remote sensing

Editorial

Special Issue "Hyperspectral Remote Sensing of Agriculture and Vegetation"

Simone Pascucci [1,*], Stefano Pignatti [1], Raffaele Casa [2], Roshanak Darvishzadeh [3] and Wenjiang Huang [4]

1 Institute of Methodologies for Environmental Analysis (CNR IMAA), National Research Council, 85050 Tito Scalo, PZ, Italy; stefano.pignatti@imaa.cnr.it
2 Department of Agricultural and Forestry scieNcEs (DAFNE), Tuscia University Via San Camillo de Lellis, 01100 Viterbo, Italy; rcasa@unitus.it
3 ITC—Faculty of Geo-Information Science and Earth Observation, Department of Natural Resources, University of Twente, PO Box 217, 7500 AE Enschede, The Netherlands; r.darvish@utwente.nl
4 Aerospace Information Research Institute, Chinese Academy of Sciences, Beijing 100094, China; huangwj@aircas.ac.cn
* Correspondence: simone.pascucci@cnr.it

Received: 2 November 2020; Accepted: 3 November 2020; Published: 9 November 2020

Abstract: The advent of up-to-date hyperspectral technologies, and their increasing performance both spectrally and spatially, allows for new and exciting studies and practical applications in agriculture (soils and crops) and vegetation mapping and monitoring atregional (satellite platforms) andwithin-field (airplanes, drones and ground-based platforms) scales. Within this context, the special issue has included eleven international research studies using different hyperspectral datasets (from the Visible to the Shortwave Infrared spectral region) for agricultural soil, crop and vegetation modelling, mapping, and monitoring. Different classification methods (Support Vector Machine, Random Forest, Artificial Neural Network, Decision Tree) and crop canopy/leaf biophysical parameters (e.g., chlorophyll content) estimation methods (partial least squares and multiple linear regressions) have been evaluated. Further, drone-based hyperspectral mapping by combining bidirectional reflectance distribution function (BRDF) model for multi-angle remote sensing and object-oriented classification methods are also examined. A review article on the recent advances of hyperspectral imaging technology and applications in agriculture is also included in this issue. The special issue is intended to help researchers and farmers involved in precision agriculture technology and practices to a better comprehension of strengths and limitations of the application of hyperspectral measurements for agriculture and vegetation monitoring. The studies published herein can be used by the agriculture and vegetation research and management communities to improve the characterization and evaluation of biophysical variables and processes, as well as for a more accurate prediction of plant nutrient using existing and forthcoming hyperspectral remote sensing technologies.

Keywords: hyperspectral remote sensing for soil and crops in agriculture; hyperspectral imaging for vegetation; plant traits; high-resolution spectroscopy for agricultural soils and vegetation; hyperspectral databases for agricultural soils and vegetation; hyperspectral data as input for modelling soil, crop, and vegetation; product validation; new hyperspectral technologies; future hyperspectral missions

1. Introduction

The use of hyperspectral technology for an optimal quantification of crop and soil biophysical variables at various spatial scales is an important aspect in agricultural management practices and monitoring [1,2]. Moreover, there is a great interest to update (i.e., research of new variables) and optimize the retrieval of crop biophysical variables using drone and available satellite data [2–17], as well as future high spatial resolution hyperspectral satellites. To this aim, the exploitation of different approaches for assimilation of the retrieved biophysical parameters into agricultural models is also of primary interest. As it would allow deriving agronomical proxy variables addressing the issues of the multi-scale and multivariate nature of the retrieved variables [6,7,11–19]. For example, a complete and updated knowledge of the spatial distribution of leaf area index (LAI), pigments like chlorophyll content and nitrogen can support sustainable agricultural practices and optimize related costs, through optimal use of fertilizer, pesticides and water that are strictly subdued to an improvement of crop yields and quality. Hyperspectral imaging has great potential for applications in agriculture, particularly precision agriculture, owing to their ample spectral information sensitive to different plant and soil biophysical and biochemical properties [11–25]. Multiple platforms (satellites, airplanes, unmanned aerial vehicle (UAVs), and close-range platforms) have become more widely available in recent years for collecting hyperspectral data with different spatial (from centimeter to decameter), temporal, and spectral resolutions. These platforms have different strengths and limitations in terms of spatial coverage, flight endurance, flexibility, operational complexity, and costs. These factors need to be evaluated when choosing the hyperspectral platform(s) for specific research purposes, e.g., increasing productivity, expanded coverage, and reduced use of fertilizers, pesticides, and water. Further technological developments are also needed to overcome some of the limitations, such as the short battery endurance in UAV operations and high cost of hyperspectral sensors [4].

All in all, hyperspectral remote sensing (RS) represents an attractive and efficient technology capable of estimating soil and crop biophysical variables of interest from regional to intra-field scales.

Research advances are still required to validate methods and applications for the estimation of additional crop biophysical variables and proxy agronomical products [14–25] and for their assimilation into spatially distributed agricultural models (e.g., grains quality, pest and disease dynamic, water-driven, and crop growing models), also by comparing different assimilation approaches [10–24].

This special issue was set up to highlight and diffuse the recent advances in hyperspectral RS studies and their practical applications for agriculture (soils and crops) mapping and monitoring from regional to within-field scales. Our objectives as guest Editors were to encourage studies and applications on this topic and to assemble high-quality, peer-reviewed research and review articles in a special issue of *Remote Sensing* dedicated to this theme. We accepted manuscripts concerned with all aspects of hyperspectral RS (optical domain) for crop and natural vegetation. This included hyperspectral studies of agricultural soils, crops, as well as other vegetation types using the ground, drone, air-, and space-borne platforms (VIS-NIR, SWIR, and TIR). With various focus on: field, and laboratory hyperspectral measurements for monitoring agriculture and vegetation; retrieval of plant traits at leaf and canopy level from hyperspectral measurements; new methods for hyperspectral data processing and atmospheric compensation techniques; hyperspectral sensors calibration and products validation for agriculture and vegetation monitoring; statistical and computational methods for hyperspectral data analysis in agriculture and vegetation applications; integration or combined use of hyperspectral data from the optical domain with other Earth Observation (EO) technologies; modelling of soils, crops, and vegetation using hyperspectral data; next-generation hyperspectral technologies and missions, platforms, and sensors for agriculture and vegetation.

A total of 18 manuscripts were submitted and peer-reviewed by fifty anonymous, scrupulous reviewers. Of these, 11 manuscripts achieved the level of quality and innovation expected by *Remote Sensing* and were at the end published in this special issue. A total of 77 authors contributed to these 11 articles and hailed from six different nations: Brazil (26 authors), Canada (8), Australia (5), Finland (3), China (23), UK (1), Iran (3), Belgium (1), Spain (1), Poland (3), Ethiopia (1), and USA (2).

2. Overview of Contributions

The works composing this Special Issue cover a wide range of topics, from the use of high spectral resolution hyperspectral LiDAR (light detection and ranging) for vegetation parameters extraction, to the estimation of chlorophyll content in peanut leaf, to the estimation of heavy metal contents in grapevine foliage, to the application of UAV-based multiangle hyperspectral data in fine vegetation classification, to the use of artificial neural networks for modeling hyperspectral response of water-stress induced lettuce plants, to different classification methods and algorithms for agricultural biophysical variables retrieval, plants and invasive species retrieval, and to predict nutrient content. They are presented below in chronological order of acceptance.

First, Jiang et al. [25] employed and evaluated the use of high spectral resolution hyperspectral LiDAR (Acousto-optical Tunable Filter HSL-AOTF-HSL, active and non-contact instrument), with 10 nm spectral resolution, for leaf vegetation red edge parameters extraction. The results were compared with the referenced value from a standard SVC© HR-1024 spectrometer (Spectra Vista Corporation,

Poughkeepsie, NY 12603 USA) for validation. Green leaf parameter differences between HSL and SVC results were minor, which supported the notion that HSL was practical for extracting the employed parameter as an active method. This paper is just the beginning of using the high spectral resolution HSL for vegetation index detection, which might inspire the estimation of other vegetation parameters or biochemical content using this advanced LiDAR technique.

Second, the estimation of peanut leaf chlorophyll content with dorsiventral leaf adjusted ratio index (DLARI), performed by Xie et al. [26]. The study is one of the first attempts to assess the impact of spectral differences among dorsiventral leaves caused by leaf structure on leaf chlorophyll content (LCC) retrieval. The authors' objectives were to (1) analyze spectral differences in the adaxial and abaxial surfaces of peanut leaves; (2) identify the optimal wavelengths of the modified Datt (MDATT) index for estimating peanut LCC; (3) develop a novel index based on a four-band combination to reduce spectral differences in dorsiventral leaves for improving LCC retrieval; (4) compare the performance of the indices developed in this study with those widely used in the literature. The reliability of narrow-band indices can be influenced by a range of phenotypic characteristics. Further work is required to assess the application of DLARI to estimate LCC for other crop species. The robust wavelength regions proposed (715–820 nm) should provide a good starting point for optimizing the index for other crop species.

Third, [27], in their work applied five treatments of heavy metal stress (Cu, Zn, Pb, Cr, and Cd) to grapevine seedlings and hyperspectral data (350–2500 nm) and heavy metal contents were collected based on in-field and laboratory experiments. The partial least squares (PLS) method was used as a feature selection technique, and multiple linear regressions (MLR) and support vector machine (SVM) regression methods were applied for modelling purposes. Based on the PLS results, visible and red-edge regions were found most suitable for estimating heavy metal contents in the present study. The authors pointed out that each heavy metal has a special effect, leading to distinct responses depending on the plant species (including leaf color changes, chlorosis, necrosis, dwarfism, giant, leaf, and root spreading, etc.).

Fourth, Yan et al. [28] applied UAV-based multi-angle remote sensing for fine vegetation classification by combining a bidirectional reflectance distribution function (BRDF) model for multi-angle remote sensing and object-oriented classification methods. Bands of high importance for the fine classification of vegetation included the blue band (466– nm), green band (494–570 nm), red band (642–690 nm), red-edge band (694–774 nm), and near-infrared band (810–882 nm). The importance of the BRDF characteristic parameters are discussed in detail and the research results promote the application of multi-angle remote sensing technology in vegetation information extraction and provide important theoretical significance and application value for regional and global vegetation and ecological monitoring.

Fifth, [29] evaluated the hyperspectral response of water-stress induced lettuce (*Lactuca sativa* L.) using artificial neural networks (ANN). Hyperspectral response was measured four times, during 14 days of stress induction, with an ASD Fieldspec HandHeld spectroradiometer (325–1075 nm). Both reflectance and absorbance measurements were calculated. Different biophysical parameters were also evaluated. The performance of the ANN approach was compared against other machine learning algorithms. Authors' results showed that the ANN approach could separate the water-stressed lettuce from the non-stressed group with up to 80% accuracy at the beginning of the experiment. Absorbance data offered better accuracy than reflectance data to model it. This study demonstrated that it is possible to detect early stages of water stress in lettuce plants with high accuracy based on an ANN approach applied to hyperspectral data. The methodology has the potential to be applied to other species and cultivars in agricultural fields.

Sixth, a review of waveband selection in hyperspectral classification of plants was performed by [30]. The authors reviewed the last 22 years of hyperspectral vegetation classification literature that evaluate the overall waveband selection frequency, waveband selection frequency variation by taxonomic, structural, or functional groups. The influence of feature selection choice by comparing methods as stepwise discriminant analysis (SDA), support vector machines (SVM), and random forests (RF) is studied. They concluded that characteristics of plant studies influence the wavebands selected for classification and advised caution when relying upon waveband recommendations from the literature to guide waveband selections or classifications for new plant discrimination applications. In this regard, recommendations appear to be weakly generalizable between studies.

Seventh, Sabat-Tomala et al. [31] study proposed a comparison of SVM and RF algorithms for invasive and expansive species classification using airborne hyperspectral data (HySpex Visible and Near Infrared-VNIR-1800 scanners and a Shortwave Infrared-SWIR-384 scanner; Hyspex NEO, Oslo, Norway). These invasive species are considered a threat to natural biodiversity because of their high adaptability and low habitat requirements. Maps of the spatial distribution of analyzed species were obtained; high accuracies were observed for all data sets and classifiers. In particular, the authors verified whether the expansive/invasive *Rubus* spp., *Calamagrostis epigejos*, and *Solidago* spp. were characterized by a specific set of spectral characteristics that allowed them to be distinguished from the surrounding species, which altogether created a mix of fuzzy, covered patterns. Moreover, an analysis of the impact of the number of pixels in training data set on the classification accuracy was performed. The accuracy assessment method presented in the paper confirmed that all analyzed species can be identified in heterogeneous habitats through hyperspectral airborne remote sensing.

Eight, machine learning (ML) algorithms were applied by [32] to predict macro- and micronutrient nutrient content (N, P, K, Mg, S, Cu, Fe, Mn, and Zn) in Valencia-Orange from leaf hyperspectral measurements. A Fieldspec ASD FieldSpec® HandHeld 2 (Malvern PANalytical Ltd, Malvern, WR14 1XZ, United Kingdom) spectroradiometer was used and the surface reflectance and first-derivative spectra from the spectral range of 380 to 1020 nm (640 spectral bands) was evaluated. K-Nearest Neighbor (kNN), Lasso Regression, Ridge Regression, Support Vector Machine (SVM), Artificial Neural Network (ANN), Decision Tree (DT), and Random Forest (RF) ML algorithms were tested. The methods were assessed based on Cross-Validation and Leave-One-Out. The Relief-F metric of the algorithms' prediction was used to determine the most contributive wavelength or spectral region associated with each nutrient. RF model was the most suitable to model most of them. The results indicate that, for the Valencia-orange leaves, surface reflectance data is more suitable to predict macronutrients, while first-derivative spectra are better linked to micronutrients.

Ninth, a review article provided by [33] analyzed the recent advances of hyperspectral imaging technology and applications in agriculture. Due to limited accessibility outside of the scientific community, hyperspectral images have not been widely used in precision agriculture. In recent years, different mini-sized and low-cost airborne hyperspectral sensors (e.g., Headwall Micro-Hyperspec, Cubert UHD 185-Firefly) have been developed, and advanced space-borne hyperspectral sensors have also been or will be launched (e.g., PRISMA, DESIS, EnMAP, HyspIRI). Hyperspectral imaging is becoming more widely available to agricultural applications. Meanwhile, the acquisition, processing, and analysis of hyperspectral imagery remain a challenging research topic (e.g., large data volume, high data dimensionality, and complex information analysis). The imaging platforms and sensors (airplane, UAV, satellite, close-range ground- or lab-based) together with analytic methods used in the literature, were discussed. Performances of hyperspectral imaging for different applications (e.g., crop biophysical and biochemical properties' mapping, soil characteristics, and crop classification) were also evaluated. This review intended to assist agricultural researchers and practitioners to better understand the strengths and limitations of hyperspectral imaging to agricultural applications and promote the adoption of this valuable technology. Recommendations for future hyperspectral imaging research for precision agriculture were also presented.

Tenth, Zhang et al. [34] presented a study on the detection of canopy chlorophyll content for three growth stages of corn using continuous wavelet transform (CWT) analysis. The reflectance spectrum increased in the 325–400 and 761–970 nm regions as the growth stage advanced and the growth period shifted. The reflectance decreased in the 401–700 and 971–1075 nm regions as the growth stage advanced. The characteristic bands related to chlorophyll content in the spectral data and the wavelet energy coefficients were screened using the maximum correlation coefficient and the local correlation coefficient extrema, respectively. A partial least square regression (PLSR) model was established. Results showed that bands selected via local correlation coefficient extrema in a wavelet energy coefficient created a detection model with optimal accuracy.

Last, a different study in terms of application is proposed by [35], who studied the nutrient content of tef (*Eragrostis* tef), an understudied plant that has importance due to both food and forage benefits, and investigated the replicability of methods across two study sites situated in different international and environmental contexts [35]. The research aims were to (1) determine whether calcium, magnesium, and protein of both the tef plant and grain can be predicted using hyperspectral data and PLSR model through waveband selection, and (2) compare the replicability of models across varying environments. Results suggest the method can produce high nutrient prediction accuracy for both the plant and grain in individual environments, but the selection of wavebands for nutrient prediction was not comparable across study areas. Results using PLSR model with hyperspectral data from non-milled grains were generally positive, and wavebands for protein prediction generally agreed with other studies. While more research is needed to determine whether these consistencies are true positives or are affected by other factors. This study contributes to the gap in the literature related to non-milled grains. Therefore, there is a need for greater attention to methods and results replication in remote sensing, specifically hyperspectral analyses, in order for scientific findings to be repeatable beyond the plot level.

3. Concluding Remarks

Hyperspectral remote sensing for studying agriculture and natural vegetation is a challenging research topic that will remain of great interest for different sciences communities for the next decades. As a matter of fact, Space agencies, on a worldwide basis, have ongoing programs to develop hyperspectral satellite missions to assure global coverage at high spatial resolution that will have a noteworthy impact on agricultural and natural vegetation monitoring studies. The eleven manuscripts collected in this special issue and, therefore, represent some meaningful progress in the application of hyperspectral EO data for agricultural and vegetation research themes. Further work in this area is required in view of the recent advances and funding opportunities in this field. We expect that the studies published herein will help the agriculture and vegetation research and management communities to better characterize and assess biophysical variables and processes, as well as more effectively predict plant nutrient using upcoming hyperspectral remote sensing technologies.

Author Contributions: All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Acknowledgments: The guest editors would like to thank the authors who contributed to this special issue and the reviewers who helped to improve the quality of the special issue by providing constructive recommendations to the authors. We would like to especially thank all 77 contributing authors who dedicated their research and time to this special issue. Likewise, we want to explicitly thank the fifty reviewers for their great work and effort put in this often-underestimated task. The careful, suitable, and original comments provided by the reviewers improved each of the papers published in this special issue. A special thanks goes to Quenby Qu.

Conflicts of Interest: The guest editors declare no conflict of interest.

References

1. Gara, T.W.; Darvishzadeh, R.; Skidmore, A.K.; Wang, T.; Heurich, M. Evaluating the performance of PROSPECT in the retrieval of leaf traits across canopy throughout the growing season. *Int. J. Appl. Earth Obs. Geoinf.* **2019**, *83*, 101919. [CrossRef]
2. Weiss, M.; Jacob, F.; Duveiller, G. Remote sensing for agricultural applications: A meta-review. *Remote Sens. Environ.* **2020**, *236*, 111402. [CrossRef]
3. Sahoo, R.N.; Ray, S.S.; Manjunath, K.R. Hyperspectral remote sensing of agriculture. *Curr. Sci.* **2015**, *108*, 848–859.
4. Adão, T.; Hruška, J.; Pádua, L.; Bessa, J.; Peres, E.; Morais, R.; Sousa, J. Hyperspectral Imaging: A Review on UAV-Based Sensors, Data Processing and Applications for Agriculture and Forestry. *Remote Sens.* **2017**, *9*, 1110. [CrossRef]
5. Mariotto, I.; Thenkabail, P.S.; Huete, A.; Slonecker, E.T.; Platonov, A. Hyperspectral versus multispectral crop-productivity modeling and type discrimination for the HyspIRI mission. *Remote Sens. Environ.* **2013**, *139*, 291–305. [CrossRef]
6. Marshall, M.; Thenkabail, P. Advantage of hyperspectral EO-1 Hyperion over multispectral IKONOS, GeoEye-1, WorldView-2, Landsat ETM+, and MODIS vegetation indices in crop biomass estimation. *ISPRS J. Photogramm.* **2015**, *108*, 205–218. [CrossRef]
7. Transon, J.; d'Andrimont, R.; Maugnard, A.; Defourny, P. Survey of Hyperspectral Earth Observation Applications from Space in the Sentinel-2 Context. *Remote Sens.* **2018**, *10*, 157. [CrossRef]
8. Zarco-Tejada, P.J.; Suarez, L.; Gonzalez-Dugo, V. Spatial resolution effects on chlorophyll fluorescence retrieval in a heterogeneous canopy using hyperspectral imagery and radiative transfer simulation. *IEEE Geosci. Remote Soc.* **2013**, *10*, 937–941. [CrossRef]
9. Lu, B.; He, Y.; Dao, P.D. Comparing the Performance of Multispectral and Hyperspectral Images for Estimating Vegetation Properties. *IEEE J. Stars* **2019**, *12*, 1784–1797. [CrossRef]
10. Darvishzadeh, R.; Wang, T.; Skidmore, A.K.; Vrieling, A.; O'Connor, B.; Gara, T.W.; Ens, B.J.; Marc, P. Analysis of Sentinel-2 and RapidEye for Retrieval of Leaf Area Index in a Saltmarsh Using a Radiative Transfer Model. *Remote Sens.* **2019**, *11*, 671. [CrossRef]
11. Darvishzadeh, R.; Skidmore, A.K.; Abdullah, H.; Cherenet, E.; Ali, A.M.; Wang, T.; Nieuwenhuis, W.; Heurich, M.; Vrieling, A.; O'Connor, B.; et al. Mapping leaf chlorophyll content from Sentinel-2 and RapidEye data in spruce stands using the invertible forest reflectance model. *Int. J. Appl. Earth Obs. Geoinf.* **2019**, *79*, 58–70. [CrossRef]
12. Xie, R.; Darvishzadeh, R.; Skidmore, A.K.; Heurich, M.; Holzwarth, S.; Gara, T.W.; Reusen, I. Mapping leaf area index in a mixed temperate forest using Fenix airborne hyperspectral data and Gaussian processes regression. *Int. J. Appl. Earth Obs. Geoinf.* **2020**, *95*, 1–13. [CrossRef]
13. Ali, A.M.; Skidmore, A.K.; Darvishzadeh, R.; van Duren, I.C.; Holzwarth, S.; Mueller, J. Retrieval of forest leaf functional traits from HySpex imagery using radiative transfer models and continuous wavelet analysis. *Isprs J. Photogramm. Remote Sens.* **2016**, *122*, 68–80. [CrossRef]
14. Casa, R.; Castaldi, F.; Pascucci, S.; Palombo, A.; Pignatti, S. A comparison of sensor resolution and calibration strategies for soil texture estimation from hyperspectral remote sensing. *Geoderma* **2013**, *197*, 17–26. [CrossRef]
15. Castaldi, F.; Palombo, A.; Santini, F.; Pascucci, S.; Pignatti, S.; Casa, R. Evaluation of the potential of the current and forthcoming multispectral and hyperspectral imagers to estimate soil texture and organic carbon. *Remote Sens. Environ.* **2016**, *179*, 54–65. [CrossRef]
16. Castaldi, F.; Palombo, A.; Pascucci, S.; Pignatti, S.; Santini, F.; Casa, R. Reducing the Influence of Soil Moisture on the Estimation of Clay from Hyperspectral Data: A Case Study Using Simulated PRISMA Data. *Remote Sens.* **2015**, *7*, 15561–15582. [CrossRef]
17. Castaldi, F.; Chabrillat, S.; Jones, A.; Vreys, K.; Bomans, B.; van Wesemael, B. Soil Organic Carbon Estimation in Croplands by Hyperspectral Remote APEX Data Using the LUCAS Topsoil Database. *Remote Sens.* **2018**, *10*, 153. [CrossRef]

18. Casa, R.; Pascucci, S.; Pignatti, S.; Palombo, A.; Nanni, U.; Harfouche, A.; Laura, L.; Di Rocco, M.; Fantozzi, P. UAV-based hyperspectral imaging for weed discrimination in maize. In *Precision Agriculture '19*; Stafford, J.V., Ed.; Wageningen Academic Publishers: Wageningen, The Netherlands, 2019; pp. 24–35.
19. Yue, J.; Feng, H.; Yang, G.; Li, Z. A comparison of regression techniques for estimation of above-ground winter wheat biomass using near-surface spectroscopy. *Remote Sens.* **2018**, *10*, 66. [CrossRef]
20. Casa, R.; Castaldi, F.; Pascucci, S.; Basso, B.; Pignatti, S. Geophysical and Hyperspectral Data Fusion Techniques for In-Field Estimation of Soil Properties. *Vadose Zone J.* **2013**, *12*, vzj2012.0201. [CrossRef]
21. Casa, R.; Castaldi, F.; Pascucci, S.; Pignatti, S. Potential of hyperspectral remote sensing for field scale soil mapping and precision agriculture applications. *Ital. J. Agron.* **2012**, *7*, 43. [CrossRef]
22. Upreti, D.; Pignatti, S.; Pascucci, S.; Tolomio, M.; Huang, W.; Casa, R. Bayesian Calibration of the Aquacrop-OS Model for Durum Wheat by Assimilation of Canopy Cover Retrieved from VENμS Satellite Data. *Remote Sens.* **2020**, *12*, 2666. [CrossRef]
23. Wang, Z.; Skidmore, A.K.; Darvishzadeh, R.; Wang, T. Mapping forest canopy nitrogen content by inversion of coupled leaf-canopy radiative transfer models from airborne hyperspectral imagery. *Agric. For. Meteorol.* **2018**, *253*, 247–260. [CrossRef]
24. Zheng, Q.; Huang, W.; Ye, H.; Dong, Y.; Shi, Y.; Chen, S. Using continous wavelet analysis for monitoring wheat yellow rust in different infestation stages based on unmanned aerial vehicle hyperspectral images. *Appl. Opt.* **2020**, *59*, 8003–8013. [CrossRef]
25. Jiang, C.; Chen, Y.; Wu, H.; Li, W.; Zhou, H.; Bo, Y.; Hyyppä, J. Study of a high spectral resolution hyperspectral LiDAR in vegetation red edge parameters extraction. *Remote Sens.* **2019**, *11*, 2007. [CrossRef]
26. Xie, M.; Wang, Z.; Huete, A.; Brown, L.A.; Wang, H.; Xie, Q.; Ding, Y. Estimating Peanut Leaf Chlorophyll Content with Dorsiventral Leaf Adjusted Indices: Minimizing the Impact of Spectral Differences between Adaxial and Abaxial Leaf Surfaces. *Remote Sens.* **2019**, *11*, 2148. [CrossRef]
27. Mirzaei, M.; Verrelst, J.; Marofi, S.; Abbasi, M.; Azadi, H. Eco-Friendly Estimation of Heavy Metal Contents in Grapevine Foliage Using In-Field Hyperspectral Data and Multivariate Analysis. *Remote Sens.* **2019**, *11*, 2731. [CrossRef]
28. Yan, Y.; Deng, L.; Liu, X.; Zhu, L. Application of UAV-Based Multi-Angle Hyperspectral Remote Sensing in Fine Vegetation Classification. *Remote Sens.* **2019**, *11*, 2753. [CrossRef]
29. Osco, L.P.; Ramos, A.P.M.; Moriya, É.A.S.; Bavaresco, L.G.; Lima, B.C.D.; Estrabis, N.; Imai, N.N. Modeling hyperspectral response of water-stress induced lettuce plants using artificial neural networks. *Remote Sens.* **2019**, *11*, 2797. [CrossRef]
30. Hennessy, A.; Clarke, K.; Lewis, M. Hyperspectral Classification of Plants: A Review of Waveband Selection Generalisability. *Remote Sens.* **2020**, *12*, 113. [CrossRef]
31. Sabat-Tomala, A.; Raczko, E.; Zagajewski, B. Comparison of Support Vector Machine and Random Forest Algorithms for Invasive and Expansive Species Classification Using Airborne Hyperspectral Data. *Remote Sens.* **2020**, *12*, 516. [CrossRef]
32. Osco, L.P.; Ramos, A.P.M.; Faita Pinheiro, M.M.; Moriya, É.A.S.; Imai, N.N.; Estrabis, N.; Li, J. A Machine Learning Framework to Predict Nutrient Content in Valencia-Orange Leaf Hyperspectral Measurements. *Remote Sens.* **2020**, *12*, 906. [CrossRef]
33. Lu, B.; Dao, P.D.; Liu, J.; He, Y.; Shang, J. Recent Advances of Hyperspectral Imaging Technology and Applications in Agriculture. *Remote Sens.* **2020**, *12*, 2659. [CrossRef]
34. Zhang, J.; Sun, H.; Gao, D.; Qiao, L.; Liu, N.; Li, M.; Zhang, Y. Detection of Canopy Chlorophyll Content of Corn Based on Continuous Wavelet Transform Analysis. *Remote Sens.* **2020**, *12*, 2741. [CrossRef]
35. Flynn, K.C.; Frazier, A.E.; Admas, S. Nutrient Prediction for Tef (Eragrostis tef) Plant and Grain with Hyperspectral Data and Partial Least Squares Regression: Replicating Methods and Results across Environments. *Remote Sens.* **2020**, *12*, 2867. [CrossRef]

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

© 2020 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/).