Is Atmospheric Correction Needed For Deep Learning Methods To Successfully Segment Phytoplankton Blooms?

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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.

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 15,743 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.

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.

Each model was trained using 8664 images, with 5008 images kept as validation data. The models were trained for 5 epochs to initialise their heads, 10 epochs to initialise the first 3 layers, and finally 100 epochs to tune hyperparameters. Figure 2 presents final stage loss.

Classification and segmentation accuracy results (Table 2) were generated using 2017 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 require division of Sentinel 2 imagery.

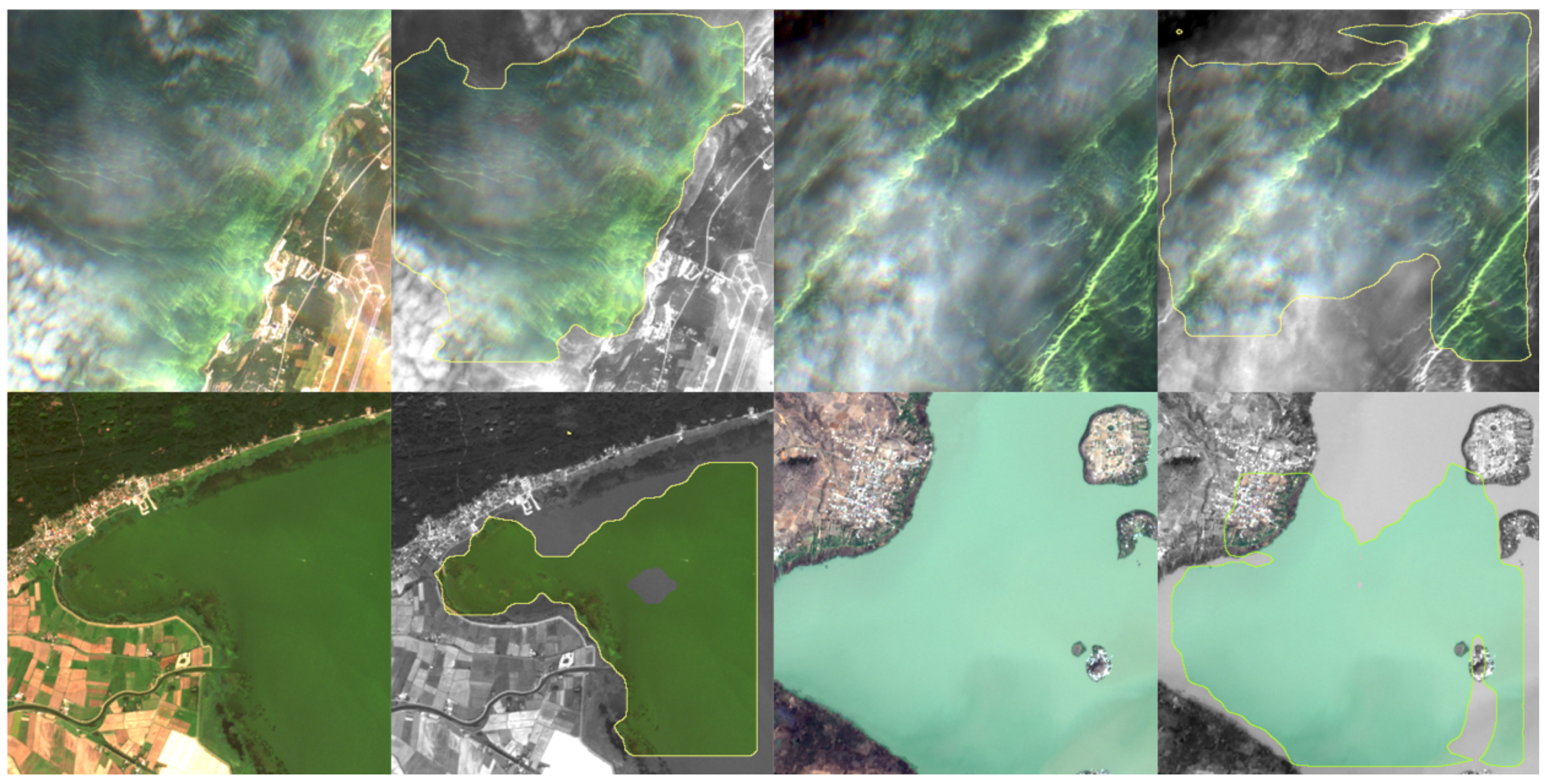

Figure 1: Unclassified and classified counterparts of sentinel 2 imagery.

(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.

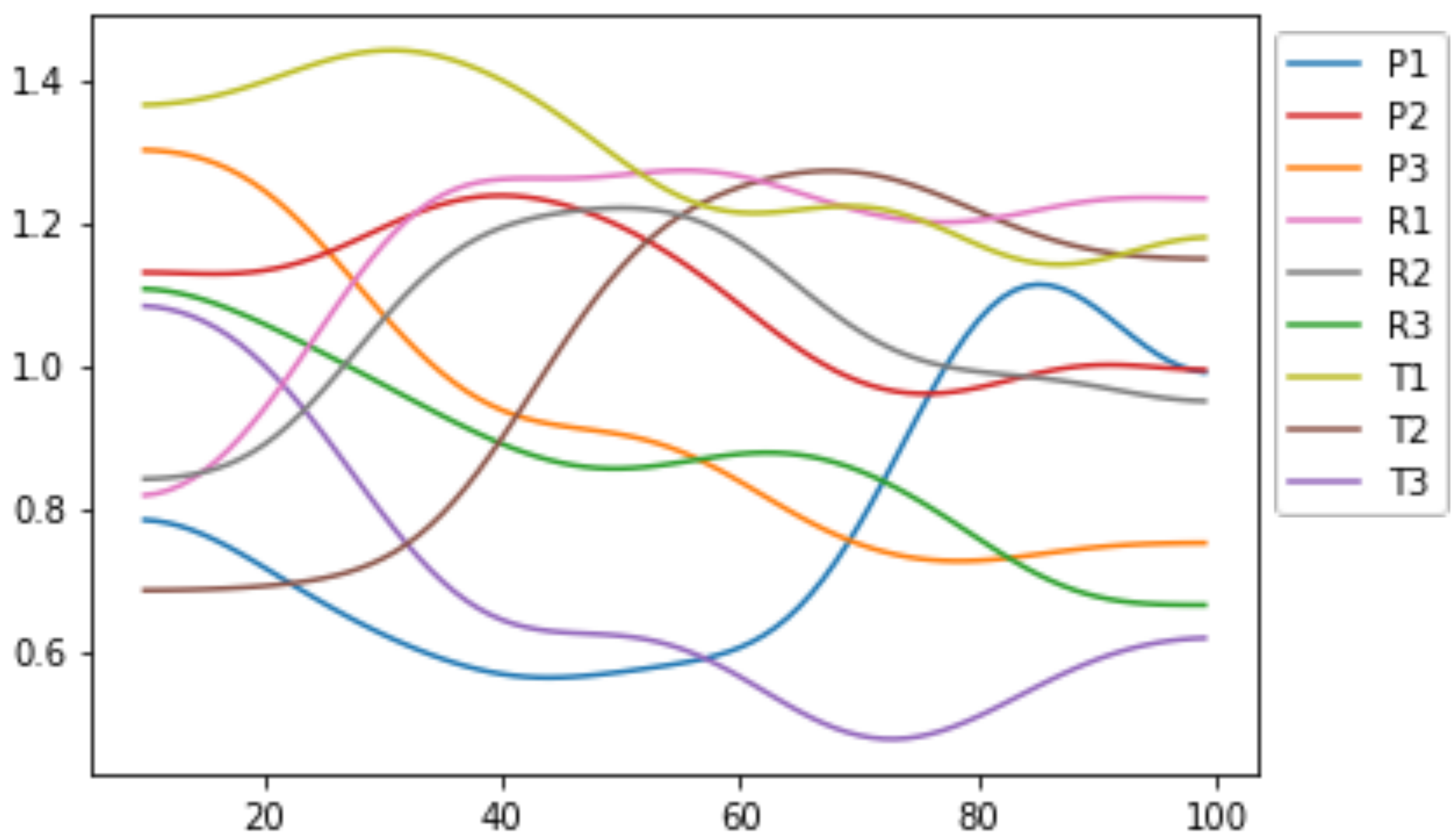

Figure 2: Training loss of each model during hyperparameter tuning, each of the 3 configurations converges at a similar loss level.

CONFIG:	T1	T2	T3	R1	R2	R3	P1	P2	P3
IOU	0.004	0.109	**0.724**	**0.664**	0.020	0.204	0.230	**0.674**	0.165
F1	0.005	0.122	**0.797**	**0.748**	0.025	0.235	0.334	**0.757**	0.186

Table 2: Mask RCNN performance under Intersection over Union (IOU) and F1 score at each configuration after 150 epochs of training. T(x) represents top of atmosphere data, R(x) represents Rayleigh corrected data and P(x) represents full POLYMER correction output

Results

During training loss metrics converge according to the three configurations with configuration 1(RGB) apparently performing worst, and configuration 3 (all bands) performing best. When examining the results and evaluating for the Intersection over Union and F1 score the Top of Atmosphere all bands configuration performs best, however a Raleigh correction can reduce the band dependence to purely RGB bands while a full atmospheric correction from polymer is dependant on the inclusion of infrared bands.

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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.