Summary Report
WP4 – Feasibility tests using new data generated by the project

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Introduction

The purpose of the 'GRASS improvement using Satellite TECHnologies – GRASSS-TECH' project is to investigate the feasibility of measuring grass yield and quality using remote sensing technologies. If successful, this project will serve as proof-of-concept for the development of a service that will enable farmers to improve grass yield and quality. This report summarises the outcomes of Work Package 4 (WP4) which focused on evaluating monitoring data collected during the project to assess the feasibility of measuring grass growth using remote sensing as well as testing the most appropriate methods identified in WP3. This report will:

- Provide an overview of the next stage of trialling methods in assessing grass growth using remote sensing.
- Further evaluate the most appropriate sources of satellite data.
- Propose an approach and calibration equations to be implemented in a prototype tool.
- Identify the implications of these findings on the development of an operational service.

This work package was supported by the preceding activity:

- WP1: Literature review
- WP3: Feasibility test using historic data

Findings from Work Package 1

Following a preliminary review of literature in WP1, it was determined that the majority of previous studies focused on the use of optical remote sensing to monitor grassland environments. In particular, it was demonstrated that information in the optical; particularly the visible, infra-red and red-edge regions of the spectrum, are critical for monitoring. This study, therefore, focused on evaluating the feasibility of monitoring grass growth using a series of Vegetation Indices (VIs) that focus on wavebands in these regions. Considering the rapid development of grasslands, it was also identified that systems that could deliver imagery with a high temporal frequency were required. Also, to be an effective monitoring tool for the UK, satellite data must cover a reasonably large area with each data acquisition/scene. As a result, optical imagery from the Landsat 8 and Sentinel-2 platforms were identified as appropriate sources of satellite data. In addition, given the constraints related to cloud cover for optical sensors in the UK, the utility of microwave systems which are not impacted by cloud, such as that on Sentinel-1, was also recommended.

Findings from Work Package 3

WP3 developed relationship between EO-based vegetation indices and biomass information at the field / paddock level based on historical EO data and ground measurements, i.e. recorded prior to the project. A number of ground reference datasets were potentially available, but due to issues associated with data collection and the consistency of weekly grass growth data and management information, the results from Munday Farm were the focus of 'Feasibility Testing Using Historic Data' (WP3) which amounted to 25 paddocks near Exeter.

Figure 1 presents the biomass measurements collected between January and November 2016. Overall, there was a large amount of variation in biomass due to management practices with the lowest grass cover value (1200 kg DM/ha) being measured following a silage cut in October 2016 and the largest grass cover value (5890 kg DM/ha) being recorded prior to a grazing event on 1st June 2016. On-going management of grasslands with silage cuts or grazing events taking place regularly throughout the season. Landsat 8, Sentinel-1 and Sentinel-2 were collected for the area of Munday Farm to compare with the ground measurements of biomass.

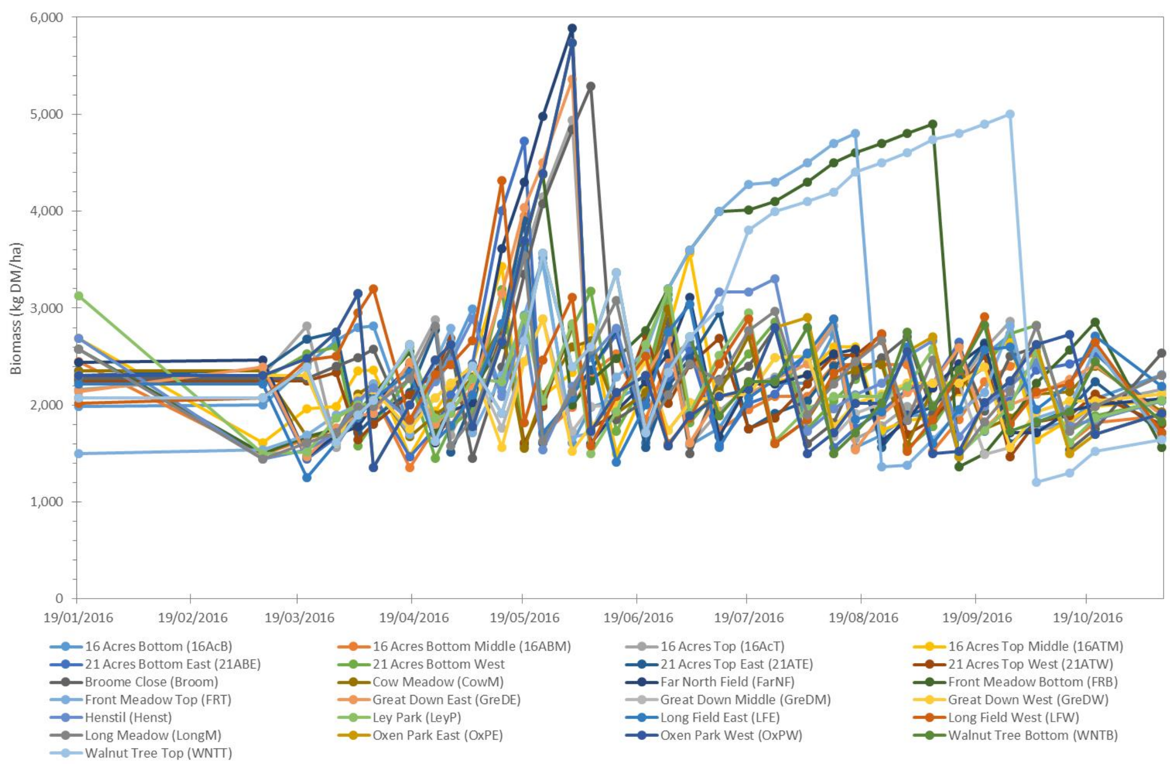

Figure 1 Grass growth data for 25 paddocks at Munday Farm, Exeter.

Landsat 8, Sentinel-1 and Sentinel-2 were collected for the area of Munday Farm to compare with the 2016 ground measurements of biomass. Figure 2 presents example imagery for each of the sensors proposed in the work package compared to the paddocks at Munday Farm to show the differing spatial resolution and response recorded by the different systems. Sentinel-2 gives the clearest representation of the surface with 10 m pixels compared to the Landsat-8 data and the absence of the speckle present in the Sentinel-1 SAR data.

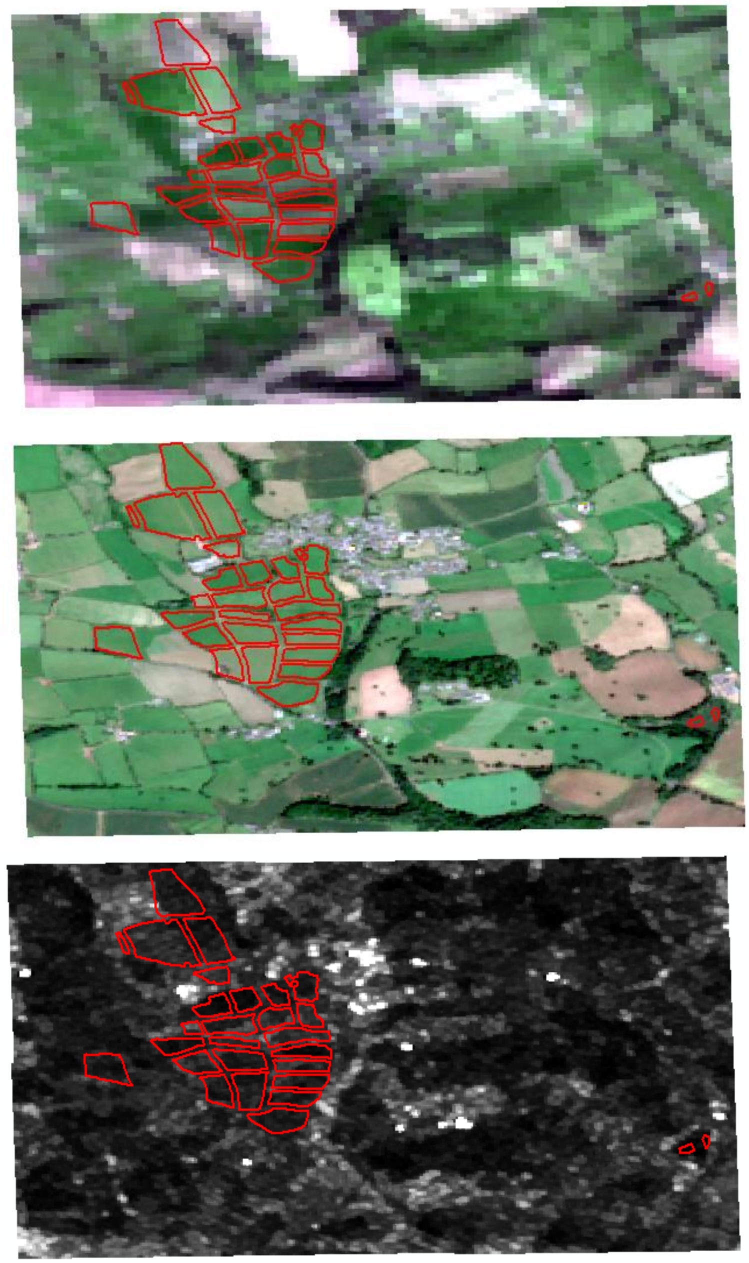

Figure 2 Example imagery for a) Landsat 8, b) Sentinel-2 and c) Sentinel-1, paddock boundaries shown in red.

Due to issues related to cloud cover in 2016, there were a limited number of optical image acquisitions available for the study period, particularly during the largest growth period (April-July), with Landsat-8 providing 4 images and Sentinel-2 only 2. SAR data from Sentinel-1 is unaffected by cloud cover and was also tested.

An initial exploration of the relationships between biomass and the individual spectral bands in the optical sensors supported the use of vegetation indices as proposed by work package 1. A set of vegetation indices were then tested to assess which best related to the biomass measurements for the paddocks at Munday Farm. It was obvious when plotting the results that there were a number of outliers from the main distribution which needed to be better understood and, if justified, removed from the analysis. Some were caused by temporal alignment issues where the field had been grazed between the image acquisition and field measurement. Also, fields left for silage with very high biomass measurements produced anomalous vegetation index results. The individual indices will be explained in more depth below, but the Wide Dynamic Range Vegetation Index (WDRVI) was found to give the strongest correlation to biomass when using Landsat 8 data. The WDRVI was less successful for Sentinel-2 but some image calibration issues were identified and there were only two images available.

With the Sentinel-1 SAR data the plots of biomass and backscatter showed a broad unstructured distribution of points for both polarisations with little, if any, relationship to biomass.

In summary, work package 3 appeared to show the optical systems to be the most promising from this work, although further investigation should be directed at SAR systems. The Landsat 8 data from the USGS in surface reflectance format was a stable and robust source of spatio-temporal data from which to calculate paddock level vegetation indices. Sentinel-2 offered great potential for increasing the number of images acquired per year due to its increased acquisition frequency and its ability to work in tandem with Landsat 8 due to their similar specifications.

Methodology

The aim of work package 4 was to repeat and extend the work of work package 3 with an expanded ground reference dataset across multiple farms and the inclusion of more EO data, primarily from the optical EO systems.

Grass Growth Data

Weekly grass growth and grass quality was collected from 3 fields on each of 3 farms for 8 weeks. This information will also be used in the subsequent modelling work package (WP5). Growth was measured with a rising plate meter.

22 sites were identified in Wales, Herefordshire/Gloucestershire and Yorkshire. These were sampled for both growth and quality on 3 dates. Quality analysis was measured by NIR to give D Value, Metabolisable energy (ME), Non-digestible Fibre (NDF), Ash, Oil, Crude Protein, Sugar, Nitrate N, Buffering Capacity. Sample Date 1: Target month April: when a radar sensing satellite passed overhead. This was sampled in any cloud conditions and was within 2 or 3 days of the satellite image being taken. Sample date 2: Target month: May: This was on a sunny day when an optical sensing satellite has successfully acquired a cloud-free image. Sampling was done within 2 or 3 days of the image being taken. Sample date 3: Target month June: This was on a sunny day when an optical sensing satellite has successfully acquired a cloud-free image. Sampling was done within 2 or 3 days of the image being taken. The same growth and quality parameters were measured as for the 3 farms that were monitored weekly.

Rising Plate Meter (RPM) approach

Once the target field and sampling date had been specified, the following sampling procedure was carried out;

- Mark out approximately one hectare area of field for sampling. Mark the corners of this area with canes and record the location of the corners using a GPS device.

- Use a rising plate meter (see below) to measure the grass growth (measured in tonnes biomass per hectare) at 20 randomly selected positions within the one hectare area. Record the average grass growth value over the 20 measurements.
- Collect samples of grass from six randomly selected positions within the one hectare area. Bulk and mix up the grass samples and send off a subsample that fills the pre-paid addressed bag supplied by Sciantec to their labs for quality analysis. (FN02 Grass for silage NIR: D Value, Metabolisable energy (ME), Non-digestible Fibre (NDF), Ash, Oil, Crude Protein, Sugar, Nitrate N, Buffering Capacity.

Figure 3 Rising plate meter

Available and collected data

Although a larger amount of ground reference data was collected in 2017, unusually high cloud cover amounts during the survey period resulted in only a limited number of ground measurements with corresponding optical EO data. The situation can be demonstrated by the plots in Figure 4 which show that the differing sampling intervals across the farms and the relative paucity EO data. The plots also show how rapidly the biomass can change and the need to have the EO data and ground measurements closely synchronised. In some cases, there are few ground reference measurements per paddock, but they have been timed to coincide exactly with EO acquisitions.

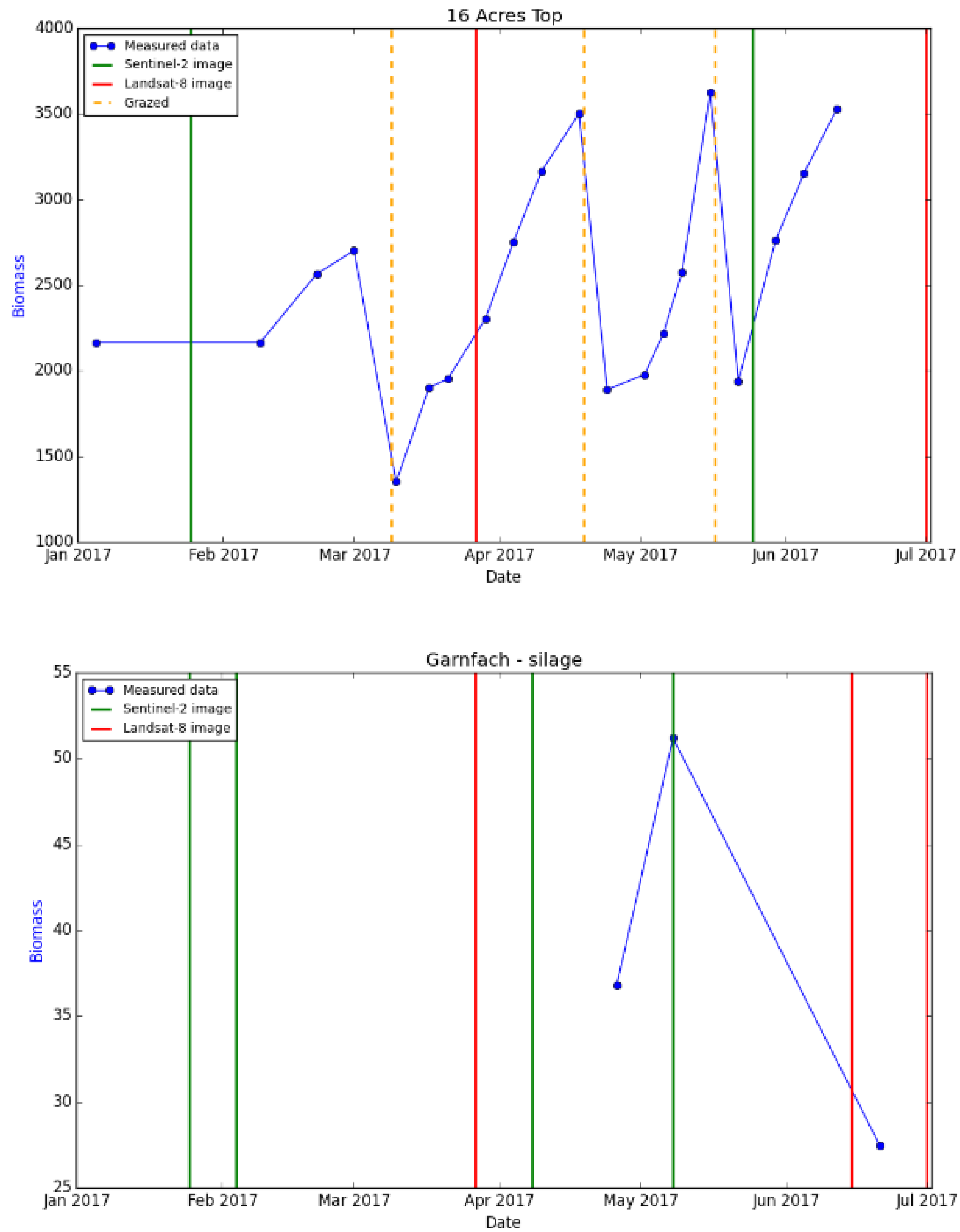

Figure 4 Temporal plots for individual paddocks comparing grass growth measurements and grazing events to the availability of EO data.

Satellite Imagery

Using locations of the paddocks at the surveyed farms and the dates of the ground reference data, all available imagery from within the sampling period was downloaded and processed for Landsat 8, Sentinel-2 and Sentinel-1.

The sensors used in this work package collect spectral measurements (the response of the surface at a particular range of wavelengths or colours). In the case of optical sensors (Landsat 8 and Sentinel-2) this is a measure of reflectance, while for microwave sensors (Sentinel-1) it is a measure of backscatter. These different spectral measurements interact with different properties of the surface which we aim to relate to the biomass of the grass canopy within the paddocks.

Optical

Optical EO makes use of passive, i.e. illuminated by the Sun, visible, near infrared and short-wave infrared measurements of the solar radiation reflected from targets on the ground. Different materials reflect and absorb radiation differently at different wavelengths allowing targets to be differentiated or their properties characterised by analysis of their spectral reflectance signatures. Optical remote sensing systems are classified into a number of different types, depending on the number of spectral bands and spatial resolution used in the imaging process. The optical sensors used in this project are classified as high spatial resolution (10 – 30 m pixels) multi- / super- spectral (5 – 15 bands) scanners.

Sentinel-2

Sentinel-2 is an EO mission developed by ESA as part of the Copernicus Programme to perform terrestrial observations in support of services such as forest monitoring, land cover changes detection, and natural disaster management. Sentinel-2 carries an innovative wide swath high spatial resolution multi-spectral imager with 13 spectral bands in visible, near infrared (NIR) and shortwave infrared (SWIR) regions. The combination of high spatial resolution, novel spectral capabilities, a swath width of 290 km, a constellation of two identical satellites in the same orbit and frequent revisit times provides unprecedented imaging capabilities. Sentinel-2A was launched on 23 June 2015 and Sentinel-2B followed on 7 March 2017, giving 2-3 day revisit times in the UK depending on cloud cover.

Imagery from the Sentinel-2 missions are available from a number of sources with different levels of pre-processing, which accounts for extraneous influences on the imagery and aims to provide analysis ready data. The Sentinel-2 data for this project were acquired from the UK Joint Nature Conservation Committee (JNCC) which has been running a pre-operational ARD project to support Sentinel-2 users in the UK. These files were offered as an analytical resource for the whole of the UK processed to bottom-of-atmosphere (or, surface) reflectance. Due to issues related to cloud cover, however, there were only 9 Sentinel-2 images available for the required sites during the study period (Appendix 2).

Landsat 8

Landsat 8 is an American EO satellite launched on February 11, 2013. The Landsat programme began in 1972 and Landsat-1 was the first satellite to be launched that was designed to study and monitor the Earth's land masses. It is the eighth satellite in the Landsat program and the seventh to reach orbit successfully. The Landsat 8 satellite sensor system consists of the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). This project has only used OLI data which measures in the visible, NIR and SWIR portions of the spectrum. Its images have 15 m panchromatic and 30 m multi-spectral spatial resolutions along a 185 km wide swath. The entire Earth falls within view once every 16 days due to Landsat 8's near-polar orbit.

Landsat 8 imagery for this project was acquired from the USGS EarthExplorer tool and processed to surface reflectance using the Landsat Surface Reflectance Code (LaSRC). Due to issues related to cloud cover, however, there were only 2 Landsat 8 images available for the required sites during the study period (Appendix 2).

Optical processing and indicators

To assess if optical imagery is capable of detecting differences in grass cover between paddocks and monitor this change through a season, all analysis ready Landsat 8 and Sentinel-2 imagery were first subset to the regions of interest around the study sites.

Using the relevant bands for each sensor, where possible, all VIs listed in

Table 1 were calculated for each image date. These indices were selected based on the outcomes of WP1, WP3 and the priorities of this work package to further test the feasibility of detecting and monitoring grass growth remotely.

Zonal statistics were extracted for the calculated VIs and sensor wavebands. This provided a mean value for each waveband and VI for each paddock. The statistics were calculated for on all pixels located within a 10 m buffer around the boundary for each paddock to avoid interference from other surface features such as hedgerows.

Table 1 Vegetation Indices (VIs) calculated as part of the analysis of optical imagery for WP4.

Vegetation Index	**Description**	**Formula**	**Wavebands**
Canopy Chlorophyll Content Index (CCCI)	The CCCI measures crop nitrogen status.	$CCCI = \frac{\frac{NIR - red\ edge}{NIR + red\ edge}}{\frac{NIR - Red}{NIR + Red}}$	Red Red edge NIR
Canopy Chlorophyll Content Index - alternative (CCCI2)	Another variation of the CCCI used for measuring canopy N content. Derived from NDRE (below).	$CCCI = \frac{\mathrm{NDRE} - NDRE_{min}}{NDRE_{max} - NDRE_{min}}$	Red edge NIR
Chlorophyll Index Red-Edge (CIRE)	This VI estimates canopy chlorophyll or N content.	$\mathrm{CI}RE = \frac{NIR}{red\ edge} - 1$	Red edge NIR
Normalised Difference Red Edge index (NDRE)	Assesses the health of vegetataion.	$NDRE = \frac{NIR - red\ edge}{NIR + red\ edge}$	Red edge NIR
Enhanced Vegetation Index, EVI	EVI is sensitive to changes in areas of high biomass. It is also capable of reducing the influence of atmospheric conditions and canopy background signals.	$EVI = 2.5 * \frac{NIR - Red}{(NIR + (6 * Red) - (7.5 * Blue)) + 1}$	Red Blue NIR
Normalised Difference Vegetation Index, NDVI	NDVI is an index of plant greenness or photosynthetic activity.	$NDVI = \frac{NIR - Red}{NIR + Red}$	Red NIR
Normalised Green-Red Difference Index, NGRDI	NGRDI measures surface greenness and is an index that can be used to detect live green plant canopies. The index is suitable to analyse crops in all growth stages.	$NGRDI = \frac{Green - Red}{Green + Red}$	Red Green
Transformed Normalised Difference Vegetation Index, TNDVI	TNDVI is a modified NDVI that provides an improved correlation for the amount of green biomass found in a pixel.	$TNDVI = \sqrt{\frac{NIR - Red}{NIR + Red}} + 0.5$	Red NIR
Wide Dynamic Range Vegetation Index, WDRVI	WDRVI is a modified NDVI that is more sensitive to moderate-to-high LAI values. This allows more robust characterisation of crop physiological and phenological characteristics.	$WDRVI = \frac{0.1 * NIR - Red}{0.1 * NIR + Red}$	Red NIR
Normalised Difference Moisture Index, NDMI	NDMI provides a measure of vegetation moisture and is capable of detecting subtle changes in moisture conditions.	$NDMI = \frac{NIR - SWIR}{NIR + SWIR}$	NIR SWIR

SAR

In contrast to Landsat 8 and Sentinel-2 optical sensors, Synthetic Aperture RADAR (SAR) sensors, such as Sentinel-1, provide a measure of surface roughness rather than optical properties. The surface roughness measure is based on the concept that different surface features exhibit different backscatter values due to their structural arrangement. For instance, smooth water produced very little backscatter as the radar pulse is reflected away from the sensor while groups of building can produce high backscatter as the arrangement of walls and surfaces can reflect almost all the energy back toward the sensor. Therefore, it was suggested that paddocks with different covers and densities of grass might be detected through variations in surface roughness. SAR also has the added advantage of being able to acquire images through cloud, which is particularly useful in temperate situations.

Sentinel-1

Images from the Sentinel-1 missions, part of the European Union Copernicus programme, were acquired from the UK Joint Nature Conservation Committee (JNCC). The SAR works at a single waveband, but records two different backscatter responses due to the polarisation of the illumination and recorded signals. It illuminates the surface with vertically (V) polarised radiation, but records both the vertical (V) and horizontally (H) polarised backscatter responses (referred to as 'Sigma-0') resulting in VV and VH combinations. Sentinel-1 imagery was provided as analysis ready data that had been processed by JNCC to provide a backscatter coefficient product using the European Space Agency's (ESA) SNAP toolbox.

SAR processing

To evaluate the feasibility of this approach, all Sentinel-1 imagery was first subset to the region of interest. For each polarisation combination (orientation of transmitted and received signals – VV, vertical transmit and vertical receive, and VH, vertical transmit and horizontal receive), values for each image date were extracted via zonal statistics in a similar way to the optical data. These values were then converted to backscatter coefficient values ready for analysis using Equation 1:

$$Backscatter\ Coefficient = 10\ \times log10(DNvalue) \qquad \text{Eq. 1}$$

Interpolation of RPM measurements

Due to a range of factors it is not always possible to take biomass measurements in the paddocks at exactly the same time as the images are acquired. Previously, the nearest biomass measurements in time to the image acquisition have been selected. However, it was noted that biomass increases can be quite dramatic over a few days and also any intervening grazing event will both cause problems when trying to develop calibration equations between an EO-derived indicator and biomass. For 2017 some of the field work was designed to be coincident with satellite over passes, but a large proportion of the ground reference data still came from farms which undertook regularly (~weekly) biomass measurement.

In Figure 5 it can be seen that the closest ground reference measurement may not adequately represent the true biomass in the paddocks. In this case the late April Landsat 8 image was acquired at a time when the biomass in this paddock was increasing rapidly and an interpolation between the closest two measurements would be appropriate to provide a better estimate of biomass. In the case of the late June Sentinel-2 image the paddock was grazed between the closest measurement and the image acquisition, therefore an extrapolation from the subsequent biomass measurements would be more realistic.

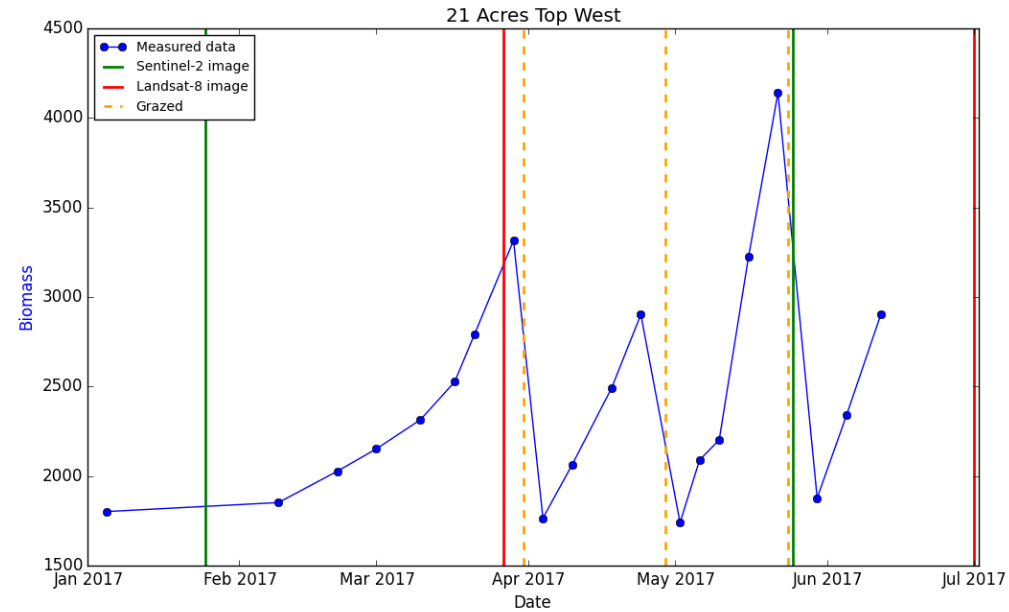

Figure 5 Example of ground reference data from regular sampling and the need to interpolate or extrapolate the results to obtain more realistic values.

For the paddocks with regular biomass measurements, an interpolated or extrapolated estimate of biomass was calculated depending on the actual date of the image acquisition and any grazing or silage cutting events.

Feasibility Testing Using Targeted Data

The available satellite and ground based information from 2017 provided a rich, but highly multi-dimensional data of different dates, sensors, VIs, management practices and paddocks across a number of farms and landscape situations. The feasibility testing, therefore, was divided into a set of stages that continued to explore the capabilities of each sensor and sensor types:

- Firstly, the optical sensors were evaluated using scatterplots and linear regression analysis with a focus on Sentinel-2 which was now fully operational in 2017 and offered additional indicator capabilities compared to Landsat 8.
- The outcomes of the Sentinel-2 analysis and Landsat 8 results from 2016 then guided the consideration of the Landsat 8 data from 2017.
- The Landsat 8 and Sentinel-2 data and results were then compared as they have the potential to be combined in time series analysis then using truly analysis ready data.
- Finally, the Sentinel-1 data were evaluated using scatterplots and linear regression analysis independently as they have very different capabilities and provide different surface characteristics.

Results

Introduction

As shown earlier in this document (Figure 1), the management and subsequent changes in biomass at pasture farms are highly variable between paddocks and over time. There appears to be a number of general trends including regular grazing/regrowth, early season growth for silage then grazing and, later in the season, prolonged growth and cutting plus combinations of the above. This results in a complex set of temporal behaviours for biomass per paddock which will be challenging to capture and assess using satellite sensors that have an acquisition interval controlled by their orbits and other temporal limitations such as the presence of cloud cover and the asynchronous nature of the ground measurements.

Figure 6 compares the 2016 in-situ measurements of biomass for the four example paddocks in Figure 1 with image acquisition dates for each sensor overlain on the graph. It can be seen that even this relatively dense series of acquisitions does not capture all of the changes taking place within the paddocks. It is particularly limited when dealing with the rapid changes in biomass caused by grazing events which may only last a day. Unfortunately, the differences in technology of the various sensors and some calibration issues means that the acquisitions shown cannot be combined into a single time series and needs to be subset giving less frequent acquisitions.

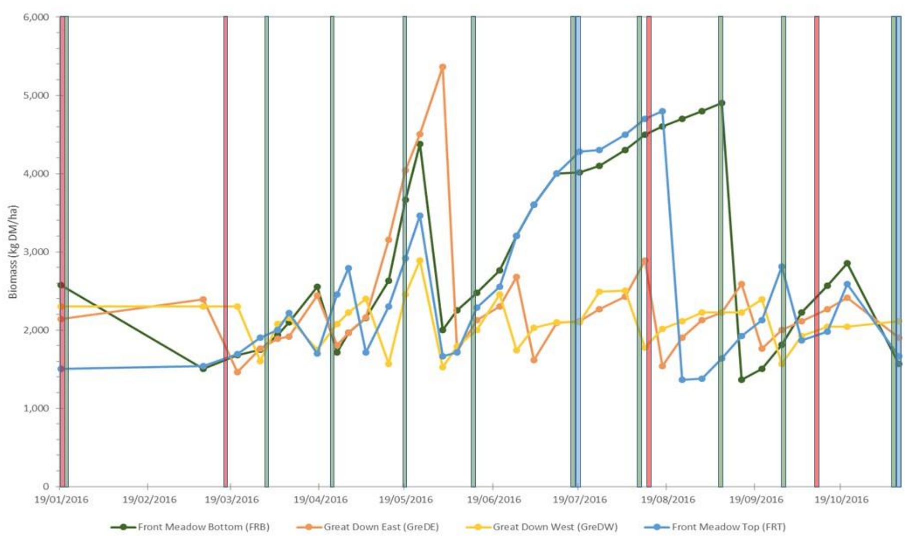

Figure 6 Comparison of the available EO data (Green – Sentinel-1, Blue – Senintel-2 & Red – Landsat 8) for 2016 and the dynamics of the paddocks at Monday Farm, Exeter.

In Figure 7 it can be seen that while additional Sentiel-1 imagery was available for the site, only 2 dates were selected to coincide exactly with the date of measurement, and at the times where grass samples were taken.

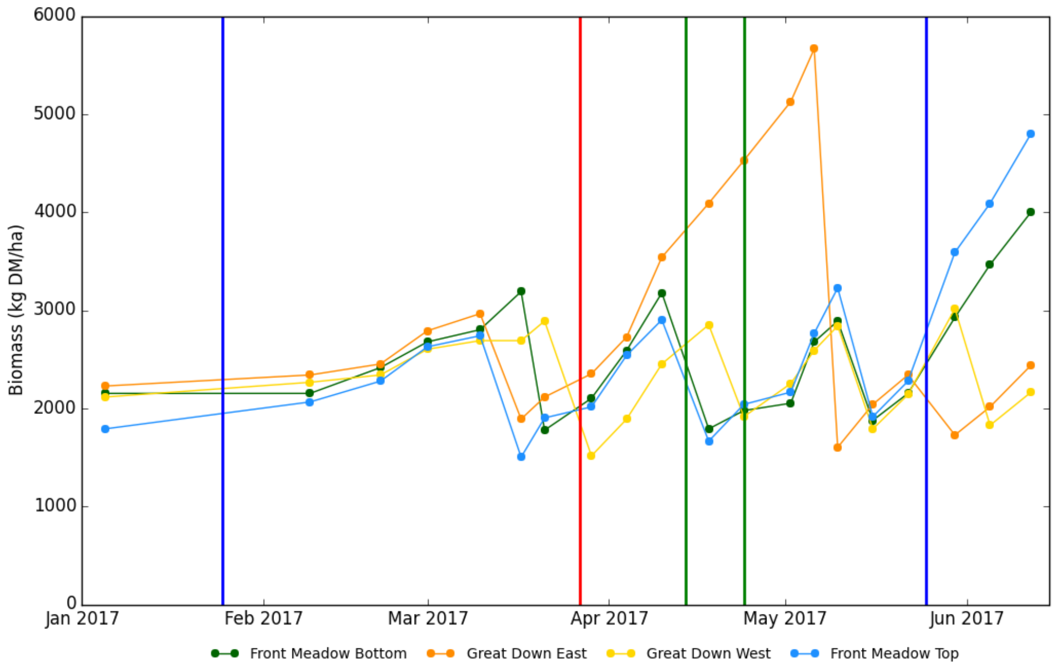

Figure 7 Comparison of the available EO data (Green – Sentinel-1, Blue – Senintel-2 & Red – Landsat 8) for 2017 and the dynamics of the paddocks at Monday Farm, Exeter.

Figure 8 and

Table 2 compare the number and range of biomass values from the field data samples for each farm which correspond to EO acquisitions. The initial plan was to use a balanced sample across the selected farms to avoid a bias towards the well monitored paddocks at Munday's Farm. However, the weather conditions in 2017 restricted the availability of EO data therefore it was necessary to use the full dataset for Munday's Farm in 2017.

This resulted in 2017 having less ground reference points with corresponding EO data than 2016. It can be seen on Figure 8 that only 3 points in 2017 were outside the biomass range of the 2016 data and these were all greater biomasses. Also, the sample became very heterogeneous, both spatially and temporally, across the different farms with only 2 viable points at Rosemaund going up to 48 at Munday's.

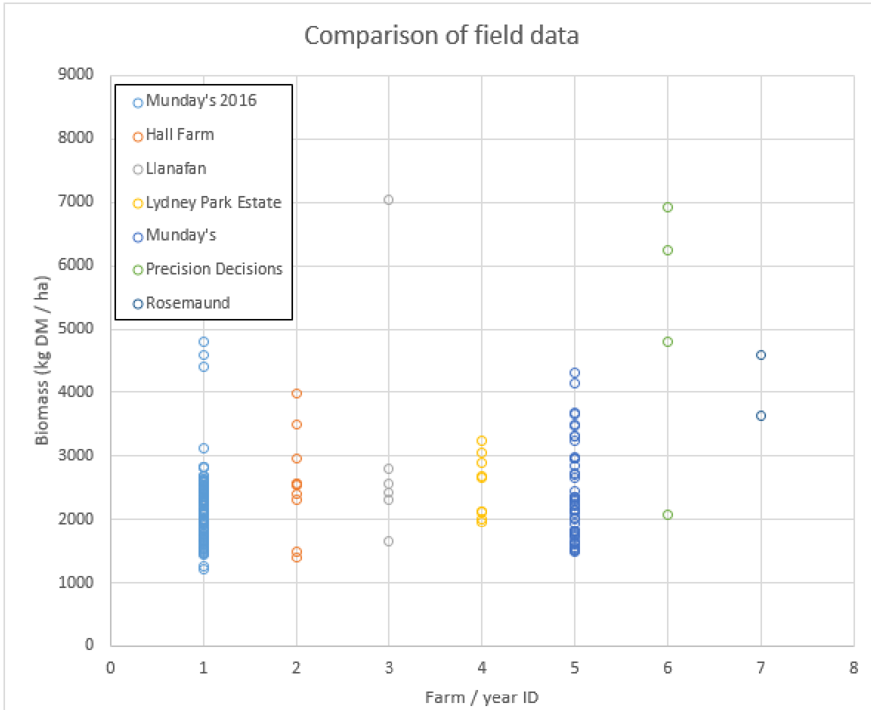

Figure 8 Comparison of the field data samples used in the comparison of the optical EO indicators and biomass for 2016 (dataset 2 - Munday's 2016) and 2017 (datasets 2 to 7).

Table 2 Number of field data samples used in the comparison of the optical EO indicators and biomass for 2016 and 2017 combined.

No.	Farm	Samples
1	Munday's 2016	100
2	Hall Farm	10
3	Llanafan	6
4	Lydney Park Estate	9
5	Munday's 2017	48
6	Precision Decisions	4
7	Rosemaund	2

Sentinel-2

The Sentinel-2 and ground reference data combined from 2017 offered 50 sample points from all six farms with dates ranging from late January to late May. The analysis of this dataset initially used closest ground reference data in time to the image acquisition, but immediately it was necessary to remove two paddocks at Munday's Farm that were grazed between field measurements and EO data acquisition. Also, it had been noted in WP3 that using ground data before or after image acquisition made a difference to the results, so it was vital to use the interpolated and extrapolated results as described above. It was also found necessary to exclude the extremely large biomass values associated with silage as it was clear that the VIs were not able to discriminate samples with a biomass above 4000 kg/ha.

Biomass

The relationships between the different EO-based vegetation indices and the average biomass of the paddocks were assessed by producing scatter plots (Figure 9) and calculating linear correlation coefficients (Table 3). Overall the relationships were of moderate strength due to the scatter that remains in the data caused either by the ground reference measurements, the EO data or more likely both. The indices which exploit the red edge bands seem to perform better than the more conventional indices which use broader spectral bands. However, these indices are only possible when using images from Sentinel-2. Interestingly the NDMI, which measures the moisture content of vegetation and would potentially be related to biomass, outperforms the visible / NIR indices, such as EVI and NDVI. This had been expected to be the case when analysing the 2016 data in WP3, but it produced a lower correlation coefficient in all cases in 2016.

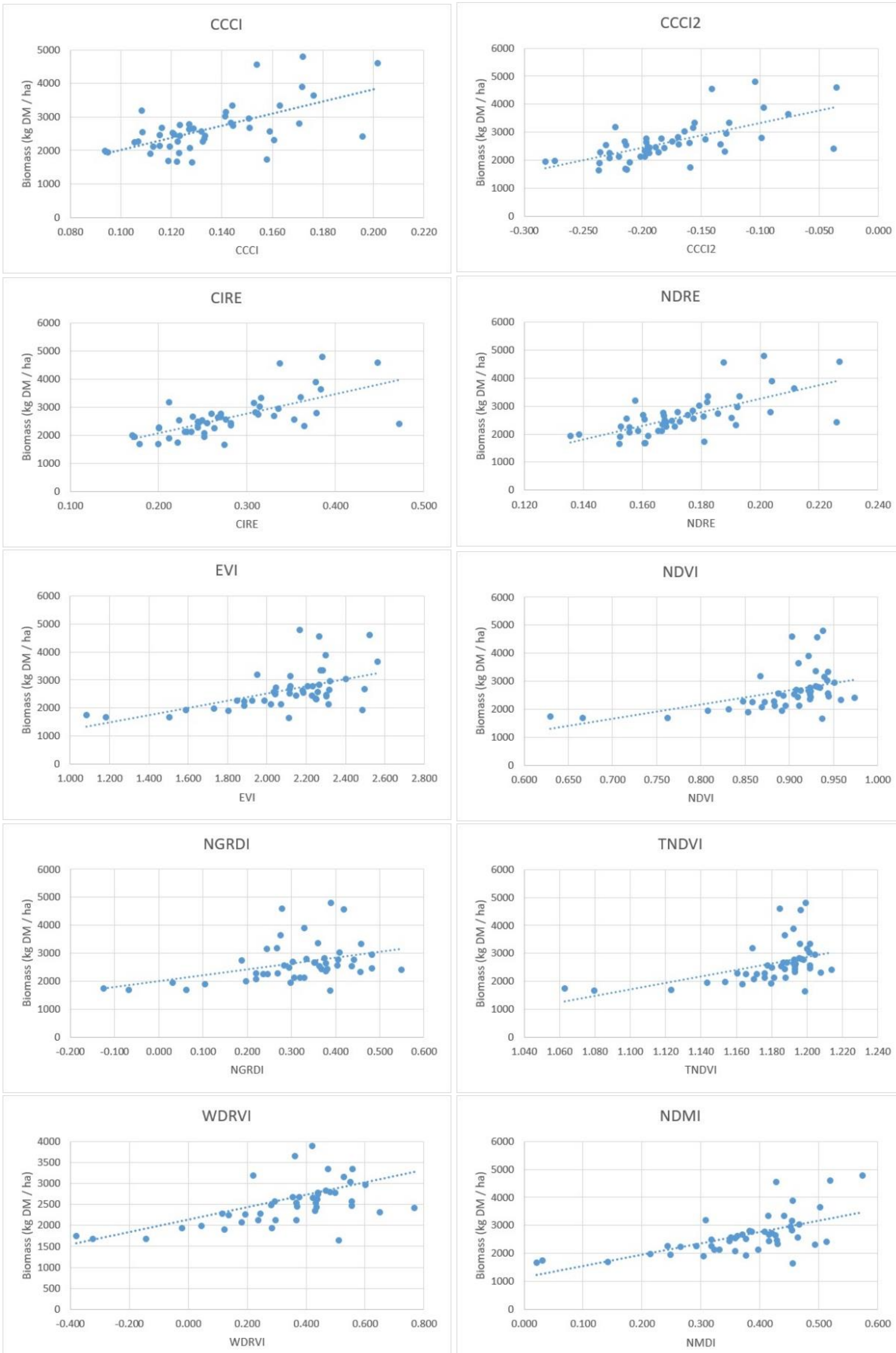

Figure 9 Scatterplots for the Sentinel-2 based indicators against the ground reference measurements of biomass.

Table 3 Linear correlation coefficients for the Sentinel-2 based indicators against the (interpolated) ground reference measurements of biomass.

Index	R^2
CCCI	0.3764
CCCI2	0.4359
CIRE	0.4509
NDRE	0.4359
EVI	0.2894
NDVI	0.2121
NGRDI	0.1561
TNDVI	0.2094
WDRVI	0.2217
NDMI	0.3902

By farm

When working with a range of farms in different landscape settings it is necessary to consider if the context of the measurement is impacting on the derived relationship. Selected indices were used to examine the impact of the farms / context by producing the scatterplots with suitably coloured points (Figure 10). There are no obvious separations between farms / context. However, there may be some slight differences in the trends, but there are not enough points to confirm this. The silage paddocks with high biomass again appear to fall outside the main distributions.

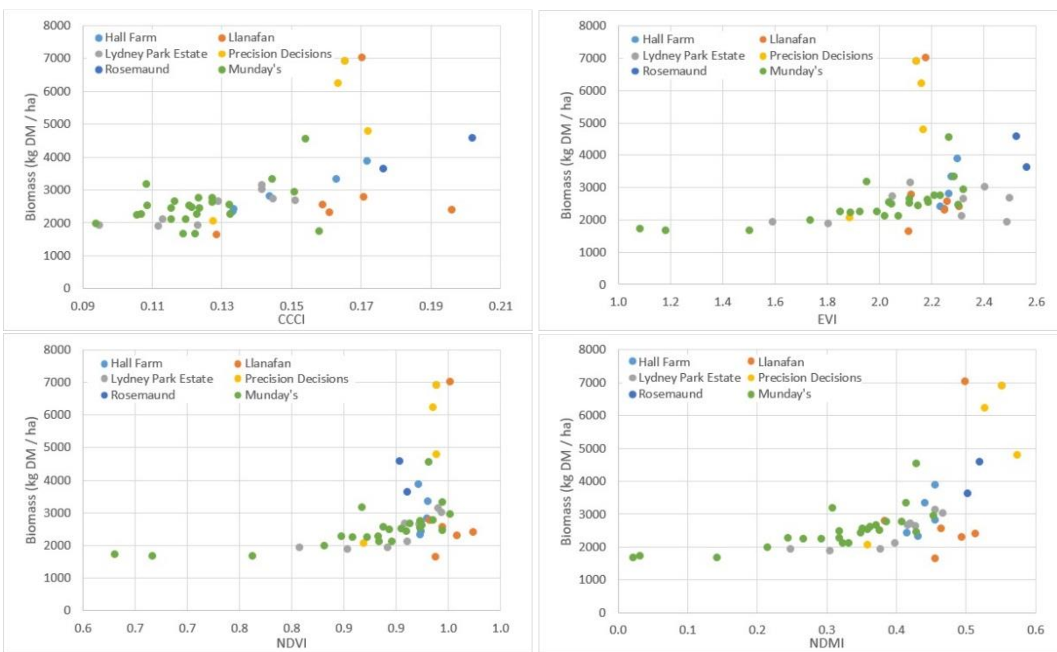

Figure 10 Scatterplots for selected Sentinel-2 based indicators against the ground reference measurements of biomass to show the impact of farms / context.

By date

In a similar way to the farm / context the results can also be examined by date to see if there are any impacts of the time of year when the images were acquired. Again, there was no obvious separation between dates, but the points are not evenly distributed between dates ranging from 2 to 26 samples per date.

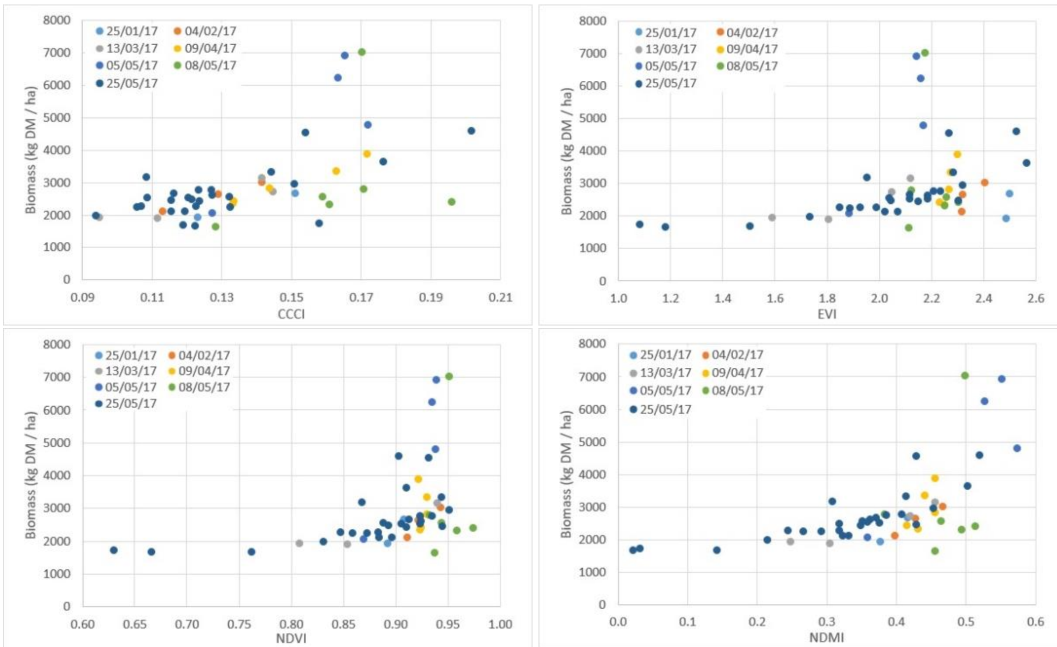

Figure 11 Scatterplots for selected Sentinel-2 based indicators against the ground reference measurements of biomass to show the impact of time of year.

Landsat 8

The Landsat 8 and ground reference data combined from 2017 offered only 29 sample points from only two farms with only two dates, both in March. As with the Sentinel-2 data, the analysis of this dataset initially used closest ground reference data in time to the image acquisition, but it was found necessary to use the interpolated and extrapolated results as described earlier. As both Landsat 8 images were in March it was not necessary to exclude the extremely large biomass values associated with silage as the paddocks at the two farms considered had not been able to accumulate sufficient biomass for silage by this time.

Biomass

The relationships between the different Landsat 8 based vegetation indices and the average biomass of the paddocks were assessed by producing scatter plots (Figure 12) and calculating linear correlation coefficients (

Table 4). Overall the relationships for Landsat 8 are stronger than those for Sentinel-2 even though some scatter remains in the data caused either by the ground reference measurements, the EO data or more likely both. As with Sentinel-2, the NDMI outperforms the visible / NIR indices suggesting a potential role in a grass monitoring service as it is working well with both optical sensors. Some of the success of Landsat 8 may be due to only two farms supplying data and for two images within 12 days, thus minimising farm / context and time of year issues which may other increase the scatter.

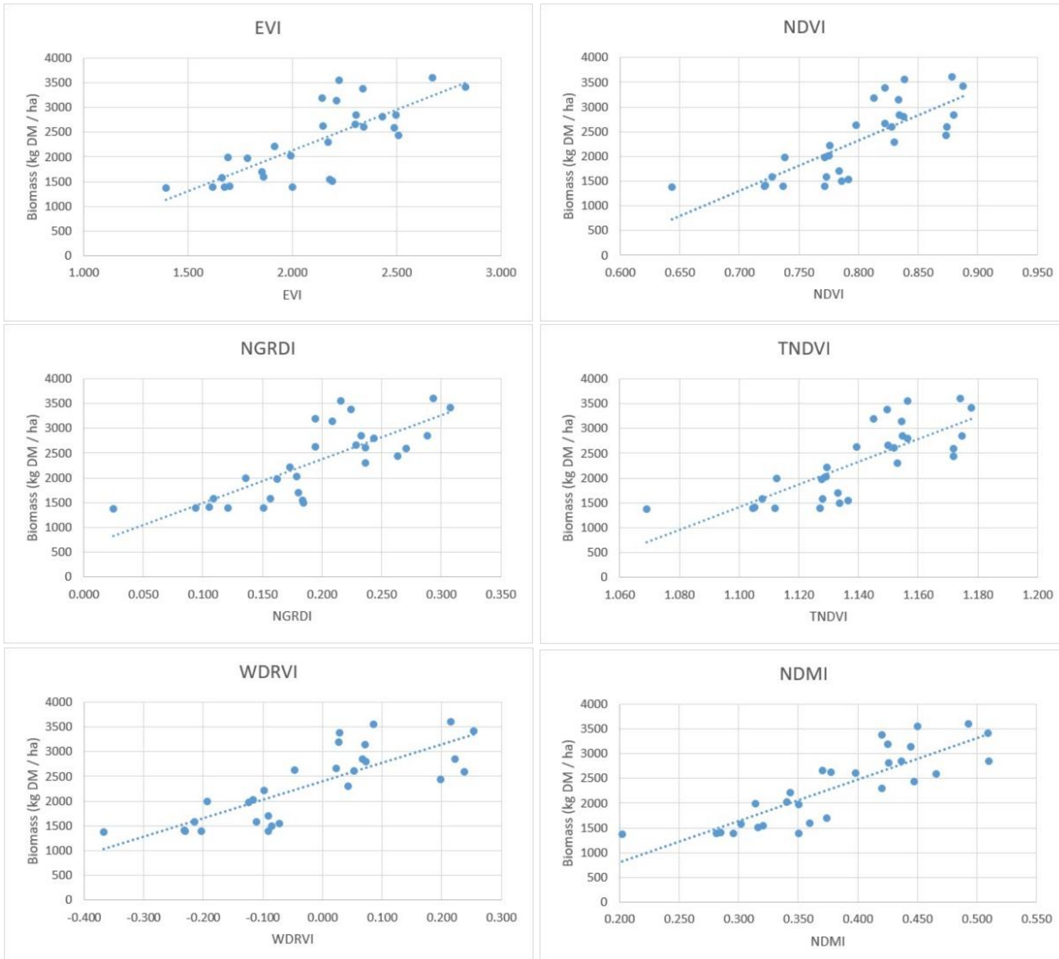

Figure 12 Scatterplots for the Landsat 8 based indicators against the ground reference measurements of biomass.

Table 4 Linear correlation coefficients for the Landsat 8 based indicators against the interpolated ground reference measurements of biomass.

Index	R^2
EVI	0.6025
NDVI	0.6212
NGRDI	0.6054
TNDVI	0.6169
WDRVI	0.6416
NDMI	0.7239

By farm & by date

As there were only two farms and two dates the assessment of the impact of farm / context and time of year was combined into a single analysis. Figure 13 shows the Hall Farm results for the 15th March 2017 and the Munday's Farm results for the 27th March 2017. There is no obvious separation by date or site in the Landsat 8 results.

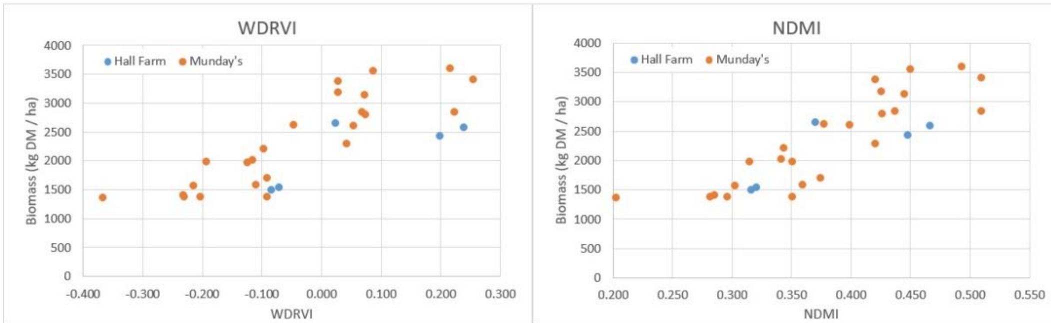

Figure 13 Scatterplots for selected Landsat 8 based indicators against the ground reference measurements of biomass to show the impact of farms / context and time of year.

Combined 2016 and 2017 results

The Landsat 8 data from 2016 had been successfully used to generate calibration equations between the WDRVI and biomass for Munday's Farm, therefore it was useful to compare the combined Landsat-8 for both years. The Hall Farm 2017 data seems to fit well within the data from 2016, but there were only 5 sample points. The Munday's Farm 2017 data is reasonably well aligned with the data from 2016, but it looks like there may be a different trend, possibly caused by the presence of some higher biomass points. This suggests that further research is required to fully understand the causes of these different trends. If the three datasets are combined a correlation coefficient of 0.4149 was produced, which was not as good as the individual relationships suggesting some confounding factors need to be accounted for.

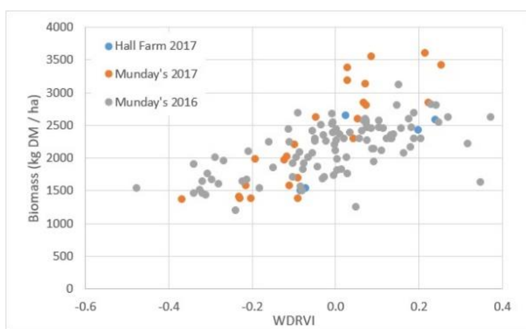

Figure 14 Comparison of the Landsat 8 derived WDRVI from 2016 and 2016 against the ground reference measurements of biomass.

Combined Sentinel-2 / Landsat 8 results

Within an operational system it will be necessary to combine Sentinel-2 and Landsat-8 data to get the best time series of grass biomass estimates and improve the likelihood of cloud-free data being available. The global remote sensing community is now working towards a situation where different sensors, of a similar class (i.e. spatial and spectral resolution), can be easily combined to produce large area coverages and rich time series through the concept of a virtual constellation of satellites. At the core of this development is the integration of Landsat 8 and Sentinel-2 imagery which could result in global 20 m spatial resolution coverages on a 2–3 day repeat cycle given suitable cloud cover conditions. These types of acquisitions, in particular, could support a grassland monitoring service such as those proposed in this project. Therefore, a temporally detailed time series (through the combination of Landsat 8 and Sentinel-2) has again been explored WP4.

Figure 15 show the comparisons of the relationships of the common indicators derived from Sentinel-2 and Landsat 8 against biomass. For a number of the Vis there are some deviations and different trends between the sensors, which could be related to calibration or band width differences. Of the six indicators that both sensors can produce, EVI and NDMI seem to give the more similar results. For some VIs it will be necessary to use different calibrations for Landsat and Sentinel-2.

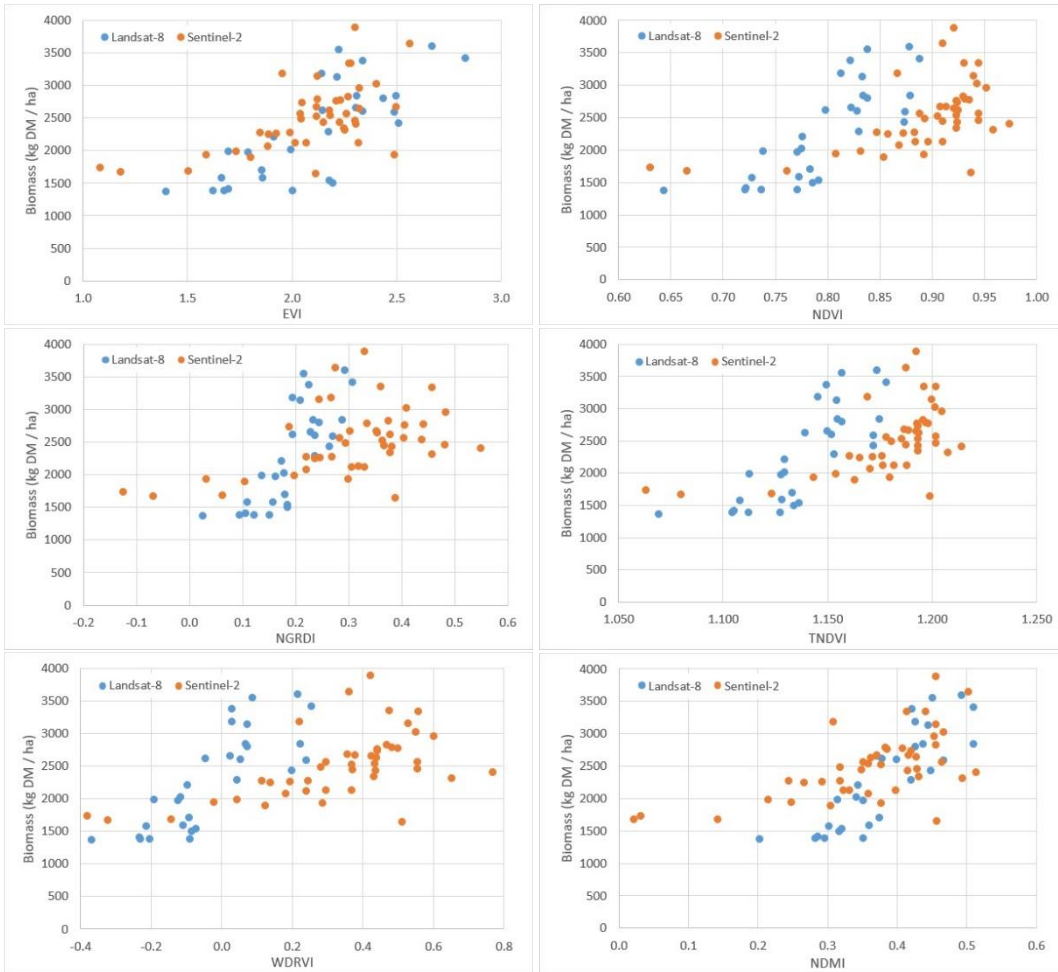

Figure 15 Scatterplots for the common Sentinel-2 and Landsat 8 based indicators against the ground reference measurements of biomass for 2017.

Sentinel-1

Initial investigation of the relationship between biomass and backscatter in WP3 involved plotting all the results for the paddocks and dates by polarisation. Both polarisations showed a broad scatter of points with little, if any, relationship to biomass. The Sentinel-1 analysis was repeated in WP4 to assess whether it was effective across a broader landscape context and potentially with greater high biomass paddocks in the sample.

Biomass

As with the WP3 Senitel-1 results there is little if any relationship between backscatter and biomass (Figure 16). Examination of the results by farm (Figure 17) did not provide any additional clarity. It would be expected that there would be a positive relationship between backscatter and biomass as greater amounts of vegetation would have more surfaces with the potential to scatter the incoming microwave energy back towards the sensor. In these results, it appears that paddocks with a range of biomasses can have the same backscatter and those with the same biomass can have a range of backscatters. Unfortunately, this tends to confirm the conclusion that the penetration capability of C-band SAR collected by Sentinel-1 is limited and the backscatter is restricted to the top canopy layers. Therefore, changes in biomass beneath closed canopy may not be detectable.

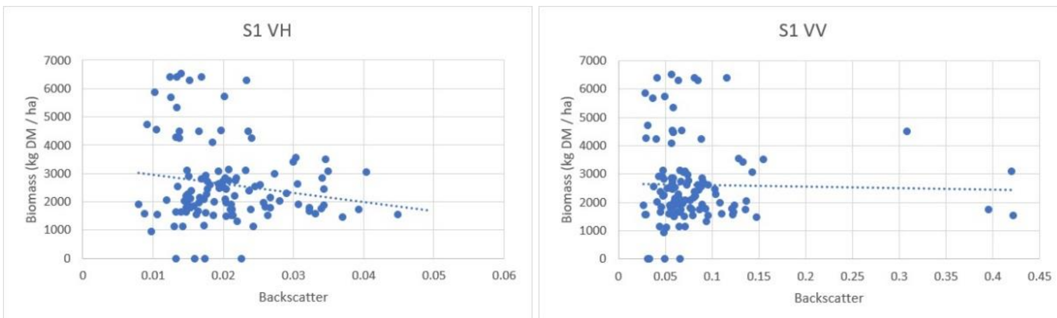

Figure 16 Scatterplots of Sentinel-1 backscatter against the ground reference measurements of biomass for 2017.

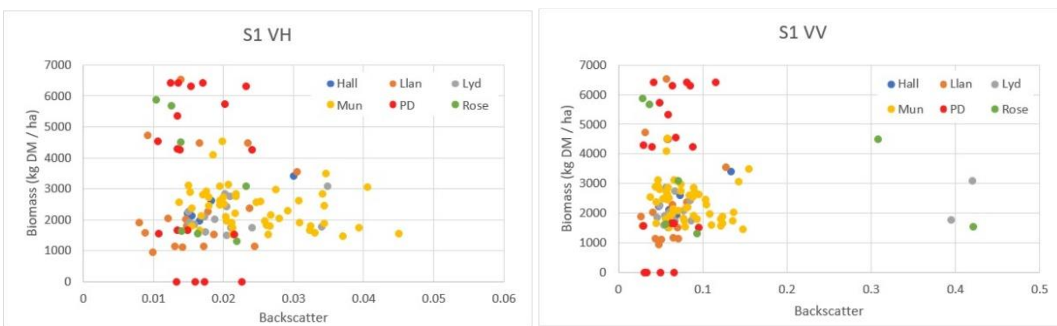

Figure 17 Scatterplots of Sentinel-1 backscatter against the ground reference measurements of biomass for 2017 by farm.

Grass Quality

Cloud cover for the optical imagery also limited the amount of data available for analysing the grass quality data. While data was collected on 3 different dates for each paddock sampled, only 18 of the sample incidents coincided with an optical image acquisition. These incidences were across 6 different farms and on different dates, making the data a mix of environments. All incidences coincided with Sentinel-2 satellite data, meaning continuity for the images. However, because there was never more than one date for each sample locations, regional analysis of the data was not possible.

The calculated Sentinel-2 VIs were then plotted against the grass sample results of Dry Matter, Crude Protein and Metabolisable Energy (ME). Figure 18 shows the scatterplots for the best performing VI for each sample parameter. Very little correlation can be seen between the Vis and grass sample parameters. It should be noted that there are only 18 data points, so additional data may improve the correlation.

Furthermore, imagery was only available from Sentinel-2. It would have been useful to have imagery from Landsat 8, although it is unlikely to provide a significant improvement in correlation.

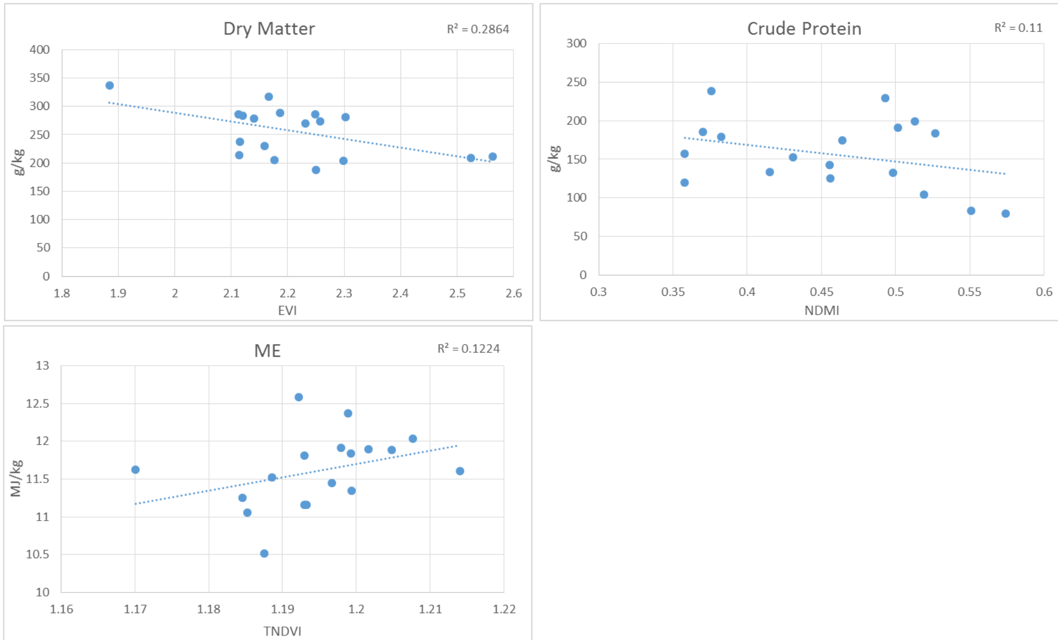

Figure 18 Scatterplots for the best Sentinel 2 based indicators against grass sample results for Dry Matter, Crude Protein and Metabolisable Energy (ME),

Calibrations for exploitation

From the relationships identified above between optical sensors and biomass measurements it was possible to develop calibration equations from the 2016 to 2017 data which can be applied to Landsat 8 and Sentinel-2 data via a selected vegetation index to estimate biomass remotely. These calibration equations will be deployed in the exploitable applications to be developed in WP6.

The following details of the indices and calibrations to convert EO data to biomass were supplied to the exploitation team.

Landsat 8 : Wide Dynamic Range Vegetation Index (WDRVI)

WDRVI is a modified NDVI that is more sensitive to moderate-to-high leaf area index (LAI) values. This allows more robust characterisation of crop physiological and phenological characteristics.

$$WDRVI = (0.1 * NIR - Red) / (0.1 * NIR + Red)$$

With Landsat 8 this becomes …..

$$WDRVI = (0.1 * Band\ 5 – Band\ 4) / (0.1 * Band\ 5 + Band\ 4)$$

Calibration to biomass …..

$$Biomass\ (kg\ DM / ha) = 1920.7*WDRVI + 2209.6 \qquad R^2 = 0.4149$$

Landsat 8 : Normalised Difference Moisture Index (NDMI)

NDMI provides a measure of vegetation moisture and is capable of detecting subtle changes in moisture conditions.

NDMI = (NIR - SWIR) / (NIR + SWIR)

With Landsat 8 this becomes …..

NDMI = (Band 5 – Band 6) / (Band 5 + Band 6)

Calibration to biomass …..

Biomass (kg DM / ha) = 8390.4 * NDMI - 878.4 $R^2 = 0.7239$

Sentinel 2 : Chlorophyll Index Red-Edge (CIRE)

CIRE provides a Leaf chlorophyll content which is an important variable because of its close relationship to leaf nitrogen content.

$C\mathrm{IRE} = (NIR\ /\ red\ edge) - 1$

With Sentinel 2 this becomes …..

CIRE = (Band 8 / Band 5) – 1

Calibration to biomass …..

Biomass (kg DM / ha) = 6990.7 x CIRE + 679.25 $R^2 = 0.5155$

By applying the calibration equations to the vegetation indicator data it is possible produce continuous variable maps of biomass for the paddocks at each farm. In the examples in this section the WDRVI has been used and the results show larger biomass values as darker shades of red. Figure 19 shows that the EO sensors are capable of replicating remotely the measurements that are made in the field by RPM or other approaches. It also shows the improvement in spatial detail that can be achieved by moving from field averages to Landsat 8 (30 m spatial resolution) to Sentinel-2 (10 m spatial resolution). The Sentinel-2 data in particular shows how EO data can be used to manage within paddock variation and track the progressing grazing of larger paddocks.

27/03/2017 Landsat 8 | 25/05/2017 Sentinel-2 | Interpolated / extrapolated ground data

Figure 19 Comparison of the biomass results using different sensor (left and middle) and ground reference (right) data from RPM. Darker red is larger biomass. Note all datasets are from different dates, so direct comparison is not possible.

Figure 20 shows the performance of the calibration of Sentinel-2 WDRVI to biomass across multiple farms surveyed during the 2017 field collection. In all cases the EO-based biomass maps are capable of providing useful information to the farmers.

Munday's | Hall | Lydney

Figure 20 Comparison of the biomass results from Sentinel-2 for different farms (darker red is larger biomass).

Implications of Research Findings

From the results of WP3 and WP4 the following conclusions can be drawn.

- The optical systems appear to be the most promising from this work, as although SAR systems are not hindered by cloud cover the subtle changes in biomass required by farmers are not detectable with C-band systems.
- The Landsat 8 data from the USGS and the Sentinel-2 data from the EU Copernicus programme in surface reflectance format offer a stable and robust source of spatio-temporal data from which to calculate paddock level vegetation indices.
- The red-edge bands of Sentinel-2 provide some additional capabilities compared to Landsat 8, but therefore present issues to combined time series. Work on intercalibrating the biomass estimates from different vegetation indicators is required.
- The usefulness of the NDMI in the 2017 analysis was very promising and could form part of a complimentary set of indicators mapping different aspects of the biomass.
- Sentinel-2B, which only became fully operational in summer 2017, offers great potential for increasing the number of images acquired per year due to its increased acquisition frequency and its ability to work in tandem with Landsat 8 due to their similar specifications.
- The establishment of a virtual constellation of Landsat 8 and Sentinels 2A & 2B through robust pre-processing to Analysis Ready Data could provide free input imagery with a 20 m spatial resolution at potentially 2 – 3 day intervals. The time interval could be reduced further by the inclusions of other systems with slightly different specifications and commercial costs.
- The expansion of the ground reference data collection, both spatially and temporally, in WP4 was aimed at extending and improving the calibration activities with the EO data. However, the poor cloud cover conditions and lack of Sentinel-2B data prevent this from being fully achieved.
- Beyond this project more farms / paddocks could be sampled to capture a wider range of biomass values and more evenly distributed across the range.
- The high biomass and silage paddocks remain an issue as they have very different characteristics in terms of VIs compared to the regularly grazed paddocks. Further work is needed to increase the number of these paddocks considered and temporally sample them in more detail.
- There is still quite a lot of scatter around the best fit line for even the best relationships observed, so other site factors should be considered for inclusion in the analysis to improve this.
- With the provision of the EO-based biomass products via an online tool it will be necessary to assess the fitness for purpose of the estimates of biomass to understand and quantify the uncertainties relative to the RPM measurements, what is acceptable to farmers in their decision making and what is required for model inputs.
- The supplied RPM data for calibrating the EO-based vegetation indices should be quality checked as at least one instance identified a mismatch between the RPM and the EO data.

Appendix 1 – Details of Existing Grass Growth Data Acquired

Farmer	Location	Grass data	Paddocks for detailed analysis
Jack and David Munday	Munday Farm, Sandford, Exeter, EX17 4LS	25 paddocks	16 Acres Bottom 16 Acres Bottom Middle 16 Acres Top 16 Acres Top Middle 21 Acres Bottom East 21 Acres Top East 21 Acres Top West 21 Acres Bottom West Broome Close Cow Meadow Far North Field Front Meadow Bottom Front Meadow Top Great Down East Great Down Middle Great Down West Henstil Ley Park Long Field East Long Field West Long Meadow Oxen Park East Oxen Park West Walnut Tree Bottom Walnut Tree Top
John Owen	Gelli Aur College, Carmarthenshire, SA32 8NJ	3 paddocks	Station Meadow 1 Station Meadow 2 Gelli Aur 1
Keith Davis	Lydney Park Estate, Lydney, Gloucestershire, GL15 6BU	5 paddocks	20 Acre A 19 Acre Canal B Middle Piece Factory Field
Ben Walker	Hall Farm, Attleborough, Norfolk, NR17 2AJ	5 paddocks	Allotments 2 Malthouse Colespit Blackpond Ladies Walk

Appendix 2 – Acquisition Dates for Analysed Imagery

Site/Collector	Paddock	Image 1		Image 2		Image 3	
		Date	Sensor	Date	Sensor	Date	Sensor
Hall	Allotments 2	15/03/2017	L8	09/04/2017	S2		
Hall	Ladies Walk	15/03/2017	L8	09/04/2017	S2		
Hall	Blackpond 2	15/03/2017	L8	09/04/2017	S2		
Hall	Malthouse	15/03/2017	L8	09/04/2017	S2		
Hall	Colespit4	15/03/2017	L8	09/04/2017	S2		
Llanafan	Pantwhylog - silage	08/05/2017	S2				
Llanafan	Brynele	08/05/2017	S2				
Llanafan	Cwmmarch	08/05/2017	S2				
Llanafan	Garnfach - grazed	08/05/2017	S2				
Llanafan	Garnfach - silage	08/05/2017	S2				
Llanafan	Pantwhylog - grazed	08/05/2017	S2				
Lydney	Factory Field	25/01/2017	S2	04/02/2017	S2	13/03/2017	S2
Lydney	Middle Piece	25/01/2017	S2	04/02/2017	S2	13/03/2017	S2
Lydney	20 Acre A	25/01/2017	S2	04/02/2017	S2	13/03/2017	S2
Lydney	19 Acre	25/01/2017	S2	04/02/2017	S2	13/03/2017	S2
Lydney	Canal B	25/01/2017	S2	04/02/2017	S2	13/03/2017	S2
Munday	16 Acres Bottom	27/03/2017	L8	25/05/2017	S2		
Munday	16 Acres Bottom Middle	27/03/2017	L8	25/05/2017	S2		
Munday	16 Acres Top	27/03/2017	L8	25/05/2017	S2		
Munday	16 Acres Top Middle	27/03/2017	L8	25/05/2017	S2		
Munday	21 Acres Bottom East	27/03/2017	L8	25/05/2017	S2		
Munday	21 Acres Bottom West	27/03/2017	L8	25/05/2017	S2		
Munday	21 Acres Top East	27/03/2017	L8	25/05/2017	S2		
Munday	21 Acres Top West	27/03/2017	L8	25/05/2017	S2		
Munday	Broome	27/03/2017	L8	25/05/2017	S2		
Munday	Cow Meadow	27/03/2017	L8	25/05/2017	S2		
Munday	Far North Field	27/03/2017	L8	25/05/2017	S2		
Munday	Front Meadow Bottom	27/03/2017	L8	25/05/2017	S2		
Munday	Front Meadow Top	27/03/2017	L8	25/05/2017	S2		
Munday	Great Down East	27/03/2017	L8	25/05/2017	S2		
Munday	Great Down Middle	27/03/2017	L8	25/05/2017	S2		
Munday	Great Down West	27/03/2017	L8	25/05/2017	S2		
Munday	Henstil	27/03/2017	L8	25/05/2017	S2		
Munday	Ley Park	27/03/2017	L8	25/05/2017	S2		
Munday	Long Field East	27/03/2017	L8	25/05/2017	S2		

Munday	Long Field West	27/03/2017	L8	25/05/2017	S2		
Munday	Long Meadow	27/03/2017	L8	25/05/2017	S2		
Munday	Oxen Park East	27/03/2017	L8	25/05/2017	S2		
Munday	Oxen Park West	27/03/2017	L8	25/05/2017	S2		
Munday	Walnut Tree Bottom	27/03/2017	L8	25/05/2017	S2		
Munday	Walnut Tree Top	27/03/2017	L8	25/05/2017	S2		
Precision Decisions	Well Lane - FRID-A	05/05/2017	S2				
Precision Decisions	Well Lane - FRID-B	05/05/2017	S2				
Precision Decisions	Well Lane - FRID-C	05/05/2017	S2				
Precision Decisions	JC-A	05/05/2017	S2				
Precision Decisions	JC-B	05/05/2017	S2				
Precision Decisions	JC-D	05/05/2017	S2				
Precision Decisions	SHIP-A	05/05/2017	S2				
Precision Decisions	SHIP-B	05/05/2017	S2				
Precision Decisions	SHIP-C	05/05/2017	S2				
Precision Decisions	SHIP-D	05/05/2017	S2				
Precision Decisions	RAM	05/05/2017	S2				
Rosemaund	Waterloo	25/05/2017	S2				
Rosemaund	Lower Meadow	25/05/2017	S2				
Rosemaund	Wilden	25/05/2017	S2				