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Exploring the Synergy of Optical and Radar imagery Towards Improving Thematic Mapping Accuracy of EO Data

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Abstract

Earth Observation (EO) technology provides a unique means of obtaining information on land use/cover and of its changes, which is of key importance in many scientific and practical applications. Such data is already widely used, for example, in environmental practices or decision making related to food availability and security. As such, it is imperative to examine the suitability of different EO datasets for this purpose, including their synergies. Through a case study focusing on Wales, this work aims at exploring the added value of the synergistic use of Optical and Radar data (from the Landsat TM and ASAR sensors respectively), towards improving the accuracy of land cover classifications from EO datasets. Two classifications – one based on optical data alone and another one developed from the synergy of optical and RADAR datasets acquired nearly concurrently were developed for the studied region. Evaluation of the derived land cover maps was performed on the basis of the confusion matrix using validation points derived from a Phase 1 Habitat map of Wales. In addition, McNemar's test was implemented to assess the statistical significance of the obtained results. The results showed statistically significant evidence that the use of optical data synergistically with the radar data provides more accurate land cover maps in comparison with the use of optical data alone.

Keywords: *Landsat, ASAR, land cover mapping, object-based classification*

1. Introduction

The European Space Agency (ESA) has long provided satellite based data for global and regional applications such as forestry, agriculture, environmental protection, and urban management. This has been mainly achieved through the Copernicus program (European Commission, 2012). Contributing to this extensive program is an array of satellite missions including optical instruments as well as altimetry systems, radiometers and spectrometers (European Space Agency, 2013a). The continual supply of reliable Earth Observation (EO) data and subsequently the derived products can provide key information on the distribution of land use/land cover (LULC) changes, both locally and at global scales. Such datasets can be analysed to indicate

changes due to anthropogenic activities, natural hazards or even climate change as a whole. The availability of this data is a key input to environmental policy makers the world over.

Food security is a global issue, the importance of which is highlighted by Lagi et al. (2011), in which the lack of economic access to food and water was identified as a major trigger for the 2008 African riots and 2011 Middle East riots. Organizations exist worldwide which aid a common goal of achieving a global food security. The foremost of these is the Food and Agricultural Organization of the United Nations (FAO), which aims to create and share critical information about food, agriculture and natural resources. A recent study by the FAO has found that approximately 870 million people around the world were chronically undernourished between 2010 and 2012 (Food and Agriculture Organization of the United Nations, 2012a). A key input into the policy making of the European Commission (EC) and other such organizations, is the information derived from remotely sensed EO data and it is at this point we can begin to discuss the role of remote sensing in the context of food security. For example, the European Monitoring Agricultural Resources Unit (MARS) is a project which aims to provide such information and it has been doing so since 1988. MARS activity has provided scientific and technical support on European agriculture and food security policies based on data at national, regional and continental scales, the likes of which have been used to inform the policy makers of the CAP (Joint Research Centre, 2013). Another such program, which operates on a larger scale, is the Copernicus Program, which is a joint collaboration between the EC, ESA and the European Environment Agency (EEA).

In terms of providing more specific information for food security purposes, crop mapping has been extensively undertaken using optical imagery (Petropoulos et al., 2012; Elatawneh et al., 2012; Devadas et al., 2012; Petropoulos et al., 2013; Lamine et al., 2018). Furthermore, the benefits of using remote sensing data for this purpose have been widely demonstrated (Congalton et al., 1998; Oetter et al., 2000) and the importance of time series data for high accuracy classification highlighted (Simonneaux et al., 2008; Srivastava et al., 2016). However, an ever occurring problem with the use of optical satellite data is the presence of cloud cover (Lamine et al., 2018). A method that overcomes this problem entirely, and a recent trend in remote sensing for food security and agriculture purposes, is the use of Unmanned Aerial Systems (UAS). Cloud cover becomes no longer an issue due to these instruments operating below the cloud. One such program, a joint collaboration between the Welsh Assembly Government, Environment Systems and Callen-Lenz Associates is Project URSULA (UAS Remote Sensing for Use in Land Applications). The project explored the potential for advanced remote sensing in land applications, primarily in high input arable farming (Project URSULA, 2013). This furthers research into the farm management strategy known as Precision Agriculture (PA) (Liaghat & Balasundram, 2010). PA aims to bring about an increase in the production efficiency, productivity and profitability of farms and as such, it contributes to food security as a whole.

SAR data has been used alone for purposes such as topographic mapping, oceanography, weather forecasting, geology mapping and crop and forest inventories. This therefore demonstrates the added value SAR can bring to LULC classifications. Studies have been able to produce accurate classifications of forest growth (Izzawati et al., 2006) biomass estimation (Le Toan et al., 1992) and forest architecture (Lucas et al., 2006). Specifically, the benefits of combining optical and SAR datasets to the process of generating a forest inventory and similar products have been outlined in detail by (Fernandez-Ordóñez et al., 2009).

Such data has indeed been shown to be useful in food security applications such as producing agriculture and crop monitoring (Blumberg, 2007; Chatziantoniou et al., 2017; Bao et al., 2018; Whyte et al., 2018). In terms of the latter, the need for data throughout the growing period has been highlighted and it is noted that when information gaps occur due to haze and/or cloud cover, classification accuracies generally become inadequate (McNairn et al., 2002). The ability of SAR systems to image throughout day and night whilst remaining immune to the issue of cloud cover can fill such information gaps during overcast periods, and therefore allow for reliable mapping of agricultural crops (Ban, 2003; Chatziantoniou et al., 2018). Furthermore, Vinay Dadhwal, Director of the India's National Remote Sensing Centre (ISRO), outlined the importance of EO data gathered through SAR sensors in the production of rice yield models during monsoon seasons – when cloud cover is extensive (Dadhwal, 2012).

Ling et al., (2012) was able to produce a forest and non-forest classification with accuracy in excess of 80% using multi-temporal alternating polarization (HH, HV) data. Another study using the same data (Thiel et al., 2009) further demonstrated the high accuracy that can be achieved with ASAR data in the production of a basic land cover classification. Additionally, the higher resolution Radarsat-2 instrument (also C-band) has been used alone in grassland studies and has been shown to provide a good separation of crops and improved grasslands through use of quad-pol (HH, HV, VV, VH) data (Buckley & Smith, 2010).

The present study focuses on the utilization of EO datasets in food security applications such as land and livestock yield modelling. The main aim of the present work is the implementation of two different techniques for the identification and discrimination of key land use/cover types in Wales; namely, the improved grasslands that are used as grazing land for livestock. The radar data used in this study was acquired from the Envisat ASAR C-Band SAR instrument which has already been proven to yield accurate classification results when used alone; several studies have demonstrated its use in producing land cover classifications. The techniques implemented are, one based on optical data alone, and another one developed from the synergy of optical and synthetic aperture radar (SAR) datasets acquired nearly concurrently. The two techniques are evaluated and the added value of a synergistic approach to LULC classification is assessed.

2. Materials and Methods

2.1. Study site

The country of Wales lies on the western side of the island of Great Britain and forms part of the United Kingdom. It has a coastline of approximately 870 miles and is bordered by England to the east and the Irish Sea to the west; Wales' total land cover is approximately 20,000 km² and it is primarily a mountainous country (Lucas et al., 2011). The study area itself is located in the coastal region of mid-west Wales within Cardigan Bay and has an Ordnance Survey grid reference of SN. Aberystwyth is the main urban area that can be observed in the study area and lies on the mouth of the river Ystwyth to the southwest of the image (Figure 1). The northern extent is marked by the distinctive Dovey estuary, whilst eastwards the study area reaches into the Cambrian Mountains. The total size of the study area is approximately 400 km².

Welsh land cover is known for its high diversity (Blackstock et al., 2007). Accordingly, a variety of land cover types are contained within the study area, from the lowlands near the coast to the uplands in the west of the image. Lowland areas do not exhibit many areas of unimproved grassland and consist mainly of land used for agricultural purposes. Therefore, large amounts of

improved grasslands, containing *Lolium Perenne*, are present, in addition to arable land. The lowland areas also contain an extensive mass of raised bog located at Borth Bog and, in addition to Aberystwyth, smaller urban settlements are noticeable. The uplands are home to a wide range of habitats, which include bogs, heather moors and water bodies. The most noticeable, in the right-center of the image (Figure 1), is Nant y Moch reservoir. Furthermore, the Cambrian Mountains account for a large portion of Welsh blanket bog as well as wet and dry heathland. Also found here, are areas of Atlantic Oak woodlands (Cambrian Mountains Society, 2013). Additional areas of upland woodland consist of Sitka Spruce plantations and European Larch; Broadleaved and mixed woodlands can be found in the lowlands (Lucas et al., 2011). Other species found in upland areas include bracken and gorse, in addition to *Vaccinium*- and *Molinia*-dominated marshy grasslands. A substantial amount of dry, wet and blanket bog with hummock forming species including *Caluna Vulgaris* and *Juncus* are also present. Grasslands include some improved areas, as well as acid and neutral grasslands, and extensive areas of unimproved grassland.

Figure 1. Location and extent of the study area.

2.2. Datasets

For the purpose of our study multi-sensor EO datasets were used in order to show how the synergy of such data can improve classification results. SAR and optical satellite data were used for this purpose. Envisat ASAR Alternating Polarisation (AP) data was used and acquired from the Landmap service (<http://www.landmap.ac.uk>). Data was provided with a Level 0 Alternating Polarization product (AP0) from an ascending orbit. Focusing of the raw data to a Single Look Complex (SLC) image was carried out, followed by multi-looking; a technique which improves the radiometric resolution of the data at the expense of the spatial resolution. This is achieved by processing portions of the signal responses individually before combining them to create the final result of an N-look image, where N is the number of processed portions, or looks (Rees, 1999). A spatial resolution of 25m was achieved. As a result of the multi-looking process, speckle is reduced. However, for further speckle reduction, an additional spatial filter was applied utilizing a moving window across the image. Landmap used the Frost filter, described as an adaptive filter,

which calculates the pixel values within a window using an adaptive exponential impulse response (Sarmap, 2007). A 5x5 pixel window size was used.

The images were then geocoded and terrain corrected using 75m Shuttle Radar Topographic Mission (SRTM) data and projected to the British National Grid. Lastly, radiometric calibration was carried out to produce image data displaying the geocoded backscattering coefficient (Sigma-nought, σ^0) values as a linear (decimal) figure. The backscattering coefficient is a conventional measure of the strength of radar signals reflected by a distributed scatterer. Therefore, it denotes the effectiveness of a surface at scattering the radiation incident upon it (Rees, 1999). The steps detailed above were carried out using the SARscape extension in ENVI 4.7. The end-result, and thus the dataset provided by Landmap, consists of two coherent greyscale SAR images (HH and HV) in GeoTiff format. The images are projected to the British National Grid at a spatial resolution of 25m and the pixel values correspond to the observed backscattering coefficient.

The optical data used in this study was a Landsat 5 TM scene acquired from the USGS GloVis service (available at <http://glovis.usgs.gov>). Landsat 5 had a repeat cycle of 16 days and carried a MSS instrument along with the TM (Loveland & Dwyer, 2012). A Level 1T product was downloaded, indicating that standard terrain correction had been carried out using ground control points from the Global Land Survey 2000 (GLS2000). The data was acquired as a GeoTiff file in raw digital number format. The location of the full scene was at Path 204, Row 23, as close as possible to that of the SAR data. No significant cloud cover was present in the total scene (170 km x 185 km). The data was provided resampled to the Universal Transverse Mercator (UTM) Zone 30N – World Geodetic System (WGS) 84 geographic projection using the cubic convolution method (United States Geological Survey, 2013). Overall, spatial resolution was 30m in the reflectance bands and 60m in the thermal band.

In addition to the satellite-based data, several other datasets were acquired. A shapefile containing the administrative boundaries of Wales was acquired and used in the validation of data georeferencing. The file was provided by DIVA-GIS¹, a free web-based spatial data resource. Additionally, a Digital Elevation Model (DEM) for the study area was acquired at a 30m spatial resolution to be used as a factor in the classification process. It has been shown in numerous studies that the inclusion of elevation data can yield better classification results when compared to the optical data alone (Elumnoch & Shrestha, 2000). A further supplementary dataset, the Phase 1 habitat map, was acquired in shapefile format and used as a reference when selecting appropriate representative training areas. It should be noted that the Phase 1 habitat map dates back to the year 1997 and therefore land cover may have changed between the completion of the map and the acquisition of the satellite data. As such, it was used as a guide only, with thought given to land cover observed in the Landsat scene, reference to high-resolution imagery available through Google Earth, as well as personal knowledge of the area developed through a field study. The Phase 1 habitat map was acquired through the Countryside Council for Wales's website (available at <http://www.ccw.gov.uk/landscape--wildlife/habitats-species/terrestrial/habitats/habitat-surveys.aspx?lang=en>). A summary of all the satellite data used in this study is provided in Table 1.

Table 1. Distribution of land cover types across the study area.

	Optical dataset	SAR dataset
Sensor name	Landsat 5 TM	Envisat ASAR

¹ www.diva-gis.org

Date of acquisition	Sept. 13, 2003	Sept. 25, 2003
Spatial resolution	30m	25m
Band information	Blue (0.45 – 0.52 μ m) Green (0.52 – 0.60 μ m) Red (0.63 – 0.69 μ m) NIR (0.76 – 0.90 μ m) MIR (1.55 – 1.75 μ m) TIR (10.40 – 12.50 μ m) MIR (2.08 – 2.35 μ m)	C-Band (5.6cm)
Polarization		HH/HV

2.3. Pre-processing

In order to prepare the datasets for analysis, it was necessary to undertake several pre-processing steps. The first steps consisted of the radiometric correction of the Landsat TM data to Top of Atmosphere (TOA) reflectance. Additionally, the ASAR AP intensity product was converted to the backscatter coefficient in units of decibels (dB). Georeferencing and subsetting of the data then followed, after which a Cloud and Cloud Shadow mask was generated. The next steps consisted of the derivation of further data products in the form of radar texture measures and the NDVI, as well as the generation of a synergistic data file, which is used in the sample selection, rule set generation and classification processes. The final steps consisted of performing an evaluation of classification accuracies followed by a direct comparison using McNemar's test.

The process of Top of Atmosphere (TOA) correction was carried out to convert the digital numbers (DNs) in the raw data to meaningful reflectance values suitable for interpretation. The USGS provided the data as separate image bands in GeoTiff format. Band calibration was therefore carried out individually using the Landsat Calibration tool in ENVI 4.7 (Excelis Visual Information Solutions, 2013) before being combined into a single GeoTiff file. This study made use of the reflectance bands only (bands 1 -5); the thermal band (6) was omitted.

Georeferencing is the process of spatially aligning datasets to ensure that they are aligned to the same geographical area. The importance of such a procedure must be stressed when working with data from different sensors and at different spatial resolutions. Registration errors between datasets have been identified as a major limiting factor in the accuracy of products derived from a multi-sensor approach to remote sensing data analysis (Alecu et al., 2007). In the context of LULC classifications, it is imperative that data is aligned over the same surface features to enable a reliable classification. Therefore, a significant amount of time was dedicated to this process in order to achieve the desired outcome of a sub-pixel accuracy. The Landsat TM Level 1T product was acquired in the UTM projection, Zone 30N, WGS84 datum. The shapefile representing the boundary of Wales was used to validate the projection. Additionally, the DEM was acquired at this projection and the alignment validated similarly. When projected to WGS84 UTM Zone 30N, the ASAR AP data was not correctly aligned with the other datasets and therefore georeferencing was necessary. Due to its geometric accuracy, the Landsat TM scene was chosen to act as a base image onto which the ASAR AP (distorted image) data would be warped.

Finally, as stated before, one of the factors hindering observations using optical remote sensing systems is cloud cover, some of which is present in the Landsat TM imagery acquired. Cloud shadows particularly can be difficult to classify as they vary spectrally based on the features they cover (Sawaya et al., 2003). The areas of cloud and cloud shadow within the imagery were removed through the use of a mask produced by manually digitizing the areas. Thus, thematic

layers were created allowing these areas to be classified and therefore masked from the rule-based classification process.

2.4. Derived products

Texture measures were computed for both the HH and HV polarized ASAR images, similarly to other relevant studies, such as Haack et al. (2000), Chu et al. (2010), and Laurin et al. (2013). Radar data generally exhibits a high amount of texture in comparison to optical data due to the complex interactions of the radar signal (Haack et al., 2000). Texture data can therefore better classify areas where there is not necessarily a unique reflectance or backscatter value, but a variance of the value. The incorporation of various forms of digital texture measurements has been shown to improve classification accuracies (Simard et al., 2000; Singh et al., 2016; Dekker, 2003; Chatziantoniou et al., 2018; Whyte et al., 2018;). The methods used herein to extract the texture measures were based on the use of the Grey Level Co-occurrence Matrix (GCLM). This matrix is used as a foundation on which textural variation can be quantified (Sonka et al., 1998). These measures are calculated using moving array of cells referred to as a window. The texture value of the center cell within the window is derived through a mathematical equation which considers all cell values within the moving window (Haralick et al., 1973).

The Normalized Difference Vegetation Index (NDVI) was used for acquiring the phenological information regarding the land cover represented within each image. NDVI values were estimated on a per-pixel basis using the corresponding bands of the TM instrument (band 3 represents the red reflectance values and band 4 the NIR reflectance values).

In addition to the generation of the NDVI and SAR texture products, the data was merged to form a single multi-band GeoTiff file; the synergistic dataset. This consisted of the six reflective bands of the TM instrument assigned to bands 1 through 6, with bands 7 and 8 corresponding to the ASAR backscatter coefficient values in decibels at HH and HV polarizations, respectively. The NDVI was assigned to band 9 and the following five bands, from 10 to 14, contained the texture measures. In order, these were the Mean, Variance, Homogeneity, Entropy and Correlation texture data calculated from the HH polarized ASAR image using a 9x9 window size. The same texture measures corresponding to the HV polarized image make up bands 15 through 19. The final ten bands (20 through 29) are comprised of the same HH and HV textures measures, this time calculated using a 13x13 moving window.

In the creation of this one file, all data to be used, having the same spatial resolution and extent, is stored together. In addition to providing a container for the data, the synergistic data file allowed the incorporation of the SAR data and texture measures in the generation of color composite images. Overall, this allowed for a better visual interpretation of the study area.

2.5. Classification

The approach adopted to produce the two thematic maps, one based on the optical data and the other produced using the synergistic dataset, was based on an Object-Based Image Analysis (OBIA) approach. The analysis of EO datasets through use of OBIA methods is a trend that has seen increased attention within the past decade (Blaschke, 2010; Whyte et al., 2018). It differs from the more traditional pixel-based approach by analyzing groups of pixels together as opposed to each pixel individually. All analysis was carried out in Trimble eCognition Developer (Trimble,

2013), a commercial OBIA software package. Implementation of OBIA for image classification consists of a Segmentation process followed by a Classification of the segments into user-specified classes. Here, image segmentation was performed using the Multi-resolution Segmentation algorithm. This bottom-up region-merging technique uses an algorithm which considers each pixel as a separate object before merging similar pixels to form larger image objects, or segments (Rahman & Saha, 2008). Pixels are only merged to form segments when a segment homogeneity criterion is satisfied. This criterion is determined through definition of Scale, Shape and Compactness parameters, which specify the properties that the resulting segments should have.

An initial chessboard segmentation using a scale parameter of 1 was executed and resulted in each pixel becoming a separate segment. This was to allow the individual pixels displaying areas of cloud and cloud shadow to be classified as such, and thus allow only the cloud-free image data to be segmented for the rule-based classification. Following the classification of Cloud and Cloud Shadow, the remaining unclassified pixels were classified as either Uplands or Lowlands based on thresholding the DEM. Areas below an elevation of 260 meters were classified as Lowlands and those above this height classified as Uplands. Subsequently, these areas were individually segmented to appropriate sized segments through use of the multi-resolution segmentation algorithm.

Having masked out Cloud and Cloud Shadow and established appropriately sized image segments, the next step was to select sample areas for the classes. As this study is interested in demonstrating the added value of SAR data to the classification process, certain control measures were implemented. The first of these was the use of a common set of sample areas. This was to ensure that any greater separability that may arise from one approach, would not be the result of better sample area selection. Similarly, the second control measure was to ensure that the accuracy assessment of both thematic maps would make use of the same set of test areas. This was necessary to allow a comparison of the accuracy of each classification.

The chosen classes were the generalized land cover types that can be observed in the study area: Improved Grasslands, Unimproved Grasslands, Arable/Dry Land, Raised Bog, Urban, Woodlands, Standing Water and Sea. Sample areas were selected for each of these classes based on a combination of visualizing different color composites of the data, using personal knowledge and the examination of the Phase 1 map in addition to higher resolution satellite imagery courtesy of the Google Earth software program. Naturally, visual examination and experience of interpreting satellite imagery was sufficient for the selection of Sea, Standing Water, and Urban sample areas. The addition of study area knowledge allowed for the selection of areas of Raised Bog. In addition to the previous selection methods, Improved Grasslands, Unimproved Grasslands, Woodland, and Arable/Dry Land areas were selected by further referring to the Phase 1 map overlaid onto the Landsat TM data. High resolution satellite imagery available from Google Earth was examined over these areas to provide some validation. Only areas which had shown no extensive temporal change were chosen as samples. The mean spectral responses from the samples for each class are provided in Figure 2.

Figure 2. Spectral response of each class across the Landsat TM bands (Band 6 on the graph corresponds to band 7 of the TM instrument (SWIR2)).

The selection of class sample areas allowed for the examination of their corresponding reflectance, backscatter, elevation, texture and NDVI characteristics. It was with this information that rule sets with the goal of classifying the land cover into the given classes were generated. Two separate rule sets and classifications were produced. The first was generated through consideration of class responses in the Landsat TM bands, NDVI and the DEM of the study area. The second rule set considered these in addition to incorporating the ASAR HH and HV backscatter coefficients, as well as the corresponding texture measures and the difference and ratio images. In both cases, the feature histograms for each class were examined extensively to determine those features which allowed for a greater degree of separation between the classes. Rules were then developed to act as conditions that a segment must satisfy in order to be classified as the respective class. Single thresholds were used in addition to simple Boolean operations and more complex fuzzy membership functions. Following the application of each rule set to the image data, a corresponding thematic map was produced. To aid visual interpretation and improve the map aesthetics all segments within a class were merged into larger image objects. The results of both classification procedures were subsequently exported as shapefiles, with attribute tables containing the class names, for further manipulation.

3. Results

As a result of the individual classifications of the optical and synergistic approaches, two corresponding thematic maps were produced, while the selection of test areas allowed for an accuracy assessment of the two maps. The results obtained are provided below.

3.1. LULC classifications

The resulting thematic maps based on the optical and synergistic approaches, are shown in Figures 3 and 4, respectively. Firstly, Sea was separable from the other classes through a

characteristically low NDVI as well as SWIR values. Using the synergistic approach, the backscatter values for HH in decibels allowed for a higher degree of separability of the Sea class. This was due to the prevalence of surface reflectance and therefore the HH dB feature was used in this rule set. The thresholds used to classify the Standing Water class in the optical approach were also based on the NDVI and SWIR1 features, with the inclusion of Blue reflectance to separate it from the similar Sea class. In the rule set generated for the synergistic approach, the backscatter values observed at the HV polarization were very distinguishing features of Standing Water. Due to the stationary nature of water bodies such as lakes, surface reflectance is the majority scattering mechanism observed. Conversely, very little volumetric scattering takes place and as a result the backscatter measured at the HV setup was very low. Furthermore, it was consistently low over the sample areas and as such, the main feature selected for this class was the Mean texture measure derived from the HV polarized image. It appeared that the window sizes used in the generation of the texture measures, in this case and overall, did not have a large effect on the observed separability of the classes; any differences were negligible.

Urban areas and areas of Arable/Dry Land were quite similar spectrally. Even with the use of the NDVI and DEM there was some overlap between the classes. However, these two classes became immediately separable on examination of the SAR data, both at the HH and HV polarizations. This is attributed to the different scattering mechanisms observed; arable land is generally flat land, meaning surface reflectance is more prominent, whereas the abundance of buildings in urban areas creates more of the double bounce scattering mechanism. A much greater degree of volumetric scattering was observed in the Urban class when compared to Arable/Dry land and the neighboring classes in the image. Furthermore, the HV Correlation texture measure was able to highlight this fact and as a result, both the HV dB and the HV Correlation (using a 9 by 9 window) features were used in the synergistic classification of Urban areas.

Figure 3. LULC thematic map produced using the optical classification approach.

Figure 4. LULC thematic map produced using the synergistic (i.e. optical & RADAR) classification approach.

Arable/Dry Land areas on the other hand were classified using the Mean, Variance and Homogeneity texture measures derived from the HH polarization. This was because not only did these areas show greater surface scattering, but there was little variance in this, and the backscatter values were largely consistent over the areas. Again, the textures produced using a 9 by 9 window were used.

Another class which was shown to be highly separable in the SAR data was Woodland. In the optical classification approach, the NDVI and SWIR2 reflectance values were used in the rule set, as well as reflectance in the Green band. With the incorporation of the SAR data it was clear to see the Woodland areas due to the large amount of volume scattering that is characteristic of such areas. Therefore, the backscatter values at HV polarization were used in the synergistic rule set in place of the reflectance in the Green Band. The result was that the synergistic classification (Figure 4) was able to pick up more of the smaller areas of woodland in the study area, including some areas near the Dinas Reservoir (found in the lower right corner of the map), as well as small areas in the lowlands.

Borth bog, the prominent region of raised bog in the study area, was classified in the optical approach through use of the NDVI as well as the DEM, as it exists at a very low elevation. In addition, its reflectance at the Green and SWIR1 bands were selected as they were shown to be quite definitive. When examining Borth bog in the SAR imagery, the samples showed a largely consistent value of backscatter at the HH polarization. This was highlighted in the HH Variance texture measure (9 by 9 window size), and was therefore used in the synergistic rule set along with the NDVI and DEM thresholds. When examining the two classifications, the synergistic result has classified a larger area of raised bog.

The final two classes of Improved and Unimproved Grasslands were shown to be spectrally similar; Figure 2 illustrates this point well. As a result, the optical-based rule set of the two classes, was built around the NDVI and the reflectance in the Red and NIR bands. Improved Grasslands, generally being healthier, exhibited a characteristically higher NDVI value than the Unimproved Grasslands and therefore a simple threshold was applied. However, the reflectance of the two classes in the Red and NIR bands varied. As a result, fuzzy membership functions were computed and used in the rule set for each class.

Notably, the incorporation of the SAR data did not enhance the separability of these classes. After thorough examination of the backscatter responses and texture measures, it was apparent that no SAR-derived feature would further aid the classification. The features which mostly defined these two classes remained to be the NDVI and the Red and NIR reflectance values. This illustrates that, in this case, the difference between the two classes came down to their spectral properties as opposed to their structural properties.

3.2. Accuracy assessment and McNemar's test

The confusion matrices corresponding to the optical and the synergistic classification approaches are shown in Tables 2 and 3, respectively. Table 4 provides the contingency table, forming the basis of McNemar's test. The first step of McNemar's test is to calculate the chi-squared value from the information provided in that table. This is calculated as follows:

$$\chi^2 = \frac{(0-11)^2}{0+11} \therefore \chi^2 = 11 \quad (1)$$

When compared to the critical value for the 95% confidence interval (3.84), the chi-squared value calculated above is greater than the critical value. Thus, the condition on which to reject the null hypothesis is satisfied and the alternative hypothesis is accepted. Therefore, McNemar's test clearly shows a significant improvement in the LULC classification produced through the synergistic approach over that produced through the optical approach. The improvement is shown to be statistically significant at the 95% confidence interval. Furthermore, on examination of the critical values for the 99% and 99.9% confidence intervals (6.64 and 10.83, respectively), the chi-squared value of 11 is greater than both of these critical values. Therefore, not only is the improvement in the classification result statistically significant at the 95% confidence interval, but it is significant up to the 99.9% confidence interval.

Table 2. Confusion matrix corresponding to the LULC map produced by the optical approach (Figure 3). UP: Uplands; LOW: Lowlands; SW: Standing Water; W: Woodland; IG: Improved Grasslands; UG: Unimproved Grasslands; RB: Raised Bog; S: Sea; U: Urban; A/D: Arable/Dry Land. Green cells indicate correct allocations.

Classification	Sample	UP	LOW	SW	W	IG	UG	RB	S	U	A/D	Sum
UP		0	0	4	4	0	1	0	0	0	0	9
LOW		0	0	0	2	0	0	2	0	2	0	7
SW		0	0	5	0	0	0	0	0	0	0	5
W		0	0	0	11	0	0	0	0	0	0	10
IG		0	0	0	0	13	2	0	0	0	0	15
UG		0	0	0	0	1	6	0	0	2	0	9
RB		0	0	0	0	0	0	3	0	0	0	3
SW		0	0	0	0	0	0	0	4	0	0	4
U		0	0	0	0	0	0	0	0	6	2	8
A/D		0	0	0	0	0	0	0	0	1	4	5
Sum		0	0	9	17	14	9	5	4	11	6	75
Overall Accuracy		0.69									Total Correct	52
Kappa Coefficient		0.65										

Table 3. Confusion matrix corresponding to the LULC map produced by the synergistic approach (Figure 4). Notation is explained in Table 2. Green cells indicate correct allocations.

Classification	Sample	UP	LOW	SW	W	IG	UG	RB	S	U	A/D	Sum
UP		0	0	3	0	0	1	0	0	0	0	4
LOW		0	0	0	0	0	0	0	0	2	2	4
SW		0	0	6	0	0	0	0	0	0	0	6
W		0	0	0	17	0	0	0	0	0	0	17
IG		0	0	0	0	13	2	0	0	0	0	15
UG		0	0	0	0	1	6	0	0	1	0	8
RB		0	0	0	0	0	0	5	0	0	0	5
SW		0	0	0	0	0	0	0	4	0	0	4
U		0	0	0	0	0	0	0	0	8	0	8
A/D		0	0	0	0	0	0	0	0	0	4	4
Sum		0	0	9	17	14	9	5	4	11	6	75
Overall Accuracy		0.84									Total Correct	63
Kappa Coefficient		0.81										

Table 4. Contingency table based on confusion matrices shown in Tables 2 and 3.

Synergistic approach			
Optical approach	Correct	Incorrect	Total
Correct	52	0	52
Incorrect	11	12	23
Total	63	12	75

4. Discussion

It is clear that the incorporation of the SAR data and derived texture measures has yielded a LULC classification with an increased accuracy. However, the accuracy of the optical classification approach alone is surprisingly low considering the basic land covers used. This is attributed to the

test area distribution, as over one-third of the test areas were in the Woodland and Urban classes; classes which were more accurately determined through the synergistic approach. As such, the accuracy of the optical approach seems to have been affected. However, it can be seen from the confusion matrices and from visual comparison of the two thematic maps that the synergistic approach did perform better in overall, and the improvement in accuracy was statistically significant. Therefore, there is a strong case for further development of the methods shown here to provide more research into synergistic LULC classifications.

In this study, the inability of the SAR data to provide separation of the Improved and Unimproved Grasslands is attributed to the wavelength of the Envisat ASAR instrument relative to the scattering features of these classes; from the C-band perspective both classes appeared to exhibit a similar surface roughness. The wavelength of the ASAR instrument is approximately 5.6 cm; therefore, due to the similarity observed in the class responses, it can be inferred that overall the classes were shown to have scattering objects of a similar size and distribution. However, this itself could be a result of using the broad class labels of Improved and Unimproved Grasslands; a point that will be further discussed below. It is therefore understood that the use of X-band SAR data, such as that from the TerraSAR-X instrument, over the study area would aid in the separation of these classes due to its use of a smaller wavelength (3cm). Furthermore, the TerraSAR-X instrument can provide quadrature-polarized (quad-pol) data (HH, VV, HV, VH, all gathered simultaneously), with which polarimetry can be further investigated. Buckley & Smith (2010) demonstrated the application of quad-pol data polarimetry in the monitoring of grasslands in Canada, highlighting the benefits associated with the quad-pol setup.

In respect to the texture measures used in this study, derived from the ASAR data, there were negligible differences observed between those generated using a 9 by 9 window and those generated using a 13 by 13 window. This can be attributed to the fact that some of the land cover types manifest on a large scale and therefore, in general, the 9 by 9 and 13 by 13 pixel windows pick up a similar distribution of data values. For large scale applications, window sizes of 15 by 15, 31 by 31, and 61 by 61 have been shown to provide constructive results (Blom & Daily, 1982).

In regards to the rule-based classification method that was used in this study, it can be seen that several different methods exist, including the Maximum Likelihood Classifier (MLC) and the Nearest Neighbor (NN) both used by Laurin et al. (2013). These algorithms are used extensively in remote sensing studies and are the most commonly used parametric and non-parametric classifiers, respectively (Laurin et al., 2013). However, the image classification strategy implemented here, made use of a rule-based procedure as implemented by Haack et al. (2000). Several other studies in Wales, concerned with producing land cover classifications either on a relatively small scale (Lucas et al., 2007) or country-wide scale (Lucas et al., 2011), have also diverged from the semi-automated approach. The reason for this was to bring knowledge into the classification procedure through the development of a rule set, which has been used over the study area previously (Lucas et al., 2011), has been shown to be a reliable method of classification (Lucas et al., 2007), it allows knowledge to be incorporated, and it allows for the integration of additional data as it becomes available. Additionally, this approach has been used for the purpose of providing information to policy makers in the form of the Phase 1 habitat map. Therefore the likelihood of the rule-based approach being used for future LULC in Wales is high. As such, in this study's aim to demonstrate the added value of SAR data in a LULC classification in Wales, it was appropriate to implement a rule-based classification approach.

Therefore the methodology implemented in this study is one that is capable of being applied across Wales or even the UK and has the ability to adapt to the generation of more information. As

a result of the Sentinel missions a greater amount of EO data will be available from different sensor types and resolutions in the years to come. The ability to refine the classification with more up-to-date, reliable data is important when the data is used to inform food security policy makers – whether they are responsible for global or European policies, or smaller scale issues.

Furthermore, as Sentinel data is free of charge, it is possible to produce reliable and timely LULC maps for food security purposes at relatively low costs overall. This is especially important when considering smaller scale food security projects such as those in the field of Precision Agriculture (PA). PA investigations usually take place on a small scale and the work can include land management studies, crop mapping/monitoring and field surveys to monitor disease. All of the information gathered this way, can feed into larger scale food security models and policy decisions. Therefore, it is important that such investigations take place; something which is helped by maintaining low running costs. This can be achieved not only through use of freely available EO data, but open source software too.

Finally, further development and improvement of the results could arise from several approaches. Firstly, the use of multi-temporal data could allow for the inclusion of rules based on land cover phenology and morphology. The Integration of shorter wavelength SAR data – The use of X-band SAR data, such as that provided by the TerraSAR-X instrument, could facilitate further discrimination between Improved and Unimproved grassland areas. Furthermore, a quad-pol setup could allow for a deeper investigation into SAR polarimetry. Additionally, more sample areas would encompass greater variance in the features and therefore facilitate the generation more reliable rules. At the same time, a greater number of test areas would allow for a greater degree of accuracy assessment. Another improvement would be the further investigation into use of texture measures. Different texture measures could be calculated in addition to the ones used in this study. Such measures could be computed using the window sizes recommended by Blom & Daily (1982). An examination of the different permutations' ability to discriminate land cover types could then be carried out. In addition, the incorporation of Slope and Aspect features has been shown to aid in the classification procedure. Lucas et al. (2007) used a threshold of Slope to help identify urban areas as well as scree/cliff ledges. Furthermore, the use of fractional images, derived from optical data, has been shown to be of benefit to LULC classifications (Adams et al., 1995; Lu & Weng, 2004). Such images show the relative proportions of different components (or endmembers) that make up a pixel. Additionally, PCA has been used extensively in order to reduce the dimensionality of datasets whilst maintaining the information content (Henderson et al., 2002). As such, it could be used in cases where there is a large amount of data due to the derived products. Finally, the use of EO data with a finer spatial resolution would enhance the spatial separability of the classes. Moreover, it would allow for greater delineation of sparser land cover types; this could particularly enhance the classification in the uplands where some land cover types (e.g. Bracken) are known to manifest on a smaller scale.

5. Conclusions

In the present study Landsat TM data was used alone as a basis for producing a LULC map of an area of Wales. In addition, a methodology was developed to allow the incorporation of Envisat ASAR data and derived texture measures into the process, thus developing a synergistic LULC classification approach. The two approaches were evaluated using the traditional method of the comparison of the overall accuracies. This evaluation was then expanded by a statistical assessment of the results; a hypothesis-based testing framework was implemented through use of McNemar's test. The results show that not only was the synergistic classification of a greater

accuracy, but the improvement was shown to be statistically significant. Therefore, as this study has demonstrated the potential benefits of a synergistic approach to LULC for food security purposes, it is hoped that research in this area will continue and accelerate due to the data provided by the Sentinel missions. Therefore, a foundation is provided on which to further establish synergistic approaches.

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Author Contributions

AC conducted the research described in this study under the supervision and guidance of GPP and KF and GPP prepared this manuscript for submission to the journal.

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