# A multispectral multiplatform based change detection tool for vegetation disturbance on Irish peatlands

Jerome O Connell\*, John Connolly and Nicholas M. Holden. UCD School of Biosystems Engineering, University College Dublin, Ireland.

# ABSTRACT

In this study satellite data from five different multispectral sensors were used in a change detection study of vegetation disturbance on an Irish active raised bog. Radiometric normalisation was performed using Temporally Invariant Clusters (TIC) and cross calibration applied using linear regression of radiometrically stable ground-based targets. Erdas Imagine's Spatial Modeller was used to create a change detection model using pixel-to-pixel based subtraction with a Standard Deviation (SD) threshold. The effectiveness of the cross calibration process was shown with the aid of Kolmogorov Smirnov sample tests which showed a reduced D value between master and slave cumulative distribution curves after cross calibration. The spatial accuracy of various SD threshold levels was assessed, with 1.5 SD producing 0.19% error when compared to actual ground truth boundary data of change. An error matrix of change/ no change verified 1.5 SD as the optimum threshold for change detection, with user, producer, overall and kappa values all above 95%. Vegetation disturbance in the study was predominantly attributed to turf cutting on the boundaries of the bog. However in May 2008 a large burn event occurred on the northeastern side of the bog which removed all surface vegetation, equating to an area of 36ha (or 7.85% of total area).

Keywords: change detection, multi-platform, multispectral, multi-temporal, EVI2, peatlands

# **1. INTRODUCTION**

In Ireland, maintenance of peatland Carbon (C) stock has taken on a renewed importance with articles 3.3 and 3.4 of the Kyoto Protocol / Marrakech Accords recognising soil organic carbon as a biosphere sink [10]. Peatlands in Ireland cover approximately 20% of the land surface [3] and account for between 53% (1071.13 Mt C) to 62% (1503 Mt C) of national soil carbon stock [24, 7]. Extensive anthropogenic disturbance to pristine peatland habitats can have negative impacts on sequestration rates, and in extreme cases, can convert such habitats from net sinks to a net source's of C emissions [2]. The dynamics of some of these disturbance events can be high, requiring temporally frequent observations in order to quantify the true extent of each event.

Irish peatlands are spatially extensive and relatively inaccessible; therefore satellite based multispectral imagery is ideally suited to the monitoring of peatland vegetation change due to its high spatial and temporal resolution [15]. Kyoto/ Inter-governmental Panel on Climate Change (IPCC) state the importance of "dynamic data sources" [1] in land use and land use change related to carbon inventory reports. Satellite data can now provide a cost effective, high resolution temporal and spatial data source for land use dynamics [1]. However Ireland's extensive cloud cover means that over 78% of all optical based satellite imagery taken throughout the year is completely obscured [21]. An alternative approach in a change detection study that requires a high temporal resolution is to use multiplatform data [12, 4]. The use of multiplatform data reduces the effect of cloud cover on the temporal resolution of a change detection study by increasing the likelihood of unobstructed data due to the varying orbits and overpass times of the various satellite platforms.

Change detection has now become one of the principle applications in environmental remote sensing [14]. The techniques involved in change detection are varied and generally depend on the format of the input data and the requirements of the output data [4]. Simpler techniques, such as image differencing and image ratioing, while easy to apply, produce basic information on areas of change. More complex procedures, such as change vector analysis, can be more difficult to apply, but may yield more information of change and land cover dynamics.

The objective of this study was to create an image difference based change detection tool for Irish peatlands that incorporates multispectral data from a variety of platforms.

\*oconnell.jerome@gmail.com

Remote Sensing for Agriculture, Ecosystems, and Hydrology XIII, edited by Christopher M. U. Neale, Antonino Maltese, Katja Richter, Proc. of SPIE Vol. 8174, 81740F  $\cdot$  © 2011 SPIE  $\cdot$  CCC code: 0277-786X/11/\$18  $\cdot$  doi: 10.1117/12.898562

## 2. METHODOLOGY

## 2.1 Study Area

Clara bog (Figure 1) is located near to the south of Clara village in North Offaly (N 53.3211°, W 7.6272°). The peatland is at 55 m elevation, with an average annual precipitation of 900 mm [8]. Clara bog achieved Special Area of Conservation (SAC) status and is one the most important Midland raised bogs in Ireland, with unique hummock, hollow and soak systems [NPWS17]. Today, only 7% of active rasied bogs in Ireland remain intact [5]. Clara bog is the largest example of these active systems, giving it international status as an Annex 1 habitat in the EU Habitats Directive [17] as well as a wetland site of international importance under the Ramsar Convention [6]. Despite its prestine status under the Habitats Directive and the Ramsar Convention, Clara is in fact divided in two by a regional road, with areas of relatively undisturbed vegetation to the west, and a network of drains to the east. Although these drains have been blocked for over 15 years [OPW20], this area of Clara had significant hydrological and vegetative differences to the western section. Vegetation in Clara is dominanted by *Sphaghnum* in waterlogged areas and Common Heather (*Calluna vulgaris*) and Cottongrass (*Eriophorum* spp.) in dry areas [9]. While peat extraction and drainage have all but ceased on the bog, some peat cutting is still present in the southern margins as well as some recent large burn events in the eastern section of the site.



Figure 1. Study site

## 2.2 Data

Multispectral data was acquired for Clara from a variety of different satellite platforms (Figure 2). The majority of satellite data was acquired via the SPOT Image Incentive for the Scientific use of Images from the Spot system (ISIS), and the European Space Agency's (ESA) Category 1 Proposal. Any remaining data was obtained from the US Geological Survey (USGS) via their Global Visualization Viewer (http://glovis.usgs.gov/). The temporal resolution of the data varied, depending on image availability from the above programs. Auxiliary data used in training and verification of the change detection model were obtained from various sources:

- 1 m Aerial photography : Ordinance Survey Ireland
- Commonage Framework Plans : National Parks and Wildlife Service
- Habitat maps/ surveys : National Parks and Wildlife Service (NPWS)
- Digital Images : NPWS rangers / in person
- Local correspondence : NPWS rangers
- High resolution (1-5 m) satellite data : ESA Category 1 Proposal

## 2.3 Data Pre-processing

All satellite based multispectral data was converted from digital numbers (dn) to Top-Of-Atmosphere (TOA) reflectance (Equation 1), which was incorporated into an Erdas Imagine Spatial model for automated processing [19].

$$ToA = ((\pi^*Lsat))/(Eo^*cos(\emptyset))$$
(1)

Atmospheric correction was also included in the model via Dark Object Subtraction (DOS). The DOS process evaluated the lowest 5% of pixels in each image band, and subtracted the mean of these values from all other pixels within the image [19]. All data was then converted from TOA reflectance to Enhanced Vegetation Index 2 (EVI2) for further processing [22]. EVI2 was found to be the best vegetation index for detection the various habitats within Irish peatlands [19] as well as showing high correlation the ground based LAI data [18]. Topographical correction was then performed on data with solar elevations below 38° in accordance with Nichol et al. [16].



Figure 2. Temporal acquisition of multispectral data for Clara bog. Master image is underlined, with all other data normalized to this image.

All the data was geo-referenced to a sub pixel level to a predefined master image (Figure 3), with a maximum RMSE of 0.25 and a standard deviation of 0.35 [4, 11]. The master image was selected based on its radiometric and temporal properties as well as having the lowest level of disturbed vegetation in relation to all other images within the database. Once selected, the master image was then used in a linear regression based radiometric normalization procedure, using urban and water pixels to transform slave data to the same radiometric scale as the master image [19]. Density slicing in combination with spatial and spectral thresholds was used in the delineation of spectrally stable urban and water pixels from master and slave data.

## 2.4 Cross Calibration

Cross calibration was then applied (Figure 3) with all data calibrated to a global master image (Figure 2). In this process urban, water, peatland and conifer pixels were used in the regression process. The Erdas Imagine Area Of Interest (AOI) tool was used to regulate the spectral and spatial properties of the temporally invariant pixels, with difference images between master and slave data ensuring homogenous pixels with little or no change present. The use of multi-target spectra in the cross calibration process ensures a more representative cross-platform transformation due to a more stable linear equation [23, 13]. The validation process was performed by examining histograms before and after cross calibration, as well as mean and standard deviation statistics. The Kolmogorov Smirnov test was used to assess the distribution of pixel values between master and slave and master and cross calibrated slave data. The distance (D) between the cumulative distribution of the master and slave data gave a quantifiable measure of the effectiveness of the cross calibration process.



Figure 3. Flow diagram of processing steps from TIC normalization to change detection

## 2.5 Model Calibration

Aerial photography and high resolution Ikonos data were used to train and validate the model parameters with known disturbance events (i.e. May 2008 burn event in Figure 2). Areas of change were calculated for various SD threshold levels and compared to the actual area of change on the ground. Percentage error between actual and detected change gave a quantitative assessment of the accuracy of each SD threshold. Aerial photography and high resolution satellite imagery acquired around the time of the May 2008 burn event was also used to set the spatial threshold. Given the scale of the study area and the resolution of the data, a threshold of 9 pixels (or 0.36ha) was deemed most accurate at delineating areas of actual change on the ground, while eliminating isolated pixels of change [4]. An error matrix was

created for Clara bog by using 300 random sample points distributed around Clara bog. Each SD threshold was assessed against ground truth data acquired from the high resolution satellite data as well as aerial photography. The results of the error matrix were plotted on a line graph to assess the most accurate SD threshold in terms of user, producer, overall accuracy and kappa value.

#### 2.6 Change Detection

The monitoring process only required change / no change information; therefore vegetation index based image differencing was the most effective method of change detection. A model was created in Erdas Imagine Spatial Modeler to automate the process (Figure 3). The model incorporated a mean  $\pm$ SD and spatial threshold to allow spectral and spatial adjusting to the resulting change images. The spatial threshold was necessary to eliminate the "salt and pepper" effect in the difference image, and reduce isolated pixels that are the result localized topographical or atmospheric anomalies [4]. SD thresholds were used to mask out subtle change between master and slave data that invariably will contain erroneous data associated with atmospheric inconsistencies, sun illumination differences and minor pixel misregistration [14, 12].

## 3. RESULTS

#### 3.1 Cross Calibration

Visual inspection of image histograms for master and slave EVI2 data before and after cross calibration (i.e. TM Cross Cal in Figure 2) reveled a noticeable shift in the distribution of the slave data after cross calibration (Figure 4). The distribution of the TM data post cross calibration fits neatly within the profile of the SPOT 2 master data. Image statistics (Table 1) show a corresponding reduction in mean and SD EVI2 when comparing slave and cross calibrated data, bring it in line with the spectral properties of the master image. More detailed analysis of the similarities in spectral distribution between master, slave and cross calibrated data (Figure 5) show a mark reduction in the distance (D) between the cumulative distributions of master vs. slave (0.327), when compared to master vs. cross calibrated (0.255).



Figure 4. EVI2 histograms of Clara bog for master, slave and slave cross calibrated (TM Cross Cal). The master image was acquired by SPOT 2 in 4<sup>th</sup> of April 2007, and the slave image was acquired by Landsat TM in the 17<sup>th</sup> of July 2006.

Image	Min	Max	Mean	StD
Master	0.191	0.552	0.307	0.021
Slave	0.144	0.570	0.328	0.041
Cross Cal	0.252	0.394	0.313	0.014

Table 1. Minimum, maximum, mean and standard deviation (StD) EVI2 for master, slave and cross calibrated (Cross Cal) data for Clara. The master image was acquired by SPOT 2 in 4<sup>th</sup> of April 2007, and the slave image was acquired by Landsat TM in the 17<sup>th</sup> of July 2006.



Figure 5. Cumulative EVI2 distribution curves for master, slave (a) and slave cross calibrated (b). Kolmogorov Smirnov D values before (a) and after (b) are shown. The master image was acquired by SPOT 2 in 4<sup>th</sup> of April 2007, and the slave image was acquired by Landsat TM in the 17<sup>th</sup> of July 2006.

## 3.2 Model Calibration

Spatial assessment of actual and modeled change over various SD thresholds (Figure 6) was used to establish the optimum SD for implementation in the change detection model. A 1.5 SD threshold gave the most accurate spatial estimation of change, producing 36 ha, with an omission error of 0.19%. The highest percentage error (24.08) occurred at 2.5 SD, illustrating the effect of that SD level has on change detection accuracy. SD values 0.5, 1.0 and 2.0 remain within  $4\% \pm 1\%$  error, with 0.5 and 1.0 SD giving and area greater than 35.93 ha (Actual change), and 2.0 SD giving an area less than 35.95 ha. In the error matrix the value of 1.5 SD was determined to be the optimum level of User, Producer and Overall accuracy as well as Kappa value (Figure 7). There was a marked reduction in Kappa and Producer "change" accuracy at 2.5 SD, with User and Kappa "change" value below 76% accuracy at 0.5 SD. Overall and producer no change accuracy remained above 95% across all SD threshold levels.

#### 3.3 Change Detection

Areas of change between master and slave data show clear trends across the time period of the study (Figure 8). Increases in the area of change (i.e. slave < master) are small prior to the May 2008 burn event. Decreases in change (i.e. slave > master) are due to some turf cutting on the periphery of the bog in the master image which was not present pre-April 2007 (Point A, Figure 7). The May 2008 burn event was clearly evident (Point B, Figure 7) as the area of increased change (36 ha) showed a sudden and prominent rise. Transition from increased change to decreased change from the summer of 2008 to the summer of 2009 was also evident (Point C, figure 7). The May 2008 burn event, while significant, still only equated to 7.85% of the total area of the bog (Table 2).



Figure 6. Areas of change (in ha) related to the SPOT 2 image from May 2008 using various SD thresholds. "Actual" area of change was calculated from high resolution Ikonos imagery as well as aerial photography. Percentage error is a function of actual change.



Figure 7. User, Producer, Overall and Kappa values plotted as a function of SD threshold value for Clara. Data that were used in the change detection process were a SPOT 2 image from May 13<sup>th</sup> 2008 (slave), and a SPOT 2 image from the 4<sup>th</sup> of April 2007 (master).



Figure 8. Difference data (+ solid line, - dashed line) for Clara from the 17<sup>th</sup> of July 2006 to the 9<sup>th</sup> of September 2009. Points A, B and C signify significant trends in the data.

Date	Change Area (ha)	% Change
17/07/2006	4.64	1.01
07/06/2007	3.76	0.82
24/10/2007	9.08	1.98
13/11/2007	9.28	2.02
13/05/2008	36	7.85
31/10/2008	1.88	0.41
03/06/2009	0	0.00
13/09/2009	1	0.22

Table 2. Area of change (ha) and percentage change (as a function of total area) for 8 slave images against SPOT 2 master image from 4<sup>th</sup> of April 2007 for Clara bog. Note that only positive change (i.e. slave < master) is shown.

## 4. DISCUSSION AND CONCLUSION

In this study cross calibration via temporally invariant clusters successfully transformed EVI2 data to the same radiometric scale as a predefined master image. Histograms and spectral statistics for before and after the cross calibration process showed the effectiveness of the procedure in normalizing data across a variety of platforms. Cumulative EVI2 distribution curves derived from Kolmogorov Smirnov tests showed a reduced D value between master and cross calibrated data, as to master and slave data. This gave a quantifiable measure, at a 95% confidence interval, of the effect that the cross calibration process has transforming the distribution of slave data to the same scale as the master image.

The spatial correlation between actual and modeled change across a variety of SD threshold levels revealed that 1.5 SD was the optimum for achieving accurate results with an omission error of just 0.19%. Accuracy assessment via an error matrix verified 1.5 SDs as giving the optimum compromise between User, Producer and Overall accuracy as well as Kappa value. Low Kappa and Producer "change" at higher SD values illustrated high "change" omission due to greater proportions of data being masked in the final change detection image. On the other hand, low User "change" and Kappa values at low SD (e.g. 0.5) signified a high error of commission due to large proportions of difference image being included in the final change detection image.

Difference data from the change detection process plotted on a line graph clearly illustrate the May 2008 burn event in Clara. The drift in mean area of change from positive (i.e. change in slave) to negative (change in master) post the 2008 burn event was evident as the removal of native vegetation (*Sphagnum, Trichophorum, Calluna* and *Eriophorum* spp.) resulting in a re-colonization by more vigorous non-native grass species [18]. The net effect of this was a 79% increased EVI2 values post burn, giving greater negative change attributed to above average EVI2 values in disturbed (post fire recovery) areas of Clara. This illustrates the importance of assessing negative and positive difference data in the final change detection data, as both negative and positive change values can signify disturbance. In spatial terms, the burn event accounted for 7.85% (or 36 ha) of the total area of Clara bog. Other vegetation disturbance in the study area was predominantly attributed to turf cutting on the boundaries of the bog, which accounted for less than 2% of total bog area.

This study successfully applied multi-platform cross calibration and image difference based change detection over an active raised bog in the midlands of Ireland. The model and procedures used in this study can be applied to other peatland areas throughout the country. Further work needs to be done on the calibration of the model in upland blanket bog and heath areas, as well as further statistical analysis on the implications of spatially ambiguous ground truth data in assessing change detection accuracy in other areas. This study also illustrated the issue of master image selection in continuously disturbed habitats such as peatlands. This means that vegetation distribution in a pre-selected master image rarely represents pristine conditions; therefore resulting change detection images contain both positive and negative values due to the presence of disturbed vegetation in both master and slave data.

## REFERENCES

- [1] Achard, F., Grassi, G., Herold, M., Teobaldelli, M. and Mollicone, D., "Use of satellite remote sensing in LULUCF sector". IN GOFLCD Ed IPCC guidance on estimating emissions and removals of greengouse gases from land uses such as agriculture and forestry. Land Cover Project Office, (2008).
- [2] Connolly, J., Holden, N. M., Connolly, J., Seaquist, J. W. and Ward, S. M., "Detecting recent disturbance on Montane blanket bogs in the Wicklow Mountains, Ireland using the MODIS enhanced vegetation index", International Journal of Remote Sensing, 9, 32, 2377 - 2393, (2011).
- [3] Connolly, J., Holden, N. M. and Ward, S. M., "Mapping Peatlands in Ireland using a Rule-Based Methodology and Digital Data", Soil Science Society of America Journal, 2, 71, 492-499, (2007).
- [4] Coppin, P., Jonckheere, I., Nackaerts, K. and Muys, B., "Digital change detection methods in ecosystem monitoring: a review", International Journal of Remote Sensing, 9, 25, 32, (2004).
- [5] Crushell, P., Connolly, A., Schouten, M. and Mitchell, F., "The changing landscape of Clara Bog: the history of an Irish raised bog", Irish Geography, 1, 41, 89-111, (2008).
- [6] Crushell, P. H., Schouten, M. G. C., Smolders, A. J. P., Roelofs, J. G. M. and Giller, P. S., "Restoration of minerotrophic vegetation within an Irish raised bog soak system". Proceedings of the Royal Irish Academy. (2006).
- [7] Eaton, J. M., Mcgoff, N. M., Byrne, K. A., Leahy, P. and Kiely, G., "Land cover change and soil organic carbon stocks in the Republic of Ireland 1851–2000", Climatic change, 3, 91, 317-334, (2008).
- [8] <u>http://www.met.ie/climate/rainfall.asp</u>
- [9] Fossitt, J., "A guide to habitats in Ireland", Heritage Council/Chomhairle Oidhreachta, (2000).
- [10] Ipcc, "Agriculture, Forestry and Other Land Use". IN IPCC Ed 2006 IPCC guidelines for national greenhouse gas inventories. IPCC, (2006).
- [11] Kleinod, K., Wissen, M. and Bock, M., "Detecting vegetation changes in a wetland area in Northern Germany using earth observation and geodata", Journal for Nature Conservation, 2-3, 13, 115-125, (2005).
- [12] Lu, D., Mauselm, P., Brondizio, E. and Moran, E., "Change detection techniques", International Journal of Remote Sensing, 12, 25, 44, (2003).
- [13] Martinez-Beltran, C., Jochum, M., Calera, A. and Melia, J., "Multisensor comparison of NDVI for a semi-arid environment in Spain", International Journal of Remote Sensing, 5, 30, 1355-1384, (2009).
- [14] Mas, J. F., "Monitoring land-cover changes: a comparison of change detection techniques", International Journal of Remote Sensing, 1, 20, 139-152, (1999).
- [15] Mcgovern, E. A., Holden, N. M., Ward, S. M. and Collins, J. F., "Remotely sensed satellite imagery as an information source for industrial peatlands

management", Resources, Conservation and Recycling, 28, 17, (2000).

- [16] Nichol, J., Hang, L. and Sing, W., "Empirical correction of low Sun angle images in steeply sloping terrain: a slope-matching technique", International Journal of Remote Sensing, 3, 27, 629-635, (2006).
- [17] <u>http://www.npws.ie/en/ProtectedSites/</u>
- [18] O Connell, J., Connolly, J. and Holden, N. M., "Can Leaf Area Index estimated from Satellite Imagery be used as an Indicator of Disturbance of Irish Peatlands?", Irish Geography, (Under Review).
- [19] O Connell, J., Vermote, E. F., Connolly, J. and Holden, N. M., "Radiometric normalisation of a multispectral database of satellite imagery of peatlands for change detection monitoring.", International Journal of Remote Sensing, In review, (Under Review).
- [20] Opw, "Ecological Impact Assessment (EcIA) of the Effects of Statutory Arterial Drainage Maintenance Activities on Raised Bogs & Associated Habitats". Series of Ecological Assessments on Arterial Drainage Maintenance No 2. Galway, Office of Public Works, (2006).
- [21] Palle, E. and Butler, C., "Sunshine records from Ireland: cloud factors and possible links to solar activity and cosmic rays", International Journal of Climatology, 6, 21, 709-729, (2001).
- [22] Rocha, A. and Shaver, G., "Advantages of a two band EVI calculated from solar and photosynthetically active radiation fluxes", Agricultural and Forest Meteorology, 2, 149, 1560-1563, (2009).
- [23] Teillet, P. M., Barker, J. L., Markham, B. L., Irish, R. R., Fedosejevs, G. and Storey, J. C., "Radiometric crosscalibration of the Landsat-7 ETM+ and Landsat-5 TM sensors based on tandem data sets", Remote Sensing of Environment, 1, 78, 39-54, (2001).
- [24] Tomlinson, R. W., "Soil carbon stocks and changes in the Republic of Ireland", Journal of Environmental Management, 1, 76, 77-93, (2005).