



Detection of Upland Burn with Sentinel-1 Coherence Data through collaborative development within Jupyter Notebooks

Document Version

Final published version

[Link to publication record in Manchester Research Explorer](#)

Citation for published version (APA):

Lavender, S., Millin-Chalabi, G., & Johnston, A. (2022). *Detection of Upland Burn with Sentinel-1 Coherence Data through collaborative development within Jupyter Notebooks*. Poster session presented at ESA Living Planet Symposium 2022, Bonn, Germany.

Citing this paper

Please note that where the full-text provided on Manchester Research Explorer is the Author Accepted Manuscript or Proof version this may differ from the final Published version. If citing, it is advised that you check and use the publisher's definitive version.

General rights

Copyright and moral rights for the publications made accessible in the Research Explorer are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

Takedown policy

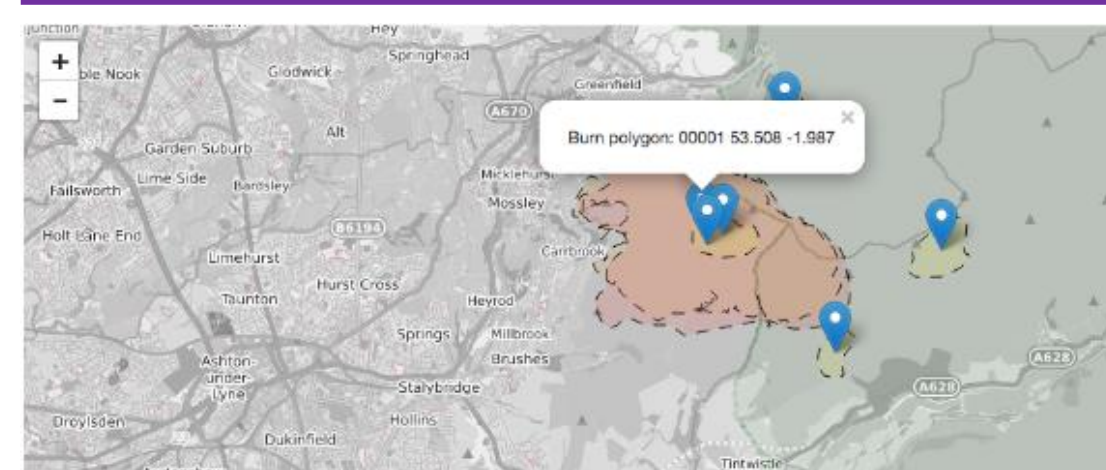
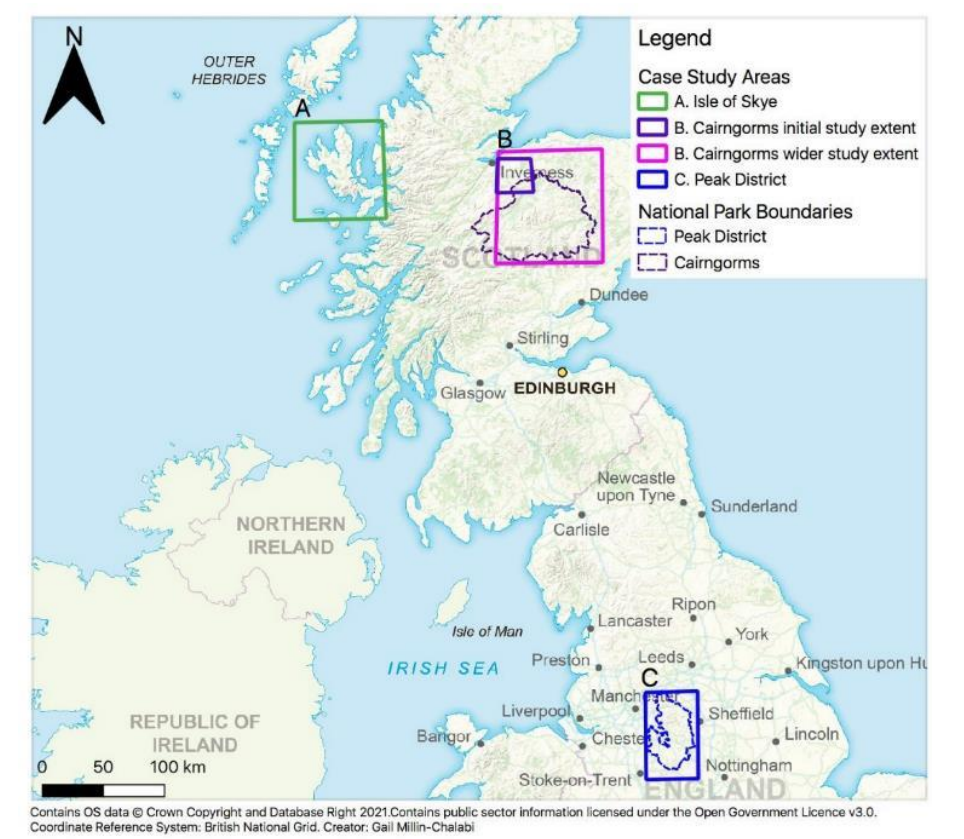
If you believe that this document breaches copyright please refer to the University of Manchester's Takedown Procedures [<http://man.ac.uk/04Y6Bo>] or contact uml.scholarlycommunications@manchester.ac.uk providing relevant details, so we can investigate your claim.



In response to a DEFRA ITT, a six-month research project focused on developing techniques for identifying burn scar areas from the Sentinel-1A and -1B satellite data.

Workflows implemented in Jupyter Notebooks downloaded, pre-processed and applied detection algorithms. The outputs were compared to imagery for known burn areas, and discrepancies investigated. Three case study areas were used for testing and analysis: Isle of Skye and Eastern Cairngorms in Scotland and England's Peak District National Park.

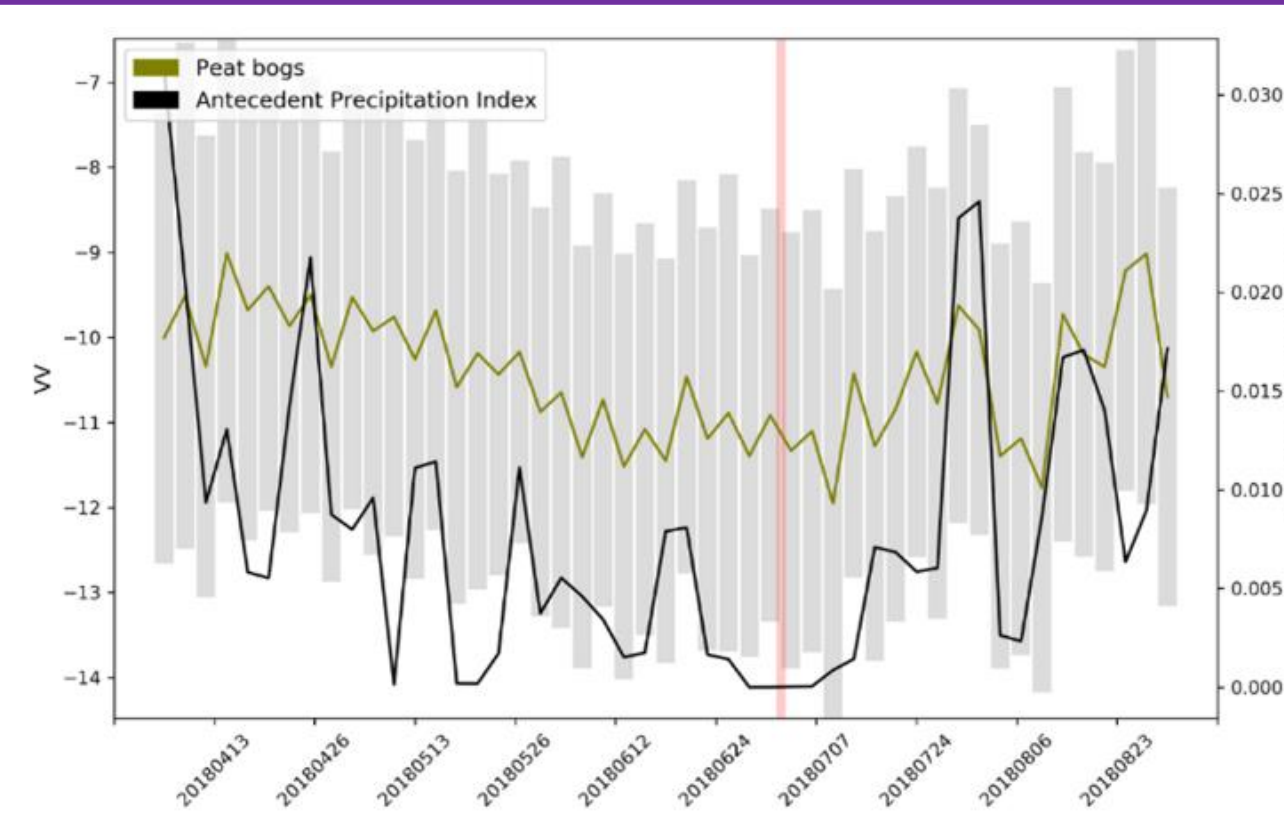
The flow of the Combined Workflow Jupyter Notebook for comparing the Sentinel-1 dataset, Antecedent Precipitation Index (API) derived from ERA5 data and CORINE Land Cover information with the manually digitized burn scars as interactive figures, xarray tables and comparison plots is shown on the right with example shown below.



Preview of burned areas showing a Peak District National Park example; background is courtesy of Open Street Map.

date	sensor	seconddate	rorbit	direction	perpbaseline	
1	2018-02-05	AB	2018-02-11	96	DESCENDING	0
2	2018-02-05	AA	2018-02-17	103	ASCENDING	0
3	2018-02-07	AB	2018-02-13	125	DESCENDING	0
4	2018-02-10	AA	2018-02-22	1	ASCENDING	0
5	2018-02-11	BA	2018-02-17	96	DESCENDING	0
6	2018-02-11	BB	2018-02-23	103	ASCENDING	0
7	2018-02-12	AA	2018-02-24	30	ASCENDING	0
8	2018-02-12	AA	2018-02-24	23	DESCENDING	0
9	2018-02-13	BA	2018-02-19	125	DESCENDING	0
10	2018-02-17	AB	2018-02-23	96	DESCENDING	0
11	2018-02-17	AA	2018-03-01	103	ASCENDING	0
12	2018-02-19	AB	2018-02-25	125	DESCENDING	0

Example showing data filtering for the Cairngorms coherence data.

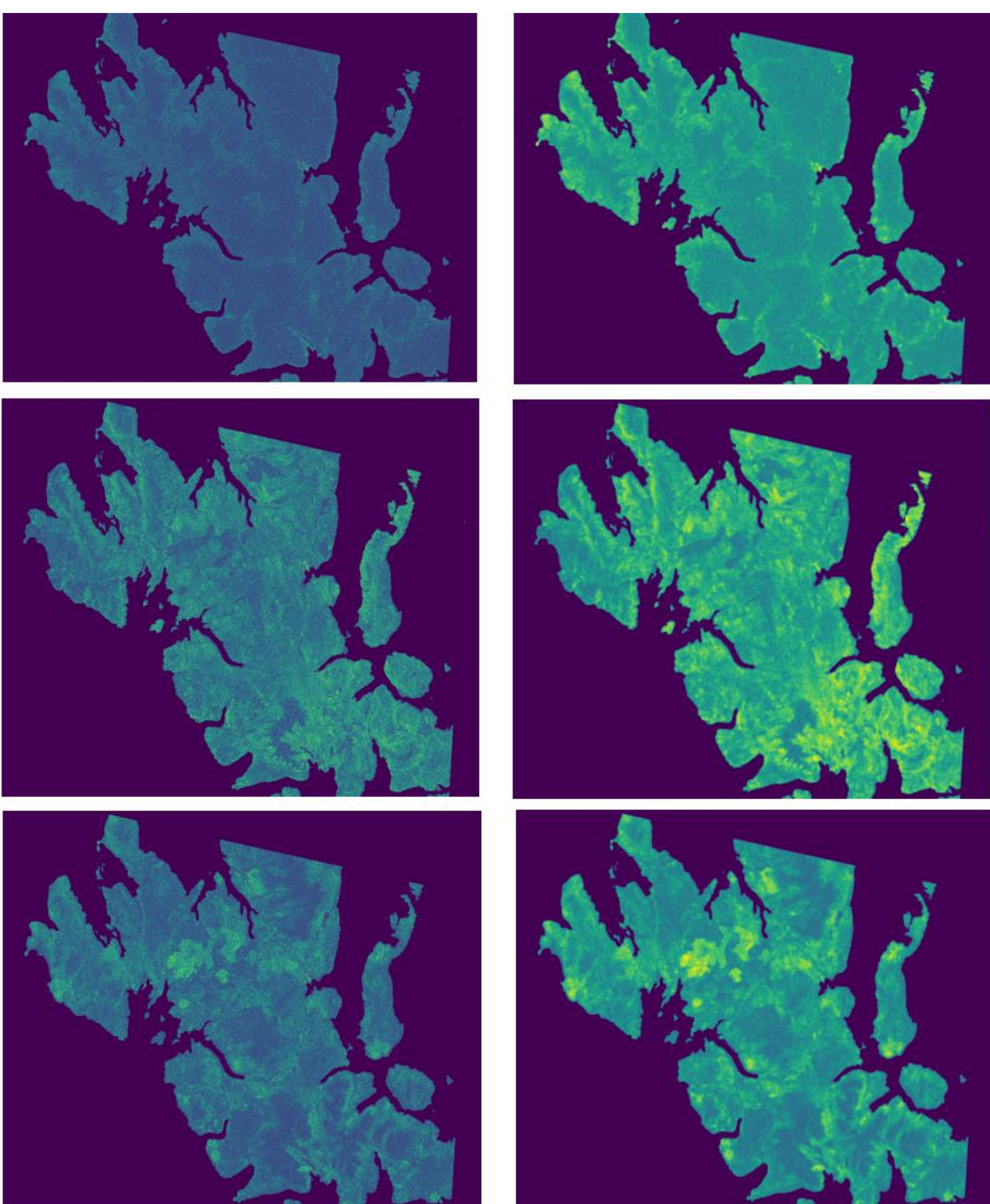


Plot of Peat bog Sentinel backscatter alongside API, red line is date of known burn scar

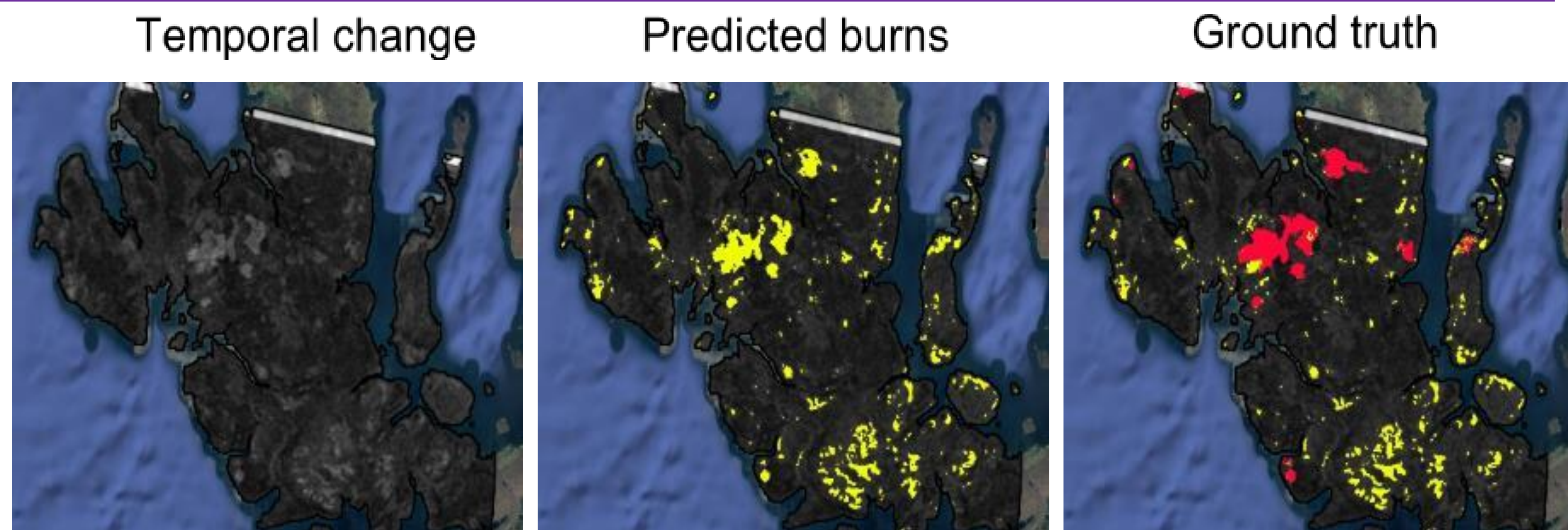


Results (left) showed that burn scars were visible in coherence data. Burn areas showed low coherence in image pairings that covered the burn date, followed by high coherence in the images that followed, presumably due to lack of vegetation/growth.

Coherence data are normalised between 1 and 0 for each image, which introduces a potential hurdle for an automated detection algorithm as images will all have the same scale range regardless of their relative coherence. Therefore, the first step was to reverse this normalisation. Although this is impossible to do correctly without the initial maximum and minimum values used to normalise the image, the effect could be replicated by dividing each image by its median value.



A comparison of several coherence images, from February and March 2018, before (left) and after (right) the initial de-normalisation and smoothing steps.



An average coherence value was created for every pixel across the date range used. Then, the absolute difference between each image and the temporal mean image was calculated before all images were summed. A threshold was then applied to extract the most changed pixels likely to be burn areas.

In summary, the findings suggest that burn areas' detectability with coherence improves over one year following fire. However, further ground-truth work on post-fire regrowth is needed to understand the mechanisms responsible for this response. The Jupyter Notebooks have been made publicly available and will continue to be developed for this application alongside being reused in future collaborative projects.

<https://github.com/pixalytics-ltd/upland-burn-detection>

Acknowledgements: Data courtesy of Copernicus/ESA and ECMWF