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Editorial

Editorial for the Special Issue Entitled *Hyperspectral Remote Sensing from Spaceborne and Low-Altitude Aerial/Drone-Based Platforms*—Differences in Approaches, Data Processing Methods, and Applications

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1. Introduction

Nowadays, several hyperspectral remote sensing sensors from spaceborne and low-altitude aerial/drone-based platforms with a variety of spectral and spatial resolutions are available for geoscientific applications [1–4]. Advances in hyperspectral remote sensing imagery have fostered the progress of novel image processing techniques, which have yielded auspicious outcomes in a wide range of fields, such as soil geochemistry, water quality assessments, forest species mapping, agricultural stress, mineral alteration mapping, etc. In the last two decades, multiple spaceborne hyperspectral sensors have been launched by different space agencies (e.g., Hyperion in November 2000 by the National Aeronautics and Space Administration (NASA), USA; Hyperspectral Imager Suite (HISUI) in December 2019 by the Japan Aerospace Exploration Agency (JAXA); and Precursore IperSpettrale della Missione Applicativa (PRISMA) in March 2019 by the Italian Space Agency (ASI)) [1,5,6]. These sensors have made significant use of hyperspectral data and also led to innovative approaches to data processing, from noise removal to spectral mapping. Previous studies have highlighted the limitations of hyperspectral spaceborne sensors in identifying a pure target and in identifying spectral targets with subdued spectral signatures, as these hyperspectral sensors have coarse spatial resolution (generally 20 m to 30 m) and poor signal-to-noise ratios (e.g., Hyperion has a poor signal-to-noise-ratio (SNR) in the shortwave electromagnetic domain) [7–10]. However, these spaceborne sensors have yielded encouraging results in environmental monitoring (for example, forest cover classification, the detection of phonological changes in forests, land use/land cover mapping, agriculture land cover characterization, crop stress estimation, mapping lithology and minerals [11–13]). Hyperspectral image processing addresses the main difficulties associated with classification methods, such as the high dimensionality of the associated data and the limited availability of standard processing techniques [14]. To confront these limitations, several machine learning algorithms have recently been established, supplementing the high potential of hyperspectral data processing [14].

Due to the lack of global coverage of spaceborne hyperspectral sensors, routine aircraft-based and drone-based hyperspectral surveys are carried out in different countries using different advanced hyperspectral sensors, such as the advanced visible infrared spectrometer (AVIRIS) and its latest version, AVIRIS-next generation (AVIRIS-NG); HyMap; the digital airborne imaging spectrometer (DAIS), etc. These sensors are capable of collecting

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high-spatial- and spectral-resolution data with optimum spectral fidelity [15]. Unmanned aircraft systems (UAS) with low-altitude platforms are suitable for fine-scale remote sensing applications, for the collection of data along asymmetrical design pathways or in close proximity for specific feature observations, and for momentarily altering pathways due to unfavorable environmental conditions. By mounting multispectral and hyperspectral sensors on unmanned aerial vehicle (UAV) platforms, high-resolution, georeferenced data can be acquired for studying spatial and temporal changes in geological and environmental applications [16,17]. The applications of hyperspectral data from spaceborne, aircraft-based platforms to drone-based platforms have not yet been explored and deciphered appropriately. Machine learning and deep learning techniques can be used to understand and utilize the higher-order variation of field grade spectral data collected using these low-altitude airborne sensors to automate spectral feature-based target detection. It is now important to capitalize on the comparatively high potential of spaceborne and airborne hyperspectral remote sensing datasets based on analyzing different applications that have been addressed by hyperspectral data from different platforms to identify the specificity of each of these two platforms.

In this context, this Special Issue, "*Hyperspectral Remote Sensing from Spaceborne and Low-Altitude Aerial/Drone-Based Platforms—Differences in Approaches, Data Processing Methods, and Applications*", presents the latest achievements in the field of hyperspectral remote sensing data processing and its related applications. A total of 18 manuscripts, all of which were evaluated by professional Guest Editors and reviewers, were submitted for publication in this Special Issue. Subsequently, 11 of them were deemed to be of the appropriate level of quality (based on the standard set by the *Remote Sensing* journal) and were revised, accepted, and published in this Special Issue. The contributions each article within this Special Issue makes to the literature are summarized in the following section.

2. Summary of Papers Presented in This Special Issue

Cristóbal et al. [18] used airborne Hyspex imaging spectrometer data to map the Arctic wetlands in the Yukon Flats National Wildlife Refuge, Alaska. A subset of 120 selected spectral bands with 1 m spatial resolution were used for wetland mapping. A six-class legend was documented based on previous U.S. Geological Survey (USGS) and U.S. Fish and Wildlife Service (USFWS) information and maps. Three different classification methods, namely hybrid classification, spectral angle mapper classification, and maximum likelihood classification, were implemented at selected sites. The best classification performance was achieved using the maximum likelihood classifier with a Kappa index of 0.95. The spectral angle mapper (SAM) classifier and the hybrid classifier showed inferior performances, with Kappa indices of 0.62 and 0.51, respectively. Guha et al. [19] investigated the spectral bands of airborne hyperspectral data of Advanced Visible Infrared Imaging Spectrometer-Next Generation (AVIRIS-NG) data to demarcate the surface signatures associated with the base metal mineralization in the Pur-Banera area, Bhilwara district, Rajasthan, India. Ratio images derived from applying the multi-range spectral feature fitting (MRSFF) method were used to identify the Banded Magnetite Quartzite (BMQ), unclassified calcareous silicates, and quartzite as host rocks of Cu, Pb, Zn mineralization in the study region. The surface imprints of mineralization, such as gossans, and sericitization associated with high Pb-Zn-Cu anomalies were detected in a NE-SW trending structure. Ground-based residual magnetic and laboratory studies (X-ray fluorescence analysis and petrographic study) were also implemented to verify the remote sensing study. The results revealed that the spatial alignment of alteration zones along the structural features are high-potential zones for future detailed Pb-Zn-Cu exploration programs in the study area.

Lu et al. [20] estimated water quality from UAV-borne hyperspectral imagery using nine machine learning algorithms in the Beigong Reservoir, Liuzhou, Guangxi Zhuang Autonomous Region, China. The machine learning algorithms were analytically assessed for the inversion of water quality parameters together with chlorophyll-a (Chl-a) and suspended solids (SS). The experimental results showed that the prediction performance of the Catboost regression (CBR) model was superior compared to the other algorithms. Additionally, the prediction performances of the Multi-layer Perceptron regression (MLPR) and Elastic net (EN) models were highly unacceptable for the inversion of water quality parameters. Finally, a water quality distribution map for the study area, which can be utilized for large-scale and constant inland water quality monitoring, was generated. Letsoin et al. [21] used unmanned aerial vehicle (UAV) RGB imagery and a transfer learning algorithm to detect sago palm trees in Merauke Regency, Papua Province, Indonesia. A transfer learning strategy was implemented using three deep pre-trained networks, namely SqueezeNet, AlexNet, and ResNet-50, to predict the sago palm trees based on their physical morphology (e.g., their leaves, trunks, flowers, or fruits). The results showed that the ResNet-50 model was the primary model for the flowers, leaves, and trunks for sago palm detection. This baseline model is the first of its kind in the field, and in future studies, it is expected to have high accuracy, including a training validation accuracy of up to 90%, with less elapsed time and an improved number of epochs, which also allows for the use of more datasets of sago palms.

Shirazi et al. [22] developed a Neuro-Fuzzy–Analytic Hierarchy Process (NFAHP) technique for fusing Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) alteration mineral image maps and geological datasets such as lithological maps, geochronological maps, structural maps, and geochemical maps to identify high-potential zones for volcanic massive sulfide (VMS) copper mineralization in the Sahlabad mining area of East Iran. In this study, band ratio and Selective Principal Components Analysis (SPCA) techniques were applied to ASTER VNIR and SWIR bands. Ore mineralization, host–rock lithology, alterations, geochronological, geochemistry, and distance from high-intensity lineament factor communities were considered for applying the Back Propagation Neural Network (BPNN) technique. Subsequently, the Fuzzy–Analytic Hierarchy Process (Fuzzy-AHP) method was implemented to fuse and weigh the information layers. Therefore, a potential map of copper mineralization for the study area, which identified some high-potential zones, was generated. Hashim et al. [23] mapped greenhouse gas (GHG) concentration using the unmanned aerial vehicle-based Sniffer4D sensor in the Pasir Gudang and Tanjung Landsat industrial areas in Johor, Peninsular Malaysia. The results revealed that CO_2 has the highest concentration (mean of 625.235 mg/m^3), followed by CH_4 (mean of 249.239 mg/m^3). The mapped UAV GHG concentration also indicated good agreement with the in situ observations, with an RMSE of 7 and 6 mg/m^3 for CO_2 and CH_4 concentration, respectively. An ozone and nitrogen dioxide mixture (O_3 + NO_2) with a mean concentration of 249 µg/m^3 and an RMSE of 9 µg/m^3 had the other significant concentrations described.

Ding et al. [24] fused ASTER and Sentinel-2 remote sensing images using small-scale geochemical data based on a linear regression model that enhanced the resolution of geochemical elemental layers. This study was conducted in the Xianshuigou area of Northwest China. The regression equation was established using the low-frequency images obtained from image decomposition. Subsequently, the detailed spatial information on the high-frequency images was injected for the fusion. Quantitative correlation coefficients, visual observation, and field sampling emphasized the validation of the fusion results. This approach provided fused large-scale regional geochemical data for mineral exploration, which was key because large-scale geochemical data for areas such as Xinjiang and Tibet in Western China are lacking. Mehranzamir et al. [25] implemented a ground-based lightning locating system using a particle swarm optimization (PSO) algorithm for lightning mapping and monitoring in a 400 km^2 study area at the University Technology Malaysia (UTM), Johor, Peninsular Malaysia. The PSO algorithm was used as a mediator to identify the best location for a lightning strike. It was initiated with 30 particles, considering the outcomes of the magnetic direction finding (MDF) and time difference of arrival (TDOA) techniques. The integration of MDF and TDOA techniques in the PSO-based lightning locating system (LLS) resulted in an accurate lightning detection system with a mean location error of 573 m for a specific local region. This development has enhanced the location accuracy of lightning strikes in the region. Based on the results of this study, it can be inferred that the LLS using PSO is proficient in precisely identifying and charting lightning discharges in the designated coverage region, thereby validating it as an effective lightning detection system.

Logan et al. [26] used UAV-based hyperspectral imaging for river algae pigment estimation in several locations along the Upper Clark Fork River (UCFR) in Western Montana, USA. Image data were collected across a spectral range of 400–1000 nm with a 2.1 nm spectral resolution. Some spectral indices for the detection of algal standing crops were developed using brute-force analysis. The results show that spectral band ratios provide a suitable method for assessing chlorophyll a and phycocyanin standing crops contained within, near, and on the surface of the blooms of the filamentous nuisance algae growing in the UCFR. Hashim et al. [27] mapped and analyzed consecutive changes in land-use–land-cover (LULC) and water yield (WY) between 2000 and 2015 in the Johor River Basin (JRB), Peninsular Malaysia, by explicitly comparing satellite-based and in situ-derived WY and depicting changes in WY in relation to LULC change magnitudes within watersheds. The WY was estimated using the water balance equation, which determines the WY from the equilibrium of precipitation minus evapotranspiration (ET). The precipitation and ET information were derived from the Tropical Rainfall Measuring Mission (TRMM) and moderate-resolution imaging spectroradiometer (MODIS) satellite data, respectively. The LULC maps were extracted from Landsat-Enhanced Thematic Mapper Plus (ETM+) and Landsat Operational Land Imager (OLI). From the year 2000 to 2015, agricultural areas other than oil palm-based areas enlarged to 11.07%, forest areas diminished to 32.15%, oil palm-based areas enlarged to 11.88%, urban areas were amplified to 9.82%, and WY improved to 15.76%. The results of this study indicate a good agreement between the satellite-based derived quantities and in situ measurements, with an average bias of $\pm$20.04 mm and $\pm$43 mm for precipitation and ET, respectively. Abedini et al. [28] developed a novel approach to optimize remote sensing-based evidential variables using constructed mining geochemistry models for machine learning (ML)-based copper mineralization prospectivity mapping (MPM). The geochemical mining methods and satellite remote sensing data (Landsat ETM+) processing were scrutinized to select the optimal evidential variables for constructing a mineralization prospectivity map using a random forest (RF) approach in the Toroud-Chah Shirin (TCS) belt and the Alborz magmatic belt, North Iran. The lithology, structure, alterations, and geochemical evidential layers were integrated using the RF algorithm to achieve the regional-scale prospectivity mineral mapping of porphyry copper deposits. As a result, this study explored buried copper deposits in the TCS belt through innovative approaches by integrating multi-source geoscientific datasets.

3. Concluding Remarks

We would like to thank Ms. Helen Wang (Assistant Editor), as well as all authors and reviewers who donated their time, research, and effort to this Special Issue. We wish to extend our sincere gratitude to the MDPI editorial team for supporting the Guest Editors in efficiently processing each manuscript. The sympathetic and judicious comments delivered by the reviewers improved each of the papers published in this Special Issue, which came to fruition only because their authors were willing to volunteer their time and attention. We hope that the studies published in this Special Issue will provide insights to other remote sensing researchers about the application of hyperspectral remote sensing data for geological mapping and environmental monitoring and modeling.

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