



Remote and Proximal Assessment of Plant Traits

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The inference of functional vegetation traits from remotely sensed signals is key to providing efficient information for multiple plant-based applications and to solve related problems. Functional traits can be of morphological, biochemical, physiological, structural or phenological nature and reveal performance and vitality of plants. These traits, variables or physiological characteristics include, for instance, plant height [1], leaf area index [2], biomass [3], nutrient contents [4], water status [5], pigments [6], photosynthetic activity [7], disease resistance [8], yield prediction [9] or stress detection, being used by a diversity of ecological and agricultural applications. Spatial–temporal information of these traits is needed in numerous ecosystem applications, such as agriculture (crop breeding/monitoring/yield estimation) or biodiversity and landscape ecology. Therefore, the development and adaptation of fast, efficient, accurate and generic retrieval algorithms for quantification of vegetation traits, directly or indirectly from remote sensing observations, is required. In this context, variable data-driven as well as radiometric-data driven methods are continuously expanding over the time with rising remotely sensing data processing applications and studies. Drivers of this methodological expansion are, among others, the increase in computational power, the easier availability and increasing dimensionality of Earth observation (EO) data, and finally the ongoing progress in designing and planning spaceborne imaging spectroscopy missions. All methods have their respective limitations and advantages. Most importantly, they should be provided on appropriate platforms and (free-to-use) software tools, in order to be evaluated by plant physiologists, agronomists, remote sensing scientists and ecologists.

With the ambition to collect current state-of-the-art research, the Special Issue (SI) of “Remote and Proximal Assessment of Plant Traits” aimed to address contributions about estimation of morpho-physiological and biochemical plant traits from EO data in agricultural and ecological contexts, supporting food security and sustainability. Overall, with 14 published studies including 12 research studies, one technical note and one review study, a wide range of applications was covered meeting the expectations of the call for papers.

The majority of studies aimed at estimating functional vegetation traits at local and a few at regional scale within different ecosystems (mainly agriculture). Remote sensing of plants (crops) was performed at leaf- or canopy-levels by means of diverse sensors on field-level to spaceborne platforms, covering multi- and hyperspectral resolutions and applying a multitude of retrieval algorithms. In addition, these quantification studies, Castrignanò et al. [8] explored a classification method for the detection of biotic stress and two studies used time series analysis for assessing phenology [10] and yield [1]. Table 1 provides an overview of all the studies including the respective meta-information.



Citation: Herrmann, I.; Berger, K. Remote and Proximal Assessment of Plant Traits. *Remote Sens.* **2021**, *13*, 1893. <https://doi.org/10.3390/rs13101893>

Received: 6 May 2021

Accepted: 11 May 2021

Published: 12 May 2021

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Table 1. Overview of papers published in the Special Issue (order in publishing date), with short description of objectives, targeted type of variables (traits), type of ecosystem/vegetation studied, scale (local/regional/global) including level (leaf, canopy or atmosphere), platform/sensors, spectral resolution and applied methods, as well as type of paper.

#	Reference	Topic/Short Title	Targeted Traits	Ecosystem (Vegetation Type)	Scale (Level)	Platform, Spectral Resolution (Sensor)	Retrieval Methods	Study Type
1	Wang et al. [10]	Effects of weather variation on rice phenology.	phenology	Ag (rice)	regional (canopy-level)	satellite, hyperspectral (MODIS)	time series analysis	Research
2	Miraglio et al. [5]	Joint use of PROSAIL and DART for fast LUT building.	gap fraction, leaf chlorophyll content, leaf carotenoid content, leaf water content and leaf mass per area (LMA)	woodland savanna (oak stands)	local/stands (canopy-level)	airborne, hyperspectral (AVIRIS) and proximal sensing (ASD field spectrometer)	RTM (inversion with look-up table)	Research
3	Kennedy et al. [6]	Monitoring vegetation variables in Arctic environments using multi-angle hyperspectral data.	leaf and canopy chlorophyll content (LCC, CCC) and plant area index (PAI)	herbaceous plants, shrubs, mosses, sedges and grasses and lichens	local plots (canopy-level)	proximal sensing, hyperspectral (ASD field spectrometer)	RTM (numerical optimization and look-up tables), VIs and GPR	Research
4	Qiu et al. [3]	Estimation of the key rice growth indicators by means of commercial RGB cameras of unmanned aerial vehicles (UAVs).	leaf dry biomass, leaf area index and leaf total nitrogen	Ag (rice)	local plots (canopy-level)	UAV (multispectral)	VIs: Green Leaf Index (GLI) and Red Green Ratio Index (RGRl), Modified Green Red Vegetation Index (MGRVI), Excess Red Vegetation Index (ExR)	Research
5	Aharon et al. [11]	Evaluation of image-driven plant phenotyping methods to facilitate effective and accurate selection for early vigor in cereals.	various morphological growth parameters	Ag (triticale and ryegrass)	stands and local plots (single plant and canopy)	ground-based and UAV (RGB)	3D and 2D modeling, time series, VI: excessive green (ExG)	Research
6	Castrignanò et al. [8]	Early Detection of Xylella fastidiosa in Olive Trees Using UAV	scale of symptom severity	Ag (olive groves)	local stands (leaf- and canopy level)	UAV, multispectral (DJI Mavic Pro drone with a four-band multispectral camera)	non-parametric classification method	Research
7	Berger et al. [12]	Survey and experimental case study about active learning for solving regression problems	leaf carotenoid content, leaf water content	Ag (winter wheat and maize)	fields (canopy-level)	airborne (HyMAP) resampled to EnMAP, hyperspectral	hybrid (RTM and GPR), active learning	Review
8	Ronay et al. [7]	Characterization of physiological changes in corn during early growth due to crop-weed competition, detected through hyperspectral measurements.	relative water content, leaf chlorophyll content, photosynthetic rate and stomatal conductance, intercellular CO ₂	Ag (maize)	pots in greenhouse (leaf-level)	proximal sensing, hyperspectral (ASD field spectrometer)	hyperspectral VIs	Research
9	Mahajan et al. [4]	Remote sensing methods to characterize foliar nutrient status of mango.	P, K, Ca, Mg, S, Fe, Mn, Zn, Cu, B, N	Ag (mango)	regional (leaf-level)	proximal sensing, hyperspectral (GER1500 spectroradiometer)	VI, partial least square regression (PLSR), principal component regression and support vector regression (SVR)	Research

Table 1. Cont.

#	Reference	Topic/Short Title	Targeted Traits	Ecosystem (Vegetation Type)	Scale (Level)	Platform, Spectral Resolution (Sensor)	Retrieval Methods	Study Type
10	de Sá et al. [2]	Exploration of noise impact on hybrid inversion of PROSAIL using Sentinel-2 data.	leaf chlorophyll content, leaf dry matter content, leaf water content, leaf area index		local (canopy-level)	synthetic, multispectral (Sentinel-2)	hybrid (RTM and GPR, random forests, artificial neural networks (ANN) and multi-task neural networks)	Research
11	Rufo et al. [9]	Evaluation of a 4-band multispectral camera on-board an unmanned aerial vehicle (UAV) and ground-based RGB imagery to predict agronomic and biophysical traits.	leaf area index (LAI), agronomic traits (grain yield and number of grains)	Ag (wheat)	local (canopy-level)	airborne (UAV) and proximal sensing (JAZ-3 Ocean Optics STS VIS spectrometer), multispectral	VIs (modified triangular vegetation index—MTVI2, NDVI, GNDVI), stepwise multiple regression analysis	Research
12	Khak Pour et al. [13]	developing mobile platform for field-based high-throughput wheat phenotyping	canopy height, temperature, humidity	Ag (wheat and similar crops)	local (canopy level)	ground level (multispectral active sensor, ultra-sonic and thermal)	mounting sensors and developing software	Technical note
13	Estévez et al. [14]	Top-of-atmosphere retrieval of multiple crop traits by means of hybrid retrieval workflow.	leaf water content, leaf chlorophyll content, fractional vegetation cover, leaf area index, canopy chlorophyll content, canopy water content	Ag (winter wheat, maize)	local—regional (top-of atmosphere and top-of-canopy)	satellite, multispectral (Sentinel-2)	hybrid (RTM & GPR)	Research
14	Varela et al. [1]	Growth dynamics and yield prediction of sorghum using high temporal resolution UAV imagery time series and machine learning.	canopy cover, biomass, canopy height	Ag (sorghum)	local (canopy level)	UAV (multispectral)	3D modeling, VIs, random forest (RF), time series	Research

¹ Ag stands for agriculture; Na stands for natural; RTM stands for radiative transfer model; VIs stands for vegetation indices; ML stands for machine learning.

The commonly accepted taxonomy of retrieval methods (for short overviews and appropriate references see Berger et al. [12], Estevez et al. [14] or Mahajan et al. [4]) was nicely reflected by the studies of our SI:

- (i) Parametric regressions, mainly referring to the use of different (hyperspectral) vegetation indices (VI) [3,4,6,7,9];
- (ii) Nonparametric regressions, which include chemometric methods, such as partial least square regressions (PLSR), as well as machine learning (ML) regression algorithms, such as artificial neural networks, support vector regression (SVR) or Gaussian process regression (GPR) [4,6];
- (iii) Physically based or inversion of leaf and canopy radiative transfer models (RTM), for instance the 1D approaches of PROSAIL [6] or 3D DART model families [5];
- (iv) Hybrid approaches, where simulated RTM data serve for training of ML regression algorithms [2,12,14].

With the methodology covered by the published studies, we can recognize a clear trend towards more complex retrieval methods (ii–iv) moving away from the traditional and still most frequently used parametric regressions (i), towards a deeper understanding of underlying physical processes of the radiation–vegetation interactions by exploring RTMs (iii). Hybrid approaches (iv), combining RTMs with efficient and fast ML regression algorithms, emerged as most promising category as demonstrated by three studies [2,12,14]. These methods could become the key player of next-generation retrieval strategies in respect of a potential routine delivery of global vegetation products by future spaceborne

imaging spectroscopy missions. For instance, top-atmosphere retrieval from Sentinel-2 data of multiple vegetation traits was suggested by Estévez et al. [14], which could be extended to spaceborne hyperspectral data in the future. Moreover, the implementation of intelligent sampling methods (active learning) to provide faster and lighter retrieval models, particularly useful for implementation into cloud computing platforms, such as the Google Earth Engine (GEE), was proposed by Berger et al. [12]. In this context, an appealing solution for further reduction of computation times was presented by Miraglio et al. [5]: Hereby, reflectance curves from the complex 3D DART model were approximated using the simpler and faster 1D PROSAIL model, with this drastically reducing model running time for generation of a reflectance database. According to Mahajan et al. [4], the combination of different nonparametric approaches can also provide efficient, elegant and highly accurate solutions for the prediction of multiple plant nutrients from hyperspectral data, as the authors nicely demonstrated with the synergistic use of PLSR and SVR models. Moreover, the studies of Aharon et al. [11] used image analyses and 3D modeling to assess morphological traits for weed competitiveness and recommended for future work to add machine learning techniques. Wang et al. [10] analyzed imagery at larger spatial (county) and temporal (16 years) scales to assess phenology in relation to weather conditions based on a time series approach. To complete the scale range, a close range phenotyping system based on sensing techniques was developed by Khak Pour et al. [13], who presented their high throughput data collection platform with an exemplary wheat monitoring case study.

Regarding sensor systems, a decisive trend of increasing UAV data exploitation could be identified. This was particularly the case for the prediction of agronomic traits within breeding programs [1,9] and stress detection [8], but also for managing crop production [3]. Except for one study [12], simulating data from the German environmental mapping and analysis program (EnMAP), spaceborne imaging spectroscopy data were not explored by the published papers. This is about to change, with increasing data streams to be provided by current (PRISMA) or near-term missions, such as EnMAP, or future CHIME. Moreover, the synergistic usage of multiple optical sensors systems could greatly enhance the information content in respect to the different research questions as addressed in the published articles. Still, some other gaps and challenges remain, such as handling of large amounts of data, dealing with spatial and temporal structures in a more efficient way and also improvements of retrieval accuracy in particular of the leaf-level traits. To address this, an attractive option could be the exploitation of deep learning methods.

In summary, the 14 studies published here not only reflect the continuous advancement of new Earth observation sensors and methods, but also may support in further stimulating the ongoing progress in the field of vegetation traits retrieval and related applications. This ongoing progress will contribute towards more efficient operational monitoring of plants and crops, from plant organs, small plots, sub-field, field over regional to global scales, providing breeders, farmers and ecologists with relevant information for their decision-making processes in the context of Agriculture 4.0, as well as for additional research.

Author Contributions: Conceptualization and writing was done by I.H. and K.B. All authors have read and agreed to the published version of the manuscript.

Funding: K.B. is funded within the EnMAP scientific preparation program under the DLR Space Administration with resources from the German Federal Ministry of Economic Affairs and Energy, grant number 50EE1923. Further, this publication is the result of the project implementation: “Scientific support of climate change adaptation in agriculture and mitigation of soil degradation” (ITMS2014+313011W580) supported by the Integrated Infrastructure Operational Programme funded by the ERDF.

Data Availability Statement: All published papers of the Special Issue named “Remote and Proximal Assessment of Plant Traits” are available in https://www.mdpi.com/journal/remotesensing/special_issues/Remote_Proximal, accessed on 12 May 2021.

Acknowledgments: The authors would like to acknowledge all authors of the published papers for choosing our Special Issue to publish their research. The research was also supported by the Action CA17134 SENSECO (Optical synergies for spatiotemporal sensing of scalable ecophysiological traits) funded by COST (European Cooperation in Science and Technology, www.cost.eu, accessed on 12 May 2021). We further thank Jochem Verrelst for revision.

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

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