Design and Implementation of an Agricultural Monitoring System for Smart Farming

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***Abstract*—The integration of modern information technologies into industrial agriculture has already contributed to yield increases in the last decades. Nowadays, the emerging Internet of Things (IoT) along with Wireless Sensor Networks (WSNs) with their low-cost sensors and actors enable novel applications and new opportunities for a more precise, site-specific, and sustainable agriculture in the context of Smart Farming. In this paper, we present a holistic agricultural monitoring system, its design, and its architectural implementation. The system primarily focuses on in-situ assessment of the leaf area index (LAI), a very important crop parameter. Moreover, we introduce real-world challenges and experiences gained in various deployments. Finally, first results are exemplarily demonstrated in order to briefly address the potential of our system.**

I. Introduction

The climate change and the increasing demand of food pose serious challenges to modern agriculture. The global population is predicted to increase significantly and, therefore, food production must increase by 70 percent until 2050 [7]. At the same time, the scarcity of water and shortage of arable land is growing. Thus, there is a demand for an adequate selection of crop types, a suitable adaption of farming practices, and sustainability. Fertilization, crop treatment, pest control, and most notably irrigation management need to be adapted to continuously changing conditions. Farming activities have to be conducted in a sophisticated manner to save scarce resources.

To achieve this, apart from agriculture and agronomy, research expertise of many other domains need to be efficiently combined. Much effort of using scientific achievements and novel technologies from other domains has already been made. More and more digital innovations have been integrated into the agricultural sector producing the notion of Precision Agriculture [12]. Recently, Internet of Things (IoT) concepts extend Precision Agriculture with smart, distributed, and collaborating sensors and technologies that are nowadays well established in other industrial sectors and also in home automation [6]. This extension is often referred to as Smart Farming and comprises all steps from sensor-based data gathering and communication to data processing, storage, and analytics. Moreover, analytic results can be visualized by IoT frontends and feed decision support systems in order to help farmers to make better and more sustainable decisions.

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In the context of arable farming, IoT systems have the potential to provide new insights and provide an up-to-date situational awareness with a much higher level of spatio-temporal granularity of monitoring [6]. They support the understanding of factors influencing crop growth and yields, which is very crucial for a sustainable agriculture. Via site-specific management, IoT systems help to significantly save farm resources and, thus, increase farm output. Furthermore, IoT-based crop monitoring also improves yield modeling and the quality of yield predictions. Overall, the emerging digital revolution, particularly IoT integration into modern agriculture, is a key enabler that allows to automate many processes and support them with valuable additional information.

Since the basis of the IoT chain from crops to farmers is sensor-based data gathering, sensor devices and their in-situ deployment is fundamental for the success of Smart Farming. Such devices range from small, low-cost, and resource-constrained sensors to complex high-accuracy sensor platforms that could be very expensive. For a large-scale crop monitoring, generally many sensors are required. Hence, from an economic perspective, the price of individual sensors is crucial for the return on investment (RoI). In Wireless Sensor Networks (WSNs), such cheap devices are typically used for environmental sensing of physically measurable parameters [1]. These are wirelessly interconnected and designed for large-scale and long-term deployments. As they are predominantly battery-driven, they are likewise highly resource-constrained. Thus, individual sensors have limited sensing accuracy that is compensated by the large number of collaborating devices continuously collecting environmental information. Moreover, ground-based WSNs can be complemented by remote sensing that is based on airborne imagery. This is usually acquired by satellites or recently by drones and, amongst others, is used to derive information about crop growth. This is particularly beneficial to approximate WSN-based in-situ information to even larger areas.

During the last decade, WSNs were already deployed in the agricultural domain, improving remote monitoring of agricultural resources and products, e.g., [8], [13]. Their potential of increasing productivity and waste reduction has been shown to be very promising [2]. More recently, suchlike deployments are successfully integrated into IoT platforms [15] using modern cloud technology. In this paper, we present an agricultural crop growth monitoring system and report on

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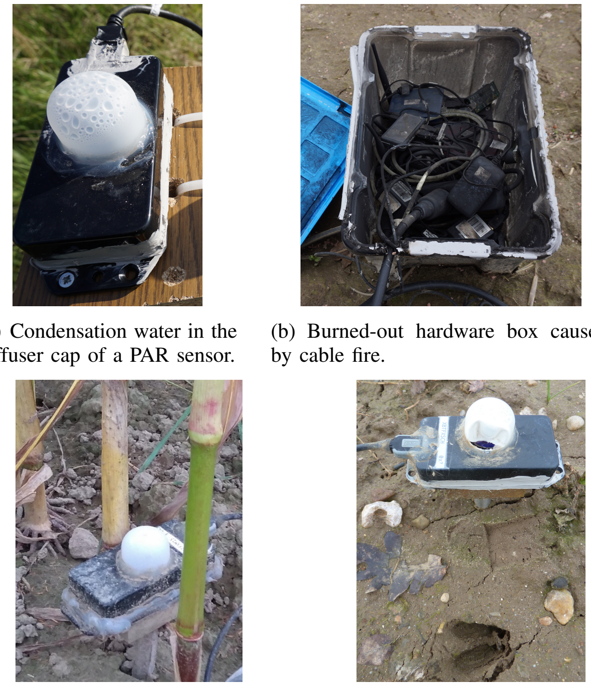
our experience of real-world deployments. The focus of these deployments is on a specific crop parameter, namely the leaf area index (LAI). The LAI is a widely-used key parameter that provides information about the photosynthetically performance and vital conditions of plants, cf. [10]. The parameter is related to vegetative biomass and simply defined as a dimensionless quantity of leaf area per ground surface area. Since it also serves as an indicator for yield-reducing processes caused by diseases or mismanagement, it is very interesting in the agricultural context and used for yield modeling. The overarching goal of our system is long-term continuous crop monitoring that enables LAI profiles with a fine-grained spatio-temporal resolution. Therefore, our previously developed sensor prototype [4] (cf. Fig.1) is used. It senses the ambient light in the photosynthetically active radiation (PAR) range. From two simultaneous PAR measurements, one below and the other one above the canopy, the transmittance of solar irradiation through the canopy can be derived that allows an estimation of the LAI.

II. Real-World Challenges

Although a considerable progress has been made in the last decade, the deployment and maintenance of real-world WSNs are still very challenging. Beyond the general WSN challenges, i.e. hardware constraints of small sensor devices, their power consumption, and low-power communication (cf. [1]), there are specific additional challenges for long-term outdoor deployments. The main reasons of such challenges can be grouped into two categories: (1) environmental induced challenges and, particularly for agricultural deployments, (2) wildlife caused challenges. Figure 1 provides a little impression by a selected set of pictures showing technical problems with which we were faced in our deployments.



(a) Condensation water in the diffuser cap of a PAR sensor.

(b) Burned-out hardware box caused by cable fire.

(c) Mud on a ground-level PAR sensor.

(d) Bite marks from wildlife.

Fig. 1. Impressions of harsh outdoor impacts on WSN equipment.

A. Environmental Challenges

The natural environment has a strong impact on the operability of a WSN. Sensor motes are exposed to harsh weather conditions with probably high temperature fluctuations and rainfalls. Also humidity and soil moisture tends to be comparatively high, particularly if devices are directly deployed in the field. During our first deployment, it turned out for instance that the cases we designed were not completely sealed and durably water-resistant. As a consequence, condensation water occurred under the diffuser cap of some sensors (cf. Fig. 1(a)). Moreover, motes are prone to corrosion and short circuits which could lead to operational instabilities. Even worse, serious hardware failures are possible and have actually been occurred (cf. Fig.1(b)). Furthermore, in dry seasons, dust can impair sensors, whereas in rain periods, mud can influence sensors that are placed at ground level (cf. Fig. 1(c)).

However, not only the sensor hardware is affected by adverse weather effects, but also the connectivity of the entire network since radio link qualities are sensitive about highly variable environmental conditions. Moreover, agricultural fields usually are far away from the electricity grid. While this has not impact on low-power and already battery-driven WSN devices, the lack in reliable power sources does affect more complex IoT components such as weather stations and Internet gateways. Hence, it has to fall back on solar energy solutions. Unfortunately, in some of our deployments, the installed solar energy equipment appeared to be not fully reliable and led to partial disruptions.

B. Wildlife-related Challenges

Whenever sensors are deployed in rural areas for an unattended operation, conflicts with animals and wildlife are unavoidable. Moved sensors, nibbled cables, or even bit marks on sensors (cf. Fig.1(d)) are not uncommon for ground-level equipment. But also sensors placed on higher stands above crop level could temporarily be covered by birds. Particularly in our use case that depends on PAR measurements, this covering is totally interfering. Finally, also insects forming nests in sensor housings can have negative impacts.

Overall, suchlike challenges of both categories were also reported by [11], more than one decade ago, but still relevant and existing in the community as recent publications on this subject show. In addition, farming activities and, sadly, vandalism are reported to be a problem for agricultural WSNs [8] but fortunately did not occur in our deployments.

Some of these challenges could be mitigated by industrial outdoor cases, enhanced solar energy equipment, professional uninterruptible power supply (UPS) systems, more robust and shielded cables, or by electric fences. However, it is costly and a tradeoffs between such additional costs and operational safety arise. Nevertheless, It is hardly possible to tackle all challenges that potentially could occur in real-world deployments and unforeseen situations should still be expected. In practice, a non-disruptive WSN operation could not be guaranteed and erroneous sensors could never totally prevented. Thus, we believe that sensor redundancy is the most reasonable approach to cope with adverse and unpredictable situations. As a consequence, with regard to the return on investment (RoI), production costs of individual sensors become relevant. Hence, it is crucial to realize a cost-efficient sensing platform as already proposed with our sensor prototype [4].

III. System Design

A. Concept & Architecture

In order to cope with both types of challenge mentioned in the previous section we use well-tried principles. Our key approaches are hardware redundancy, software simplicity, and remote control of the entire system. The architecture we have developed primarily comprises a WSN-based monitoring system that is tailored for in-situ LAI assessment. Therefore, two essential measurement positions are required: a ground-level sensor below the canopy (G) and a corresponding above reference sensor (R), both measuring incoming solar irradiation in the PAR range, cf. [4]. Both devices must not be located at the same position, but their spatial distance should not be too large either in order to ensure similar irradiation conditions. Hence, we believe that clustering of several spatially distributed ground sensors in communication range with a single above reference acting as cluster head is reasonable for LAI monitoring WSNs. Thus, sensor motes were organized in clusters using a simple star-topology within each cluster. Cluster heads compared to ordinary ground sensors were assumed not to be power-constrained and always active. This appears reasonable because this kind of sensor devices could in practice be powered by small solar panels. In conclusion, in our current system, there is no demand for routing protocols. Also time synchronization protocols are not required, since cluster heads are constantly reachable to ground sensors. Thus, they could also adjust their reference sampling to the receive events of ground packets. Cluster heads, in turn, are connected to a central base station. Depending on the WSN size, multi-hop routing might be necessary for this connections but are currently not yet considered in our deployments. Instead, cluster heads are connected via WLAN.

The overall architectural concept consists not only of the WSN itself, but also of an IoT-based infrastructure as sketched in the architectural overview of our system in Figure 2. For that purpose, the central base station acts as a gateway to a conventional IP-based IoT network. Internet connectivity is established via public land mobile networks (PLMN) communication which is realized by an LTE modem attached to the gateway. The data gathered by sensors and collected by the base station is further transmitted to a farm management information system (FMIS) in general (or a customized server in our case) for data analytics and visualization. Data transport, is realized by MQTT [3], a publish-subscribe messaging protocol with hierarchical structured topics for individual message streams. MQTT clients can act as a publisher and/or as a subscriber and exchange messages according to specific topics.

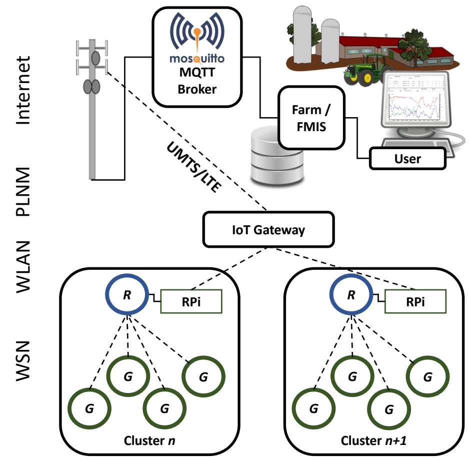


Fig. 2. Architectural Overview. Clustered ground-level sensors (G) and above reference motes (R) are connected to Raspberry Pis (RPi). Via PLMN communication, they are further integrated in an MQTT-based IoT architecture, making in-situ crop information instantaneously available.

A central broker manages connections to these clients and their registrations. MQTT is suitable to exchange periodically gathered sensor data from agricultural WSNs, cf. [5], [14]. In the current state of our architecture, MQTT is used at the IoT layer only, but following [14], the integration of MQTT into the WSN is planned as future work.

Overall, our architecture is modularly designed and flexible because standard open-source IoT software and commercial off-the-shelf (COTS) hardware is used. Further types of agricultural sensors such as soil moisture and temperature sensors can seamlessly be integrated. Also a smartphone-based LAI assessment [9] has been prototypically connected. The linking to complementary technologies such as remote sensing would be feasible as well and very interesting for our future work.

B. In-situ WSN

1) Hardware Components: The low-cost IEEE 802.15.4 compliant sensor prototype introduced in our preliminary work [4], i.e. a TelosB[1]-based platform (8 MHz TI MSP430 MCU, 10 kB RAM), is used as basic sensor in our monitoring WSN. This open-source COTS mote has three integrated environmental sensors for temperature, humidity, and light. Using a suitable optical filter and diffuser accessory, the latter sensor has been shown to be appropriate for PAR measurements that allow to derive reliable LAI estimates. In addition, further external sensors can be connected using the platform's SPI or I^2C bus and its GPIOs.

In harsh outdoor environments, wireless communication is prone to be affected by adverse weather conditions. Link qualities are known to be highly varying in practice. Signals in the 2.4 GHz radio band, as used in WLANs and also in WSNs, are attenuated by humid air and wet plants. In fact, high error rates were observed in our deployments. These can be mitigated by forward error correction (FEC) techniques such as network coding, which has already been demonstrated

[1] https://www.advanticsys.com/shop/mtmcm5000msp-p-14.html

TABLE I
HARDWARE OVERVIEW OF IN-SITU COMPONENTS.

Component	Description	Task	Costs (*USD*)
TelosB	802.15.4 mote + antenna	sensing/gateway	105
Accessory	case, diffuser, filter, cf. [4]	sensing/safety	35
Raspberry Pi 3	single-board computer + accessory	cluster head/ gateway	55
Huawei E3372	LTE modem	Internet comm.	45
joy-IT StromPi	UPS	safety	40
DS1302	RTC	safety	2

to be feasible for our scenario [14]. On the other hand, also wired links are prone to failure due to farming or wildlife activities. Because of inherently unreliable data delivery and in order to increase redundancy, we precautionary decided to use both, wireless and wired connections for redundant sensor data transmissions in our first deployment generation. Since an exchange of batteries during the deployment would be very interfering, we also reused USB connection for additionally powering all sensors. Also reprogramming of sensors in case of software reconfigurations or failures was easily possible via USB. That allowed testing and evaluation of different software applications. According to the cluster concept, we used clusters of four ground motes. Each mote was attached via USB to a linux-based Raspberry Pi 3, a small, fully-equipped, and cost-efficient single-board computer that is widely used in the IoT context. These computers were wirelessly integrated into a WLAN provided by a central ALIX.6F2 router with UMTS connectivity. Already in laboratory environments, we observed occasional software crashes and freezing. Thus, for reasons of operational safety, we decided to install mechanical timers to regularly power off all components during night phases when sensor readings are not required. By this means, we ensure that the system resumes at least the following day.

In the second deployment generation, the WSN was rearranged to a completely wireless operability, i.e. wireless communication and battery-driven sensors. In addition, Raspberry Pis were also used as cluster heads along with TelosBs as WSN gateways. These motes were additionally equipped with external antennas to amplify radio performance and communication range. For consistency and software unification, the ALIX router acting as IoT gateway was replaced by a central Pi with LTE modem. Each Pi was additionally equipped with real time clocks (RTCs) which eases the operation in many ways. For sake of completeness, the hardware costs of both in-situ devices that are composed for the monitoring system are listed in Table I.

2) Software Components: The basic acquisition software of our system is installed on the sensor platform. We use TinyOS[2], a common open-source operating system tailored for resource-constrained devices, and adapted the sensing application from [4]. This application is still kept as simple and light-weight as possible and focused on essential features. Furthermore, we use extensive logging of all possible data that can be retrieved on both, the universal asynchronous receiver-transmitter (UART) and the radio interface, extended with time stamps and sequence numbers (SNs). This also includes additional reports about various events such as resets/reboots of all involved hardware components or NTP synchronization events, for instance. Again, it has to be differentiated between the first and the second generation of our deployments. In the former that uses a wired backbone for energy supply, a constant sampling rate of 30 samples/h was used, whereas the rate is precautionary reduced to 6 samples/h for the battery mode of second generation. Here, low power listening (LPL), the duty cycling of TinyOS, is activated that switches devices to low-power modes during idle periods. That means, an LPL interval of 10 min is configured, to further reduce the energy demand of ground-level sensor devices.

In both generations, each sensor sample consists of a collection of readings from all environmental sensors available on the platform, i.e. temperature, humidity, and PAR, one by another. In order to get more reliable averages and also to purposely observe small-scale fluctuations, the PAR sensor is sampled multiple times in a short burst of 25 readings with a temporal spacing of 50 ms. Immediately after all sensors were sampled, gathered data is then merged and added as payload to an 802.15.4 frame, together with continuously incremented SNs. This data frame is then transmitted as broadcast. Thus, it can be received by all active motes in communication range, in particular by the cluster heads or the base station that forwards the payload to the backbone system. By using broadcast transmission, ground sensors can receive transmissions amongst each other. These are leveraged to keep track of link qualities from neighboring devices, since received signal strength indicator (RSSI) and link quality indicator (LQI) information can be retrieved from the 802.15.4 radio chip. That is particularly relevant in the first deployment generation with always active motes. For the purpose of link quality monitoring, here suchlike information is continuously collected and transmitted in conjunction with each sample and could be used for future analysis and network protocol optimizations. Indeed, in both deployment generations, the selected sampling rate is a vast oversampling and particularly not required for a pure LAI assessment. However, our goal is to create an always-on multipurpose WSN testbed as well as an extensive data set. This set is intended to be adequate for advanced analysis of various factors such as link quality investigations or relevant impacts on WSN-based LAI assessment.

As reliable operations of hard- and software components during an entire deployment are not expectable, we implemented various safety mechanism. One mechanism is passive SN synchronization that replaces a strict time synchronization protocol. That means, whenever a sensor receives a transmission of neighboring motes, it inspects the containing SN. If there is a certain gap to its own SN state, which probably is caused by a software reset, the current SN is adapted. Due to LPL in the second deployment generation, the

[2]https://github.com/tinyos

SN synchronization requires a modification. Here, motes are programmed to remain active for a certain time after reboots in order to capture potential transmissions of other devices.

Moreover, we also implemented safety mechanism on the fully-equipped devices. For instance, for an unattended operation, Raspberry Pis are responsible for monitoring incoming data of each attached cluster sensor and automatically reboots of affected sensors. Furthermore, the central gateway establishes a permanent SSH reverse tunnel to the Internet server that allows remote access to Pis and sensors that could manually be reprogrammed and adapted to unforeseen challenges.

3) Energy Considerations : In order to evaluate the energy demand of motes and to validate whether the battery capacity is sufficient to ensure an operation across the growing season of common crop types, an empirical energy assessment was conducted. We measured the electric current in Ampere with a Fluke 289 True-RMS industrial multimeter for a duration of 100 h and found the average consumption to be roughly 0.2 mA. That is consistent to the TelosB specification and, assuming common capacities of two AA alkaline batteries, even a very conservative energy estimation results in a sensor lifetime that will be perfectly adequate for usual crop growing cycles and most agricultural applications.

C. Remote Monitoring

The core of the IoT infrastructure is the Mosquitto[3] MQTT broker that is running on the Internet server. The WSN-IoT gateway periodically publishes sensor data in specific messages to that broker. These messages are efficiently serialized with Google protocol buffers[4] (protobuf) and subscribed and stored in a data base. An Apache server provides a web-based graphical user interface (GUI) and queries the data base. It is responsible for data analytics and appropriate visualization of user-initiated content such as temperature and humidity graphs or LAI trajectories. Furthermore, current sensor status information is retrievable in the GUI. Therefore, the server monitors the operability of the network and informs the user of connectivity disruptions or sensor failures. Using periodic sensor data as keep-alives, failures are recognized and notifications are displayed in the GUI. In addition, smartphone notifications via instant messengers are also conceivable. At the same time, the server provides access to individual sensors for sake of remote reconfiguration and reprogramming. Beyond WSN data, the Internet server uses external weather information provided by the Deutscher Wetterdienst (DWD)[5] that can be combined with WSN-gathered information.

IV. Real-world Deployments & Preliminary Experimental Results

We have experimentally deployed our monitoring system in the 2016 and 2017 growing seasons at two sites with experimental crop fields in Lower Saxony, Germany: (1) at the Institute for Crop and Soil Science, Julius Kühn-Institute (JKI), Braunschweig and (2) at the Faculty of Agricultural Sciences and Landscape Architecture (AuL), University of Applied Science, Osnabrück. During these deployments, we observed LAI developments of three economically important crop types, namely winter wheat, rape, and maize. A key data overview of the deployments and sampling properties is given in Table II.

TABLE II
Deployment overview.

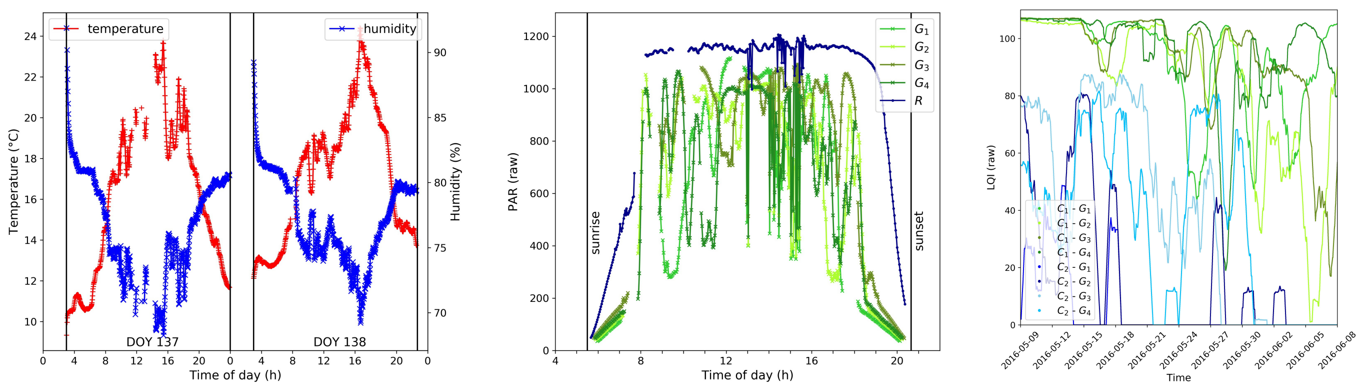
Deployment	JKI 1	JKI 2	AuL 1	AuL 2
Location	52.296° N, 10.436° E		52.311° N, 8.115° E	
Software	1st generation		2nd generation	
Year	2016	2016/17	2017	2017
DOY	105–178	293–11	138–184	187–227
Duration (days)	74	85	47	41
Crop type	wheat	rape	wheat	maize
Operation (h/day)	21		19	
Sampling interval (min)	2		10	
Sampling phase	03:00 – 00:00		04:00 – 23:00	
# Samples/day	630		114	

An analysis of the collected data is promising to have a lot of potential. It could bring new insights such as findings on the environmental impacts on WSN-based LAI assessment, for instance. However, such an analysis is very extensive, currently work in progress, and will be part of our future work. Thus, it is out of scope of this paper which focuses on system design and experiences gained in real-word deployments. Nevertheless, some preliminary results are exemplarily demonstrated by Figure 3 as an outlook.

Figure 3(a) shows the temperature and the humidity curves of two days, gathered by a ground-level sensor that was deployed in a wheat field. The midday peak of both curves can be observed and also that they are similar but inverse to one another. The humidity curve also confirms the relatively high humidity perceived by sensors at ground level on both days. The second subfigure (Fig. 3(b)) visualizes the daily time series of PAR values collected by a single cluster, i.e. one above reference sensor (R in blue) and four ground-level sensors (G_i, shaded in green). From the ratio G_i to R, LAI estimates can be derived (cf. [4]). However, the time series in this subfigure also reveal that only at dawn or dusk, PAR curves are found to have a certain stability, whereas during the remaining day, they are highly varying. Thus, an appropriate processing will be required for a reliable LAI assessment.

Finally, in Figure 3(c), averaged link qualities within cluster C_1 are shown for a period of one month in the beginning of the wheat growing season. These are represented by LQI averages of transmissions from ground sensors $G_1 - G_4$ to their cluster head (shaded in green). Moreover, transmissions of sensors from the neighboring cluster C_2 (shaded in blue) were occasionally received by C_1's cluster head. In large-scale deployments, frequency division amongst different clusters is easily possible in our approach, but due to the sparse channel utilization not applied here. The LQI curves show that link qualities were naturally varying and, moreover, also decreasing during the specific month visualized in the subfigure. The

[3]https://mosquitto.org
[4]https://developers.google.com/protocol-buffers/
[5]https://www.dwd.de/EN/Home/home_node.html



(a) Temperature and humidity of two days (single sensor).

(b) PAR measurements of cluster C_1 at DOY 126 (single cluster; sensors $G_1 - G_4$).

(c) LQI values captured by the cluster head of C_1 (neighboring clusters C_1 and C_2).

Fig. 3. Exemplary time series of different information gathered in-situ by the first agricultural deployment (JKI 1).

reason for the latter observation is presumably the crop growth. An analysis of this interesting relationship will be part of our future work.

V. Conclusion

In this paper, we presented a holistic IoT-based agricultural monitoring system. The main component of this system is an in-situ WSN that is tailored for the collection of sensor information that is of special interest for Smart Farming. The focus of the sensor network is on the continuous assessment of the LAI that is relevant for a precise monitoring of crop growth processes. Using an MQTT-based IoT infrastructure and PLMN connectivity, this sensor network is connected to a central server. The server is responsible for data persistence, analytics, and also for visualization that can be used as decision support for farmers. As future work, we plan to integrate additional types of environmental sensors into our system to enrich the monitoring range. This could allow a wider analysis, further improve decision support, and enable additional agricultural insights and applications.

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