Classification and Segmentation of Blooms and Plumes from High Resolution Satellite Imagery Using Deep Learning

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Introduction

High resolution multispectral satellite sensors allow experts to spot and trace algal blooms and river plumes in individual images (examples right). Deep learning convolutional neural networks have previously been applied to reflectance data collected from airborne and satellite platforms for land classification. We hypothesize that, by re-training these established models, it is possible to recognize key optical features in inland and coastal waterbodies.

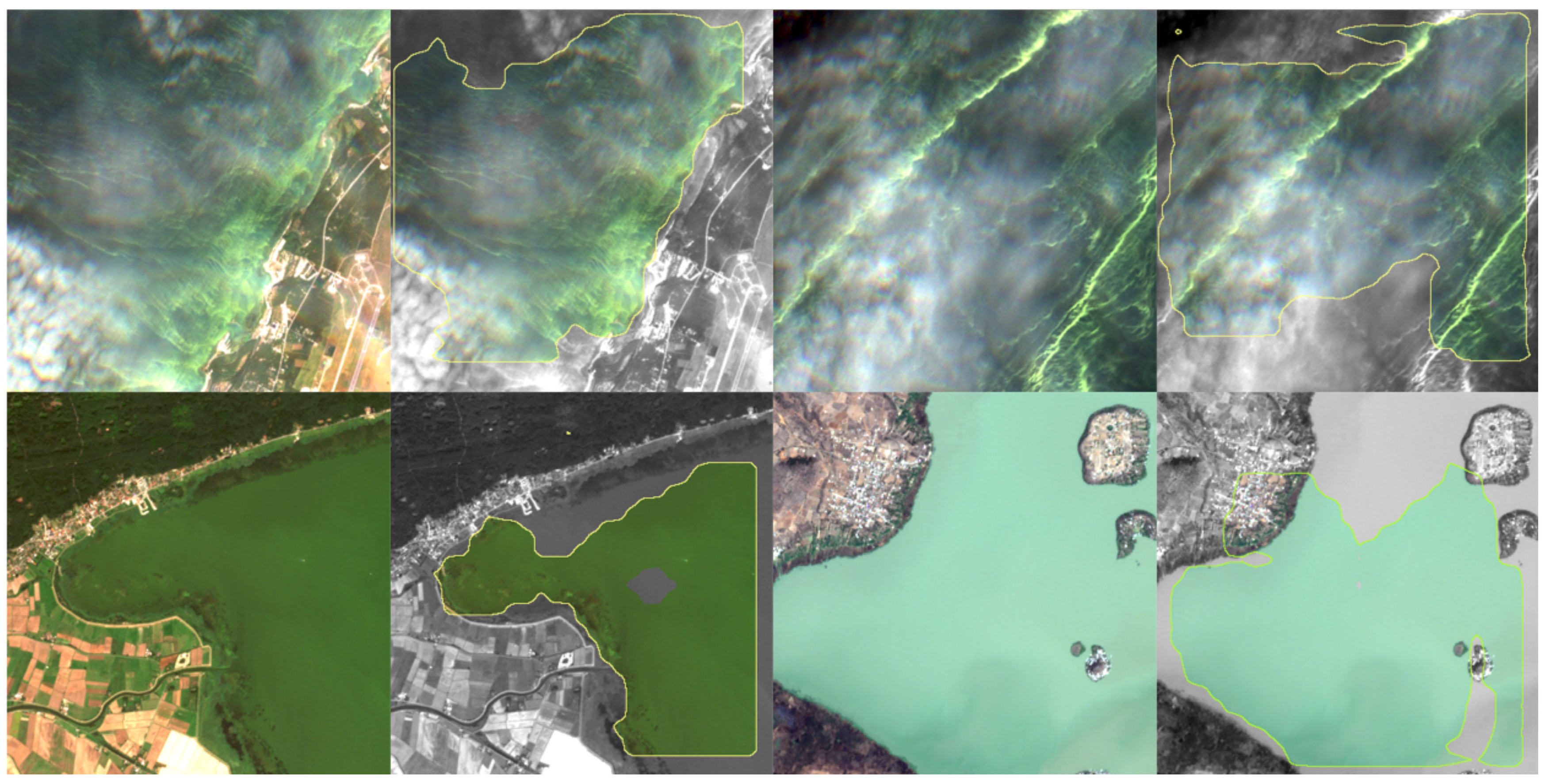

Figure 1: Unclassified and classified counterparts of sentinel 2 imagery. Classified with config R2 below

Training data

There is no openly available, well-labelled dataset suitable to address this challenge. A new dataset has been created from 100 Sentinel 2 scenes. When tiled into images for training, this dataset is made of more than 10,000 manually labelled 400 x 400 pixel images. Algal blooms with confirmed cyanobacteria presence visible at the surface and plumes generated by rivers were manually created while land and cloud masks generated by IdePix [1].

These images are provided with top of atmosphere radiance, as well as Rayleigh corrected and atmospherically corrected data produced by the POLYMER [2] atmospheric correction software package.

(nm)	443	492	560	665	704	740	783	833	865	1614	2202
1		X	X	X							
2		X	X	X						X	X
3	X	X	X	X	X	X	X	X	X	X	X

Table 1: Sentinel 2 Band configurations.

CONFIG:	T1	T2	T3	R1	R2	R3	P1	P2	P3
Accuracy (% pixels correct)	42.4	44.3	48.1	57.2	56.7	44.3	36.8	69.4	83.6
Precision	50.2	71.8	69.6	51.2	55.8	44.0	81.2	77.2	73.1
Confusion	49.7	28.2	30.4	48.8	44.2	56.0	18.8	22.9	26.9

Table 2: Mask RCNN performance at each configuration after 500 epochs of training. T(x) represents top of atmosphere data, R(x) represents Rayleigh corrected data and P(x) represents full POLYMER correction output

Methods

To establish the capability of current natural-image classifiers in this context, one of the current state of the art models, Mask RCNN [3,4], was extended to accept multispectral data. The model was trained using transfer learning from weights generated with the ImageNet challenge training dataset.

Three band configurations (Table 1) were used with top of atmosphere, Rayleigh corrected and POLYMER corrected data. The configurations have been selected to show the best case for Sentinel 2 and demonstrate potential overlap with two other sensors, LANDSAT 8 and PLANETSCOPE.

In each case the same subset of 800 images was used due to hardware constraints, divided into training, validation and unseen imagery. These images were selected to represent a diverse range of observation conditions and landscapes.

Classification and segmentation accuracy results (Table 2) were generated using 80 images randomly selected from the overall training dataset and unseen during training. When used in real classification scenarios these models can classify images up to 1024 x 1024 pixels, which would mean division of Sentinel 2 imagery.

Challenges

The current training dataset will mark algal blooms (such as seen in the classifications in Figure 1) as confusion with cloud, which is not necessarily true. This can be repaired by removing cloud polygons from the dataset where a label has been generated manually.

In configurations developed with Rayleigh and top of atmosphere data there is heavy confusion with land segments, this can be improved by filtering polygons identified over land. These confusion instances tend to be characterised by large groupings of trees or grassland.

Conclusions

It is possible to use current state-of-the-art Convolutional Neural Networks to delineate the extents of an algal bloom in Sentinel 2 imagery. The results above show that applying a Rayleigh correction produces acceptable accuracy for RGB and RGB + near infra-red data, while a full atmospheric correction with all Sentinel 2 bands will provide the best accuracy given the training data available.

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3. Abdulla, W., 2017. Mask R-CNN for object detection and instance segmentation on Keras and TensorFlow. *GitHub repository*.
4. Lebreton, C., Stelzer, K., Brockmann, C., Bertels, L., Pringle, N., Paperin, M., Danne, O., Knaeps, E., and Ruddick, K., 2016. Cloud and cloud shadow masking of high and medium resolution optical sensors-an algorithm inter-comparison example for Landsat 8. *European Space Agency, (Special Publication) ESA SP*, SP-740 (May), 9–13.