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Generalised classification of hyperspatial resolution airborne imagery of fluvial scenes with deep convolutional neural networks.

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Enabled by the development of drone technology, hyperspatial resolution (<10 cm) images of fluvial scenes are an increasingly common data source for a range of ecological and geomorphological investigations. However, the task of image classification remains challenging for this type of imagery. When viewed at hyperspatial resolutions, many landscape features considered semantically uniform (e.g. 'river' or 'forest' units) display a significant variety of pixel colours and patterns. Consequently, the application of traditional classification algorithms such as Maximum Likelihood to such images gives unsatisfactory results. Alternative classification approaches based on traditional machine learning and deep machine learning models are emerging in earth sciences as the obvious solution to the classification problem. In this contribution, we explore the possibility that a so-called 'generalised' classifier of river imagery can be based on such Artificial Intelligence (AI) methods. This generalised classifier would be capable of classifying a new set of river images to a high accuracy without the need for further training or a priori information of this new dataset. We assemble a dataset composed of existing images from 11 rivers in Canada, Italy, Japan, the UK and the US. These images are from a mix of manned and unmanned flights but all have resolutions below 10 cm. The images were partially classified into 5 classes: water, dry sediment, green vegetation, senescent vegetation and paved roads. In total, in excess of 5 billion pixels were thus labelled and partitioned for the tasks of training and validation by reserving the equivalent of 15 thousand tiles of 75 X 75 pixels in the image set of each river for model training. This is equivalent to a split of approximately 1 billion pixels for training and 4 billion pixels for validation. First, we use a subsample of the data to conduct a test of traditional vs novel AI approaches using the Tensorflow API, QGIS and other open source tools. We compare the classification success, using the F1-score, of Maximum Likelihood, a depth-limited neural network with 5 hidden layers, a random forest and the NASNet convolutional neural network (CNN) architecture. Results show F1-scores of 71%, 78%, 72% and 95%, respectively. Second, we use the whole dataset to examine the potential of the NASNet CNN for generalised classification. We split our data once again and we train the CNN based on the training data for only 5 of 11 rivers. We then use the resulting model to predict the validation data for all 11 rivers. For rivers used in model training F1-scores reach 95%. For rivers not used in model training, performance degrades but still reaches 84% despite the fact that the model has absolutely no training data from these rivers. Based on these performances, we argue that CNN architectures are on the verge of matching human classification performance and that in the near future, an open source classifier capable of fully automated image classification is a real possibility.