Deep learning for feature tracking in optically complex waters

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Introduction

High resolution optical satellite sensors collect multispectral data over a large geographic area. Algal blooms and river plumes can be easily spotted in individual images (examples right) and traced through image sequences. Deep learning neural networks have previously been applied to reflectance data collected from airborne and satellite platforms for land classification. By re-training these established models it should be possible to recognize key optical features in waterbodies.

Research objectives

- Establish key optical and morphological features that describe algal blooms and river plumes.
- Assess performance of existing land-based classifiers for aquatic environments.
- Optimise and improve these models for water feature labelling.
- Develop multi-scene boundary tracking algorithms.

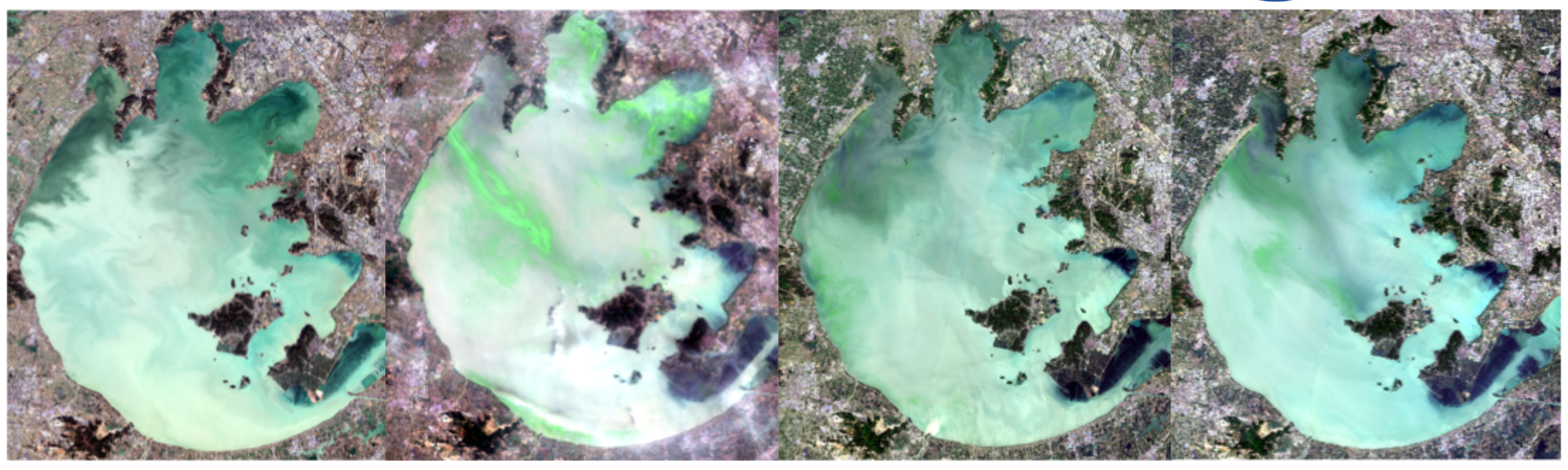

Figure 1: Algal blooms and high turbidity covering Lake Taihu, acquired between January and May 2018 observed by sentinel 2 (60m resolution), Credit: ESA

Figure 2: River Plume from the Guadalquivir River, Spain, between the 7th and 21st of November 2012 observed by MODIS Aqua (500m resolution) (MODIS Land Science Team, 2015)

Methods

Separate convolutional neural network branches for extraction of spectral and spatial features. Feed the outputs into a fully connected layer to finally produce labelling maps. A depiction of the basic shape of the architecture can be seen in Fig 3.

Assessment of current implementations of this architecture, as well as alternative spatial-only feature recognisers, will be based on the overall accuracy and confusion matrices of labels.

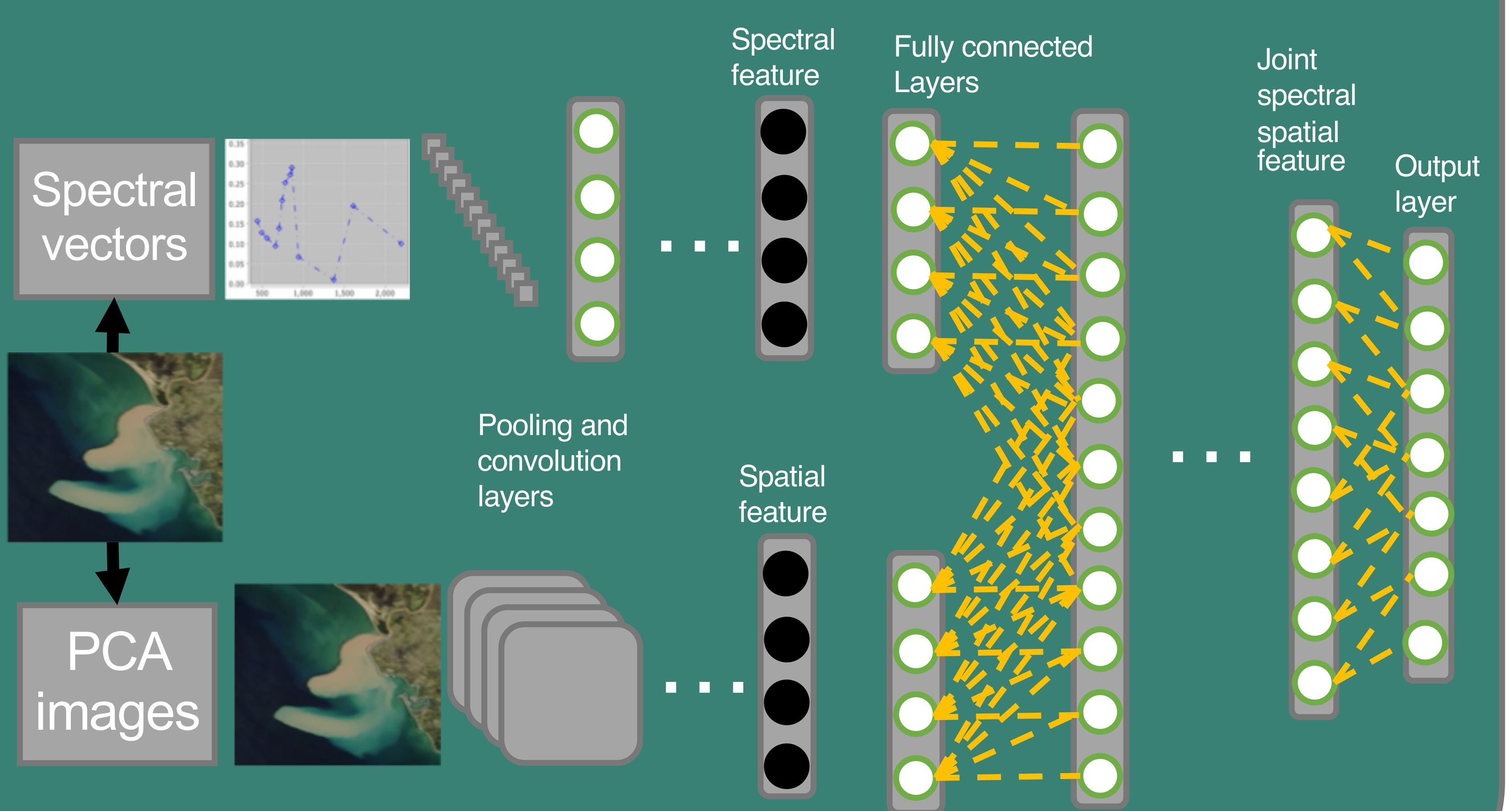

Figure 3: Joint Spectral-Spatial Convolutional Neural network architecture

Challenges

Cloud cover and adjacency effects typical of near-shore ocean-colour remote sensing data will influence the detection of spectral features and may interfere with spatial feature identification. Current cloud-mask and cloud-shadow classifiers have been shown to perform reasonably well over water. Adjacency effects require further research (explore use of atmospheric-correction algorithms that account for adjacency effects).

The scarcity of well-labelled satellite scenes over water bodies, combined with the optically-complex nature of the target means that training datasets must be produced by manually annotating images (library of labelled images is being developed). A workflow for atmospherically-corrected images has been developed in the flow chart in Fig 4.

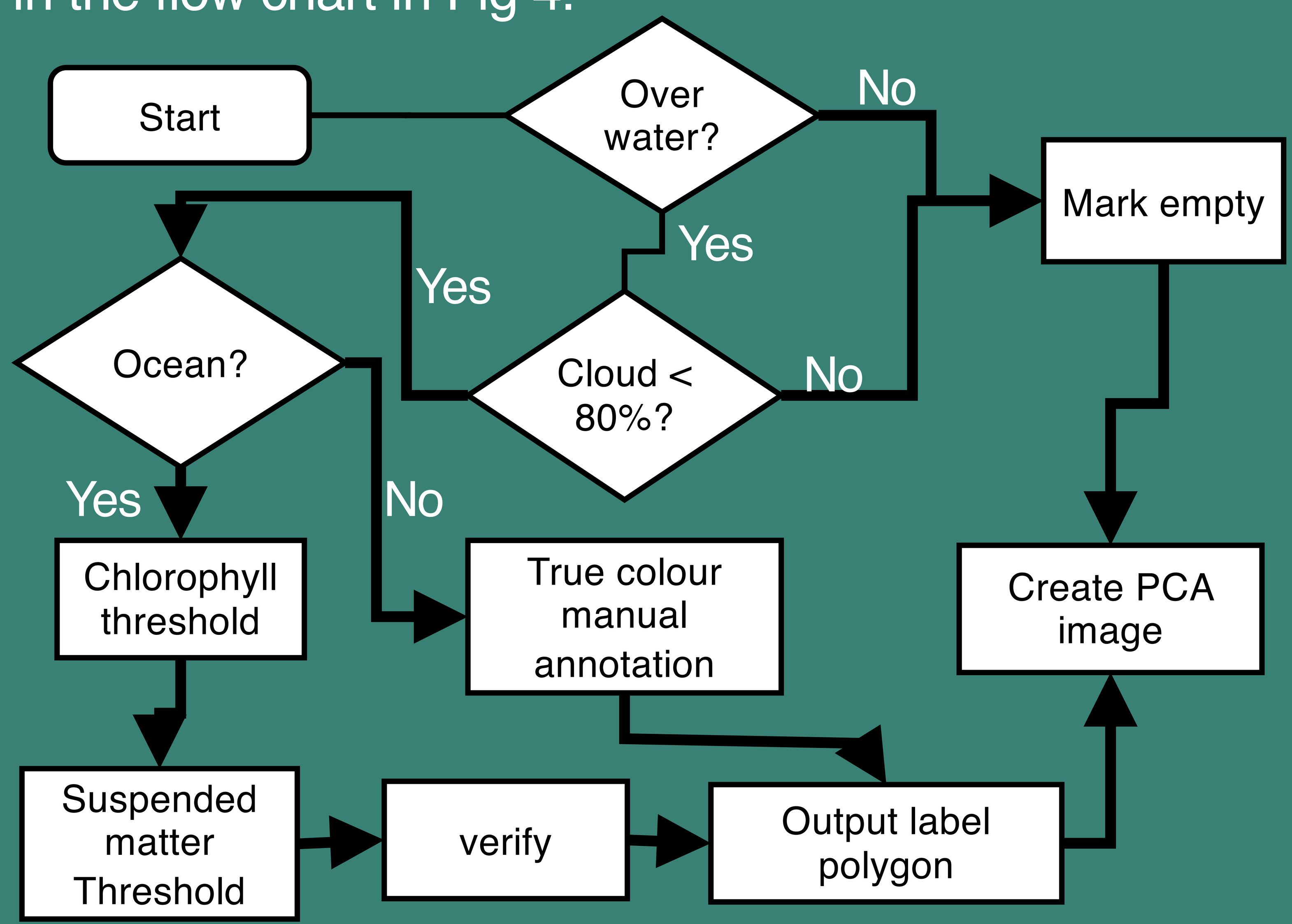

Figure 4: Satellite scene annotation workflow

Aim: The system will produce searchable water contents label maps from satellite images observed by selected sensors. The quality of the classification will be evaluated for a number of optically complex waterbodies from around the world, with specific focus on European and Chinese locations.

Figure 5: Intended classification workflow and outputs.