



Rural Payments
Agency



Department
for Environment
Food & Rural Affairs

Streamlining Land Change Detection to Improve Control Efficiency

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Rural Payments Agency

Research and Development Teams



Ordnance
Survey

CATAPULT
Satellite Applications



apmgeo

Purpose

The talk presents the methodology and results of a research project on using both deterministic ruleset and machine learning for automated non-agricultural land cover change detection on Aerial Photographs and Satellite Images.

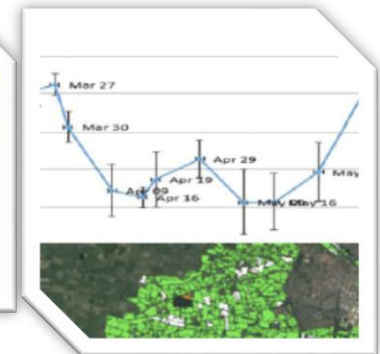
Examples of Non-Agricultural land covers include sheds, solar panels, roads, trees, ponds etc., basically representing the area we deduct from parcels for subsidy.

Contents

- Background
- Project
- Methodology
- Results
- Conclusions

Background – Why did we want an automated method?

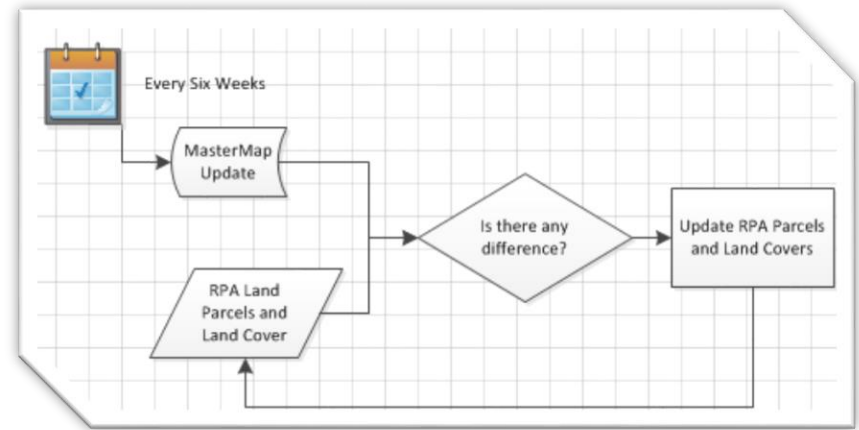
- The RPA has decided that all reference intelligence used for LPIS validation should be newer than 3 years.
- The current process to keep intelligence up to date is resource and cost intensive.
- Change detection is subjective to the photointerpretation skills of the digitisers.
- Defra wishes to reduce the customers efforts in reporting land changes to the RPA.
- Commission is encouraging MS to substitute OTSC with continuous EO-data based monitoring.



Background - A bit of history

But, we have tried automated change detection before...

- Project ALIC (Automated Land Intelligence Consumption) (2015)
 - Automatically compare new features in Ordnance Survey MasterMap update with in-house layer, and simply import relevant features and changes.
 - The process was withdrawn after a short run.
 - Technical defects - Drained system resources and produced unexpected results.
 - OSMM currency itself was found to be quite old in rural areas.



Background – What did we want project to deliver?

- The project was asked to research and develop:
 - Innovative combinations of image and geospatial data processing methods to automatically identify and detect change in non-agricultural land cover
 - Scalable and repeatable business process that meets the RPA model of land cover and land use.
 - The solution was expected to be agnostic of image type and resolution e.g. AP, Satellite Images.
 - Propose how to best consume change intelligence in the map update process.

Project - Overview

Research Objectives

- Develop and Compare accuracy of classifications of land covers using both Aerial Photography and Very High Resolution Satellite Images.
- Develop change detection methods using the intelligence (i.e. AP or RS) which results in the most accurate classification.
- Develop methods to quantify the accuracy of the change detection methods.

Research Teams

1. Ordnance Survey (www.os.uk)- Experts in eCognition and Aerial Photography based land cover mapping.
2. Satellite Applications Catapult (sa.catapult.org.uk) – Experts in Machine Learning and Satellite images based land cover mapping.
3. apmgeo – provided overall guidance.

Project - Study Areas

- Four study areas were chosen.
- Selection Criteria:
 - Areas were selected based on whether we had AP and Satellite images from the same season and year.
 - Areas also had to have a varieties of land covers.
 - Data from 2015 matched the conditions.
 - Zone 2 was eventually not considered for further analysis because suitable semi-processed AP could not be obtained.



Methodology – High Level

Task Breakdown between research teams

- Ordnance Survey Team
 - O1. Perform segmentation on AP+H, VHR images in eCognition.
 - O2. Perform ruleset classification in eCognition using AP+H, VHR and ancillary data e.g. OS GreenSpace, MasterMap
 - O3. Develop change detection and reporting algorithms based on best land cover classification.
- Satellite Applications Catapult Team
 - S1. Perform machine learning classification algorithm (Random Forest) in scikit
 - S2. Identify important variables useful for ruleset classification (task O2).
 - S3. Provide a quantitative insight into the relative value offered by each dataset used within this study.

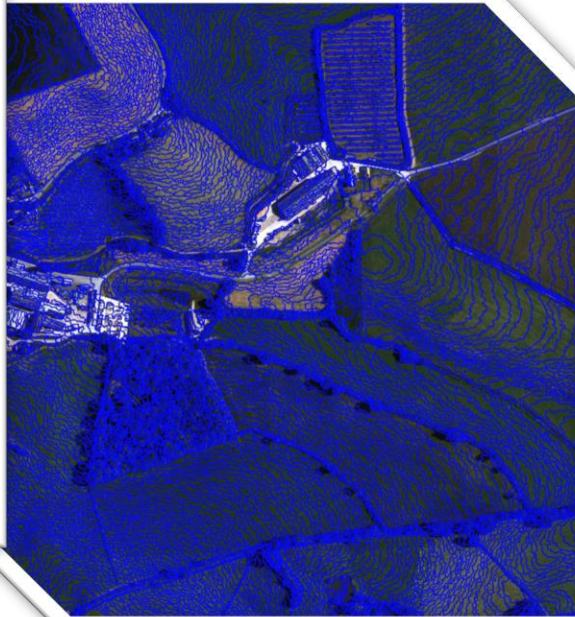
Methodology – eCognition OBIA Ruleset vs Random Forest Machine Learning

OBIA and Deterministic Ruleset	Random Forest Machine Learning
<p>Pixels are grouped into homogenous Objects based on associated spatial, spectral and textural properties, also called <i>region growing</i>.</p> <p>Objects classes (e.g. trees, house) obtained from a single run of pre-defined decision tree of rules developed by an expert, based on exhaustive association of image properties with object classes.</p> <p>Doesn't allow discovery of new image-properties-to-class associations.</p>	<p>Also, uses a pre-defined lookup table of object classes with respective image properties. But, overall decision tree is unknown initially.</p> <p>Classification is derived by numerous iterations of numerous randomly generated decision trees (using subsets of input look up table), and continuously evaluating and correcting decision trees to find one that matches most of the associations in lookup table.</p> <p>New image-properties-to- class associations are derived by exhaustive permutations.</p>

Methodology – eCognition OBIA Ruleset vs Random Forest Machine Learning

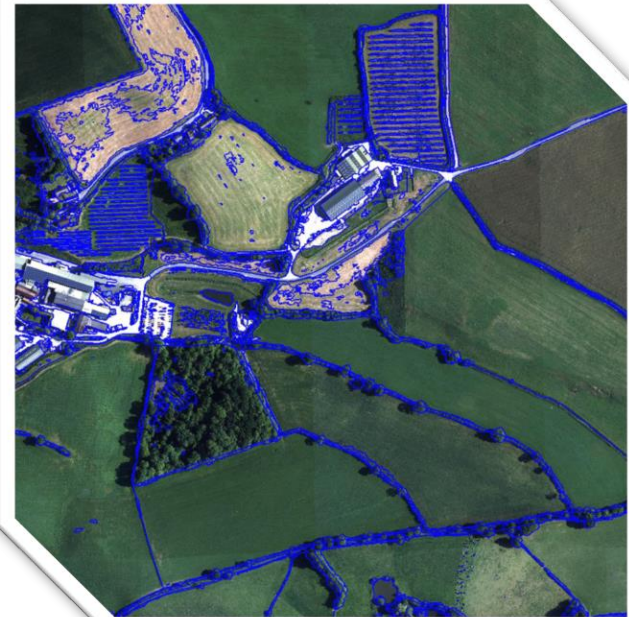


Aerial Photograph

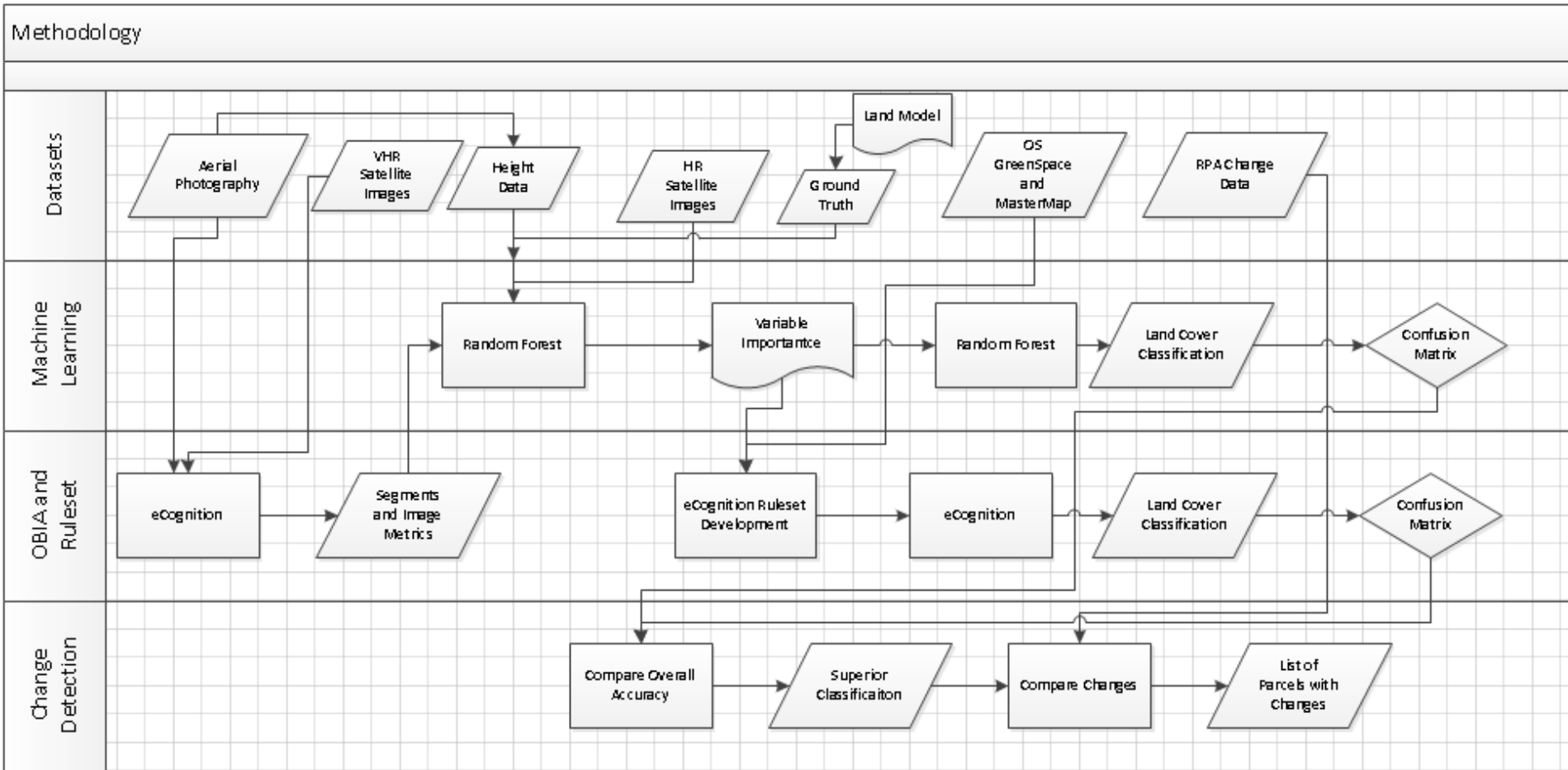


**Initial Segmentation or
Regions Growing-10641
Objects**

**Final Segmentation -2839
Objects**



Methodology – High Level



Methodology - Input Datasets and Software

- **Raster Datasets**

- Semi-Processed (important) 4-band Aerial Photographs
- Non-pansharpened (important) 8-band Worldview images
- Sentinel-1 Analysis Ready Images
- Landsat-8 images
- Normalised Digital Surface Model derived from Aerial Photographs.
 - $nDSM = DSM - DTM$

- **Vector Datasets**

- LPIS Parcels and Land Cover, both pre and post-update.
- Change file that stores the difference between pre- and post-update
- OS MasterMap
- OS Greenspace Open Data

- **Software Stack**

- eCognition, for (OBIA) segmentation and ruleset classification
- FME, for data ETL
- sci-kit, for machine learning (RandomForest)

Methodology - Generalisation of Land Model

- It is non-trivial to automatically identify and classify landforms on images to match their exact specification in the CAP land model.
- For example, it is not straightforward to identify the various configurations of rivers and drains in relation to the parcel boundary.
- For example, it is non-trivial to work out the use of a building based on image however important it is for the calculation of subsidy.
- It is also difficult to identify temporary wire fences.
- Therefore, the RPA model had to be generalised.

Original 42		Classif mask		Prop.
U/LCC	Class	LU/LCC code	Class	
212	Hedges			Scrub
218	Bank			Bank
219	Buffer Strip			Buffer Strip
		113	Arable - Buffer Strip (2015)	
		132	Permanent Grassland - Buffer (2015)	
291	Fence			Fence
241	Drain/ditch/dyke			DrainDitchDyke
588	Drain/ditch/dyke on a boundary			
243	Pond			Inland Water
581	River on a boundary			
582	Rivers type 2			
583	Rivers type 3			
271	Heap			Heap
		270	Heaps - Permanent	
		260	Heaps - Temporary (2015)	
		261	Heaps - Temporary (2015)	
332	Woodland			Tree
		233	Trees - Clump (2015)	
338	Residential Gardens			Garden
371	Farm Building			Building
391	House			
376	Glasshouse			Glasshouse
379	Farmyards			Made Area
551	Hard Standing			
		550	Hardstanding	Solar Panels
531	Solar Panels			
571	Storage Area			Storage Area
		570	Storage Area	
631	Metalled track			Made Transport
		632	Metaled Track - No Access	
633	Roads			Natural Transport
643	Track - Natural Surface			
663	Sports and Recreation			Sports
		112	Temporary Grass	Grass/Crop
		131	Permanent Grassland	
		116	Catch and Cover Crops	
		117	N Fixing crops	
		118	Other Arable Crops	
		141	Perennial Crops	
		110	Arable Land	Surface
			Bare Earth	

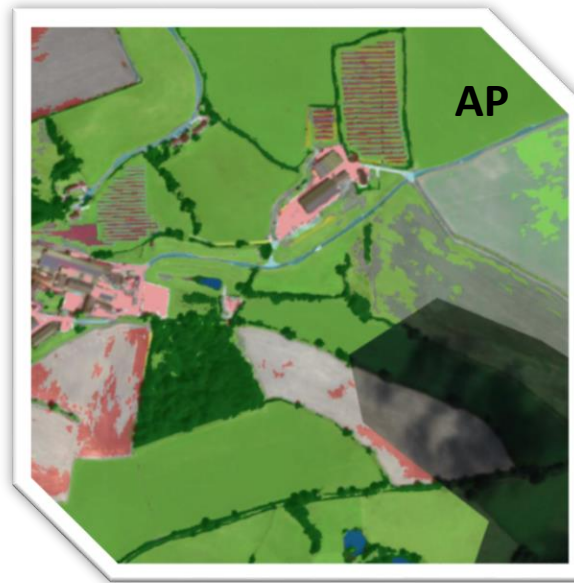
Methodology - Change Detection

Logic

- The RPA "Change File" was used as the reference dataset for the change detection accuracy assessment for land covers. Only valid changes from the change files were used for comparison with automatically predicted changes
- Changes in parcel boundary was also recorded.
- Both appearance and disappearance of land covers and parcel boundaries were recorded.
- Change assessment was carried out manually twice (to remove bias)
- Assessment process recorded the accuracy in following measures:
 - TP (True Positive) = Relevant (i.e. selected features from land model) correctly identified RWC predictions
 - TP_WC = As above, but incorrect label of the change
 - OI (Other Ineligible) = Other ineligible change
 - FP (False Positive) = Invalid Change Detected
-

Results

Comparison of RuleSet classification using AP+H and WV2 Images

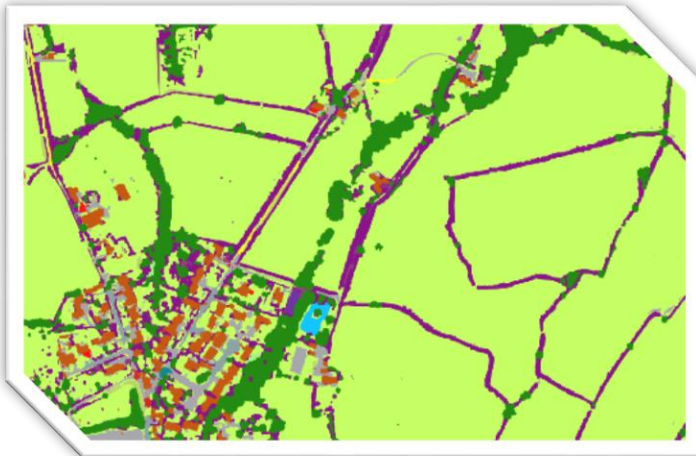


	Overall Accuracy	
Zone	AP+H	WV2
1	74%	65%
3	69%	61%
4	78%	54%

- AP+H based eCognition classification was more accurate than WV2 based eCognition classification.

Results

Comparison of Random Forest and Ruleset Classification on AP+H data



Random Forest

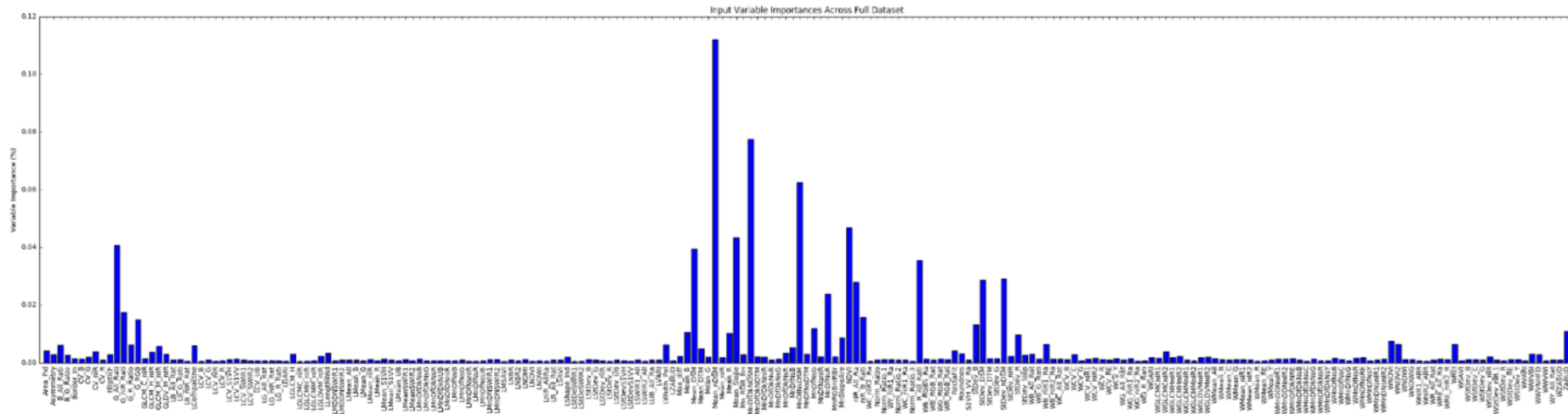


eCognition

	Overall Accuracy	
Zone	Ruleset	RF
1	74%	84%
3	69%	81%
4	78%	93%

Results

Importance of Variables – *Height is very important*

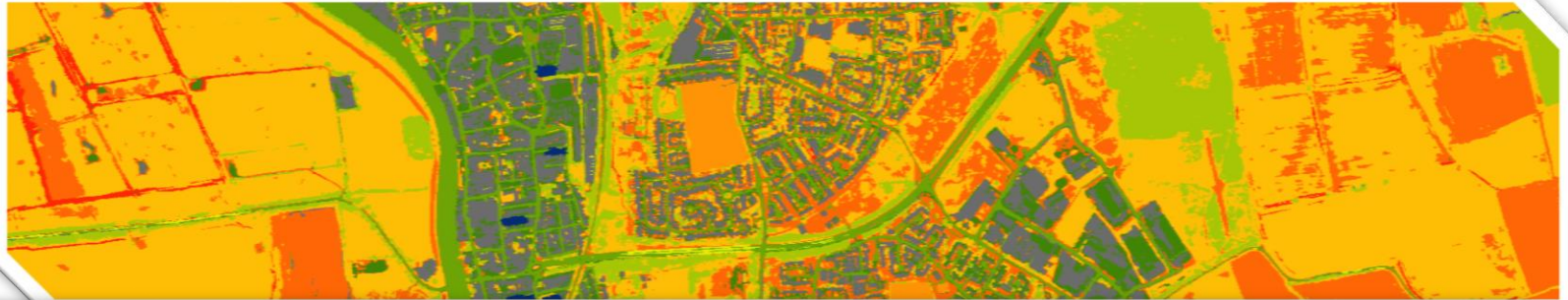


- Aerial Photography and Height related variables contribute to at least 40% of the accuracy in the classification.
- Landsat related variables were least useful, presumably due to coarse resolution.

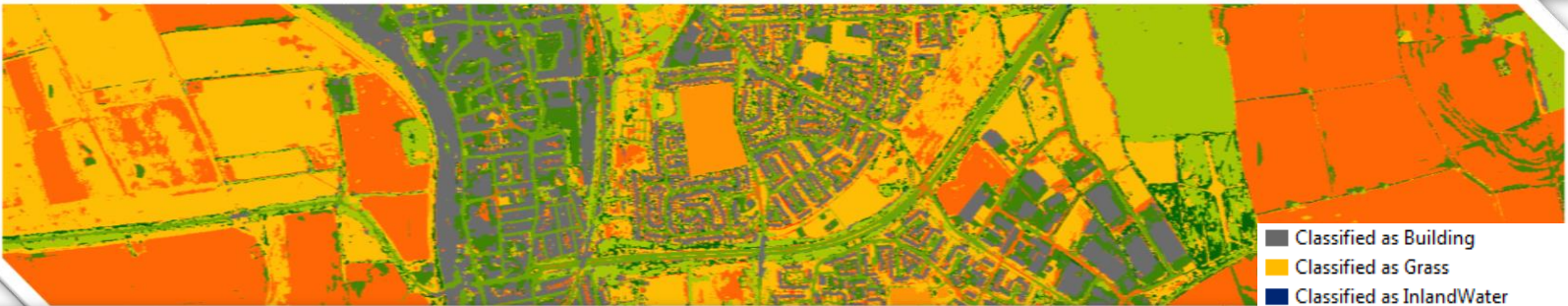
Results

Land cover classification. *AP+H is better looking*

WorldView
Classification



AP + Height
Classification



2015 AP



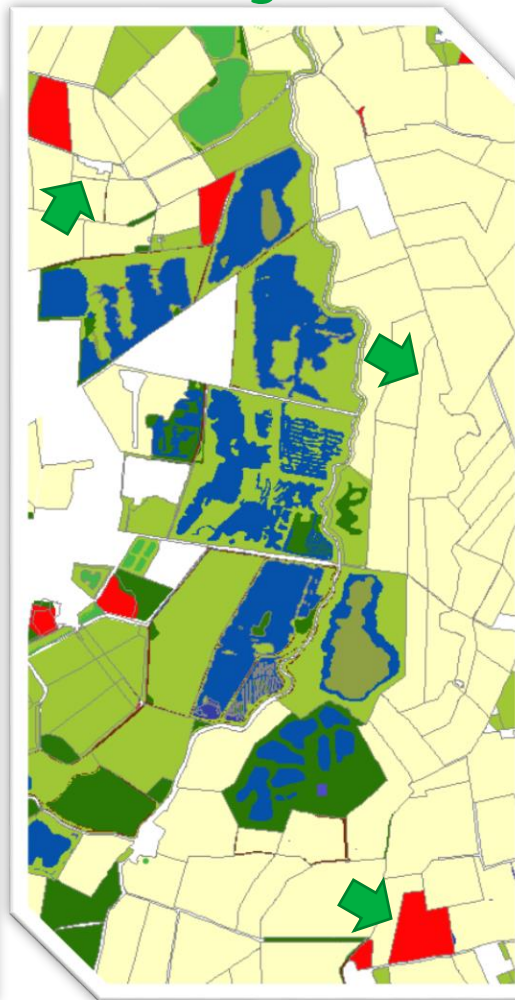
- Classified as Building
- Classified as Grass
- Classified as InlandWater
- Classified as MadeTransport
- Classified as NaturalTransport
- Classified as Scrub
- Classified as SolarPanels
- Classified as Sports
- Classified as Tree
- Classified as _ElevFromSurface
- Classified as _PossGrass
- Classified as _PossTrees
- Classified as _Surface
- Classified as _SurfaceSealed

Results

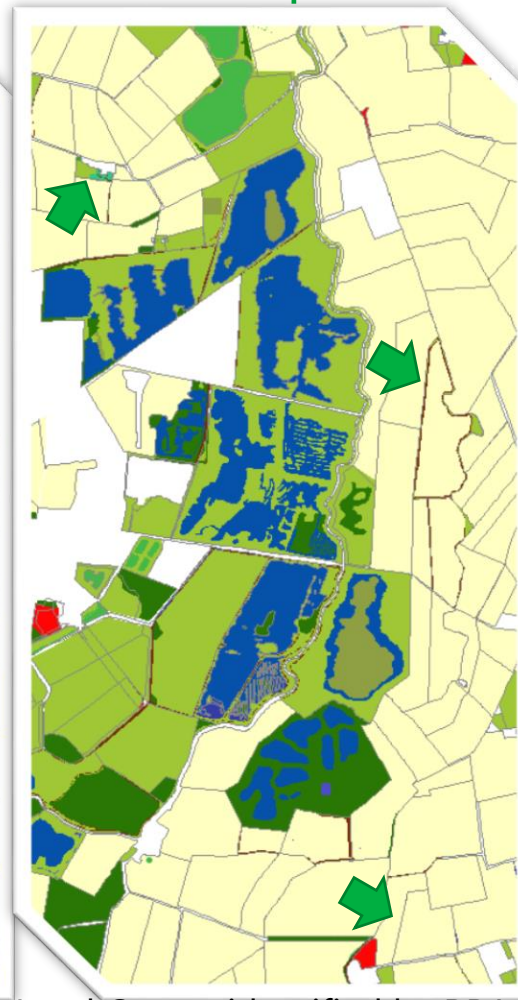
Examples of automated change detection – RPA Inputs



AP July 2015



Land Covers on 1/4/2015

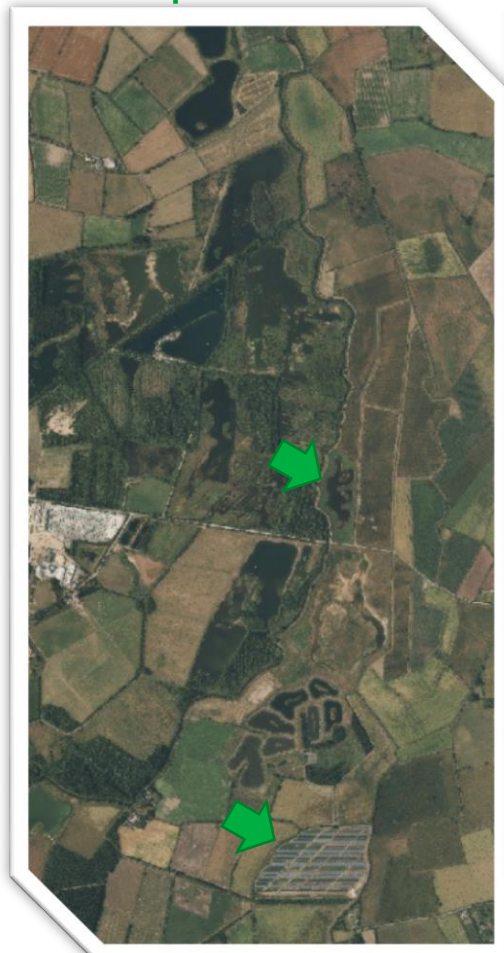


Land Covers identified by RPA on 1/1/2016

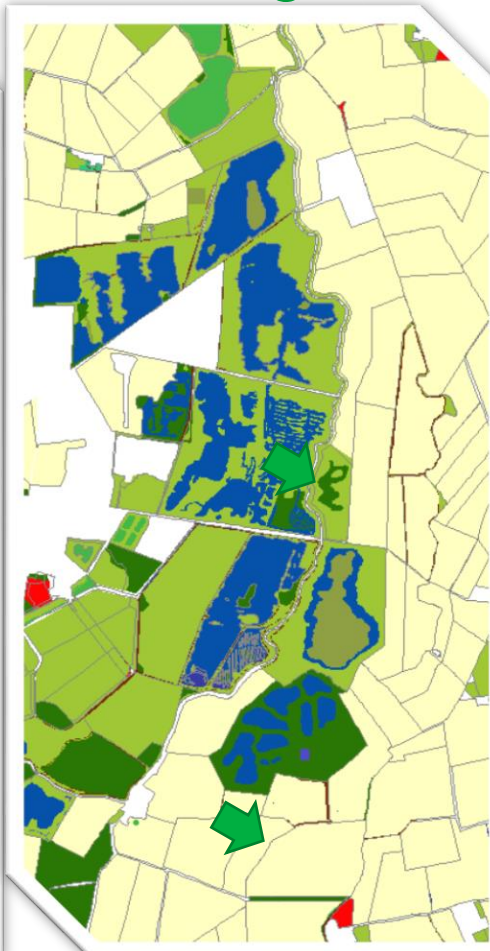
- Arable
- Grassland
- Inland Water
- Woodland
- Scrub
- Unknown
- Hard Standing
- Storage Area
- Track

Results

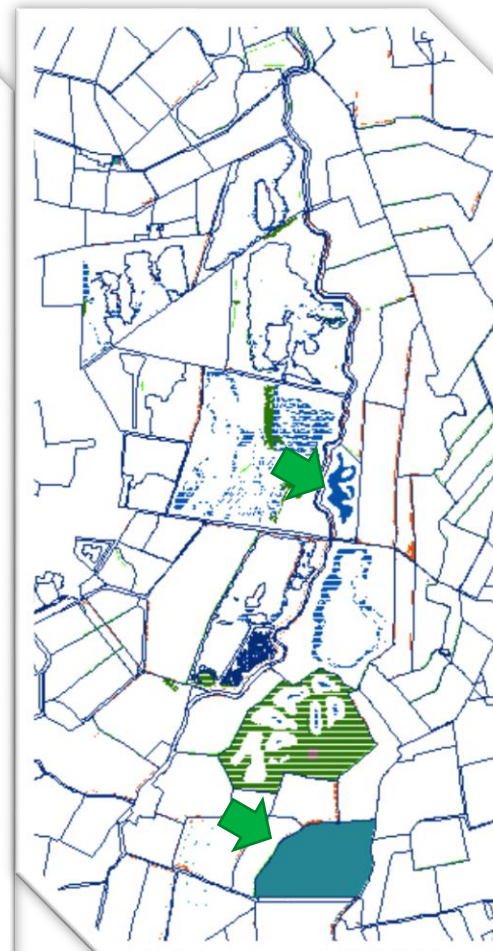
Examples of automated change detection



AP July 2015



Land Covers on 1/1/2016



Detected/Missed Changes

RPA Land Covers

- Arable
- Grassland
- Inland Water
- Woodland
- Scrub
- Unknown
- Hard Standing
- Storage Area
- Track

Predictions

- BoundaryDemol
- BoundaryNew
- BuildingDemol
- BuildingNew
- InlandWaterDemol
- InlandWaterNew
- MadeTransportDemol
- MadeTransportNew
- NaturalTransportDemol
- NaturalTransportNew
- SolarPanelsNew
- SportsNew
- TreeDemol
- TreeNew
- SurfaceSealedDemol
- SurfaceSealedNew

Results

Change Detections

- 1/3rd of predicted changed were valid real world change.
- 87.5% of change predictions belonged to the correct land cover class.
- Although accuracy of proposed change predictions is relatively lower, the proposed solution identified more TP changes.
- Most common FP land cover change was TreesNew.
- Boundary change prediction have comparable accuracy to land cover predictions
- Narrow boundaries such as fences and walls yielded worst detection.
- 70% of Parcels are predicted to have had no change!

Land Cover

		TP	TP(WC)	FP	TOTAL	Correctness TP only	Correctness TP+TP(WC)
RPA Change File	ST40 (Zone 1)	70	-	57	124	56.5%	-
	SK78 (Zone 3)	63	-	47	110	57.3%	-
	TF25 (Zone 4)	85	-	26	111	76.6%	-
Automatic Change Predictions	ST40 (Zone 1)	156	39	278	473	32.9%	41.2%
	SK78 (Zone 3)	209	25	417	651	32.1%	35.9%
	TF25 (Zone 4)	153	1	283	437	35.0%	35.2%

Parcel Boundary

		TP	FP	TOTAL	Correctness
RPA Change File	ST40 (Zone 1)	65	4	69	94.2%
	SK78 (Zone 3)	78	18	96	81.3%
	TF25 (Zone 4)	26	7	33	78.8%
Automatic Change Predictions	ST40 (Zone 1)	95	210	305	31.1%
	SK78 (Zone 3)	53	170	223	23.8%
	TF25 (Zone 4)	53	245	298	17.8%

Thanks!

Presentation only covers some of the salient aspects of the project. For more details, please contact me on

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