On the Potential of Wireless Sensor Networks for the In-Situ Leaf Area Index Assessment using Gap Fraction Analysis

Jan Bauer[a,*], Bastian Siegmann[b], Thomas Jarmer[b], Nils Aschenbruck[a]

[a] *University of Osnabrück, Institute of Computer Science, Albrechtstr. 28, 49076 Osnabrück, Germany*
[b] *University of Osnabrück, Institute for Geoinformatics and Remote Sensing, Barbarastr. 22b, 49076 Osnabrück, Germany*

Abstract

A precise and fine-grained in-situ monitoring of bio-physical crop parameters is crucial for the efficiency and sustainability in modern agriculture. The leaf area index (LAI) is an important key parameter, which allows to derive vital crop information. As it serves as a valuable indicator for yield-limiting processes, it contributes to situational awareness ranging from agricultural optimization to global economy. This paper presents a feasible, robust, and low-cost modification of commercial off-the-shelf photosynthetically active radiation sensors, which significantly enhances the potential of Wireless Sensor Network (WSN) technology for the non-destructive in-situ LAI assessment. In order to minimize environmental influences such as direct solar radiation and scattering effects, we upgrade such a sensor with a specific diffuser combined with an appropriate optical band-pass filter. We validate our approach in various field campaigns, analyze the accuracy of bio-physical crop characteristics derived from WSN data, and evaluate the robustness of our sensor modification.

Keywords: Wireless Sensor Network, Precision Agriculture, Crop Parameter, Gap fraction, Leaf area index, LAI-2200.

*Corresponding author. Tel.: +49 541 969 7167; fax: +49 541 969 2799.
Email addresses: bauer@uos.de (Jan Bauer), bsiegmann@igf.uos.de (Bastian Siegmann), tjarmer@igf.uos.de (Thomas Jarmer), aschenbruck@uos.de (Nils Aschenbruck)

1. Introduction

The Climate change and the increasing world population pose serious challenges to the primary economic sector as a whole and, in particular, to agriculture. Crop types, fertilization, irrigation, and crop protection have to be adapted to changing conditions. An earlier and more precise situational awareness of the status of agricultural fields is crucial for agricultural management and could, moreover, improve the prediction of yield rates. For the realization of a spatial fine-grained and timely situational awareness, there is a high demand for in-situ exploration of bio-physical and bio-chemical crop characteristics by advanced sensor technology.

In this context, the leaf area index (LAI) is one of the most important bio-physical plant parameters and an indispensable factor in climatological, meteorological, ecological, and agricultural modeling. (Asner et al., 2003). It is a valuable indicator and an integrative measure for the photosynthetic performance of plants. Since the LAI provides important information for yield models, it also serves as an indicator for yield-reducing processes caused by diseases or mismanagement (Carter, 1994; Boegh et al., 2002). For flat-leaf vegetation, Jonckheere et al. (2004) define the LAI as the ratio of the on-sided foliage area to the ground surface area (m^2/m^2).

In the recent years, various methods for the LAI assessment have been developed. The *destructive* assessment of LAI usually provides the most precise results, but is time-consuming, expensive, and, therefore, often limited to small areas (Bréda, 2003; Jonckheere et al., 2004). Diverse methods of *non-destructive* (also referred to as indirect) LAI assessment exist. On the one hand, the LAI can be estimated in-situ. Jonckheere et al. (2004) and Weiss et al. (2004) provide a comprehensive survey on common in-situ methodologies. An intercomparison of these methods comprising digital hemispherical photography (DHP) (e.g., Ryu et al., 2012; Francone et al., 2014) and specific handheld instruments, which measure the solar transmittance of plant canopy (gap fraction analysis) (e.g., AccuPAR, SunScan, or LAI-2200) is given by Wilhelm et al. (2000) and Gar-

rigues et al. (2008). On the other hand, the LAI assessment derived from remote sensing images (airborne or satellite) represents an established non-destructive alternative (e.g., Boegh et al., 2002; Jarmer, 2013). However, common drawbacks of all assessment methods are their relatively low temporal and/or spatial resolution as well as the required (monetary) effort.

Wireless Sensor Networks (WSNs) comprise a large number of small, low-cost, and low-power sensor devices wirelessly interconnected in a self-organizing manner (Akyildiz et al., 2002) The primary task of each individual device within such a network is environmental sensing of physically measurable parameters, e.g., temperature, humidity, or ambient light. Beyond this data acquisition, the device is responsible for data transmission and forwarding to a central base station, possibly connected to the Internet. As WSNs are designed for large-scale and long-term deployments, sensor devices are highly resource-constrained (Anastasi et al., 2009) and, thus, have limited sensing accuracy. However, this limitation is compensated by the large number of collaborating devices, which are able to continuously provide sensor information at high temporal as well as spatial resolution. Hence, WSNs are tailored for in-situ monitoring of crop parameters as has been realized by research in the context of smart farming since one decade, cf. Langendoen et al. (2006). A promising progress has already been made in this area (e.g., Yuan et al., 2009; Bauer et al., 2014; Qu et al., 2014b). Eventually, WSNs have the potential to reduce time and labor costs of conventional in-situ acquisition and to beneficially assist the validation of parameter maps derived from remote sensing data.

In this paper, we continue our previous approach (Bauer et al., 2014) of non-destructive in-situ LAI assessment. We present a novel low-cost sensor modification which significantly enhances the investigated potential in terms of accuracy and robustness. Moreover, we evaluate the benefit of our approach in various field campaigns. At the same time, we turn our attention to its feasibility in practice. The core contributions of this paper are:

- the design of a novel low-cost sensor modification,
- six extensive field campaigns including comparative analyses, and
- an evaluation showing the impact of our approach.

2. Related Work

First preliminary experiences gained with an in-situ WSN deployment in the area of precision agriculture are shared by Langendoen et al. (2006). The authors report many engineering difficulties of large-scale and long-term deployments and create a foundation for future WSN research. Pioneer research in the special domain of non-destructive LAI assessment based on WSN technology is presented by Yuan et al. (2009). The authors propose an iterative scheme to deploy sensors into farmland and apply statistical filters to the raw sensory data in order to cope with variations of light reflection and refraction. Nonetheless, they do not take advantage of any optical filter or diffuser. A continuous LAI monitoring WSN is proposed by Shimojo et al. (2013) and demonstrated using commercial off-the-shelf (COTS) sensor nodes in a tomato greenhouse. The authors emphasize that diffuse light conditions are crucial for the LAI assessment based on gap fraction analysis. Hence, a diffusing hemispherical plastic cover is used on top of each sensor. LAINet (Qu et al., 2014b) represents another holistic WSN for agricultural LAI monitoring. Recently, Qu et al. (2014a) focused on the in-situ assessment of the clumping index, which is closely related to the LAI. Moreover, the authors presented details of MLAOS, a custom multi-point optical sensor system, which provides the basis of LAINet. MLOAS uses optical diffusers and band-pass filters in order to minimize the influence of scatter light.

In our previous work (Bauer et al., 2014), we investigated the LAI accuracy achieved by a COTS sensor platform by conducting a direct comparison of WSN results and values obtained by conventional standard instrumentation, namely the LAI-2200 (LI-COR Inc., USA). Moreover, we suggest the *view pipe* concept

as simple modification of the optical sensor, which is shown to significantly improve the correlation between both devices and, thus, the potential of WSNs. However, this approach requires multiple sensors with multiple view pipes, which hinders the use of a COTS sensor platform and its practicability. Following our previous approach, our general goal is a feasible low-cost sensing system with sufficient accuracy.

In this paper, we reuse the chosen sensor platform. Again, we validate the achieved accuracy by a correlation analysis with the LAI-2200 (LI-COR, 2011) as also done by Qu et al. (2014b). With regard to the sensor unit, MLAOS (Qu et al., 2014a) is most related with our approach. However, we consider a different range in the solar spectrum and achieve feasible results with a single COTS sensor.

3. Background

3.1. Theoretical Background

In the visible (VIS) region of the electromagnetic spectrum (390–770 nm), spectral reflectance and transmittance of vegetation are dominated by the impact of pigments, e.g., chlorophyll and carotenoids (Gitelson et al., 2002). Due to the fact that green vegetation strongly absorb the energy of radiation in the range of blue (400–500 nm) and red light (600–700 nm) in order to carry out photosynthesis, reflectance and transmittance in these ranges are on a very low level, whereas being higher in the in the green domain (500–600 nm). This effect is known as the so-called green peak. In the near infrared (NIR) region (700–1400 nm), resulting from the cell structure, reflectance and transmittance first highly increase, while then remain on a high level which greatly reduces the NIR absorption (Gausman and Allen, 1973). Such a typical vegetation reflectance spectrum is visualized in Figure 1 which shows an exemplary spectrum for maize (*Zea mays L.*) measured in-situ with an ASD FieldSpec III (ASD Inc., USA) spectroradiometer as well as a wheat (*Triticum aestivum L.*) spectrum acquired by a SVC 1024i (Spectra Vista Corporation, USA) spectroradiometer.

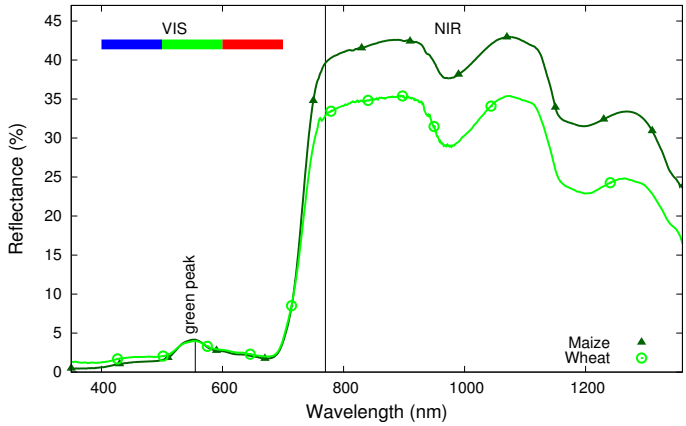


Figure 1: Typical reflectance spectrum curves of crops (maize and wheat) in the VIS and NIR region of solar radiation gathered by in-situ spectroradiometer measurements.

The properties of light transmittance of plants in the VIS spectrum is leveraged by the indirect LAI determination which is based on the quantitative interaction between solar radiation and plant canopy, cf. Jonckheere et al. (2004). The *Monsi-Saeki model* (Monsi and Saeki, 2005), as used by Yuan et al. (2009), Shimojo et al. (2013), and Bauer et al. (2014), applies the well-known *Beer-Lambert* law for assessing the LAI (L). It results in

$$L = -\frac{1}{C}\, ln\left(\frac{B}{A}\right), \tag{1}$$

where A is the light intensity observed above-canopy, B the corresponding intensity below-canopy, and the cultivar-specific term C. This term is the so-called *extinction coefficient*. It is given by the quantity of the specific light absorption property of plant's foliage and depends on various factors such as the leaf orientation angle. Moreover, the solar altitude has an significant impact on this coefficient. Please refer to Monsi and Saeki (2005) or Jonckheere et al. (2004) for further details.

The ratio of B to A represents the *transmittance*, which is gathered by standard optical instruments. These devices usually focus on a special spectral range within the VIS region where reflectance and transmittance of foliage is relatively low, e.g., in the range of blue light, cf. Figure 1. By doing so, the

maximum contrast between leaf and sky is achieved (Jonckheere et al., 2004). However, it is recommended to measure the light intensity under fully diffused sky conditions to cope with scattered radiation from leaf surfaces. Indeed, there exist more sophisticated approaches to remove the scattered radiation effect and provide an opportunity for LAI measurements even under sunny weather conditions, e.g., Kobayashi et al. (2013), as well as practical approaches tackling the challenge of scattered radiation, e.g., Qu et al. (2014a).

3.2. Standard Instrumentation

Reliable ground truth LAI values are very difficult to obtain. Only destructive measurements provide high accuracy and precision, but are time-consuming and cost-intensive and, thus, sparsely conducted. Nonetheless, depending on the agricultural application, in-situ non-destructive solutions may achieve a sufficient accuracy. The LAI-2200 instrument, for instance, is one of the standard measuring devices for the non-destructive LAI assessment and widely used in agricultural research. We hence use the LAI-2200 in order to validate the LAI results gathered by WSN devices.

The LAI-2200 instrument consists of a measurement wand with a fish-eye optical sensor and a handheld control unit. The sensor's field of view is divided into five rings. For each ring i, a usual measurement of the LAI-2200 consists of a number (N_{obs}) of above (A_{ij}) and below canopy readings (B_{ij}). The former measure the total incoming light intensity above the canopy and the latter the residual incoming light which is neither reflected nor absorbed by the canopy. Thereby, according to LI-COR (2011), the LAI (L) can be approximated with

$$L = 2\sum_{i=1}^{5} \overline{K_i} W_i \,, \text{ with } \overline{K_i} = \frac{1}{N_{obs}} \sum_{j=1}^{N_{obs}} \frac{-ln\left(\frac{B_{ij}}{A_{ij}}\right)}{S_i} \,. \tag{2}$$

The factors W_i and S_i are specific weightings for the individual rings. For more details, please refer to LI-COR (2011).

4. Measurement Architecture

The practical meaning of Equations 1 and 2 in Section 3 is that a pair of optical sensors (one above and one below the canopy) allow the LAI assessment. Hence, our long-term vision is a continuous WSN deployment for in-situ crop monitoring comprising a few sensors above the canopy as reference stations and plenty of sensors below the foliage, similar to the implementation of LAINet (Qu et al., 2014b). However, as a start of our research, our initial goal is a COTS sensor enhancement with sufficient accuracy and robustness concerning LAI estimation in practice. Therefore, we use the same architecture as presented by Bauer et al. (2014), which is briefly described in the remainder of this section.

For the validation of our approach and the evaluation of the achieved accuracy, we perform a comparative analysis with the LAI-2200. Regarding the correlation between both devices, their similar positioning and orientation is a crucial requirement for reliable and comparable results. Hence, in order to exclude such potential error sources and inaccuracies resulting from instrumental errors when using a pair of sensor nodes, we limit our measurement setup to a single node, directly mounted onto the measurement wand of the LAI-2200. Thus, we use the same sensor node for above and below data acquisition, simultaneously to the corresponding acquisition of the LAI-2200. Nevertheless, the gathered sensor data still is transmitted to a fully-equipped device as central instance for LAI computation, logging, and visualization. To this end, we use the smartphone application introduced by Bauer et al. (2014).

4.1. Hardware Components

After various tests with diverse IEEE 802.15.4 (Baronti et al., 2007; IEEE, 2011) compliant COTS sensor platforms regarding their capabilities for the LAI assessment based on gap fraction analysis, we came to the conclusion that the TelosB[1] sensor platform (Memsic, USA), which is also used by Shimojo et al.

[1] http://www.memsic.com/userfiles/files/Datasheets/WSN/telosb_datasheet.pdf

(2013), is greatly suited for our purpose (Bauer et al., 2014). Among its environmental sensors (temperature, humidity, and light), it features a photosynthetically active radiation (PAR) sensor (Hamamatsu S1087), which covers the desired spectral response rage from 320 to 730 nm with a peak sensitivity at a wavelength of 560 nm. In particular under natural light conditions, we evaluated this sensor as highly applicable for our purpose.

4.2. Software Components

The software framework consists of a data acquisition application running on the TelosB platform and an LAI determination and visualization application on the fully-equipped device, e.g., a smartphone. We implemented the data acquisition application using TinyOS 2.1.2[2](Levis et al., 2005), a widespread open source operating system for low-power wireless devices, with a reasonable memory footprint remaining enough memory for time synchronization (Römer et al., 2005), data aggregation (Fasolo et al., 2007), routing algorithms (Akkaya and Younis, 2005), and energy optimizations (Anastasi et al., 2009), which are currently not yet integrated in our application. Since we do not only gather the VIS light intensity perceived by the PAR sensor, but also monitor the temperature and humidity for future purposes, we achieve a sampling rate of roughly 3 Hz. Details can be found in Bauer et al. (2014).

The LAI computation is performed by a fully-equipped device because the data has to be filtered and fused, in particular in case of distributed sensors (as in the intended WSN deployment). Thus, the readings of each individual sensor are transmitted to that device. We combine (temporarily buffered) readings in a batch of 17 samples per packet in order to utilize the maximum packet size of IEEE 802.15.4. These packets are broadcasted with a rate of roughly 10 packets/min. Indeed, a more sophisticated, sparse, and energy-efficient sensor data transmission would be required for a long-term deployment which is part of our future work.

[2] http://www.tinyos.net

The central data sink application that receives these broadcasts averages the readings of each individual PAR sensor. In order to mitigate varying small-scale environmental noise, in our field campaigns, we take the mean of all 51 sensor samples included in three consecutive data packets (denoted by $\overline{A}$ and $\overline{B}$). Using the means, the transmittance is determined. Finally, the LAIs of individual pairs of sensors are estimated according to Equation 2 (Section 3.2). As it is not possible to differentiate the angle of incoming light with a single COTS sensor, we cannot divide the field of view in rings as done by the LAI device of LI-COR. Instead, we rely on an averaged transmittance which results in:

$$L = 2 \sum_{i=1}^{5} \overline{K_i} W_i \text{ with } \overline{K_i} = \frac{-ln\left(\frac{\overline{B}}{\overline{A}}\right)}{S_i} . \tag{3}$$

Adopting the weighting factors from LI-COR (2011), the LAI can be expressed with:

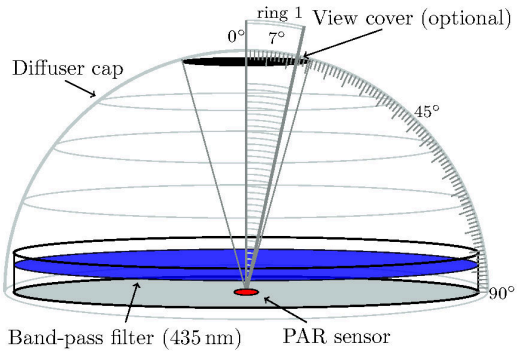
$$L = -\omega \cdot ln\left(\frac{\overline{B}}{\overline{A}}\right), \tag{4}$$

where ω is roughly 1.2401 and contains the extinction coefficient mentioned in Section 3.1. Note that in our current measurement setup, which directly compares manually measured LAIs, we do not face large-scale noise, e.g., effected by wind or rain. Thus, more complex statistical filters as applied by Yuan et al. (2009) are not required here.

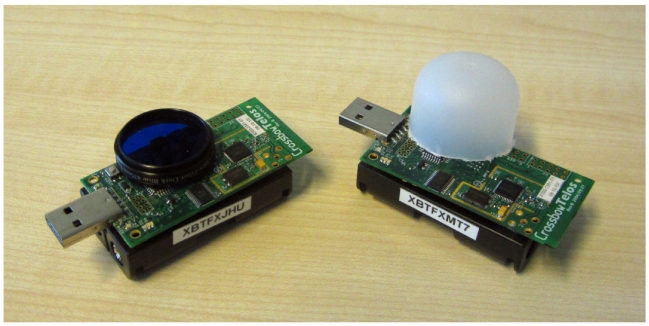
5. Design of a Sensor Enhancement

Bauer et al. (2014) introduced the *view pipe* approach, a simple, yet effective modification of the sensor's field of view, and demonstrated promising results. The idea is to imitate the individual rings in the visibility field of the LAI-2200 instrument by adjusting the COTS sensor's field of view in a similar manner. Using a short pipe mounted onto the sensor, its lower (i.e., more horizontal) field of view is restricted. However, concerning its feasibility, the view pipe approach has an inherent drawback: In order to entirely map the five rings of

the LAI-2200's fish-eye sensor, five PAR sensors with corresponding view pipes would be necessary. Moreover, view pipes only restrict the lower bound of the visibility field.



(a) View cap concept: The diffusivity of incoming light is improved by an adequate diffuser cap, the spectral response range is restricted by a band-pass filter, and an optional view cover mitigates potential direct solar radiation from the zenith angle.



(b) Practical realization of the view cap concept: TelosB sensor node with a dark-blue band-pass filter (left) and an additional diffuser cap mounted on top of the filter (right).

Figure 2: Concept and realization of the sensor enhancement.

Due to this certain lack of feasibility, we reconsidered our previous approach and take a different direction. In our novel setup, referred to as *view cap* approach, we take advantage of an optical diffuser in form of a hemispherical cap, following the approaches of Shimojo et al. (2013) and Qu et al. (2014a). How-

ever, based on previous experiences, the LAI accuracy (validated by comparative LAI-2200 results) is significantly impaired, if the sensor is not restricted somehow. Thus, we choose a restriction on a spectral level according to the black body assumption (LI-COR, 2011), which assumes a black foliage compared to the sky. This is achieved by an optical band-pass filter which rejects any incoming radiation with certain wavelengths in order to increase the contrast between foliage and sky and to mitigate scattering effects. Nonetheless, an additional restriction by an opaque cover that avoids direct sunlight from the zenith angle might be beneficial. Hence, we add an optional *view cover* at the top of the diffuser cap. This cover is designed to fade out the zenith visibility field (0 – 10 °) corresponding to the first ring of the LAI-2200 whose influence is also reduced to roughly 4 % by a small weighting factor, cf. (LI-COR, 2011). The overall concept of our new approach is depicted in Figure 2(a) and its practical realization is shown in Figure 2(b).

For the above mentioned spectral restriction, it is advisable to fade out the green peak in the reflectance spectrum of vegetation, cf. Section 3.1 and Figure 1. That could be easily realized by optical band-pass filters in the blue or red range of visible light. In contrast to Qu et al. (2014a), we decided to utilize a (low-cost) dark blue 435 nm band-pass filter (Baader Planetarium, Germany). The reason of this decision is that both reflectance and transmittance of vegetation in the blue spectrum is slightly lower than in the red spectrum, as exemplarily illustrated in Figure 3, that again visualizes the two reflectance spectrums from Figure 1 (maize and wheat), but in the specific spectral response range of the Hamamatsu PAR sensor. This characteristic of very low transmittance in the blue spectrum is advantageous concerning the black body assumption. Moreover, using the blue spectral range has the additional advantage that this region in the reflectance spectrum is only slightly changed under stress conditions, whereas red reflectance and transmittance is known to typically increase significantly (Slonecker, 2012). The LAI assessment based on a red band-pass filter might thus be prone to underestimation.

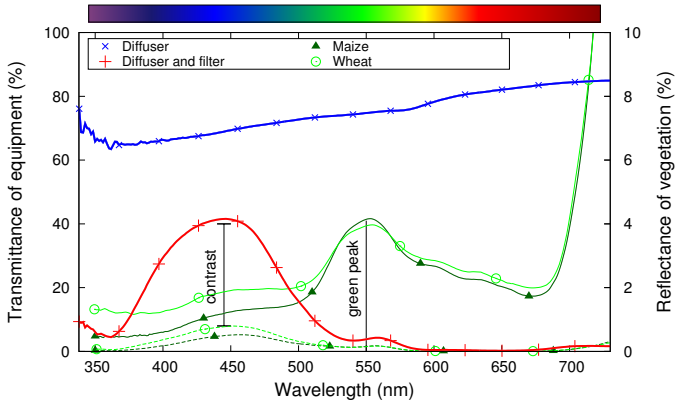


Figure 3: Spectral analysis of the transmittance (y1-axis) of the chosen diffuser with and without band-pass filtering within the spectral response range of the Hamamatsu S1087 sensor. Besides, reflectance spectrum curves of crops (maize and wheat) are shown on the y2-axis as measured in the field (solid line) and as perceived by the sensor after being filtered (dashed line).

Using the SVC 1024i (Spectra Vista Corporation, USA) spectroradiometer, we tested different diffusers in a laboratory environment and measured their transmittance as well as their transmittance in combination with the chosen band-pass filter. A detailed presentation of results are out of scope of this paper. However, a visualization of the properties of the selected diffuser are included in Figure 3. As the transmittance of the diffuser is relatively constant in the total response range of the PAR sensor and the diffuser does not decrease incoming radiation by more than roughly a third, it is suitable for LAI estimation. In addition, combining the diffuser with a dark blue band-pass filter, exactly the range of interest is passed. Moreover, considering the approximation of both plant reflectance curves perceived by the sensor after being filtered (dashed lines), the *green peak* ($\approx$550 nm) is eliminated as intended. Finally, the transmittance and reflectance of vegetation is less than 10 %, thus, offering a high contrast to the sky.

6. Evaluation in Field Trials

The goal of the field trials comprising six measurement campaigns in a maize field (*Zea mays L.*) is to investigate the sensing accuracy of COTS sensor technology (TelosB) enhanced by the presented view cap concept. By a comparative analysis with the results simultaneously measured by the LAI-2200 device, we validate this accuracy and emphasize the potential of WSNs for a large-scale and long-term agriculture deployment. We hope to achieve a similar accuracy and a strong linear correlation between the LAI estimates derived from both devices. Although the field measurements are exemplarily carried out in maize fields, we are convinced that our sensing architecture is applicable to other flat-leaf crop types. A validation of this assumption with various field campaigns in different crop types is planned to be part of our future work.

6.1. Study Area and Measurement Details

The maize field which was investigated during the growing seasons 2014 and 2015 has a size of 3.5 ha and is located near the University of Osnabrück in the north-western part of Germany. The mean annual precipitation of the area is about 700 mm and the mean annual temperature between 8 and 9 °C.

Four maize measurement campaigns were carried out on July 23^{rd}, Aug. 6^{th}, Aug. 21^{st}, and Sept. 25^{th} in 2014, two additional campaigns on Aug. 12^{th} and Aug. 20^{th} in 2015. In every campaign, the LAI of 25–65 plots with seasonal variations and different growth characteristics were measured to cover a wide range of LAI values. In order to guarantee diffuse light conditions, which are a basic prerequisite of the LAI-2200 device, all measurements were only conducted either in the dawn between 6 am and 9 am ($0\,° \leq$ solar zenith angle $\leq 15\,°$) or between 9 am and 3 pm on days with a stable cloud cover ($15\,° \leq$ solar zenith angle $\leq 55\,°$).

In every campaign, the TelosB device was installed directly on the LAI-2200's measurement wand, close to the fish-eye sensor. It simultaneously samples incoming radiation as described in Section 4.2 and periodically transfers its sensor data to the fully-equipped device, which finally determines the LAI.

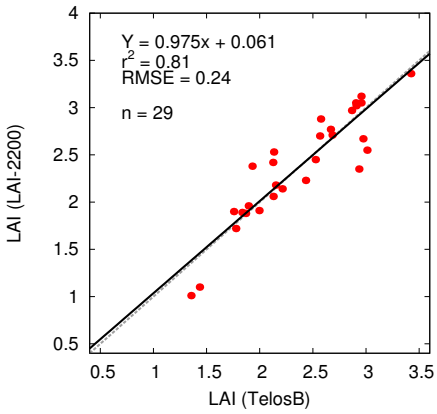


Figure 4: Comparison of LAI estimates by the enhanced TelosB sensor and LAI-2200 as reference in a first in-situ validation experiment (Campaign 1).

6.2. Results

As an initial proof of concept, we validated the basic setup (i.e., a sensor enhanced by diffuser and optical band-pass filter) in the first campaign. The comparative analysis of agreement between our setup and the LAI-2200 is shown in Figure 4 using a scatter plot. One can observe a clear linear relationship with a coefficient of determination (r^2) of 0.81 as well as a low root-mean-square error (RMSE) of 0.24. This initial result may seem similar to results of the view pipe approach proposed by Bauer et al. (2014). However, the latter results did not take the entire LAI-2200 visibility field into account, but only ring 1 and 2 (hereinafter denoted as LAI23). Thus, the quality of the new approach is much more promising. Moreover, by adopting the weighting factors and the implicit extinction coefficient from the computation formulas of LI-COR (2011) (cf. Section 4.2), the LAI domains of both devices agree surprisingly well as the linear regression line is nearly overlapping the 1:1 line (dashed). Nevertheless, since the number of samples taken in this first campaign ($n = 29$) are insufficient to draw a sound conclusion, additional campaigns are required.

After the proof of our concept, we take a step backwards and quantitatively compare results from our previous concept (view pipes) with our new approach. Furthermore, we evaluate the impact of using an optical filter. Therefore, we

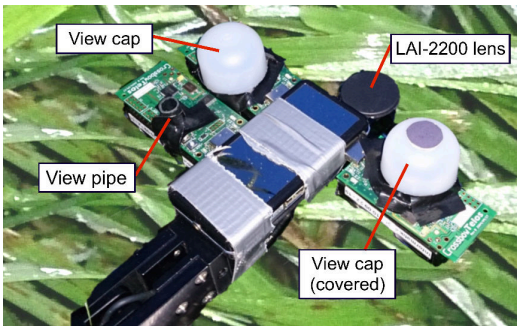
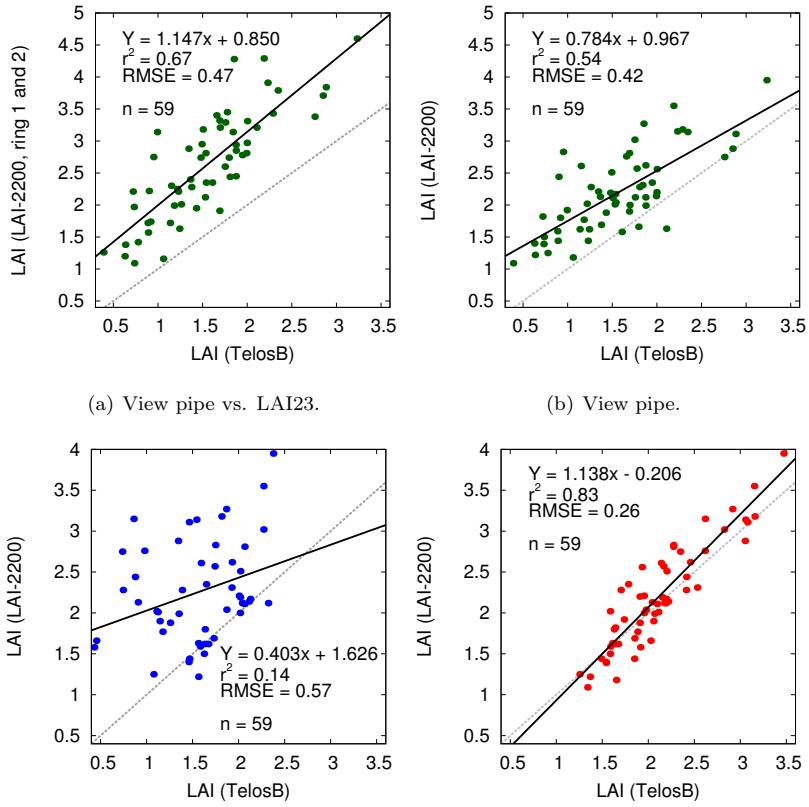


Figure 5: Measurement setup used for the comparative analysis of indirect LAI estimation using WSN devices with different approaches (view pipe and view cap concept (w and w/o view cover)) versus the conventional LAI-2200 methodology.

mounted TelosBs with different sensor modifications onto the LAI-2200 wand, as exemplarily illustrated in Figure 5. Although we might slightly loose proximity between the mounted sensors and the reference one, we thereby are able to perform all measurements simultaneously ensuring a spatiotemporal comparability.

The results are depicted in Figure 6. Both subfigures (a) and (b) concretize the weakness of the view pipe approach: Using a single sensor and a view pipe that limits its visibility according to the first two LAI-2200 rings, it is only possible to achieve an acceptable correlation ($r^2 = 0.67$, Figure 6(a)) regarding the corresponding LAI23 value (i.e., only ring 1 and 2 are used in the LAI-2200 processing). Otherwise, the correlation is further decreased, represented by the lower coefficient of determination ($r^2 = 0.54$, Figure 6(b)).

Concerning our new approach, we investigated the impact of an optical filter. Figure 6(c) shows the poor performance ($r^2 = 0.14$, RMSE $= 0.57$) of the TelosB PAR sensor, if only a diffuser is used, but the perceived solar radiation is not filtered. In contrast, using the same setup with an optical filter integrated in the diffuser cap, we observe a significant increase of correlation with the reference device ($r^2 = 0.83$, RMSE $= 0.26$, Figure 6(d)). Thus, for the sensor's potential and the accuracy of our approach, the optical band-pass filter is an extremely important component of our architecture.



(a) View pipe vs. LAI23.

(b) View pipe.

(c) Diffuser cap.

(d) View cap (diffuser and filter).

Figure 6: Comparison of LAI estimates using different modifications of TelosB sensors and LAI-2200 as reference (Campaign 2). LAI23 in (a) represents the LAI-2200 LAI estimate that corresponds to the visibility field of the view pipe (rings 3–5 are blocked in processing).

Besides the accuracy, the robustness of a measurement architecture against environmental influences is a relevant criteria for the potential of unattended long-term WSNs. Amongst others, the influence of direct sunlight is a crucial factor regarding the robustness and also a well-known source of error in the LAI-2200 architecture, which is applicable only at sunrise, sunset, or on cloudy days (LI-COR, 2011; Kobayashi et al., 2013). In order to evaluate the robustness of our approach with regard to direct sunlight, we took a closer look at the light intensity perceived by all modified sensors used in the second campaign (i.e.,

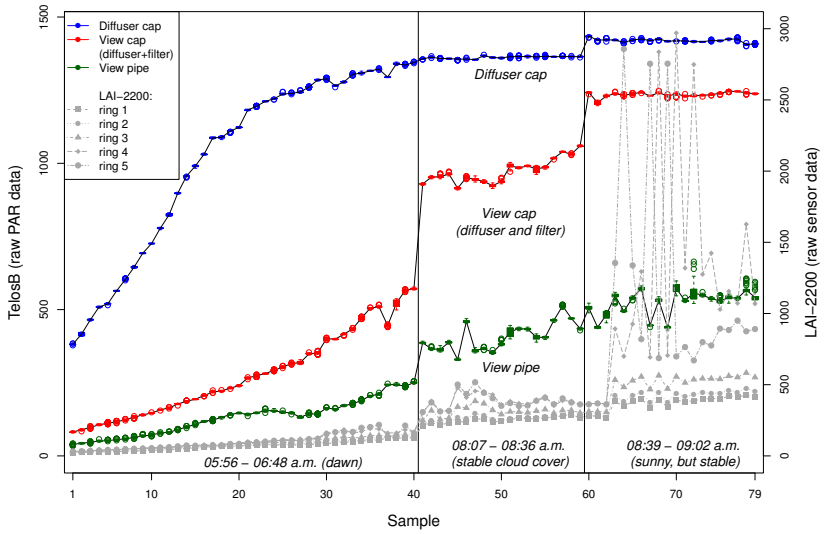
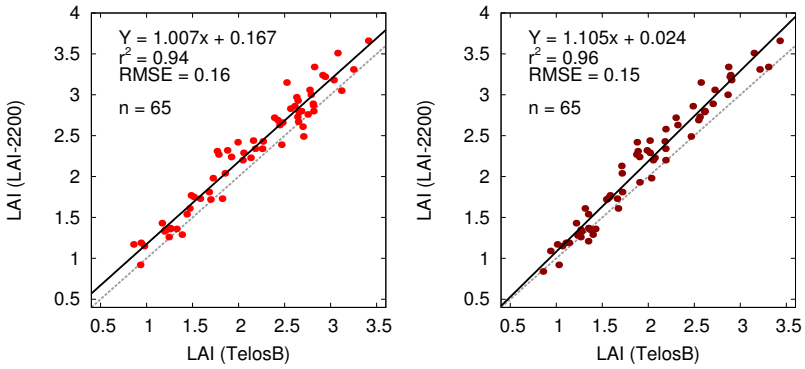


Figure 7: Intensity and variance of PAR measurements of different sensors gathered above canopy level in the second campaign. Both, the sequence of a sensor with a diffuser and in particular the sequence of a sensor with the view cap, show acceptable stability over time in all three phases, whereas the stability of the view pipe approach as well as the stability of the LAI-2200 (ring 4 and ring 5) suffer from direct radiation.

view pipe, diffuser cap, and view cap) during each above canopy measurement. The sequences of the gathered intensities of different sensors and also of each individual ring of the LAI-2200 instrument are shown in Figure 7.

Indeed, the sensitivity of individual sensors generally differ as expected because of different setups which absorb incoming light in a different manner and/or because of individual fields of view. Note that each measurement sample of the modified sensors represents the mean of 51 sensor readings (cf. $\overline{A}$ in Section 4.2). These readings are visualized by confidence intervals in the figure, but hardly distinguishable due to negligible variances.

There were three different phases: a dawn phase (samples 1–40) with ideal environmental conditions, a stable cloud cover phase (samples 41–59) with acceptable conditions, and a phase with sunny conditions (samples 60–79) baring the risk of direct radiation. Given stable environmental conditions, the sequences of samples of each sensor are assumed to be stable as well. Hence,



(a) View cap without cover. (b) View cap with view cover.

Figure 8: Comparison of LAI estimates using enhanced TelosB sensors and LAI-2200 as reference (Campaign 3 and 4).

during the first phase, a strictly monotonic increase of intensity sequence is expected due to the sunrise, whereas the sequences in the latter phases are expected to result in a nearly steady state. However, the evaluation confirms that this expectation could not be achieved by conventional approaches. Figure 7 emphasizes the high variance in the intensity sequences of the view pipe setup after the first phase as well as extreme outliers recorded by the LAI-2200 sensor, which is inoperative in direct sunlight (third phase) as predicted above. For this reason, the values measured in the third phase were excluded from the comparative analysis (cf. Figure 6). On the other hand, Figure 7 demonstrates that the diffuser approach tackles the challenge of direct sunlight since the diffuser cap sequence shows a smooth characteristic. As the variance only slightly increases when the diffuser is combined with the band-pass filter, our novel view cap approach enables the robustness required for an unattended deployment.

Finally, the benefit of the optional view cover intended to avoid potential inaccuracies by direct sunlight is investigated in Campaign 3 and 4. Figure 8 shows the quality of the setup so far (a) and of the setup extended by the opaque view cover (b). In both cases, there is a substantial correlation with the reference device. However, the view cover is identified to result only in a minor

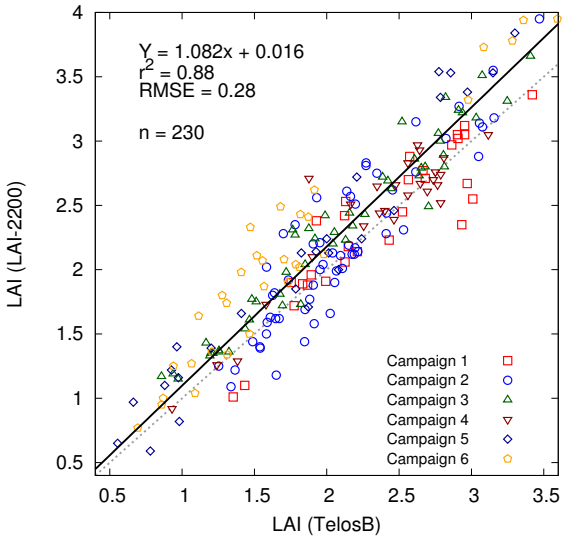


Figure 9: Comparison of the summarized LAI estimates of TelosB with view cap sensor enhancement and LAI-2200 in all maize campaigns.

improvement of the investigated correlation ($r^2 = 0.94$ to $r^2 = 0.96$). Though, by relying on the LAI-2200 comparison only and by neglecting more reliable destructive measurements, a general conclusion is hardly possible. Nevertheless, the cover does not seem to have a negative impact on the correlation on the other side. This result is very beneficial for the long-term unattended deployment in practice because dirt or dust particles might settle down on top of the diffuser cap and are expected to have a similar negligible impact.

6.3. Discussion

In conclusion, the estimates of both devices measured in all six field campaigns are compared in an overall scatter plot, cf. Figure 9. Note that a reasonable campaign-based clustering of estimates could not be observed since we considered different growth characteristics in each campaign and, thus, covered a wide range of LAI values each time.

Table 1: Performance of related approaches

Approach	Technique	Species	Result (r^2)	Reference
Ryu et al. (2012)	DHP	trees	0.94	LAI-2000
Confalonieri et al. (2013)	DHP	rice	0.97	destructive
Francone et al. (2014)	DHP	grass	0.86	AccuPAR
		maize	0.92	AccuPAR
		reed	0.88	AccuPAR
Qu et al. (2014b)	WSN	maize	0.27–0.97	LAI-2000
Bauer et al. (2014)	WSN	shrubs	0.85–0.90	LAI-2200

Figure 9 confirms the strong agreement of our approach with the reference instrument ($r^2 = 0.88$, RMSE $= 0.28$) and, thus, its appropriate accuracy. Moreover, due to the extensive number of measured LAI values ($n = 230$) under different seasonal and environmental influences as well as in various phenological stages, its robustness is implicitly demonstrated.

With regard to the related work, this strong and robust linear correlation can compete with results obtained by state-of-the-art approaches, which are exemplarily itemized in Table 1. The results generally are based on fewer measurement samples ($n \leq 30$) and, thus, do not provide information about their robustness. In contrast to these approaches, our novel sensor enhancement has the advantage of being simpler, yet more effective and cost-efficient. Compared to DHP approaches, no complex data processing is required, which demands more powerful and energy-consuming devices. On the other hand, no custom array of multiple sensors is necessitated as by related WSN approaches. Hence, our sensor enhancement increases the feasibility of low-cost and large-scale WSNs for the in-situ LAI assessment.

7. Conclusion

This paper presented a novel sensor approach based on COTS technology that significantly enhances the potential of IEEE 802.15.4 WSNs for the in-situ assessment of LAI, which is one of the most important metrics for bio-physical crop characteristics. It was shown that our approach enables new opportunities in terms of feasibility and robustness. Moreover, a comparative analysis reveals that substantial accuracy is achieved. Results are qualitatively comparable with state-of-the-art results by specific commercial instruments (e.g., AccuPAR, SunScan, and LAI-2200) and the complementary hemispherical photography approach, but enabled by small, low-cost, and energy-efficient devices.

In our future work, additional investigations in different crops are intended. For that purpose, we will systematically conduct destructive LAI measurements and occasionally process remote sensing data to widely validate our results. Furthermore, we plan to deploy a long-term WSN prototype enabling LAI acquisition with high spatiotemporal resolution.

Acknowledgments

This work was supported by the "Stifterverband für die Deutsche Wissenschaft" (H170 5701 5020 20951).

References

Akkaya, K., Younis, M., 2005. A survey on routing protocols for wireless sensor networks. Ad hoc networks 3 (3), 325–349.

Akyildiz, I. F., Su, W., Sankarasubramaniam, Y., Cayirci, E., Mar. 2002. Wireless Sensor Networks: A Survey. Computer Networks 38 (4), 393–422.

Anastasi, G., Conti, M., Francesco, M. D., Passarella, A., 2009. Energy conservation in wireless sensor networks: A survey. Ad Hoc Networks 7 (3), 537 – 568.

Asner, G. P., Scurlock, J. M. O., A. Hicke, J., 2003. Global synthesis of leaf area index observations: implications for ecological and remote sensing studies. Global Ecology and Biogeography 12 (3), 191–205.

Baronti, P., Pillai, P., Chook, V. W., Chessa, S., Gotta, A., Hu, Y. F., 2007. Wireless sensor networks: A survey on the state of the art and the 802.15.4 and ZigBee standards. Computer Communications 30 (7), 1655 – 1695.

Bauer, J., Siegmann, B., Jarmer, T., Aschenbruck, N., 2014. On the Potential of Wireless Sensor Networks for the In-Field Assessment of Bio-Physical Crop Parameters. In: Proc. of the 9th IEEE Int. Workshop on Practical Issues In Building Sensor Network Applications (SenseApp). Edmonton, Canada, pp. 523–530.

Boegh, E., Soegaard, H., Broge, N., Hasager, C. B., Jensen, N. O., Schelde, K., Thomsen, A., 2002. Airborne multispectral data for quantifying leaf area index, nitrogen concentration, and photosynthetic efficiency in agriculture. Remote Sensing of Environment 81 (2–3), 179–193.

Bréda, N., 2003. Ground-based measurements of leaf area index: a review of methods, instruments and current controversies. Journal of Experimental Botany 54, 2403–2417.

Carter, G. A., 1994. Ratios of leaf reflectances in narrow wavebands as indicators of plant stress. International Journal of Remote Sensing 15 (3), 697–703.

Confalonieri, R., Foi, M., Casa, R., Aquaro, S., Tona, E., Peterle, M., Boldini, A., Carli, G. D., Ferrari, A., Finotto, G., Guarneri, T., Manzoni, V., Movedi, E., Nisoli, A., Paleari, L., Radici, I., Suardi, M., Veronesi, D., Bregaglio, S., Cappelli, G., Chiodini, M., Dominoni, P., Francone, C., Frasso, N., Stella, T., Acutis, M., 2013. Development of an app for estimating leaf area index using a smartphone. trueness and precision determination and comparison with other indirect methods. Computers and Electronics in Agriculture 96 (0), 67 – 74.

Fasolo, E., Rossi, M., Widmer, J., Zorzi, M., April 2007. In-network aggregation techniques for wireless sensor networks: a survey. Wireless Communications, IEEE 14 (2), 70–87.

Francone, C., Pagani, V., Foi, M., Cappelli, G., Confalonieri, R., 2014. Comparison of leaf area index estimates by ceptometer and PocketLAI smart app in canopies with different structures. Field Crops Research 155, 38–41.

Garrigues, S., Shabanov, N., Swanson, K., Morisette, J., Baret, F., Myneni, R., 2008. Intercomparison and sensitivity analysis of Leaf Area Index retrievals from LAI-2000, AccuPAR, and digital hemispherical photography over croplands. Agricultural and Forest Meteorology 148 (8–9), 1193–1209.

Gausman, H. W., Allen, W. A., 1973. Optical parameters of leaves of 30 plant species. Plant Physiology 52 (1), 57–62.

Gitelson, A. A., Zur, Y., Chivkunova, O. B., Merzlyak, M. N., 2002. Assessing Carotenoid Content in Plant Leaves with Reflectance Spectroscopy. Photochemistry and photobiology 75 (3), 272–281.

IEEE, 2011. IEEE Standard for Local and metropolitan area networks–Part 15.4: Low-Rate Wireless Personal Area Networks (LR-WPANs). http://standards.ieee.org/getieee802/download/802.15.4-2011.pdf, checked: January 2016.

Jarmer, T., 2013. Spectroscopy and hyperspectral imagery for monitoring summer barley. International Journal of Remote Sensing 34 (17), 6067–6078.

Jonckheere, I., Fleck, S., Nackaerts, K., Muys, B., Coppin, P., Weiss, M., Baret, F., 2004. Review of methods for in situ leaf area index determination: Part I. Theories, sensors and hemispherical photography. Agricultural and Forest Meteorology 121 (1–2), 19–35.

Kobayashi, H., Ryu, Y., Baldocchi, D. D., Welles, J. M., Norman, J. M., 2013. On the correct estimation of gap fraction: How to remove scattered radiation

in gap fraction measurements? Agricultural and Forest Meteorology 174–175 (0), 170–183.

Langendoen, K., Baggio, A., Visser, O., 2006. Murphy loves potatoes: experiences from a pilot sensor network deployment in precision agriculture. In: Proc. of 20th Int. Parallel and Distributed Processing Symposium (IPDPS). Rhodes Island, Greece.

Levis, P., Madden, S., Polastre, J., Szewczyk, R., Whitehouse, K., Woo, A., Gay, D., Hill, J., Welsh, M., Brewer, E., et al., 2005. Tinyos: An operating system for sensor networks. In: Ambient intelligence. Springer, pp. 115–148.

LI-COR, 2011. LAI-2200 Plant Canopy Analyzer – Instruction Manual. http://www.licor.co.za/manuals/LAI-2200_Manual.pdf, checked: January 2016.

Monsi, M., Saeki, T., 2005. On the Factor Light in Plant Communities and its Importance for Matter Production. Annals of Botany 95 (3), 549–567 (originally published in German: Über den Lichtfaktor in den Pflanzengesellschaften und Seine Bedeutung für die Stoffproduktion. Japanese Journal of Botany, 1953).

Qu, Y., Fu, L., Han, W., Zhu, Y., Wang, J., 2014a. MLAOS: A Multi-Point Linear Array of Optical Sensors for Coniferous Foliage Clumping Index Measurement. Sensors 14 (5), 9271–9289.

Qu, Y., Zhu, Y., Han, W., Wang, J., Ma, M., Feb 2014b. Crop Leaf Area Index Observations With a Wireless Sensor Network and Its Potential for Validating Remote Sensing Products. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 7 (2), 431–444.

Römer, K., Blum, P., Meier, L., 2005. Time synchronization and calibration in wireless sensor networks. Handbook of sensor networks: Algorithms and architectures 49, 199.

Ryu, Y., Verfaillie, J., Macfarlane, C., Kobayashi, H., Sonnentag, O., Vargas, R., Ma, S., Baldocchi, D. D., 2012. Continuous observation of tree leaf area index at ecosystem scale using upward-pointing digital cameras. Remote Sensing of Environment 126 (0), 116 – 125.

Shimojo, T., Tashiro, Y., Morito, T., Suzuki, M., Lee, D., Kondo, I., Fukuda, N., Morikawa, H., 2013. A Leaf Area Index visualization method using wireless sensor networks. In: Proc. of Int. Conf. on Instrumentation, Control, Information Technology and System Integration Conference (SICE). Nagoya, Japan, pp. 2082–2087.

Slonecker, T., 2012. Analysis of the effects of heavy metals on vegetation hyperspectral reflectance properties. In: Thenkabail, P., Lyon, J., Huete, A. (Eds.), Hyperspectral remote sensing of vegetation. CRC, Ch. 23 Analysis of the Effects of Heavy Metals on Vegetation Hyperspectral Reflectance Properties, pp. 561–578.

Weiss, M., Baret, F., Smith, G., Jonckheere, I., Coppin, P., 2004. Review of methods for in situ leaf area index (LAI) determination: Part II. Estimation of LAI, errors and sampling. Agricultural and Forest Meteorology 121 (1–2), 37 – 53.

Wilhelm, W., Ruwe, K., Schlemmer, M. R., 2000. Comparison of three leaf area index meters in a corn canopy. Crop Science 40 (4), 1179–1183.

Yuan, Y., Li, S., Wu, K., Jia, W., Peng, Y., 2009. FOCUS: A cost-effective approach for large-scale crop monitoring with sensor networks. In: Proc. of the Int. Conf. on Mobile Adhoc and Sensor Systems (MASS). Macao, China, pp. 544–553.