Rural Payments Agency

Applications of Machine Learning in Common Agricultural Policy at the Rural Payments Agency

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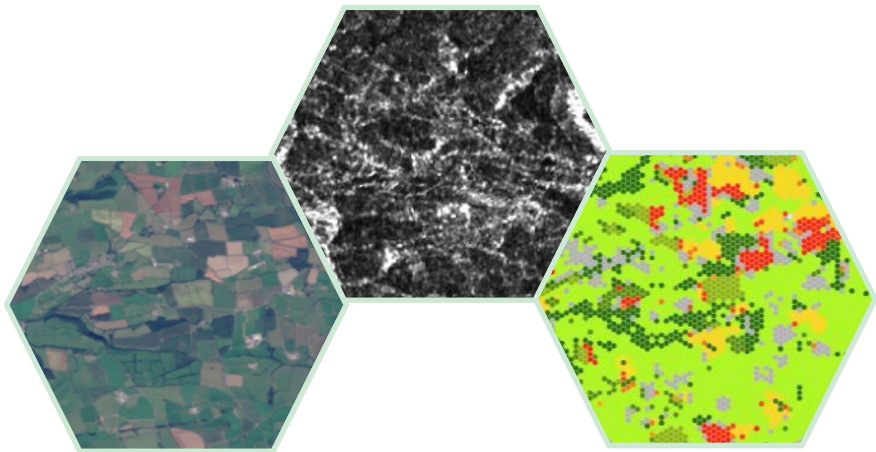
Reading



What are you gonna find out?

- Knowing me and RPA (and knowing you - aha ?!)
- How are we using Machine Learning at the RPA?
  - Current Activities
    - Random Forest for Making Crop Map of England
  - Work in Progress Activities
    - Deep Learning for Crop Map of England, Land Cover Segmentation, and locating Radio Frequency Interference
- I will cover more on applications of Machine Learning for RPA operations, and less about technical solutions.

My resume so far…

Academics

- Geology — University of Delhi
- GIS — University of Leicester
- GeoComputation — UCL

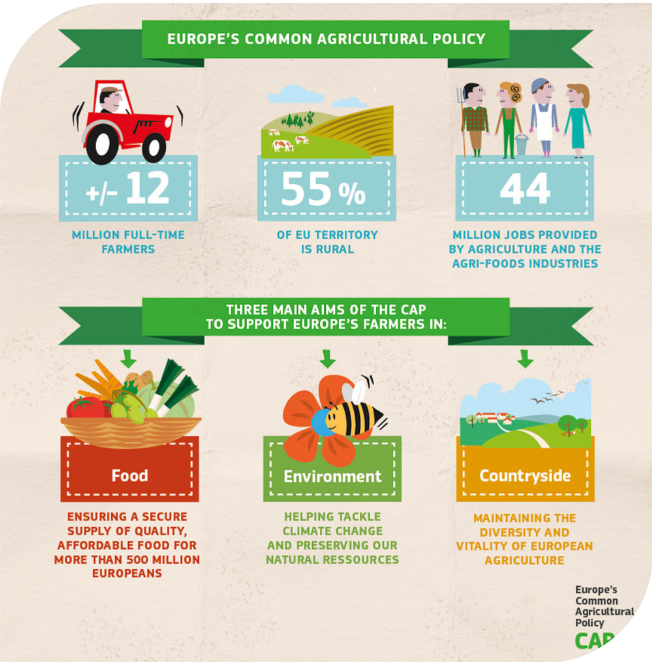
Profession

- Radio DJ — आकाशवाणी (AIR)
- Researcher & Lecturer — UCL, University of Leicester
- Consultant — BLOM (Imaging the World)
- Civil Servant — Rural Payments Agency

Rural Payments Agency

Rural Payments Agency (RPA) is the Defra agency responsible for the distribution of subsidies to farmers and landowners in England under all the EU's Common Agricultural Policy (CAP) schemes.

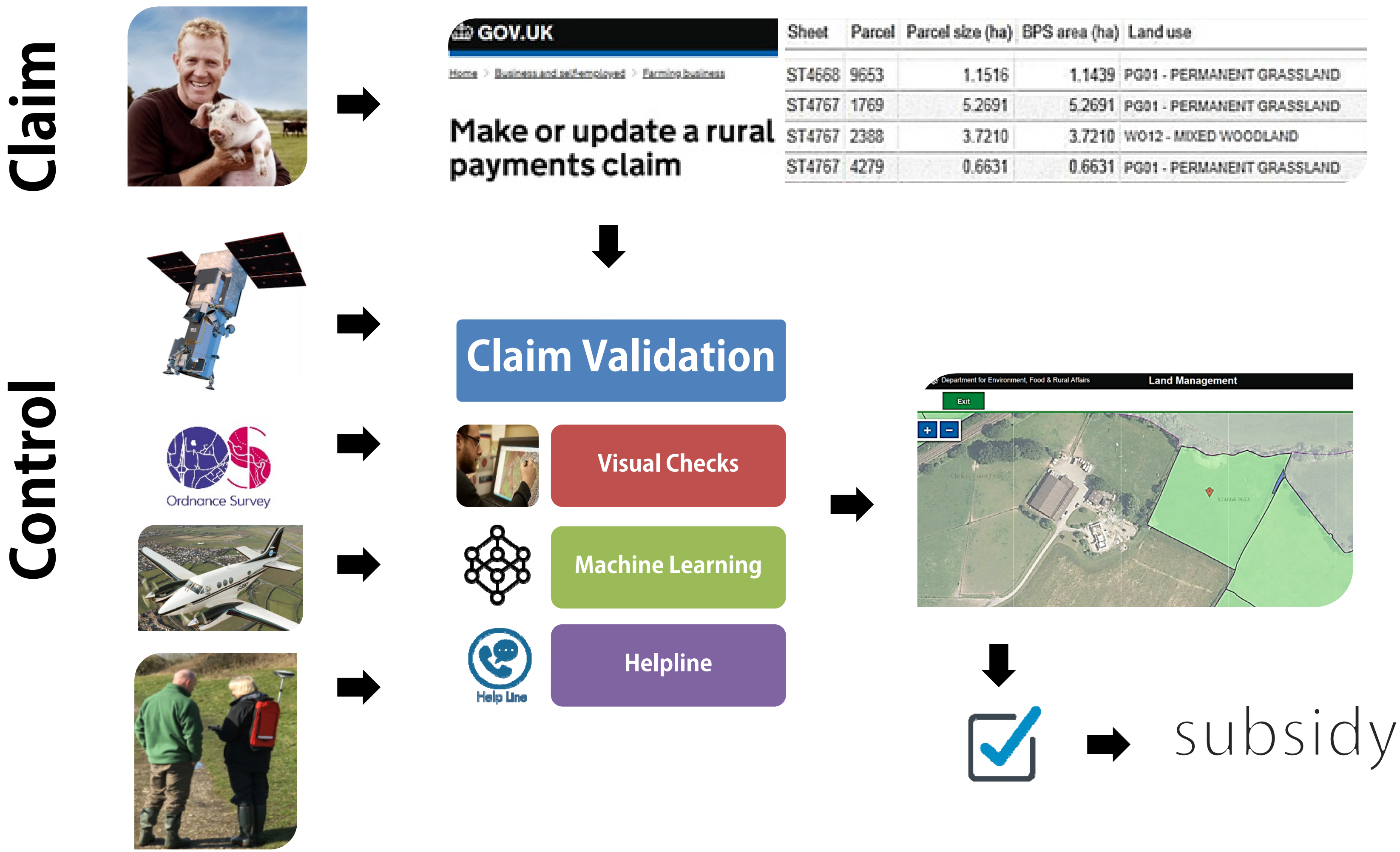
£2 billion subsidy



~130,000 Claimants

~2.6 million registered parcels, 73% of land in England

Area Based Payments/Subsidies



Sheet	Parcel	Parcel size (ha)	BPS area (ha)	Land use
ST4668	9653	1.1516	1.1439	PG01 - PERMANENT GRASSLAND
ST4767	1769	5.2691	5.2691	PG01 - PERMANENT GRASSLAND
ST4767	2388	3.7210	3.7210	WO12 - MIXED WOODLAND
ST4767	4279	0.6631	0.6631	PG01 - PERMANENT GRASSLAND

A bit more info on Controls

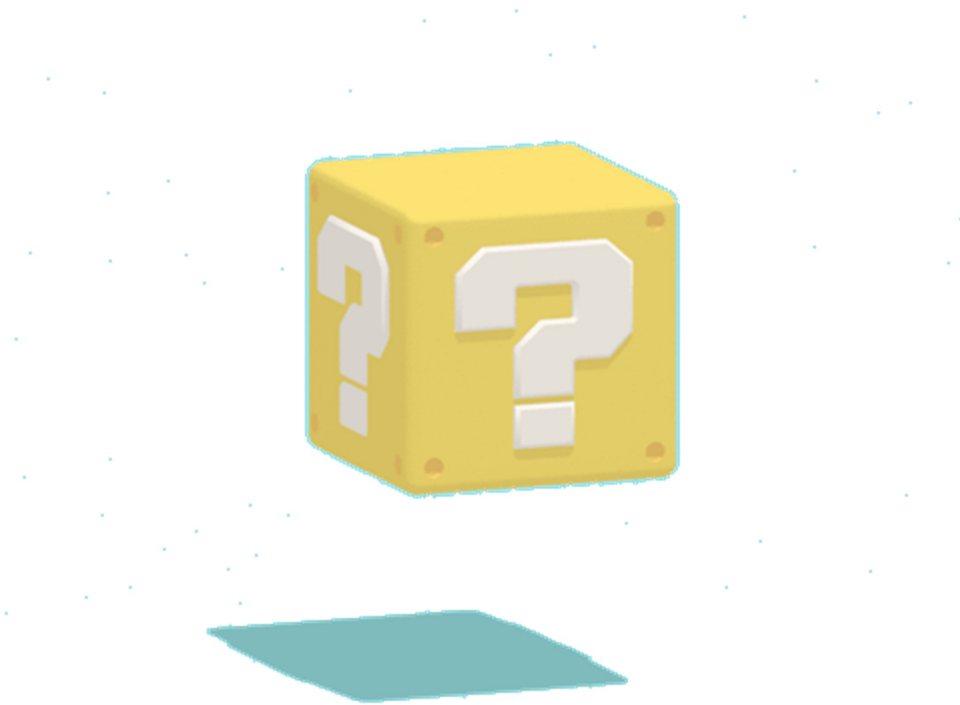
- To calculate correct CAP payments, the RPA Land Parcel Information System (LPIS) is constantly being updated with information from customers, OS MasterMap, Aerial Photographs and Satellite Images.
- But, in addition as per EU regulations, claims from approximately 5% of customers must be controlled (i.e. checked) annually. Failure to make correct payments lead to large penalties for Member States. France had a disallowance of 1 billion euro for mismanaging CAP funds during 2009-2013.
- Controls/Checks are done either through regular Field Inspections (20%), or Remotely with Very High Resolution Satellite Images (80%) for specific areas* to ascertain farmer declaration of agricultural (e.g. grass, crops etc.) and non-agricultural areas (e.g. trees, solar panels, ponds) are correct.

Subsidy (£) = Payment Rate (£) * Eligible Area

Eligible Area = $\boldsymbol{Sum}(\boldsymbol{Parcel\ Area}) - \boldsymbol{Sum}(\boldsymbol{non} - \boldsymbol{agricultural\ area})$

- And then in 2015, things got complicated as major changes were announced in CAP to make farmers follow environmentally friendly farming practices……stay tuned

* Control with Remote Sensing (CwRS)



Part 1- Current Activities

Application of Random Forest Classification for Crop Mapping

2015: Start of Machine Learning at RPA

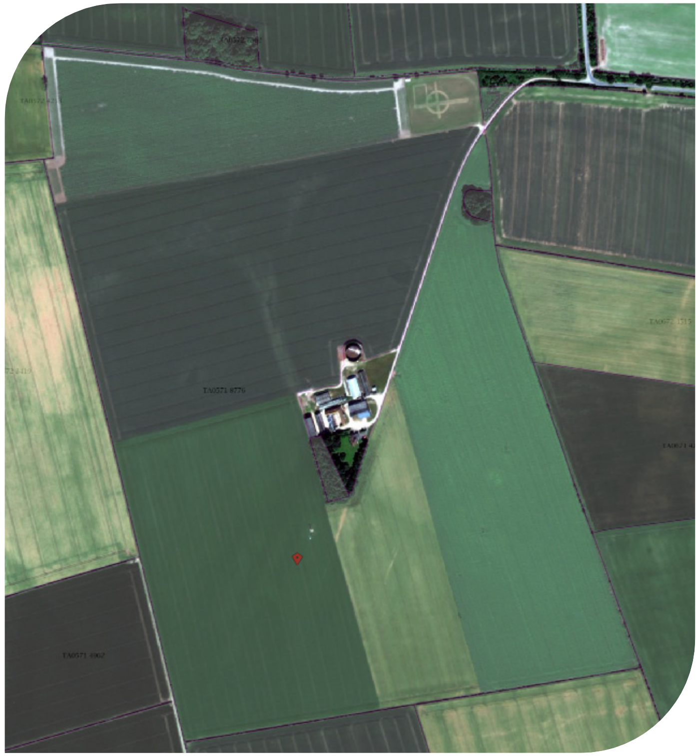
- In 2015, claim validation process became lot more complex:
  - To address the impact of farming on the environment, Greening requirements were added by EU. One such Greening requirement is that some arable farmers have to perform Crop Diversification i.e. grow 2 or more varieties of crops over their land depending upon their claimed arable area.
  - But, it's not possible to validate compliance manually because:
    - Visual identification of a crop type from a satellite image is neither straightforward nor advisable,
    - Farmers don't provide information crop splits in a multi-crop parcel.
- Only solution was therefore to make a crop map by using a time-series[1] of very high-resolution[2] multi-spectral[3] optical[4] satellite images and a supervised image classification. And this is what our CwRS contractor set out to do……

Crop Diversification

Claim from the Customer

LUCODE	Name	Area (ha)
AC66	Winter Wheat	22
AC01	Spring Barley	17
AC67	Winter Oilseed	17
AC44	Potato	8
AC63	Winter Barley	7

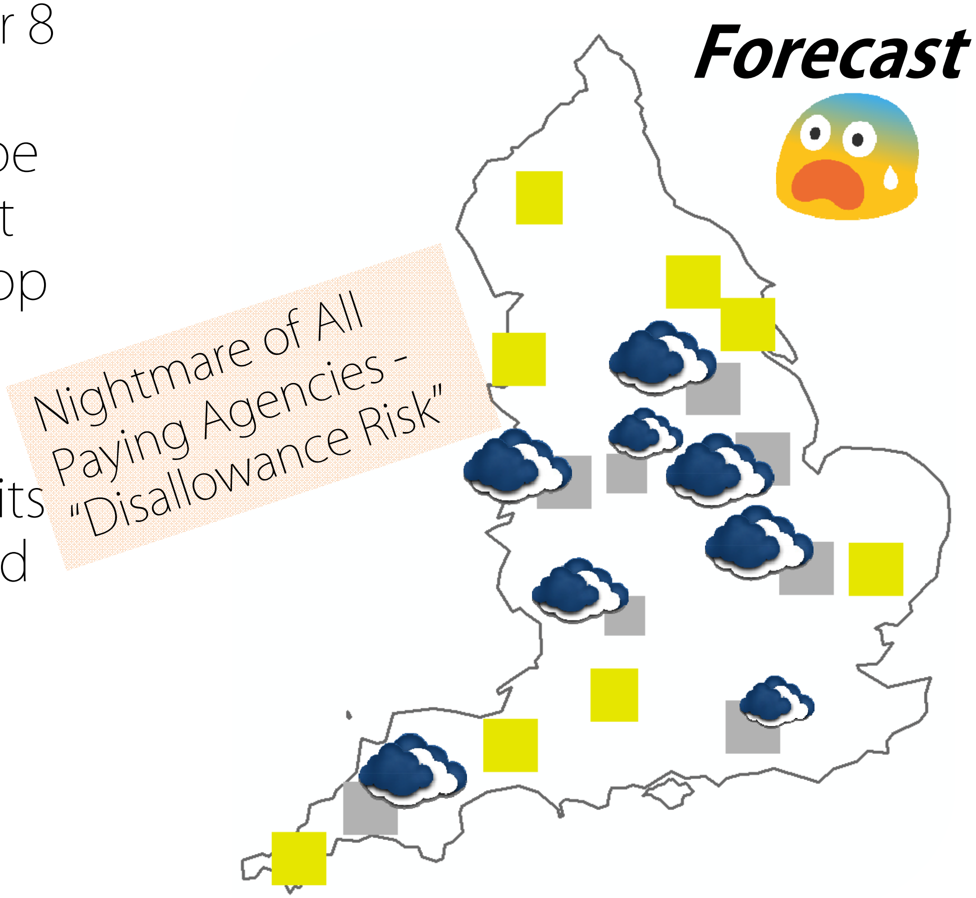
Which green colour indicates which crop??



Multiple Crops In a Parcel

Then it became even more challenging

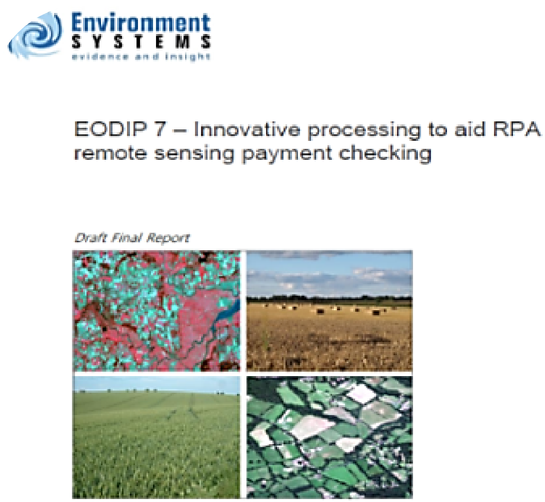
- Optical Satellite images for 8 out of 15 Remote Sensing Control Zones could not be captured due to persistent cloud cover during the crop windows.
- Organising Rapid Field Visits to all affected farms proved challenging.
- Potentially, penalties were on way due to risk of no checks for crop diversification.



2015 RS Control Zones

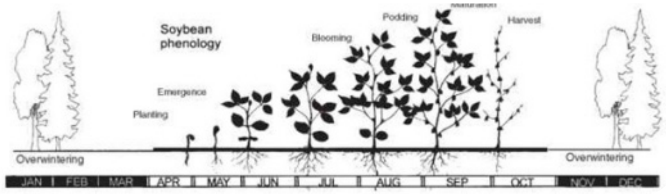
Sentinel-1 *the Saviour*

- In 2016, funding call for R&D projects at Defra as part of Earth Observation Data Improvement Pilots came about.
- We obtained the funding and “steered” project’s Machine Learning (Random Forest) methodology of crop classification using Sentinel-1 Radar and Optical Images, into an existing live processing flow **line** ! – and the successful outcome was runner-up for 2016 Civil Service Innovation Awards!
- But we learnt the lesson that relying solely on Optical Satellite Images was too much of a risk.
  - CwRS Crop Mapping Methodology was revised to include Sentinel-1 Radar with Optical images.
  - A Radar-Only Methodology was developed by the RPA for entire England

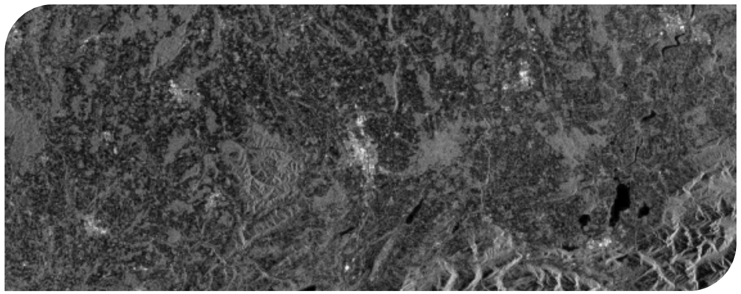


Sentinel-1

- **C-Band Radar Satellites by the European Space Agency launched in 2014.**
- **Advantages of using Sentinel-1 radar images**
  - Unaffected by cloud, therefore there is a more continuous record of crop growth.
  - Certain crops and land cover are not apparent on optical images indices.
  - Free of cost.
  - Good classification results.



sentinel-1



- **Limitations of Sentinel-1 radar images**
  - Spatial Resolution is rather too coarse for the Interferometric Wide Swath (IW) mode images.
  - Processing is still limited to only a few RS image processing software.

Crop Map of England (CROME)

- CROME Design and deployment
  - Specification – *what's in it for "everyone"?*
  - Deployment – *make sure to have second opinions*
- Methodology
  - Data/Software/Hardware – *expensive and high performance equipment*
  - Overall Flow line – *putting everything together*
  - Examples – *pretty pictures!*
  - Quality Assurance – *caveat emptor*
- Case studies – *so, who else finds it useful then?*
- Further Product Enhancements – *more ingredients will make it better*

CROME Design - Schema

Data Type	Geospatial Polygon Data Layer
Scope – Themes and Geographical Coverage	Over 20 main crop types, grassland and non-agricultural land cover in England (including some small isles).
Provenance	Automated classification of multi-temporal series of Sentinel-1 Radar images, and also Sentinel-2 images used mainly for quality correction and assurance purposes.
Data Structure	Hexagon grid tessellation (though production can be easily modified for a land parcel geometry). It is not a Defra Control Layer for CAP
Data Volume	Approximately 32 million hexagon polygon cells;
Format and Supply	File GeoDatabase/WMS on data.gov.uk
Scale	Each Hexagon Cell Edge is 40m long, thus area of 4157 sq.m./~0.4157 ha.
Update Frequency and Temporal Coverage	Annual (Aug-Sep) i.e. just after end of Cropping Season. 2015 - continued

CROME Design - Attribution

Crop and Land Cover Types

- Grassland
- Spring and winter varieties of cereals such as Wheat, Barley, Oilseed, Triticale, Oats, Linseed, Maize
- Spring and winter varieties of leguminous crops such as Field Beans, Peas, Potato, Beet
- Trees
- Water bodies
- Fallow Land
- Non-Agricultural (e.g. Urban Areas, Solar Panels, Roads, Sealed Surfaces, bare rocky/loose surface)

Attribute Schema

NAME	TYPE	PROPERTIES	EXAMPLE
CROMEID	TEXT	PRIMARY KEY	RPA471586173678
LUCODE	TEXT	NOT NULL	PG01
REFDATE	INTEGER	NOT NULL	20181127
SHAPE	SDO_GEOM	NOT NULL	

CROME Design – Why Hexagon??

Advantages:

- Unlike raster cell based visualisation (e.g. CropScape by USDA), the non-rectangular arrangement provides a superior data structure to model and visualise the arbitrary arrangement and dimension of land cover forms and parcels.

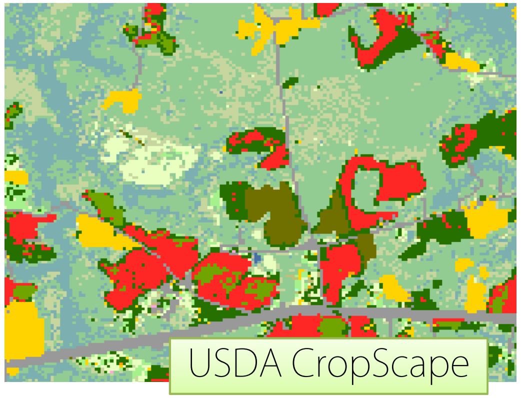
- Unlike other polygonal representations (e.g. CEH Crop Map Plus), it is not dependent on the availability of any pre-existing geometry, e.g. RPA reference parcels, Aerial Photographs/Satellite Images, and Ordnance Survey MasterMap.

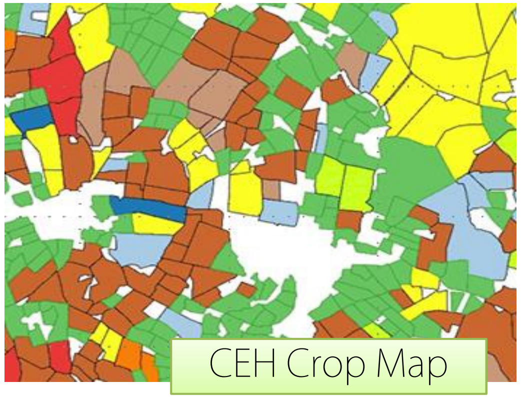
- It is data-licensing agnostic because it doesn't use reference parcel boundaries so can be released by the RPA in the public domain. *

Disadvantages:

- Lack of parcel outlines and large-ish cell size limits visualisation unless further processing is carried out to improve cartographic aesthetics.

- Most mainstream GIS applications don't use hexagonal cell representation.

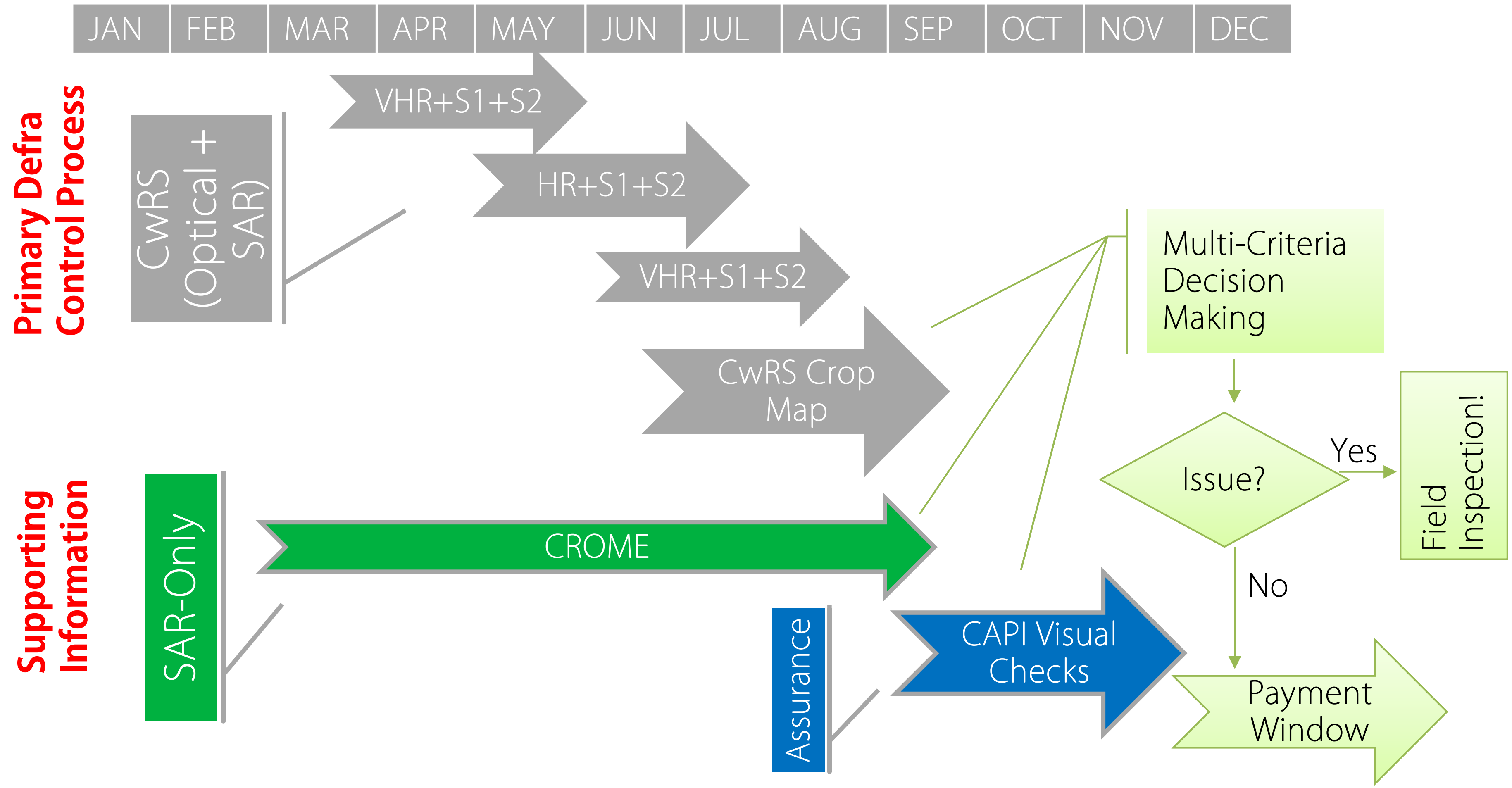

USDA CropScape


CEH Crop Map

* Recent opening up of OSMM may lift this restriction

CROME Deployment

CROME information is moderated with other CwRS CD Checks



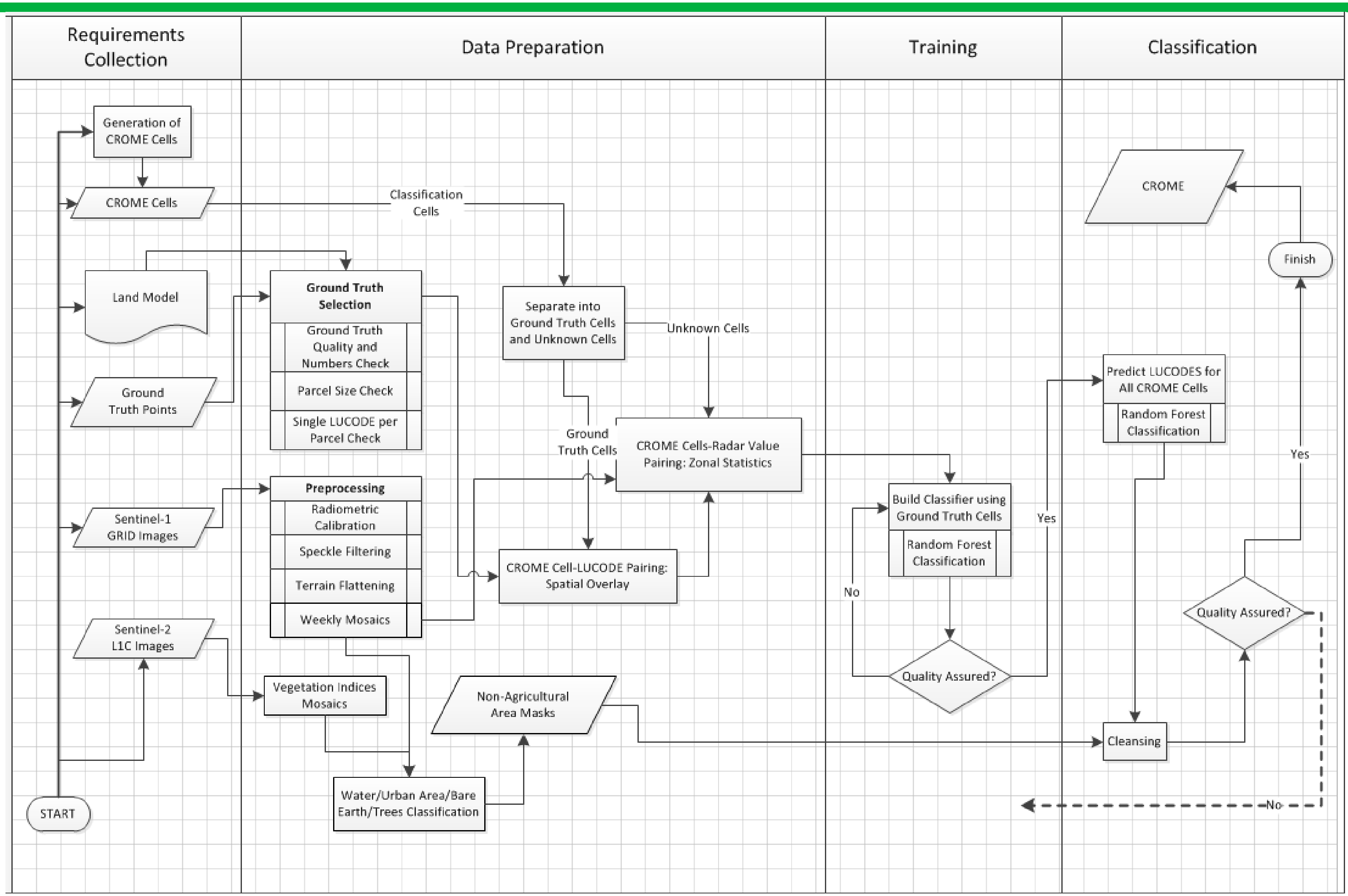
CROME Hardware and Software

- Data
  - Sentinel-1 IW GRD -Sentinel-2 L1C
  - Ground Truths

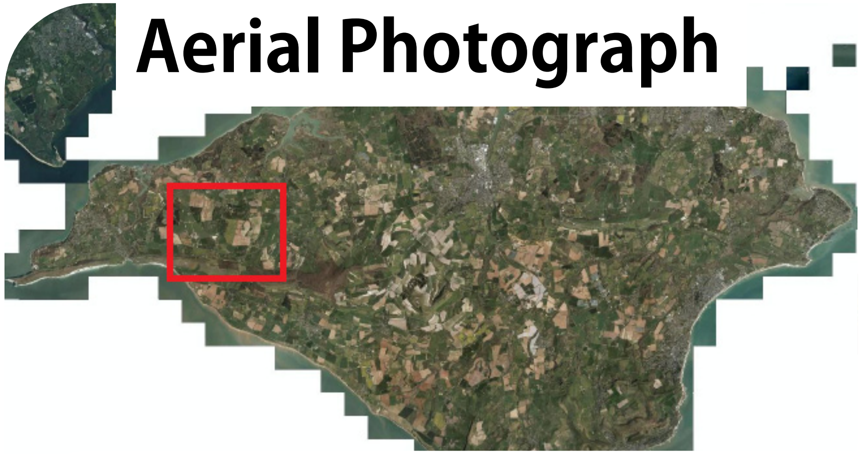
- Software
  -SNAP 64-Bit -SAGA GIS - GDAL 2.1.1
  - R -ArcMap -FME 64-Bit
  -Python -ERDAS Imagine

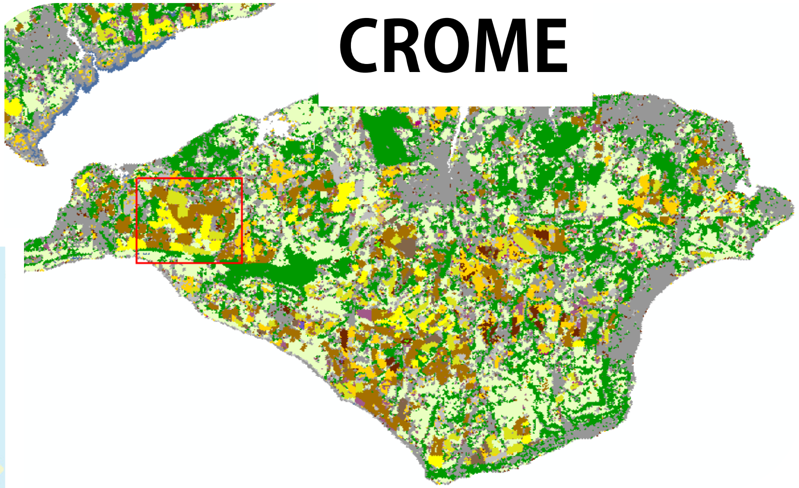
- Hardware
  -Windows 10 64-Bit Custom-build workstation
  -2 x Intel Xeon E5 2.4 GHz (20 Cores)
  -NVidia GPUs for Compute
  -512GB RAM
  -Fast Solid State Drives for Application Data
  -8 TB Spinning Hard Drives for Data Backup

CROME Production Flowline



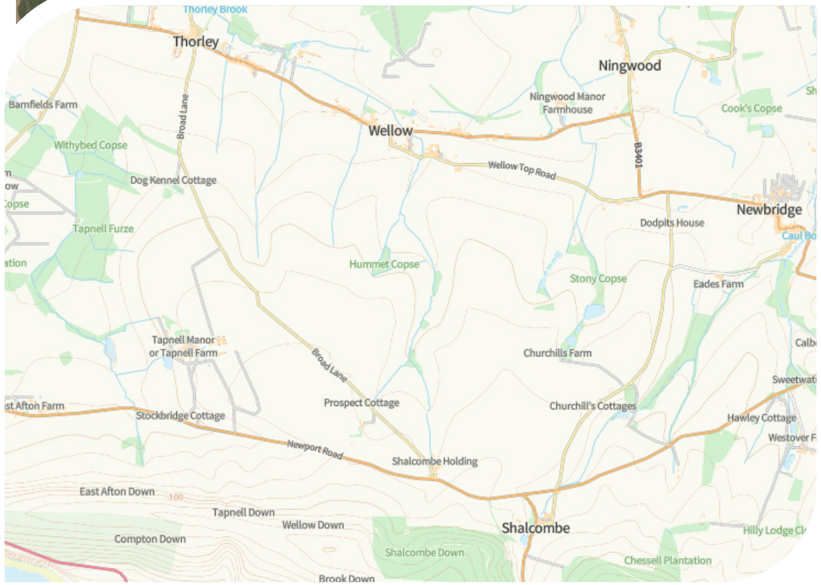
CROME Examples – Isle of Wight

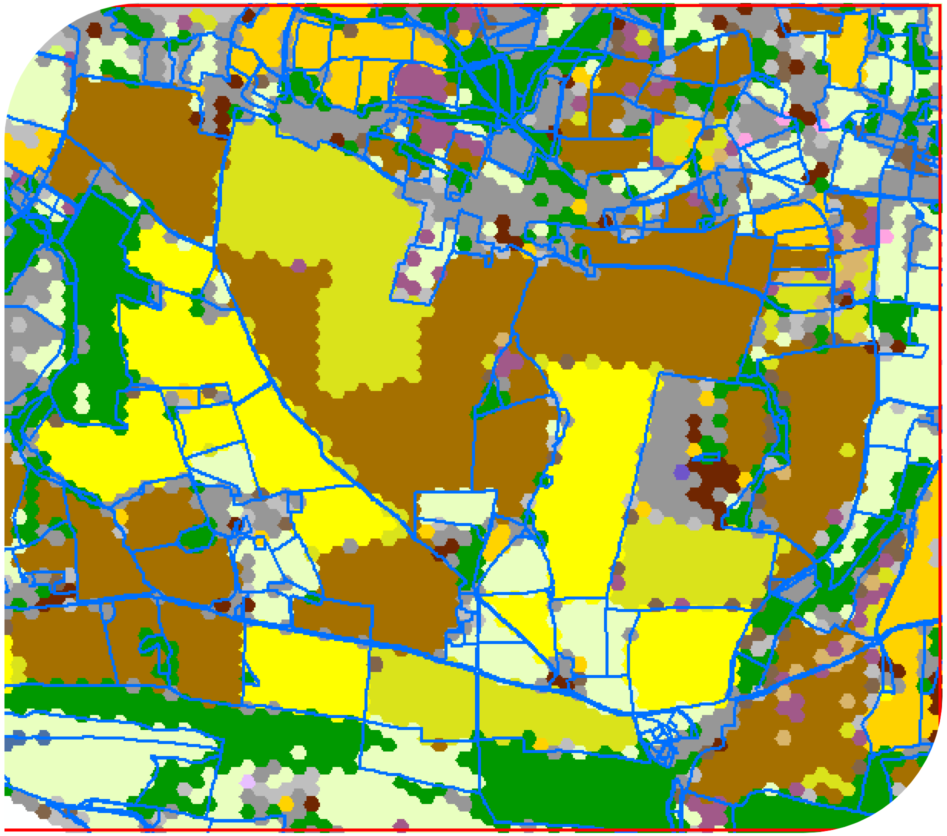




Let's Zoom In

CROME Examples- Isle of Wight

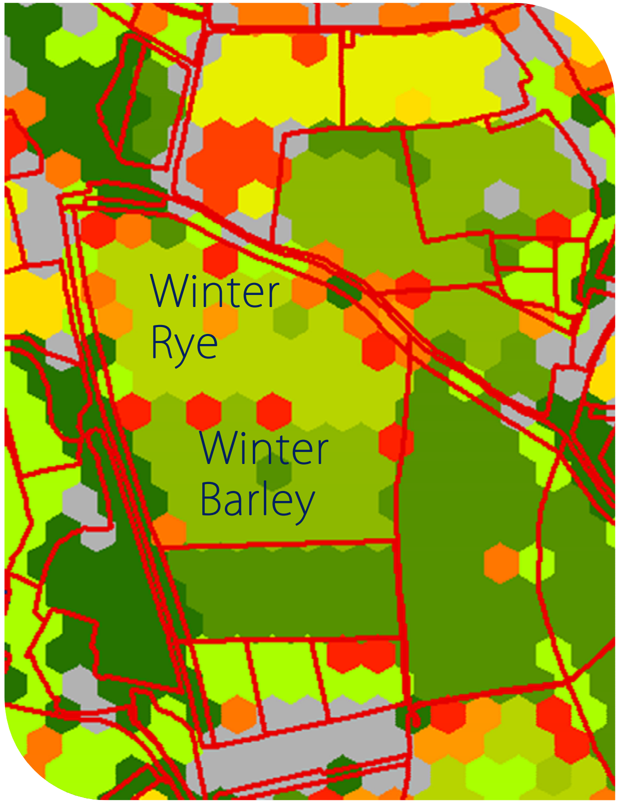




CROME and Parcels

CROME Examples- Multiple Crops Parcel

Only parcels with a single-crop were used for training. So, the detection of multiple crops in a parcel was highly successful.



CROME Quality Assurance

- Quality Checks
  - Random Forest Classification Out-Of-Bag-Error Estimates
  - Confusion Matrix i.e. Users Accuracy, Producers Accuracy and Kappa Coefficient.
  - Use multi-crop type parcels
  - Accuracy tests by Independent Assessors
  - Visual Checks using Sentinel-2 Natural Colour Composites
- Quality Assurance
  - Consistent construction and documentation of computation steps for repeat results.
  - Established standards for computation of accuracy
  - Common documentation of QC steps

CROME 2017 Users Accuracy (Parcel Level based on visual checks)

Land use	Spring	Winter
Grassland	85%	
Wheat	88%	93%
Barley	86%	94.8%
Oilseed	100%(s)	97%
Beans	83%	95%
Peas	90%	n/a
Potato	86%	
Maize	79%	
Beet	71%	
Trees	95%	

Overall Accuracy: 86%

PS. Other Uses of Random Forests

- Land cover classification of Common Land into scrub, grass, trees etc.
  - Non-agricultural (e.g. ungrazeable scrub, trees) areas of common land are ineligible for subsidies.
  - Methodology developed by Natural England
  - Key Aspects:
    - Based on a combination of a variety of inputs i.e. geospatial datasets such as Optical Satellite Images, Sentinel-1 Radar Images, Height and biophysical variables.
    - Polygonal areas to be classified are derived by segmenting optical images into “objects” using eCognition, and these polygons form the areas that are classified as land covers.

CROME Case Studies

- Environment Agency

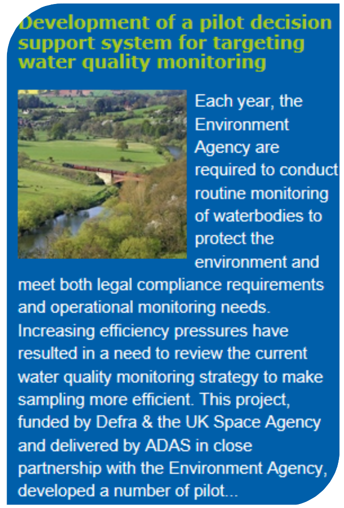
  Enabling Smart Reductions to Water Quality Monitoring

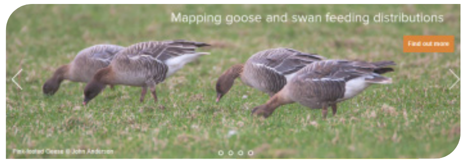
  - *"smarter and more efficient location of ~8,000 water quality monitoring points. Much of the nation's WQ issues are driven by diffuse pollution from agricultural crops – which vary in effect by crop-type – so detailed spatial crop data is great for this application"*
  - *http://www.adas.uk/News/development-of-a-pilot-decision-support-system-for-targeting-water-quality-monitoring Natural England*

- Natural England

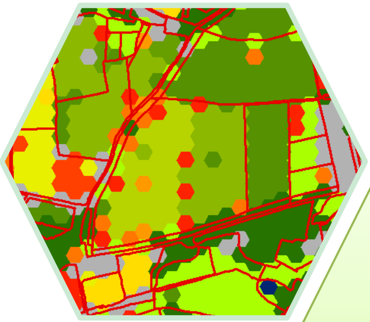
  Wildfowl energetics, the profitability of functionally linked land and the extent of habitat required to support protected populations

  - *"applying a predictive model to assess potential SPA functionally linked land used by Pink Footed Geese in West Lancashire"*
  - *http://monitoring.wwt.org.uk/our-work/goose-swan-monitoring-programme/feeding-distributions/*





CROME Future Work



Improve cartographic representation

Mitigate Single Point of Failure by using Cloud

Improve accuracy by segmenting land using OBIA

Use Deep Learning to make it more accurate!

So you wonder about future for CROME after Brexit when there is no CAP?

" In addition, EO is used to support the production of discreet data products, such as bracken and scrubland maps and hedgerow datasets, and to produce the RPA's own crop classification map – the Crop Map of England (CroME).

The use of EO for crop classification removes the need for physical crop diversification inspections. This offers operational efficiency savings of approximately £535-575K per year, based on RPA estimates

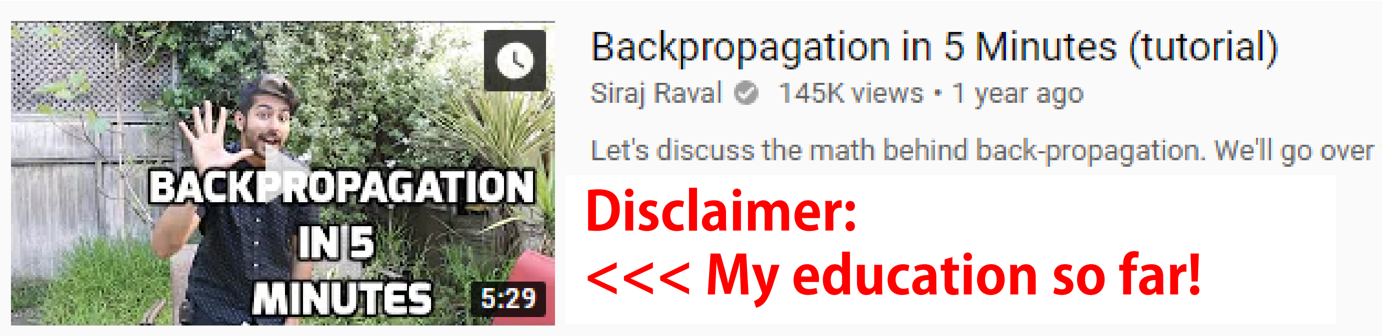
Wider use of CroME data across Defra can also support other policy objectives. For example, the Environment Agency can use crop map data to identify risk factors that may contribute to agricultural water pollution. If this data is used to support actions that could mitigate this pollution by just 1%, total catalytic benefits are estimated at £12.3 million per year. "

Part 2- Work In Progress Activities

Application of Deep Learning (DL) for Crop Mapping and Land Change Detection

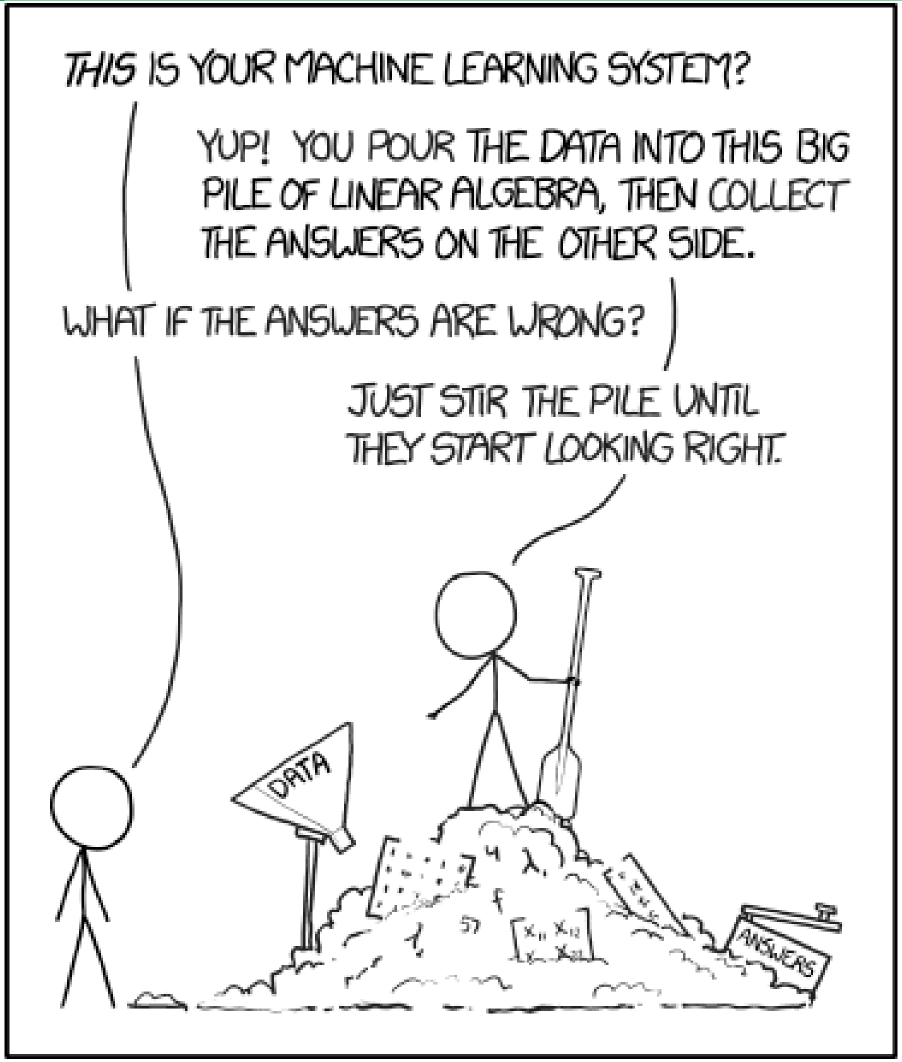
Using DL for CROME and Change Detection

- Why ramble into Deep Learning at all?
  - Recent papers from academics (e.g. Kusul et al., 2017) and EU JRC researchers (e.g. d'Andrimont et al., 2018) have proposed that Deep Learning Techniques are a superior alternative to Random Forest.
  - The Convolutional Neural Networks (CNNs) in Deep Learning domain are uniquely relevant to feature recognition based on images, which if applied successfully in RPA, could substantially improve the land cover mapping process and ability to handle anomalous data in images.
  - Image Classification is possible even with standard RGB Aerial/Satellite Images.



Disclaimer:
<<< My education so far!

Software Tools



TensorFlow

NumPy

ANACONDA

jupyter

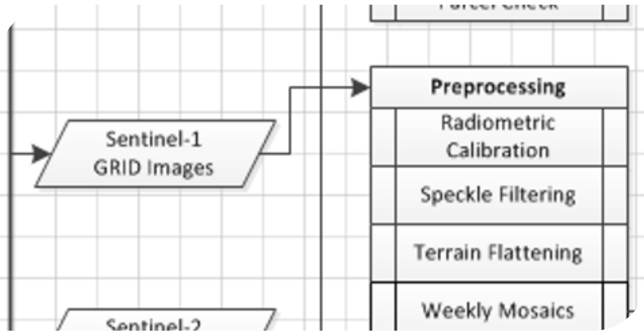
NVIDIA CUDA

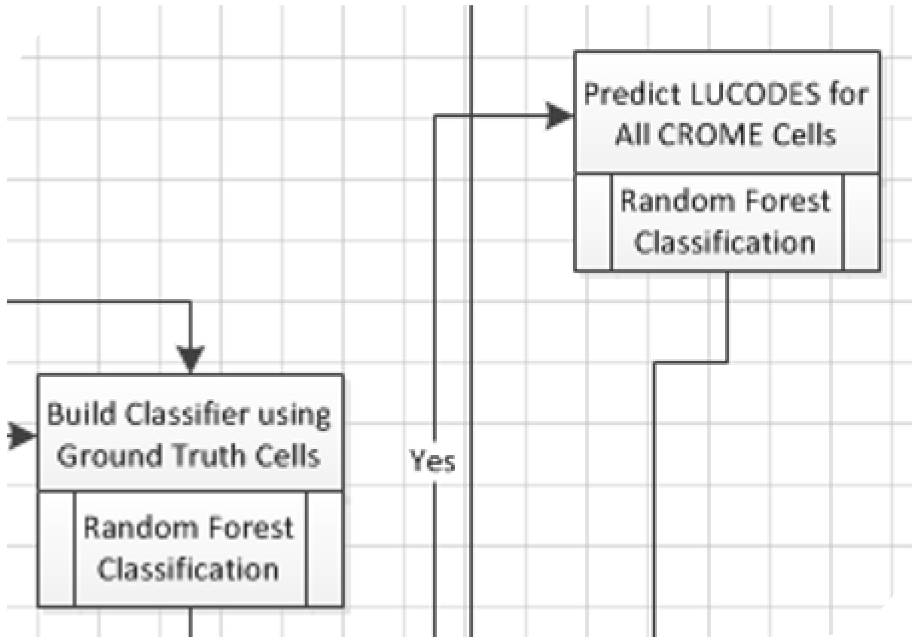
scikit learn

Using DL for CROME

Two investigations:

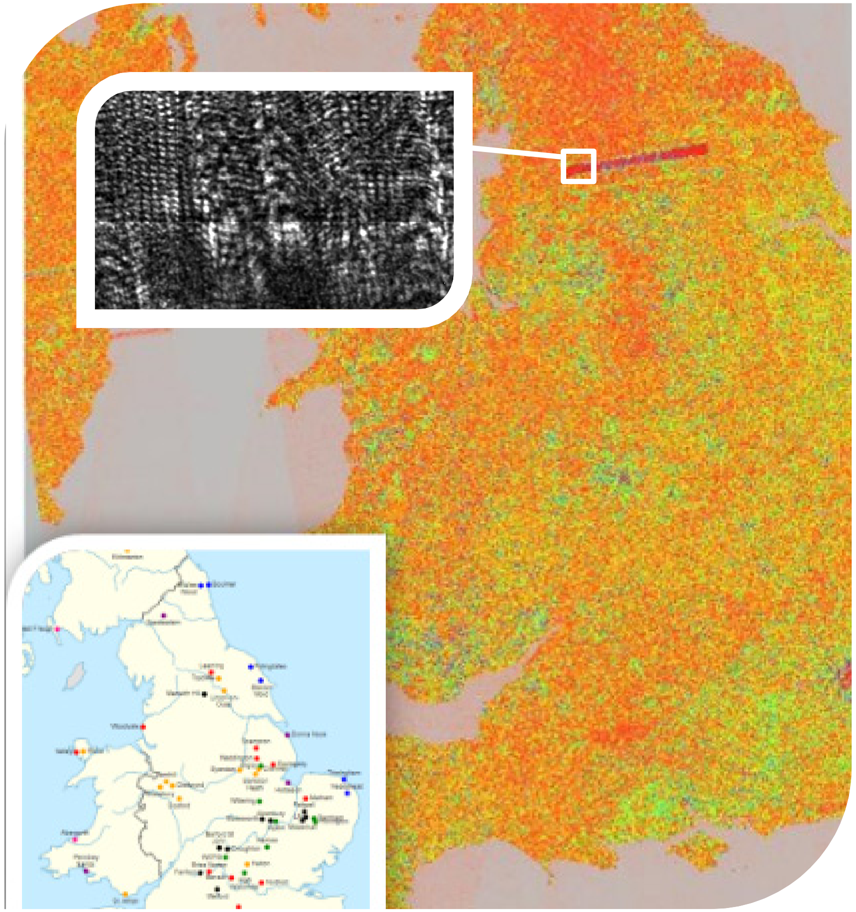
1. Identification of Areas affected by the Radio Frequency Interferences (RFI)
2. Crop Classification





Using DL for CROME - RFI

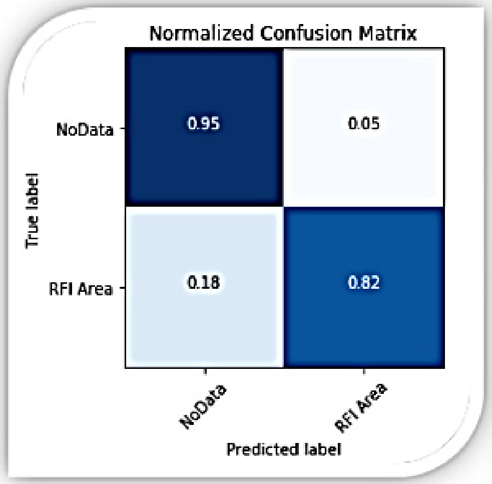
- Sentinel-1 radar images used for Crop Map contain artefacts due to Radio Frequency Interference (RFI) from RAF Radar.
- These artefacts can affect the accuracy of the crop classification.
- At present, only a manual check can reveal where RFI is present, and is therefore time consuming and human error-prone.
- The unique texture of RFI areas make them easy to be located using neural networks.

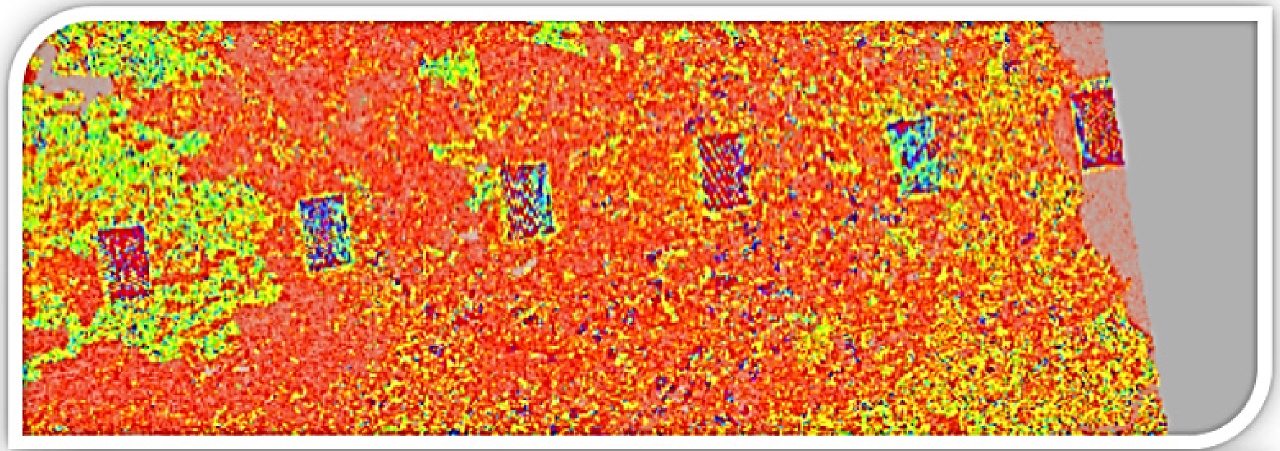


Using DL for CROME - RFI

- Classification utilised U-net architecture in Keras for Training, using "Adam" as optimizer and "binary_crossentropy" as loss function.
- Layers
  - Sentinel-1 Analysis Ready Images
  - Images resized to 256x256 10m tiles.
- Input Labels/Output Classes
  - Binary Image Masks i.e. NoData or RFI
- Validation
  - Labels were randomly split 50/50 into Training and Test populations
- Results
  - The RFI instances can be automatically identified with high accuracy thereby revealing the obvious and non-obvious locations.

Using DL for CROME - RFI



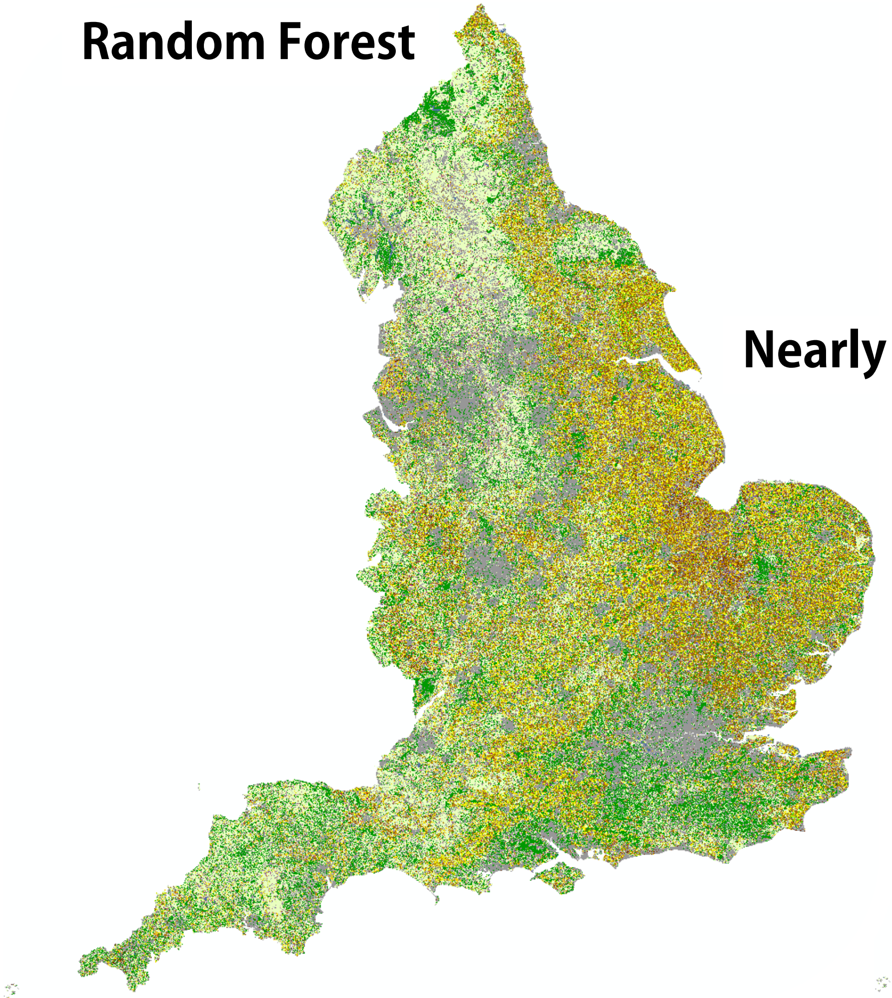


Using DL for CROME – Crops

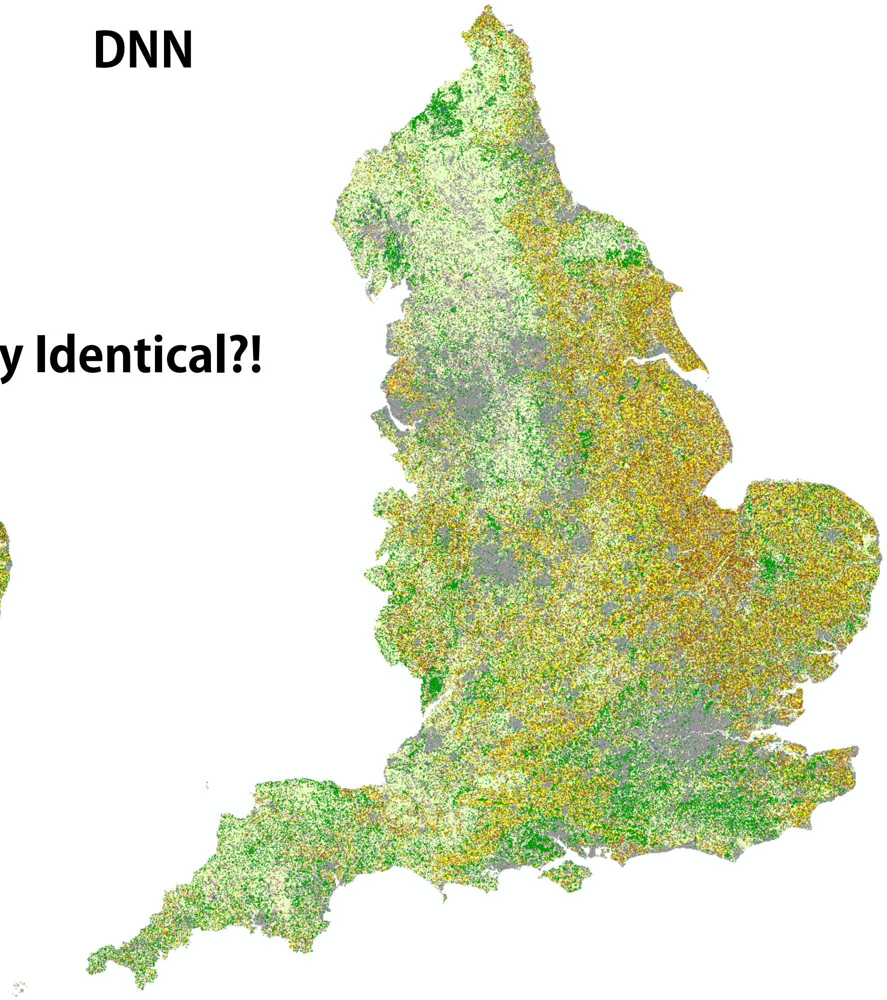
- Classification utilised 3 fully-connected layers with 92 nodes, "Adam" as optimizer, and "sigmoid" activation function.
- Used TFLearn module with Tensorflow-GPU, so I ran several combinations of epochs, batch size, and learning rate.
- Layers
  - Ground Truth Zonal Statistics - 92 weekly averages of VV, VV, and VV/VH backscattering coefficient values in 2018.
- Training/Validation
  - Training data was randomly sorted to avoid spatial autocorrelation bias.
  - Training data was split 50/50 into using StratifiedShuffleSplit into Training and Test populations to maintain presence of all crop codes in training and test populations.

Using DL for CROME – Crops

Random Forest



DNN



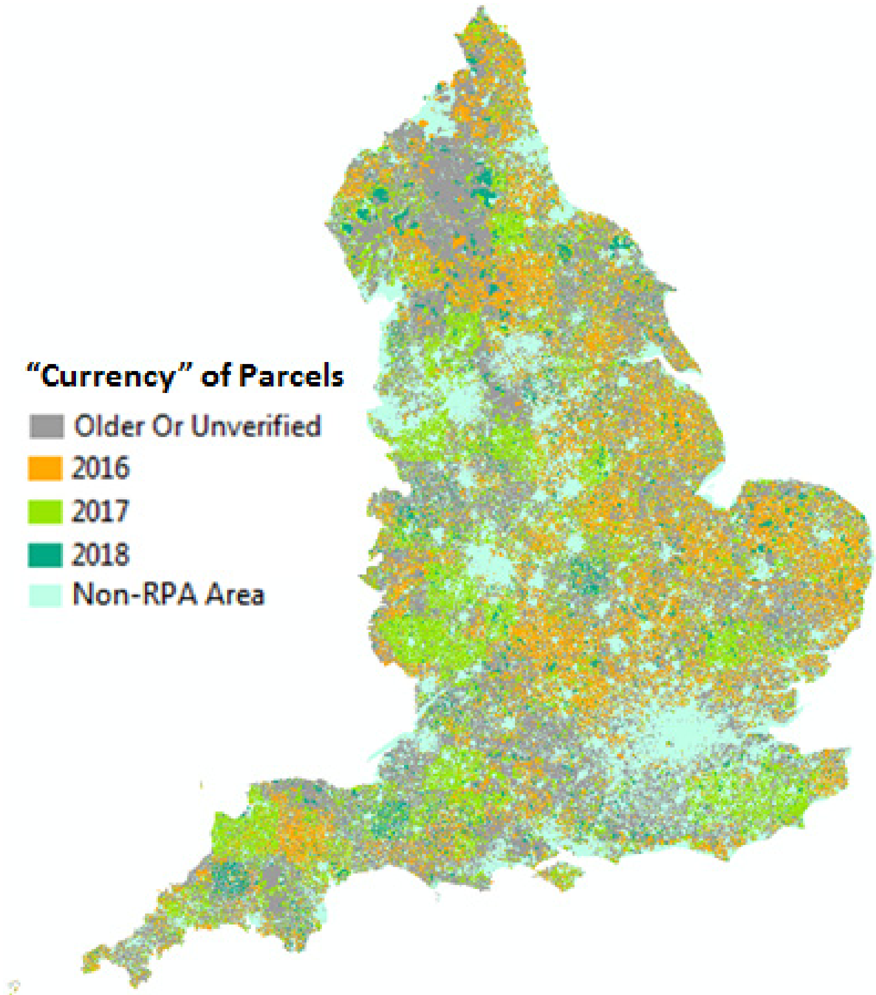
Nearly Identical?!

Using DL for CROME – Crops

- Accuracy (Caveat Emptor - Very preliminary results)
  - 2018 CROME produced from Random Forest is compared with one produced from DNN.
  - Most surprising (and potentially positive) result:
    - DNN picked up some crop types, which were completely over-fitted by Random Forest into some other types.
  - User Accuracy of 7 out of top 10 crops (by claimed area) is on average 6% higher in DNN in comparison to RF

Using DL for Land Cover Classification

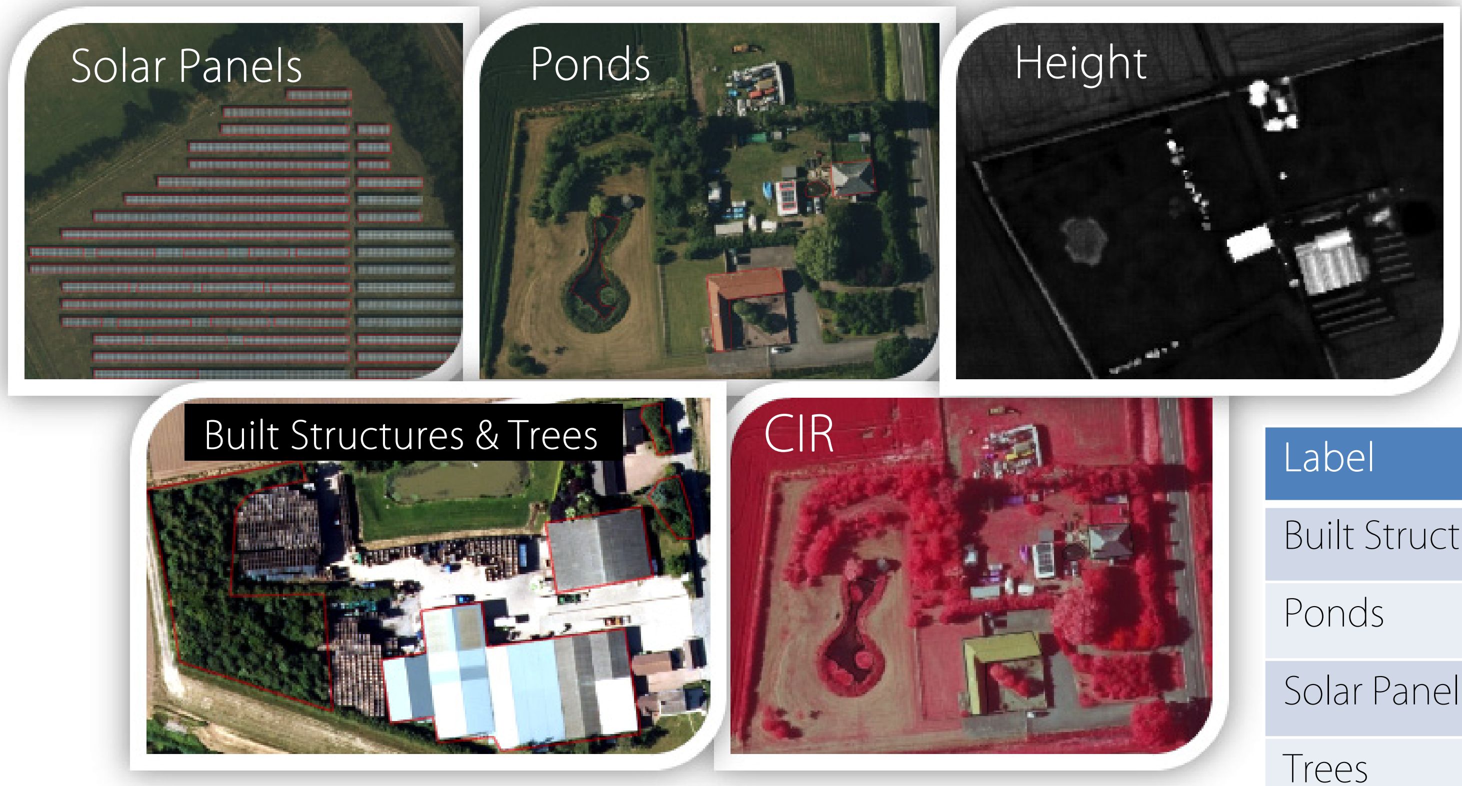
- The RPA is in a continuous process of updating the maps of land parcels and land covers such that all the features have been checked with "intelligence" no older than 3 years old.
- At present, about 42% of 2.6m parcels are out of date and require updating.
- Existing change detection process is time consuming, costly, and vulnerable to the errors in human interpretation.
- The OS have previously proposed that up to 70% of parcels remain unchanged year on year.



Using DL for Land Cover Classification

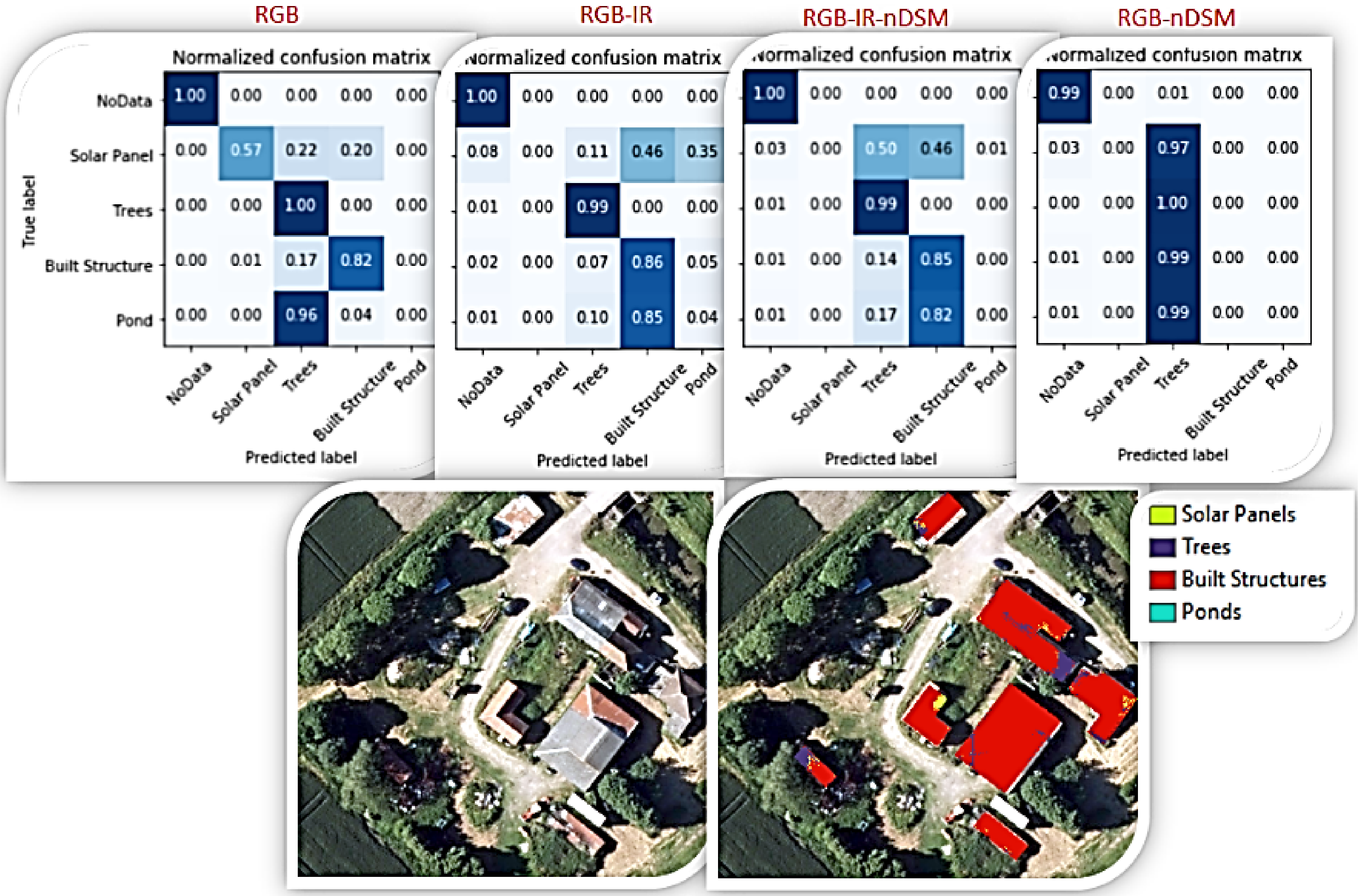
- Classification utilised U-net architecture in Keras for Training using “Adam” as optimizer, “categorical_crossentropy” as loss function and “softmax” activation function. Disclaimer: A very small experiment!
- Key Aspects
  - Layers:
    - RGB-IR Bands from Aerial Photographs
    - Digital Surface Models
    - Vegetation Indices (NDVI, NDWI)
    - Layers resampled to 256x256 25cm tiles
    - Layer permutations were done to converge for best accuracy.
  - Input Labels/ Output Classes:
    - Image chips containing Solar Panels, Trees, Built Structure, Pond. These had to be obtained manually because the several stored in the RPA land cover layer were either out of date or included too much neighbouring unrelated areas.
  - Validation
    - Labels were randomly split 50/50 into Training and Test populations
  - Training was done on a CPU so only at most 50 epochs, which took several hours.

Using DL for Land Cover Classification



Label	Count
Built Structures	1577
Ponds	114
Solar Panels	170
Trees	2249

Using DL for Land Cover Classification



Conclusions and Questions

- Lessons Learnt
  - Deep Learning Techniques will provide highly accurate results for agricultural land cover classification applications BUT
  - Make sure ALL labels are correct!
  - Do everything on GPU!
- 85% overall accuracy appears to be upper limit of what's possible with fully automated Machine Learning based Multi-Class Land cover classification.
    - So, how to report usefulness of land cover classification with single metrics?
- Why is DL giving better results than RF for Crop Classification?
- Is there a way of estimating DL network variables (learning rate, epochs, batch size etc.) from input ordinary data metrics?

Further Information

- Acknowledgements
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  - SNAP Discussion forum members on very helpful tips on improving the performance of batch processing and issues surround Sentinel-1 Radar data
  - Data Science Accelerator by GDS and Data Science Team at UKHO, specially my mentor Cate.
- CROME data available on data.gov.uk.
- Contact me for more information on CROME classification:
  - sanjay.rana@rpa.gov.uk
- Download jupyter notebooks at https://github.com/drsanjayrana/dsa/ for Deep Learning for RFI and Land cover Classification