remote sensing

Editorial

An Overview of the Special Issue "Remote Sensing Applications in Vegetation Classification"

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Abstract: One of the ideas behind vegetation monitoring is the ability to identify different vegetation units, such as species, communities, habitats, or vegetation types. Remote sensing data allow for obtaining such information remotely, which is especially valuable in areas that are difficult to explore (such as mountains or wetlands). At the same time, such techniques allow for limiting field research, which is particularly important in this context. Remote sensing has been utilized for vegetation inventories for many decades, using airborne and spaceborne platforms. Developing newer tools, algorithms and sensors is conducive to more new applications in the vegetation identification field. The Special Issue "Remote Sensing Applications in Vegetation Classification" is an overview of the applications of remote sensing data with different resolutions for the identification of vegetation at different levels of detail. In 14 research papers, the most frequent different types of crops were analysed. In three cases, the authors recognised different types of grasslands, whereas trees were the object of the studies in two papers. The most commonly used sensors were Copernicus Sentinel-1 and Sentinel-2; however, to a lesser extent, MODIS, airborne hyperspectral and multispectral data, as well as LiDAR products, were also utilised. There were articles that tested and compared different combinations of datasets, different terms of data acquisition, or different classifiers in order to achieve the highest classification accuracy. These accuracies were assessed quite satisfactorily in each publication; the overall accuracy (OA) for the best result varied from 72% to 98%. In all of the research papers, at least one of the two commonly used machine learning algorithms, random forest (RF) and support vector machines (SVM), was applied. Additionally, one paper presented software ARTMO's machine-learning classification algorithms toolbox, which allows for the testing of 13 different classifiers. The studies published in this Special Issue can be used by the vegetation research teams and practitioners to conduct deeper analysis via the utilization of the proposed solutions.

Keywords: Sentinel-2; multispectral; multitemporal; identification; detection; species; crops; trees; plant

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1. Introduction

One of the ideas behind vegetation monitoring is the ability to identify species, communities, and habitats. Remote sensing data allow for obtaining such information remotely, which is especially valuable when access to the analysed area is difficult. Remote sensing has been utilized for vegetation inventories for many decades, using airborne and spaceborne platforms. At the same time, such techniques allow for limiting field research, which is particularly important in protected areas, as well as inaccessible regions, such as mountains and wetlands. Remote sensing data also play a significant role in mapping species in urban areas, where, due to the legacy of species, it is most often impossible to identify them based only on ground-based techniques. Crop monitoring is also an important application, which is effective in using a high temporal resolution of the data.

Depending on the remote sensing data platforms used (unmanned aerial vehicles—UAVs, airborne or spaceborne), the analysis can be conducted on local, regional, continental and global scales, which is objectively and uniformly impossible with any other kind of data.

The classification of vegetation is possible as a result of the constantly evolving classification algorithms, sensors, and the increasing possibilities that computer equipment provides. This is of particular importance in the era of big data in which we currently live. The methodologies used in the research are in line with current trends and face the challenges related to the large volume of data and the vast amount of information (for instance, hyperspectral data, multitemporal data or different sensors data fusion).

The Special Issue "Remote Sensing Applications in Vegetation Classification" is an overview of the applications of remote sensing data with different resolutions for the identification of species and types of vegetation. Among the 28 submitted manuscripts, 16 had the appropriate level of content and innovation and were published in the Special Issue. This editorial presents an overview of the findings and contributions from the published studies.

2. Summary of Contributions

The published manuscripts covered a wide range of topics regarding vegetation classification using remote sensing techniques. In 14 research papers, the classifications were performed to identify different types of vegetation [1–14]. Different types of crops were analysed most frequently [2–4,6,6,9,12]. In three cases, the authors recognized different types of grasslands [8,11,14], whereas trees were the object of the studies in two papers [1,10]. Additionally, there were also literature review and technical note, both concerning different perspective of vegetation identification [15,16].

Generally, it can be stated that most of the methods use optical data [2–6,6,8–11,14]; however, one employs radar data [12]. In nine cases, free Copernicus data Sentinel-1, Sentinel-2 or both were analysed [2–6,8,9,12,13]. The optical Sentinel-2 data were used to classify crops [2,13], pastures [6] and semi-natural vegetation [5].

To classify 13 crop types in the complex agriculture area of Henan Province (China), an approach based on integrating the terrain, time series characteristics, priority, and seasonality with Sentinel-2 satellite imagery was used [13]. The authors used a random forest (RF) classifier and tested the impact of using the cultivated land mask on accuracy. They noticed that incorporating the masking step in the classification process results in higher accuracy.

Another paper related to crop analyses focused on improving maize identification; thus, the spectral variance at key stages (SVKS) computed via an object self-reference combined algorithm was tested in the eastern North China Plain [2]. The results showed that this method helps to increase interclass spectral separability and attain better identification accuracy than other identification indexes.

In [12], the authors investigated whether the long short-term memory (LSTM) network is more advantageous compared to the RF algorithm for large-scale crop classifications by carrying out them in three countries (the Netherlands, Austria, and France) for the years 2016–2020 with Sentinel-1 and additional meteorological data. The results demonstrated that both classifiers achieve similar results for simple classification tasks; however, with increasing Fisher discriminant ratio F1 (FDR1) values, the LSTM networks outperformed RF, which suggests that the ability of LSTM networks to learn long-term dependencies and identify the relation between radar time series and meteorological data becomes increasingly important for more complex applications.

Based on Sentinel-2 data, ARTMO's machine-learning classification algorithms (MLCA) toolbox was introduced [5]. The toolbox allows for the training, validation, and application of pixel-based models to remote sensing imagery. It was used to classify the plant type (shrub land, grassland, semi-shrub land, and shrubland–grassland vegetation) in a semi-steppe Iranian landscape. In the study, 13 different algorithms were tested; however, the best results were acquired using the Gaussian process classifier. The analysis demonstrated the efficacy of ARTMO's MLCA toolbox for testing different classifiers.

The fusion of images from Sentinel-1 and Sentinel-2 was used to classify crops [3,4,9] and grasslands [8]. To map 10 crop types at the field level in Spain, multitemporal PolSAR Sentinel-1 and Sentinel-2 data were combined and classified with the support vector machine (SVM) algorithm [3]. The results indicate the importance of Sentinel-1 PolSAR data in crop classification, being particularly useful in areas with frequent cloud coverage. Alabi et al. [4] developed an operational banana mapping framework by combining UAV, Sentinel-1 and Sentinel-2 imagery with RF and SVM classifiers. The authors identified bananas in heterogeneous smallholder farming systems in sub-Saharan Africa to guide rapid and efficient banana-bunch top virus surveillance. Sentinel-1 and 2 data were also used for elaborating efficient, repeated and timely national-scale crop type mapping approaches in Germany based on monthly temporal metrics [9]. A total of 17 crop types were classified with the use of the RF algorithm. The authors indicated that similar accuracies for the most widespread crop types as well as for smaller permanent crop classes were reached as in other Germany-wide crop type studies, highlighting its potential for repeated nationwide crop type mapping. In grasslands-oriented research, the authors assessed the suitability of the RF algorithm with normalized difference vegetation index (NDVI) and dense coherence variables for classifying extensively and intensively managed permanent grassland throughout Slovenia [8]. They proved that the proposed classification using combined data can provide more satisfying and stable results for grasslands than single optical or radar data on such large heterogeneous areas.

To accurately map more heterogeneous vegetation, different data fusion platforms were used [1,7,10,11,14]. Feng et al. [1] utilized Sentinel-2, shuttle radar topography mission (SRTM) and light detection and ranging (LiDAR) data for the classification of bamboo forests covering a large spatial range in the south-eastern hilly region of China. They performed RF classification by including phenological and morphological features to enhance the difference between bamboo and other vegetation categories. More classifiers were tested in [7], where two convolutional neural networks (CNNs), RF and SVM were used to classify 17 coastal vegetation land cover types, some of them at the species level, located on the west coast of central Florida, using high-resolution multispectral images from UAV camera and LiDAR data. Different spectral band combinations and the use of canopy height models (CHMs) extracted from two different sources were examined. The authors highlighted the advantage of using deep learning networks to classify high-resolution images in highly diverse coastal landscapes.

A framework for producing a species-specific woody vegetation map in Arizona, USA, including five of the most abundant woody species in a large semi-arid region, was provided in [10] by utilizing a fusion of simultaneously acquired airborne LiDAR and high spatial resolution hyperspectral data to improve classification accuracies. The authors used three classifiers, RF, SVM, a classification and regression tree (CART) and multitemporal datasets, and they found an evident influence of fusing spectral and structural information in a RF classifier for tree identification. Additionally, they noticed that a multitemporal dataset slightly increases classification accuracies over a single data collection.

The combination of UAV aerial photographs, MODIS NDVI, and machine learning algorithms to clarify the spatial differentiation and variation (compared with the 1980s) of grassland classes was used to map the grassland classes of a temperate steppe in Inner Mongolia in China [11]. The authors utilized the decision tree (DT), gradient boosting decision tree (GDBT), RF, and logistic regression (LR) algorithms; based on the results, they observed a significant transformation of grasslands since the 1980s.

In another study, the authors fused GaoFen 1/6 images with MODIS data using the enhanced spatial and temporal adaptive reflectance fusion model (STARFM) algorithm to obtain a cloudless enhanced vegetation index (EVI2) time-series for the Ordos region (China) [14]. They extracted six phenological features from the time-series and used them together with spectral bands and principal component analysis (PCA) of EVI2 time-series results for the classification of five grassland types utilizing the SVM classifier. The authors concluded that the proposed approach can be used as the basic method in the grassland communities classification of large areas.

One of the papers in the SI is a literature review concerning one-class classifiers for natural vegetation identification [15]. The paper covers the 2013–2020 period and describes 136 articles. The results showed that one-class classifiers were used to map potential and actual vegetation areas, were used in long-term monitoring, as well as to generate multiple ecological variables, and could be performed on open-source data. The biggest advantages were a reduction in plotting effort and the quantification of over-detection.

The last paper is a technical note introducing dynamic vision transformer (DViT) architecture for plant and animal species' recognition using aerial images and geo-location environment information [16]. The model tested in the USA reduces the effect of small image discrepancies and improves the results.

3. Concluding Remarks

A significant part of the research focused on areas in Asia, mostly China [1,2,5,6,6,11,14]. Five studies were conducted in Europe [3,8,9,12,16], three in North America [7,10,16], and one in Africa—Nigeria [4]. The most commonly used sensors were Copernicus Sentinel-1 and Sentinel-2 [1–6,6,8,9,12]. It appears that the spatial and spectral resolutions of these data are enough to identify different types of vegetation: forests, bushes, grasslands, and crops. What is an undoubted advantage of these data is the ability to use them for classification in the multitemporal aspect, which was used by the authors. The MODIS sensor was utilized in two papers in such a context [11,14], both for large-areas grasslands mapping, which can be related to larger pixel size. Aerial hyperspectral data potential was assessed only once [10], while multispectral data from UAVs were investigated in four studies [4,7,10,11]. Also LiDAR data high-related derivatives were presented in three papers [1,7,10].

The accuracy of vegetation maps was assessed quite satisfactorily in each publication; the overall accuracy (OA) for the best result varied from 72% to 98%. In each of the 14 research papers at least one of the two following machine learning algorithms was used: RF and SVM; RF was used 12 times [1,2,4–13], while SVM was used 7 times [3–5,7,10,13,14]. It can be concluded that these classifiers provide good results using different inputs; however, in studies where different algorithms were tested, better results were achieved for LSTM, U-Net or Gaussian process classifiers [5,7,12]. Additionally, one of the studies presented software ARTMO's machine-learning classification algorithms toolbox, which allows for the testing of 13 different classifiers, thus allowing one to match the appropriate algorithm to the data and purpose [5].

Further work in the field of vegetation classification is required in view of the advances in remote sensing technology as well as dynamic changes in vegetation. We believe that the studies published in this SI will expand the knowledge of practitioners and help vegetation research teams to conduct deeper analysis via the utilization of the proposed solutions.

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