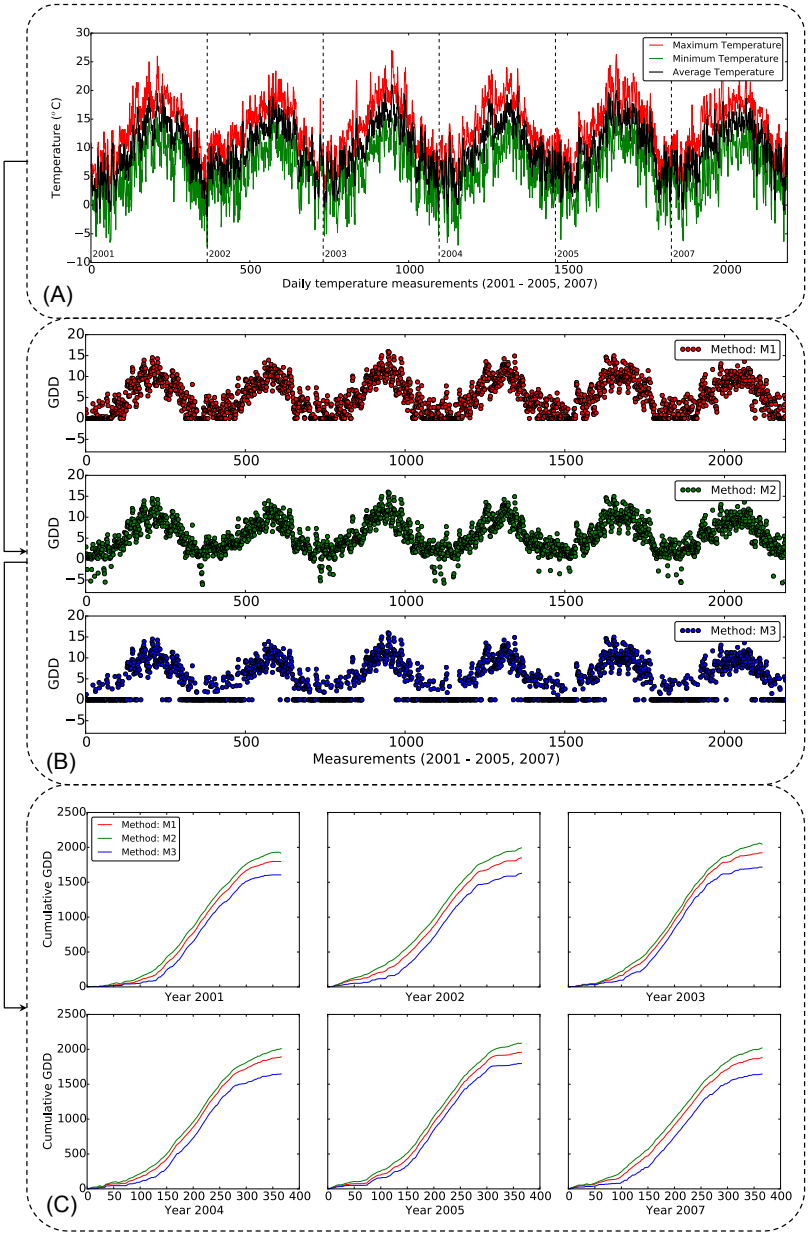


Figure 1: (A): Daily maximum, minimum and agerage temperature since January 2001. (B): the output profile of GDD for Method 1, Method 2 and Method 3. (C): the corresponding year wise accumulated growing degree days profiles for three methods (M1, M2 and M3).

Five vegetation indices (Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI-2), Soil Adjusted Vegetation Index (SAVI), Modified Soil Adjusted Vegetation Index (MSAVI) and Optimized Soil Adjusted Vegetation Index (OSAVI)) were calculated from red and Near Infrared MODIS bands, and along with ground measurements and weather data were used for model development. Vegetation indices were filtered using the Savitzky-Golay algorithm, which is widely used to smooth high frequency variability. Principal Component Analysis (PCA) was then applied to reduce the data dimensionality and variable dependencies. Figure 2 shows the work-flow and processing steps of the approach implemented.

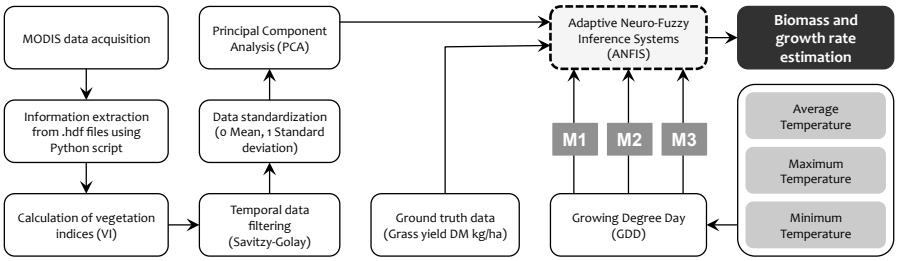


Figure 2: Work-flow of the scheme implemented for grassland biomass and growth rate estimation.

To assess the performance of the ANFIS approach to estimate grassland biomass (DM kg/ha) and growth rate (DM kg/ha/day), statistical measures including root mean square error ($RMSE$ (units: biomass = DM kg/ha, growth rate = DM kg/ha/day)) and coefficient of determination (R^2) were used.

3. Results and discussion

Table 1 shows the results with and without the integration of accumulated GDD information with satellite driven vegetation indices. As GDD is strongly linked to the plant development, or phenological elements, an improvement in estimation for both biomass rate and yield is observed. However the degree of improvement depends on the method of GDD calculation used.

Table 1: Comparison of model performance for biomass and growth rate estimation using only VI, and combination of VI and GDD.

Using VI		R^2 ($p < 0.05$)	RMSE DM kg/ha/day DM kg/ha	Difference from just using VI +improvement / -decline	
Growth rate		0.76	15.35		
Biomass		0.72	384.79		
Using VI and GDD	Method	R^2 ($p < 0.05$)	RMSE	R^2	RMSE
Growth rate:	M1	0.79	14.05	+0.03	+1.30
	M2	0.72	16.57	-0.04	-1.22
	M3	0.77	14.61	+0.01	+0.74
Biomass:	M1	0.81	374.32	+0.09	+10.47
	M2	0.77	397.78	+0.05	-12.99
	M3	0.80	376.64	+0.08	+8.15

3.1. Grassland biomass and growth rate retrieval using VI

In the first step grassland biomass and growth rate were modelled exclusively based on vegetation indices. Results show that the model performed slightly better in the case of growth rate retrieval ($R^2 = 0.76$) as compared to the biomass ($R^2 = 0.72$) as shown in Table 1 and Figure 3. For both (growth rate and biomass), 2005 gave the most inconsistent over and/or under estimations, due to the high complexity of the patterns for this year as a result of management practices (e.g., intensive grazing) compared to the others.

3.2. Grassland biomass and growth rate retrieval using VI and GDD

In the next step we modified the input feature vector to estimate the grassland biomass (DM kg/ha) and growth rate (DM kg/ha/day) using both remote sensing vegetation indices and accumulated GDD information.

3.2.1. Growth rate retrieval

For the growth rate estimation, in the case of M1, performance increased by 3.95% and root mean square error decreased from 15.35 to 14.05. It was

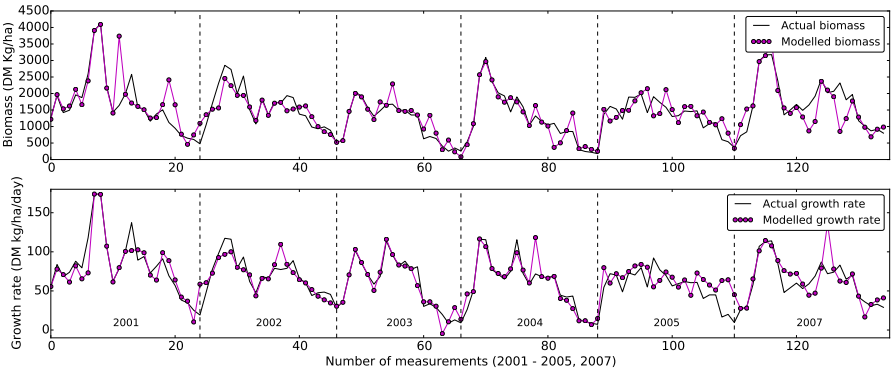


Figure 3: Observed and modelled biomass and growth rate using satellite driven vegetation indices.

observed that M1 produced the best results followed by M3, both of which have a positive output value, while M2 can have both a positive and negative range of values (see Figure 1).

Figure 4 shows the actual and modelled growth rate for the three different GDD methods. It was observed that a few data points were under (e.g., in 2001, 2004) and over (e.g., in 2007) estimated by all three methods.

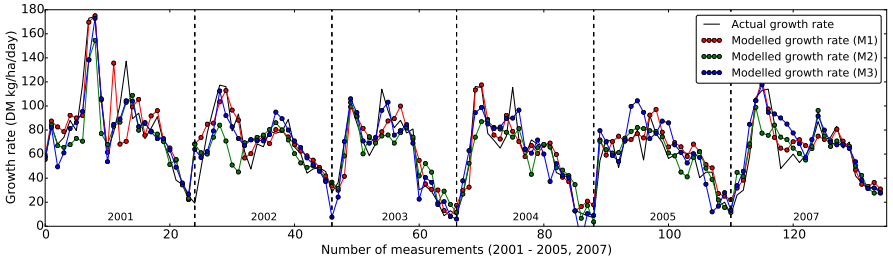


Figure 4: Observed and modelled growth rate using vegetation indices and three GDD methods (M1, M2 and M3).

Figure 5 (A) shows the scatter plot for the three GDD methods of the measured growth rate against that estimated using satellite driven VI. The RMSE (DM kg/ha/day) was slightly improved from 15.35 to 14.05 (M1) and 14.61 (M3), and the over all trend of line fitting and slope was similar to the trend

of VI based estimation model. In order to further analyse the performance of each individual year, the evaluation was undertaken for each year separately. Figure 9 (A) shows the year-wise scatter and boxplots of three GDD methods, where M1 and M3 produced the best results compared to M2, and boxplots show that the spread of the residuals values for M1 are also very compact and the mean is close to zero. Higher actual growth rates tend to be underestimated by the model and at the lowest growth rates, overestimated. 2002 has a different pattern compared to the other years, where the range of growth rate values is between 40 and 110 (DM kg/ha/day), which could be due to the management practices and light to moderate grazing. Overall, growth rate is marginally improved by incorporating GDD, with different models performing slightly better in different years according to the conditions of that year.

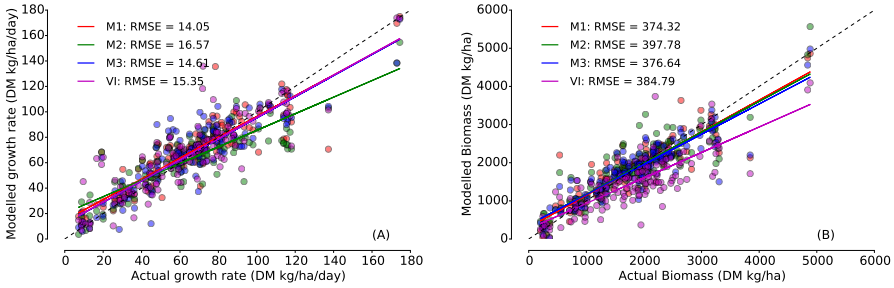


Figure 5: Scatter plots of observed and modelled (A) growth rate (RMSE DM kg/ha/day), and (B) biomass (RMSE DM kg/ha) using satellite driven vegetation indices and GDD (coloured points represent the different models).

3.2.2. Biomass retrieval

Similarly, in the case of biomass estimation, M1 produced the best results with 12.5% increase in performance (R^2) and 2.72% decrease in RMSE (DM kg/ha). M2 performance increased by 6.49% and RMSE (DM kg/ha) increased by 3.38%, and M3 shows an increase of 11.11% in performance (R^2) and 2.12% decrease in RMSE. Figure 5 (B) shows the scatter plot of observed and modelled grassland biomass for the three GDD methods, and M1 gives the lower RMSE value compared to M2, M3 and VI.

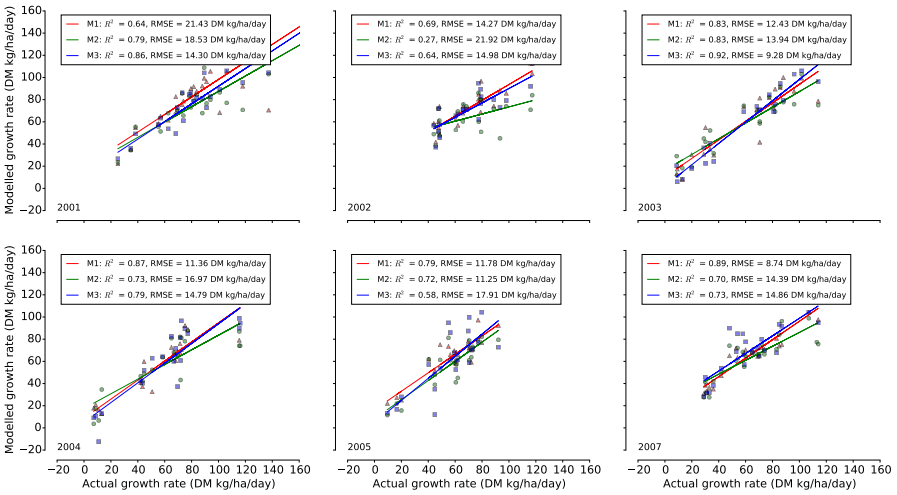


Figure 6: Yearly performance (RMSE DM kg/ha/day) of observed and modelled growth rate using three GDD methods (coloured points represent the different models: M1, M2 and M3).

Figure 7 shows the observed and model biomass using all three GDD methods. M1 produced the best results with only a few under (in 2002) and over (in 2003) estimation errors. In the case of M2 a consistent over estimation is evident e.g., in year 2001, 2004 and 2007. The output of M3 ($R^2 = 0.80$) was similar to M1 ($R^2 = 0.81$) without any major over and under estimation errors.

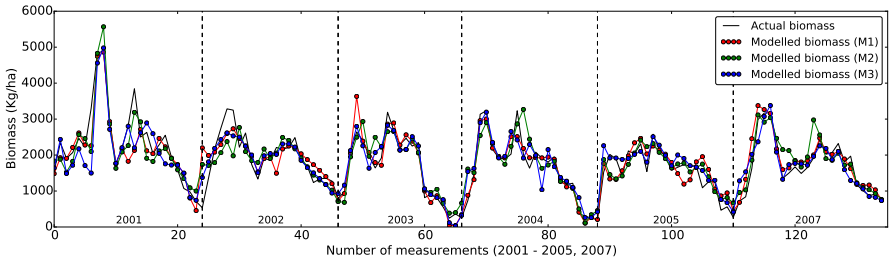


Figure 7: Observed and modelled biomass using vegetation indices and three GDD methods (M1, M2 and M3).

Figure 8 shows the year-wise performance of each GDD method for biomass estimation. In most cases M1 produced improved results as compared to the other two GDD methods except for 2002 and 2005. For these two years the

spread and range of biomass values is small compared to the other years (also shown in Figure 7). Figure 1 shows that there is no major variation in climate variables during these years that causes the low biomass and therefore they are potentially due to the intensive grazing and farm management practices. For 2001 M2 gave a higher value of correlation coefficient ($R^2 = 0.84$, $RMSE = 426.07$ DM kg/ha) than M1 ($R^2 = 0.79$, $RMSE = 500.05$, DM kg/ha), but the boxplot shows that M2 has a wide range of residual error compared to the M1 and M3 methods (Figure 9 (B)). In general the model tracks from low to high biomass better than growth rate, although Figure 5 suggests that the model slightly overestimates at low levels of biomass. Including GDD allows better tracking of actual biomass than VI only, especially as the biomass increases.

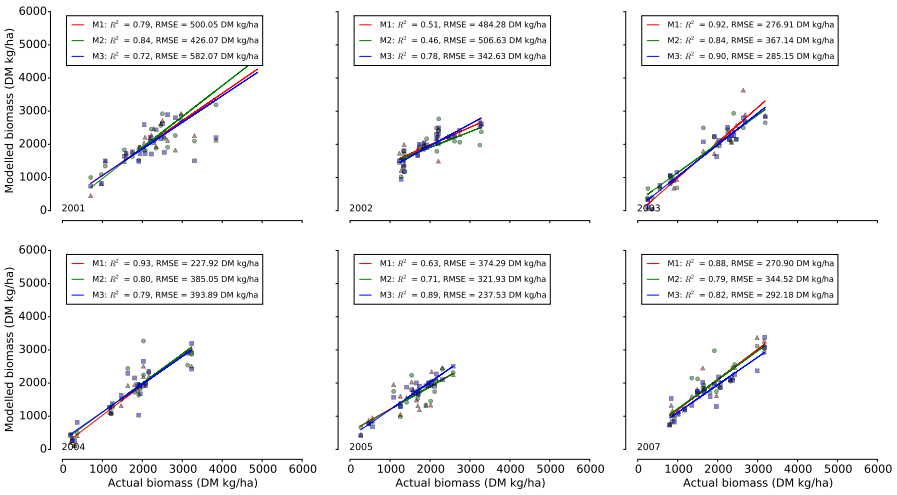


Figure 8: Year-wise performance of observed and modelled biomass using three GDD methods (M1, M2 and M3).

In term of performance (Figure 9), in most cases M1 and M3 give the smallest spread of interquartile range (IQR) of residuals. In the case of biomass retrieval (Figure 9 (B)) for 2005, M1 produced the biggest range of error compared to the M2 and M3, however for 2002 the spread of IQR for all three GDD methods is comparable.

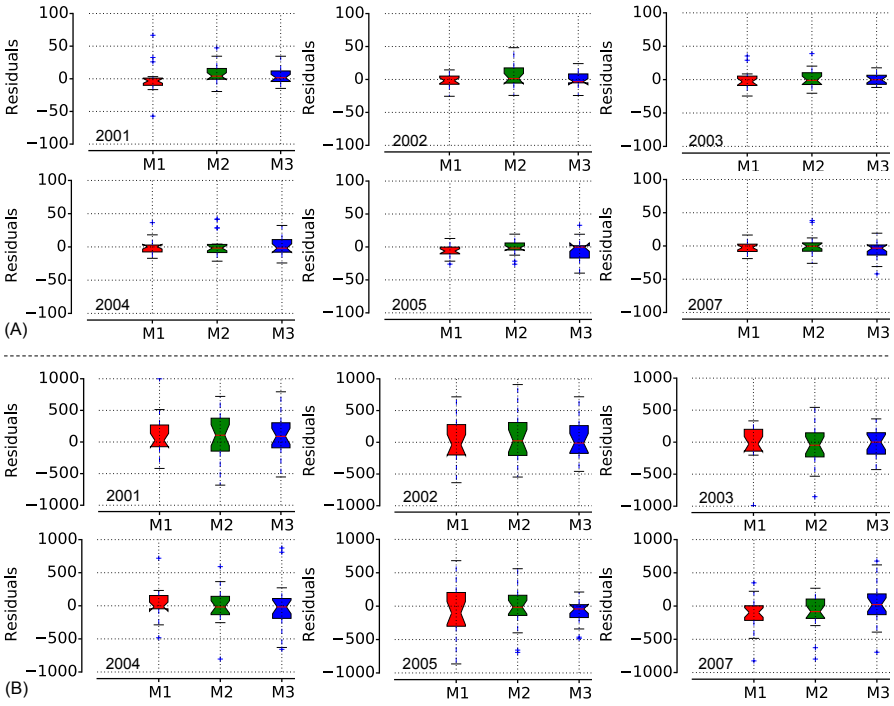


Figure 9: Year-wise boxplot of residuals of three GDD methods for growth rate (A) and biomass (B) retrieval.

3.3. Limitations of GDD

Growing Degree Days is a useful approximation of the growth accumulation and development across a wide range of species. However it is only a linear approximation and therefore can map poorly to the actual growth rate. For example, for each vegetation/species type there is a minimum and maximum temperature acceptance threshold, and beyond these thresholds growth will be retarded [24]. Therefore careful and precise selection of base temperature for each vegetation type is crucial for better approximation [25]. In the case of a single base temperature selection over mixed vegetation areas, errors in prediction can become fairly substantial. In this investigation the study site covers only pasture fields without any mixture of other land-cover or vegetation type, therefore the single base temperature assumption is appropriate. GDD assumes

that the development rates are a linear function of temperature, however temperature has non-linear effects too, especially when it approaches the upper and lower threshold.

The assumption of GDD that development rate is only a function of temperature is not always true [26], it is also linked to the use of fertilizers, pesticides and management practices, which can explain some of the inter-annual variability in the results. Lastly, in order to build an accumulated GDD profile a consistent long term record of weather data (daily recorded temperature values) is required, and for large area mapping and to avoid the effect of different climatic zones in the region, a spatially distributed sampling of collected or modelled weather data is also very important.

4. Conclusion

Growth rate and plant phenology are highly influenced by the weather conditions, therefore it is important to investigate and understand the influence of climatic variables (i.e., temperature, rainfall) on grassland parameters. Overall it can be concluded that incorporating GDD into estimates of grass biomass from satellite data does improve the performance of the model, and of the three GDD configurations tested M1 and M3 methods gave improved results. Accumulated GDD method M1 gives the best results, both in terms of higher correlation coefficient value and lower RMSE. The results show that for both grassland growth rate and biomass, the inclusion of GDD information has improved the overall estimation performance (R^2) of the model by 3.95% and 12.5% respectively. The GDD equation has different interpretations and each of them produced a different results, therefore it is strongly recommended that authors should clearly describe the method and implementation scheme (in terms of defining conditions and scenarios as discussed in section 2.4) so that results are correctly interpreted by others, in this paper we have evaluated the three methods of interpreting the GDD equation using a 5°C base temperature. This study explains the potential and benefit of a synergetic approach as well as the

features derived from weather data to retrieve grassland parameters. The combination is potentially beneficial, especially in the case of biomass, but we need to understand why it is less effective with the growth rate. The method might benefit from higher spatial (and temporal) resolution VI data in which case the VI might perform equally well on its own, without having to use GDD, however achieving a weekly VI at a higher resolution remains a problem in temperate mid-latitude regions where cloud cover is prevalent.

Acknowledgment

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References

[1] J. D. Derner, G. E. Schuman, Carbon sequestration and rangelands: A synthesis of land management and precipitation effects, Journal of Soil and Water Conservation 62 (2) (2007) 77–85.

[2] I. Ali, F. Cawkwell, E. Dwyer, S. Barrett, B. Green, Satellite remote sensing of grasslands: from observation to management–a review (article in press), Journal Of Plant Ecology.

[3] I. Ali, F. Cawkwell, S. Green, E. Dwyer, Application of statistical and machine learning models for grassland yield estimation based on a hypertemporal satellite remote sensing time series, in: Geoscience and Remote Sensing Symposium (IGARSS), 2014 IEEE International, 2014, pp. 5060–5063. doi:10.1109/IGARSS.2014.6947634.

[4] C. Schuster, I. Ali, P. Lohmann, A. Frick, M. Förster, B. Kleinschmit, Towards detecting swath events in TerraSAR-x time series to establish NATURA 2000 grassland habitat swath management as monitoring parameter, Remote Sensing 3 (12) (2011) 1308–1322. doi:10.3390/rs3071308.

[5] I. Ali, C. Schuster, M. Zebisch, M. Förster, B. Kleinschmit, C. Notarnicola, First results of monitoring nature conservation sites in alpine region by using very high resolution (VHR) x-band SAR data, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 6 (5) (2013) 2265–2274. doi:10.1109/JSTARS.2013.2241735.

[6] D. Bella, R. Faivre, F. Ruget, B. Seguin, M. Guérif, B. Combal, M. Weiss, C. Rebella, Remote sensing capabilities to estimate pasture production in france, International Journal of Remote Sensing 25 (23) (2004) 5359–5372. doi:10.1080/01431160410001719849.

[7] V. Loris, G. Damiano, Mapping the green herbage ratio of grasslands using both aerial and satellite-derived spectral reflectance, Agriculture, Ecosystems & Environment 115 (1-4) (2006) 141–149. doi:10.1016/j.agee.2005.12.018.

[8] B. Xu, X. C. Yang, W. G. Tao, Z. H. Qin, H. Q. Liu, J. M. Miao, Y. Y. Bi, Modis based remote sensing monitoring of grass production in china, International Journal of Remote Sensing 29 (17-18) (2008) 5313–5327. doi:10.1080/01431160802036276.

[9] L. Vescovo, D. Gianelle, Using the MIR bands in vegetation indices for the estimation of grassland biophysical parameters from satellite remote sensing in the alps region of trentino (italy), Advances in Space Research 41 (11) (2008) 1764–1772. doi:10.1016/j.asr.2007.07.043.

[10] B. Ji, Y. Sun, S. Yang, J. Wan, Artificial neural networks for rice yield prediction in mountainous regions, The Journal of Agricultural Science 145 (03) (2007) 249–261. doi:10.1017/S0021859606006691.

[11] M. K. Goyal, B. Bharti, J. Quilty, J. Adamowski, A. Pandey, Modeling of daily pan evaporation in sub tropical climates using ANN, LS-SVR, fuzzy logic, and ANFIS, Expert Systems with Applications 41 (11) (2014) 5267–5276. doi:10.1016/j.eswa.2014.02.047.

[12] C. Serele, Q. Gwyn, J. Boisvert, E. Pattey, N. McLaughlin, G. Daoust, Corn yield prediction with artificial neural network trained using airborne remote sensing and topographic data, in: Geoscience and Remote Sensing Symposium, 2000. Proceedings. IGARSS 2000. IEEE 2000 International, Vol. 1, 2000, pp. 384–386 vol.1. doi:10.1109/IGARSS.2000.860527.

[13] R. K. Kharb, S. L. Shimi, S. Chatterji, M. F. Ansari, Modeling of solar PV module and maximum power point tracking using ANFIS, Renewable and Sustainable Energy Reviews 33 (2014) 602–612. doi:10.1016/j.rser.2014.02.014.

[14] G. Karimi, S. B. Sedaghat, R. Banitalebi, Designing and modeling of ultra low voltage and ultra low power LNA using ANN and ANFIS for bluetooth applications, Neurocomputing 120 (2013) 504–508. doi:10.1016/j.neucom.2013.04.021.
URL http://www.sciencedirect.com/science/article/pii/S0925231213005274

[15] S. Rajesh, S. Arivazhagan, K. P. Moses, R. Abisekaraj, ANFIS based land cover/land use mapping of LISS IV imagery using optimized wavelet packet features, Journal of the Indian Society of Remote Sensing 42 (2) (2014) 267–277. doi:10.1007/s12524-013-0276-1.

[16] I. Ali, F. Cawkwell, E. Dwyer, S. Green, Modeling managed grassland biomass estimation by using multitemporal remote sensing data–a machine learning approach (article in press), Journal of Selected Topics in Applied Earth Observations and Remote Sensing.

[17] F.-J. Chang, W. Sun, Modeling regional evaporation through ANFIS incorporated solely with remote sensing data, Hydrology and Earth System Sciences Discussions 10 (5) (2013) 6153–6192. doi:10.5194/hessd-10-6153-2013.

[18] N. Guindin-Garcia, A. A. Gitelson, T. J. Arkebauer, J. Shanahan, A. Weiss, An evaluation of MODIS 8- and 16-day composite products for monitoring

maize green leaf area index, Agricultural and Forest Meteorology 161 (2012) 15–25. doi:10.1016/j.agrformet.2012.03.012.

[19] G. S. McMaster, W. W. Wilhelm, Growing degree-days: one equation, two interpretations, Agricultural and Forest Meteorology 87 (4) (1997) 291–300. doi:10.1016/S0168-1923(97)00027-0.

[20] A. B. Frank, Evaluating grass development for grazing management., Rangelands Archives 18 (3) (2006) 106–109.

[21] G. K. Hutchinson, K. Richards, W. H. Risk, Aspects of accumulated heat patterns (growing degree-days) and pasture growth in Southland., Vol. 62, New Zealand Grassland Association, 2000, pp. 81–85.

[22] R. . F. Fealy, The spatial variation in degree days derived from locational attributes for the 1961 to 1990 period, Irish Journal of Agricultural and Food Research 47 (2008) 1–11.

[23] J.-S. Jang, ANFIS: adaptive-network-based fuzzy inference system, IEEE Transactions on Systems, Man and Cybernetics 23 (3) (1993) 665–685. doi:10.1109/21.256541.

[24] S. Wolfram, J. R. Michael, Estimating the impact of climate change on crop yields: The importance of nonlinear temperature effects, Working Paper 13799, National Bureau of Economic Research (February 2008). doi:10.3386/w13799.

[25] A. Government of Alberta, Agroclimatic Atlas of Alberta: Agricultural Climate Elements (2003).
URL http://www1.agric.gov.ab.ca/$department/deptdocs.nsf/all/sag6301

[26] G. N. M. Intyre, W. M. Kliewer, L. A. Lider, Some Limitations of the Degree Day System as Used in Viticulture in California, American Journal of Enology and Viticulture 38 (2) (1987) 128–132.

4.2 ADDITIONAL COMMENTARY

In order to minimize the weather data requirements from the on-ground installed weather stations, and to develop a forecast model for biomass production. The potential use of weather forecast data is tested. Weather forecast data (from February – June, 2014) from IBM Deep Thunder was used for a preliminary analysis of grassland biomass estimation. For this demonstration a date of June 10^{th} was selected due to the availability of cloud free MODIS remote sensing data for this date. The model was trained on the Grange test site (2001 – 2005, 2007) and was tested on features (VI and GDD) extracted over a large area (150Km $\times$ 150Km) from June 10^{th}, 2014. The resolution of the weather data was 1.5 Km, therefore it was re-sampled to the MODIS 250 m resolution.

Figure 10 shows the NDVI, accumulated GDD and estimated biomass map of June 10^{th}, 2014. Major trends in the estimated biomass map are comparable with the NDVI and accumulated GDD. For example, same color boxes in Figure 10 (A), (B) and (C) show same area, it can be seen that the different areas with different NDVI and corresponding accumulated GDD values are differentiable. For example, areas with low NDVI and low accumulated GDD gives the less biomass (blue and white boxes), similarly the area with high biomass surrounded by water (magenta box) was also corrected labelled. In the training samples the range of biomass values in the month of June is around 2000 kg/ha, which is comparable to the estimated biomass. But still the bias is there because the training data only cover the grassland area,

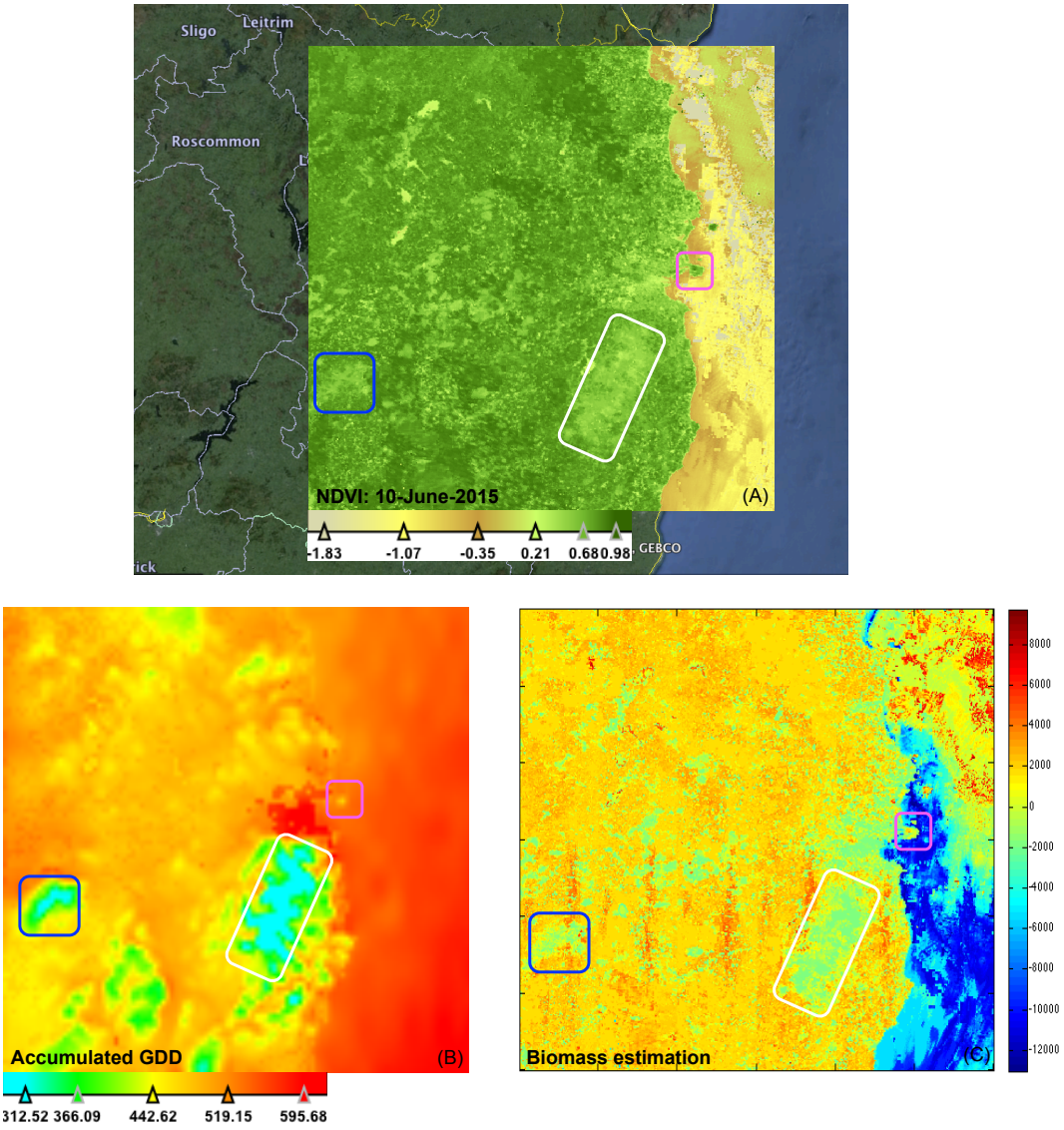


Figure 10: Large scale model evaluation to retrieve grassland biomass using IBM weather forecast data and remote sensing VI. A: NDVI, B: accumulated GDD and C: biomass estimation of the selected date.

while the test data have multiple target features to be labelled e. g., water bodies, urban area and forest patches. Therefore, it is very important to discuss the case of skewed classes, where more number of samples are from one type of class than the other classes. This can be resolved by having an

equal proportion of number of samples from all classes involved in the test dataset.

These preliminary findings are encouraging, but still need to be validated by using a spatially distributed large sample size, high resolution remote sensing and weather data, as well as different trends of growing and biomass regimes from different regions. lastly, masking off the sea and urban areas will give more freedom to the learning algorithm to avoid false negative errors.

Part III

SYNTHETIC APERTURE RADAR INTERFEROMETRY ON GRASSLANDS

5

RETRIEVAL OF GRASSLAND BIOPHYSICAL PARAMETERS USING SAR INTERFEROMETRY

The issue is not just size—we've always had big data sets—the issue is granularity.

— Prof. Dr. Michael Jordan

CHAPTER PUBLICATION:

This chapter has been submitted as a research article for publication in "Journal of Selected Topics in Applied Earth Observations and Remote Sensing, IEEE":

Ali, I.; Barrett, B.; Cawkwell, F.; Green, S.; Dwyer, E.; Neumann, M.: **2016**, *"Limitations Of Repeat-Pass TerraSAR-X (Staring Spotlight Mode) InSAR Coherence To Monitor Pasture Biophysical Parameters"*, Journal of Selected Topics in Applied Earth Observations and Remote Sensing, IEEE. [Accepted (IF: 3.026)]

5.1 PAPER—4

5.1.1 ***Ali, I.;*** *Barrett, B.; Cawkwell, F.; Green, S.; Dwyer, E.; Neumann, M.:* ***2016****, "Limitations Of Repeat-Pass TerraSAR-X (Staring Spotlight Mode) InSAR Coherence To Monitor Pasture Biophysical Parameters", Journal of Selected Topics in Applied Earth Observations and Remote Sensing, IEEE. [Accepted (IF: 3.026)]*

Currently several operational SAR instruments have the ability to acquire high-resolution radar images (e. g., TerraSAR-X, COSMO-SkyMed) independent of the weather conditions, therefore day and night acquisitions can be obtained. The SAR signal's ability to penetrate through the vegetation is mainly dependent on its wavelength, for example, shorter wavelength (X-band) is scattered from the vegetation canopy layer, however the longer wavelengths (e. g., C, L and P-band) are scattered from the trunks and ground surface. Due to the thin structure and short grass height, X-band is more sensitive to the small changes in grass cover due to its growth, cutting and grazing. In pasture management, both destructive (cut and dry or clipping) and non-destructive methods (i. e., Rising Plate Meter (RPM)) are being used to estimate the amount of pasture biomass available in farm paddocks. The amount of available biomass is strongly linked to the grass height, and RPM gives the biomass estimation based on grass height. In a recent study on Bermudagrass, Pittman et al. (2015) have reported that the value of the Pearson correlation coefficient (R) between the grass height

and dry matter (R = 0.83) is higher than the correlation between NDVI and dry matter (R = 0.75). A precise grass height estimation using SAR data will not only give an improved biomass estimate, but also will minimize the effects of saturation in VI which are calculated using spectral bands of the optical imagery and can result in them being ineffective for high biomass vegetation states.

Initially, SAR applications were limited to the exploitation of only the amplitude of the radar signal. Further development in the field of SAR interferometry revealed that the phase of the radar signal also carried useful information for remote sensing applications (Zebker and Goldstein, 1986; Wegmüller, 1997).

Assuming that at time T_1, a satellite passes over an area of observation (A_{Target}) the radar signal emitted from the satellite will be scattered from the target (at distance R_1) and will be recorded by the satellite. If at any point in time T a change or deformation occurs, then the same satellite (or another satellite of the same constellation, e. g., COSMO-SkyMed) will acquire the second (or post event) image (T_2) of the same target area (at distance R_2) as shown in Figure 11. The difference in path length is proportional to the phase difference between the two acquisitions as given in Equation 2:

$$\phi = -\frac{4\pi}{\lambda}\delta R \tag{2}$$

where, ϕ is the phase, λ is the wavelength and δR is the difference in path length.

In SAR interferometry, coherence–a degree of similarity between the two acquisitions/images (Hanssen, 2001)–is another important measure. The InSAR coherence is defined as the normalized complex cross-correlation of the backscatter intensity values v_1 and v_2 at position R_1 and R_2 as shown in Equation 3:

$$\gamma = |\frac{\langle v_1 v_2^* \rangle}{\langle v_1 v_1^* \rangle \langle v_2 v_2^* \rangle}| \tag{3}$$

where v_1^* and v_2^* are complex conjugates of v_1 and v_2. The coherence describes the noise in the interferometric phase: 0.0 = Pure noise, 1.0 = Perfectly smooth phase, or similarity.

Another important component of SAR interferometry is baseline (the horizontal distance between the master (Pass 1) and slave (Pass 2) acquisition pass of the satellite). There is a certain limit to which the two satellites can be separated and after that threshold all the information required for interferometric analysis is lost. This is called a critical baseline ($B_{\perp,crit}$) and is mathematically expressed in Equation 4 (Bamler and Hartl, 1998):

$$B_{\perp,crit} = \frac{\lambda R tan(\theta)}{2R_{ps}} \tag{4}$$

where λ is the wavelength, R is the satellite altitude, θ is the incidence angle and R_{ps} is the pixel spacing in range direction.

In SAR image acquisition, spatial resolution is directly proportional to the illumination time and inversely proportional to the swath dimensions. For example Figure 12 shows a comparison of the spatial coverage and reso-

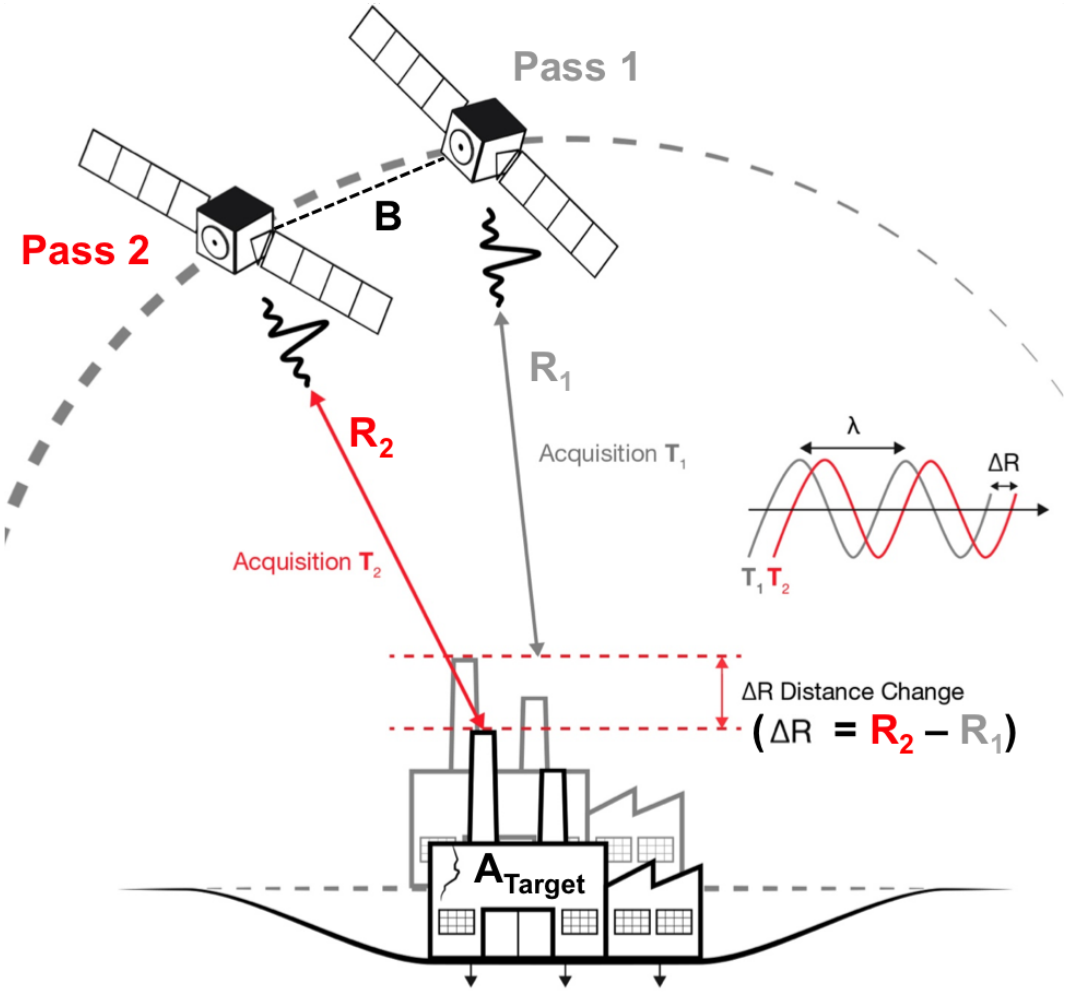


Figure 11: SAR interferometric imaging geometry of repeat-pass data acquisition concept, where B is the baseline, λ is the wavelength, T_1 and T_2 are the two acquisition times, R_1 and R_2 are the range vectors to the resolution cell and δR is the path length (or range) difference (source: modified from (Gosselin, 2015)).

lution of TerraSAR-X's SpotLight, Staring SpotLight and Envisat-ASAR's Image modes. The newly introduced TerraSAR-X Staring SpotLight mode has the highest target illumination time and spatial resolution (up to 0.25m) with smallest swath size (4Km (width) x 3.7Km (length)), compared to the SpotLight (spatial resolution up to 2m: 10km (width) x 10km (length)) and

Envisat-ASAR's Image (spatial resolution $\leqslant$ 30m: 100km (width) x 100km (length)) acquisition mode.

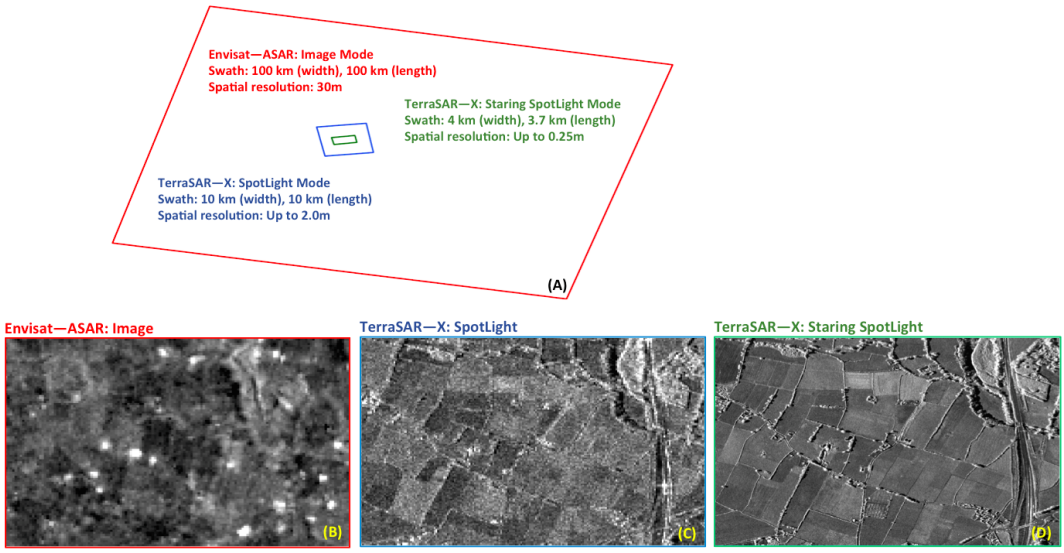


Figure 12: (A) Footprints of Envisat-ASAR image mode (red), TerraSAR-X high resolution spotlight mode (blue) and TerraSAR-X staring spotlight mode (green). (B),(C) and (D) show the screen shorts (covering an area of intensively managed grassland in Ireland) of these three modes respectively.

In relation to precision farming, or to monitor the variations within and between the paddocks, very high spatial resolution data are required. Additionally, a dense time series can be used to detect events such as mowing in managed grasslands (Schuster et al., 2011), and vegetation phenological development (Lopez-Sanchez et al., 2012). To date most precision agriculture has relied on optical data from satellites, aircraft and unmanned aerial vehicles, acquired at a sub-metre resolution.

Spaceborne SAR data are available in different polarizations–orientation of the signal sent and received by the antenna–i. e., VH (vertically emitted and horizontally received, also called cross-polarized channel), HV (hor-

izontally emitted and vertically received) and HH/VV (horizontally/vertically emitted and horizontally/vertically received, also called like or co-polarized channels). SAR sensors are designed to acquire data in different polarization modes e. g., single polarized (one channel: HH or VV or VH or HV), dual polarized (two channels: HH-VV or HH-VH or HH-VH) and fully polarimetric (four channels: HH-VH-HV-VV) mode. SAR fully polarimetric data have the ability to fully decompose the target. Conventional SAR data acquisition modes record data in one or two (single or dual) channels; while in the case of fully polarimetric SAR acquisition the measurements are carried out in all four channels. Fully polarimetric data has the capability to identify the different scatters based on the discrimination of different scattering mechanisms (Lee and Pottier, 2009). The first spaceborne fully polarimetric SAR sensor SIR-C/X-SAR was launched in 1994 and the current generation of operational spaceborne fully polarimetric SAR sensors includes: RADARSAT-2 (Canadian C-band sensor, 2007-present), TerraSAR-X (German X-band sensor, 2007-present) and ALOS PALSAR-2 (continuation of ALOS PALSAR-1, Japanese L-band sensor, 2014-present).

SAR polarimetric data has been available since the early 1980s, but the studies related to SAR polarimetry have only been reported in the literature in recent years. One potential reason for this could be the complexity of the SAR polarimetry theory and processing. Smith and Buckley (2011) carried out a comparative analysis of Radarsat-2 and Landsat-5 TM for the classification of cultivated crops, summer fallow, improved and native grassland. Even though the classification accuracy for Radarsat-2 (kappa: 0.65) was less than Landsat-5 TM (kappa: 0.81) due to the backscattering

similarities between native and improved grasslands, it was still able to successfully discriminate the cultivated crops from grasslands. In another study Dusseux et al. (2014) reported a contradictory findings where SVM classification results of fully polarimetric Radarsat-2 (accuracy: 98%) outperformed the optical (SPOT-5, Landsat-5 TM, accuracy: 81%) data. Moreover, a recent study by Schuster et al. (2015) shows that with the high spatial and temporal resolution SAR data can produce results (TerraSAR-X: 91.1%) comparable to high resolution optical data (RapidEye: 91.7%) to classify different grassland types.

In addition to monitoring and mapping, polarimetric data have the capability to monitor grassland related management practices. For example, Voormansik et al. (2013) used a TerraSAR-X dual polarimetric SAR time series to detect the grassland cutting practices, and showed the potential of a SAR polarimetry approach to distinguish among standing grass (Figure 13 (a, b)), when the grass was cut (Figure 13 (c)) and after it had been collected from the field (Figure 13 (d)).

In SAR polarimetry, tests on different data fusion approaches–e. g., multi angle and multi frequency data fusion–have been reported in the literature. Buckley and Smith (2010) used a combination of multi angle Radarsat-2 quad-pol for grassland classification, and improved classification results (SVM: 80%) were achieved compared to the individual incidence angle. In another study, Metz et al. (2012) tested a multi frequency (X and C-band) approach to discriminate the Natura-2000 and high nature value habitats based on the Maximum-Entropy principle, and the highest accuracy was achieved with combined use of a TerraSAR-X and Radarsat-2 time series.

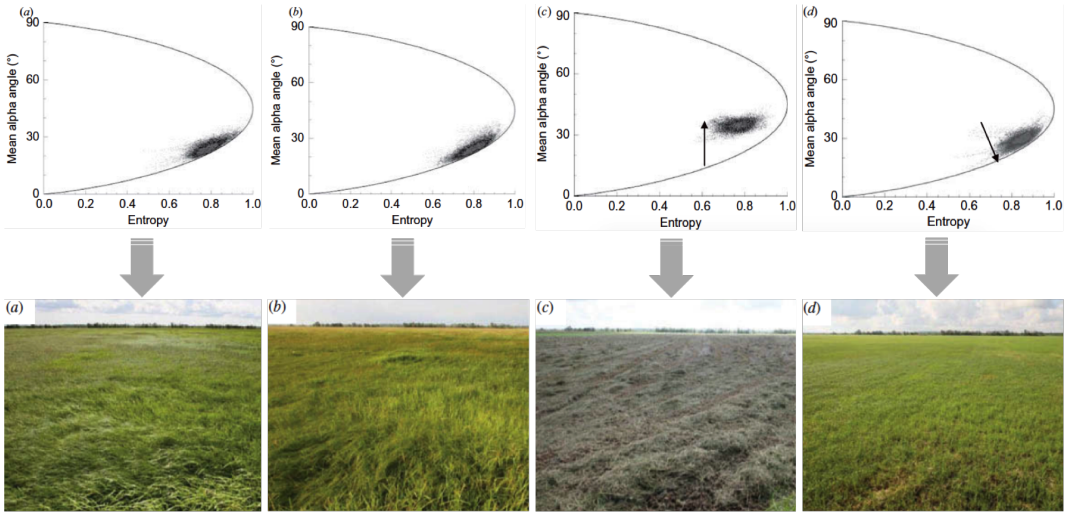


Figure 13: Top row: H2α entropy/mean scattering alpha angle distribution plots of 19 June (a), 11 July (b), 2 August (c), and 24 August (d). Black arrows indicate the two-way movement after the grass was cut and after it was collected, Bottom row: Photographs taken on 18 June (a), 11 July (b), 1 August (c), and24 August (d) [Source: (Voormansik et al., 2013)].

The use of SAR data with different configurations (e. g., multi-frequency, multi-angle, different polarizations and acquisition modes, high spatial resolution) have the great potential for grassland monitoring and biophysical parameters retrieval applications.

In this paper the potential of repeat-pass synthetic aperture radar interferometry (InSAR) over intensively managed pastures is investigated. The highest resolution spaceborne SAR data available from the TerraSAR-X Staring Spotlight (TSX-ST) and a time series of images over a 12 month period was acquired. Initial findings show the possibility of detection of changes due to grass growth, grazing and mowing events by using interferometric coherence information. But it is not possible to automatically categorize these changes only based on the SAR backscatter and coherence,

due to the ambiguity caused by the tall grass laid down due to the wind. Figure 14 shows the graphical abstract of this paper.

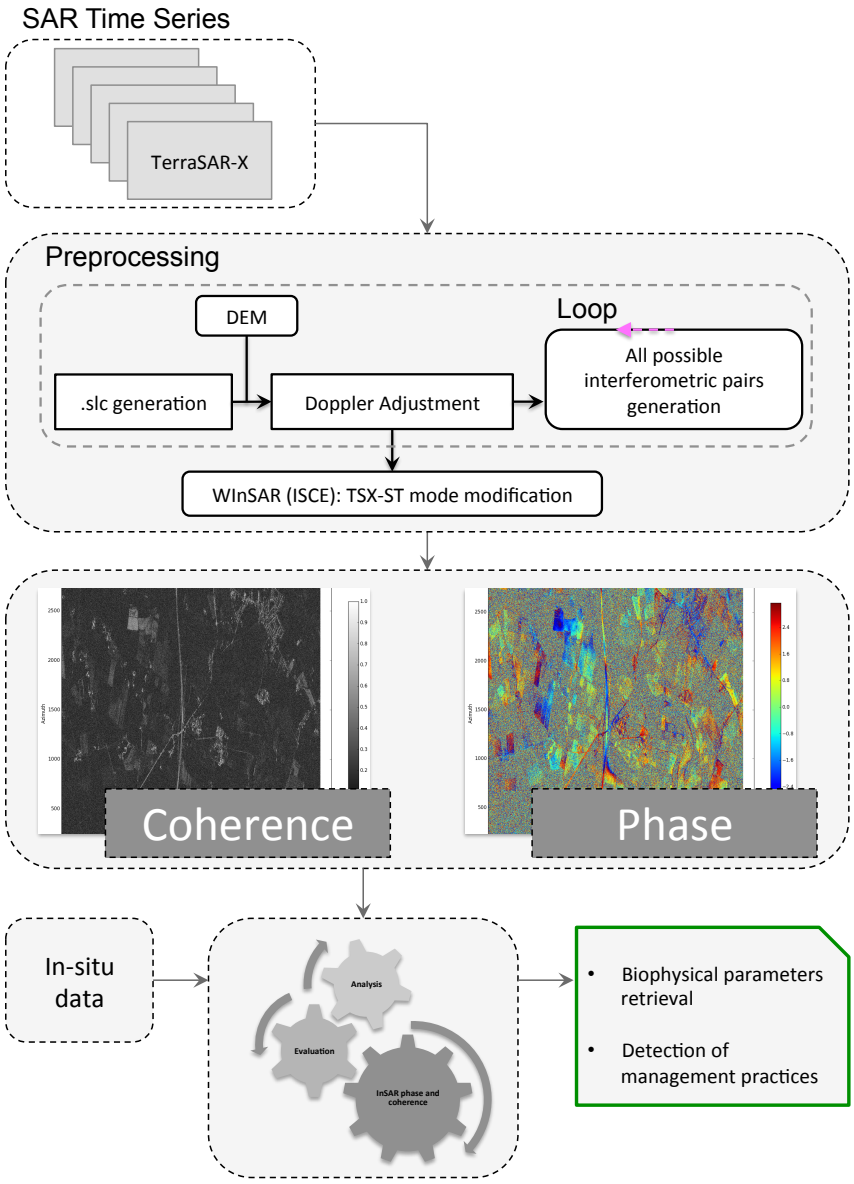


Figure 14: Graphical abstract of this paper: **Ali, I.;** Barrett, B.; Cawkwell, F.; Green, S.; Dwyer, E.; Neumann, M.; **2016**, *"Modelling managed grassland biomass estimation by using multitemporal remote sensing data—a machine learning approach"*, Journal of Selected Topics in Applied Earth Observations and Remote Sensing, IEEE. [Submitted (IF: 3.026)]

CONTRIBUTION STATEMENT

Declaration of own contribution to the published (or intended for publication) scientific papers within my dissertation.

DISSERTATION TITLE: Retrieval of grassland biophysical parameters using multitemporal optical and radar satellite data.

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OWN CONTRIBUTION IN THIS WORK: Concept development (fully), Literature search (fully), Methods development (fully), Research design (fully), Data collection (mainly), Data pre-processing (fully), Data analysis (fully), Construction of the manuscript (fully), Argumentation (fully), Critical revision of the article (mainly).

Iftikhar Ali, MSC

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Limitations Of Repeat-Pass TerraSAR-X (Staring Spotlight Mode) InSAR Coherence To Monitor Pasture Biophysical Parameters

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Limitations Of Repeat-Pass TerraSAR-X (Staring Spotlight Mode) InSAR Coherence To Monitor Pasture Biophysical Parameters

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Abstract

This paper describes the potential and limitations of repeat-pass synthetic aperture radar interferometry (InSAR) to retrieve the biophysical parameters of intensively managed pastures. We used a time series of 8 acquisitions from the TerraSAR-X Staring Spotlight (TSX-ST) mode. The ST mode is different from conventional Stripmap mode therefore we adjusted the Doppler phase correction for interferometric processing. We analysed the three interferometric pairs with an 11-day temporal baseline, and among these three pairs found only one gives a high coherence. The results show that the high coherence in different paddocks is due to cutting of the grass in the month of June, however the temporal decorrelation in other paddocks is mainly due to the grass growth and high sensitivity of the X-band SAR signals to the vegetation cover. The coherent paddocks show a good correlation with SAR backscatter ($R^2_{dB} = 0.65,\ p < 0.05$) and grassland biophysical parameters ($R^2_{Height} = 0.55,\ p < 0.05$, $R^2_{Biomass} = 0.75,\ p < 0.05$). It is thus possible to detect different management practices (e.g., grazing, mowing/cutting) using SAR backscatter (dB) and coherence information from high spatial, short baseline X-band imagery, however the rate of decorrelation over vegetated areas is high.

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Index Terms

Biophysical parameters, TerraSAR–X Staring Spotlight, interferometry, managed pastures, InSAR coherence.

I. INTRODUCTION

Grasslands are one of the most prevalent and widespread land cover vegetation types, covering 31.5% of the global landmass [1]. After forests, grasslands are the largest terrestrial carbon sink [2] and, as such, play a vital role in regulating the global carbon cycle [3]. Most of the earth observation studies on grasslands have been based on optical imagery for various applications e.g., classification [4], biomass [5], conservation status [6] and growth rate [7]. But in recent years, after the launch of high-resolution spaceborne SAR sensors like TerraSAR-X (X-band German SAR sensor launched in 2007) and COSMO-SkyMed (X-band constellation of four Italian satellites launched in 2007 to 2010), new investigations on grasslands using SAR data regarding mapping [8], monitoring management strategies [9] and parameter retrievals [10] have been reported in the research literature.

SAR being an active sensor, has an advantage over optical sensors of acquiring data in nearly all-weather conditions irrespective of day or night. Space borne synthetic aperture radar interferometry (InSAR) is being used for various applications e.g., monitoring landslides, subsidence and deformation [11]. This domain of InSAR is very rich and has been studied in detail over different regions using data from different sensors for more than 25 years, especially after the launch of the ESA satellite ERS-1 in 1991. The interferometric coherence, or correlation, serves as a quality measure for interferometric phase variation. The coherence is dependent on multiple factors such as: temporal decorrelation, SAR processing, signal to noise ratio, co-registration, volume decorrelation and baseline decorrelation [12]. Two geophysical decorrelation terms, the volumetric and temporal coherence [13], are especially important for parameter retrieval applications and are under active investigation [14].

The literature suggests that, with the development and availability of spaceborne SAR data with improved spatial and temporal resolution recent studies have investigated various aspects of grasslands, for example, management [9], [15], soil moisture [10], [16] and classification [8]. Before that, in 1999, Hill et al. [17] conducted a very detailed experiment on grassland biophysical properties using SAR backscatter calculated from multi-frequency (C, L and P band)

and multi-polarized (HH, HV and VV) airborne (JPL/NASA airborne imaging system) SAR data. Significant relationships were formulated between the measurement of grass height and the SAR backscatter, demonstrating the potential that might be offered with repeat-pass satellite imagery.

Interferometric coherence is affected by the physical changes of vegetation and ground properties that occur between the acquisition times, a phenomenon known as temporal decorrelation [18]. Studies [19], [20] show that for both SAR interferometry and polarimetric SAR interferometry [21] temporal decorrelation is one major limitation [18] which increases with shorter wavelengths [13].

In 2014 TerraSAR-X activated a new acquisition mode, staring spotlight (ST) has a longer target illumination time and high spatial resolution (up to 25cm), compared to the high-resolution spotlight (SL) mode (up to 1m). This high spatial resolution is achieved at the cost of spatial coverage, with staring spotlight mode spatial coverage of approximately 4Km (width) x 3.7Km (length), compared to the SL which covers 10Km (width) x 5Km (length). TerraSAR-X has an 11-day repeat cycle and is suitable for repeat-pass SAR interferometry analysis. The ST mode is very different from the conventional stripmap mode as the antenna beam keeps staring/focusing at the same ground target for a longer period of time (called target illumination period), which result in very high spatial resolution.

To the best of our knowledge there is no study reported in the literature on the application of repeat-pass SAR interferometry on managed grassland/pasture to evaluate its potential to monitor biophysical parameters. A recent investigation by Morishita and Hanssen [14] on pasture using repeat-pass multi-frequency SAR interferometry is to analyse and develop a temporal decorrelation model, however no work has been done on the retrieval of grassland biophysical parameters and management practices using spaceborne SAR interferometry. Other studies on grasslands [22] and crops [23] using X and C-bands are based on Tandem mode SAR acquisitions where the temporal baseline is very short allowing high coherence to be achieved. Mostly the interferometry analysis on vegetation, especially on crops and grasslands, are undertaken either by using longer wavelengths or with Tandem mode–data acquisition from a sensor constellation.

The results presented here are based on the highest spatial resolution available from a spaceborne SAR sensor. In this experiment we have tested the behaviour of SAR interferometric coherence against the biophysical parameters (height, biomass) of intensively managed pastures and SAR backscatter values. The objective of this study is to investigate the potential and lim-

itations of repeat-pass TSX–ST interferometry to retrieve biophysical parameters of intensively managed grasslands and detection of management practices.

II. Materials and Methods

A. Study site

The study area covers a Teagasc (Irish Agriculture and Food Development Authority) research farm located in the south of Ireland ($50°\ 07'$ N, $08°\ 16'$ W). The Teagasc Curtins Research Farm covers an area of 48ha and has a primary focus on sustainable pasture-based dairy systems, grassland and grazing management. The area has a temperate climate where annual mean temperature ranges from 9.4–10.1 °C, while the annual rainfall varies between 854 and 1208 mm.

B. TSX-ST time series

A time series of TerraSAR-X's newly launched ST mode was acquired from June to November 2014 with a total of 8 acquisitions ([format = acquisition#: ddmmyy] 1: 080614, 2: 190614, 3: 110714, 4: 220714, 5: 020814, 6: 240814, 7: 150914, 8: 090914). All acquisitions have the same specifications (wavelength (λ) = 3.1 cm, incidence angle (θ) = 41.09°, orbit/dir = 147/Asc, polarization = HH, critical baseline = [-15270.66, 15270.66]).

C. In-situ data

Intensive field campaigns were planned on the day of each SAR acquisition in order to collect the grassland height (cm) and soil moisture. The grassland biomass (kg DM/ha) was collected every Monday throughout the 6 month period and SAR acquisitions were planned either on a Monday or close to a Monday. For paddock biomass estimation, a strip of grass (approximately 1 meter wide and 3.5 meter long) was cut and dried for grassland dry matter (DM) calculation. Soil moisture was measured using a Stevens Hydra Probe II (Seyfried and Murdock, 2004) sensor connected to a hand-held reader or PDA to record the measurements. The Hydra Probe has a reported accuracy of $\pm 3\%$ soil moisture. An A4 size paper was placed on top of the grass and by using a ruler the height of the paper was taken. For each of the 33 paddocks 12 samples were collected in order to have a mean grass height of the plot (see Figure 1). Digital photographs were also taken of each paddock for the purpose of cross validation and analysis.



Figure 1: Ground truth data collection methods for grassland (A) biomass, (B) soil moisture and (C) height measurements.

III. Methodology

SAR processing for σ^0 [dB]: The TerraSAR-X ST time series data was received as a L1A product in single look complex (SLC) format. After standard preprocessing steps (multi-looking, co-registration and multi-temporal filtering) geometric and radiometric calibration was performed to get the backscatter coefficient values of σ^0 (dB), which were geocoded to the Irish Transverse Mercator (ITM) projection.

SAR interferometry processing: For interferometric processing we used the JPL/Caltech SAR interferometric tool ISCE (InSAR Scientific Computing Environment) developed by JPL and Stanford University. The acquisition geometry of the SAR Staring Spotlight mode is different from the Stripmap mode, therefore Doppler rate corrections were implemented as demonstrated by Eineder et al. [24]. These modifications of Doppler rate correction were integrated into the ISCE tool in order to support the TSX–ST mode interferometric processing. Another critical component is the temporal separation between the acquisitions, which is very important for vegetated areas. The volumetric decorrelation has to be taken into account due to the presence of a perpendicular baseline component between the satellites and a vertical distribution of scatterers [11], [25]. Figure 2 shows the details of the implemented scheme.

All 28 possible interferometric pairs were generated, and the SRTM digital elevation model of 30 meters resolution was used to calculate and remove the topographic phase. For each pair, flattened interferometric coherence and phase were calculated for further analysis.

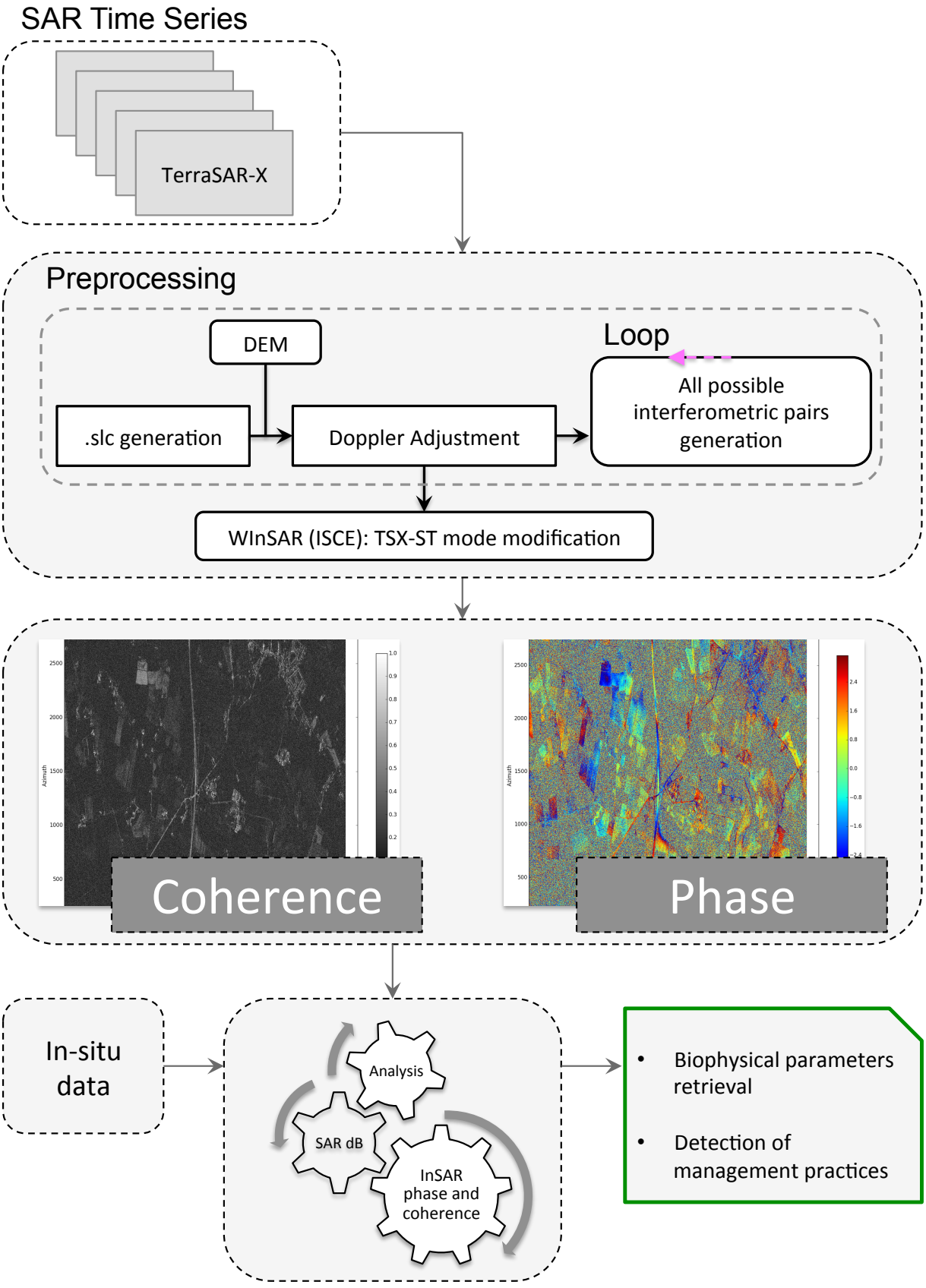


Figure 2: InSAR processing workflow scheme.

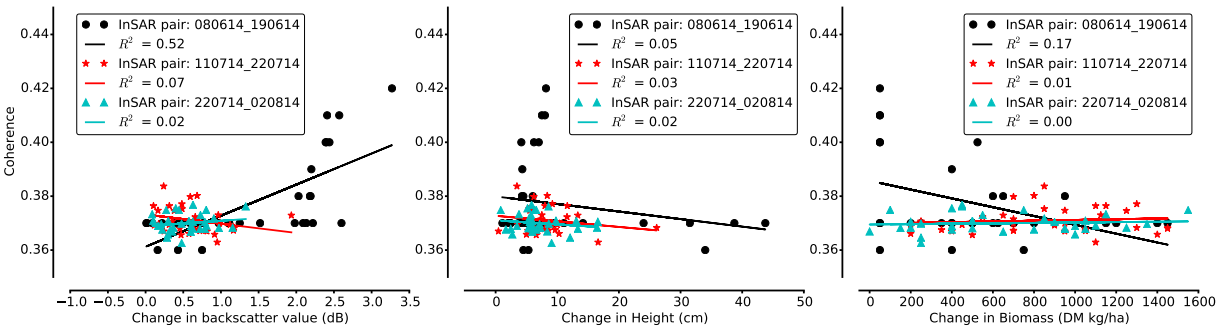


Figure 3: Relationship of calculated coherence with backscatter value, grass height and biomass of three SAR interferometric pairs with 11 days baseline (black = 080614_190614, red = 110714_220714 and cyan = 220714_020814).

IV. Results and Discussion

A. *Utility of repeat-pass InSAR time series for investigating grasslands*

Wegmuller and Werner [26] have addressed the issue of temporal decorrelation for spaceborne repeat-pass InSAR over vegetated areas. Studies show that the effect of temporal decorrelation decreases in the case of TanDEM mode–data acquisition from a constellation of SAR sensors e.g., TanDEM-X, ERS-1/2 and COSMO-SkyMed–SAR acquisitions [22], [27], due the very short temporal baseline. The temporal baseline for all 28 pairs of ST data has a range from 11 days to 154 days. Due to the rapid temporal decorrelation over vegetated areas, it was decided to use only the three pairs with the 11-day temporal baseline.

The X-band SAR signals are scattered back to the antenna by the upper canopy component, due to their shorter wavelength (3.1 cm) which cannot penetrate through the canopy layer. Due to this sensitivity of the X-band signal to vegetation cover, the decorrelation rate is extremely fast especially during the growing season. In the case of 11-day repeat-pass (110714_220714 and 220714_020814) the correlation between interferometric coherence, the observed parameters (grass height and biomass) and SAR backscatter values is very low as shown in Figure 3. However, the pair 080614_190614 shows a large variation and spread compared to the other two pairs as shown in Figure 3. In this case a high correlation ($R^2 = 0.52,\ p < 0.05$) between InSAR coherence and SAR backscatter values is observed. For the grass height and biomass, correlation values are low ($p > 0.05$) but the spread of the scatter plot is wider in comparison to

110714_220714 and 220714_020814. A detailed investigation is performed in order to understand this behaviour and the variation in the 080614_190614 InSAR pair.

B. Inter and intra paddock variations

Due to the shorter wavelength, the X-band signals are very sensitive to small changes in vegetation cover, especially during the growing season when grass grows, and the rate of change of coherent sum of the scatterers in the resolution cell is very high. Figure 4 shows the temporal, as well as the intra- and inter-paddock, variation of the X-band signals for four adjacent grassland paddocks. Grassland paddocks (9 and 15) with short grass height during the first acquisition (080614) (mean height: 2–4 cm) can be distinguished from paddocks 8 and 12 with tall grass (mean height: 25–35 cm). It is evident that in paddocks 9 and 15 the backscatter values in 080614 decreased in the later acquisitions (190614 and 110714) due to the grass growth. This variation is one of the main reasons that led to the high temporal decorrelation over most of the vegetated areas.

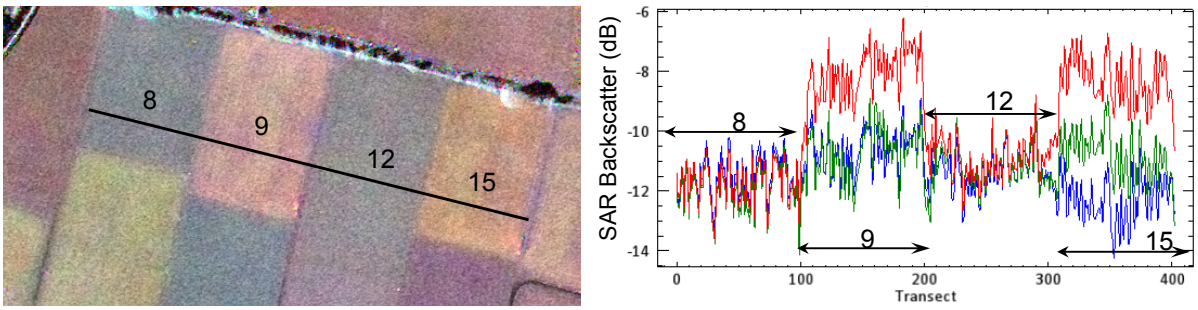


Figure 4: Transect based (black line) backscatter scatter profile of four paddocks extracted from colour composition of TerraSAR-X staring spotlight mode acquisitions (red=080614, green=190614, blue=110714).

Figure 5 (A) shows an example where the highest correlation over grassland area is observed in the first InSAR pair (080614_190614), and complete decorrelation occurs in all other InSAR pairs except for the roads and urban structures. The potential reasons for decorrelation of the other two 11 days InSAR pairs are discussed in the next section. The analysis was originally performed on all pairs, but the results are not shown here, as decorrelated data do not contribute to pasture

biophysical parameters retrieval. For this study, we considered the coherent pair 080614_190614 for further analysis in order to retrieve the biophysical parameters.

C. Detailed analysis of 080614_190614 pair

1) Change in SAR backscatter and its relation to coherent/non-coherent plots: Grassland paddocks with short grass height (low biomass) show higher backscatter (dB) because short grass (or paddocks after mowing) have less diffuse scattering compared to the tall grass, especially in the case of the X-band sensors, where signal backscatter mainly comes from the vegetation top canopy layer.

In the case of managed grasslands, the coherent grassland plots follow three types of backscattering patterns:

I High coherence is observed with no change in the mean backscatter (dB) value between the two acquisitions over some plots where, in both acquisitions, a high proportion of each plot is bare or sparsely vegetated (i.e., paddock: 4 and 9, an example of paddock 4 is shown in Figure 5 (B) and Figure 5 (C)).

II High coherence is also observed over the areas where the change in the mean backscatter is more than 2 dB (similar to the findings reported by Wegmuller and Werner [26]). This is due to the presence of short grass height and gradual growth (i.e., paddock: 15, 16, 17, 20, 22, 23, 24, 27 and 28, as an example see paddock 16 and 17 in Figure 5 (B) and Figure 5 (C)).

III Similar to the coherent paddocks (where mean backscatter (dB) is > 2 dB), comparatively less coherent plots (i.e., paddock: 29, 30 and 31) follow the similar pattern where the mean change in backscatter is less than 2 dB. Paddock 31 is more coherent than 29 and 30 due to the short grass height (as shown in Figure 5 (B)).

Some paddocks (i.e., 2 and 5) are not coherent but still have a change in the mean backscatter of more than 2 dB. This ambiguity is due to the fact that the grass in the first acquisition (080614) was tall but lying horizontally due to the wind (see Figure 5 (C)). There is however a high backscatter value in the second acquisition (190614) due to the short grass height (after mowing). Similarly in the case of paddock 6, 7 and 8, the difference in backscatter value is due to the gradual grass regrowth (or short grass height in second acquisition as compared to the first).

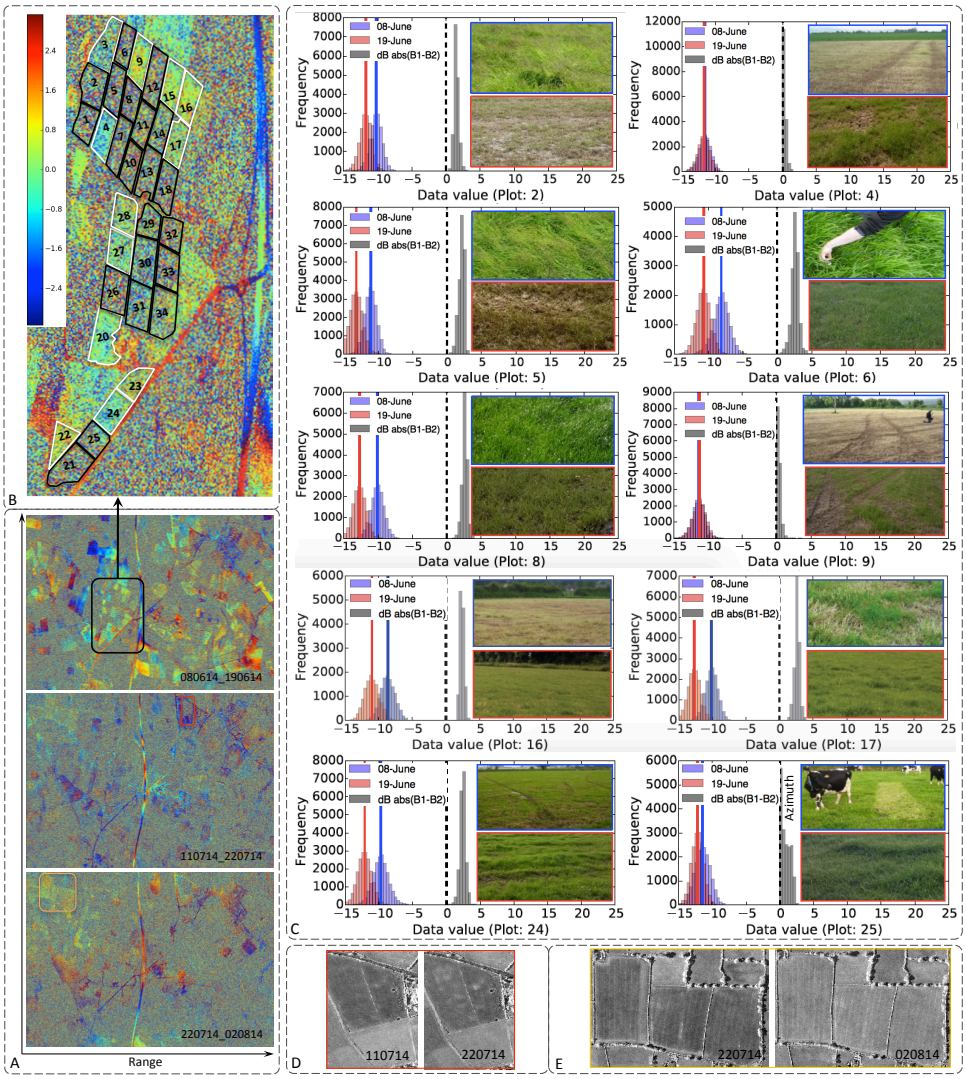


Figure 5: (A): A single baseline interferometric phase (flattened) of three 11 day temporal baseline pairs. (format: ddmmyy$_{master}$_ddmmyy$_{slave}$). (B): InSAR phase (flattened) for pair 080614_190614. Polygons with their number show the plots analysed in this study. Grass plots with white boundaries represents the coherent plots while the plots with black boundaries are non-coherent plots. (C): In each plot (and inset photograph) the blue colour represents the master (080614) and the red colour represents the slave (190614) image. The dark blue lines (080614) and the red lines (190614) represents the mean value of each band, while the dotted black line represents the zero reference. The gray histogram represents the absolute value of the difference between the two acquisitions $abs(080614-190614)$ for each plot. (D): Example of coherent patch from the pair 110714_220714. (E): Example of coherent patch from the pair 220714_020814

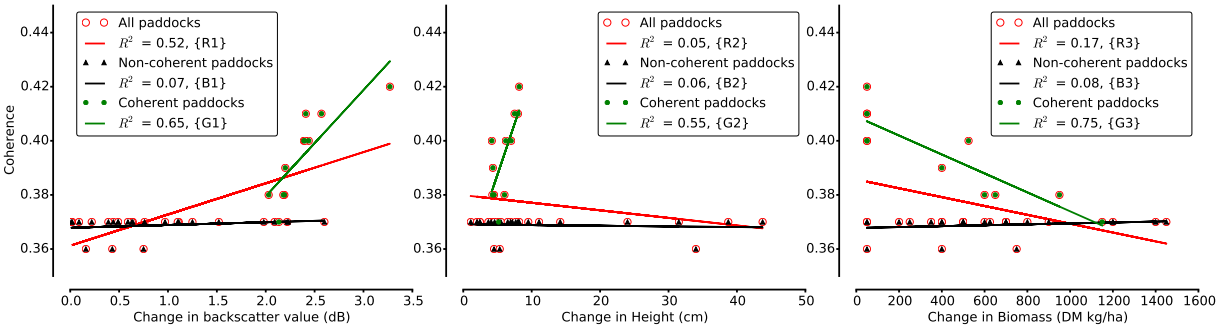


Figure 6: Relationship between calculated coherence with backscatter value (dB) [left], height (cm) [middle] and biomass (kg DM/ha) [right]. Black color represents all the plots, blue points represent the non-coherent plots (plots with black boundaries in Figure 5 (B)) and green points represent the coherent plots (plots with white boundaries in Figure 5 (B)).

The different sources (anthropogenic and natural) of decorrelation are thus due to:

i grass growth (i.e., paddock: 6, 7, 8, 11, 12, 13 and 26),

ii grazing (i.e., paddock: 18, 21 and 25), and

iii mowing event (i.e., paddock: 1, 2 and 5)

It can be concluded that from looking at the SAR backscatter only it is not possible to identify the nature of management practices (and/or changes), however by combining both SAR backscatter change and the level of coherence we can identify the type of event that has occurred. For example plot 16 and 17 show a similar change in dB, but 17 is not as coherent as 16 (see Figure 5 (B) and 5 (C)).

We further investigated the reasons as to why the other two 11 day InSAR pairs decorrelated completely except in a few areas. Based on the intensive field validation data it was found that during the month of June most of paddocks are cut for silage, which led to the high coherence due the presence of bare soil and short grass height after cutting. In Figure 5 (A) the InSAR pair 080614_190614 shows that there are many fields outside the study site where high coherence is also achieved due to the silage cut, but in the later acquisitions the InSAR pairs 110714_220714 and 220714_020814 the same fields were decorrelated due to grass growth and high biomass value. For example, in pair 110714_220714 (red inset box in Figure 5 (A)) the upper part is decorrelated due to low backscatter values (or high biomass/grass) while the lower part is coherent

due to the high backscatter value (or low biomass/grass), as shown in Figure 5 (D). Similarly in the other pair with 11 days temporal baseline (220714_020814) an example (yellow inset box in Figure 5 (A)) of a coherent patch is shown. These are crop fields where high coherence is due to cutting by the second acquisition and a mean change in SAR backscatter value is more than 2 dB, Figure 5 (E) shows the low backscatter in the first acquisition (220714) and high backscatter in second acquisition (020814).

2) Relationship between InSAR coherence and grassland biophysical parameters 080614_190614*:* For the retrieval of grassland biophysical parameters using SAR interferometric coherence, based on the visual assessment the plots under investigation were divided into three groups: *(i)* all plots shown in Figure 5 (B), *(ii)* non-coherent plots (plots with black boundaries in Figure 5 (B)) and *(iii)* coherent plots (plots with white boundaries in Figure 5 (B)). For each group the relationship of InSAR coherence with the backscatter (dB), grass height (cm) and biomass (DM kg/ha) is discussed.

- *Coherence versus backscatter:* SAR backscatter and interferometric coherence show a good correlation ($R^2 = 0.65,\ p < 0.05$) for coherent plots ($\{G1\}$: plots with white boundaries) as compared to the non-coherent plots ($\{B1\}$: plots with black boundaries, ($R^2 = 0.07,\ p > 0.05$)) and the combination of both ($\{R1\}$: all plots, ($R^2 = 0.52,\ p < 0.05$), see Figure 6). The high correlation in case of $\{R1\}$ is due to the inclusion of $\{G1\}$. As discussed in the previous section, it is evident that the absolute change in backscatter values in coherent plots is more than 2 dB, which leads to the high correlation between InSAR coherence and SAR backscatter values for these plots.
- *Coherence versus height:* Figure 6 $\{R2\}$ shows that the coherence and absolute values of change in grass height have a very low correlation for the non-coherent plots (Figure 6 $\{B2\}$). In the case of coherent plots a reverse behaviour is observed ($R^2 = 0.55,\ p < 0.05$). The reason for this trend is due to the fact that if the change in canopy height is less than 10 cm (or in case of coherent areas/plots) they will either have a constant or increasing trend of height (see Figure 6 $\{G2\}$). As soon as height starts increasing above the threshold of 10 cm, the coherence will also start decreasing. Similar findings can also be seen in other studies that have been done on grasslands [22] and crops [27].
- *Coherence versus biomass:* Coherent plots (Figure 6 $\{G3\}$) show a strong relationship between the coherence and grassland biomass. High values of coherence occur when there

is low biomass (or less percentage canopy cover), and a gradual decrease in coherence is due to the increase of biomass (see Figure 6 $\{R3\}$, Wegmuller and Werner [26] also reported the similar findings). For the coherent paddocks, the relationship between the interferometric coherence and grassland biomass $(R^2 = 0.75,\ p < 0.05, \{G3\})$ is stronger than the relationship with the SAR backscatter $(R^2 = 0.65,\ p < 0.05, \{G1\})$ and grassland height $(R^2 = 0.55,\ p < 0.05, \{G2\})$.

In addition to detecting management practices over intensively managed grassland pastures, the interferometric coherence calculated from high resolution spaceborne data has a great potential to retrieve pasture biomass and height. High coherence over the paddocks cut for silage during the summer season is an important finding especially in terms of calculating carbon budget, as these paddocks show good correlation with the biomass and grass height. The SAR backscatter is an important parameter that can be used in combination with the interferometric coherence in order to determine the type of change that has happened on ground that led to the high or low interferometric coherence.

The SAR backscatter is strongly linked (or responds) to the temporal developments in vegetation, similarly interferometric coherence is very sensitive to the changes in the resolution cell especially for a large temporal baseline over vegetated areas. The effect of temporal decorrelation is minimized in the case of InSAR tandem acquisitions.

This investigation was performed on a single farm with very high quality ground truth data and very high resolution spaceborne SAR time series. It is, however, very clear that in order to test the robustness over different vegetation types, this approach must be further investigated on a larger scale including more auxiliary data (e.g., soil moisture, climate variables)

V. Conclusion

In this study we used a very high resolution TerraSAR-X ST time series. Due to the fact that ST acquisition geometry is different from the conventional SAR stripmap mode, geometric and Doppler related adjustments were implemented and later integrated into the ISCE tool. SAR interferometric coherence and phase were calculated for all combinations of baselines. For the detailed analysis we selected three InSAR pairs with an 11-day temporal baseline (080614_190614, 110714_220714 and 220714_020814). For the InSAR pairs 110714_220714 and 220714_020814 the values of correlation between the interferometric coherence and the

grassland biophysical parameters were very low, the primary reason for this is due to the decorrelation caused by the grass regrowth after the silage was cut. Initial findings from the June pair show the possibility of change detection due to the grass growth, grazing and mowing events by using InSAR coherence information. However, it is not possible to automatically categorize different paddocks undergoing these changes based only on the SAR backscatter and coherence values, due to the ambiguity caused by tall grass flattened by the wind. Decorrelation over vegetated areas is a very complex and dynamic process which is influenced by many factors, but where there is coherence there is also a good correlation with height and biomass. The lack of coherence suggests that the X-band wavelength is too short, and therefore affected by even minor grass growth, causing decorrelation of the signal. This study concludes that, for X-band SAR interferometry even an 11 day temporal baseline is too long for grassland biophysical parameter retrieval, except for the fields with short grass height or during the cutting season when the grass is cut for silage.

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REFERENCES

[1] J. Latham, R. Cumani, I. Rosati, and M. Bloise, "Global land cover SHARE (GLC-SHARE): database beta-release version 1.0-2014," 2014.

[2] J. D. Derner and G. E. Schuman, "Carbon sequestration and rangelands: A synthesis of land management and precipitation effects," *Journal of Soil and Water Conservation*, vol. 62, no. 2, pp. 77–85, Mar. 2007.

[3] A. J. Franzluebbers, "Soil organic carbon in managed pastures of the southeastern united states of america," in *Integrated crop management*, vol. 11, 2010, p. Chapetr VIII.

[4] T. Esch, A. Metz, M. Marconcini, and M. Keil, "Combined use of multi-seasonal high and medium resolution satellite imagery for parcel-related mapping of cropland and grassland," *International Journal of Applied Earth Observation and Geoinformation*, vol. 28, pp. 230–237, May 2014.

[5] I. Ali, F. Cawkwell, S. Green, and N. Dwyer, "Application of statistical and machine learning models for grassland yield estimation based on a hypertemporal satellite remote sensing time series," in *Geoscience and Remote Sensing Symposium (IGARSS), 2014 IEEE International*, Jul. 2014, pp. 5060–5063.

[6] C. Corbane, S. Lang, K. Pipkins, S. Alleaume, M. Deshayes, V. E. García Millán, T. Strasser, J. Vanden Borre, S. Toon, and F. Michael, "Remote sensing for mapping natural habitats and their conservation status new opportunities and challenges," *International Journal of Applied Earth Observation and Geoinformation*, vol. 37, pp. 7–16, May 2015.

[7] X. Yang, B. Xu, Y. Jin, Z. Qin, H. Ma, J. Li, F. Zhao, S. Chen, and X. Zhu, "Remote sensing monitoring of grassland vegetation growth in the beijing tianjin sandstorm source project area from 2000 to 2010," *Ecological Indicators*, vol. 51, pp. 244–251, Apr. 2015.

[8] C. Schuster, T. Schmidt, C. Conrad, B. Kleinschmit, and M. Förster, "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*, vol. 34, pp. 25–34, Feb. 2015.

[9] C. Schuster, I. Ali, P. Lohmann, A. Frick, M. Förster, and B. Kleinschmit, "Towards detecting swath events in TerraSAR-x time series to establish NATURA 2000 grassland habitat swath management as monitoring parameter," *Remote Sensing*, vol. 3, no. 12, pp. 1308–1322, Jun. 2011.

[10] M. E. Hajj, N. Baghdadi, G. Belaud, M. Zribi, B. Cheviron, D. Courault, O. Hagolle, and F. Charron, "Irrigated grassland monitoring using a time series of TerraSAR-x and COSMO-SkyMed x-band SAR data," *Remote Sensing*, vol. 6, no. 10, pp. 10 002–10 032, Oct. 2014.

[11] P. Rosen, S. Hensley, I. Joughin, F. K.Li, S. Madsen, E. Rodriguez, and R. M. Goldstein, "Synthetic aperture radar interferometry," *Proceedings of the IEEE*, vol. 88, no. 3, pp. 333–382, Mar. 2000.

[12] R. F. Hanssen, *Radar Interferometry: Data Interpretation and Error Analysis*. Springer Science & Business Media, Apr. 2001.

[13] H. Zebker and J. Villasenor, "Decorrelation in interferometric radar echoes," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 30, no. 5, pp. 950–959, Sep. 1992.

[14] Y. Morishita and R. Hanssen, "Temporal Decorrelation in L-, C-, and X-band Satellite Radar Interferometry for Pasture on Drained Peat Soils," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 53, no. 2, pp. 1096–1104, Feb. 2015.

[15] I. Ali, C. Schuster, M. Zebisch, M. Förster, B. Kleinschmit, and C. Notarnicola, "First results of monitoring nature conservation sites in alpine region by using very high resolution (VHR) x-band SAR data," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 6, no. 5, pp. 2265–2274, 2013.

[16] I. Ali, F. Greifeneder, J. Stamenkovic, M. Neumann, and C. Notarnicola, "Review of machine learning approaches for biomass and soil moisture retrievals from remote sensing data," *Remote Sensing*, vol. 7, no. 12, p. 15841, 2015.

[17] M. J. Hill, G. E. Donald, and P. J. Vickery, "Relating radar backscatter to biophysical properties of temperate perennial grassland," *Remote Sensing of Environment*, vol. 67, no. 1, pp. 15–31, Jan. 1999.

[18] M. Lavalle, M. Simard, and S. Hensley, "A Temporal Decorrelation Model for Polarimetric Radar Interferometers," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 50, no. 7, pp. 2880–2888, Jul. 2012.

[19] M. Wei and D. Sandwell, "Decorrelation of L-Band and C-Band Interferometry Over Vegetated Areas in California," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 48, no. 7, pp. 2942–2952, Jul. 2010.

[20] P. A. Rosen, S. Hensley, H. A. Zebker, F. H. Webb, and E. J. Fielding, "Surface deformation and coherence measurements of Kilauea Volcano, Hawaii, from SIR-C radar interferometry," *Journal of Geophysical Research: Planets*, vol. 101, no. E10, pp. 23 109–23 125, Oct. 1996.

[21] S. Cloude and K. Papathanassiou, "Polarimetric SAR interferometry," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 36, no. 5, pp. 1551–1565, Sep. 1998.

[22] K. Zalite, K. Voormansik, J. Praks, O. Antropov, and M. Noorma, "Towards detecting mowing of agricultural grasslands

from multi-temporal COSMO-SkyMed data," in *Geoscience and Remote Sensing Symposium (IGARSS), 2014 IEEE International*, Jul. 2014, pp. 5076–5079.

[23] M. Santoro, U. Wegmuller, and J. Askne, "Signatures of ERS #x2013;Envisat Interferometric SAR Coherence and Phase of Short Vegetation: An Analysis in the Case of Maize Fields," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 48, no. 4, pp. 1702–1713, Apr. 2010.

[24] M. Eineder, N. Adam, R. Bamler, N. Yague-Martinez, and H. Breit, "Spaceborne Spotlight SAR Interferometry With TerraSAR-X," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 47, no. 5, pp. 1524–1535, May 2009.

[25] R. Bamler and P. Hartl, "Synthetic aperture radar interferometry," *Inverse Problems*, vol. 14, no. 4, p. R1, Aug. 1998.

[26] U. Wegmuller and C. Werner, "Retrieval of vegetation parameters with SAR interferometry," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 35, no. 1, pp. 18–24, Jan. 1997.

[27] X. Blaes and P. Defourny, "Retrieving crop parameters based on tandem ERS 1/2 interferometric coherence images," *Remote Sensing of Environment*, vol. 88, no. 4, pp. 374–385, Dec. 2003.

Part IV

CONCLUSION AND BIBLIOGRAPHY

6

CONCLUSION AND FUTURE RESEARCH

Drawing general conclusions about your main weaknesses can provide a great stimulus to further growth.

— Alexander Kotov

MONITORING grassland and pastures from space using imaging satellites is becoming more and more feasible due to improved spatial, temporal and spectral resolution. A review of published studies on grassland suggests that the remote sensing community and agronomists are increasingly working together in order to utilize the potential of remote sensing technologies, with the aim of developing real time decision support systems. Consistent and regular monitoring of the world's second largest terrestrial ecosystem is not only important for

the grazing industry, but also for the environment where grasslands play a crucial role in regularization of the carbon cycle.

The work presented in this thesis investigates the use of optical and radar time series to estimate the grassland biomass using both statistical linear regression and state of the art machine learning algorithms. More than 80% of agricultural land in Ireland is grassland, providing a major feed source for the pasture based dairy farming and livestock industry. Intensive grass based systems demand high levels of intervention by the farmer, with estimation of pasture cover (biomass) being the most important variable in land use management decisions, as well as playing a vital role in paddock and herd management. In grassland management and the livestock business, grazing capacity and intensity are the key factors, and for sustainable farming need to be monitored consistently in order to optimize the feeding resources and to avoid grassland degradation.

This dissertation presents a detailed state of the art review of satellite remote sensing of grasslands, with a comprehensive overview of the global presence of grassland types and their classification. It is evident from the literature that the application of very high resolution data for remote sensing based precision agriculture approaches to grassland is now evolving to the same level of maturity as experienced by arable agriculture. However, the use of hyper-spectral/temporal (optical) and fully polarimetric (radar) data for grassland classification and parameters' retrieval using machine learning approaches has not been fully explored. New methodological developments in designing new classifiers and retrieval algorithms are being explored for grassland related investigations. From an operational perspec-

tive it can be concluded from this review that in order to enhance the utilization of remote sensing technologies a consensus needs to be reached before the development of standardized and pre-validated user-friendly products. These products will help to bridge the gap between remote sensing scientists and farm managers.

Multiple linear regression is one of the most widely adopted modelling approaches biophysical parameters from satellite and in situ data, but with growing data volumes new state of the art modelling methods have been developed to better manage the high dimensionality and non-linearity of many of the datasets. Artificial neural networks (ANN) are one of the most commonly used machine learning algorithms which have the ability to learn from complex patterns in a dataset, and fuzzy logic approaches have the power to reason and generate rules from the dataset. Adaptive-neuro fuzzy inference systems (ANFIS) are the integration of both ANN and fuzzy logic, combining the power of both methods to provide an approach with improved predictive or approximation ability.

In this study, in situ and satellite data covering 12 years for the Moorepark and 6 years for the Grange study sites were used to predict grassland biomass through application of classical multiple linear regression and state of the art machine learning algorithms (ANN and ANFIS). The results demonstrate that a dense (8-day composite) MODIS image time series, along with high quality in situ data, can be used to retrieve grassland biomass with high performance ($R^2 = 0.86$ $p < 0.05$, RMSE = 11.07). Due to the combined features of ANN and fuzzy logic, the ANFIS has the ability to accurately model complex and chaotic systems, and the results concur with

those of the literature which report a high predictive power of ANFIS compared to the ANN. The ANFIS model allows multiple inputs to produce a single output, however to achieve a higher level of accuracy a large sample size from different locations might be required to drive the model, with the model performance also dependent on the data quality and study design.

The model for Grange was modified to evaluate the synergistic use of vegetation indices derived from remote sensing time series and the accumulated GDD information. As GDD is strongly linked to the plant development, or phenological stage, an improvement in biomass estimation would be expected, but high quality daily weather data are required to build an accumulated GDD profile of the area. Daily minimum, maximum and average temperature data from an on-site weather station were used to calculate the GDD for the Grange study site. It was observed that using ANFIS the biomass estimation accuracy increased from $R^2 = 0.72$ ($p < 0.05$) to $R^2 = 0.81$ ($p < 0.05$) (12.5% improvement) and root mean square error reduced by 2.72%, however for large scale mapping spatially distributed sampling of weather data is required in order to minimize the effects of different climatic zones. A key point here is that the satellite data alone is showing very good prediction of the biomass and including GDD, growth rate estimates were only marginally improved (3.95%). It is important to highlight that satellite driven VI are very powerful input features, and the use of VI derived from high resolution imagery might produced an improved estimation as with the inclusion of GDD.

The work on optical remote sensing data was further developed using a TerraSAR-X Staring Spotlight mode time series over the Moorepark

study site to explore the extent to which very high resolution SAR data of interferometrically coherent paddocks can be exploited to retrieve grassland biophysical parameters. After filtering out the non-coherent plots it is demonstrated that interferometric coherence shows a good correlation with backscatter (dB) value, height and biomass, and that it is possible to detect changes due to the grass growth, and grazing and mowing events, when the temporal baseline is short (11 days). However, it not possible to automatically uniquely identify the cause of these changes based only on the SAR backscatter and coherence, due to the ambiguity caused by tall grass laid down due to the wind. This study provides a detailed investigation of managed grasslands where the management practices and biophysical parameters are known at a paddock scale. This was for one pair (out of three pairs with 11 days temporal baseline) only and more work is needed to determine the consistency of these results. But it highlights the limitations caused by the short wavelength X-band SAR and a large temporal baseline:

I Interferometry coherence loss over vegetative areas due to temporal and volumetric decorrelation

II P, L and C band wavelengths (which are used for soil moisture and forest monitoring due to their canopy penetration and reflection from trunks) are strongly backscattered from the soil in grassland areas due to the short height and thin structure of the vegetation. This has been shown in various studies done on wetlands where the signal penetrates through the vegetation cover and reflects from the water layer underneath

III The repeat-pass interferometry over vegetated areas using short wavelengths is a challenging task. Decorrelation rates over vegetated areas are very high, therefore most of the InSAR pairs were decorrelated. As far an optimum temporal baseline is concerned, for interferometric analysis over vegetated areas, SAR acquisitions in tandem mode are recommended.

Overall, the work presented in this dissertation has demonstrated the potential of dense remote sensing time series to predict grassland biomass in intensively managed enclosed systems, using machine-learning algorithms, where high quality ground data were available for training. At present a major limitation for national scale biomass retrieval is the lack of spatial and temporal samples, which can be partially resolved by minor modifications in the existing PastureBaseIreland database by adding the location and extent of each grassland paddock. As far as weather data is concerned, in Ireland data from 25 well-distributed weather-observing stations (Met Éireann) are available and are sufficient for the proposed methodology, however it cannot be known whether these data will have the same impacts for other locations as they did for Grange. In future, with an increased availability of in situ samples and a higher spatial and temporal resolution of optical imaging systems, this strategy should generate more robust estimates of grassland biomass at a national scale. The InSAR approach is feasible if there are enough coherent interferometric pairs available, however this is difficult to achieve due to the temporal decorrelation of the signal. In future InSAR pair acquisition in Tandem mode will minimize the tempo-

ral decorrelation over vegetation areas, however due to multiple sources of decorrelation, high quality ground truth data will be required for corrected interpretation and identification of the changes in the field. The proposed approaches complements the current paradigm of Big Data in Earth Observation, and illustrates the feasibility of long term remote sensing and a high quality field measurements to retrieve grassland biomass and growth rate. In future, this framework can be used to prototype an operational decision support system for retrieval of grassland biophysical parameters based on data from long term designed missions such as Landsat and Sentinel.

The key highlights of the findings of this thesis are:

- Until recently, the use of optical remote sensing data was dominant, but after the launch of very high resolution spaceborne SAR sensors (TerraSAR-X, TanDEM-X, COSMO-SkyMed, Advanced Land Observing Satellite (ALOS)-2 and RADARSAT-2) the investigation of grasslands using SAR data have increased. More dedicated and detailed investigations on grasslands using fully polarimetric SAR and hyperspectral optical data are yet to be studied.

- Remote sensing time series data along with high quality ground measurements can be used for grassland biomass estimates using state of the art machine learning algorithms, and ANFIS was used for the first time for biophysical parameters retrieval.

- An improvement in biomass and growth rate retrieval was observed with the fusion of remote sensing and GDD derived from weather data.

- The repeat-pass InSAR coherence approach has the potential to retrieve grassland biophysical parameters. However, due to the rapid temporal decorrelation over vegetated areas it is not recommended to use repeat-pass InSAR for reliable monitoring. Instead, SAR acquisitions in Tandem mode with a shorter temporal baseline are more feasible for consistent monitoring.

6.1 FUTURE RESEARCH

There are many different methods to monitor and retrieve grassland biophysical parameters. The ground-based methods (i.e., land survey) are mostly feasible for small scale studies and assessment. But for the large scale, and consistent monitoring and assessment, the most feasible approach seems to be monitoring from space by using imaging satellites Wulder and Coops (2014).

Currently many space borne satellites are in operation and others are in the planning or commissioning phase; which means that huge amount of datasets from various sources (optical, SAR, InSAR, LiDAR, in-situ observations) are currently or will be available in the future. Furthermore, the size of this data is expected to increase exponentially in future. According to an IBM report 90% of data today we have in this world has been produced in last 2-3 years[1]. Today's world has entered into the age of *"big-data"* and Earth Observation datasets are an example of this. Different space agencies are producing various types of remote sensing data sets, both raw imagery

1 http://www-01.ibm.com/software/data/bigdata/what-is-big-data.html

and derived products, that can be used for the regional and global scale monitoring of large ecosystems like grasslands, forests and water.

In order to properly utilize the upcoming influx of remote sensing data, computationally cost effective, reliable and reproducible frameworks are essential. The main challenge for this research will be to formulate a workflow that can be used to integrate the data from different sources (SAR, optical, SMAP, Sentinel, Lidar and in-situ) in order to retrieve the biophysical parameters of grasslands. The focus of future research could be to investigate the potential of a data assimilation approach to answer the following key questions:

I Does a data assimilation approach provide a feasible mechanism for multi-source data integration that can improve the retrieval of grassland biophysical parameters (growth rate, biomass, and anomalies)?

II How will the climate change affect the relationship between soil moisture and grassland's carbon stocks? In this step the soil moisture product from NASA's newly launched satellite missions, Soil Moisture Active Passive (SMAP) and the European Space Agency's Soil Moisture and Ocean Salinity (SMOS) can be used into the data assimilation model as a proxy in order to analyse their contributions for parameter retrieval.

Climate change dominated the G7 agreement in Germany and global in Paris summit in 2015 as world leaders backed a full de-carbonisation vision acknowledging that the world needs to deliver *"decarbonisation of the global*

economy over the course of this century"[2]. Grasslands, forests and crop lands play a crucial role in the regulation of the global carbon cycle (see Chapter 1 Table 1 for details). The use of remote sensing technology for regional to global biomass estimation of different vegetation types (grasslands, forests, crop lands) has been in operation for many years; and lot of research has been done on methodologies and implementations.

With the passage of time and availability of new satellite data (with improved spectral, spatial and temporal resolution) and development in computing and modelling approaches the methods for grassland (or biosphere) biophysical parameters retrieval have evolved and improved in terms of accuracy and computational stability. Apart from carbon regularization, grasslands are of importance for the livestock industry and for that reason the need of the hour is to develop more robust and consistent methods for retrieving grassland biophysical parameters at a large scale from space and airborne platforms. With the availability of high quality remote sensing data new and more robust methods/algorithms have been developed and the methodological approach is now shifting from linear regression models to non-parametric (machine learning) models (SVM, ANN, RF, SGB) for their ability to better learn the patterns from the highly complex and non-linear data/features.

Each remote sensing acquisition technique (optical and radar) has advantages and disadvantages. The proposed approach of data assimilation (or integration) will define a unified mechanism to extract useful information

2 http://www.theguardian.com/world/2015/jun/08/g7-leaders-agree-phase-\
out-fossil-fuel-use-end-of-century

from each available data source in order to retrieve the grassland parameters.

Model–Data Fusion or *'data assimilation'* describes the method of combining as much data as possible from different spatial scales and sources. Data assimilation techniques such as Ensemble Kalman Filter Evensen (1994), the Particle Filter Arulampalam et al. (2002); Gordon et al. (1993) or variational methods like 4D–VAR Courtier et al. (1994) integrates the in-situ measurements into terrestrial models for an improved description of the real environmental conditions Montzka et al. (2012), and reduce the prediction uncertainties.

Currently more and more terrestrial observation networks are being installed in various regions to monitor climate and land-use changes. Networks like FLUXNET, the European Integrated Carbon Observation System (ICOS) and the German Terrestrial Environmental Observatories (TERENO) are producing huge amount of data streams at different scales. But the volume of data from satellites is even much more than these terrestrial monitoring networks. Taking these factors into consideration, in addition to future needs, a data assimilation approach should be investigated using ground-based and remotely sensed data.

The potential of data assimilation for grassland parameters, retrieval has not been explored yet, nor has the inclusion of features derived from remote sensing sensors. The reason for choosing a data assimilation approach is due to the fact that it has improved capabilities against the *inversion* approach as discussed by Rayner (2010):

- only the assimilation approach allows prediction
- data assimilation reduces the under-determinacy of the inverse problem Kaminski et al. (2001)
- the data assimilation approach can integrate much more multi-source and multi-scale data

Indeed the major requirement for the development of any operational system is the size and quality of dataset. Many new spaceborne missions are being launched to ensure the long term data availability for future needs of environmental and ecosystem modelling applications. In the context of Ireland, the following measures are recommended as a first step towards the development of an operational decision support system for grassland precision farming from space.

i Due to the complex structure of the *PastureBaseIreland* database it is very hard to retrieve and interpret the growing amount of information stored there. This can be resolved by simple modifications in the data structure and design, so that this valuable dataset can be used with remote sensing information.

ii In order to develop an operational decision support system, all the methods need to be trained, tested and validated at multiple locations in order to ensure their robustness and transferability. For this process of validation and calibration, the exact location and extent of all the farms used in this process is required. It is highly recommended to

include the geo-referencing and boundary information of the existing and newly registered farms in the database.

Overall, a data assimilation approach seems the most feasible for varying spatial scales and variables due to the increasing complexity of models, observation operators and measurements. The current work can be further developed by integrating data from high resolution remote sensing sensors with long term weather data to uncover the influence of extreme weather events on farm productivity, profitability and future management decisions. However, a long term goal should be the development of schemes to integrate remote sensing and plant growth models for near real-time forecasting of grass growth, biomass and status. Figure 15 gives an overview of the roadmap to develop an operational decision support system for farm management.

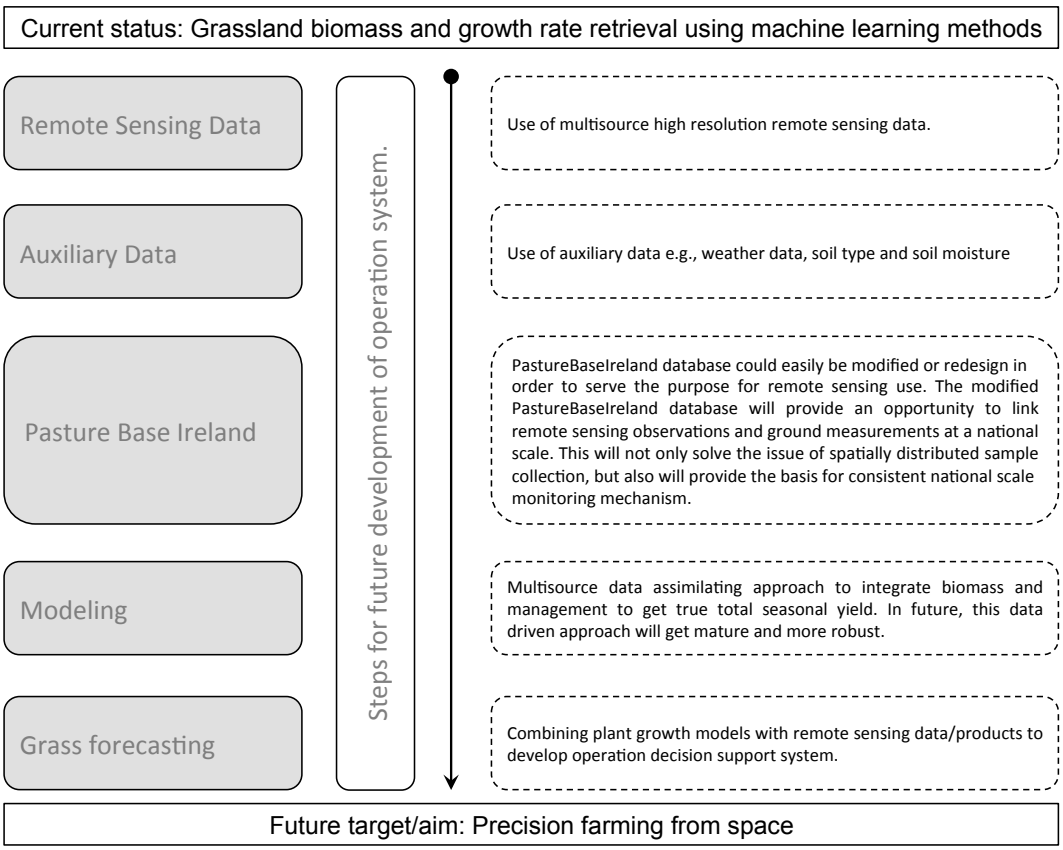


Figure 15: Framework for future work in order to develop operation decision support system for digital/precision farming from space.

BIBLIOGRAPHY

M.S. Arulampalam, S. Maskell, N. Gordon, and T. Clapp. A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking. *IEEE Transactions on Signal Processing*, 50(2):174–188, February 2002. ISSN 1053-587X. doi: 10.1109/78.978374.

Richard Bamler and Philipp Hartl. Synthetic aperture radar interferometry. *Inverse Problems*, 14(4):R1, August 1998. ISSN 0266-5611. doi: 10.1088/0266-5611/14/4/001.

Anthony D. Barnosky, Elizabeth A. Hadly, Jordi Bascompte, Eric L. Berlow, James H. Brown, Mikael Fortelius, Wayne M. Getz, John Harte, Alan Hastings, Pablo A. Marquet, Neo D. Martinez, Arne Mooers, Peter Roopnarine, Geerat Vermeij, John W. Williams, Rosemary Gillespie, Justin Kitzes, Charles Marshall, Nicholas Matzke, David P. Mindell, Eloy Revilla, and Adam B. Smith. Approaching a state shift in earth/'s biosphere. *Nature*, 486(7401):52–58, June 2012. ISSN 0028-0836. doi: 10.1038/nature11018. URL http://www.nature.com/nature/journal/v486/n7401/full/nature11018.html.

Brian Barrett, Ingmar Nitze, Stuart Green, and Fiona Cawkwell. Assessment of multi-temporal, multi-sensor radar and ancillary spatial data for grasslands monitoring in ireland using machine learning approaches.

Remote Sensing of Environment, 152:109–124, September 2014. ISSN 0034-4257. doi: 10.1016/j.rse.2014.05.018. URL http://www.sciencedirect.com/science/article/pii/S0034425714002065.

Elizabeth T. Borer, Eric W. Seabloom, Daniel S. Gruner, W. Stanley Harpole, Helmut Hillebrand, Eric M. Lind, Peter B. Adler, Juan Alberti, T. Michael Anderson, Jonathan D. Bakker, Lori Biederman, Dana Blumenthal, Cynthia S. Brown, Lars A. Brudvig, Yvonne M. Buckley, Marc Cadotte, Chengjin Chu, Elsa E. Cleland, Michael J. Crawley, Pedro Daleo, Ellen I. Damschen, Kendi F. Davies, Nicole M. DeCrappeo, Guozhen Du, Jennifer Firn, Yann Hautier, Robert W. Heckman, Andy Hector, Janneke HilleRis-Lambers, Oscar Iribarne, Julia A. Klein, Johannes M. H. Knops, Kimberly J. La Pierre, Andrew D. B. Leakey, Wei Li, Andrew S. MacDougall, Rebecca L. McCulley, Brett A. Melbourne, Charles E. Mitchell, Joslin L. Moore, Brent Mortensen, Lydia R. O'Halloran, John L. Orrock, Jesus Pascual, Suzanne M. Prober, David A. Pyke, Anita C. Risch, Martin Schuetz, Melinda D. Smith, Carly J. Stevens, Lauren L. Sullivan, Ryan J. Williams, Peter D. Wragg, Justin P. Wright, and Louie H. Yang. Herbivores and nutrients control grassland plant diversity via light limitation. *Nature*, 508 (7497):517–520, 2014. URL http://dx.doi.org/10.1038/nature13144.

Mirco Boschetti, Stefano Bocchi, and Pietro Alessandro Brivio. Assessment of pasture production in the italian alps using spectrometric and remote sensing information. *Agriculture, Ecosystems & Environment*, 118(1-4):267–272, January 2007. ISSN 0167-8809. doi: 10.1016/j.agee.

2006.05.024. URL http://www.sciencedirect.com/science/article/pii/S0167880906001770.

J.R. Buckley and A.M. Smith. Monitoring grasslands with radarsat 2 quad-pol imagery. In *Geoscience and Remote Sensing Symposium (IGARSS), 2010 IEEE International*, pages 3090–3093, July 2010. doi: 10.1109/IGARSS.2010.5652367.

Lucien Carlier, Ioan Rotar, Mariana Vlahova, and Roxana Vidican. Importance and Functions of Grasslands. *Notulae Botanicae Horti Agrobotanici Cluj-Napoca*, 37(1):25–30, 2009. ISSN 1842-4309. doi: 10.15835/nbha3713090. URL http://www.notulaebotanicae.ro/index.php/nbha/article/view/3090.

Gabriele Cavallaro, Morris Riedel, Matthias Richerzhagen, Jon Atli Benediktsson, and Antonio Plaza. On Understanding Big Data Impacts in Remotely Sensed Image Classification Using Support Vector Machine Methods. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, pages 1–13, 2015. ISSN 1939-1404, 2151-1535. doi: 10.1109/JSTARS.2015.2458855. URL http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=7185322.

Yu-Han Chen and Ronald G. Prinn. Estimation of atmospheric methane emissions between 1996 and 2001 using a three-dimensional global chemical transport model. *Journal of Geophysical Research: Atmospheres*, 111(D10):D10307, May 2006. ISSN 2156-2202. doi: 10.1029/

2005JD006058. URL http://onlinelibrary.wiley.com/doi/10.1029/2005JD006058/abstract.

Emilio Chuvieco. Satellite observation of biomass burning. In Emilio Chuvieco, editor, *Earth Observation of Global Change*, pages 109–142. Springer Netherlands, January 2008. ISBN 978-1-4020-6357-2, 978-1-4020-6358-9. URL http://link.springer.com/chapter/10.1007/978-1-4020-6358-9_6.

Dave Clark, Annette Litherland, Gonzalo Mata, and Robert Burling-Claridge. Pasture monitoring from space. Technical report, January 2013. URL http://www.side.org.nz/IM_Custom/ContentStore/Assets/7/74/58d8ae4353832551a174e54bd2c826f9/Satellite%20grass%20monitoring.pdf.

P. Courtier, J.-N. Thépaut, and A. Hollingsworth. A strategy for operational implementation of 4d-Var, using an incremental approach. *Quarterly Journal of the Royal Meteorological Society*, 120(519):1367–1387, July 1994. ISSN 1477-870X. doi: 10.1002/qj.49712051912. URL http://onlinelibrary.wiley.com/doi/10.1002/qj.49712051912/abstract.

Pauline Dusseux, Thomas Corpetti, Laurence Hubert-Moy, and Samuel Corgne. Combined use of multi-temporal optical and radar satellite images for grassland monitoring. *Remote Sensing*, 6(7):6163–6182, June 2014. doi: 10.3390/rs6076163. URL http://www.mdpi.com/2072-4292/6/7/6163.

Asoka Edirisinghe, Dave Clark, and Deanne Waugh. 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, June 2012. ISSN 03032434. doi: 10.1016/j.jag.2011.11.006. URL http://adsabs.harvard.edu/abs/2012IJAEO..16....5E.

Environmental Protection Agency EPA. Ireland's Provisional Greenhouse Gas Emissions in 2014, 2014. URL http://www.epa.ie/pubs/reports/air/airemissions/irelandsghgemissionsin2014.html#.VnApbbSsCyN.

Geir Evensen. Sequential data assimilation with a nonlinear quasi-geostrophic model using Monte Carlo methods to forecast error statistics. *Journal of Geophysical Research: Oceans*, 99(C5):10143–10162, May 1994. ISSN 2156-2202. doi: 10.1029/94JC00572. URL http://onlinelibrary.wiley.com/doi/10.1029/94JC00572/abstract.

FAOSTAT. Food and agriculture organization of the united nations: STATISTICS DIVISION, 2014. URL http://faostat.fao.org/site/377/DesktopDefault.aspx?PageID=377#ancor.

Günther Fischer, Harrij Van Velthuizen, Freddy O. Nachtergaele, and Arne Jernelöv. *Global Agro-Ecological Zones Assessment: Methodology and Results*. 2000.

FoodWise-2025. Local Roots Global Reach, Food Wise 2025: A 10-year vision for the Irish agri-food industry, 2015. URL http://www.agriculture.gov.ie/foodwise2025/.

Alan J. Franzluebbers. Soil organic carbon in managed pastures of the southeastern united states of america. In *Integrated crop management*, volume 11, page Chapetr VIII, 2010.

Natasha Gilbert. One-third of our greenhouse gas emissions come from agriculture. *Nature*, October 2012. ISSN 1476-4687. doi: 10.1038/nature.2012.11708. URL http://www.nature.com/doifinder/10.1038/nature.2012.11708.

N.J. Gordon, D.J. Salmond, and A.F.M. Smith. Novel approach to nonlinear/non-Gaussian Bayesian state estimation. *Radar and Signal Processing, IEE Proceedings F*, 140(2):107–113, April 1993. ISSN 0956-375X.

Robert Connor Gordon. *Range Vegetation Type Mapping and Above-ground Green Biomass Estimates Using Multispectral Imagery*. Department of Geology, University of Wyoming, 1974.

Claire Gosselin. Obtaining Millimetre Precision - Interferometry, 2015. URL http://effigis.com/obtaining-millimetre-precision-using-satellite-sensors-science\-or-fiction/.

K. Gutjahr, R. Perko, H. Raggam, and M. Schardt. 3d-mapping from terrasar-x staring spotlight data. In *Geoscience and Remote Sensing Symposium (IGARSS), 2015 IEEE International*, pages 1817–1820, July 2015. doi: 10.1109/IGARSS.2015.7326144.

Ramon F. Hanssen. *Radar Interferometry: Data Interpretation and Error Analysis*. Springer Science & Business Media, April 2001. ISBN 9780792369455.

Quazi K. Hassan and K. Mahmud Rahman. Applicability of remote sensing-based surface temperature regimes in determining deciduous phenology over boreal forest. *Journal of Plant Ecology*, 6(1):84–91, 2013. doi: 10.1093/jpe/rts010. URL http://jpe.oxfordjournals.org/content/6/1/84.abstract.

W. W. Immerzeel, P. Droogers, S. M. de Jong, and M. F. P. Bierkens. Large-scale monitoring of snow cover and runoff simulation in Himalayan river basins using remote sensing. *Remote Sensing of Environment*, 113(1):40–49, January 2009. ISSN 0034-4257. doi: 10.1016/j.rse.2008.08.010. URL http://www.sciencedirect.com/science/article/pii/S0034425708002575.

IPCC. Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. Technical report, IPCC, Geneva, Switzerland, 2014.

Thomas Kaminski, Peter J. Rayner, Martin Heimann, and Ian G. Enting. On aggregation errors in atmospheric transport inversions. *Journal of Geophysical Research: Atmospheres*, 106(D5):4703–4715, March 2001. ISSN 2156-2202. doi: 10.1029/2000JD900581. URL http://onlinelibrary.wiley.com/doi/10.1029/2000JD900581/abstract.

Brendan Kearney. The Past, Present and Future of Irish Agriculture, 2010. URL http://www.iiea.com/blogosphere/brendan-kearney-on-the-past-present-and-future-of-irish\-agriculture.

V. P. Khanduri, C. M. Sharma, and S. P. Singh. The effects of climate change on plant phenology. *The Environmentalist*, 28(2):143–147, 2008. ISSN 1573-2991. doi: 10.1007/s10669-007-9153-1. URL http://dx.doi.org/10.1007/s10669-007-9153-1.

John Latham, Renato Cumani, Iiaria Rosati, and Mario Bloise. Global land cover SHARE (GLC-SHARE): database beta-release version 1.0-2014. Technical report, 2014.

Jong-Sen Lee and Eric Pottier. *Polarimetric Radar Imaging: From Basics to Applications*. CRC Press, February 2009. ISBN 9781420054989.

Jack J. Lennon. Potential impacts of climate change on agriculture and food safety within the island of Ireland. *Trends in Food Science & Technology*, 44(1):1–10, July 2015. ISSN 0924-2244. doi: 10.1016/j.tifs.2014.07.003. URL http://www.sciencedirect.com/science/article/pii/S0924224414001551.

Dejun Li, Catherine J. Watson, Ming Jia Yan, Stan Lalor, Rashid Rafique, Bernard Hyde, Gary Lanigan, Karl G. Richards, Nicholas M. Holden, and James Humphreys. A review of nitrous oxide mitigation by farm nitrogen management in temperate grassland-based agriculture. *Journal of Environmental Management*, 128:893–903, 2013. ISSN 0301-4797. doi: 10.1016/j.jenvman.2013.06.026. URL http://www.sciencedirect.com/science/article/pii/S0301479713004295.

Hsiao-Wen Lin, Yufang Jin, Louis Giglio, Jonathan A. Foley, and James T. Randerson. Evaluating greenhouse gas emissions inventories for agri-

cultural burning using satellite observations of active fires. *Ecological Applications*, 22(4):1345–1364, January 2012. ISSN 1051-0761. doi: 10.1890/10-2362.1. URL http://www.esajournals.org/doi/abs/10.1890/10-2362.1.

J.M. Lopez-Sanchez, S.R. Cloude, and J.D. Ballester-Berman. Rice phenology monitoring by means of sar polarimetry at x-band. *Geoscience and Remote Sensing, IEEE Transactions on*, 50(7):2695–2709, July 2012. ISSN 0196-2892. doi: 10.1109/TGRS.2011.2176740.

Fabian Löw and Grégory Duveiller. Defining the spatial resolution requirements for crop identification using optical remote sensing. *Remote Sensing*, 6(9):9034, 2014. ISSN 2072-4292. doi: 10.3390/rs6099034. URL http://www.mdpi.com/2072-4292/6/9/9034.

Yan Ma, Haiping Wu, Lizhe Wang, Bormin Huang, Rajiv Ranjan, Albert Zomaya, and Wei Jie. Remote sensing big data computing: Challenges and opportunities. *Future Generation Computer Systems*, 51:47–60, October 2015. ISSN 0167739X. doi: 10.1016/j.future.2014.10.029. URL http://linkinghub.elsevier.com/retrieve/pii/S0167739X14002234.

A. Metz, A. Schmitt, T. Esch, P. Reinartz, S. Klonus, and M. Ehlers. Synergetic use of TerraSAR-x and radarsat-2 time series data for identification and characterization of grassland types – a case study in southern bavaria, germany. In *Geoscience and Remote Sensing Symposium (IGARSS), 2012 IEEE International*, pages 3560–3563, July 2012. doi: 10.1109/IGARSS.2012.6350649.

J. Mittermayer, S. Wollstadt, P. Prats-Iraola, and R. Scheiber. The terrasar-x staring spotlight mode concept. *Geoscience and Remote Sensing, IEEE Transactions on*, 52(6):3695–3706, June 2014. ISSN 0196-2892. doi: 10.1109/TGRS.2013.2274821.

Carsten Montzka, Valentijn R. N. Pauwels, Harrie-Jan Hendricks Franssen, Xujun Han, and Harry Vereecken. Multivariate and Multiscale Data Assimilation in Terrestrial Systems: A Review. *Sensors*, 12(12):16291–16333, November 2012. doi: 10.3390/s121216291. URL http://www.mdpi.com/1424-8220/12/12/16291.

D. O'Brien, T. Hennessy, B. Moran, and L. Shalloo. Relating the carbon footprint of milk from Irish dairy farms to economic performance. *Journal of Dairy Science*, 98(10):7394–7407, October 2015. ISSN 1525-3198. doi: 10.3168/jds.2014-9222.

Donal O'Brien, Laurence Shalloo, Paul Crosson, Trevor Donnellan, Niall Farrelly, John Finnan, Kevin Hanrahan, Stan Lalor, Gary Lanigan, Fiona Thorne, and Rogier Schulte. An evaluation of the effect of greenhouse gas accounting methods on a marginal abatement cost curve for Irish agricultural greenhouse gas emissions. *Environmental Science & Policy*, 39:107–118, May 2014. ISSN 1462-9011. doi: 10.1016/j.envsci.2013.09.001. URL http://www.sciencedirect.com/science/article/pii/S1462901113001780.

Phillip O'Brien. Data Analysis and Estimation of Greenhouse Gas Emissions and Removal for the IPCC Sector Land Use, Land-

Use Change and Forestry Sectors in Ireland. Technical report, 2007. URL https://www.epa.ie/pubs/reports/research/air/erc7-obrien-report-for-web1.pdf.

Michael O'Donovan and Pat Dillon. Measurement of Grassland Management Practice on Commercial Dairy Farms, 1999.

F. P. O'Mara. The role of grasslands in food security and climate change. *Annals of Botany*, 110(6):1263–1270, November 2012. ISSN 1095-8290. doi: 10.1093/aob/mcs209.

V. V. Pavlu, M. Hejcman, and J. Mikulka. Cover estimation versus density counting in species-rich pasture under different grazing intensities. *Environmental Monitoring and Assessment*, 156(1-4):419–424, September 2009. ISSN 1573-2959. doi: 10.1007/s10661-008-0494-0.

Jeremy Joshua Pittman, Daryl Brian Arnall, Sindy M. Interrante, Corey A. Moffet, and Twain J. Butler. Estimation of biomass and canopy height in bermudagrass, alfalfa, and wheat using ultrasonic, laser, and spectral sensors. *Sensors*, 15(2):2920, 2015. ISSN 1424-8220. doi: 10.3390/s150202920. URL http://www.mdpi.com/1424-8220/15/2/2920.

I. Colin Prentice, Wolfgang Cramer, Sandy P. Harrison, Rik Leemans, Robert A. Monserud, and Allen M. Solomon. A Global Biome Model Based on Plant Physiology and Dominance, Soil Properties and Climate. *Journal of Biogeography*, 19(2):117–134, 1992. ISSN 0305-0270. doi: 10.2307/2845499. URL http://www.jstor.org/stable/2845499.

Peter J Rayner. The current state of carbon-cycle data assimilation. *Current Opinion in Environmental Sustainability*, 2(4):289–296, October 2010. ISSN 1877-3435. doi: 10.1016/j.cosust.2010.05.005. URL http://www.sciencedirect.com/science/article/pii/S1877343510000370.

Duccio Rocchini. Earth observation for ecosystems monitoring in space and time: A special issue in remote sensing. *Remote Sensing*, 7(6):8102, 2015. ISSN 2072-4292. doi: 10.3390/rs70608102. URL http://www.mdpi.com/2072-4292/7/6/8102.

Micol Rossini, Sergio Cogliati, Michele Meroni, Mirco Migliavacca, Marta Galvagno, Lorenzo Busetto, Edoardo Cremonese, Tommaso Julitta, Consolata Siniscalco, Umberto Morra Di Cella, and Roberto Colombo. Remote sensing-based estimation of gross primary production in a subalpine grassland. *Biogeosciences*, 9:2565–2584, 2012. ISSN 1726-4170. doi: 10.5194/bg-9-2565-2012.

Christian Schuster, Iftikhar Ali, Peter Lohmann, Annett Frick, Michael Förster, and Birgit Kleinschmit. Towards detecting swath events in TerraSAR-x time series to establish NATURA 2000 grassland habitat swath management as monitoring parameter. *Remote Sensing*, 3(12): 1308–1322, June 2011. ISSN 2072-4292. doi: 10.3390/rs3071308. URL http://www.mdpi.com/2072-4292/3/7/1308.

Christian Schuster, Tobias Schmidt, Christopher Conrad, Birgit Kleinschmit, and Michael Förster. Grassland habitat mapping by intra-annual time series analysis - comparison of RapidEye and TerraSAR-x satel-

lite data. *International Journal of Applied Earth Observation and Geoinformation*, 34:25–34, February 2015. ISSN 0303-2434. doi: 10.1016/j.jag.2014.06.004. URL http://www.sciencedirect.com/science/article/pii/S0303243414001378.

Anne M. Smith and Joseph R. Buckley. Investigating RADARSAT-2 as a tool for monitoring grassland in western canada. *Canadian Journal of Remote Sensing*, 37(1):93–102, February 2011. ISSN 1712-7971. doi: 10.5589/m11-027. URL http://pubs.casi.ca/doi/abs/10.5589/m11-027.

David Styles and Michael B. Jones. Miscanthus and willow heat production–An effective land-use strategy for greenhouse gas emission avoidance in Ireland? *Energy Policy*, 36(1):97–107, January 2008. ISSN 0301-4215. doi: 10.1016/j.enpol.2007.08.030. URL http://www.sciencedirect.com/science/article/pii/S030142150700376X.

Caroline A. Sullivan, Micheline Sheehy Skeffington, Mike J. Gormally, and John A. Finn. The ecological status of grasslands on lowland farmlands in western ireland and implications for grassland classification and nature value assessment. *Biological Conservation*, 143(6):1529 – 1539, 2010. ISSN 0006-3207. doi: http://dx.doi.org/10.1016/j.biocon.2010.03.035. URL http://www.sciencedirect.com/science/article/pii/S0006320710001242.

J. M. Suttie, Stephen G. Reynolds, and Caterina Batello. *Grasslands of the World*. Food & Agriculture Org., January 2005. ISBN 9789251053379.

Kaupo Voormansik, Thomas Jagdhuber, Aire Olesk, Irena Hajnsek, and Konstantinos P. Papathanassiou. Towards a detection of grassland cutting practices with dual polarimetric TerraSAR-x data. *International Journal of Remote Sensing*, 34(22):8081–8103, September 2013. ISSN 0143-1161. doi: 10.1080/01431161.2013.829593. URL http://dx.doi.org/10.1080/01431161.2013.829593.

Urs Wegmüller. Land Applications of SAR Interferometry. In Horst Groll and Ivan Nedkov, editors, *Microwave Physics and Techniques*, number 33 in NATO ASI Series, pages 235–250. Springer Netherlands, 1997. ISBN 978-94-010-6333-3 978-94-011-5540-3. URL http://link.springer.com/chapter/10.1007/978-94-011-5540-3_17.

Anne B. Willems, Cara A. Augustenborg, Simone Hepp, Gary Lanigan, Tamara Hochstrasser, Claudia Kammann, and Christoph MÃŒller. Carbon dioxide emissions from spring ploughing of grassland in Ireland. *Agriculture, Ecosystems & Environment*, 144(1):347–351, November 2011. ISSN 0167-8809. doi: 10.1016/j.agee.2011.10.001. URL http://www.sciencedirect.com/science/article/pii/S0167880911003355.

Michael A. Wulder and Nicholas C. Coops. Satellites: Make Earth observations open access. *Nature*, 513(7516):30–31, September 2014. ISSN 0028-0836, 1476-4687. doi: 10.1038/513030a. URL http://www.nature.com/doifinder/10.1038/513030a.

www.independent.ie. EU milk quota ends: Move raises cheers as well as dire warnings, 2015.

URL http://www.independent.ie/business/farming/eu-milk-quota-ends-move-raises-cheers-as-well-as-dire-warnings-31\111366.html.

Howard A. Zebker and Richard M. Goldstein. Topographic mapping from interferometric synthetic aperture radar observations. *Journal of Geophysical Research: Solid Earth*, 91(B5):4993–4999, April 1986. ISSN 2156-2202. doi: 10.1029/JB091iB05p04993. URL http://onlinelibrary.wiley.com/doi/10.1029/JB091iB05p04993/abstract.

DECLARATION

Honesty is the first chapter of the book wisdom.

— Thomas Jefferson [1743 — 1826]

I hereby certify that this material, which I now submit for assessment on the programme of study leading to the award of *doctorate degree (PhD, Dr. –)* is entirely my own work, that I have exercised reasonable care to ensure that the work is original, and does not to the best of my knowledge breach any law of copyright, and has not been taken from the work of others save and to the extent that such work has been cited and acknowledged within the text of my work.

Cork, Ireland, February, 2016

Iftikhar Ali, MSC

April 17, 2016

BIOGRAPHY: IFTIKHAR ALI



I was born in 1986 in a small village near Multan, Pakistan. I received my BS. degree in Applied Mathematics from Bahauddin Zakariya University, Multan, Pakistan, in 2008, and the M.Sc. degree in Geodesy and Geoinformation Science (specialization in remote sensing) from Technical University of Berlin, Germany, in 2011. I worked on Natura 2000 habitat monitoring in alpine (north of Italy) and non-alpine (west of Berlin) region by using high resolution SAR (TerraSAR-X and COSMO-SkyMed) time series under joint collaboration of EURAC Bolzano/Bozen, Italy and Technical University of Berlin, Germany. From July 2011 to December 2011 I was with Technical University of Berlin on CARE-X project. From January 2012 to June 2012 I worked as a remote sensing researcher at Institute of Applied Remote Sensing, EURAC, Bolzano, Italy.

Recently, I was working as a JPL visiting researcher (JVSRP) at JPL/NASA—California Institute of Technology (Pasadena, CA, USA), where I worked on Synthetic Aperture Radar Interferometry (InSAR) analysis of TerraSAR-X satellite data processing. The focus of this work was more on SAR image processing in order to better understand the effect of temporal decorrelation and farm activities on vegetated area with respect to the vegetation height and biomass.

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