

PI

Dr. Simon Fraval, University of Edinburgh

Collaborators

Prof. Alan Duncan (University of Edinburgh)
Dr. Mark van Wijk (The International Livestock Research Institute)
Mr. Andrew Horne (University of Edinburgh)
Mr. James Crone (University of Edinburgh)
Dr. Michael Bareford (University of Edinburgh)
Dr. Kristina Tamane (University of Edinburgh)
Prof. Iain Woodhouse (University of Edinburgh)

Acknowledgement

This work was carried out with the support of the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 801215, and the University of Edinburgh Data-Driven Innovation programme – part of the Edinburgh and South East Scotland City Region Deal. It was also supported by the International Livestock Research Institute's Sustainable Livestock Systems programme. The authors acknowledge Planet for providing the satellite imagery on a trial basis, and also acknowledge the previous work on field boundary delineation by Franz Waldner, Sentinel Hub as well as CSIRO.



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Engineering and
Physical Sciences
Research Council



This work used the Cirrus UK National Tier-2 HPC Service at EPCC funded by the University of Edinburgh and EPSRC (EP/P020267/1).

Agricultural field boundary delineation: enabling sustainable land stewardship



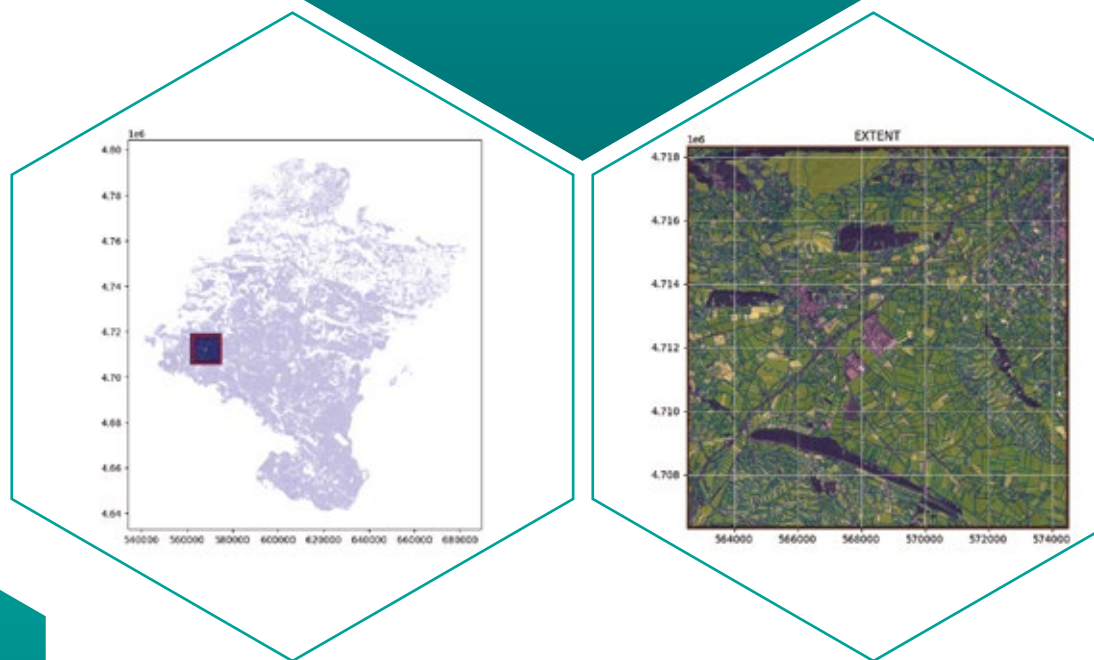
Across the globe, agriculture is under strain from economic and environmental pressures and farmers often have to make decisions in the absence of full information. Earth Observation satellite data can help inform decisions, but the benefits are limited by the complex nature of delineating field boundaries. Research led by the University of Edinburgh has used Machine Learning techniques to increase the accuracy and decrease the costs of doing this.

Food systems are becoming increasingly strained under economic and environmental pressures. The responsibility for addressing these challenges largely falls on 540 million dedicated farmers world-wide. These farmers make decisions in complex and information-scarce environments to maximise their profitability while meeting consumer demands and environmental objectives. Farm decision making will only become more challenging as climatic variability increases due to climate change.



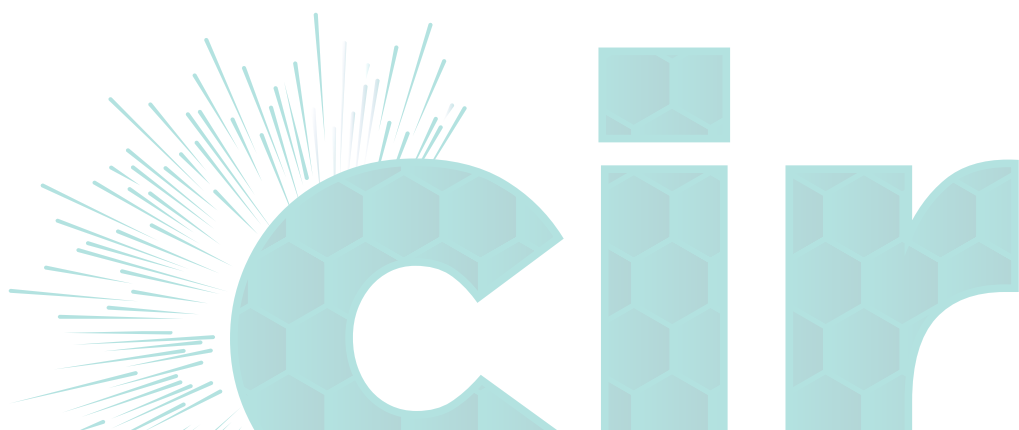
Earth Observation data can be used to lift part of the decision-making burden from farmers, replacing a lengthy farm inspection with readily-available satellite's-eye-view metrics – such as crop yield. Delineating the boundaries of agricultural fields is an essential first step in making Earth Observation metrics ready for decision making. However, manually drawing field boundaries is time-consuming, technically complex and error-prone, limiting the applicability for farmers and undermining the economic viability of Earth Observation service providers. Computer vision technologies now provide a means of quick and cost-effective automatic field boundary delineation. The race is now on to make automatic agricultural field boundary delineation accurate enough for use by farmers and their support services.

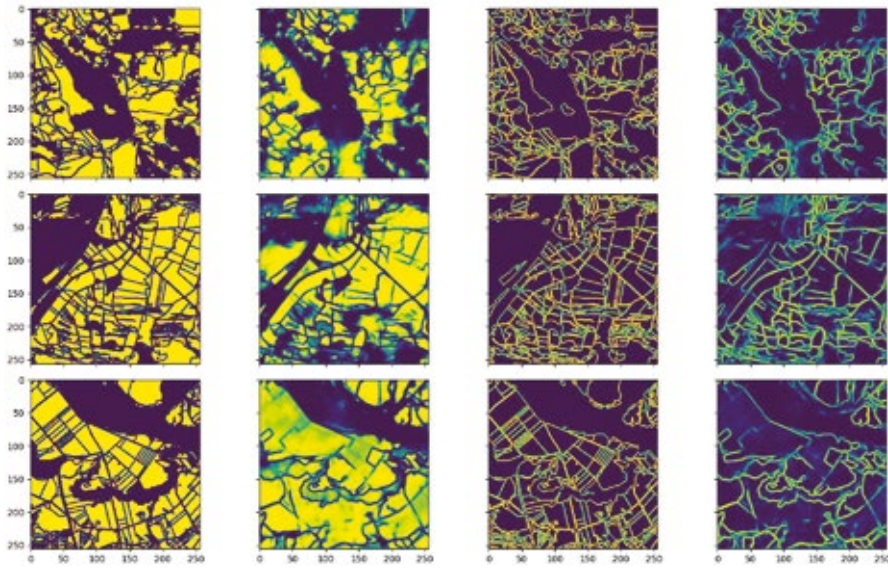
To progress the state of the art, we trained a UNET neural network on high resolution multi-spectral satellite imagery (PlanetScope, 3.7m). The neural network learned to predict agricultural extent and field boundaries using a sample from 700,000 agricultural field boundaries from northern Spain. Prediction accuracy was improved by 16% when compared to lower resolution Sentinel 2 imagery (10.0m). This is a substantial improvement in accuracy, indicating that high resolution data will be essential in delivering accurate products to decision makers.



Location and sample of reference data from Spain. Left: extent of data. Right: sample of a specific location in the west of Navarra province, Spain.

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Reference and prediction comparisons in four training locations. Columns: reference extent, predicted extent, reference boundary and predicted boundary.

Training on the Cirrus supercomputer took 164 GPU hours. The memory available on the Nvidia V100 GPUs was a critical success factor in this analysis – enabling the training and prediction from high resolution satellite imagery.

This innovation has the potential for substantial cost savings. The current lowest cost option for field boundary delineation would be approximately £100,000 for the whole of the UK – using Airbus’ custom algorithm and SPOT 6/7 satellite imagery (1.5m). Our approach has the potential to achieve a similar level of accuracy while bringing the cost down to be under £5,000 for the whole of the UK. Given the tumbling costs of GPU processing and satellite imagery, it will be possible to generate annual and seasonal products at a fraction of the current price tag.

Further innovations will require even more compute power, satellite imagery and reference data. Firstly, incorporating the temporal features of field boundaries will require more memory than any one GPU can manage – necessitating distributed deep learning frameworks, such as Horovod. Secondly, processing satellite imagery at global scale will necessitate vast amounts of storage space. Thirdly, globally accurate models will require reference data of all the farming systems from around the world. For example, in Egypt (right) irrigated cropland has expanded by 33% since the 1980s and field boundaries have not been adequately mapped. Incorporating reference data from comparable irrigation regions will increase the accuracy of predictions for Egypt – a location with growing needs for food and productive-sustainable innovations.

We are now on the cusp of “democratising” Earth Observation metrics for sustainable land stewardship. The first humble step has been to automate field boundary delineation. The next daring steps will be taken by farmers and stakeholders in countless rural communities.



Landsat Timelapse: Forty years of cropland expansion in Egypt.

