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Identification of vegetation types and its boundaries using artificial neural networks

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Abstract. The applicability of artificial neural networks (ANN) for the identification of vegetation types using satellite multispectral imagery was studied. The study was focused on the three main vegetation types found in the south of the Krasnoyarsk Region: mixed forest, boreal forest and grassland. Sentinel-2 satellite images were used as a data source for the neural networks. It was shown that vegetation type can be identified pixel-by-pixel using 12 spectral channels and simple feed forward ANN with good quality and reliability. Analysis of the input layer of the trained neural networks allowed several spectral bands to be selected that were the most valuable for the ANN decision and not used in the classic NDVI vegetation index.

1. Introduction

Remote sensing is a perspective direction of Earth sciences. Multispectral satellite imaging is in wide use in remote sensing studies. It allows terrestrial vegetation to be studied using the NDVI index and other important ecological indicators. The automatic processing of raw data is also an important objective in remote sensing. There are two main approaches to methods of automating image processing: statistical methods (conventional for remote sensing) and machine learning (ML) [1], [2], [3]. In the case of statistical methods, we can explain every step in image processing. This is simultaneously both an advantage and a disadvantage of the methods. The “transparency" of algorithms based on mathematical basis (for example, zero-hypothesis testing and empirical orthogonal vectors) allows the terms of use to be outlined and the accuracy of methods to be known. However, if known statistical methods are not able to obtain a satisfactory result, we need to create a new one, which is no easy task.

At the same time, machine learning methods are usually not "transparent" (especially in the case of neural networks), meaning that we know how they work only in general. However, ML methods can solve image processing tasks automatically. Certainly there are several problems with a ML system: we should have a big dataset to train it, and the ML model should be adequate for the chosen task. However, in the case of modern satellites obtaining remote sensing, big data is not a problem and the question is what kind of ML model is more adequate.

Chen et al [3] use three ML methods to predict average ground biomass with Sentinel-2 data: multilayer perceptron or ANN [4], support vector machines for regression (SVR) [5], and random forest [6]. They also used Geographically Weighted Regression (GWR) [7] as a non-ML method. GWR showed the worst results in terms of the mean average error while SVR and ANN were the best.

Not only spectral channels were used in [3] as predictors, but also vegetation indices, which are functions of these channels. This approach may be useful for SVR to increase the vector size, but the ANN can form its own functions from datasets if it is necessary for the task. The aim of our work is to evaluate the possibility of using only spectral channel data for ANN analyzers and to select the most valuable of them. We train the neural network to classify the vegetation type, not to predict the average ground biomass.

2. Datasets and Neural Network

In this work we used feed-forward neural networks to identify vegetation types and borderlines. We used 12 spectral channels (see table 1) from a Sentinel-2 satellite to train the neural network. As with Chen et al [3] we did not use channel B01 (443 nm, coastal aerosols) because this band is obviously not informative for the current objective.

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

Band name	Wavelength nm	Description
B02	490	Visible Blue
B03	560	Visible Green
B04	665	Visible Red
B05	705	Vegetation red edge
B06	740	Vegetation red edge
B07	783	Vegetation red edge
B08	842	Near IR
B09	945	Water Vapour
B10	1375	Short wave IR
B11	1610	Short wave IR
B12	2190	Short wave IR
B08A	865	Vegetation red edge

The ANN was trained as a classifier of three classes: mixed forest, boreal forest and grassland. The structure of the ANN was a multilayer perceptron with three hidden layers. The input layer has 12 neurons, one per band, and each input neuron has only one input synapse for its "own" band. The output layer has three neurons, one per each class. The ANN was trained on Sentinel-2 images from May to September 2018. To train classifier backpropagation, algorithm [8] was used.

For training we use several regions with known vegetation types:

- Bulleted list Field near the village of Pogorelca (Krasnoyarsk region) (see figure 1);
- Mixed forest near Krasnoyarsk (see figure 2);
- Boreal forest near Krasnoyarsk (56.015, 92.7).

As a data source, the Sentinelhub EO browser (https://apps.sentinel-hub.com/eo-browser/) was used. We have applied both data-processing levels provided by the EO Browser for Sentinel-2: L1C (orthorectified Top-Of-Atmosphere reflectance) and L2A (orthorectified Bottom-Of-Atmosphere reflectance).

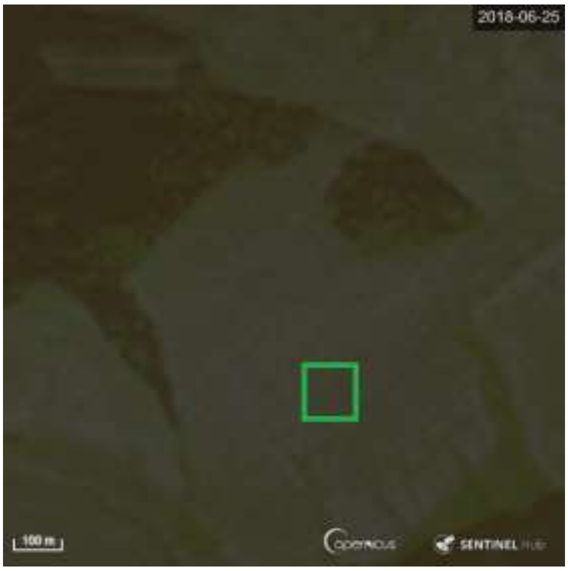

Figure 1. A field near the village of Pogorelca.

Figure 2. Mixed forest near Krasnoyarsk.

The frame in figure 1 shows the sample region. The frame in figure 2 shows the sample region.

3. Results

The best results were obtained using the neural network structure 12-15-15-15-3 (number of neurons in layers). The results are shown in figure 3.

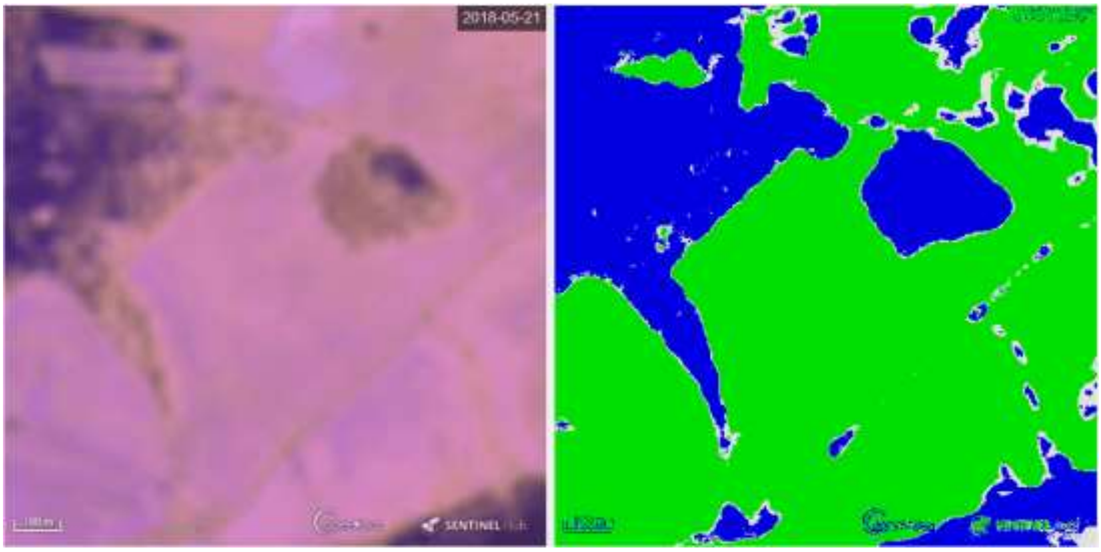

Figure 3. Results of NN-Classifier work. Right - satellite RGB imagery of three channels (B11, B12, B08A), left - map with the classifier's results. Blue – mixed forest, green – grassland, white – undetermined area.

As can be seen above, the ANN successfully recognizes forest and grassland, but sometimes makes "false-forest" detections on grassland. To determine the sources of this mistake, additional field research is necessary. One of the most obvious explanations is that the grassland of "false-forest-positive" regions has plant species different from the sample region and has spectral characteristics more similar to mixed forest than to grassland.

Table 2. Input layer synapses with maximum absolute values for six trained ANNs.

	ANNs					
Bands	1	2	3	4	5	6
B 02	-0.0002	0.0003	0.0003	0.0002	-0.0003	-0.0003
B 03	-0.0078	-0.0018	-0.0046	-0.0001	0.0259	0.0023
B 04	0.0364	-0.0007	-0.0145	-0.0011	0.0005	0.0005
B 05	-0.0047	**0.0096**	-0.0229	**0.0106**	*-0.0512*	-0.0069
B 06	*-0.0767*	**0.0096**	0.0367	*-0.0112*	0.0256	**0.0084**
B 07	0.0478	-0.0003	*-0.0473*	-0.0013	*-0.0456*	-0.0011
B 08	-0.0364	0.0078	-0.0142	0.0094	0.0263	0.0064
B 09	*-0.0609*	-0.0064	-0.0140	-0.0093	0.0274	0.0064
B 10	**0.0867**	*-0.0127*	**0.0483**	*-0.0157*	**0.0521**	**0.0106**
B 11	-0.0022	-0.0011	6.71E-05	-0.0005	0.0003	0.0002
B 12	**0.1608**	*-0.0120*	**0.0450**	*-0.0115*	**0.0511**	**0.0085**
B 08A	0.0258	0.0080	0.0105	0.0060	-0.0314	-0.0027

Bold text in table 2 are maximum positive synapse for ANN, italic text - minimum negative.

ANN vegetation-classifier accuracy can be improved by extra training on the GPU with wider training area coverage and a bigger number of classes. However, simple ANN architecture allows some interesting conclusions to be drawn about the principles of vegetation identification by the trained ANN. By the analysing the input layers of the trained ANNs we can see which spectral bands are more valuable (informative) for the ANN. As can be seen from table 2, bands 10 (1375 nm) and 12 (2190 nm) are the most valuable for all six trained ANNs. It is interesting that bands B04 and B08 which are used in the NDVI index are not as valuable for all the trained ANNs.

Conclusion

It was shown that a simple feed-forward ANN with three hidden layers can work as a vegetation classifier on Sentinel-2 images. The classifier was trained over the whole vegetation period from May to September. The trained ANN can successfully recognize vegetation types on Sentinel-2 images over the whole vegetation period, but sometimes makes "false-forest-positives" on grassland. The cases of these mistakes should be the aim of future field investigations. Analysis of trained ANN input layers showed that all trained ANNs are most sensitive for band 10 (1375 nm) and band 12 (2190 nm).

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