Usage of different neural networks in identification of plant types

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Abstract. Since introduction of neural networks into remote sensing they demonstrate good efficiency in remote sensing data analysis. This work is devoted to processing of multispectral (12 bands) images from Sentinel-2(A, B) satellites. Satellite images of areas in Krasnoyarsk Region and Khakassia with known vegetation types are used as task books to train neural networks. Trained neural networks have been reduced to determine which bands are significant for vegetation type identification. Reduction of trained neural network show that vegetation type can be determined from only four infrared bands without significant loses in performance in comparison with non-reduced neural network.

1. Introduction

The study of global changes in the biosphere is impossible without monitoring the state of terrestrial vegetation. Field observations provide the most complete information about the state of vegetation, but they are very time-consuming and expensive. Remote sensing through multispectral satellite imagery allows global monitoring of vegetation, but the amount of information received is much smaller and does not give complete picture of its state.

Global climate change entails changes in the habitats of plant species, which makes monitoring the boundaries of these habitats necessary for the study of biosphere dynamics. There are ~160 variants of vegetation indices calculated for different spectral ranges and related to vegetation parameters in a given pixel of the image. For example, the vegetation index NDVI is an indicator of the amount of photosynthetically active biomass. These indices are selected empirically, based on the known features of the spectral reflectivity curves of vegetation and soils.

Global climate changes make monitoring the boundaries of vegetation and tracking changes in its types necessary to get the information on the changes occurring in the Earth's biosphere. The appearance of satellites with a wide range of spectral channels allows raising the question of the possibility of distinguishing vegetation types from spectral data. The development of technologies of neural network information processing gives possibility to answer the question almost technologically, setting the task of determining the necessary and sufficient number of channels for determining the type of vegetation.

Artificial neural networks (ANN) have more than twenty years’ story of application in remote sensing [1][2][3][4]. ANNs show better accuracy then statistical classifiers [1][4], allow to use prior knowledge of class occurrence [5] and multiple data-source (different sensors) [6]. ANN in remote sensing can recognize objects by their shape [3] or analyze multispectral "hypercolor" of each pixel of
image [4][7]. For biosphere monitoring one-pixel analysis is more appropriate than shape analysis. Modern remote sensing satellites, such as Landsat-8 and Sentinel-2(A,B) have many spectral channels (13 for Sentinel) but relatively low spatial resolution (10 meter per pixel and more). In [4] "one-pixel" ANN was used to predict biomass, and in [7] by similar neural network was trained to recognize vegetation types.

The first aim of this work is to test can ANN quality be increased by using small area of pixels instead of single pixel. The second and third: find out what spectral channels are more important for vegetation type recognition by reduction of trained neural network and how much neural network can be reduced.

2. Datasets and model

Sentinel-2 remote sensing satellite constellation consists of two satellites: Sentinel2A and B. Both satellites have 13 spectral channels (see Table 1). We used 12 spectral channels (see Table 1) from Sentinel-2 satellite constellation to train neural network. We did not use channel B01 (443 nm, coastal aerosols) because this band is obviously not informative for current objective.

Table 1. Multispectral bands from Sentinel-2 used to train neural network.

| Band name | Wavelength nm | Description          |
|-----------|---------------|---------------------|
| 0 B01     | 443           | Coastal Aerosol     |
| 1 B02     | 490           | Visible Blue        |
| 2 B03     | 560           | Visible Green       |
| 3 B04     | 665           | Visible Red         |
| 4 B05     | 705           | Vegetation red edge |
| 5 B06     | 740           | Vegetation red edge |
| 6 B07     | 783           | Vegetation red edge |
| 7 B08     | 842           | Near IR             |
| 8 B09     | 945           | Water Vapor         |
| 9 B10     | 1375          | Short wave IR       |
| 10 B11    | 1610          | Short wave IR       |
| 11 B12    | 2190          | Short wave IR       |
| 12 B08A   | 865           | Vegetation red edge |

Several areas of Krasnoyarsk region and Khakassia with a priori known types of vegetation were used for training and testing neural networks:

- Mixed forest and grassland near Pogorelka village (56°21'5.10"N 93° 0'56.38"E)
- Mixed and boreal forest near Pamyaty 13 Bortsov village (56° 9'48.64"N 92°11'46.35"E)
- Mixed forest and grassland in Khakassia (54°31'14.20"N 89°44'44.73"E)

Images were uploaded from Sentinelhub EO-browser (https://sentinel-hub.com/explore/eobrowser). We used images from June-August 2018 and 2019 of the study areas. To train neural network small (64x64 pixels) areas with only one vegetation types were picked (see figure 1). To pick areas for training set we used images from June to August 2018 and 2019. Only images with zero cloud cover were used. At every training step we randomly picked three pixels (or 3x3 FOVs) with boreal forest, mixed forest and grassland from our learning set. Trained neural network was tested on 512x512 pixels images.
Figure 1. An example of training data. Red square is boreal forest (*Abies*) and green square is mixed forest (*Pópulus trêmula*).

Two types of ANNs were studied: network with one-pixel input and network with 3x3 pixels field of view. In both cases one pixel has 12 spectral channels. Both ANNs were conventional multilayer perceptrons [8] and were trained by backpropogation algorithm [9]. After training neural network was reduced [10] to determine significant channels for vegetation type identification.

To reduce ANN size we:
1. Make synapses with low magnitude equal to zero. Threshold was changed empirically and was 0.01 for this task.
2. Retrain ANN without changing synapses nullified in 1.
3. If retraining success and accuracy is the same or better then before reduction – go to 1. Else – break.

3. Results
ANN with 3x3 FoV was more accurate then one-pixel network (figure 2). The best result was occurred with three hidden layers with 10, 10 and 3 neurons per hidden layer. After size reduction we have ANN with 5, 7 and 3 neurons on hidden layers. Also reduced neural network used only four spectral channels: B09-B12 and B08A. There is no significant accuracy decreasing after reduction of ANN (figure 3).
Figure 2. Sentinel image with channels B11, B12, B08A (A), one-pixel network results (B) and 3x3 pixel network results (C). On raw satellite image boreal forest is darker than mixed forest. Red color in B and C represent boreal forest, green - mixed forest, blue - grassland, white - not recognized.

Figure 3. Sentinel-2 images with B08, B09, B10 (A) and B11, B12, B08A (B) bands and vegetation type maps of the same region generated with trained ANN (C) and reduced ANN (D). Red color in C and D represent boreal forest, green - mixed forest, blue - grassland, white - not recognized.
As can be seen from the figure, ANN can recognize mixed and boreal forest correctly in general. The actual forest types can be seen in infrared images - the boreal forest more dark.

An example of neural network size reduction can be seen on figure 4. Input synapses also can be removed during ANN size-reducing. There was a surprise result that 3x3 FOV net can use only several (up to 4) spectral bands but one-pixel ANN can work only if it has all 12 bands. There were no statistically significant differences between 3x3 FOV ANN and one-pixel ANN in terms of accuracy.

![Figure 4. Original (left) and reduced (right) neural networks. Red lines represent positive synapses, blue lines - negative synapses.](image)

### 4. Conclusion

It was shown that vegetation type recognition with ANN using small area of pixels (3x3) can be done with only 4 spectral bands while one-pixel ANN must use 12 spectral bands. This result suggests that the texture of the image is no less important than the color of the pixel. Vegetation type recognition can be done with only 4 spectral channels without significant decreasing of accuracy in comparison with 12-channels network. The possibility of multiple reduction of the number of weight coefficients while maintaining the quality of recognition is demonstrated.

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