

# PROXIMAL AND DRONE BASED HYPERSPECTRAL SENSING FOR CROP NITROGEN STATUS DETECTION IN HISTORIC FIELD TRIALS

Gregor Perich<sup>1,2</sup>, Patrick Meyer<sup>3,4</sup>, Alice Wieser<sup>1,2</sup> and Frank Liebisch<sup>1,2</sup>

<sup>1</sup> Department of Environmental Systems Science, Institute of Agricultural Sciences, ETH Zurich, Universitätstrasse 2, Zurich 8092, Switzerland

<sup>2</sup> Agroecology and Environment, Water Protection and Substance Flows, Agroscope, Reckenholzstrasse 191, 8046, Zurich, Switzerland

<sup>3</sup> Gamaya, Route de la Longeraie 7, 1110 Morges

<sup>4</sup> Agroline, Nordring 2, 4147 Aesch

## ABSTRACT

Remote sensing holds vast potential for precision and smart farming and for field phenotyping applications. We present a small, but high-quality dataset consisting of ground truth, handheld spectrometer (proximal) and drone (remote sensing) data gathered in one of the world's oldest long-term field experiments (>70 yrs). The proximal and the remote sensing approaches showed comparable performance. Medium to strong correlations with the ground truth parameters were shown. Long-term field experiments are a valuable source for sensor calibration, calibration and validation of remote sensing products and applications. Vice versa, remote sensing methods and technology can support, improve and enhance data acquisition in field trials, particularly in long-term experiments.

**Index Terms**— Proximal sensing, remote sensing, high throughput phenotyping, drones, field experimental trials

## 1. INTRODUCTION

Remote sensing techniques are increasingly used in the framework of precision agriculture [1] and for agricultural research [2,3]. The research work can be divided in two domains focusing on 1) spatial and environmental monitoring and on 2) plot-based experimentation through high throughput phenotyping (HTP). Although the presented paper will focus on the latter, the underlying principles and obtained results are also relevant and applicable to the first.

The concept of HTP was mainly initiated by the breeding community [4], because of their demand to efficiently assess large field trials with hundreds to thousands of different plots [5]. Today, phenotyping of field trials is increasingly applied to other research purposes in agriculture including plant protection and fertilization trials [1]. The large variety of applications implies the high value of the methodology.

In this work we present the use of ground-based (proximal) and drone-based (remote) hyperspectral sensing

as a tool to evaluate plant biomass and nitrogen (N) status in a long term fertilizer trial comparing mineral and organic nutrient sources with respect to sustainable management of the soil resources and agronomic productivity. The idea is to partly replace laborious and costly manual in-field sampling with fast and non-destructive sensing methods. The feasibility of both investigated sensing approaches and instruments for this purpose will be discussed.

## 2. METHODS

### 2.1. Experiment and crop cultivation

For this study we used the historic (long-term) field trial 'Zurich Organic Fertilization experiment' (ZOFE), which was established in 1949 and is located at Agroscope in Zürich (47°25'36" N, 8°31'08" E, 420 masl).

The soil has an average density of 1.6 g cm<sup>-3</sup> and is a carbonate-free Luvisol. Soil properties in the 0–20 cm layer at the start of the trial were 14% clay, 27% silt, and 57% sand; organic C content was 1.3% and soil pH 6.5. Mean annual temperature and precipitation of the location is 9°C and 1040 mm, respectively [6]. The experiment was conducted from the beginning of July to August 2020 in grain maize (Corn). Crop management was performed according to local practice with a seeding date in late April.

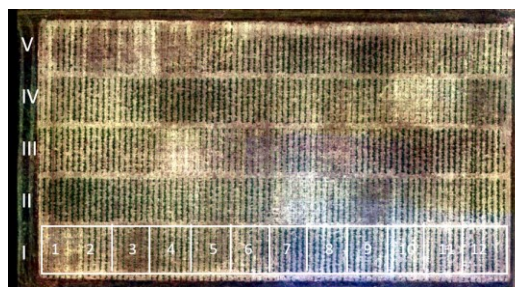


Figure 1: Aerial image of the experiment with indicated plot (x-axis) and block arrangement (y-axis).

The trial consisted of 12 different fertilization treatments systematically replicated in five blocks (Figure 1) with plots of 5\*7 m. The mineral and organic fertilizers were applied in single or combined use including a zero control (no fertilization) and a mineral full mineral fertilization control (Table 1). The original purpose of the trial was to identify sustainable fertilizer strategies to secure soil organic matter and agricultural productivity [6].

Table 1: Treatments and their respective N, P and K inputs.

Nr.	Treatment	Nutrient input (min/org) [kg ha <sup>-1</sup> ]		
		N	P	K
1	Zero control	0/0	0/0	0/0
2	Manure	0/86	0/27	0/117
3	Sewage sludge	0/174	0/163	0/9
4	Compost	0/93	0/21	0/106
5	Manure +PK	0/87	45/27	195/117
6	Sewage sludge +PK	0/174	45/163	195/10
7	Compost +PK	0/93	45/21	195/106
8	Peat +PK	0/0	45/0	195/1
9	N0P2K2	0/0	45/0	195/0
10	N2P1K1	100/0	22/0	98/0
11	N2P2K2	100/0	45/0	195/0
12	N2P2K2Mg/ mineral control	100/0	45/0	195/0

## 2.2. Ground truth data collection

Plant biomass was measured on the 16<sup>th</sup> July 2020 as the standing above ground dry matter biomass (DM). For the plant N status determination, the N concentration ( $N_{conc}$ ) in DM was measured and plant N uptake ( $N_{UP}$ ) was calculated as  $N_{UP} = DM * N_{conc}$ . Additional crop traits such as phenology stage, plant count per m<sup>2</sup>, germination rate and plant height were obtained regularly (data not shown).

## 2.3. Proximal and remote sensing methodology

The proximal and remote sensing measurement approaches were conducted throughout the experimental campaign. The data shown in this paper originate from measurements on the 7<sup>th</sup> and 8<sup>th</sup> July 2020, one week before biomass harvest. The proximal and remote sensed parameters involved two spectral indices: The Normalized Difference Vegetation index (NDVI) and the Normalized Difference Red Edge index (NDRE) as well as canopy cover (CC). The two spectral indices were calculated as  $NDVI = (NIR - R) / (NIR + R)$  and  $NDRE = (NIR - RE) / (NIR + RE)$  as used in [1] for both sensing approaches.

For the proximal sensing approach, canopy reflectance was measured using a portable field Spectroradiometer (PSR+3500, Spectral Evolution, USA). The used

wavelengths for spectral index calculation were R=660 nm, RE=735 nm and NIR=790 nm. To determine CC, a mobile phone's camera (iPhone 6s, Apple Inc., USA) was used in combination with the 'EasyPCC' algorithm [7].

For the remote sensed approach, a modified drone (Tarot T960 Hexacopter, China) equipped with the Iris VNIR hyperspectral camera system (Gamaya, SA, Lausanne, Switzerland) was used. The Camera was operated with a new internal calibration compared to previous studies [8] and the imagery was calibrated by ground reflectance panels during post processing. Plot-based reflectance values based on the full plot sizes were extracted from the orthophoto using QGIS (version 3.10.11). CC was determined using a threshold of  $NDVI \geq 0.5$  to differentiate between soil and vegetation. The spectral indices were calculated using the broadband channels (18 nm bandwidth) at center wavelengths R=660 nm, RE=735 nm and NIR =790 nm.

The applicability of the two sensing approaches was evaluated by means of an ANOVA of the plot-based values. The proximal and the remote sensing approaches were compared by correlation and regression analysis between the ground truth and the sensed parameters, respectively.

## 3. RESULTS

### 3.1. Ground truth data

For DM and  $N_{UP}$ , highly significant differences between the treatments were observed while there was no effect on germination rate affecting plant count per m<sup>2</sup> (Table 2). Thus, the treatment differences observable by proximal and remote sensing were mainly caused by differences in biomass and greenness.

Table 2: Two-way ANOVA for three investigated maize traits plant density, dry matter (DM) and nitrogen uptake ( $N_{UP}$ ). Significance: \*\*\* =  $p < 0.001$ , \*\* =  $p < 0.01$ , \* =  $p < 0.05$

Crop trait	Treatment	Replicate
Plant count (# m <sup>-2</sup> )	0.511	0.425
DM (kg m <sup>-2</sup> )	3.43e-09 ***	0.609
$N_{up}$ (g m <sup>-2</sup> )	2.3e-08 ***	0.924

For DM, and  $N_{UP}$ , the zero control exhibited the overall lowest values while the mineral control showed relatively high values. The two control groups exhibited the least intra-treatment variance across the treatments. No significant differences were found in  $N_{conc}$  for the two control groups. Acute N limitation indicated by  $N_{conc} < 2\%$  was found for treatment 8 (Peat +PK). The organic treatments showed larger in-group variances with treatment three showing values close to the zero control, caused by severe potassium limitation. The combined organic and mineral treatments also exhibited a high in-group variance compared to the other treatments. The highest biomass production (DM) was found in the

combined treatments with the overall highest DM observed in treatment seven.

In general,  $N_{conc}$  and  $N_{UP}$  showed increasing values with increasing nutrient application levels (Table 1). Lowest  $N_{conc}$  were detected in five different fertilizer treatments (1, 3, 8, 9 and 10) independent of their composition (mineral, organic or combined). Highest concentrations were found for fertilization with sewage sludge, manure + PK and  $N2P2K2$ .

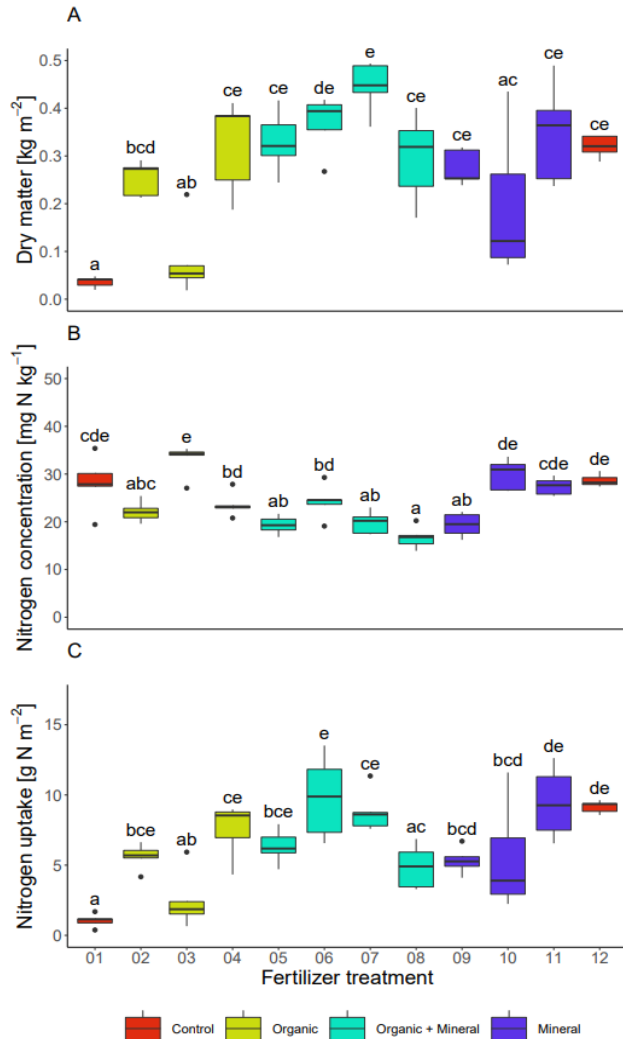


Figure 2: Dry matter (A), nitrogen concentration (B) and nitrogen uptake (C) for the 12 fertilizer treatments (Table 1) at harvest on the 16<sup>th</sup> July 2020. Different letters indicate significant differences between fertilizer treatments based on a one-way ANOVA Tukey HSD test ( $p < 0.05$ ).

### 3.2. Proximal and remote sensed traits

Proximal and remote sensed NDVI, NDRE and CC showed very similar patterns across the 12 treatments following the

same pattern as DM and  $N_{UP}$ . The proximal approach however, exhibited slightly higher in-group variance than the remote sensing approach.

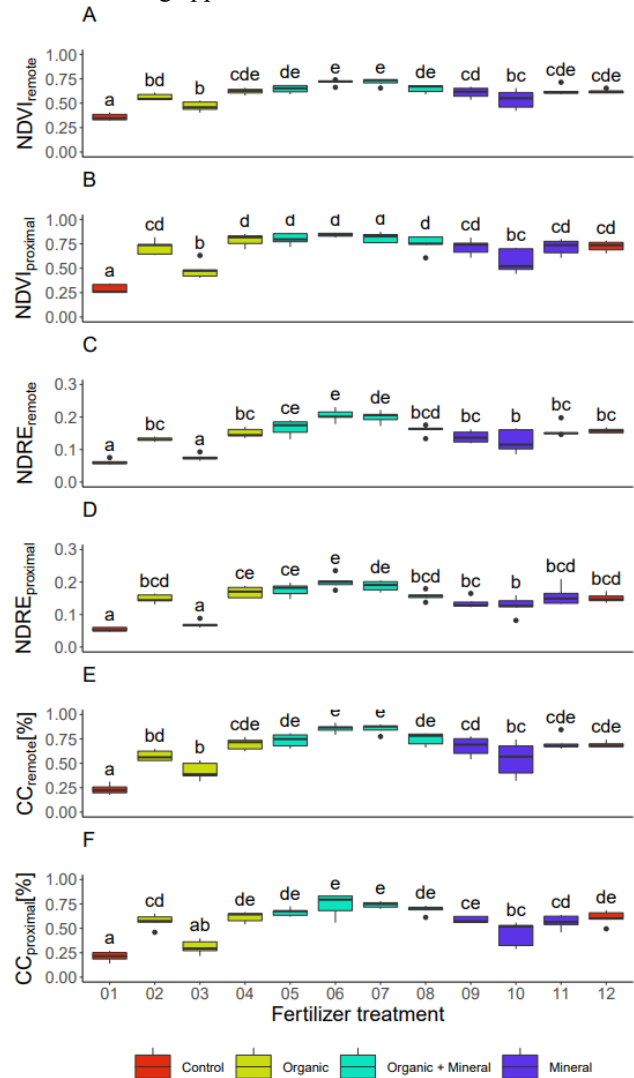


Figure 3 NDVI (A,B), NDRE (C,D) and canopy cover (E,F) measured on the 7<sup>th</sup> of July 2020 of the 12 fertilizer treatments (Table 1) using a proximal (B, D, F) and remote (A, C, E) sensed approach. Different letters refer to significant differences between fertilizer treatments based on the one-way ANOVA Tukey HSD ( $p < 0.05$ ).

The zero control group showed the lowest values and the highest values were observed for the combined and the mineral treatment groups. However, these two groups were not significantly different. The organic treatments also showed high in-group variance, similar to the DM (Figure 2A). Overall, the NDVI values compared well to the DM, and to a lesser extent to the  $N_{UP}$ , values. The NDRE however, followed the  $N_{UP}$  more closely than the NDVI (Figure 2).

The linear regression models showed that the evaluated proximal and remote sensed parameters explain large parts of the variation observed in the trial caused by the different fertilizer treatments (Table 3). The NDRE had higher coefficients of determination than NDVI and CC which are in a similar range, indicating that these traits might be redundant. The remote sensed parameters exhibited higher correlations than the proximal sensed ones. Combined with the lower correlation with  $N_{UP}$ , this indicated that the parameters NDVI, NDRE and CC reflect mostly plant biomass, and to a lesser degree canopy N status.

Table 3: Coefficients of determination (adjusted  $R^2$ ) from linear regression of dry matter (DM) and N uptake ( $N_{UP}$ ) with NDVI, NDRE and Canopy Cover (CC).

Method	Trait	DM [ $\text{kg m}^{-2}$ ]	$N_{UP}$ [ $\text{g N m}^{-2}$ ]
Remote	NDVI	0.73	0.54
	NDRE	0.78	0.60
	CC	0.73	0.55
Proximal	NDVI	0.62	0.44
	NDRE	0.69	0.56
	CC	0.61	0.37

### 3.3. Relationship of proximal and remote sensing data

A comparison of proximal and remote sensed parameters over two to three different measurement dates showed generally very high linear correlations between the two sensing approaches (Figure 4). The respective slopes and intercepts indicated that the relations are more or less close to the 1:1 line. For NDVI and NDRE, no saturation effect was observed, likely due to the large inter row spaces typical for corn crops.

## 4. DISCUSSION

The large overall variation in ground truth values (e.g. crop traits) observed in this experiment (Figure 2) is ideal for calibration and validation experiments because the range is much larger than the range found in most real-field situations [9]. Therefore, historical field trials such as the ZOFÉ trial are particularly valuable for calibration and validation experiments of new sensors and sensing platforms, but also for algorithms for crop trait retrieval.

Proximal and drone based hyperspectral measurements, two of the most applied methods for field phenotyping [10], were successfully applied in this study. The observed patterns in treatment differences were similar to the treatments found in the ground truth data, which was obtained by manual sampling and subsequent physical and chemical analysis. However, they were not exactly alike, pointing to the fact of different measurement methodologies. The sensing methods

in this paper were limited to a nadir view. The fact that statistical analysis (ANOVA) of the sensed parameters showed similar treatment effects at similar significance levels indicates that ground truth measurements can partly be replaced by remote sensing technology and therefore may support higher temporal data acquisition.

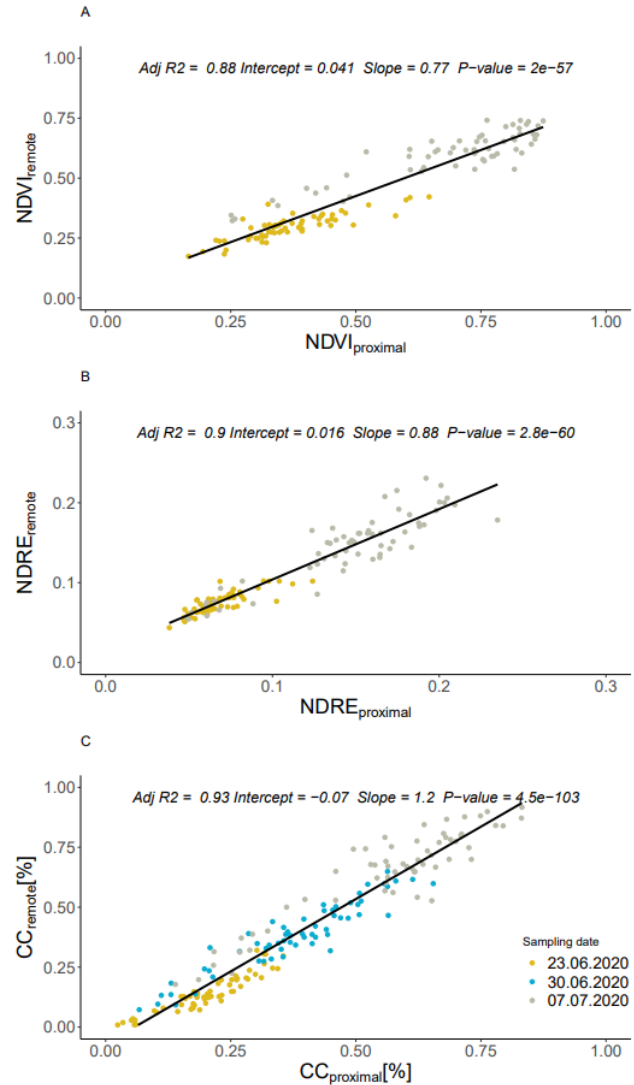


Figure 4 Linear regressions between remote and proximal sensed vegetation indices as well as canopy cover measured at three time points (23.06.2020, 30.10.2020 and 07.07.2020). Adjusted R-square, intercept, slope and P-value of the linear model are displayed.

The strong relationship of the sensed parameters with DM and  $N_{UP}$  indicates that the sensed parameters NDVI, NDRE and CC can be used to infer the crop traits canopy biomass and N status. Nevertheless, a robust calibration curve for these traits needs to be established and maintained with

frequent subsamples for quality control (e.g. ongoing measurements for constantly updated calibration curve), if the data is to be used for quantification of DM and N<sub>UP</sub>. For application in real-world farming scenarios, algorithms that have been established in such a way need further on-farm validation.

Seeing that both the proximal and the remote sensing approach can support data acquisition in field experiments, the decision which to apply can be forwarded to the availability of technology. The fact that multiple crop traits can be measured with one or few tools in fast sequence is a significant advantage compared to traditional field monitoring by taking physical samples and/or measurements. Additionally, the higher measurement frequency may enable better understanding of soil biochemical processes and soil-plant interaction and subsequently allow for better synchronization of fertilization with soil nutrient availability and plant nutrient demand.

However, proximal sensing methods often still involve manual labor in the field or with a ground-based carrier (such as tractors) and thus may pose the risk of interference with the experiment and the underlying soil through soil compaction. Therefore, we consider drone based or similar remote sensing technology as superior for high throughput phenotyping in field trials.

## 5. CONCLUSION

The presented study shows the power of proximal and remote sensing methods for HTP in experimental field trials especially with respect to nutrient input treatments. Vice versa the study reflects the high value of historical field trials to calibrate and validate sensor technology and algorithms to retrieve crop properties such as crop productivity and N status under field conditions. Therefore, proximal and remote sensing represent valuable tools to evaluate and support sustainable agricultural management and replace laborious and costly manual fieldwork.

## ACKNOWLEDGMENTS

This study was supported by the Knowledge project funded by Agroscope (contract-ID: 655017678), and the group of crop science based at ETH Zürich (A. Walter and especially J. Anderegg and H. Aasen). We thank H. Zbinden and T. Pederson for their fieldwork and J. Mayer for the ZOFE related information and discussion, the group of water protection and substance flows in general for lively discussion implementing new techniques. We also thank the Agroscope Analytics group for their work and special thanks goes to Gamaya (W. Metz and J-P. Leiva) for flying and providing the drone hyperspectral imagery.

## 11. REFERENCES

- [1] Argento, F., Anken, T., Abt, F., Vogelsanger, E., Walter, A., Liebisch, F., 2020. Site-specific nitrogen management in winter wheat supported by low-altitude remote sensing and soil data. *Precision Agric.* <https://doi.org/10.1007/s11119-020-09733-3>
- [2] Anderegg, J., Yu, K., Aasen, H., Walter, A., Liebisch, F., Hund, A., 2020. Spectral Vegetation Indices to Track Senescence Dynamics in Diverse Wheat Germplasm. *Front. Plant Sci.* 10. <https://doi.org/10.3389/fpls.2019.01749>
- [3] Perich, G., Hund, A., Anderegg, J., Roth, L., Boer, M.P., Walter, A., Liebisch, F., Aasen, H., 2020. Assessment of Multi-Image Unmanned Aerial Vehicle Based High-Throughput Field Phenotyping of Canopy Temperature. *Front. Plant Sci.* 11, 150. <https://doi.org/10.3389/fpls.2020.00150>
- [4] Araus J.L., Cairns J.E., Field high-throughput phenotyping: the new crop breeding frontier, *Trends in Plant Science*, Vol. 19, 1, 2014, 52-61. <https://doi.org/10.1016/j.tplants.2013.09.008>
- [5] Liebisch, F., Kirchgessner, N., Schneider, D. et al. Remote, aerial phenotyping of maize traits with a mobile multi-sensor approach. *Plant Methods* 11, 9 (2015). <https://doi.org/10.1186/s13007-015-0048-8>
- [6] Oberholzer, H. R., J. Leifeld, und J. Mayer. 2014. Changes in soil carbon and crop yield over 60 years in the Zurich Organic Fertilization Experiment, following land-use change from grassland to cropland. *Journal of Plant Nutrition and Soil Science* 177:696–704. <https://doi.org/10.1002/jpln.201300385>
- [7] Guo, W., Zheng, B., Duan, T., Fukatsu, T., Chapman, S., Nino-miya, S., 2017. EasyPCC: Benchmark Datasets and Tools for High-Throughput Measurement of the Plant Canopy Coverage Ratio under Field Conditions. *Sensors* 17, 798. <https://doi.org/10.3390/s17040798>
- [8] Joalland, S.; Screpanti, C.; Varella, H.V.; Reuther, M.; Schwind, M.; Lang, C.; Walter, A.; Liebisch, F. Aerial and Ground Based Sensing of Tolerance to Beet Cyst Nematode in Sugar Beet. *Remote Sens.* 2018, 10, 787. <https://doi.org/10.3390/rs10050787>
- [9] Bean, G.M., Kitchen, N.R., Camberato, J.J., Ferguson, R.B., Fernandez, F.G., Franzen, D.W., Laboski, C.A.M., Nafziger, E.D., Sawyer, J.E., Scharf, P.C., Schepers, J. and Shanahan, J.S. (2018), Active-Optical Reflectance Sensing Corn Algorithms Evaluated over the United States Midwest Corn Belt. *Agronomy Journal*, 110: 2552-2565. <https://doi.org/10.2134/agronj2018.03.0217>
- [10] Weiss, M., Jacob, F., Duveiller, G., 2020. Remote sensing for agricultural applications: A meta-review. *Remote Sensing of Environment* 236, 111402. <https://doi.org/10.1016/j.rse.2019.111402>