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Developing and Evaluating an Earth Observation-enabled ecological land cover time series system

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Executive Summary

In the past...

- CEH produced three Land Cover Maps (LCM) covering GB, in 1990, and the UK in 2000 and 2007
- Developments in remote sensing and geospatial processing techniques have led to changes in how the maps were created, especially the spatial structure of the three products
- Developments in the mapping of habitats led to differences in the thematic resolution (classes mapped) of the three LCMs
- One consequence of this is that mapping change accurately with the three LCMs is not possible

Current user requirements....

- Accurate UK-wide land cover/broad habitat maps
- Accurate, reliable assessment of stock and change
- Condition monitoring

Aim of this feasibility study...

- Assess benefits of new methods for classifying satellite data for the operational production of the national land cover products
- Assess the potential for developing change detection methods that are capable of accurately mapping change from Landsat-type data for the UK
- Investigate the potential for a set of biophysical/ecological products to provide additional information on within class land cover variability for support of condition monitoring

Key outcomes....

- New very rapid fully automated image classification techniques
- Use land cover history to train machine learning algorithms
- Assessed the relative performance of Random Forest, Support Vector Machines, and Decision Tree (C4.5) algorithms for land cover classification
- Random Forest found superior
- Tested new method for three classifications:
    - Scotland in 2000, Norfolk in 2002 and 2011.
    - The best classification accuracies, based on assessment against CS data were, for Scotland in 2000: 65.4 %, for Norfolk in 2002 87.3% and for Norfolk in 2011 80.1%.
    - Classifications are more accurate than those achieved for LCM2007.
- Assessed importance of multi-date data and ancillary data on classification accuracy. Specifically, that:
    - Three-input images will produce better classification accuracy then two-dates.
    - The best timing of input data does not appear to be predictable, although this is probably because of variable image quality.
    - The texture and NDVI/NDMI data included in the classifications did not have a noticeable effect on the classification accuracy.
    - It is possible to derive accurate classifications from Landsat bands 3, 4 and 5, as has been done for LCMs1990 to 2007. Including Landsat bands 1,2 & 7 slightly improves accuracy.
- Demonstrated that PCA and NDVI-based change detection methods have potential for change detection, 71% and 60% accuracy in preliminary change detection assessments

Summary...

The project has achieved its key aims of:

Assessing the potential for new classification methods (Random Forest trained with training areas harvested from existing LCM data)

Demonstrating the potential of change detection methods that could be built into the LCM production process to produce change detection methods

Created an initial set of demonstration products for the ecological variables, plus preliminary analysis to demonstrate their utility, however their full utility is likely to be for condition monitoring, which will require longer times-series of these values

In the future...

Next generation LCM products...

The next LCM will comprise a land cover layer of classified pixels that can be organised into a spatial framework of land parcels, giving both pixel and polygon products

The classification product will include uncertainty/probability information

Change maps will be generated as land cover time series develop

Nationwide ecological products, for example based on proxies for vegetation productivity and moisture content and impervious surfaces, will help assess the state and condition of broad habitats

The QA/validation...

Validation data are essential classification and change products. We anticipate that volunteer recording schemes can help with this

Next steps...

This project has demonstrated the potential for a new type of LCM, which caters to a wider set of needs, however, the methods are still in the early stages and additional work is needed to develop a fully operational system

We anticipate an iterative deployment of functionality, supported by a modular component based design.

Glossary

ANPP	Annual Net Primary Productivity
AWiFs	Advanced Wide Field Sensor
API	Application Programmers Interface
AVC	Aggregate Vegetation Classes
BAP	Biodiversity Action Plan
CEH	Centre for Ecology and Hydrology
CORINE	Coordination of Information on the Environment
CPU	Central Processing Unit
CS	Countryside Survey
DMC	Disaster Monitoring Constellation
DSM	Digital Surface Model
DTM	Digital Terrain Model
EAGLE	EIONET Action Group on Land Monitoring in Europe
EIONET	European Environment and Information Network
EO	Earth Observation
EUNIS	European Nature Information System
ESA	European Space Agency
FAO	Food and Agriculture Organisation
GMEP	Glastir Monitoring and Evaluation Programme
INSPIRE	Infrastructure for Spatial Information in the European Community
IRS	Indian Remote Sensing
JNCC	Joint Nature Conservation Committee
Landsat-TM	Landsat Thematic Mapper
LCM	Land Cover Map
LCSCS	Land Cover Stock and Change System
MEOW	Making Earth Observation Work for biodiversity conservation
MFW	Minimum Feature Width
MLC	Maximum Likelihood Classifier
MMU	Minimum Mappable Unit
MODIS	Moderate Resolution Imaging Spectrometer
NASA	National Aeronautics and Space Administration
NDVI	Normalized Difference Vegetation Index
NDMI	Normalized Difference Moisture Index
NIR	Near Infrared
NRW	Natural Resources Wales
OBIA	Object Based Image Analysis
ORI	Orthorectified Radar Image
OS	Ordnance Survey
OSNI	Ordnance Survey of Northern Ireland
PCA	Principal Component Analysis
RF	Random Forest
SVM	Support Vector Machine
SD	Standard Deviation
SPOT	Satellite Pour l'Observation de la Terre
SWIR	Short Wave Infrared
TC	Tassled Cap
TukeyHSD	Tukey’s Honest Significant Difference Test
UK	United Kingdom

Contents

1 Introduction

The optimal management of natural resources requires accurate land cover and habitat information across a range of spatial and thematic scales. This research is concerned with broad-scale habitat/land cover mapping from satellites. It focuses on the use of medium resolution satellite data, specifically Landsat-type data. The availability of Landsat and Landsat-type data for operational Earth Observation (EO) products appears secure in the medium-term after the successful launch of Landsat 8 in 2013 and the imminent launch of ESA's Sentinel-2 satellites. SPOT, IRS and DMC sensors can provide similar data.

Frequent, widespread observations and change detection at the broad scale have potential to inform the targeted deployment of more intensive and costly observation activities, such as those developed within the JNCC supported MEOW (Making Earth Observation Work for UK Biodiversity Conservation, http://jncc.defra.gov.uk/page-5563) projects. But the latest UK land cover map represents land cover nearly a decade ago, too old to support an integrated approach, and the interval between CEH UK land cover maps has typically been seven to ten years. The reason for this has been the complexity and cost of national land cover map production. Moreover, each map has taken several years to complete after the satellite images have become available, so even at the time of release information was already becoming stale. To fully realise its potential land cover information needs to be more up-to-date and more frequent. Lessons from the production of CEH land cover maps and from this research project have enabled us to develop techniques that will dramatically reduce production time and costs, simultaneous with increases in classification accuracy.

Due to advances in knowledge, technology, satellite-processing techniques and geographical information science the production methods for each land cover map have changed. The first CEH land cover map, LCM1990 (Fuller *et al* 1994) is a pixel product. LCM1990 preceded Biodiversity Action Plan (BAP) broad habitats so land cover is described with 25 bespoke classes. LCM2000 (Fuller *et al* 2005) is a polygon product and used Object Based Image Analysis techniques (OBIA) to classify land parcels derived from image segmentation. LCM2007 used similar OBIA techniques but land parcels were derived from digital cartography. LCM2000 and LCM2007 have similar, but not identical schemas based on BAP broad habitats. These methodological, spatial and thematic differences between CEH land cover maps make change detection difficult. Consistency of derivation is essential for accurate change detection.

A principal objective of this research is therefore to develop a consistent approach to land cover mapping to enable monitoring through time. Land cover dynamics occur across a range of temporal scales, some slow and occurring over decades; to detect these a land cover monitoring system must have longevity. For longevity careful design is essential. We present a modular component based design that will give the flexibility to respond to method changes and advances in technology. Moreover, a modular design supports sequential roll-out of functionality, so that partial benefits of the system can be realised before full functionality has been implemented. Higher levels of automation and improved functionality can be deployed as they are developed.

Spatial and thematic consistency support temporal comparisons. We propose a fixed spatial framework based on generalised OS MasterMap as a starting point for land cover monitoring. Having a fixed spatial structure will enable individual parcels of land to be tracked through time allowing spatially explicit change detection. For some kinds of analysis different types of spatial framework might be useful. A hybrid pixel-object classification technique has been developed that can support object based summaries using a variety of spatial frameworks. Should an improved national framework become available in the future it will straightforward to issue new versions of parcel based land cover products.

LCM1990 used a thematic structure designed for satellite surveillance, whereas LCM2000 and LCM2007 used Biodiversity Action Plan (BAP) broad habitats. BAP broad habitats were designed for ground based surveillance and are not well suited for satellite derived inventories. This compromised accuracy and therefore the ability to detect change. Going forward it is necessary to use inventories optimised for satellite surveillance.

The three existing CEH land cover maps have been based on maximum likelihood classification. However, maximum likelihood classification restricts the kinds of data that can be used in automated techniques. Here we explore non-parametric classification algorithms. We found them easier to use, less restrictive and they gave superior results.

Categorical descriptions of land have limitations and a better appreciation of land cover/habit condition and dynamics can be learned from continuous properties of the land surface. We therefore explore a range of optically derived biophysical variables and change detection techniques to complement land cover and change descriptions from classification analyses.

2 Classification

In this section we explore the effect of classification algorithms and information layers upon classification accuracy. Spatial and thematic structure are also important for classification accuracy and change detection and we deal with these in sections 5 and 6.

The three CEH land cover maps were each produced using a Maximum Likelihood Classifier (MLC) to classify pixels in 1990 and land parcels in 2000 and 2007. For pixel classification a MLC requires that pixels representing each land cover type have a unimodal, approximately normal distribution. In reality however a land cover type within a satellite scene can have a range of spectral variants (multimodal distribution). This is especially so for arable land cover; the variation coming from crops at different stages of development and the wide variety of crop types. To properly train a MLC and minimise interclass confusion each variant has to be explicitly identified. The same restriction holds for MLC object-based techniques that use the average spectra of land parcels (Fuller *et al* 2005; Morton et al 2011), but there is an added complication: each land parcel must accurately delineate a single land cover type. Land parcels that fail in this will contain multi-modal pixel distributions, the mean of which will not represent any of the known spectral variants leading to classification error. These requirements of MLCs make them more difficult to train than non-parametric classifiers, which do not require the explicit identification of spectral variants. Another restriction of parametric techniques is that they do not support analysis of categorical layers. In this section we therefore compare the performance of a range of non-parametric classifiers. We do not perform maximum likelihood classifications as they are incompatible with our automatically generated training data (see section 2.4).

Object based image analysis (OBIA) is often considered more accurate, preferable to, and technically more advanced, than pixel-based analysis and LCM2007 was produced using OBIA. The conventional approach of OBIA is to compute the mean spectra for a land parcel and use this to determine its most likely land cover type. One argument for this is that there are far fewer land-parcel objects than pixels, so it is computationally more efficient. But with modern computing power this argument is not compelling and the need to compute per-parcel statistics is an overhead not required when classifying pixels. Another argument is that mixed pixels and pixel irregularities from sensor malfunction and atmospheric anomalies cause local misclassifications and a ‘salt-and-pepper effect’ in pixel products, which techniques based on average land parcel spectra overcome. This is true, but filtering techniques are able to clean up many of these irregularities within pixel products and it is straightforward to use a spatial framework of land parcels to summarise classified pixels into polygon products (section 5) which will also produce a cleaner looking product. Importantly, pixel classifications retain textural information that is lost when classifying the average spectra of a land parcel; for example in habitat mosaics with high spectral heterogeneity over small areas. For multi-class land cover mapping we therefore consider pixel classification preferable to conventional OBIA, and the software we have developed in this project classifies pixels. Pixel classifications can easily be summarised by objects (section 5) to give a corresponding land parcel product.

The Department of Computer Science at the University of Waikato, New Zealand, have developed a powerful suite of open-source machine learning algorithms, written in Java and packaged together into a software workbench called Weka (Wakaito Environment for Knowledge Analysis, see Hall *et al* 2009). The Weka workbench was not designed for classifying satellite images, but provides a well-documented Application Programmers Interface (API) to the classification functionality. The API enables developers to readily incorporate Weka's machine learning algorithms into new software.

PostgreSQL is an open source object-relational database system. It has won numerous awards and industry recognition. It is powerful, stable and free. PostGIS is an open source spatial extension to PostgreSQL, providing tools for storing and manipulating raster and vector data. Software was developed to integrate Weka (Version 3.7.10) machine learning algorithms with PostGIS's (Version 2.2dev) spatial data processing functionality. Using this software images were imported into a PostgreSQL (Version 9.2) database and classified.

2.2 Hardware

All classifications were performed on a 32 bit Linux (Ubuntu 12.04.04 LTS) virtual machine, with 4GB of RAM and two virtual CPUs, assigned to Intel Xeon x5660 (2.8 GHz) physical CPUs.

2.3 Classification algorithms

To determine the best classification tools for future land cover mapping we assess the performance in terms of accuracy, processing time and usability of three popular non-parametric classification algorithms.

2.3.1 Support Vector Machines

Support vector machines (SVMs) partition training data into linearly separable sets. A plane in 2-space or hyperplane in higher dimensions, is constructed in such a way that it maximises the margin between the two sets; the hyperplanes at the boundaries of the separable sets are the support vectors (Figure 2.1). Points on opposite sides of a support vector belong to different class types. In many problems the boundaries between separable sets are non-linear and a hyperplane cannot perform a useful dissection. A method called the 'kernel trick' can be applied to transform the feature space such that the sets become linearly separable. A variety of kernel tricks have been invented. Getting the best possible classification depends on choosing optimal parameters for the SVM, choosing the best kernel and best parameters for this. With multi-parameter models it is easy to image an explosion of possible parameter combinations in order to find the optimal configuration. In this exercise we used Weka's default parameters and with a polynomial kernel.

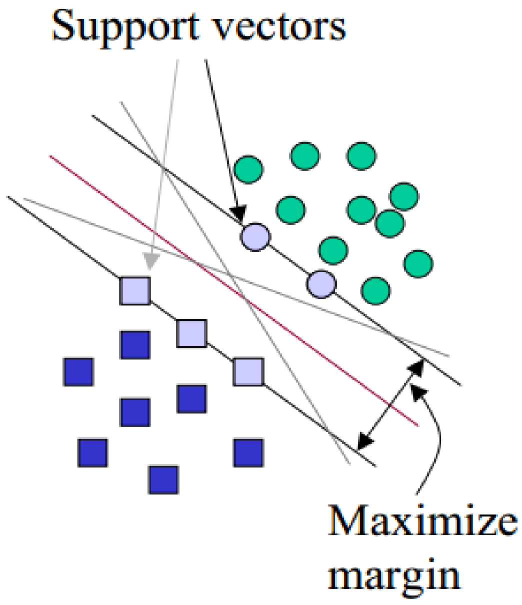

Figure 2.1 Visual Interpretation of a support-vector machine.

2.3.2 J48

Weka provides an implementation of the C4.5 machine learning algorithm (Quinlin 1993) called J48. The J48 algorithm generates a decision tree by recursively splitting the data into subsets. At each node of the tree the algorithm splits the samples by choosing the attribute that maximises information gain (entropy reduction). With single tree classifiers there is a risk of model overfitting. Overfitting occurs when a model has been so tightly matched to the training set that it describes the random noise instead of the underlying relationship. A model that has overfit will have poor predictive performance as it will exaggerate minor fluctuations in the data. When a tree has been fully constructed nodes are re-examined according to information gain and those that offer little improvement are removed, pruned. Pruning reduces overfit and improves predictive performance. The J48 algorithm is easy to use, requiring just two parameters a pruning parameter and a parameter specifying the minimum number of instances per leaf. We used Weka's default values.

2.3.3 Random Forest

The Random Forest (RF) method was developed by Leo Breiman (Breiman 2002). The standard Weka implementation of RF does not implement all the features of the original Breiman algorithm. In particular we were interested in variable importance measures and their potential for assessing the relative importance of information layers. A re-implementation of the RF classifier for Weka, FastRandomForest (http://code.google.com/p/fast-random-forest/w) was therefore used. In tests the FastRandomForest algorithm gave equivalent accuracy to the standard algorithm, in addition to variable importance measures and significant speed and memory improvements.

The RF classifier represents a 'forest' of decision trees and works on the principle that the collective prediction of an ensemble of weak predictors is strong. Trees are grown by recursively splitting the training data using a random selection of the predictor variables; each split maximises information gain. Trees may be fully grown or limited by pre-defined criteria, such as maximum tree depth. We used fully grown trees. Each tree then votes on the unknown observations and the cumulative vote for each determines its classification outcome. Random Forests, are straightforward to use; we simply specified the number of trees to use and a seed for pseudo-random number generation. Initial investigations ranging from 10 to 100 random trees did not yield significantly increasing classification accuracies. We therefore used a forest of 10 trees. Overfitting is not usually a problem with RF.

2.4 Land cover history for classifier training

Obtaining data for training and validating a classifier is usually the most expensive component of satellite image analysis. The normal practice is to gather field-based observations of land cover across the satellite scene, with sufficient samples to provide replicates of each spectral variant. In the production of LCM1990, LCM2000 and LCM2007 teams of surveyors were deployed UK-wide to gather field data. For LCM2007 to maximise spatial coverage, data were recorded from a moving vehicle using bespoke software on a GPS enabled tablet, so most points were collected adjacent to the road network. Our objective in this research is towards frequent cost-effective land cover refresh. To gather similar field-based observations for this would require a team of surveyors on standby ready to be to be deployed as soon as good satellite images become available. Cost and logistics would make this unfeasible. We have therefore developed a technique that uses patterns from historical land cover maps to classify satellite images that does not require field visits. We maintain that field observations are still essential for the validation of land cover products and we are investigating the potential of volunteer networks and ‘citizen science’ to provide cost efficiencies for this.

Land cover dynamics are frequently slow, with many sites stable over many years. If it is known which sites are unlikely to have changed significantly, these sites have potential for training and validation, and methods using stable sites have been used successfully by NASA (see Friedl *et al* 2010) to produce a 1km global land cover product from MODIS data. An advantage of using stable sites is that the same sites can be used for multiple classifications, which can simplify temporal analyses.

To detect stable sites we re-organised the three CEH land cover maps into a single spatial framework derived from generalised OS MasterMap (a pre-cursor to the final framework of LCM2007, see section 5) and a common thematic structure (see section 6). The process involved intersecting the spatial framework with each original map, computing the area of each land cover type within each land parcel of the framework and assigning the per-parcel land cover to the dominant cover. This produced three new land cover maps, with identical spatial and thematic structures. We make the assumption that sites that have retained the same land cover class across all three maps are stable over the whole period and represent suitable training sites. For some sites this assumption will be incorrect, but so long as it holds in the majority of cases it is safe. To increase the purity of data we restricted our selection of stable sites to those that have greater than 95% dominant cover. This process provides 313,980 training sites for the whole of GB. In the production LCM2007 the nation-wide field campaign provided less than 20,000 useable training and validation sites.

Having re-organised historical maps (a one-off task) the training data for classifying a satellite scene can be computed in minutes. The first step uses the raster extent to select an appropriate subset of national training sites. All pixels within these training sites are then selected. For example, for the Norfolk 2011 scene this produced 31587 training sites and 2,190,945 pixels. Associated with each pixel is a set of band values, one for each layer (see section 2.2) and a land cover type. We could feed all this pixel data to a classifier, but this is not necessary. From the full collection we sampled with replacement to gather 10,000 samples per land cover type. Sampling reduces the size of the training set without compromising classification accuracy. Moreover, for tree-based classification techniques (RF and J48) an uneven distribution of training points will bias classification results towards the dominant type; sampling to produce equal-sized sets removes this bias. Pixel data gathered in this way were compiled into Weka’s Attribute-Relation File Format (ARFF). The ARFF files can then be used for any of the Weka classification algorithms.

2.5 Satellite Images and Layer Stacks

Multiple images within a year have the potential to improve classification results because of the seasonal information they contain. We obtained satellite data over Norfolk and Scotland for this research (Figure 2.3). The two sites are strongly contrasting. The Norfolk site is relatively flat, mainly agricultural and situated in the least cloudy part of the UK. Conversely, the Scotland site is dominated by semi-natural upland vegetation types, with snow-free, cloud-free data being more limited. For Norfolk in 2002 and 2011 Landsat images representing months 4, 6 and 9 were used. For Scotland in 2000 Landsat images from months 3 and 5 were used. Suitable images later in the 2000 growing season were unavailable due to cloud, so we used an image from month 7 of the previous summer (Table 2.1). From these image sets, after cloud masking and pre-processing, 3-date satellite composites were created for each location-year.

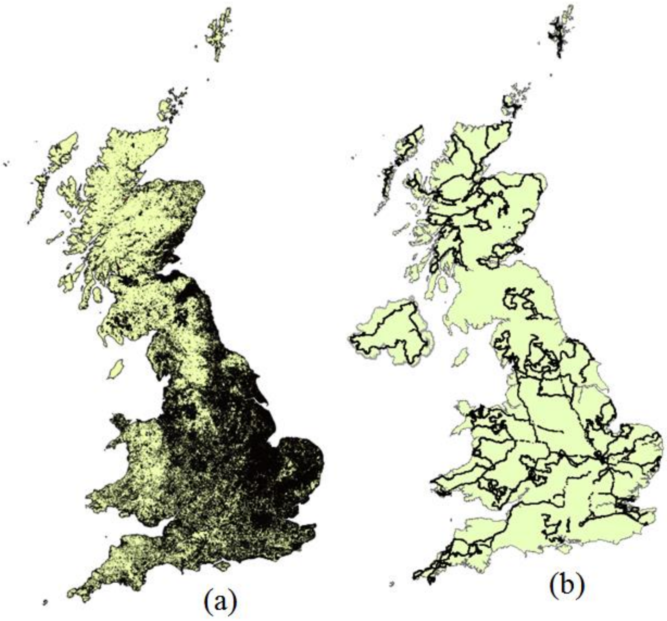

Figure 2.2. The distribution of training sites from (a) land cover history, and (b) the LCM2007 field campaign.

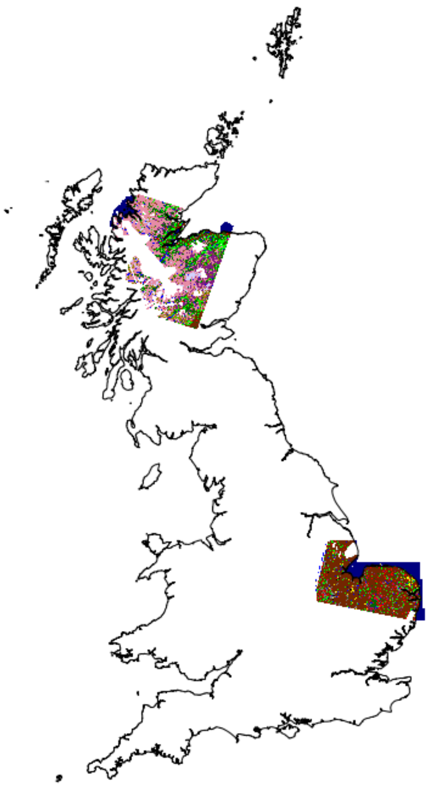

Figure 2.3. Location of Scotland and Norfolk study regions.

Table 2.1 Landsat satellite data for the Norfolk and Scotland study areas. [a] denotes Landsat ETM image, other images are Landsat TM

	Date 1	Date 2	Date 3
Norfolk 2002	6th April 2002	17th June 2002	24th September 2002
Norfolk 2011	23rd April 2011	26th June 2011	30th September 2011
Scotland 2000	18th March 2000[a]	5th May 2000[a]	29th July 1999

Good quality optical images are essential for accurate vegetation/land cover mapping but other data layers are also helpful. In the production of existing CEH land cover maps an initial classification using optical reflectance was followed by the application of knowledgebase enhancement rules, derived from ancillary data layers (for example, urban context, topography, soil type and coastal proximity), to reassign land cover and improve accuracy (Morton *et al* 2011). This approach is not consistently repeatable, as rules were heuristic and subjective. An alternative approach, which we investigate here, is to pass all the data layers into a classification algorithm and allow this to systematically determine the relationship between layers and land cover.

Exactly which layers will be useful for improving a classification is not obvious in advance. Adding layers increases the complexity of the classification model as well as increasing computation time. Inappropriate layers can degrade results. There is therefore a balance to be made. To determine the optimal application of layers we compiled a 61 layer stack for each of the three scenes (Appendix 1, Table 10.1). The layers include:

- Layers 1 to 18: The optical bands of the satellite data for date 1, date 2 and date 3 (where dates 1-3 are given in Table 2.1)
- Layer 19 to 21: The thermal band of the Landsat data for dates 1-3. The Landsat thermal band is usually excluded from land cover classification because its spatial resolution is coarse at 60m, compared to 30m for the optical bands, and it requires a different pre-processing chain. As a consequence utility is rarely assessed.
- Layers 22 to 27: The NDVI and the NDMI for each image
- Texture layers 28 to 39: Texture layers attempt to capture the spatial variability of the different land cover types. Texture has been found useful in some classification studies. In this project we quantified the spatial variability of the NDVI and the NDSWIR in two ways. First, using a 5x5 pixel window around the individual pixel, this produces a product that varies from pixel to pixel. Second, by quantifying the spectral variability of the NDVI and NDSWIR at the polygon-level taking into account existing knowledge of the landscape structure. This produces a per-polygon product, where the texture value is constant across the polygon.
- Layers 40 to 41: Layers 40 and 41 are altitudes from the NEXTMap Digital Terrain Model (DTM) and Digital Surface Model (DSM). Altitude is frequently important in separating land cover types that are similar spectrally.
- Layer 42 is the difference between layers 40 and 41. A DTM represents the land surface without any objects on it such as buildings or vegetation, whilst a DSM indicates the highest points in the terrain including the objects on it. The difference between a DSM and DTM can therefore be indicative of trees or buildings.
- Layer 43: The slope. Slope has obvious potential for land cover discrimination. For example wetland land cover types, such as lakes and fenland are unlikely on steep terrain.
- Layer 44: Aspect. In hilly areas aspect will affect illumination making certain land cover types more or less likely.
- Layers 45 to 54: These layers were derived with the generalised OS MasterMap spatial framework. DTM, DSM and Diff means and standard deviation values represent per-parcel summaries of layers 40 to 42. DTM, DSM and Diff ranges represent the differences between maxima and minimum values within parcels. These give a variety of parcel-level texture measures with potential to influence land cover.
- Layer 55: NEXTMap Orthorectified Radar Image (ORI). This national coverage gives an indication of surface texture/roughness, which could be useful for discriminating flat surfaces, such as lakes and grassland from rougher surfaces such as woodland or crops.

- OS Layers 56 to 61: OS OpenData products. We created pixel masks from 6 OS VectorMap district polygon layers representing: Buildings; Foreshore; Land; Surface water; Tidal water; and Woodland. Each of these layers has the potential to resolve certain types of spectral confusion.

The number of potential layer combinations is huge and it would not be feasible to explore all of these. Therefore, to assess the relative importance of layers we constructed a set of questions and treatments, based upon our experience of land cover classification and expectations of potential layer importance, to address these (Table 2.2). The questions are:

- **How important is multi-date data?** Relevant treatments: 1-8
- **How important is thermal data?** Relevant treatments: 9
- **How important are spectral indices?** Relevant treatments: 10-11
- **How important is per-pixel texture?** Relevant treatments: 12-13
- **How important is per-object texture?** Relevant treatments: 14-16
- **How important is topographic products?** Relevant treatments: 7-24
- **How important is Nextmap ORI layer?** Relevant treatments: 25
- **How important are OS layers?** Relevant treatments: 26
- **How important are all the layers together?** All treatments 27
- **How important are key layers?** Relevant treatments: 28-29

Analyses are based on the RF classifier. We did not find the variable importance measures that come from the RF classifier straightforward to analyse in a rigorous and systematic way. We therefore restricted analyses to statistical comparisons of replicate classifications.

Table 2.2 Classification treatments for the Norfolk 2002, Norfolk 2011 and Scotland 2000 data sets.

Treatment	Date 1	Date 2	Date 3	Thermal	NDVI	NDSWIR	Per-pixel texture NDVI	Per-pixel texture NDSWIR	Per-object texture NDVI	Per-object texture NDSWIR	DTM	DSM + Diff	slope, aspect	DTM variability	DSM variability	Diff variability	Topographic wetness index	ORI backscatter	OS layers
1	y																		
2		y																	
3			y																
4	y	y																	
5	y		y																
6		y	y																
7	y	y	y																
8	y	y	y																
9	y	y	y	y															
10	y	y	y		y														
11	y	y	y			y													
12	y	y	y				y												
13	y	y	y					y											
14	y	y	y						y										
15	y	y	y							y									
16	y	y	y				y	y	y	y									
17	y	y	y								y								
18	y	y	y								y	y							
19	y	y	y								y		y						
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24	y	y	y								y	y	y	y	y	y	y		
25	y	y	y															y	
26	y	y	y																y
27	y	y	y	y	y	y	y	y	y	y	y	y	y	y	y	y	y	y	y
28	y	y	y	y							y							y	y
29	y	y	y	y							y							y	y

RF classifiers are not deterministic with respect to training data. A different random seed will produce a different RF and therefore a slightly different classification result from a single set of training data. To compare layer combinations we must ensure that differences between treatments are not simply due to random variation. For each treatment we therefore performed five classifications, each with a different seed for random number generation.

A systematic, objective way to evaluate classification results is required. Ideally, a set of field observations spatially and temporally coincident with the satellite scenes should be used for 'ground truth', but these data do not exist. One approach is to use cross-validation. Cross-validation uses a proportion of the training data to train a classifier to classify the remainder. This process is repeated until all the data have been classified. Each iteration is called a fold. For each layer treatment we performed a ten-fold cross-validation. In each fold 9/10 of the data are used for training to classify the remaining 1/10. The end result is a confusion matrix, in which the classification results are compared with the 'known' values.

Cross validation gives an approximate indication of how well a classifier is likely to perform beyond the training data and its relative performance between classes. However, there is a circularity about using the training data to rate a classifier built with the training data; it is much better to use an independent set of observations. We therefore used data from Countryside Surveys (CS, Norton *et al* 2012) as an independent source. The process works by taking all CS squares that interact with the study region (Figure 2.4) and counting the classified pixels that intersect with each CS land parcel. A land cover value is then assigned to each parcel using the modal pixel class (Figure 2.5a) CS land parcels classified in this way were then compared to the land cover type recorded by field surveyors in the nearest year (Figure 2.5b) and for each CS square a confusion matrix was computed. From the collection of confusion matrices the areal correspondence over all squares was computed to produce a single value for each classified scene. CS-correspondence and Cross-validation correspondence results from replicate classifications were analysed using a TukeyHSD comparison of means.

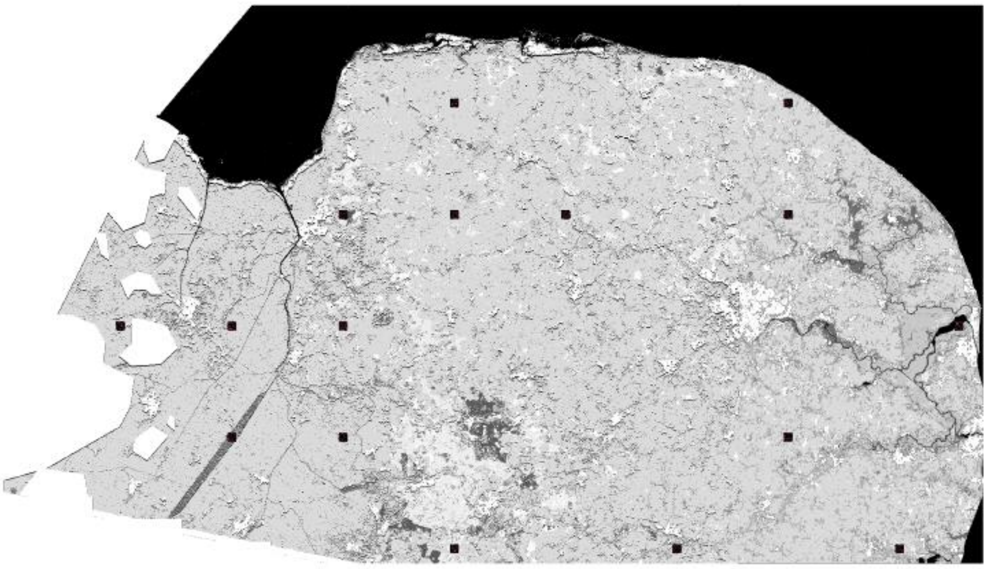


Figure 2.4. The set of CS survey squares intersecting with the Norfolk 2002 scene.

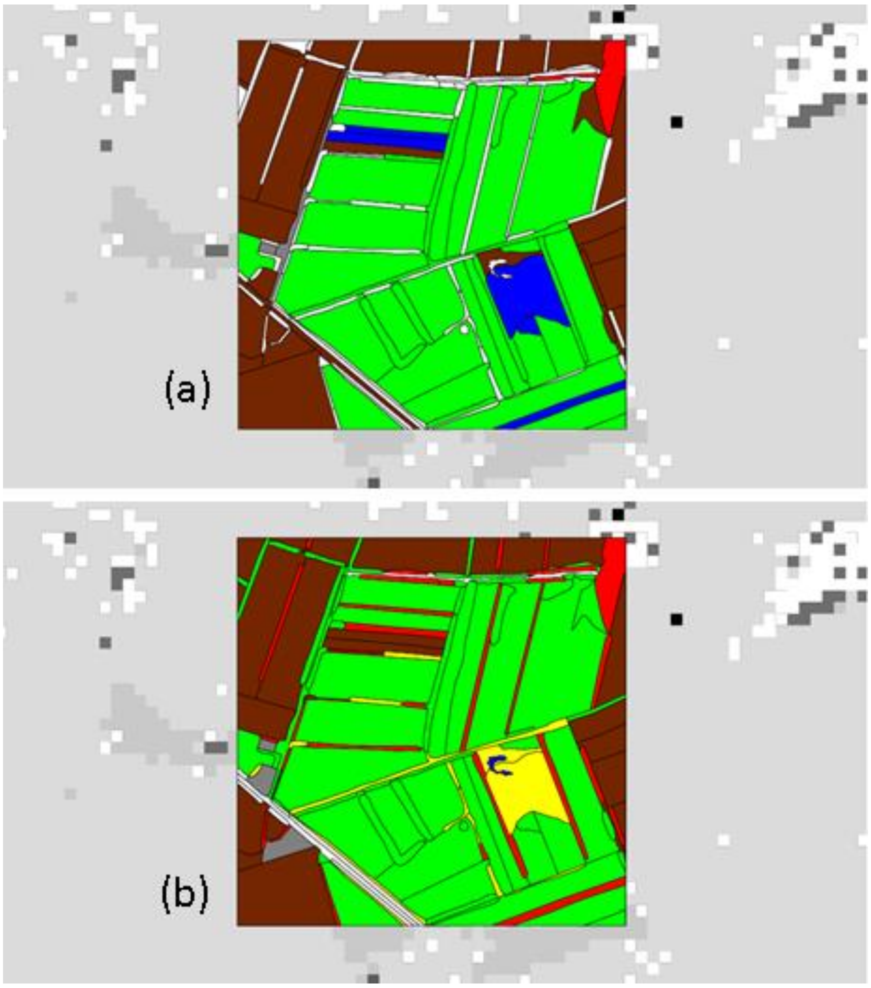


Figure 2.5. (a) Per-parcel land cover derived from a classified image. (b) Habitat records from CS field campaign. Parcels without colour in (a) are too narrow or small to contain a whole pixel. Parcels without colour in (b) are where field data are missing or represent land cover that cannot be matched with satellite derived classes. All uncoloured parcels are excluded from correspondence analyses.

2.6 Results

2.6.1 Algorithm Evaluation

Classification accuracy. For the SVM, J48 and RF algorithms we computed the average correspondence with CS squares for a single run of each classification algorithm (Table 2.3). The tests were conducted for the Norfolk 2002 layer stack. The results indicate that RF has the highest rank and this is significantly higher than the other two; SVM ranked slightly higher than J48 but the difference is not significant (Table 2.4).

Table 2.3 Mean percentage correspondence and rank of classification results for each treatment with Countryside Survey field observations.

Treatment ID	RF	J48	SVM	RF rank	J48 rank	SVM rank
1	72.09097	67.68231	63.95766	1	2	3
2	72.87601	72.35757	55.77853	1	2	3
3	76.73125	75.09029	68.85107	1	2	3
4	79.80521	77.89559	78.58771	1	3	2
5	78.05555	78.89301	79.13586	3	2	1
6	82.18285	74.58851	71.07742	1	2	3

7	83.7061	74.46869	80.89661	1	3	2
8	83.0734	76.94972	76.48627	1	2	3
9	83.1276	75.84969	81.15123	1	3	2
10	84.79736	82.57491	80.51399	1	2	3
11	79.71321	75.94411	80.014	2	3	1
12	85.25967	79.16977	81.23956	1	3	2
13	86.42037	79.21057	81.4281	1	3	2
14	82.84282	80.80916	78.72239	1	2	3
15	85.24002	77.25651	82.07179	1	3	2
16	85.04587	79.43135	82.29008	1	3	2
17	85.70384	80.16262	76.98416	1	2	3
18	83.46109	80.68527	77.3301	1	2	3
19	83.99434	82.29147	78.79991	1	2	3
20	82.01249	72.98567	77.06096	1	3	2
21	82.15109	76.50478	78.13984	1	3	2
22	84.16027	75.42004	81.4856	1	3	2
23	86.29138	82.07938	77.00738	1	2	3
24	78.435	73.09494	83.2749	1	3	2
25	83.048	83.90489	80.70014	2	1	3
26	86.23977	83.20657	81.09893	1	2	3
27	83.32948	81.54363	86.55301	2	3	1
28	86.01791	81.4712	82.73845	1	3	2
29	87.34534	82.77277	85.15947	1	3	2
Average Rank				1.172414	2.482759	2.344828

The best classification from the SVM was comparable with the best from RF and for reasons we do not yet understand is visually more appealing as it displays a reduced 'salt-and-pepper' effect (Figure 2.6a and b). The salt-and-pepper effect is most pronounced in classifications from the J48 algorithm (Figure 2.6c).

Table 2.4 Probability of equivalent algorithm performance from Wilcoxon Signed-Rank Test.

	RF	J48	SVM
RF	=	8.08E-06	7.83E-05
J48	8.08E-06	=	0.5213
SVM	7.83E-05	0.5213	=

Computation efficiency. We did not rigorously test the computational performance of each algorithm as for each speed was good and unlikely to cause a processing bottleneck in a dedicated system, so we just describe relative performance. We consider two components of a classification: the time taken to train and build a classification model; and the time to apply the model to classify a satellite scene. For model construction the rank order was RF, J48, then SVM. For classification speed all algorithms were approximately equal. The time taken to build the model and classify a satellite scene depends on layers processed. With all layers present the largest region (Scotland 2000) would require approximately half of an hour of processing time.

The classification process works on raster objects within the Postgresql, Postgis-enabled database. Postgis models rasters as a collection of independent tiles; each tile is represented as a row in a relational table. This structure is ideal for parallel processing techniques as each tile/row can be processed independently and within a multi-processor architecture computation time will be directly proportional to the number of processing nodes. It is conceivable in a parallel processing environment that computation component of satellite classification can be reduced to seconds.

Usability. All the algorithms were straightforward to use, with RF being the simplest and the SVM the most complex because of its parameter range. Had we experimented with SVM parameterisation and kernel tricks it may have been possible to achieve superior classifications, perhaps matching or exceeding those from RF, but this complicates use and would only be acceptable in a production system if parameterisation could be automated. However, given the promising and clean results of the best SVM, SVMs should not be discarded from future considerations. The J48 algorithm has been tested against MLC and found superior (Sharma *et al* 2013) but it is the weakest of the classification tools in this feasibility study.

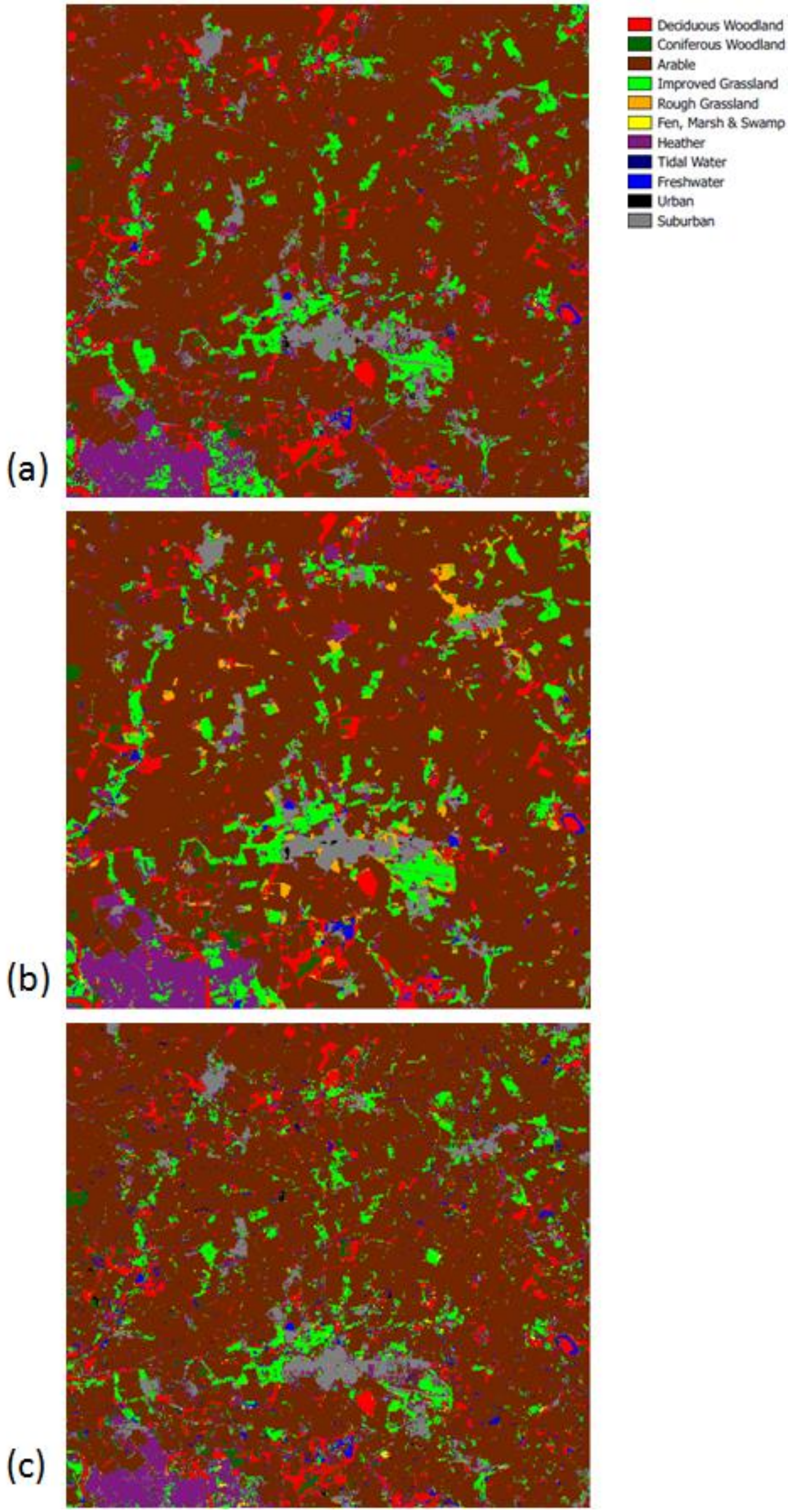


Figure 2.6. Samples from the best (a) RF, (b) SVM and (c) J48 classifications for Norfolk 2002.

2.6.2 Layer analysis

Appendix 2,
Table 11.1 to
Table 11.3 give the TukeyHSD comparisons of means from the average overall CS correspondence across all CS squares based on RF classifications. The null hypothesis is that the means are the same. For the purpose of treatment comparison we accept probability values of 0.2 or less sufficient to reject the null hypotheses. This gives a 1 in 5 chance of a statistical type-1 error, but since our goal is to spot general patterns and develop understanding we consider this risk acceptable. Similar tables from the cross-validation were computed but were less informative as almost all means were significantly different from one another, so these results are not included. To help with the assessment we ranked each treatment for each site to compute the mean rank across all sites (Table 2.5).

Table 2.5 Provides a text description of the treatment/treatment number, and correspondence (given as a rank) between the RF classification and the 2000 or 2007 CS data

Treatment details	Treatment number	Norfolk 2002	Norfolk 2011	Scotland 2000	mean rank
Single-date - date 1	1	29	28	27	28
Single-date - date 2	2	28	29	28	28
Single-date - date 3	3	27	27	29	28
2-date - dates 1 & 2	4	26	2	24	17
2-date - dates 1 & 3	5	25	23	11	20
2-date - dates 2 &3	6	23	25	26	25
3-date	7	14	18	19	17
3-date (bands3,4,5 only)	8	18	16	15	16
3-date + thermal bands	9	14	16	18	16
3-date + NDVI	10	17	19	13	16
3-date + NDMI	11	20	12	10	14
3-date + texture (pixel NDVI)	12	5	15	16	12
3-date + texture (pixel NDMI)	13	4	20	21	15
3-date + texture (object NDVI)	14	9	22	14	15
3-date + texture (object NDMI)	15	10	25	22	19
3-date + all texture	16	5	23	25	18
3-date + DTM	17	7	9	17	11
3-date + DTM + DSM +Diff	18	13	7	12	11
3-date + DTM, slope, aspect	19	8	11	9	9
3-date + DTM + DTM variability	20	19	13	2	11
3-date + DTM + DSM variability	21	22	14	5	14
3-date + DTM + Diff variability	22	12	10	23	15
3-date + DTM + topographic wetness index	23	14	7	7	9
3-date + DTM +4 alt	24	24	20	8	17
3-date + ORI backscatter	25	20	5	20	15
3-date + OS layers	26	3	4	6	4
All 61 layers	27	11	6	3	7
3-date (bands 3,4, & 5 only) , thermal, DTM, ORI, OS	28	2	3	1	2

3-date , thermal, DTM, ORI, OS	29	1	1	4	2

How important is multi-date data? Relevant treatments: 1-8

The worst performing classifications result from the single-date classifications. Adding a second-date improves the accuracy and adding a third date improves further. Multiple dates clearly improve classification results.

How important is thermal data? Relevant treatments: 9

The three date optical classification (treatment 7) ranked 17. Adding thermal (treatment 9) ranked 16 so thermal data alone does not substantially improve optical classifications, but its effects need to be assessed for key classes.

How important are spectral indices? Treatments 10 and 11

Spectral indices treatments 10 and 11 gave ranks of 16 and 16 respectively. This is a very slight improvement over rank 17 for treatment 7 but pairwise comparisons were not significant. Spectral indices did not significantly improve classification accuracy.

How important is texture? Relevant treatments: 12-16

Adding texture gives ranks 12, 15, 15, 19, 18 for treatments 12-16 respectively. That three of these are ranked more highly than the 3-date (treatment 7) rank of 17 could imply that texture slightly improves classification results. However, cross-referencing treatment 7 against treatments 12-16 from the TukeyHSD comparisons of means (Appendix 2,
Table 11.1 to
Table 11.3) indicates that no effects of texture are significant for any of the sites.

How important are topographic products? Relevant treatments: 17-24

The ranks for treatments 17 to 24 are 11, 11, 9, 11, 14, 15, 9 & 17 respectively. Contrasting with treatment 7, rank 17 all but one of these ranks are superior. This implies that topography is important for classification. However, from the pair-wise significance tests (Appendix 2,
Table 11.1) for the Norfolk sites (Appendix 2,
Table 11.1 and 12.2) treatments 17 to 24 were not significantly different from treatment 7, except for treatment 24 for Norfolk 2002 and the effect was negative (reduced correspondence). For Scotland (Appendix 2, Table 12.3) two treatments had highly significant and positive effects (treatments 20 & 21) and treatment 23 had a significant positive effect. This more pronounced effect in Scotland is not suprising as altitudinal gradients are known to affect vegetation communities and the Scotland site has more variable topography.

How important is Nextmap ORI layer? Relevant treatments: 25

The rank for 3-dates of optical images plus the ORI layer (treatment 25) was 15, just slightly better than 3-dates alone (treatment 7) result, with rank 17. However, for the pair-wise tests none of the effects were significant (Appendix 2,
Table 11.1 to 11.3).

How important are OS layers? Relevant treatment: 26

Adding the OS layers increases the average classification rank from 17 (treatment 7) to 4. This prominent difference implies a strong effect of the OS layers on accuracy. However, from the pair-wise (Appendix 2,
Table 11.1 to
Table 11.3) only Norfolk 2002 shows a statistically significant effect of adding OS layers.

How important are all the layers together? Relevant treatment: 27

One might expect that putting all the layers together, therefore providing the maximum amount of information to the RF algorithm would give the best results. Certainly 'going all in' did produce a strong classification result with an average rank of 7, but it is not the best. We suspect that information redundancy complicates tree construction, with reduced gain at each node, and consequently weakens classification results. To try and understand this result we made subjective comparisons through visual inspection of different classifications to determine which layers appeared to be import. This intuitive approach led to two extra treatments (28 and 29).

How important are key layers? Relevant treatments: 28-29

A simple comparison of correspondence values hides subtleties of layer combinations and their effects, so treatments 28 and 29 were determined from a visual assessment of different classification treatments. Treatment 29 includes all Landsat optical bands for the 3-date composites, the Landsat Thermal band for each date, altitude from the DTM, the Nextmap ORI radar backscatter layer and the 6 OS layers; treatment 28 was the same except for the optical data where just 3 bands were included for each date: Landsat bands 3, 4 & 5 representing red, near infrared (NIR) and short-wave infrared (SWIR) respectively. We expected treatments 28 and 29 to perform well and they did, each scoring an average rank of 2 across all sites; the TukeyHSD tests show that these treatments were on the whole significantly superior to all others. For both Norfolk studies treatment 29 produced the best results, whilst for Scotland treatment 28 was best. Previous CEH land cover maps have analysed just the Red, NIR and SWIR optical bands. The results here suggest that a small gain in accuracy might be possible by including fuller spectra.

The band combinations in treatments 28 and 29 performed better than one might expect from examining the individual effects of layers when combined with 3-date composite images. It is likely therefore that layer interactions increase resolving power and interaction effects might be greater than the additive effects. A class-by-class correspondence analysis is required to reveal the intricacies of layers and their effects on individual land cover classes. This is a recommended avenue for further research.

2.6.3 Comparison against LCM2007

Table 2.6 gives the correspondence between LCM2007 and CS 2007 and the best correspondence value from the RF layer analysis for each site. By this measure the new RF techniques produced better correspondence results in two of three cases. This is a very significant result considering that the new techniques are fully automated with classifications computed in minutes, whereas the techniques used for LCM2007 would require approximately two to four weeks of manual effort per region, plus field visits to gather training and validation data.

Table 2.6 Correspondence of LCM2007 with CS2007 for each of the study sites and the best average correspondence results from the Random Forest layer analyses.

	LCM2007	Best RF result
Scotland 2000	62.64	65.4
Norfolk 2002	82.66	87.3
Norfolk 2011	80.86	80.1

2.6.4 Product uncertainty

Land cover classification gives the most probable land cover class using the information available. To determine the most probable class requires that the probability of alternative classes is computed too. Therefore for each class it is possible to produce a raster probability surface (Figure 2.7). Combining these probabilities can provide a measure of overall classification uncertainty. A simple approach is to subtract the highest probability at a given pixel location from 1. This will give the high values of uncertainty where probabilities are low (Figure 2.8). How one should use probability surfaces and uncertainty information will depend on the type of analysis. For example, when assessing land cover change from one class to another, to minimise false results it might be sensible to restrict analyses to regions where confidence for the given land cover is high.

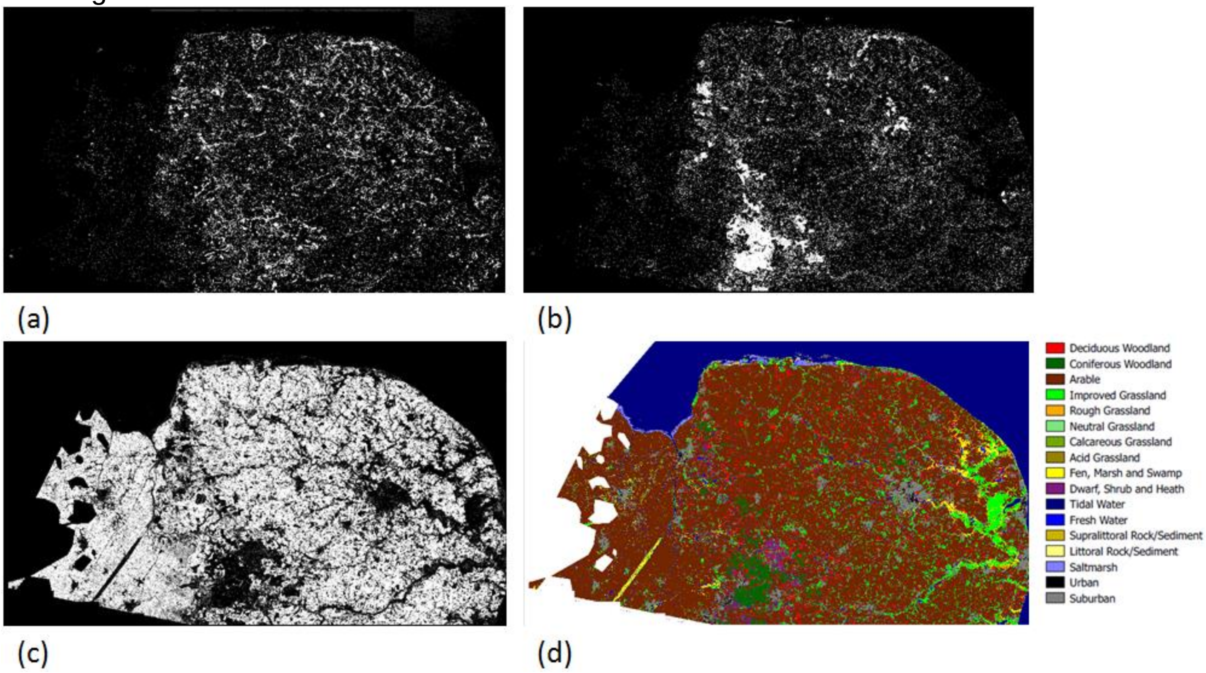


Figure 2.7 Probability surfaces of Norfolk 2002 for (a) Deciduous Woodland, (b) Coniferous Woodland and (c) Arable Land. Bright areas are where probability is high. (d) Gives the most likely land cover class.

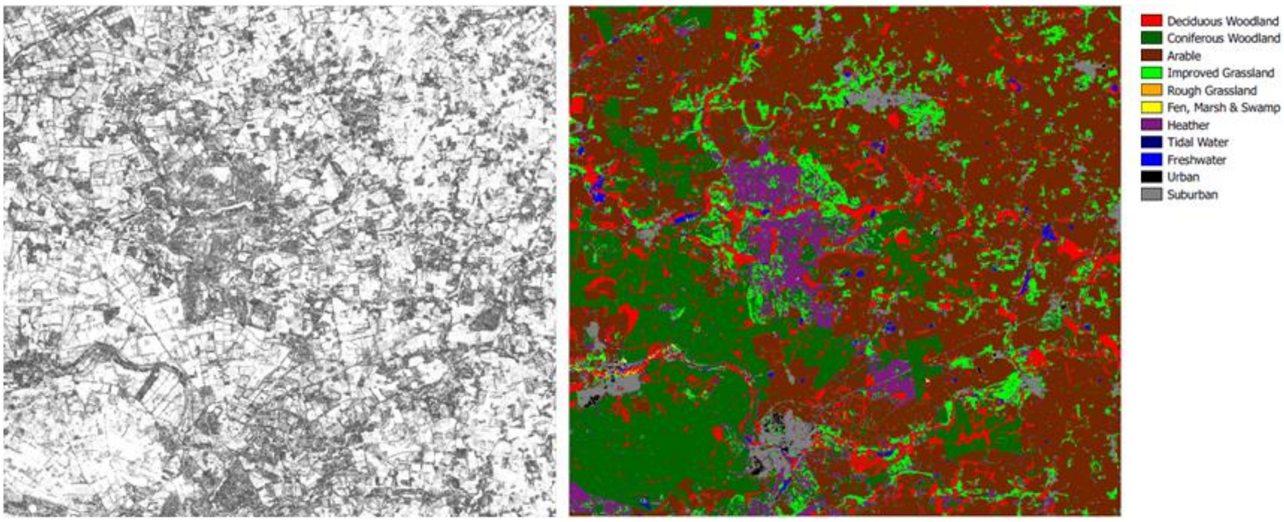


Figure 2.8 Uncertainty of classification around Thetford Forest. Darker areas in left image represent higher uncertainty.

Probability surfaces and uncertainty products also have potential for refining schema and improving classifications (See section 6). For example, in Figure 2.8 to the North East of Thetford Forest is an expansive area of relatively high uncertainty. This is Breckland, an unusual natural habitat on sandy soils which is typically covered by grass, gorse and heather and occasional Scots pine. The consistently high uncertainty in this region suggests we need another class to represent this land cover type.

2.7 Discussion

The production of LCM2007 used 34 twin-date composite images, covering 91% of the UK and 39 single date images for the remainder. A MLC was used and typically the classification of a pre-processed satellite scene took two to four weeks, with much of this effort focusing on the identification of the full range of spectral variants of each land cover type within the scene (this level of information is essential for accurate MLC results). This required significant operator input, with careful sorting of training data gathered from the field and the selection of extra training data from sources such as Google Earth and aerial photography when the field data were inadequate. Taking a conservative estimate of two weeks of elapsed time per scene it is easy to realise that, having a fully pre-processed set of satellite images, well over a year of classification effort is required to produce a national product with MLC techniques. The new highly automated training and classification processes dramatically reduce time and effort; classification of a satellite scene can now be completed in minutes. The key developments that have enabled this are the use of machine learning algorithms, which place less restrictions on the organisation of the training data and the use of land cover history, as opposed to expensive field campaigns, for classifier training. Using land cover history for training does, however, restrict analyses to the historical schema and if these do not match new information requirements then extra training data will be necessary. This point is important. When implementing an operational satellite-based land cover monitoring solution it will be necessary to derive land-cover categories that optimise the information potential of multi-temporal satellite images and provide sufficient detail to support current and as yet undefined future information requirements. The land cover categories that we have mapped in this project are related to BAP broad habitats as these are the categories of the historical maps. We do not consider BAP broad habitats as optimal information categories for broad scale land cover mapping from satellites and we return to this point in section 6.

All the software developed for this project has been based on open source technologies. Open source can provide cost savings. But equally as important, through providing access to source code and a vast availability of online support through discussion forums, open source software brings customisation and integration possibilities that cannot be easily achieved with closed solution commercial offerings. This enhances the capacity to adapt to future requirements.

We employed a hybrid classification approach, we classify pixels and summarise these using a spatial framework to produce classified land parcels. Pixel and parcel classifications give complementary information, so the hybrid approach brings the best of both. Classifying pixels also gives the opportunity to summarise classifications using a variety of spatial frameworks (see section 5).

Conventional parametric statistical techniques such as MLC have been used successfully for many decades to analyse remotely sensed data. However, they are more difficult to train than non-parametric techniques and are unable to include categorical data layers. More recently attention has therefore turned towards non-parametric techniques. Of the non-parametric classification algorithms tested here RF was clearly superior. It consistently outperformed the others for accuracy and was the easiest to use. Other studies have evaluated RF against a range tree-like classifiers that use boosting and bagging techniques (see Gislason *et al* 2006). RF was amongst the best for classification accuracy and was consistently faster and easier to use than the alternatives. Based on our studies and those elsewhere the RF classifier seems like the best candidate for use in an operational land cover monitoring system.

In this study we found the RF's variable importance difficult to interpret; their rank changed in a counterintuitive way when layer stacks were augmented or reduced. We therefore preferred to interpret variable importance by their statistical effects on overall correspondence with Countryside Survey field observations. However, Gislason *et al* (2006) and Archre & Kimes (2008) have found variable importance measures from RF give insight into the predictive qualities of information layers. More research on the use of RF variable importance and their relevance to classification strategies is therefore required.

Increasing the number of images per growing season significantly increased the classification accuracy. This was expected. More images give extra seasonal information, which helps separate vegetation surfaces with different phenologies.

Biophysical indices derived from land surface reflectance did not significantly improve classification accuracy. With hindsight this is not surprising. Biophysical indices are a function of existing optical data channels, so including them within a classifier does not provide extra information.

When humans visually analyse a satellite scene there is simultaneous consideration of context and textural information across a range of spatial scales and this process helps understanding. Texture and context are clearly important. Our attempts to quantify texture in treatments 12 to 16 aimed to capture some of this. That this failed to improve classification accuracy is not discouraging; other regional-texture summaries may prove useful.

The combination of radar backscatter (from the ORI layer) with optical reflectance slightly raised the accuracy rank but not significantly. However, through visual inspection of classified images radar backscatter appeared to improve the resolution of some classes. In particular water and forest looked better for its inclusion. It is worth pointing out that the ORI layer is over a decade old and at each location it represents just a single point in time. The first of ESA's Sentinel-1 satellites has recently achieved its operational orbit. Sentinel-1 will produce a similar type of data, although with coarser spatial resolution, but with the advantage of up to 60 revisits per annum. Our classification procedures can readily incorporate radar layers and the potential to include hypertemporal radar images has exciting implications for land cover research.

Similar to radar, the inclusion of thermal layers with optical layers slightly improved rank but differences in mean correspondence were not significant. Again visual inspection showed beneficial effects for some classes: water bodies and bare surfaces. In fact, it was visual interpretation on a class-by-class basis that led to treatments 28 and 29, which were consistently better than all others. These observations indicate that comparisons based on overall correspondence with CS are too blunt to reveal the intricate effect of data layers. Class by class analyses to determine optimal layer combinations are therefore a goal for the future. Detailed field observations will be required to support this.

The OS derived data layers and the elevation (DSM) both significantly improved classification accuracy. Both of these effects were expected. The effect of elevation was more pronounced for Scotland, which is expected given the increased topographic variability.

It is easy to image how the use of additional layers could improve the classification accuracy of some classes. But, disregarding the extra computational complexity, it is unwise to add ancillary layers without caution. Spatial data are complex. Product accuracy is often not well documented or understood and this uncertainty will propagate into derived products. Spatial resolutions of layers will differ and data integration will degrade spatial accuracy towards the least resolved. We highlight problems of this kind with an example. In the production of LCM2000 semi-natural grasslands were separated into Acid, Neutral and Calcareous grassland using a 1km pixel resolution soil acid-sensitivity map. Basic soils are relatively insensitive to acidic deposition; they retain a high pH through neutralisation and are therefore more likely to support calcareous grassland. Conversely, acid sensitive soils are likely to support acid grassland. The acid sensitivity map was the best readily available data for grassland resolution at the time. Over the interval between LCM2000 and LCM2007 more descriptive and more spatially detailed soil products became available. We believe these data improved classification accuracy in LCM2007 over LCM2000 but this point is moot with regard to change detection. As ancillary data improves so too will the accuracy of derived land cover, but temporal comparisons will reflect this evolution of ancillary data as well as real life changes on the ground. Disentangling these to determine where change has really occurred is very difficult and differences of this kind are part of the reason that existing CEH land cover products are not well suited for change detection. To avoid this kind of complication in the future ancillary layers should be restricted to those with stable and very well-known geographies. This will allow them to remain unchanged over many successive classifications, which will simplify change detection. However, over the long-term it is inevitable that methods and ancillary data will improve and too much inflexibility would become a constraint. We therefore need to develop methods for data versioning and careful storage of satellite data. Should superior ancillary data or classification techniques become available these provisions would enable reclassification across all points in time and in doing so preserve the temporal consistency of derivation necessary for change analyses. With the highly automated techniques reclassifications across time will be feasible.

Our classification procedures produce a pixel probability surface for each land cover type within the schema. Patterns of probability within a classification might have many uses. For example, if the distribution of probabilities within a region change significantly over an interval of time this may be indicative of changes in habitat condition or change due to succession. Patterns of probability give uncertainty indicators. Being able to quantify and interpret uncertainty will support the development of strategies to reduce it and thereby increase classification accuracy. The use of probability surfaces is an area for more research.

3 Ecological products

We define ecological products as biophysical indices that can be readily derived from Landsat-type satellite data. The thesis is these indices provide useful ecological information to complement class based descriptions of land cover and classified objects. They are expected to be of particular use in semi-natural areas and for differentiating grassland into higher and lower productivity types. For example, in the uplands where vegetation cover is heterogeneous simple class based descriptions are limiting and the extra information from biophysical indices could be indicative of habitat condition or productivity. The indices are also expected to have a role to play in the future in monitoring habitat condition.

3.1 Method

Three biophysical indices were assessed:

NDVI –The Normalized Difference Vegetation Index is a simple indicator of the amount of green vegetation. It is calculated as follows

NDVI = (NIR – RED) / (NIR + RED).

Red corresponds to Landsat band 3; NIR corresponds to Landsat band 4.

NDMI – The Normalized difference moisture index relates to moisture content. It is calculated as:

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

Where SWIR corresponds to Landsat band 5.

Tasselled cap – The tasselled cap spectral transformation approach transforms the original 6 optical bands of satellite data into a new set of bands, which are intended to more closely reflect the brightness, greenness and wetness characteristics of the land surface.

Three types of analysis are presented, the first, is a visual analysis of an upland polygon to demonstrate the level of heterogeneity often present within objects in object-based classifications and to illustrate how this variability is captured by the biophysical indices. This analysis is then extended to a wider area, using the LCS88 data, to demonstrate the habitat-specific variability of the NDMI and the NDVI. Finally, a quantitative analysis of the relationship between the satellite-derived indices and productivity measures produced from CS2007, to gauge the potential of calibrating the satellite data to CS2007 style measurements.

The NDVI, NDMI and tasselled cap transforms were computed for the 2002 and 2011 Norfolk Landsat images, the 2000 Scotland images and also for seven AWiFS images used in the production of LCM2007.

3.2 Visual analysis

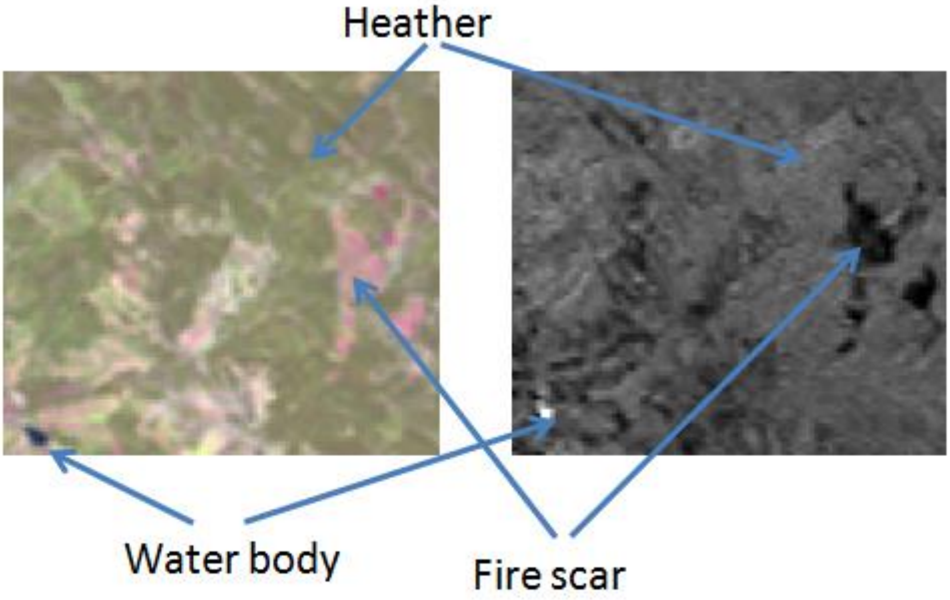


Figure 3.1 An annotated Landsat-TM False Colour composite (bands 5,4,3 as RGB) of a Heather polygon in the LCS88 classification and equivalent NDMI image for May 2000.

Visual analysis of many upland polygons reveals a high degree of heterogeneity which is poorly reflected by a single land cover type attached to a polygon. The example shown (Figure 3.1) is a section of a Heather Moorland polygon from the LCS88 data set, as the two images show there is a variation in the density of heather coverage, a fire scar and a small water body. The NDMI is also shown, the water body shows up as a bright object, whilst the burnt area shows as a very dark area, whilst the heather shows up as a mid-grey colour.

3.3 NDVI-NDMI variability for selected upland habitats

To examine the ability of the NDVI and NDMI to provide information about different habitats the mean polygon NDVI and NDMI were extracted for the LCS88 polygons covered by the Scotland images (Figure 3.2). Positive relationships between the NDVI and NDMI occur for conifers, improved grassland and Bracken, suggesting that increasing water content is associated with increasing vegetation greenness for these land cover types. A negative relationship occurs for montane, whilst the other upland classes show a boomerang-shaped relationship, with high NDMI at low NDVI values and higher productivity at lower NDMI values. The negative relationship between NDMI and NDVI, suggests that in some cases there is a constraint on vegetation productivity. This might be due to anoxic conditions typical of wet, boggy sites which prevent the decomposition of dead organic matter. That the relationship between NDVI and NDMI is not always a simple linear one indicates that both indices contain separate and complimentary information.

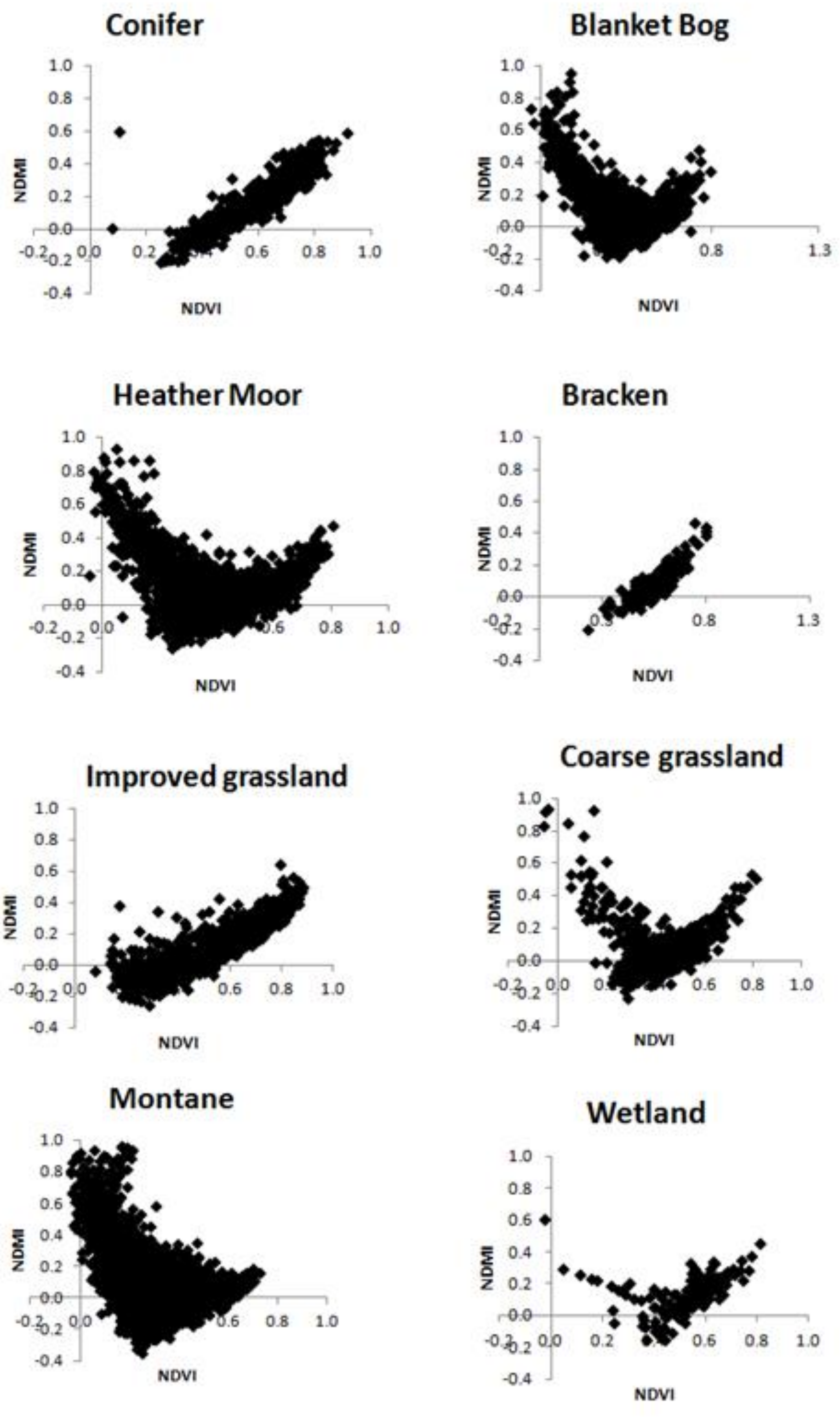


Figure 3.2 Relationship between NDVI (vegetation greenness) and NDMI (vegetation moisture content) for different habitats, based on LCS88 habitat mapping and Landsat-derived NDVI and NDMI for 2000.

3.4 NDVI and CS2007 ANPP estimates

If satellite derived indices are shown to strongly correlate with ground based measures of ecological importance then they may be used as a proxy where ground measurements are unavailable. In CS2007 over 4000 (14.4m x14.4m, 200m^2) vegetation plots were sampled

(Maskell *et al* 2008). Relationship between Estimates of percentage cover for all species with over 5% cover was recorded. These measurements enabled estimates of above ground net primary productivity (ANPP) to be produced. To compare the satellite-derived NDVI with the vegetation plot derived ANPP the individual pixels containing the vegetation plots centre were extracted.
Figure 3.3 shows the relationship between the 3-date NDVI (sum of the April, June and September NDVI) for both 2002 and 2011 with ANPP. The ANPP estimates are for the three Aggregate Vegetation Classes (AVC) that cover grassland, specifically the 'Tall grassland/herb', 'Fertile grassland' and 'Infertile grassland' classes. In this example there is a clear, positive linear relationship suggesting that NDVI could be used to estimate ANPP.

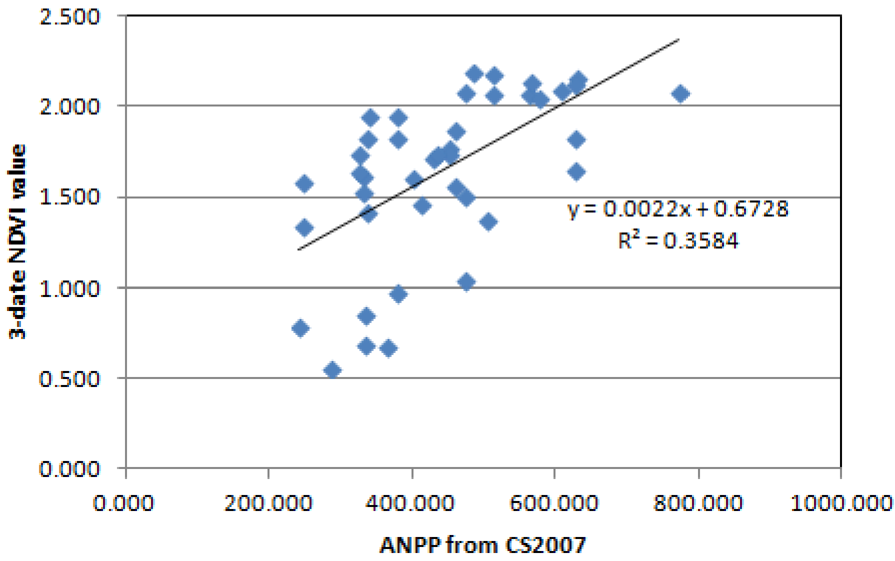


Figure 3.3 Relationship between the 3-data NDVI for 2002 and 2011 for Norfolk and the CS2007 estimates of ANPP, for the three grassland Aggregate Vegetation Classes (AVC).

The quality of relationships between the satellite derived indices and the field measurements will be affected by:

- The time lag between the satellite data and the field measurements
- Problems accurately geo-locating the plots and the satellite data, especially as relatively large differences in biophysical indices are often found in adjacent pixels.
- Spatial differences between the vegetation plot scale (14.14m x 14.14m) and the satellite data scale (30m x 30m). The vegetations plots were not designed to calibrate satellite data and would have covered larger areas if that had been their intent.

A quantitative analysis of biophysical variables (Appendix 3) shows, whilst the relationships between the satellite-derived values and the ANPP are sometimes very good, on other occasions the relationships are much poorer. However, there is a five year difference between the satellite data and the field measurements, so concurrent values might produce more consistently good relationships. The current results would not justify routinely converting the NDVI to ANPP, using the CS data, however, concurrent satellite data might. The uncertainty in calculating the ANPP could be part of any derived product.

3.5 Discussion

The input data used to create the NDVI, NDMI and TC values are part of the standard processing stream within LCM, so an additional stage of calculating the indices would require little additional effort. The indices could be presented in several ways:

- For a typical LCM-style composite image, comprised of three bands of summer data and three bands of winter data, then two per-pixel products for the summer and winter images of the respective index could be created. These values would be consistent within the bounds of a particular image, but not necessarily across adjacent scenes if images came from different dates. For analysis of small areas, within a single image, such as a set of upland polygons or an area like the Norfolk broads, then this would be acceptable. . For larger-scale applications a more consistent approach might be needed.

- Estimation of ANPP – the CS data and the equations derived from it (section 3.4) would enable conversion of the index values to ANPP for grassland areas. One of the limitations with this is that the accuracy of the relationships is affected by a number of factors, including the number of grassland ANPP estimates within the image, the timing of the image, the quality of the image. However, it should be possible to statistically quantify the uncertainty of the data.

- NDVI classes – classify the continuous NDVI values into a series of grassland NDVI classes, along the lines of:
    - Class 1: Very low NDVI grassland
    - Class 2: Low NDVI grassland
    - Class 3: Medium grassland
    - Class 4: High NDVI grassland
    - Class 5: Very high NDVI grassland

  The NDVI classes would make use of the CS ANPP data set to maintain consistency of the classes across boundaries.

- The correlation between adjacent images, when the time lag between them is small, could be used to calibrate one image to the other.

External activities may also have important impacts on how we would produce these products. The most significant development is the current revolution in how large-scale Landsat data is being processed with the production of large-scale, seamless products. A global data set of percentage forest cover has been produced (Hansen *et al* 2013) from large-scale mosaics of seamless Landsat data (Hansen *et al* 2014) – effectively lots of Landsat data is stitched together and methods are being developed for minimising the phenological differences between adjacent Landsat scenes. The current products rely heavily on Landsat-7, which was damaged in 2003 resulting in significant data loss within the image, because of this current set of products are not suitable for this purpose. However, future products based on Landsat-8 or Sentinel-2 could be.

4 Change detection

Most existing change detection methods focus on identifying change in specific habitats, for example, forestry. In such cases the change is often very specific, such as a sharp drop in NDVI, and because it follows a standard pattern it becomes relatively easy to design a reliable detection method. Change detection methods suitable for general land cover mapping purposes need to be more general and incorporate fewer assumptions about the direction and magnitude of change; this is more difficult to achieve reliably and accurately.

Three main methods of change detection were investigated:

- Post-classification – post-classification is the change between two classifications and will provide baseline accuracy against which to assess the success of the other two methods.
- Image to Image (also known as image differencing).
- Classification to Image.

4.1 Methods

4.1.1 Image-to-image change detection

Image-image change detection looks at the difference in spectral properties between two images at different points in time. Typically, differences are calculated between spectral index/transform values, rather than the image digital index, radiance or reflectance values. The method works best with ‘anniversary’ images e.g. April 2002 and April 2011, as this reduces phenological differences between images, which can be a major confounding factor in this type of analysis.
A number of spectral transforms were assessed to determine their suitability for change detection, including:

- Tasselled cap transform – the Tasselled cap (TC) transform was applied to the April 2011 and April 2002 images. The difference between the different components was then calculated, which resulted in six difference images, with band 1 showing the difference in brightness between the two-dates, band 2 showing the difference in greenness and band 3 the difference in wetness.
- Principal Components Analysis (PCA) - Principal Components Analysis (PCA) of a 12-band image based on 6 bands of Landsat-TM from April 2002 and 6-bands from April 2011. In the resultant 12-band PCA image, bands 4,5,6 were found to correspond most strongly to change, with bands 1-3 dominated by image brightness and greenness. A composite PCA index was derived from PCA bands 4, 5 and 6, as it is simpler to optimise a threshold on a single image rather than three.
- Cumulative NDVI – for both 2002 and 2011 images for April, June and September were available. The sum of the NDVI for the three 2002 NDVI images was calculated, as was the NDVI sum for 2011, this cumulative NDVI was then used to calculate the difference between 2011 and 2002.

4.1.2 Classification-to-image change detection

Classification-image change detection is a novel technique which takes a classification and a satellite image as inputs. The method uses a land cover classification to provide the land cover status at time t_1, whilst a remote sensing image provides data on land cover at t_2. Knowledge of the location of a particular class (from the classification) is used to extract class-specific spectral properties (from the satellite image). The change between land cover is assessed by calculating spectral distance between the core class spectral properties (the blue area in Figure 4.1) and the pixels corresponding to that class. Pixels that have not changed are expected to show standard spectral properties for their class and will fall in the blue area of Figure 4.1. Pixels that have changed are likely to show different spectral properties and will fall outside the core area and will be flagged as anomalous. The method assumes that spectral outliers indicate change. The method is applied on a class-by-class basis, following the stages outlined in Figure 4.2.

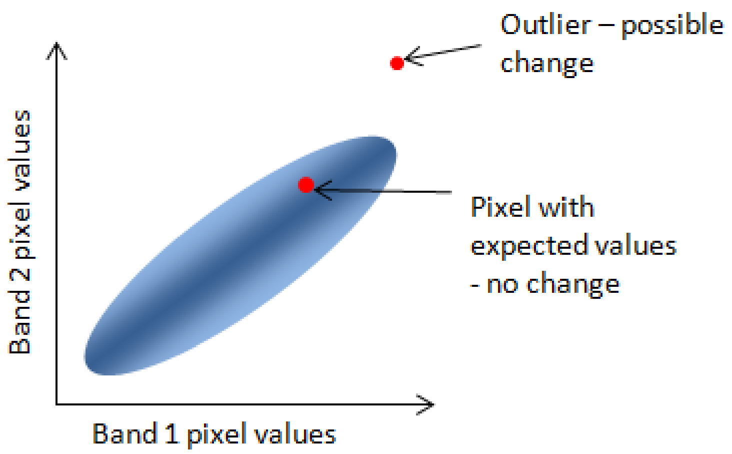


Figure 4.1 Illustration of the class-specific spectral values for class 1 (blue area) based on two spectral bands and a single outlier (change pixel).

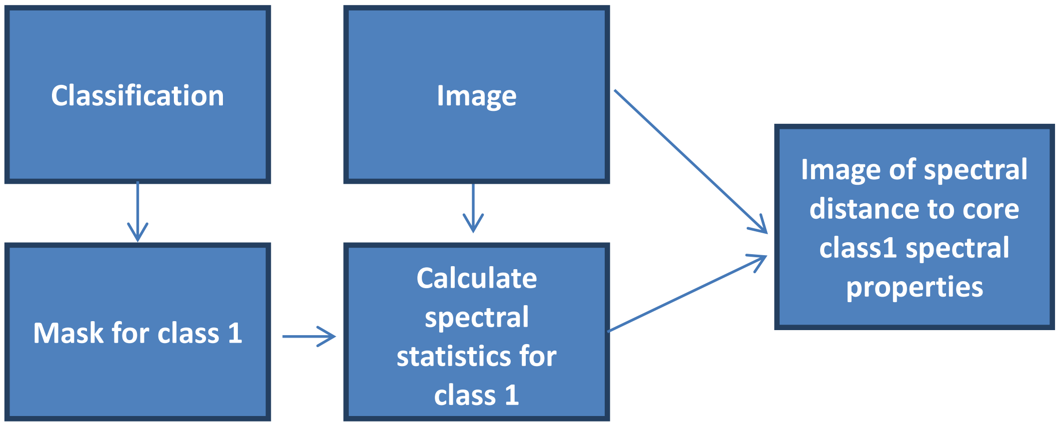


Figure 4.2 Schematic of key elements of the classification-image change detection method.

The classification-image method was applied to a Landsat TM image from May 2000, with the classification data from Land Cover Scotland 1988 (LCS88), giving a 14-year period for change to occur (visual results are presented for this)**.** The method was also to determine change between 2002 and 2011, using the satellite data from 2002 for Norfolk in comparison to the best classification from the RF algorithm for 2011 (quantitative results are presented for this).

4.1.3 Classification-to-classification change detection

Classification-to-classification change (sometimes called post-classification change) identifies change by using the difference between two classifications. The two best classifications for the Norfolk site for 2002 and 2011 were used.

4.2 Results

To assess the quality of the results they are assessed according to a visual (sections 4.2.1 and 4.2.2) and a quantitative assessment (4.2.3). For the quantitative assessment, the raster products from the PCA-based method and the NDVI-based method were converted to polygons (hereafter change polygons), filtered to remove clusters of < 4 pixels in size and then masked to remove anything classified as Arable in 2011 (using a mask derived from the 2011 classification). From this remaining set of change polygons, 30 were randomly selected and then assessed to determine whether they represented real change. To aid this assessment the change polygons were exported to Google Earth allowing the use of the time-series of aerial photography contained therein. This, in conjunction, with assessment of the satellite data from 2002 and 2011 enabled judgements to be made in most cases about whether significant change had occurred, although there were a number of change polygons where this was not clear. The full results from this analysis are in Appendix 4. Key results are reported in this chapter. A similar method was applied for the post-classification change detection, with land parcels classified as arable in 2011 removed to maintain consistency with the other validation data sets. It was not necessary to remove change polygons of < 4 pixels, as the spatial structure of the classification products prevents polygons smaller than this. Thirty random change polygons were then selected and assessed in the same manner as the raster-based products.

4.2.1 Image-to-image change detection

Figure 4.3 shows the 2002 and 2011 images, with annotated changes corresponding to:

1. Deforestation
2. Standing water in 2002
3. Great Yarmouth out Harbour (constructed 2007)
4. More prominent water channels

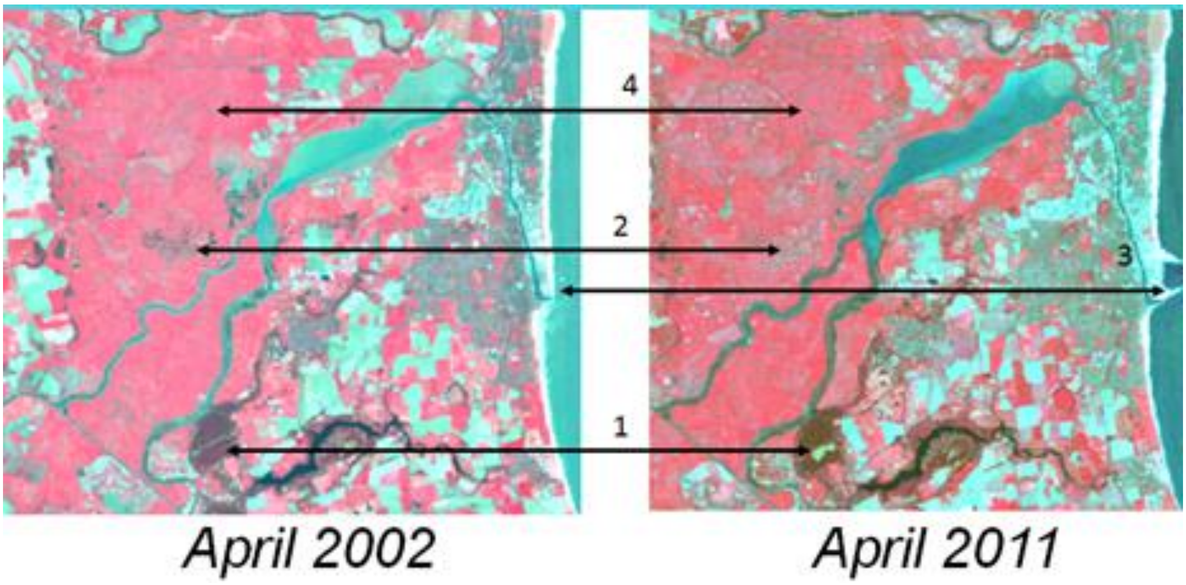


Figure 4.3 Landsat-TM False Colour Composite of Norfolk for April 2002 and 2011 illustrating both permanent and temporary changes.

The largest changes were due to changes in crop type, so these were removed using a mask of areas classified as arable in LCM2000 and LCM2007. However, visual analysis of some of the areas of greatest spectral change (brightest colour), showed that some arable fields were still visible in Figure 4.4. A composite PCA index was derived from PCA bands 4, 5 and 6 (Figure 4.5). The PCA images (Figure 4.4, Figure 4.5) clearly shows the four annotated changes identified in Figure 4.3, in addition to other changes, such as changes around one of the river channels. The alterations to the river channels are a series of new water bodies adjacent to the main river channels and were created between 2003 and 2006.

Visual assessment of the PCA images for the whole of the Norfolk area, showed that:

- Tidal state and the Nene/Ouse washes show high spectral change due to temporary rather than permanent change. This highlights one of the issues with image-image analysis, as short-term changes may cause high spectral variability between the two images, but do not necessarily represent long-term change. This suggests that class-specific methods may be needed to aid interpretation of the spectral variability.

- The sensitivity to changes varied between the three pairs of images. Visually the April image appeared to be most sensitive to change, so this was used for the quantitative analysis.

Visual assessment of the NDVI difference images and the tasselled-cap change images suggested that they were, like the PCA images, dominated by the high variability of arable spectral changes. Masking out the Arable areas enabled the change in other habitats to be assessed.

Figure 4.6 shows the three image differencing results for an area of Saltmarsh that is being restored on the North Norfolk coast. The PCA composite image picks up the change as a bright patch, whilst the tasselled-cap brightness for April picks it up as a reduced brightness; the NDVI picks up the new channel, but appears less sensitive to the vegetation changes of the northern patch, than the other two methods. The post-classification change polygons are also shown; they also pick up the change. The tasselled-cap brightness and greenness components (Figure 4.7) pick up the Saltmarsh, but the wetness component is less sensitive.

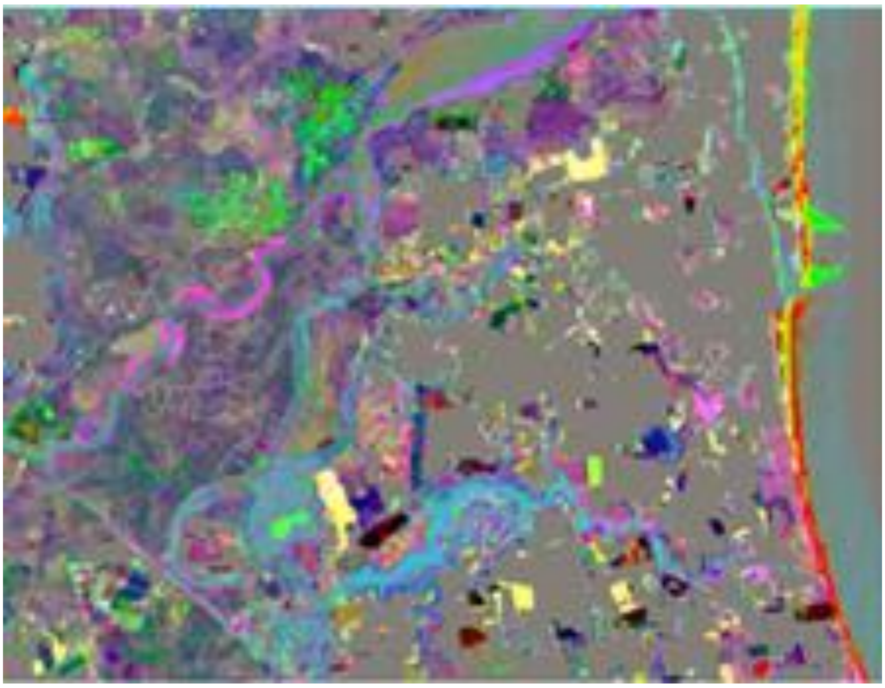


Figure 4.4. Principal Components Analysis image (bands 4,5,6 as RGB respectively) derived from a 12-band multi-temporal image comprised of the April 2002 and 2011 images.

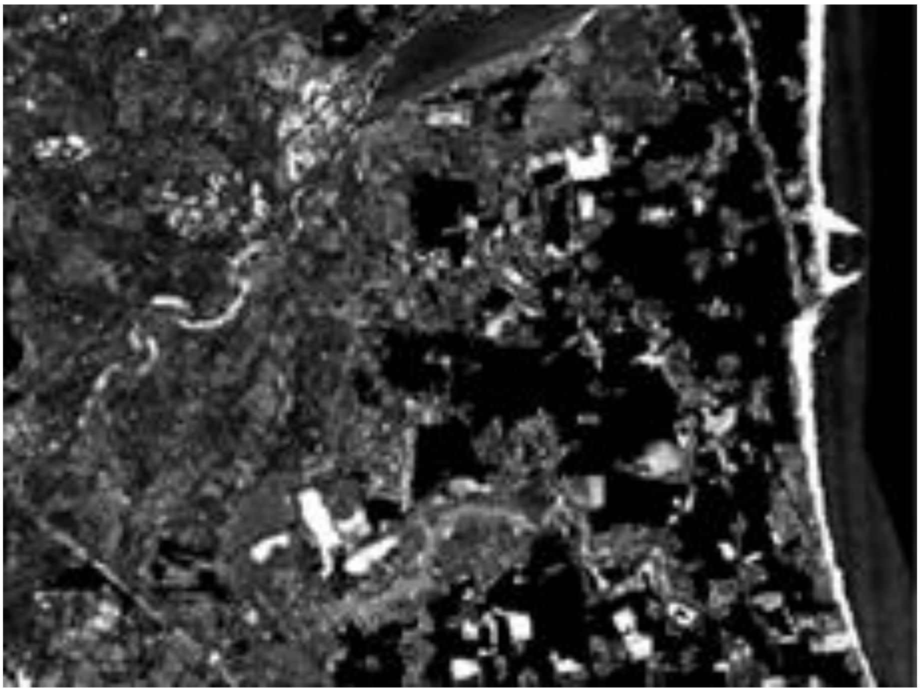


Figure 4.5 Principal component analysis composite index. Brightness represents change magnitude.

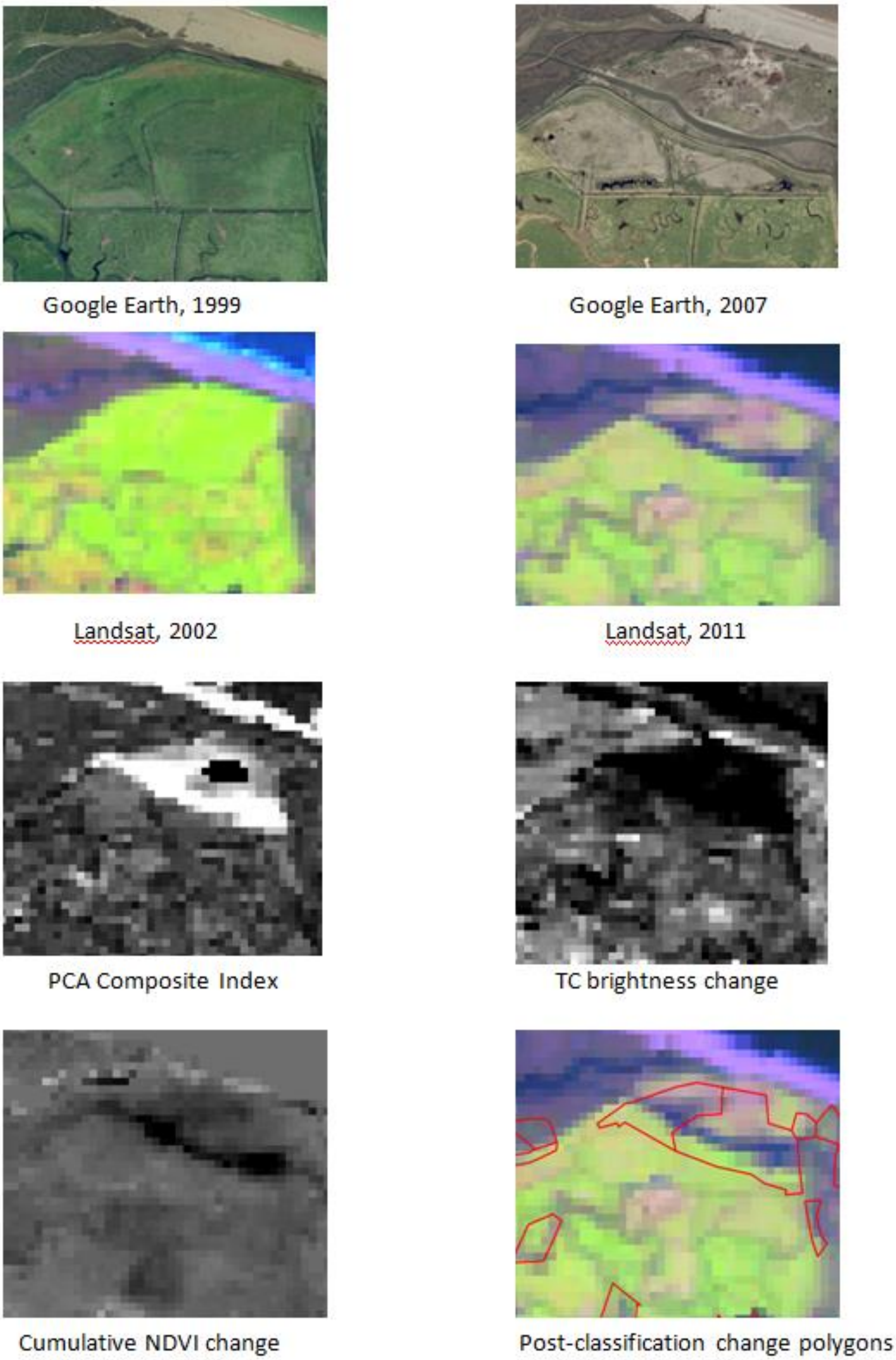
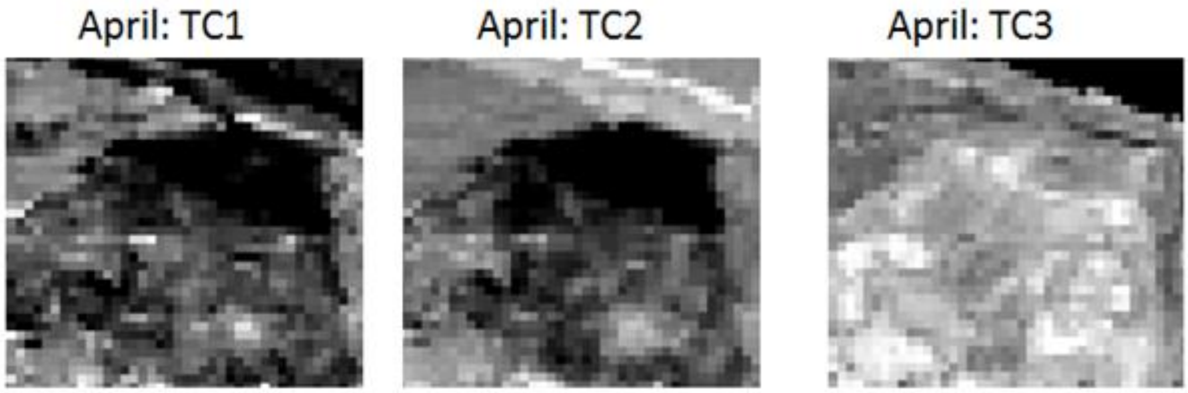


Figure 4.6 comparison of different techniques for the detection of Saltmarsh change near Blakeney, Norfolk



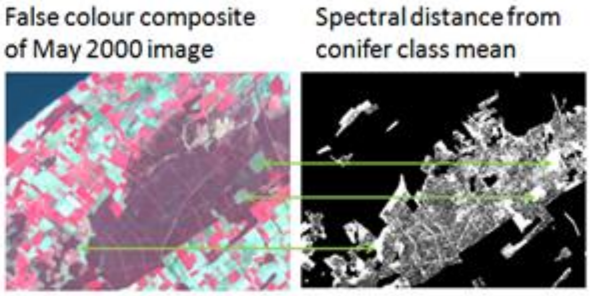


Figure 4.7 Tasselled cap change for the brightness (TC1), greenness (TC2) and wetness (TC3) components.

4.2.2 Classification-to-image change detection

Figure 4.8 shows the May 2000 image and the associated spectral distance based on the extent of the heather class in 1988 and the spectral values in 2000. Non-heather land cover in 1988 is masked from the spectral distance images, so the remaining high spectral distance pixels (white in Figure 4.8) show high spectral distance from the core heather signature and are likely to represent change. Figure 4.9 shows similar results for conifer; the highlighted changes all represent stands harvested, between 1988 and 2000.

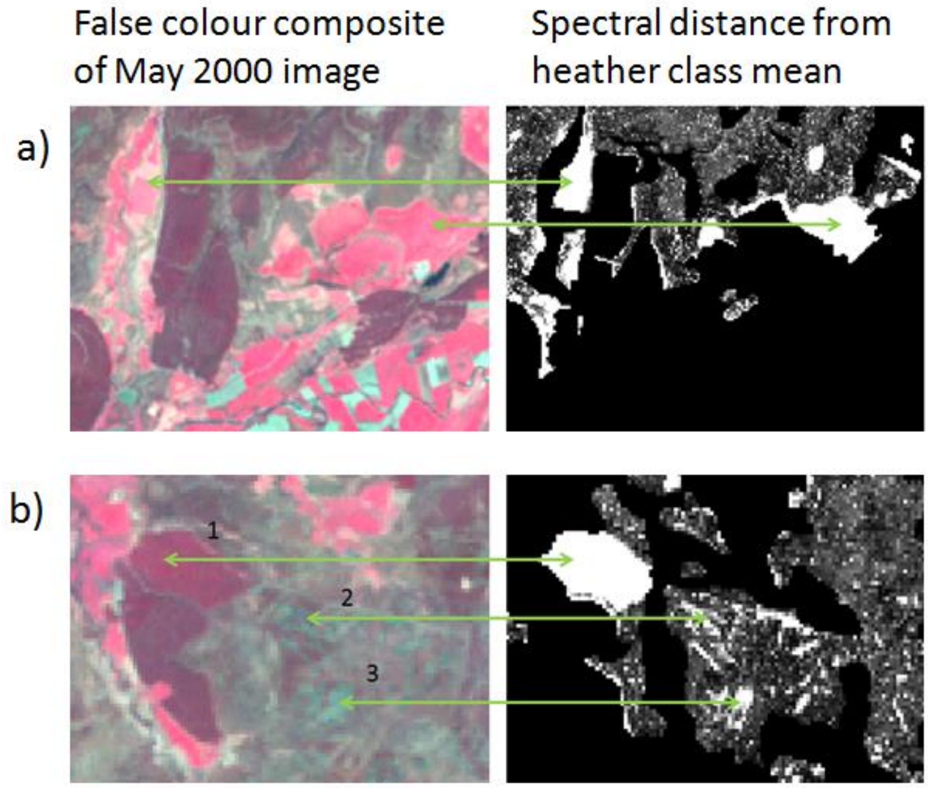


Figure 4.8 Examples of land cover change for the Scottish test site between 1988 and 2000 a) heather to improved grassland conversion; b) area 1: conversion from heather moorland to young conifer plantation; areas 2 & 3: areas of heather burning or heather clearance.

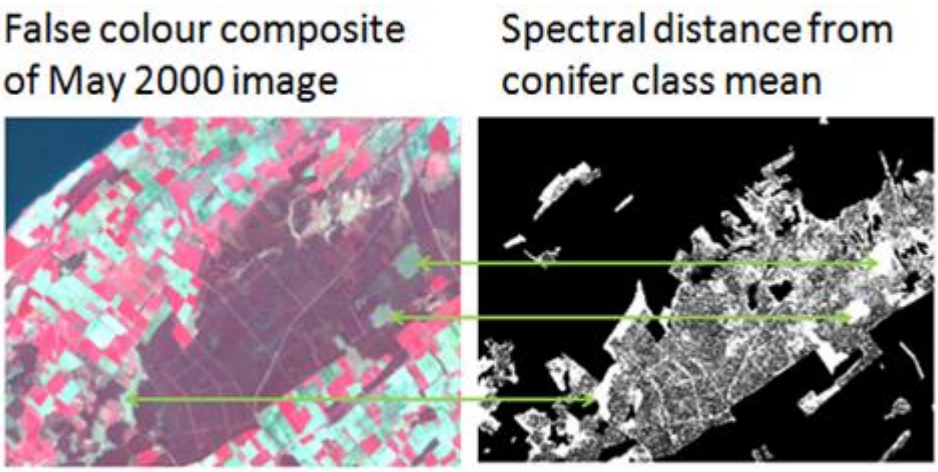


Figure 4.9 Examples of conifer harvesting for the Scottish test site between 1988 and 2000.

4.2.3 Quantitative assessment of the change detection methods

The April PCA, the cumulative NDVI change and the spectral distance method, all thresholded at 2 standard deviations (SD), produce the best results (Table 4.1). Assessing 30 change polygons was very useful for understanding the differences between the methods and the type of area they detect. However, there are order of magnitude differences in the area of change mapped across Norfolk by the different methods (Table 4.1), so further analysis is needed to explore the spatial distribution of changes, the types of change mapped best by the different methods and assessment against a standard change data set to assess the degree of omission. The validation presented here assesses the accuracy of the changes that are identified, but does not provide any information on the rate (and type) of changes that are undetected. This information is key for developing these methods further.

Table 4.1: Summary results for each of the methods for 30 randomly selected change polygons. [1]Modified to exclude the unidentified changes. Unidentified changes are those where it was not possible to identify with certainty whether a change had occurred and unallocated are those cases where it was unclear whether the magnitude of the change was significant enough to count as a change.

Method	Number of real changes (from 30)	Unidentified/ unallocated changes	% accuracy (based on assessment of 30 polygons)[1]	Total area of change polygons (km^2)	Number of change polygons identified
NDVI 1 SD	4	3	15%	365	7964
NDVI 2 SD	18	0	60%	65	1275
April PCA 1 SD	9	2	32%	184	2690
April PCA 2 SD	20	2	71%	62	1273
Post-classification	5	2	18%	483	27057
Spectral distance 2 SD	18	1	62%	23	1473

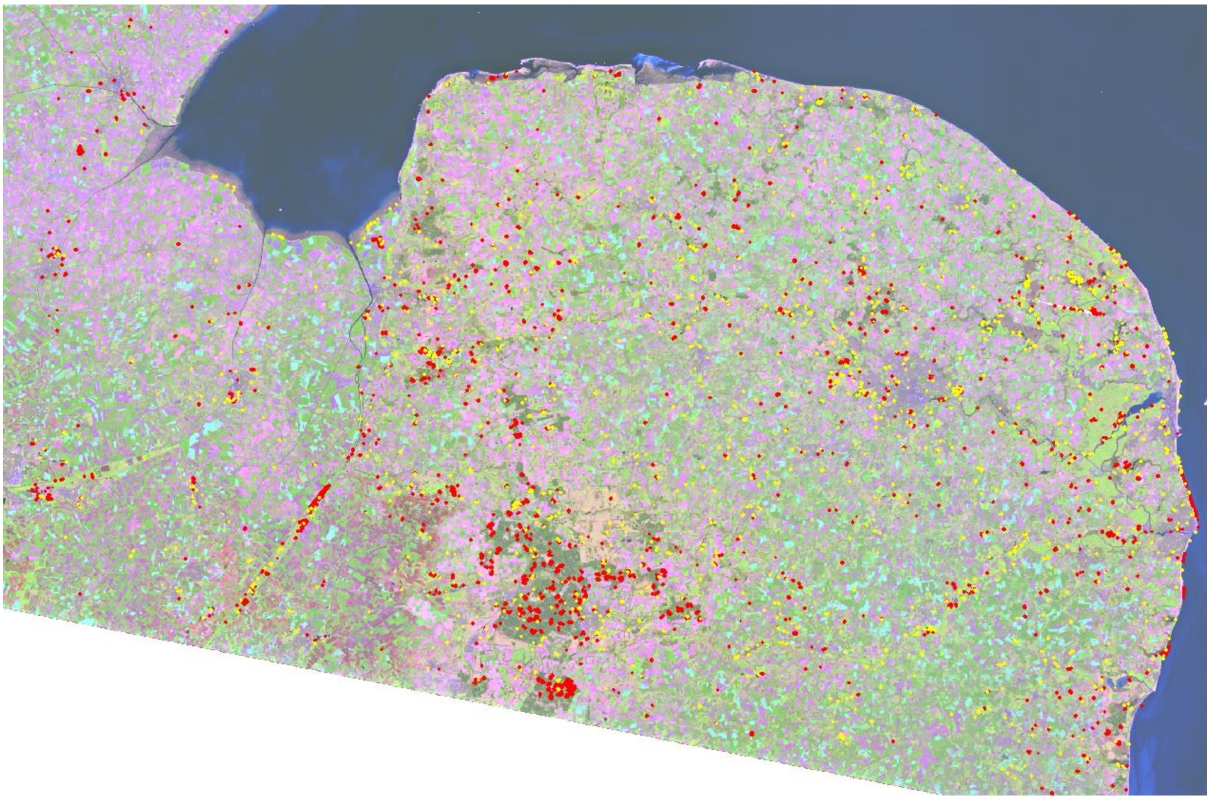


Figure 4.10 Distribution of NDVI 2 SD (yellow change polygons) and PCA 2 SD (red change polygons), after masking out Arable and off-shore changes.

4.2.4 In Summary

Cumulative NDVI with 1 SD threshold – overall, this method performed poorly and most of the polygons identified (23/30) had not changed.

Cumulative NDVI with 2 SD threshold – typically detects small change polygons that include a mix of land cover types, e.g. boundary between two fields, or a mix of water and grass. The method is very good at identifying patches of land that are bare soil/cleared land in one image and vegetation in the other. This is because it is sensitivity to sharp increases or decreases in NDVI. For example, it detects the removal of scrub at Holt Lowes to maintain the heathland habitat.

PCA 1 SD threshold – the PCA analysis is more sensitive to changes in enclosed water bodies than the NDVI analysis. These changes are likely to be temporary, although in one case the PCA detects a new lake in 2002, which had 'matured' by 2011.

PCA 2 SD threshold – the main errors were due to issues with the arable (five polygons) and coastal masking (one polygon), excluding these polygons this technique gives 20 good changes out of 24 change polygons.

Spectral distance 2 SD – The two key sources of error in the spectral distance change mapping, appear to be error in the classification, which propagates through into a false change detection (five cases) and a potential over-sensitivity to urban change (four cases of urban redevelopment were detected), plus two false detections for urban change. This suggests that the threshold for urban change needs to be increased to reduce the number of false and marginal changes and presumably reflects the high spectral variability of urban environments. More detailed analysis is required to determine whether 2 standard deviations from the mean is a sensible threshold for the other land cover types.

In general, four pixels was selected as the smallest change polygon-size for the raster-based change detection, although this may be too small, as small, narrow features are sensitive to small spatial errors and the change signature may not be strong enough.

Classification-classification

Two main types of change polygons were detected:

- **narrow features** - a pixel in width (possible less with the 30m pixel resolution data used in this project). Typically tree breaks, often with influence or arable, or roads, where the tree cover had become slightly denser, but without undergoing any significant change.
- **mixed use polygons** - typically including a mix of several land cover parcels, including roads/building, woodland and grassland. In these cases there is often no dominant land cover and even by eye it would be difficult to assign a dominant land cover.

The change polygons causing problems can be identified, as they are primarily:

- multi-modal classes
- small polygons, where a single pixel change can switch the modal class

The fact that we can identify change, suggests that we should be able to develop methods to improve the accuracy of this method, either by applying additional filtering to remove these polygons or by developing more sophisticated techniques to deal with them.

4.3 Discussion

The bands of the multi-temporal PCA that corresponded most to change were found to be bands 4, 5 and 6, although this may be scene-dependent. PCA is a statistical technique for optimising the orientation of the different components, how they are optimised is data (or image) dependent, so change may be captured by different bands of the PCA, depending on how widely change affects the scene. Application of this method to other sets of images is required to assess whether this is an issue in practice.

There are a number of outstanding issues, including:

- **Assessment of the rate of omission –** this is difficult as suitable data does not readily exist. However, a wide range of changes have been identified and validated, during the assessment of the different change methods, so from these, plus other changes noted during the course of this project, it should be possible to construct a data set of over 100 areas of change covering a wide range of changes. Applying this to the different change products will provide valuable information about the respective strengths and weaknesses of the different methods.

- **Data availability** - The image-image change methods used anniversary images i.e. the same month, but for different years. Is it realistic to require anniversary images for an operational method for the UK?
- **Combining methods** - How do we combine the methods to get the best final data product? The work so far suggests that there is potential in the various methods assessed. However, the work to-date has examined the methods individually and it seems likely that using some combination of the methods, to provide corroboration may provide the required accuracy and reliability. It seems likely that the final method will use elements of both the classification and spectral change processes to create a hybrid method that captures the best of both approaches. The classification-image method begins to develop this approach, whether it can be useful supplemented by the spectral-change methods should be assessed.
- **Spatial scale** - What is the smallest area that we can detect change for? Is it the same for the different method? How much does it vary between the best case treatment? This assessment needs to be made, as it will be a function of the area and shape of the objects as well as the spectral contrast between the change area and the surrounding area. However, we should be able to develop guidelines and a better understanding of this area. Certainly, the preliminary results suggest that 4 pixels in a vertical or horizontal line are too small to be reliably detected, as this type of linear feature is too prone to problems with georeferencing errors and mixed pixels. Any final change product will have a minimum mappable unit (MMU) and a minimum feature width (MFW). The LCM products already have these properties; however, we have to consider whether the MMU and MFW of the change detection products will be the same or different; they may need to be slightly coarser to maintain the high accuracy that most users will require.

5 Spatial Framework

We define a spatial framework as a set of land parcels for organising and summarising land cover information derived from satellite images. An appropriate structure for a spatial framework will depend on many factors, with pixel size of key importance. If land parcels within a framework are small relative to pixel size they will offer little opportunity to summarise information; for example if land parcels smaller than a pixel are permitted it will take several land parcels to describe a single pixel. Ideally a spatial framework should consist of land parcels some multiple of pixel size. LCM2000 and LCM2007 used average spectra per land parcel and maximum likelihood classification techniques. For optimal classification performance each land parcel was required to contain at least five (preferably more) pixels. LCM2000 and LCM2007 therefore had a minimum mappable unit of 0.5ha and a minimum feature width of 25m. LCM2000 had a spatial framework of image segments, whilst LCM2007 had a spatial framework derived from digital cartography integrated with image segments.

Segmentation boundaries are a function of surface reflectance and therefore time. Segmentations at different times from a single region will produce a different set of land parcels due to seasonal variations in reflectance and illumination effects. Successive maps produced from image segmentation will therefore be spatially inconsistent, which will complicate change detection. Ideally we want a fixed spatial framework that can be used repetitively to summarise classifications of the same region at different dates. This will enable the state of individual parcels of land to be tracked through time and will greatly simplify the problem of change detection. Digital cartography represents real-world, surveyed boundaries delineating land parcels, such as fields, lakes, woodlands, urban areas and so forth. These boundaries do change but generally at slow rate compared to the land cover they contain. Many of the field boundaries in the UK are aged, coming from or predating the enclosure acts from the 12th to 19th centuries. A spatial framework based on digital cartography will therefore be stable relative to land cover change, enabling units of land to be tracked through time.

The spatial framework constructed for LCM2007 was optimised for optical satellite data of 10-30m pixel resolution. It was constructed from OS MasterMap, OSNI large-scale vector and land parcels from agricultural censuses. This digital cartography is very detailed compared to 20m pixels so land parcels were generalised by merging and splitting (Smith *et al* 2007; Figure 5.1). The average-spectra, object-based classification techniques of LCM2007 required an extra step: land parcels were subdivided using image segments to delineate multi-modal pixel distributions within large land parcels. Multimodal pixel distributions within a land parcel can occur for many reasons. For example, habitat mosaics in upland and semi-natural enclosures; multiple crops grown within a single field; partial ploughing at the time of image capture; uneven stages of development within a crop due to the effects of shading or uneven fertilizer application and so forth.

Classifying pixels instead of objects relaxes the requirements of a spatial framework, as the success of classification is independent of parcel structure. We propose therefore that the LCM2007 spatial framework (pre-integration of segments) is the best available spatial framework for summarising pixel 10-30m pixel land cover. It was designed for pixels of this size and its derivation from digital cartography gives spatiotemporal stability, which supports change detection.

Figure 5.2(a) shows a pixel classification and Figure 5.2 (b) this same classification organised into the LCM2007 spatial framework with land cover assigned to the modal pixel class. The generalising effect of the parcel structure is easily seen by comparing Figure 5.2 (a) and (b). For example, in the South West corner there appears to be more woodland in the pixel map. This is because the parcel framework displays the modal class, so cannot visually match the detail provided by pixels. Woodland edges that occur on field boundaries that are narrower than the MFW and copses within fields smaller than the MMU will not be shown in the parcel map; only the dominant land cover for the parcel is shown. However, by classifying pixels and summarising by parcel we can still retain some of this detail within the parcel product. For example, the land parcel highlighted in Figure 5.3 is dominantly heather, but the frequency distribution of pixels tells us that around 30% of the land parcel is covered by grassland. Analysis of textural information of this kind is useful. It can be indicative of within class changes that might be related to condition, succession, disturbance or other change drivers and act as a stimulus for more detailed studies. Some analyses will require different kinds of spatial summary. For example catchment analyses may require summaries of the whole catchment rather than more detailed per-parcel summaries. It is conceivable that at some point in the future an improved, more up-to-date version of a parcel spatial framework will be required. But pixel classifications, because they are detached from a parcel structure, give us the ability to cope with all these changes. Therefore using the LCM2007 spatial framework now does not constrain us from this point forward. We can easily use a new improved framework when and if one becomes available.

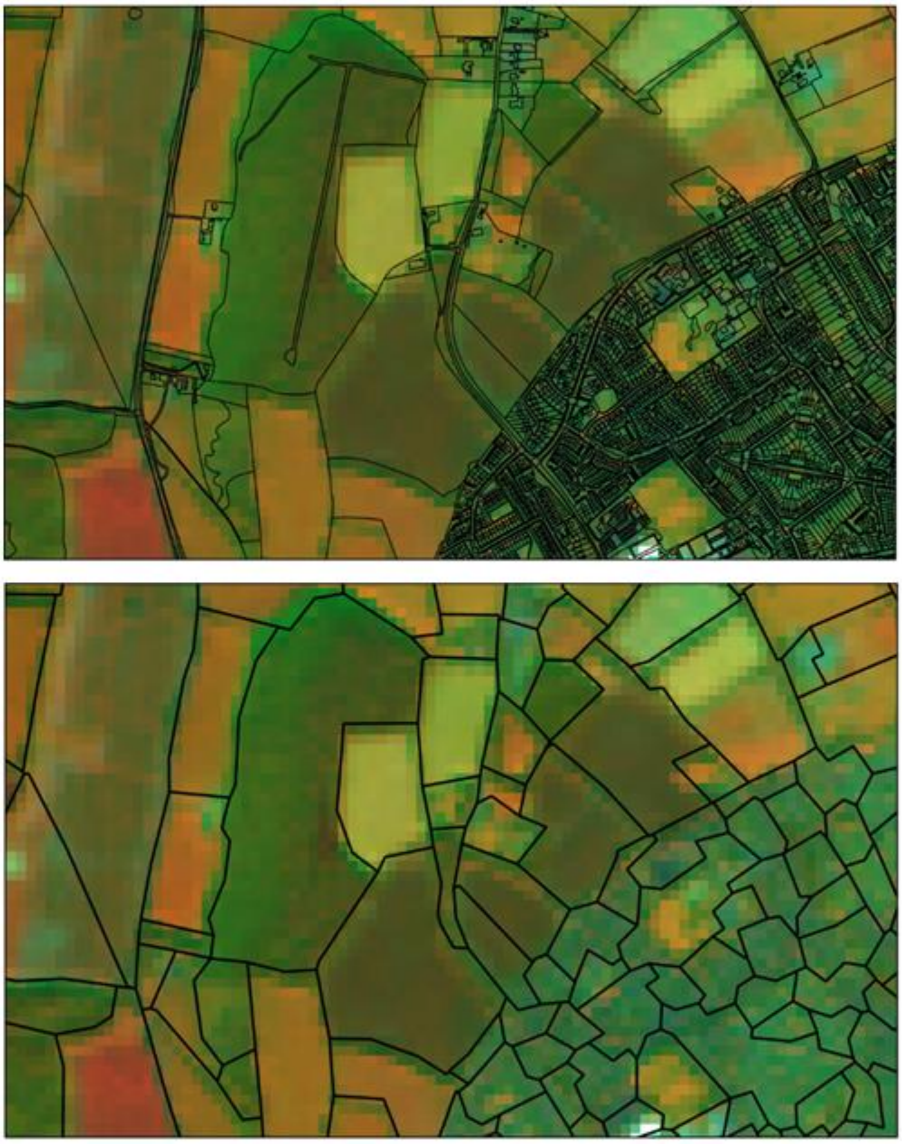


Figure 5.1. OS MasterMap before and after generalisation.

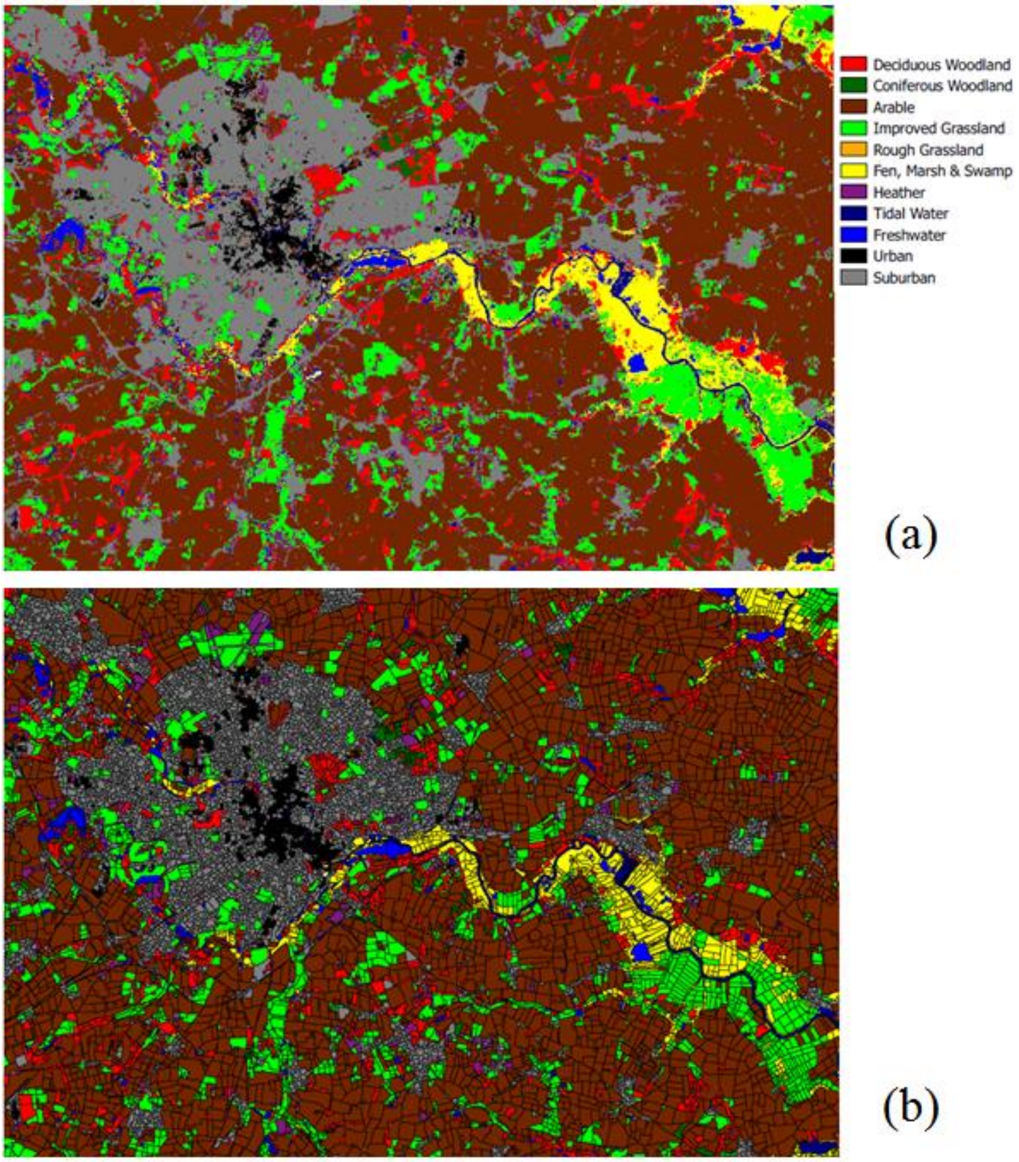


Figure 5.2. A pixel classification (a) organised according to a generalised OS MasterMap spatial framework (b)

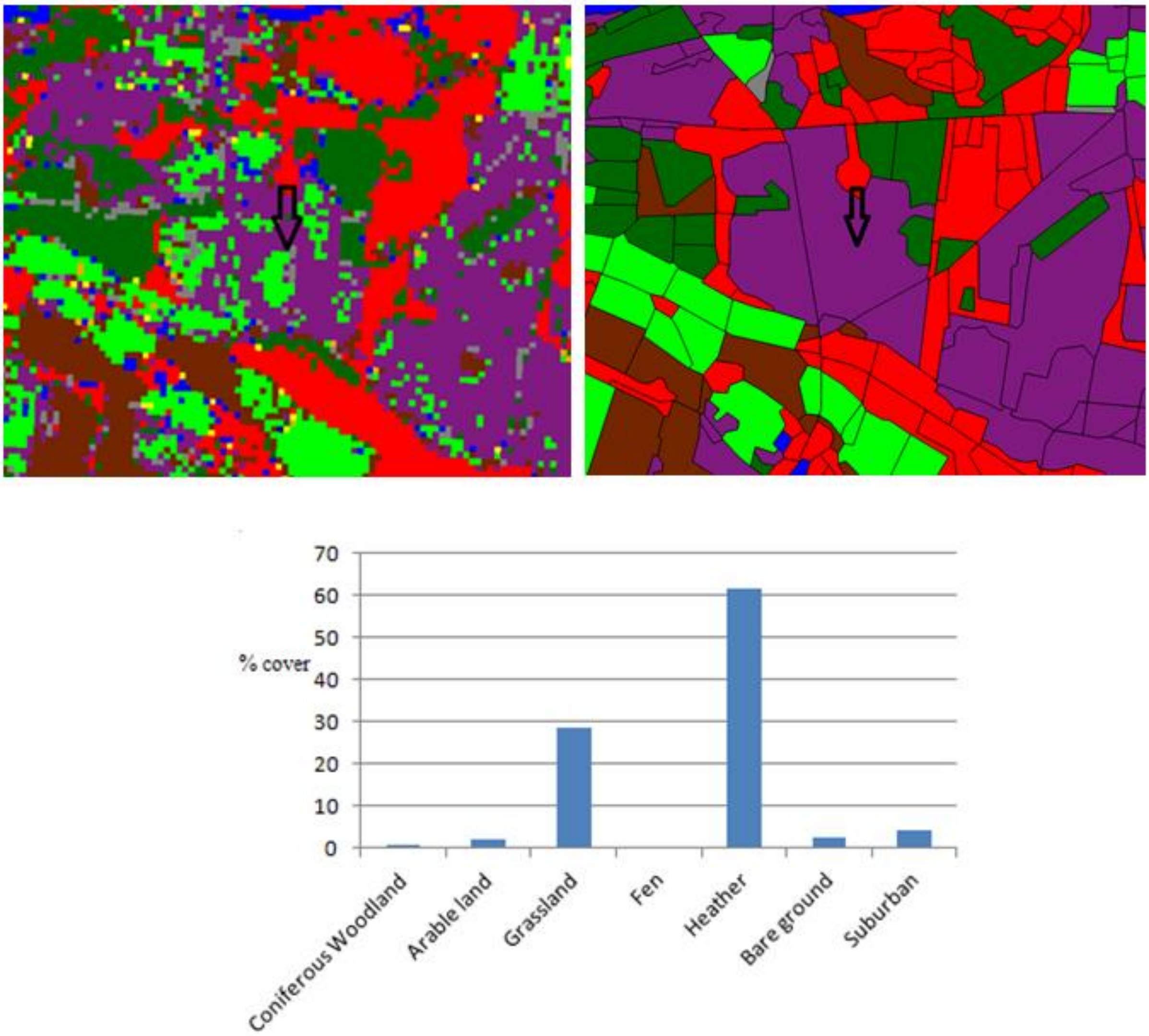


Figure 5.3. Pixel classification and corresponding parcel-based summary. The histogram shows the distribution of land cover within the highlighted (arrow) land parcel.

6 Thematic considerations

Thematic descriptions of land cover changed substantially between LCM1990 and LCM2000 and to a lesser extent between LCM2000 and LCM2007. These different ways of describing and therefore quantifying land have made change detection very difficult. For change detection thematic consistency is essential. We must therefore converge upon an optimal set of land cover descriptions and stay with them into the foreseeable future.

There are multiple existing schemas for describing land cover and habitats (UK BAP habitats; EUNIS habitats; General Habitat Categories; the FAO LCCS; and CORINE to name just a few) so deciding how to describe land is not straightforward. Most existing schemas have been designed for ground based observations or visual image interpretation and the BAP broad habitats used for LCM2000 and LCM2007 fall into the former category. Some BAP broad habitats are characterised by species composition, but species identification is not a realistic goal for most remote sensing techniques and certainly not from 20m pixels. In the production of LCM2007 we were therefore unable to achieve the desired level of accuracy for some BAP broad habitats. LCM1990 used a schema designed for satellite-based surveillance techniques and it is likely that future UK land covers schemas will be closer to this than BAP inventories.

Land cover descriptions optimised for satellite derived inventories are required. In addition habitat/land cover descriptions should support multiple reporting requirements at regional, national and international level. We expect descriptions based on plant life-forms (Raunkiær, 1934) such

as General Habitat Categories and the FAO Land Cover Classification System (http://www.fao.org/docrep/003/x0596e/x0596e00.HTM; Di Gregorio & Jansen, 2005; Kosmidou *et al* 2014) will be useful. Raunkiær life-forms classify vegetation according to morphology, biophysical, and phenological traits, which should correlate well with optical and structural remote sensing techniques. They are also recognised as a robust means for defining the essential character of habitats throughout the world and so have potential to harmonise classification systems. The European Environment Agency, EAGLE (EIONET Action Group on Land Monitoring in Europe) working group is developing an INSPIRE compliant hierarchal data model to unify land cover and land use descriptions for use in a European land monitoring framework. If this project gains traction the relationship of future nomenclatures with the EAGLE data model should be assessed to facilitate semantic translation and maximise reporting potential.
In the present study, because gathering training data relied on historical land cover inventories (see section 2.4) we used land cover descriptions related to these. To detect stable land parcels it was necessary to find a mapping to unite LCM1990, LCM2000 and LCM2007 land cover descriptions and observations. There are not one-to-one mappings between the separate schemas used in these maps so it was necessary to generalise and produce a simpler set (Table 6.1 gives these descriptions and their relationship to LCM2007 classes; LCM2007 classes are given in Table 6.2).

Table 6.1 Simplified class descriptions derived from LCM2007.

Land Cover	Description	Related LCM2007 classes (See Table 6-2)
Broad leaved woodland	Broad leaved woodland	1
Coniferous woodland	Coniferous woodland	2
Arable	All types of arable land	3
Improved grassland	Productive grassland through reseeding and fertilisation	4
Rough/Unproductive grassland	Less productive grassland	5, 6, 7
Acid grassland	Acid Grassland	8
Fen, Marsh and Swamp	Fen, Marsh and Swamp	9
Dwarf shrub/Heather	>25% cover of dwarf shrub or heather	10
Heather grassland	Mix of grassland and dwarf shrub with less than 25% dwarf shrub	11
Bare rock	All exposed rock surfaces, including coastal, montane and quarries.	14, 17, 19
Tidal water	Tidal water	15
Freshwater	Fresh water, non-tidal	16
Sediment	Mud or sand	20, 18
Saltmarsh	Saltmarsh	21
Urban	Dense urban	22
Suburban	Built up areas with gardens and green space	23

Table 6.2 LCM2007 class structure. BAP broad habitats in italic. Bold descriptions indicate deviations from BAP broad habitats (see Morton *et al* 2011 for full details).

Aggregate class	Broad Habitat	LCM2007 class	Class Identifier

Broadleaf woodland	*Broadleaved, Mixed and Yew Woodland*	**Broadleaved woodland**	1
Coniferous woodland	*Coniferous Woodland*	*Coniferous Woodland*	2
Arable	*Arable and Horticulture*	*Arable and Horticulture*	3
Improved grassland	*Improved Grassland*	*Improved Grassland*	4
Semi-natural grassland	**Rough Grassland**	**Rough grassland**	5
	Neutral Grassland	*Neutral Grassland*	6
	Calcareous Grassland	*Calcareous Grassland*	7
	Acid Grassland	*Acid grassland*	8
	Fen, Marsh and Swamp	*Fen, Marsh and Swamp*	9
Mountain, heath, bog	*Dwarf Shrub Heath*	**Heather**	10
		Heather grassland	11
	Bog	*Bog*	12
	Montane Habitats	*Montane Habitats*	13
	Inland Rock	*Inland Rock*	14
Saltwater	**Saltwater**	**Saltwater**	15
Freshwater	**Freshwater**	**Freshwater**	16
Coastal	*Supra-littoral Rock*	*Supra-littoral Rock*	17
	Supra-littoral Sediment	*Supra-littoral Sediment*	18
	Littoral Rock	*Littoral Rock*	19
	Littoral Sediment	**Littoral sediment**	20
		Saltmarsh	21
Built-up areas and gardens	*Built-up Areas and Gardens*	**Urban**	22
		Suburban	23

This simplified structure is better suited for satellite techniques as the surface descriptions relate more directly to optical reflectance. For example, in the production of LCM2000 and LCM2007 using optical reflectance alone we were not able to differentiate BAP broad habitat grassland types and had to use ancillary data. The simplified grassland descriptions in Table 6.1 are a more realistic target for broad-scale remote sensing techniques. Similarly BAP exposed rock (Littoral Rock, Supra Littoral Rock, Bare Rock) surfaces are similar spectrally so are only separable by regional context, so it is better to group them together; the same goes for unvegetated sediment surfaces.

Note that we do not represent Bog in the land cover descriptions. Bog was recorded inconsistently across CEH's three land cover maps, so the correspondence of Bog through time was inadequate to generate training data. Moreover, Bog according to BAP broad habitats contains a range of vegetation types and may be dominated by purple moor-grass (*Molinea caerulea*) or hare's tail cotton-grass (*Eriophorum vaginatum*) or dwarf shrubs and heathland, or fen, marsh and swamp. This variability of land cover associated with Bog makes it unsuitable as a class for remote sensing techniques. Montane is also excluded as a range of vegetation types and land surfaces are encountered at high altitude. So further work and research would be required to understand the level of detail that could be achieved in these upland areas.

Our assumption that this revised land cover schema is superior to those from existing CEH land cover maps is based on experience and was supported subjectively by visual inspection through juxtaposition of aerial and satellite images with classification results. The high correspondence results achieved with CS data are also encouraging (section 2). But for a proper, objective assessment, dedicated, temporally coincident validation inventories are required.

We expect that uncertainty products derived from class membership probabilities (section 2.6.4) will be helpful in determining the optimal schema. If within a scene, we detect regions of high uncertainty (low membership probability across all classes) this will indicate that the training data is insufficient to accurately describe the range of land covers or variants within a given land cover. One reason for this could be that there is a detectable land cover type that is unaccounted for in the schema. Confirmation would come if the same pattern repeats across years and through this process our understanding of the discriminative power of broad scale optical remote sensing can evolve. Extending a schema seems to run against the mantra of thematic consistency, but if it is done carefully within a hierarchal structure this should not cause problems for temporal analyses.

7 Statistical interpretation of widespread change

The techniques we have developed will enable more rapid classification of satellite images and can lead to more frequent, cost-effective land cover inventories. In the short to medium term it is unlikely that a sufficient set of image data will become available within a single year for a complete national, annual refresh. This gives the option of suspending refresh until a national image set becomes available or implementing a rolling update programme. Exactly which approach is best will become clearer as new sensors come on-line and Copernicus services (http://www.eea.europa.eu/about-us/what/seis-initiatives/copernicus) mature. But regardless of the approach taken the most current distribution of land cover is likely to be compiled from images spanning several years. Reporting requirements and conservation strategies often require annual estimates of stock and change, so a challenge is how to reliably compute annual estimates given the temporal variability of the underlying dataset.

If a fraction of national land cover data is produced in each year, an estimate of stock can be readily derived using a statistical modelling approach that fills in the missing data and estimates mean stock across the whole sample. This is done by using the estimated correlation structure of the data across years. The difficulty is in compensating for potentially different coverage areas in each year, differing amounts of data and hence a different error structure on the response of interest as compared to any assumption of independence. This type of problem is readily solved using Generalised Linear Mixed Models, which enable the user to specify an error structure appropriate to the data collected and compensate for an unbalanced design or any unobserved latent processes. The Countryside Survey used this approach to produce consistent stock and change estimates in 2007; the Mixed Model compensated for the different number of squares surveyed in each of the survey years (1978, 1984, 1990, 1998 and 2007). A similar technique has been developed for the Glastir Monitoring and Evaluation Programme (GMEP) for Wales, which is coordinated by CEH. The purpose of GMEP is to assess the impact of Glastir (the Welsh agri-environment scheme) on the quality of the welsh countryside. The monitoring comprises a rolling programme in which a fraction of widespread sites are surveyed each year. Similar rolling programme approaches have also been employed as an alternative to the single year population census in many countries where logistical problems mean a countrywide census is impractical within a single year. The most famous example is perhaps the American Community Survey. Deriving robust estimates of stock and change from rolling or partial surveys does not therefore set a statistical precedent. CEH have significant expertise with this kind of statistical problem, with tested and validated techniques that can be adapted for land cover reporting when processing chains are mature and a sufficient time series of data becomes available.

8 Overall assessment towards an operational UK Land Cover Stock and Change System

At start of this project we proposed a modular design towards an operational Land Cover Stock and Change System (LCSCS). A modular approach allows iterative deployment of components so that some of the benefits of the system can be realised before full functionality is available. It also supports adaptability: providing the interfaces between components are clearly defined, it is straightforward to replace a component with a new enhanced version. An architecture such as this is essential for system longevity and system longevity is essential to realise its benefits, as the vegetative response to the drivers of land cover change (for example climate change) can be gradual and undetectable over short intervals. In this section we assess current research and our resulting position relative to operational functionality. All the developments within this project have used well established open source tools. This minimises cost and because they have a strong user base they are likely to remain available and continually improving into the future.

8.2 Modular design

Our new high-level understanding of a LCSCS is given as a component diagram (Figure 8.1). The ball and socket connectors represent component interfaces. A socket represents an interface specification and the ball provision to that specification. For example the Classification component requires prepared images for classifying, so the Image Preparation component must supply image data to this specification. The core functionality is supplied by the LCSCS component and this is supplied by integrated functionality of internal components. There are three main artefacts of the system: Change Products (e.g. change maps, statistical estimates of change); Classification Products (e.g. pixel maps, land parcel maps) and Ecological Products (e.g. biophysical correlates of ecological function). The LCSCS receives ancillary data and satellite data from external third party sources; these are required by the Image Preparation component. The LCSCS will also require *in situ* field observations, mainly for validation but perhaps training too.

In situ. Historically *in situ* observations have provided most of the data for training and validation. We have developed a method to train a classifier using historical land cover patterns (section 2.4) so in a future system we expect field observations to mainly serve product validation. A dedicated field campaign would be expensive, but there is scope to augment existing recording schemes and to influence new ones so that validation data can be collected in a cost effective basis.

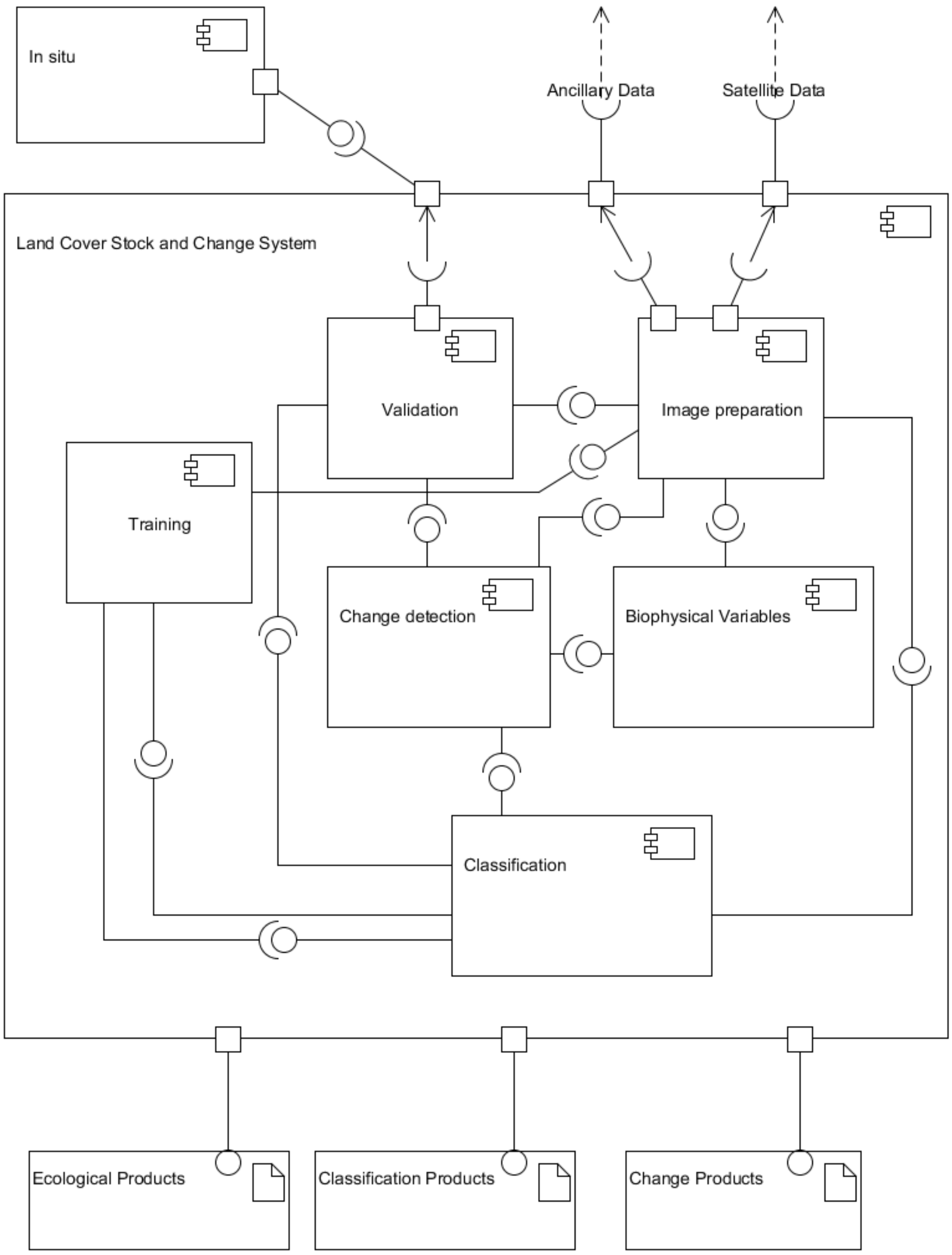


Figure 8.1 High-level component architecture for a Land Cover Stock and Change System.

Training. The training component requires data that links radiance (and ancillary data) to what is believed to be on the ground. Traditionally this data has come from field campaigns, which are costly. In this project we have demonstrated that it is possible to have a fully automated technique that generates training data from historical land cover classifications, current composite images and ancillary data. This does not exclude the possibility of using field observations too. A further advantage of using historical classifications for classifier training is that as time series develop within the LCSCS the quality of training data will continually improve and consequently so too will classification accuracy.

Validation. The validation component will need classified images and an independent set of data to assess these. It is straightforward to compute the correspondence between a classified image and independent observations and we used a fully automated process to correspond CS observations with pixel classifications (section 2.6.1) to assess their quality. CS observations, though, have restricted extent and the interval between surveys is many years, so using these data was a compromise and far from ideal. In an operational system we need more up-to-date and expansive data. The technique we have developed can use field observations from any source provided they link a parcel of land with a set of land cover observations.

Classification. Our results here have demonstrated that we are able to classify satellite images at a fraction of the time it has taken historically. Fully automating the training classification processes, through the use of land cover history and non-parametric classification techniques, was key to this. Our use of the Weka machine learning suite means that it is straightforward to switch amongst any of the classification algorithms this provides. Weka provides an extensible structure so users can develop and add their own classification tools and take full advantage of Weka's generic functionality. The FastRandomForest algorithm we used was an extension of Weka's standard functionality. This flexibility and extensibility are important for longevity and continual improvement.

Of the classification tools we tested RF offers ease of use and accuracy and is the front runner for operational activity. We classified pixels and summarise these automatically using a spatial framework. This gives pixel and polygon products and the advantages associated with each. This component is well understood and close to operational functionality.

Change detection. The change detection research took a multiple approach, looking at: (1) image-to-image change; (2) classification-to-image change; (3) and classification-to-classification change. Exactly how and which of these processes could be integrated within an operational system is not fully clear and more research is required. Image to image change is powerful but reliant on anniversary images and the widespread availability of images of this kind cannot be guaranteed. Classification-to-image change detection and classification-to-classification change detection are less sensitive to image timing and so have greater potential for generating wide-scale change products. Classification-to-classification change is the most likely to generate usable products as iterative classification is the primary function of the Land Cover Stock and Change System. Methods to combine uncertainty (section 2.6.4) and temporal class changes are an area for further research. Classification to classification change will be the currency used for statistical estimates of change (see section 7). In maintaining a set of 'fixed' parcels for classifier training it will be necessary to monitor these and make decisions as to whether they remain or are excluded from future classifications. As time flows it will also be necessary to recruit new training polygons. We expect that Classification-to-image change detection will help inform such decisions.

Biophysical variables. The rationale for calculating biophysical variables was to begin to explore their role in capturing within polygon variability and habitat condition. Their use as an input to image classification was also assessed, but did not positively affect results (section 2.6.2). Biophysical variables are sensitive to seasonal and recent meteorological events and values calculated from different images will give different values. A number of different options for dealing with this were suggested in section 3.5, but need further assessment and trialling with users will be needed to identify the best options. The value of the biophysical variables is likely to increase the length of the time-series expands and trends develop.

Image preparation. Selection and preparation (pre-processing) of images is a significant component in terms of complexity and time when land cover mapping. Typically this involves orthorectification, radiometric corrections for atmospheric effects, cloud masking and georeferencing. We did not examine the automation of these. The pre-processing steps applied by image providers are continually improving. Landsat-8 and Copernicus services are in their infancy and on these, and follow on missions, the LCSCS will largely depend. Substantial research now to streamline and automate the image preparation process would therefore be premature. It is better to wait and see what level of processing is applied.

Ancillary data and Satellite data. The production of ancillary data and satellite data are outside the functionality of the system. However, these data influence the development of the image preparation component. We assume the continuity of Optical Landsat-type data for the lifetime of the LCSCS and research described in section 2.2 indicates that radar data may also have a significant role. Ancillary data are combined with optical data to enhance class resolution by reducing spectral confusion. Choices regarding the use of ancillary data should take account of stability.

8.3 Next steps: iterative deployment

Ultimately we envisage a fully operational LCSCS in a parallel compute environment with fast access to newly available satellite data. With the highly automated techniques we have developed we believe it is possible to provide near-real time land cover products and combined with sophisticated visualisation tools such as the video wall at ISIC this could open up novel analyses and applications. Rapid turnaround such as this would represent a rolling update of land cover information, with refresh occurring when good images become available. However, in the short term it is necessary to demonstrate the feasibility of techniques developed in this research and their potential for national scale production. We believe the best way to achieve this is to produce new large-scale land cover products representing at least two points in time; pixel and polygon products using the generalised OS MasterMap spatial framework. The production at large-scale will expose production complexities not yet apparent. Two points in time will allow us to advance change detection techniques and will provide historical data for future classifier training. Production at a large-scale will also expose the full range of UK land cover types enabling us to devise the optimal satellite based land cover schema for the UK. We suggest that a large-scale test covering several adjacent images of a discrete geographical area should be conducted, to assess:

- the quality of the image classifications
- the quality and feasibility of the change products in a more operational setting
- the utility of the ecological variables

The area would ideally require three to four images to provide a good test of the methods. One possibility would be Wales, as CEH have existing field data from 2012, 2013, which could be used as validation data, as well as extensive data held by NRW.

Of the component functionality (Figure 8.1) the Training and Classification components are the best understood and very close to operational functionality. Tracing their interface dependencies using Figure 8.1 shows these to rely on pre-processed images from the Image preparation component and historical classifications. A fully prepared set of images from LCM2007 are available and ancillary data. We therefore have the source material for one point in time. A goal of the EEA's Copernicus Land Monitoring Services is to produce pan European coverages of optical satellite data of 10m to 30m pixel resolution with minimal cloud cover on a three year repeat cycle for the production of CORINE land cover maps and five high resolution land cover layers. Image 2012 is one such pan European coverage and is available at no cost and this is a candidate for the second point in time, although image quality and post-processing may mean it is necessary to restrict classification to the best regions, rather than produce a full national coverage.

Product validation is essential and gathering *in situ* data for this has traditionally been a very expensive component of land cover mapping. There are numerous recording and study groups within the UK; many coordinated by the JNCC and CEH. A body of work to assess these schemes and their potential for revision to gather data for the validation of land cover products is essential. We believe that through coordinated effort it should be possible to fulfil the In situ component. A sensible goal would be to have a programme in place within three years. A workshop to explore this potential and kick-start the process in the near future is advisable.

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10 Appendix 1: Satellite data pre-processing

Table 10.1 Example of the full listing of the sixtyone-band images used as input for the classification treatments. Example shown is for the Scottish site, the Norfolk images followed the same format.

Layer	Data set	Additional details	Data type
1	Mar 2000 TM	Landsat band 1	Date 1: Blue (0.45-0.52 µm)
2	Mar 2000 TM	Landsat band 2	Date 1: Green (0.52-0.61 µm)
3	Mar 2000 TM	Landsat band 3	Date 1: Red (0.63-0.69 µm)
4	Mar 2000 TM	Landsat band 4	Date 1: NIR (0.75-0.90 µm)
5	Mar 2000 TM	Landsat band 5	Date 1: SWIR-1(1.55-1.75 µm)
6	Mar 2000 TM	Landsat band 7	Date 1: SWIR-2(2.09-2.35 µm)
7	May 2000 TM	Landsat band 1	Date 2: Blue (0.45-0.52 µm)
8	May 2000 TM	Landsat band 2	Date 2: Green (0.52-0.61 µm)
9	May 2000 TM	Landsat band 3	Date 2: Red (0.63-0.69 µm)
10	May 2000 TM	Landsat band 4	Date 2: NIR (0.75-0.90 µm)
11	May 2000 TM	Landsat band 5	Date 2: SWIR-1(1.55-1.75 µm)
12	May 2000 TM	Landsat band 7	Date 2: SWIR-2(2.09-2.35 µm)
13	July 1999 TM	Landsat band 1	Date 3: Blue (0.45-0.52 µm)
14	July 1999 TM	Landsat band 2	Date 3: Green (0.52-0.61 µm)
15	July 1999 TM	Landsat band 3	Date 3: Red (0.63-0.69 µm)
16	July 1999 TM	Landsat band 4	Date 3: NIR (0.75-0.90 µm)
17	July 1999 TM	Landsat band 5	Date 3: SWIR-1(1.55-1.75 µm)
18	July 1999 TM	Landsat band 7	Date 3: SWIR-2(2.09-2.35 µm)
19	Thermal Mar 2000	Landsat band 6	Date 1: Thermal IR (10.4-12.5 µm)
20	Thermal May 2000	Landsat band 6	Date 2: Thermal IR (10.4-12.5 µm)
21	Thermal July 1999	Landsat band 6	Date 3: Thermal IR (10.4-12.5 µm)
22	NDVI March 2000	per-pixel	indices/spectral transforms
23	NDVI May 2000	per-pixel	indices/spectral transforms
24	NDVI July 1999	per-pixel	indices/spectral transforms
25	NDSWIR March 2000	per-pixel	indices/spectral transforms
26	NDSWIR May 2000	per-pixel	indices/spectral transforms
27	NDSWIR July 1999	per-pixel	indices/spectral transforms
28	NDVI march 2000	5x5 window	texture
29	NDVI May 2000	5x5 window	texture
30	NDVI July 1999	5x5 window	texture
31	NDSWIR March 2000	5x5 window	texture
32	NDSWIR May 2000	5x5 window	texture
33	NDSWIR April 1999	5x5 window	texture
34	NDVI March 2000	per-polygon	texture
35	NDVI May 2000	per-polygon	texture
36	NDVI July 1999	per-polygon	texture
37	NDSWIR March 2000	per-polygon	texture

38	NDSWIR May 2000	per-polygon	texture
39	NDSWIR July 1999	per-polygon	texture
40	NextMap DTM	per-pixel	altitude
41	NextMap DSM	per-pixel	altitude
42	NextMAP Diff	per-pixel	altitude
43	slope	per-pixel	geomorphology
44	aspect	per-pixel	geomorphology
45	DTM mean	per-polygon	geomorphology
46	DTM range	per-polygon	geomorphology
47	DTM std	per-polygon	geomorphology
48	DSM mean	per-polygon	geomorphology
49	DSM range	per-polygon	geomorphology
50	DSM std	per-polygon	geomorphology
51	Diff mean	per-polygon	geomorphology
52	Diff range	per-polygon	geomorphology
53	Diff std	per-polygon	geomorphology
54	TWI	per-pixel	geomorphology
55	ORI backscatter	per-polygon	structure
56	OS buildings	per-pixel	natonal mapping products
57	OS foreshore	per-pixel	natonal mapping products
58	OS land	per-pixel	natonal mapping products
59	OS surfacewater	per-pixel	natonal mapping products
60	OS tidalwater	per-pixel	natonal mapping products
61	OS woodland	per-pixel	natonal mapping products

11 Appendix 2: Classification assessments

Table 11.1 Norfolk 2002 classification correspondence with CS 1998. TukeyHSD pairwise significance tests: * < 0.2; ** < 0.1; *** <0.05

Treatment	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
Mean correspondence	72	73.2	77.3	79.4	79.5	81.8	83.5	83.2	83.5	83.3	82.8	84.8	85	84.4	84.3	84.8	84.6	83.8	84.5	83	82.6	84.1	83.5	80.1	82.8	86.4	84.2	86.7	87.3
1	===	-	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***
2	-	===	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***
3	***	***	===	-	-	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	**	***	***	***	***	***
4	***	***	-	===	-	-	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	-	***	***	***	***	***
5	***	***	-	-	===	-	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	-	***	***	***	***	***
6	***	***	***	-	-	===	-	-	-	-	-	***	***	*	*	***	***	-	*	-	-	-	-	-	-	***	-	***	***
7	***	***	***	***	***	-	===	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	***	-	***	-	***	***
8	***	***	***	***	***	-	-	===	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	***	-	***	-	***	***
9	***	***	***	***	***	-	-	-	===	-	-	-	-	-	-	-	-	-	-	-	-	-	-	***	-	***	-	***	***
10	***	***	***	***	***	-	-	-	-	===	-	-	-	-	-	-	-	-	-	-	-	-	-	***	-	***	-	***	***
11	***	***	***	***	***	-	-	-	-	-	===	-	-	-	-	-	-	-	-	-	-	-	-	*	-	***	-	***	***
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Table 11.2 Norfolk 2011 classification correspondence with CS2007. TukeyHSD pairwise significance tests: * < 0.2; ** < 0.1; *** <0.05.

Treatment	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
Mean correspondence	71.6	59.8	75.6	79.6	76.5	76.1	77.1	77.2	77.2	77	78	77.4	76.9	76.8	76.1	76.5	78.4	78.5	78.2	77.9	77.7	78.3	78.5	76.9	78.7	78.9	78.6	79.2	80.1
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Table 11.3 Scotland 2000 classification correspondence with CS1998. TukeyHSD pairwise significance tests: * < 0.2; ** < 0.1; *** <0.05.

Treatment	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
Mean correspondence	60.8	59.9	55.3	61.3	62.5	61	61.9	62.1	62	62.3	62.6	62.1	61.7	62	61	61	62	62	62	64	63.9	61.6	63.1	63	61.8	63.2	64	65.4	64
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12 Appendix 3: Quantitative analysis of biophysical variables

To determine the utility of using the CS2007 ANPP, or similar data, to calibrate the NDVI and Tasselled cap values to a known biophysical value, specifically ANPP, the strength of the linear relationships between the satellite-derived values and the ANPP were calculated.
Caveats:

- The CS estimates of ANPP data are based on field data collected in 2007.
- The AWIFS data is from the 9 & 10/06/2006 and 27/10/2005.
- The Landsat data used are mainly from 2000, 2002 and 2011.

These tables summarise the coefficient of determination (r^2) values for the correspondence between the CS2007 estimates of Aboveground Net Primary Productivity (ANPP) and the satellite-derived NDVI, NDMI and tasselled cap values. Tasselled cap band 1 corresponds to Brightness, whilst band 2 shows greenness and band 3 wetness. Summary results from these tables are provided in section 3 of the report.

Visual analysis showed that X plots are often near the edges of two or more pixels, so it maybe that extracting values for either the entire parcel, or the group of pixels closest to the X plot location would provide stronger results.

Table 12.1 summarises the highest coefficients of determination for the best relationships and the associated index. Key results from Table 12.1:

- The sum of the three NDVI values has a high r2 for all classes except the ‘Crops and weeds’ class, including the Fertile grassland class, where the r2 for the sum (0.91) is much higher than the values for individual dates. This highlights the benefits of multi-temporal data.
- Infertile grassland shows a strong correlation with the satellite-derived values for each of the three images, with NDMI, NDVI and TC2 all showing strong relationships

Table 12.1 Summary of the highest coefficients of determination (r2) for Norfolk 2002.Values with R2 < 0.10 marked as na. Nes denotes not enough samples.

AVC_class	April	Values	June	June value	September	Sept value	sum	Sum r2
Crops/weeds	na	na	na	na	TC1	0.15	na	na
Tall grassland/herb	TC2	0.29	TC4	0.52	TC2	0.25	NDVI	0.3
Fertile grassland	TC4	0.15	NDVI	0.5	NDVI, TC2	0.17	NDVI	0.91
Infertile grassland	NDMI	0.84	NDVI, TC2	0.66	TC2	0.82	NDVI	0.85
Lowland wooded	TC3	0.85	TC1	0.99	TC6	1	NDMI	0.99

Table 12.2 Summary of the highest coefficients of determination (r2) for Norfolk 2011.Values with R2 < 0.10 marked as na. Nes denotes not enough samples.

AVC_class	April	Values	June	June value	September	Sept value	sum	sum r2
Crops/weeds	na	na	na	na	na	na	na	na
Tall grassland/herb	NDVI	0.25	TC4	0.23	TC1	0.24	NDVI	0.19
Fertile grassland	TC5	0.35	na	na	TC2	0.16	na	na
Infertile grassland	TC2	0.99	nes	nes	TC2	0.99	nes	nes
Lowland wooded	na	na	TC1	0.87	TC6	1	na	na

Table 12.3 Summary of the highest coefficients of determination (r2) for Scotland 2000.Values with R2 < 0. 10 marked as na. Nes denotes not enough samples.

AVC_class	March	March value	May	May value	July	July value	sum	sum r2
Fertile grassland	TC4	0.25	TC3	0.17	TC1	0.32	NDVI	0.23
Infertile grassland	NDVI	0.27	TC2	0.3	na	na	na	na
Upland wooded	TC2	0.34	TC2	0.26	na	na	na	na
Moorland grass/mosaic	TC1	0.14	na	na	na	na	na	na
Heath/bog	na	na	na	na	na	na	na	na

Scotland 2000 Key results Table 12.3

- poor results for the Scotland images

Table 12.4 Summary of the highest coefficients of determination (r2) for AWIFS for GB. Values with R2 < 0.10 marked as na. Nes denotes not enough samples.

AVC_class	i73	i74	i75	i76	i77	i78	i79	mean
Crops/weeds	na	na	na	na	na	na	none	na
Tall grassland/herb	0.12	na	na	na	0.11	na	none	na
Fertile grassland	na	na	na	na	na	0.11	0.54	na
Infertile grassland	0.17	na	na	0.18	0.15	0.11	na	0.17
Lowland wooded	0.16	0.42	na	0.34	0.26	0.50	none	0.29
Upland wooded	na	na	0.20	na	na	0.19	na	na
Moorland grass/mosaic	na	na	none	na	0.13	none	na	na
Heath/bog	na	na	none	na	na	0.29	na	na

AWIFS Key results Table 12.4

- Correlation between NDVI and Lowland wooded for all images except i75
- Fertile grassland in i79 and Heath/bog in i78 are the only other cases to show a relationship
- Largely confirms the poor relationships between the satellite-derived values and the upland land cover types observed in Table 12.3.

The poorer relationships between the NDVI from AWIFS and the vegetation productivity are probably largely due to the coarse pixel resolution of the AWIFS imagery (60m cf. 30m for Landsat) and consequently the greater disparity between the pixel data and location and the field plot.

13 Appendix 4: Change detection

Table 13.1 Validation of 30 randomly selected polygons from the April PCA composite index, with a threshold set at mean + 1 standard deviation. For the PCA composite index, higher values represent more extreme spectral changes, so only an upper threshold is required

ID	area	change	notes_
13225	4495.7	yes	change from arable to grassland, new bldg on farm
15104	9158.3	no	gorse, may be detecting flower vs non-flowering
15333	9842.8	no	arable in both
19279	18544.1	???	fen, maybe woodier/less gi than in 2002??
23809	6018.4	no	water body
23962	6769.4	yes	bare soil 2002, grassland 2011
25697	20819.4	no	mineral extraction & water, slight shift in loc. Change but not really LU change.
26090	5723.6	no	bright Ui. sligt shift - offset in resampling?
33652	4283.2	no	arable in 2002, bare soil in 2011
35685	14003.3	yes	deciduous woodland to heathland
35825	7221.7	no	school playing field, may have picked up creation of wildlife garden?
36793	4138.7	no	redevelopment of Wisbech greyhound stadium - urban to urban change
38260	4818.6	no	fenland water body, possibly slightly different water level, or RS issue, 2002 wetter
42556	5400.0	no	fenland water body, possibly slightly different water level, or RS issue, 2002 wetter
45220	4585.4	??	periodical flooded grazing land, nr Whittlesey sluice gates, flooding differs slightly btw 02 & 11
47128	18853.4		small patch of woodland harvested, bare ground in 2002, STRANGE - CHECK NEW AP
51487	3961.8	yes	mineral extraction to grassland
53150	4093.1		new lake in 2002, 'mature' lake in 2011; looks different, but real changed preceded
53726	54067.8	yes	forest regrowth
55445	4806.7	yes	additional development at Snetterton race circuit
59460	5234.8	yes	new stand of conifers, previous land cover unknown
59577	11324.3	yes	redevelopment, sparse urban to urban
59636	28504.9	yes	forest regrowth
61725	9779.6	yes	wood to parkland, adj. to new housing development in Thetford
63005	3871.0		uncertain - possible change of RAF Lakenheath, small area may be RS issue, road moves on GE
65966	5063.9	yes	arable to grassland
68857	10559.4	no	arable to arable
69217	35618.1	yes	forest regrowth
70291	7657.9	yes	grassland to arable
70553	7547.7	no	arable & arable

Table 13.2 Validation of 30 randomly selected polygons from the April PCA composite index, with a threshold set at mean + 2 standard deviations. For the PCA composite index, higher values represent more extreme spectral changes, so only an upper threshold is required.

ID	area	change	notes
1645	12600.0	yes	grassland to arable
1917	25200.0	yes	industrial being redeveloped
4171	5400.0	yes	harvested conifers
5893	10800.0	yes	arable to grassland
6922	4500.0	yes	grassland to expanded bulb/nursery business, spalding
9770	94500.0	no	arable in both
11986	57600.0	no	arable in both
12083	21600.0	no	arable in both
12595	5400.0	yes	Grassland to BMX track, Sloughbottom park
13964	6300.0	yes	Forest regrowth
14608	17100.0	yes	Grass & channel in 2002 change to a pool, adjacent to a main channel in the Broads
14814	4500.0	??	Looks like redevelopment of urban & wasteland area
15092	3600.0	yes	arable to grazing
16576	7200.0	yes	expansion of mineral extraction
16640	27000.0	yes	arable to grassland
17364	7200.0	yes	arable to grassland
17706	14400.0	no	arable in both
18189	13500.0	yes	conifers harvested
18401	20700.0	yes	conifer regrowth
18705	5400.0	no	Difference in wetness of Ouse washes; 2002 wetter, no real change
18864	7200.0	yes	Flooding in 2002; grassland later in 2002 and in 2011
19507	7200.0	yes	Conifer's harvested by 2011
20527	4500.0	yes	changing extent of extraction and water bodies within extraction site
21234	113400.0	no	arable in both
21732	8100.0	yes	conifer harvested
22721	16200.0	no	coastal
23315	7200.0	??	narrow linear feature, along edge of small linear conifer plantation, maybe change, maybe RS issue
24015	3600.0	yes	conifer regrowth
24339	3600.0	no	arable crop to pig farm
24734	8100.0	yes	RSPB Minsmere, increase in size of water body; fen to water body

Table 13.3 Validation of 30 randomly selected polygons from the cumulative NDVI, with a threshold set at mean +/- 1 standard deviation. Note the NDVI change has extreme upper and lower values, so had an upper and lower threshold.

ID	area	change	notes
21020	6300.0	no	mix of urban and arable in both
21672	8100.0	??	marginal, saltmarsh, maybe wetter in 2011
22383	3600.0	no	no change, parkland
28479	5400.0	no	water in both
34289	3600.0	no	scrub/woodland, no obvious differences
37878	12600.0	no	arable to arable
42327	6300.0	no	most of polygon doesn't change, but one polygon overlaps an arable field in 2002 & grass in 2011
49110	5400.0	no	grass in 2011 and 2002, greener in 2002
51758	8100.0	no	forest in both
55721	5400.0	no	mix of water, grass and fen in both
68966	4500.0	no	urban in both
69921	3600.0	no	coniferous forest in both
74941	3600.0	no	very slight offset between pixels, but no change
76762	7200.0	??	possible area of soil scrape (mousehold heath) to increase heather
99867	26100.0	yes	area of new woodland
108680	5400.0	no	urban in both
119188	62100.0	no	grassland in both, maybe slightly wetter in 2011
124564	8100.0	no	arable in both
126775	3600.0	no	grassland in both
127762	7200.0	??	pig farm to crop
128756	8100.0	yes	bare soil in 2002; grass in 2011
132905	30600.0	yes	trees harvested
134992	13500.0	no	conifer in both
136569	9900.0	no	playing field in both
142723	3600.0	no	reeds
145681	3600.0	no	no change
146574	4500.0	no	water & woodland in both
146808	11700.0	no	water in both, slight offset btw then
149545	4500.0	yes	half of polygon is harvested forest
157059	3600.0	no	grassland in both

Table 13.4 Validation of 30 randomly selected polygons from the cumulative NDVI, with a threshold set at mean +/-2 standard deviations. Note the NDVI change has extreme upper and lower values, so had an upper and lower threshold.

ID	area	change	notes
4258	8100	yes	bare soil in april 2002 (reseeding grass?), grassland in 2011
5988	6300	yes	removal of scrub to maintain heath; habitat maintenance, Holt Lowes
6624	3600	no	water & trees, maturing of site, no real change
9018	3600	no	edge of water body, no change
10379	3600	no	coastal, no change
11544	3600	yes	new housing on grass camp site
15327	3600	no	water quality, different sediment levels
16607	3600	yes	arable 2002, grass 2011, falls over field boundary
18165	4500	no	mix of grass & trees
18578	6300	yes	arable to grazing
19952	6300	yes	partial change from playing field to car park
21315	7200	yes	grassland to arable
21940	3600	yes	bare soil/arable to grassland
22955	9000	no	arable in both
24385	3600	yes	Grassland to BMX track, Sloughbottom park
24423	5400	yes	football pitch to mineral extraction
25059	3600	no	arable in both
25698	5400	yes	arable in 2002, bare soil early 2011, grass late 2011
27573	3600	yes	grass/wasteland to urban
29321	6300	no	Limpenhoe marshes, slight difference in water level + phenology
29712	3600	no	arable in both
30376	8100	yes	unknown, football pitch, possible bare soil/astroturf, Watton
30922	3600	yes	arable to golf course, adj. to expanded caravan park
32172	4500	yes	mineral extraction to grass, site still active
32229	5400	yes	arable to grazing
33150	3600	no	coastal
35168	3600	no	arable in both
41744	6300	yes	Deciduous/mixed woodland to less dense woodland in 06, cleared now?
46234	4500	yes	grassland & fenland in 02; more bare soil in 2011? LC uncertain
47700	4500	yes	arable to grassland

Table 13.5 Validation of 30 randomly selected polygons from the spectral distance with a threshold set at mean +2 standard deviations

ID	GRIDCODE	area	change	notes
377	5	95273	yes	arable to grassland
773	1	5341	yes	significant tree growth (recent planting -> canopy closure)
874	6	45588	no	arable in both, classification error
1016	9	4764	no	urban in both, spectral distance error
1332	9	3604	yes	arable to urban
3552	4	11720	yes	arable to grassland
5529	1	4722	no	woodland in both, spectral distance error
5926	9	7725	yes	suburban to urban (country house to private hospital & car park)
6220	4	65780	yes	arable to grassland
6410	9	5427	yes	gravel parking to industrial units
6474	4	5164	yes	arable to grassland
6684	7	49531	yes	arable to greenhouses and water body
7022	7	26266	yes	grassland to (fishing?) lake
7074	9	5400	no	narrow polygon straddling edge of two fields; one with poly-tunnels
8359	5	30478	no	arable in both, classification error
8515	9	5991		smaller industrial unit to larger industrial unit
9890	8	5096	no	urban in both, spectral distance error
10459	1	7555	no	narrow polygon straddling edge of two fields; classification error
11254	1	5400	no	rough grassland in both; classification wrong - area too small, affected by adj. Trees
12357	9	5629	yes	Brownfield redevelopment
14765	4	6440	yes	arable to grassland
15487	2	7821	no	grassland in both (Stanford battle ground)
16540	6	10030	yes	possible arable to grassland
16716	4	8584	yes	Extensive flooding in April 2002
17210	9	11868	yes	Playing field to school buildings: Lakenheath (Gi to urban)
19950	5	19551	no	fen in both; classification error
20564	4	4627	yes	Extensive flooding in April 2002
22540	8	5400	yes	Improved grassland to car park
23340	4	7492	yes	arable to grassland
24392	9	8097	no	removal of a building at RAF Mildenhall; mainly runway in both images (spec. variability of planes?)

Table 13.6 Validation of 30 randomly selected polygons from the post-classification change detection (difference between the 2002 and 2011 classifications).

poly_id	2002_class	2011_class	area	change	notes
368822	9	4	69022.2	yes	Ouse washes; wetter in 2002 than 2011, but not flooded
370787	1	2	145666.0	yes	coniferous forest; mix of harvesting and regrowth
382159	3	4	118209.0	yes	Arable in 2002, probably grassland in 2011
1983277	1	2	17270.6	no	Conifer in both; denser by 2011
2022129	3	4	54938.0	no	Arable in both
2039154	10	2	19413.8	no	Sparse woodland, scrub & grass in both
2040001	3	23	21202.6	no	Polygon is grassland.A road is built at the edge of the polygon, which causes mixed pixels.
2043981	1	9	19311.3	no	Trees and grassland in both
2372725	1	2	7676.5	??	Narrow tree break (too narrow) (poly covers half), denser tree cover by 2011
2376688	3	4	29722.7	yes	Arable in 2002; Gi in 2011
4974487	23	16	8457.8	no	Park: mix of trees, grass, lake, urban in both: no change
4974800	23	10	5939.7	no	Mix of road & trees; tree cover denser by 2011
4980658	9	1	5741.2	no	Mix of trees and road in both; probably too narrow
5018936	3	16	5903.7	??	Not sure; small patch of land; seems to serve various uses; sometimes grass; sometimes arable
5023341	23	16	5302.9	no	Half woodland; half suburban in both
5030754	3	1	7066.9	no	GE shows is as a mix trees, garden, allotment/veg garden; prob. no major changes
5041035	1	23	5891.6	no	Mix of trees, wood and grass, in both, but affected by arable field to south
5042302	10	23	6568.3	no	Mix of grass, buildings, trees (suburban) in both
5047361	3	23	6815.6	no	Small suburban parcel, no change.
5047410	23	2	8074.2	no	Small suburban polygon; no change
5050226	3	4	22018.7	no	Small parkland polygon; no change
5052301	23	16	15158.6	no	Mix of river, road, houses & gradens; no change
5066182	4	16	6315.7	no	narrow patch of grassland, between road and trees; no chnage
5575918	3	23	9266.5	no	Small suburban polygon; no change
5592911	2	16	7002.5	no	Small suburban polygon; no change
5594897	3	1	6687.1	no	Small patch of scrub/heathland
5596337	4	1	7365.2	no	Small suburban polygon; no change
5599311	3	9	18191.7	yes	arable to grassland
6642899	3	1	5489.2	no	small suburban polygon
6643138	3	4	7516.8	no	Small suburban polygon

Table 13.7 Additional details for the 30 randomly selected polygons from the post-classification change detection (difference between the 2002 and 2011 classifications).

poly_id	2002 pixel distribution	2002 class	2011 class	2011 pixel distribution	change
368822	0,0,0,0,0,0,0,0,0,65,0,0,0,0,0,0,5,0,0,0,0,0,0,0,70,9	9	4	0,0,0,5,62,0,0,0,0,3,0,0,0,0,0,0,0,0,0,0,0,0,0,0,70,4	yes
370787	0,84,56,0,0,0,0,0,0,0,13,0,0,0,0,0,0,0,0,0,0,0,0,0,1,154,1	1	2	0,73,77,4,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,154,2	yes
382159	0,0,1,119,0,0,0,0,0,1,1,0,0,0,0,0,0,0,0,0,0,0,0,0,122,3	3	4	0,0,5,8,101,0,0,0,0,0,4,0,0,0,0,0,1,0,0,0,0,0,0,3,122,4	yes
1983277	0,8,5,3,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,16,1	1	2	0,6,10,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,16,2	no
2022129	0,0,0,36,2,0,0,0,0,0,6,0,0,0,0,0,1,0,0,0,0,0,0,12,57,3	3	4	0,0,13,4,23,0,0,0,0,0,7,0,0,0,0,0,0,0,0,0,0,0,0,10,57,4	no
2039154	0,3,0,3,0,0,0,0,0,0,7,0,0,0,0,0,3,0,0,0,0,0,0,2,18,10	10	2	0,1,4,3,3,0,0,0,0,0,4,0,0,0,0,0,2,0,0,0,0,0,0,1,18,2	no
2040001	0,0,1,7,1,0,0,0,0,0,7,0,0,0,0,0,0,0,0,0,0,0,0,2,18,3	3	23	0,0,0,1,7,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,10,18,23	no
2043981	0,8,1,0,0,0,0,0,0,4,1,0,0,0,0,0,3,0,0,0,0,0,0,1,18,1	1	9	0,3,0,0,0,0,0,0,0,12,0,0,0,0,0,0,3,0,0,0,0,0,0,0,18,9	no
2372725	0,4,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,5,1	1	2	0,0,4,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,5,2	??
2376688	0,0,0,14,14,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,28,3	3	4	0,0,0,0,28,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,28,4	yes
4974487	0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,2,0,0,0,0,0,0,5,8,23	23	16	0,1,1,0,0,0,0,0,0,0,1,0,0,0,0,0,3,0,0,0,0,0,0,2,8,16	no
4974800	0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,3,4,23	23	10	0,0,1,0,0,0,0,0,0,0,3,0,0,0,0,0,0,0,0,0,0,0,0,0,4,10	no
4980658	0,0,0,0,0,0,0,0,0,3,0,0,0,0,0,0,1,0,0,0,0,0,0,0,4,9	9	1	0,2,1,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,4,1	no
5018936	0,0,0,3,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,5,3	3	16	0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,4,0,0,0,0,0,0,0,5,16	??
5023341	0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,3,3,23	23	16	0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,2,0,0,0,0,0,0,1,3,16	no
5030754	0,0,1,5,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,6,3	3	1	0,3,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,2,6,1	no
5041035	0,2,1,1,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,5,1	1	23	0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,3,5,23	no
5042302	0,0,0,1,0,0,0,0,0,0,4,0,0,0,0,0,0,0,0,0,0,0,0,1,6,10	10	23	0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,5,6,23	no
5047361	0,0,0,4,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,2,6,3	3	23	0,0,2,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,3,6,23	no
5047410	0,2,1,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,3,7,23	23	2	0,2,5,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,7,2	no
5050226	0,0,0,8,0,0,0,0,0,5,4,0,0,0,0,1,2,0,0,0,0,0,0,1,21,3	3	4	0,2,0,0,11,0,0,0,0,0,0,0,0,0,0,0,4,0,0,0,0,0,0,4,21,4	no
5052301	0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,3,2,0,0,0,0,0,0,8,13,23	23	16	0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,7,0,0,0,0,0,1,5,13,16	no
5066182	0,1,0,0,2,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,4,4	4	16	0,2,0,0,0,0,0,0,0,0,0,0,0,0,0,0,2,0,0,0,0,0,0,0,4,16	no
5575918	0,1,1,2,2,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,7,3	3	23	0,1,2,0,1,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,2,7,23	no
5592911	0,1,2,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,4,2	2	16	0,1,0,1,0,0,0,0,0,0,0,0,0,0,0,0,2,0,0,0,0,0,0,0,4,16	no
5594897	0,1,0,3,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,5,3	3	1	0,4,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,5,1	no
5596337	0,0,0,1,2,0,0,0,0,0,1,0,0,0,0,0,1,0,0,0,0,0,0,1,6,4	4	1	0,4,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,1,0,6,1	no
5599311	0,0,0,13,3,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,17,3	3	9	0,0,0,1,3,0,0,0,0,13,0,0,0,0,0,0,0,0,0,0,0,0,0,0,17,9	yes
6642899	0,1,1,2,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,4,3	3	1	0,2,0,2,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,4,1	no
6643138	0,0,0,3,2,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,5,3	3	4	0,0,0,0,3,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,2,5,4	no