remote sensing

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Editorial

An Overview of the Special Issue on "Precision Agriculture Using Hyperspectral Images"

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Citation: Avola, G.; Matese, A.; Riggi, E. An Overview of the Special Issue on "Precision Agriculture Using Hyperspectral Images". *Remote Sens.* **2023**, *15*, 1917. https://doi.org/10.3390/rs15071917

Received: 23 March 2023
Accepted: 29 March 2023
Published: 3 April 2023

In precision agriculture systems, remote sensing has played an essential role in crop and environment monitoring, and hyperspectral imaging is a particularly effective tool in this regard. In the last few decades, a lot of research has been done on how to use hyperspectral imaging in agriculture. This is shown by the large amount of literature that has been written on the subject and the wide interest it has generated in many scientific fields, such as agronomy, Earth observation, and natural science Hyperspectral images can be used to identify and map different crop varieties, detect crop stress and disease, monitor plant growth and development, and assess soil properties, such as moisture, organic matter, and nutrient content. The connoting feature of hyperspectral imaging in agriculture is related to the hundreds of spectral bands that can be challenging for the data process, analyses, and interpretation. This complexity makes it difficult to fully comprehend the novel opportunities that arise from accurately analyzing hyperspectral data in agriculture.

This Special Issue seeks to address some of these issues by publishing a total of 13 articles employing the hyperspectral imaging technique, with advanced cutting-edge methods oriented to crop yield and biomass estimation [1], crop classification and phenotyping [2–4], plant and soil nutrient status assessment [5–9], and pest and plant disease detection [10–12]. One article [13] evaluated the spectral response of vegetation using hyper and multispectral cameras for non-destructive remote monitoring. More than half of the articles made use of deep learning approaches; two are specifically focused on methods and models addressing reductions in the spectral dimensionality of hyperspectral data. Two articles are in the form of reviews [9,12]. Below is some brief information about the content of each of them.

The research in [1] integrated two open-source systems (R language hyperspectral processing package and Python's Auto-Sklearn machine learning technology) combined with automated hyperspectral narrowband vegetation index calculation and the state-of-the-art AI-based automated machine learning technology to estimate yield and biomass in three crops (spring wheat, pea and oat mixture, and spring barley and red clover mixture). The study demonstrates the satisfactory capability of hyperspectral analysis for yield and biomass prediction in complex design fields through the use of two significant open-source software systems. Moreover, the vegetation indexes (VIs) they suggested, as well as the automatic narrowband VI calculated, might minimize data redundancy and cleaning time, as well as the computational power hardware requirements.

Rapid progress in remote sensing technology has made it possible for airborne hyperspectral imagery to provide detailed spatial data and flexibility in time, paving the way for accurate monitoring of agriculture. To extract crop spectral reflectance properties from the airborne hyperspectral images, the research in [2] proposed a fine classification method based on multi-feature fusion and deep learning. In this research, Gray-Level Co-Occurrence Matrix (GLCM), morphological profiles, and endmember abundance analysis were used to extract a range of information from images (including texture, shape, and material composition) to exploit the spatial information of the hyperspectral imagery.

Then, the spatial information is fused with the original spectral information to generate a classification result by using a deep neural network with conditional random field (DNN + CRF) model. The results proved that the method proposed helps to improve the accuracy of crop classification.

The recognition of shadowed and non-shadowed regions has become a crucial aspect in remote sensing in vegetation mapping. The canopy represents a complex and constantly changing environment where leaves interact with light. Consequently, shadows can significantly affect the estimation of biochemical or physiological status. In the study of [3], the authors introduced a series of processes to analyze an image, including a 1D CNN model (able to extract features from an image by processing its pixel values along a single dimension) to automatically characterize the spectral variation in wheat leaves and spikes in shadowed and non-shadowed regions. To achieve these objectives, two convolutional neural networks were employed to automatically map wheat canopy components in shadowed and sunlit regions and to determine their specific spectral signatures. The first method uses pixel vectors of the full spectral features as inputs to the CNN model, whereas the second method integrates the dimension reduction technique, known as linear discriminate analysis (LDA), along with the CNN to increase the feature discrimination and improves computational efficiency. Both the proposed methods achieved values equal to or slightly higher than 97% accuracy, but CNN-LDA was able to enhance the interpretability of the spectral information and to reduce the computational complexity and the processing time by half compared to the CNN-RAW method.

The reliability of remote sensing data is also adversely impacted by significant diurnal variations. The issue of diurnal variations has been highlighted in various plant phenotyping studies, but only a few studies have attempted to model the changing patterns of diurnal effects to enable accurate prediction of the degree of their impact. In this view, the research of [4] collected time-series field images with very high sampling frequencies (2.5 min) for corn plants from the vegetative stage to the reproductive stage in the 2019 growing season, for a total of 8631 hyperspectral images. The analysis of these images showed that while diurnal variations significantly affect almost all the image-derived phenotyping features, the diurnal changes follow stable patterns. Consequently, it is possible to predict imaging deviations by modeling the evolving patterns. The present study provides a comprehensive report on the specific diurnal patterns of various plant phenotyping features, including Normalized Difference Vegetation Index (NDVI), Relative Water Content (RWC), and single spectrum bands. The outcomes of this study will aid researchers in making more informed decisions regarding the optimal imaging time window during a day with greater confidence. Furthermore, the findings can be leveraged to calibrate or compensate for the time effect in remote sensing outcomes.

Airborne hyperspectral images can provide high-resolution spectral data over large areas, which can be used to generate detailed maps of nutrient status. By analyzing the reflectance values in specific wavelength bands, it is possible to estimate the concentration of different nutrients in the plant tissue. The research paper [5] utilized spectral data from a push-broom imaging spectrometer covering a range of 400–2500 nm and leaf samples from grapevine canopies that were laboratory-analyzed for six essential nutrient values. The optimal bands for nutrient regression models were selected based on this analysis. The study revealed that an ensemble feature-ranking approach, which employed six distinct machine learning feature selection techniques, produced regression results similar to those obtained using standard Partial Least Squares Regression (PLSR) feature selection and regression, while selecting fewer wavelengths. The authors identified a set of biochemically consistent bands (606 nm, 641 nm, and 1494 nm) for predicting nitrogen content.

Remote sensing of plant nitrogen status using satellite imagery is a valuable tool for monitoring and managing the nitrogen flow in agriculture, but available data for validation of satellite-based remote sensing of N are scarce. Therefore, the research paper [6] used field spectrometer measurements set at the same Sentinel-2 satellite wavelengths, which are specifically designed for vegetation monitoring by the ESA. The study evaluated the performance of normalized ratio indices (NRIs), random forest regression (RFR), and Gaussian process regression (GPR) for predicting plant-N-related traits on several world datasets, including multiple crops, field sites, and years. The results highlighted that spectral indices, such as normalized ratio indices (NRIs), performed well, but the RFR and GPR methods outperformed the NRIs. The study also identified the short-wave infrared (SWIR) region as key spectral bands for estimating plant nitrogen concentration. Moreover, the Gaussian process regression band analysis tool showed that five bands were sufficient for accurate estimation of plant N traits and leaf area index (LAI).

To prepare for the upcoming new-generation imaging spectrometer missions and the unprecedented inflow of hyperspectral data, it is necessary to develop optimized models that can routinely generate vegetation traits. For the sustainable use of nutrients, the CHIME (Copernicus Hyperspectral Imaging Mission—European Space Agency (ESA)) requirement document selects chlorophyll content as an essential eco-physiological variable for photosynthetic functioning and a major parameter for the monitoring of plant nitrogen uptake during crop development. In this framework, the research paper [7] evaluated the performance in the retrieval of selected maize traits of two hybrid approaches, with and without an active learning technique, for the retrieval of chlorophyll and N content from hyperspectral data, comparing several combinations of spectral and sample dimensionality reductions. The results achieved in the study revealed that both hybrid approaches were able to estimate chlorophyll and nitrogen with high accuracy at the canopy level. However, only the hybrid framework with the active learning technique was able to accurately retrieve the chlorophyll and leaf nitrogen content, confirming the complexity of trait retrieval at the leaf level from canopy reflectance.

Hybrid models that combine radiative transfer models with machine learning algorithms are, therefore, preferred, but they face an additional challenge due to spectral collinearity. To address this challenge, other authors [8] developed a workflow to optimize hybrid hyperspectral retrieval models, first reducing the sampling domain through active learning and then comparing two methods for reducing spectral dimensionality: principal components analysis (PCA) and band ranking. The results revealed that the PCA strategy produced slightly better retrieval results than the band-ranking procedure for all variables considered (specific leaf area, leaf area index, canopy water content, canopy chlorophyll content, the fraction of absorbed photosynthetic active radiation, and fractional vegetation cover). Both modeling approaches achieved meaningful mapping results over a heterogeneous landscape, including multiple cover types.

As the world's population keeps growing, there is more demand for agricultural products. This means that it is important to manage macronutrients like nitrogen (N), phosphorus (P), and potassium (K) in a way that is good for the environment and helps farmers grow more crops. The review paper [9] examined the current state of the art in applications of remote sensing technology in agricultural applications, particularly in the monitoring of NPK availability for commonly grown crops in Africa. The study involved an extensive literature review of the use of airborne imaging technology, processing and analysis methods, and farming practices related to hyperspectral imagery for soil agriculture investigations. The review focused on the period between 2008 and 2021, examining publications on hyperspectral imaging technology and its applications in monitoring macronutrient status for crops. The study identified knowledge gaps and challenges related to the acquisition, processing, and analysis of hyperspectral imagery for soil agriculture investigations. The review proposed a hyperspectral data-based research protocol to quantify the variability in NPK in soil and crops at the field scale, with the aim of optimizing fertilizer application.

Hyperspectral imaging is a powerful tool for detecting and monitoring changes in plant health and physiology caused by biotic and abiotic stresses. Through analysis of the spectral signature of light reflected by plant leaves, researchers can detect subtle changes in the biochemical composition and structure of plants early, which is crucial to minimize disease spread and enable real-time management practices. The research paper [10] evaluated the individual and interactive effects of the root-knot nematode (Meloidogyne incognita) and drought on the physiology and growth of different nematode-resistant genotypes. In this study, a maximum likelihood classification model of hyperspectral data was utilized, along with various dimensionality reduction techniques, to identify root-knot nematode and drought stress, and the findings demonstrate that RKN can be detected as early as 10 days after infestation, and RKN and drought stresses can be noticed with over 98% accuracy using bands ranging from 350 to 1000 nm and 350 to 2500 nm.

As we've seen, remote sensing can often be used to find pests. This is because a plant's defense mechanism is triggered when it is stressed by a pest, and this usually shows up as a change in the leaf's reflectance. In this view, the main goal of the research paper [11] was to study the use of hyperspectral proximal remote sensing and gas exchange parameters to characterize peanut leaf responses to herbivory by two major pests in South American peanut (*Arachis hypogaea*) production, namely *Stegasta bosqueella* (Lepidoptera: *Gelechiidae*) and *Spodoptera cosmioides* (Lepidoptera: *Noctuidae*). The authors observed that peanut leaf reflectance differs between herbivory caused by the two larval species but was similar in both real and simulated defoliation. Additionally, differences in photosynthetic rate, stomatal conductance, transpiration, and photosynthetic water use efficiency were observed only between the two species and not between real and simulated larval defoliation.

The advancement of imaging and data processing technologies has led to the rapid development of virus detection methods using remote and proximal optical sensors. The article [12] provided an overview of optical sensing methodologies, data processing, and disease classification modelling methods from a multidisciplinary perspective. It reviews a diverse range of tools from traditional molecular biology approaches to state-of-the-art optical non-destructive approaches that provide rapid spatial scale detection methods.

Finally, with the increasing availability of unmanned-aerial-vehicle-based commercial solutions on the market, it is essential to provide clear information on the performance of these products to guide end users in their selection and utilization for precision agriculture applications. A research article [13] compared two products, the multispectral camera DJI P4M and the hyperspectral SENOP HSC-2. The authors evaluated the accuracy of both cameras on six typical targets found in vineyards, including bare soil, bare-stony soil, stony soil, soil with dry grass, partially grass-covered soil, and canopy. The performance of the cameras was evaluated by calculating three commonly used vegetation indices (VIs) and determining the percentage error compared to ground-truth spectroradiometer measurements. Overall, the hyperspectral camera achieved higher accuracy with a lower percentage of error. Both cameras performed better on pure canopy pixel targets than on mixed targets.

This overview is an attempt to summarize the novel opportunities that arise from hyperspectral data analysis in agriculture. By leveraging the high spectral resolution of hyperspectral sensors, researchers and farmers can obtain detailed information about crops, including their health, nutrient status, and water content. These approaches will contribute to improving decision making within complex systems, with minimal human interaction, and provide a scalable framework for integrating expert knowledge of the Precision Agriculture system. The research published in this Special Issue demonstrates the significant potential of hyperspectral data analysis in transforming agriculture and enhancing food security.

Author Contributions: Conceptualization, G.A. and E.R.; investigation, G.A., E.R. and A.M.; writing—original draft preparation, G.A. and E.R.; writing—review and editing, G.A., E.R. and A.M. All authors have read and agreed to the published version of the manuscript.

Acknowledgments: We would like to thank all the authors, reviewers, and editorial staff who contributed to this Special Issue.

Conflicts of Interest: The authors declare no conflict of interest.

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