remote sensing

Editorial

Hyperspectral Imaging for Fine to Medium Scale Applications in Environmental Sciences

Michael Vohland [1,2,*] and András Jung [3]

[1] Geoinformatics and Remote Sensing, Institute for Geography, Leipzig University, Johannisallee 19a, 04103 Leipzig, Germany
[2] Remote Sensing Centre for Earth System Research, Leipzig University, Talstr. 35, 04103 Leipzig, Germany
[3] Institute for Cartography and Geoinformatics, Eötvös Lorand University, Pázmány P. Sétány 1/C., 1117 Budapest, Hungary; jung@inf.elte.hu
* Correspondence: michael.vohland@uni-leipzig.de; Tel.: +49-341-97-32798

Received: 2 September 2020; Accepted: 6 September 2020; Published: 11 September 2020

Hyperspectral imaging (HSI) combines conventional imaging and spectroscopic techniques in a way of spatially organized spectroscopy. Technical developments in the last three decades have brought the capacity of HSI to provide spectrally, spatially and temporally detailed data. The latter crucially relates to rapid data acquisition, favoured by hyperspectral snapshot technologies, i.e., no scanning as, e.g., push broom scanning as one conventionally remote sensing technique is needed for obtaining 3D image cubes. Furthermore, the development of miniaturized hyperspectral sensors has fostered their application with lightweight unmanned aerial vehicle (UAV) platforms [1–3]. HSI sensor technology with 3D reconstruction capacities is currently available [4]. Among HSI, hyperspectral microscopy imaging is another emerging field facilitating new applications [5–7].

Beyond this background, the aim of this Special Issue (SI) is to present a selection of innovative applications of HSI in the environmental and earth sciences, with a focus on the fine- to the medium-scale ranging from the microscale to field- and airborne data acquisition and analysis. The SI comprises a total of nine papers in various thematic fields, which can be organized into the following categories: geology/mineral exploration (one published paper), digital soil mapping (one), the mapping and characterization of vegetation (two) and the sensing of water bodies (including under-ice and underwater applications) (three); two rather methodically/technically oriented contributions focus on the optimized processing of UAV data and on the design and test of a receiver for simultaneous hyperspectral and differential laser absorption spectrometry (LAS) measurements.

In geological field studies, almost vertical-oriented outcrops may be mapped and characterised most properly by tripod-mounted close-range imaging instruments [8]. In this context, the study of Lorenz et al. [9] presents an adapted workflow for outcrop sensing by including atmospheric and topographic corrections, which are markedly beneficial for close- to long-range observations covering different sensing distances and viewing perspectives. For two different datasets, both acquired with an AisaFENIX push broom scanner (SPECIM, Spectral Imagig Ltd., Oulu, Finland), HSI mapping products were integrated with 3D photogrammetric data to create "hyperclouds", i.e., geometrically correct representations of the hyperspectral data cube.

Airborne hyperspectral imaging has been used in many studies to quantify soil variables, but soil studies with UAV data are still rare (see, for example, the recent review in [10]). The SI contribution of Hu et al. [11] aims at filling one gap in the UAV-based mapping of soil salinity. For this purpose, data were acquired from a UAV platform with a hyperspectral camera (Rikola Ltd., Oulu, Finland), providing data at a spatial resolution of 0.1 m and covering the 0.50–0.89 μm wavelength region with 62 spectral bands. With these data, random forest regression was used to estimate the electrical conductivity (EC) values and to generate EC maps for fields with different vegetation cover conditions, located in the region of Aksu, Western Xinjiang, China.

Different soil types were selected by Salazar et al. [12] for hyperspectral measurements from different distances to test a newly developed multichannel receiver. The configuration of this receiver allows the range-resolved collection of hyperspectral data in the 350–2500 nm range, combined with LAS measurements in the 820–850 nm wavelength region. Acquired test data indicated consistent hyperspectral measurements, independent of the range to the target. Envisioned applications include the rapid classification of soils, rocks, minerals and vegetation for ecological or agronomic research or the monitoring of earth construction sites as, for example, mine tailings.

Two SI papers focus on the forest ecosystems of different ecofloristic zones. Issues such as forest health, productivity and ecosystem services are often discussed in the context of forest diversity [13,14] and motivate researchers to seek out new inventory methods with the required spatial details. Recent developments in remote sensing technologies and image processing techniques thus extend the toolbox of forest researchers and managers [15].

Based on airborne HSI data, acquired with NEO Hyspex VNIR 1600 and NEO Hyspex SWIR 320m-e (Norsk Elektro Optikk AS, Skedsmokorset, Norway), Knauer et al. [16] evaluated the benefits of combining state-of-the-art classification techniques by turning them into an ensemble classifier, implemented for the discrimination of, in total, 15 forest tree species. The study was performed for forests of the temperate zone of the Northern hemisphere, located in Saxony Anhalt and Thuringia (Germany). The obtained results indicated that even the best available classifiers could be further improved by incorporating them into a multiple classifier system and using a specific (precision-weighted) voting strategy. Furthermore, MCLDA (multiclass linear discriminant analysis) was proposed for the image data analysis, as it performed best among different spectral dimensionality reduction methods.

The second forest-related contribution of Cao et al. [17] dealt with salt-tolerant mangroves, distributed to intertidal regions along tropical and subtropical coastlines. Over the past 50 years, global mangrove resources have rapidly decreased due to human interference and natural causes; for their monitoring and management, remote sensing techniques have been widely used [17,18].

Cao et al. [17] used a snapshot hyperspectral imager (UHD 185, Cubert GmbH, Ulm, Germany) to capture field reflectance data covering the spectral range of 450–998 nm with 138 spectral bands. They tested different hyperspectral information extraction methods to investigate the applicability of field snapshot HSI for the identification of mangrove species and to determine the spectral wavebands relevant for an effective classification. As an outcome, the authors underlined the potential of close-range HSI as a tool in monitoring mangrove forests at the species level.

Three SI contributions dealt with applications in water bodies, each with a different focus. In polar marine ecosystems, sea ice-associated algae are an essential feature characterised by a high spatiotemporal variability. The algal biomass is typically concentrated in the bottom ice layers and at the ice-water interfaces, thus not detectable with classical airborne and/or satellite remote sensing techniques [19]. Cimoli et al. have given an extensive overview about adapted capturing techniques, including spectral under-ice measurements and the use of unmanned underwater vehicles as sensing platforms [20]. In the current SI contribution [19], they coupled an AISA Kestrel 10 push broom sensor (SPECIM, Specim Spectral Imaging Ltd., Oulu, Finland) with a standard digital RGB camera and trialled this system at Cape Evans, Antarctica. For a ~20-m-long transect, ultra-high-resolution HSI data were used to quantify per-pixel algal biomass and pigments at the ice-water interface; RGB imagery was processed with digital photogrammetry to capture the under-ice structure and topography.

The use of aboveground remote sensing data of inland waters suffers from some marked limitations. The water-leaving radiation is largely affected by refraction at the water surface and atmospheric absorption and scattering. Therefore, an accurate atmospheric correction is a critical issue for the precise quantification of optically active substances (OAS) in the water column, especially from space [21,22]. For airborne hyperspectral image data with a pixel size of 2 m (AISA DUAL imaging system; SPECIM, Spectral Imaging Ltd., Oulu, Finland), Pyo et al. [23] tested different atmospheric correction approaches for their influence on the retrieval of phycocyanin (PC) and chlorophyll-a (Chl-a) for the water body of the Baekje Reservoir (Geum River, South Korea). Based on different bio-optical retrieval algorithms, the distribution maps of PC and Chl-a were generated to indicate risk regions for cyanobacterial blooms.

A different approach was followed by Seidel et al. [24] to quantify OAS (Chl-a and coloured dissolved organic matter) for a suite of freshwater lakes with different trophic levels, all located in Central Germany. Hyperspectral data for the OAS retrieval were acquired at various depths of each water column by means of a submersible hyperspectral camera (UHD 285, Cubert GmbH, Ulm, Germany), incorporated in a waterproof casing and equipped with a portable halogen lamp. Different from aboveground remote sensing methods, these measurements allowed for the monitoring of the vertical distribution of OAS in the water column; hence, they potentially bridge the gap between point sensors that provide continuous measurements at and below the water surface and spatially continuous remote sensing observations, e.g., from satellites or UAV platforms.

For the latter, the fast retrieval of high-quality and geometrically accurate mosaics of image data is still a challenge. Angel et al. [25] reviewed that existing techniques of mosaicking UAV images are often time-consuming and complex, so that there is a general need to accelerate and automate this procedure. Following this paradigm, they implemented a fully automated workflow to produce geo-rectified and mosaicked hyperspectral UAV images with an optimized co-registration strategy based on a small number of ground control points. The performance of the automated approach was evaluated by comparing its computational effort with that of other available approaches and by determining the standard metrics of spatial accuracy.

Author Contributions: The two authors contributed equally to all aspects of this editorial. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Acknowledgments: We would like to thank all authors who have contributed to this volume. Our special thanks also go to the anonymous reviewers for providing their valuable comments to help the authors improve their manuscripts. Last, but not least, we also would like to thank the Remote Sensing editorial team for its substantial support during the complete process of compiling and editing this volume. We especially thank Nelson Peng, without whom this SI could not have been realized.

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

References

1. Stuart, M.B.; McGonigle, A.J.S.; Willmott, J.R. Hyperspectral Imaging in Environmental Monitoring: A Review of Recent Developments and Technological Advances in Compact Field Deployable Systems. *Sensors* **2019**, *19*, 3071. [CrossRef] [PubMed]
2. Qin, J. Hyperspectral imaging instruments. In *Hyperspectral Imaging for Food Quality Analysis and Control*; Sun, D.-W., Ed.; Academic Press: San Diego, CA, USA, 2010; pp. 129–172.
3. Saari, H.; Aallos, V.-V.; Akujärvi, A.; Antila, T.; Holmlund, C.; Kantojärvi, U.; Mäkynen, J.; Ollila, J. Novel Miniaturized Hyperspectral Sensor for UAV and Space Applications. In *Proc. SPIE 7474, Sensors, Systems, and Next-Generation Satellites XIII, 74741M*; SPIE Remote Sensing: Berlin, Germany, 2009.
4. Renhorn, I.G.E.; Axelsson, L. High spatial resolution hyperspectral camera based on exponentially variable filter. *Opt. Eng.* **2019**, *58*, 103106. [CrossRef]
5. Pu, H.; Lin, L.; Sun, D.-W. Principles of Hyperspectral Microscope Imaging Techniques and Their Applications in Food Quality and Safety Detection: A Review. *Compr. Rev. Food Sci. Food Saf.* **2019**, *18*, 853–866. [CrossRef]
6. Bi, X.; Zhu, S.; Xian, J.; Wei, L.; Yin, H.; Li, M.; Chen, Z. Multihyperspectral Microscopic Imaging for the Precise Identification of Pollen. *Anal. Lett.* **2018**, *51*, 2295–2303. [CrossRef]
7. Wei, L.; Su, K.; Zhu, S.; Yin, H.; Li, Z.; Chen, Z.; Li, M. Identification of microalgae by hyperspectral microscopic imaging system. *Spectrosc. Lett.* **2017**, *50*, 59–63. [CrossRef]
8. Kurz, T.H.; Buckley, S.J.; Howell, J.A. Close-range hyperspectral imaging for geological field studies: Workflow and methods. *Int. J. Remote Sens.* **2013**, *34*, 1798–1822. [CrossRef]

9. Lorenz, S.; Salehi, S.; Kirsch, M.; Zimmermann, R.; Unger, G.; Vest Sørensen, E.; Gloaguen, R. Radiometric Correction and 3D Integration of Long-Range Ground-Based Hyperspectral Imagery for Mineral Exploration of Vertical Outcrops. *Remote Sens.* **2018**, *10*, 176. [CrossRef]
10. Lausch, A.; Baade, J.; Bannehr, L.; Borg, E.; Bumberger, J.; Chabrilliat, S.; Dietrich, P.; Gerighausen, H.; Glässer, C.; Hacker, J.M.; et al. Linking Remote Sensing and Geodiversity and Their Traits Relevant to Biodiversity—Part I: Soil Characteristics. *Remote Sens.* **2019**, *11*, 2356. [CrossRef]
11. Hu, J.; Peng, J.; Zhou, Y.; Xu, D.; Zhao, R.; Jiang, Q.; Fu, T.; Wang, F.; Shi, Z. Quantitative Estimation of Soil Salinity Using UAV-Borne Hyperspectral and Satellite Multispectral Images. *Remote Sens.* **2019**, *11*, 736. [CrossRef]
12. Salazar, S.E.; Coffman, R.A. Multi-Channel Optical Receiver for Ground-Based Topographic Hyperspectral Remote Sensing. *Remote Sens.* **2019**, *11*, 578. [CrossRef]
13. Brockerhoff, E.G.; Barbaro, L.; Castagneyrol, B.; Forrester, D.I.; Gardiner, B.; González-Olabarria, J.R.; Lyver, P.O.; Meurisse, N.; Oxbrough, A.; Taki, H.; et al. Forest biodiversity, ecosystem functioning and the provision of ecosystem services. *Biodivers. Conserv.* **2017**, *26*, 3005–3035. [CrossRef]
14. Ammer, C. Diversity and forest productivity in a changing climate. *New Phytol.* **2019**, *221*, 50–66. [CrossRef] [PubMed]
15. White, J.C.; Coops, N.C.; Wulder, M.A.; Vastaranta, M.; Hilker, T.; Tompalski, P. Remote Sensing Technologies for Enhancing Forest Inventories: A Review. *Can. J. Remote Sens.* **2016**, *42*, 619–641. [CrossRef]
16. Knauer, U.; Von Rekowski, C.S.; Stecklina, M.; Krokotsch, T.; Pham Minh, T.; Hauffe, V.; Kilias, D.; Ehrhardt, I.; Sagischewski, H.; Chmara, S.; et al. Tree species classification based on hybrid ensembles of a convolutional neural network (CNN) and random forest classifiers. *Remote Sens.* **2019**, *11*, 2788. [CrossRef]
17. Cao, J.; Liu, K.; Liu, L.; Zhu, Y.; Li, J.; He, Z. Identifying mangrove species using field close-range snapshot hyperspectral imaging and machine-learning techniques. *Remote Sens.* **2018**, *10*, 2047. [CrossRef]
18. Duke, N.C.; Meynecke, J.-O.; Dittmann, S.; Ellison, A.M.; Anger, K.; Berger, U.; Cannicci, S.; Diele, K.; Ewel, K.C.; Field, C.D. A world without mangroves? *Science* **2007**, *317*, 41–42. [CrossRef]
19. Cimoli, E.; Meiners, K.M.; Lucieer, A.; Lucieer, V. An Under-Ice Hyperspectral and RGB Imaging System to Capture Fine-Scale Biophysical Properties of Sea Ice. *Remote Sens.* **2019**, *11*, 2860. [CrossRef]
20. Cimoli, E.; Meiners, K.M.; Lund-Hansen, L.C.; Lucieer, V. Spatial variability in sea-ice algal biomass: An under-ice remote sensing perspective. *Adv. Polar Sci.* **2017**, *28*, 268–296.
21. Dörnhöfer, K.; Oppelt, N. Remote sensing for lake research and monitoring–Recent advances. *Ecol. Indic.* **2016**, *64*, 105–122. [CrossRef]
22. Mouw, C.B.; Greb, S.; Aurin, D.; DiGiacomo, P.M.; Lee, Z.; Twardowski, M.; Binding, C.; Hu, C.; Ma, R.; Moore, T.; et al. Aquatic color radiometry remote sensing of coastal and inland waters: Challenges and recommendations for future satellite missions. *Remote Sens. Environ.* **2015**, *160*, 15–30. [CrossRef]
23. Pyo, J.C.; Ligaray, M.; Kwon, Y.S.; Ahn, M.-H.; Kim, K.; Lee, H.; Kang, T.; Cho, S.B.; Park, Y.; Cho, K.H. High-Spatial Resolution Monitoring of Phycocyanin and Chlorophyll-a Using Airborne Hyperspectral Imagery. *Remote Sens.* **2018**, *10*, 1180. [CrossRef]
24. Seidel, M.; Hutengs, C.; Oertel, F.; Schwefel, D.; Jung, A.; Vohland, M. Underwater Use of a Hyperspectral Camera to Estimate Optically Active Substances in the Water Column of Freshwater Lakes. *Remote Sens.* **2020**, *12*, 1745. [CrossRef]
25. Angel, Y.; Turner, D.; Parkes, S.; Malbeteau, Y.; Lucieer, A.; McCabe, M.F. Automated Georectification and Mosaicking of UAV-Based Hyperspectral Imagery from Push-Broom Sensors. *Remote Sens.* **2020**, *12*, 34. [CrossRef]