https://doi.org/10.2352/EI.2025.37.3.MOBMU-309

Potential and Limitations of Computer Vision for Crop Water Stress Detection in Irrigation Scheduling

Lukasz Rojek[12], Matthias Möller[2], Markus Richter[2], Monika Bischoff-Schaefer, Reiner Creutzburg[13]

[1] SRH Berlin University of Applied Sciences, Berlin School of Technology and Architecture, Sonnenallee 221, D-12059 Berlin, Germany

[2] Berliner Hochschule für Technik, Berlin University of Applied Sciences, Luxemburger Straße 10, D-13353 Berlin, Germany

[3] Technische Hochschule Brandenburg, Department of Informatics and Media, IT- and Media Forensics Lab, Magdeburger Str. 50, D-14770 Brandenburg, Germany

E-mails: lukasz.rojek@srh.de, matthias.moeller@bht-berlin.de, markus.richter@bht-berlin.de, reiner.creutzburg@srh.de

Abstract

Computer Vision has become increasingly important in smart farming applications, including scheduling crop irrigation. A combination of various remote sensing devices enables continuous monitoring of a crop and non-destructive prediction of irrigation time. Appropriately scheduled and precisely targeted irrigation enables sustainable use of this limited resource.

In agriculture, absorption-based and thermal-based imagery are used to monitor plant conditions through indices such as the Normalized Difference Water Index (NDWI) and Crop Water Stress Index (CWSI).

This paper provides an overview of the concept and components of monitoring systems for automated irrigation scheduling. It explains the potential and limitations of applying computer vision-based systems for plant stress detection, providing insights to advance understanding in this growing field.

Introduction

Agriculture is a complex production process that relies on various interdependent factors, including irrigation scheduling, directly affecting crop quality and productivity. The efficient use of water in agriculture remains one of the most critical challenges modern technologies aim to address [1].

Irrigation significantly impacts crop yield, particularly in protected environments (e.g., greenhouses) that lack a natural water supply (such as rainwater) and in open fields. In semi-arid and humid areas, additional irrigation is often used to increase crop productivity [2]. Common irrigation methods include flooding water on the field surface, subsurface irrigation, applying water beneath the ground surface, sprinkler systems that spray water under pressure, and drip or trickle irrigation, which delivers water directly to the root zone [3].

The main goal of irrigation scheduling is to determine the correct time and amount of water to be applied to a crop to optimize production and offset adverse environmental impacts [4]. Irrigating too early or too late cannot ensure the required plant water status throughout the growing cycle [5]. Appropriately scheduled and precisely targeted irrigation concerning the actual water demand of the crop enables sustainable use of this limited resource. It also prevents environmental issues such as groundwater pollution and runoff [6][7]. Poor irrigation scheduling results, on the other hand, in under-watering or waterlogging [8].

An efficient irrigation system is based on predicting crop water demand. It requires an understanding of the dynamics of plant water use, which is related to continuously changing weather conditions, soil characteristics, and plant physiology. A close inspection of the plant using human observations, focusing on indicators such as the color of the substrate surface, the presence of flagging foliage, or slight color changes in leaves that occur in some crops just before wilting, is not precise enough. Some growers attempt to gauge plant drought stress by inserting a finger into the soil or touching the leaves. However, human touch is not a reliable measure of moisture, as the absence of moisture is typically perceived only in relatively dry conditions, which are already suboptimal for plant growth [3]. Moreover, if water stress symptoms become visible to the bare human eye, the crop is likely already suffering under a higher level of water stress. Human expertise in irrigation management is not scalable or universally accessible across all fields, farms, or crops. It is often slow in analyzing data and processing information in real time [1]. Recent research has indicated that growers who do not use any irrigation scheduling tool but rely on heuristic methods, such as manual, time-based, or volume-based irrigation, tend to register significant water losses [8].

The simplest and most cost-effective method for automating irrigation is using timers to control irrigation cycles. This approach is particularly feasible in soilless media used in greenhouses. Although this substrate has high water-holding capacity, it typically has high infiltration rates and porosity, allowing excess water to drain away readily. As a result, irrigation can be applied on a fixed schedule, so watering always occurs earlier and for longer than the crop might require. However, a purely time-based approach can also lead to suboptimal root zone moisture conditions if the substrate cannot provide adequate oxygen for the roots under saturated conditions. For instance, if the substrate depth is shallow, the plants use water relatively slowly [3].

An intelligent and automated monitoring system is a valuable tool and time-saver for farmers. Figure 1 illustrates a general system cycle pipeline. A decision-support system typically collects and processes data from various sources, such as imaging devices, weather stations, and soil sensors, to achieve a balance between water quantity and irrigation time. Modern measuring devices are often mounted on mobile platforms such as aerial drones or ground sensing rovers, providing spatial information to ensure precise and targeted irrigation. By continuously monitoring crop water status, the system assists farmers in creating effective plans for optimal plant treatment considering water availability and crop requirements.

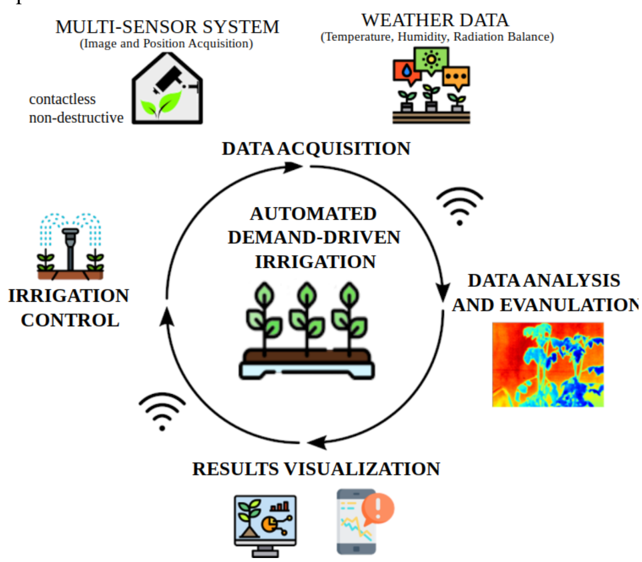


Figure 1: A general system cycle pipeline of an automated irrigation system.

This paper provides an overview of methods and components for predicting the optimal irrigation time. The structure of the paper is as follows: Section 2 reviews various irrigation scheduling methods. Section 3 details remote sensing techniques for water stress detection. Section 4 discusses the components and measurement methods of computer vision-based systems. Finally, Section 5 concludes the paper with insights into PlantSens, an automated monitoring system for remote water stress detection.

Irrigation Scheduling Methods

Irrigation scheduling methods can be categorized into the following approaches: (1) weather-based monitoring, (2) soil-based monitoring, and (3) plant-based monitoring, as shown in Figure 2.

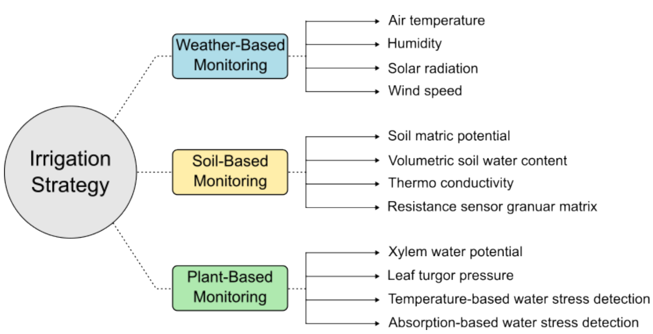


Figure 2: Schematic overview of irrigation scheduling methods [8].

Weather-based monitoring measures environmental conditions such as humidity, wind speed, solar radiation, and air temperature to estimate water loss to the atmosphere through evapotranspiration, including soil evaporation and plant transpiration. The Penman-Monteith method is the most commonly used technique for estimating reference evapotranspiration. However, as a point-based approach, it is limited to local-scale applications and unsuitable for large, heterogeneous areas [9]. This method is a useful alternative for providing an approximate irrigation schedule in cases where soil or plant measurements are not feasible.

The traditional methods for crop water stress detection are based on soil moisture measurements [9]. The soil-based monitoring involves measuring the soil water potential or soil water content. Soil sensors are conventional devices that are easy to apply and widely used for irrigation scheduling. However, since water deficiency does not occur uniformly across a field, the assessed degree of water deficit stress imposed on the plants does not necessarily represent the water deficit stress level that the plants actually experience. For instance, lower soil moisture levels could be sufficient during periods of less intensive evapotranspiration but not necessarily during high evaporative demand. Another limitation of soil-based monitoring is the high number of sensors often required for heterogeneity and precise monitoring, making the system quite expensive and difficult to maintain [10].

Plant-based monitoring refers to direct sensing of plant water status parameters and indirect sensing of plant response to stress. The direct sensing techniques, such as pressure chambers or leaf diffusion porometers, are more accurate but labor-intensive, destructive, and time-consuming [11].

Remote Sensing Methods

In recent decades, indirect methods for assessing plant stress have gained increasing importance, driven by advancements in remote sensing technology, particularly imaging systems. Numerous studies have investigated various indicators, such as leaf surface temperature and spectral absorption related to leaf water content. These techniques offer a significant advantage over direct stress detection, as infrared thermography and optical spectroscopy enable non-invasive monitoring without physical contact with plant leaves. In contrast, soil-based and direct sensing methods collect data from a single location on a specific plant or plant part, providing only an averaged representation of conditions. Therefore, these techniques are not well suited for large-scale crop monitoring due to the limited number of plants that can be measured simultaneously. However, when mounted on a moving platform, remote imaging systems enable the observation of entire areas rather than just single points, significantly enhancing monitoring efficiency [10]. The advantages of using imaging technology for remote sensing are that it can be fairly accurate, nondestructive, and yield consistent results [12].

Absorption-Based Water Stress Detection

Leaves interact with sunlight across a broad spectral range, including the visible (VIS, 400–700 nm), near-infrared (NIR, 700–1000 nm), and shortwave infrared (SWIR, 1000–3000 nm, also known as middle infrared) regions [13]. In the visible spectrum, light absorption is primarily driven by photosynthetic pigments, as water absorption in this range is minimal. A high reflectance in the visible spectrum typically indicates reduced chlorophyll content, corresponding to lower photosynthetic activity.

Machine vision is not capable of using direct reflectance measurements as a metric for plant stress detection, which is why reflectance indices (RI) that combine two or more spectral bands are used [14]. The reflectance indices for crop water stress detection are summarized in Table 1.

Table 1: Reflectance indices for crop water stress detection.

Index	Formula	References
Normalized Difference Vegetation Index	$NDVI = \frac{NIR-R}{NIR+R}$ (1)	Rouse et al., 1974 [15]
Water Index	$WI = \frac{R_{900}}{R_{970}}$ (2)	Penuelas et al., 1997 [16]
Water Index	$WI = \frac{SWIR_{1300}}{SWIR_{1450}}$ (3)	Seelig et al., 2009 [17]
Normalized Difference Water Index	$NDWI = \frac{R_{860}-R_{1240}}{R_{860}+R_{1240}}$ (4)	Gao, 1996 [18]

The normalized difference vegetation index (NDVI) is one of the most widely recognized indices. NDVI quantifies vegetation greenness, density, and yield by comparing reflectance in the near-infrared (strongly reflected by vegetation) and red (strongly absorbed by vegetation) spectral regions. The range of NDVI values is from -1.0 to 1.0, where negative values and values near zero indicate non-vegetation, positive values from 0.1 to 0.5 represent sparse vegetation, and even higher positive values from 0.6 to 1 represent dense green vegetation [19].

Besides chlorophyll, water is the second strongest absorbing molecule in leaves, with absorption peaks at approximately 970, 1200, 1450, 1950, and 2500 nm [20]. As plant dehydrates, water loss decreases absorption and increases reflectance at these wavelengths. Various spectral indices have been developed to assess plant water stress remotely by combining water-sensitive absorption bands.

Seelig et al. (2009) focused on SWIR absorption maxima and defined WI as the ratio of reflectance at 1300 nm (low water absorption) and 1450 nm (high water absorption). Gao (1996) explored water content estimation using reflectance at 860 nm and 1240 nm. While NIR absorption at 970 and 1200 nm is lower than at the more sensitive SWIR bands (1450 and 1950 nm), these longer wavelengths are often impractical for remote sensing due to strong atmospheric water vapor absorption, which limits their availability in sunlight reaching the Earth's surface. As a result, Seelig's method is challenging to implement, especially in environments without external light sources. Consequently, many studies have focused on NIR-based water indices, such as the normalized difference water index (NDWI):

$$NDWI = \frac{R_{970}-R_x}{R_{970}+R_x} \quad (6)$$

where R_x represents wavelengths such as 850, 880, or 900 nm, depending on the plant species and specific water content estimation requirements.

Temperature-Based Water Stress Detection

Indirect detection of plant water stress is often based on leaf temperature, which is inversely correlated with transpiration and stomatal opening. This effect is based on the fact that an insufficient water supply under a higher ambient temperature and vapor pressure deficit (VPD) results in the closure of leaf stomata, increasing crop temperature [10]. For instance, Figure 3 illustrates temperature differences between stressed and well-irrigated plants.

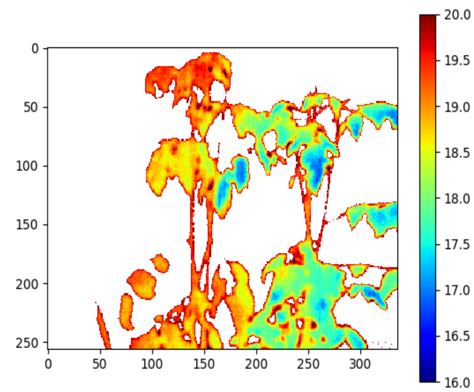


Figure 3: Temperature difference between a stressed plant (left) and non-stressed (right) [21].

Idso et al. (1981) and Jackson et al. (1981) presented a method for quantifying this stress by determining the crop water stress index (CWSI) as:

$$CWSI = \frac{T_{canopy}-T_{wet}}{T_{dry}-T_{wet}} \quad (7)$$

where T_{canopy} refers to the current canopy temperature, T_{wet} is the temperature of a non-stressed leaf transpiring at the maximum potential rate by stomata being completely open and T_{dry} is the temperature of stressed leaf not transpiring where stomata are fully closed. The CWSI tends towards 0 after irrigation and moves continuously towards 1 as soil water becomes limiting. The most challenging part of the CWSI approach is accurately determining the upper and lower limits, which correspond to the maximum stress and non-stress conditions, respectively [10].

Computer Vision-Based Systems

Computer vision has potential in agriculture since industrial cameras offer promising solutions to detect changes in plant's biochemical and biophysical characteristics. Besides imaging objects in visible light, machine vision systems can also inspect objects in spectral ranges invisible to human eyes, such as infrared.

Camera Characteristics

A high-performance vision system relies on well-tuned hardware and software to accurately capture, process, and analyze images. The following components and parameters are essential for ensuring optimal system functionality.

Image Sensor

The Image Sensor is responsible for converting light reflections into digital information. The image quality depends on several factors, such as sensor resolution, sensitivity, and noise level.

Image Processing

The Image Processor analyzes captured data and extracts meaningful information. Vision systems typically use two processing approaches: build-in and external processing. A device with a built-in processor, also known as a smart camera, reduces the need for external computing by analyzing the images internally. External processing requires transmitting raw data to a powerful computing unit like a server for advanced operations such as AI-based analysis.

Communication Interface

A Communication Interface integrates the camera into an automated system. A vision system must efficiently transmit data between the camera and the processing unit. Standard communication interfaces include USB 3.0, GigE (Gigabit Ethernet), and Camera Link.

Remote Communication

A reliable network connection is required to transmit data from the camera system to external systems. Depending on the application, this may involve Ethernet protocols, wireless communication, or cloud integration for remote processing and monitoring.

Camera Lens

An appropriate camera lens ensures that all relevant objects and details are visible in the image. It can also control the amount of light entering the lens.

Lighting

Proper lighting is important for obtaining high-quality images. An additional light source may be needed if the required wavelength is insufficient or completely unavailable in the measuring environment.

Image Acquisition Techniques

As shown in Figure 4, the most common types of industrial cameras are RGB, multispectral, hyperspectral, and thermal cameras.

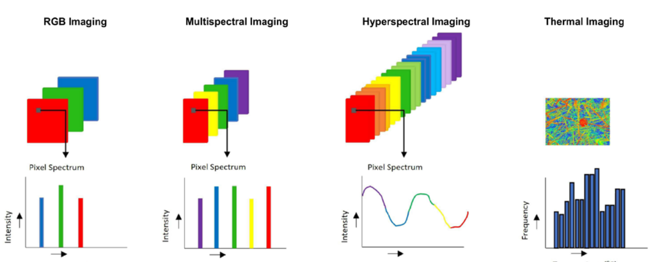


Figure 4: Overview of the common camera types [19].

Each type has distinct characteristics and applications in precision agriculture and other fields. RGB imaging is widely used for capturing visible light and for various precision agriculture applications such as vegetation indices or disease detection. Multispectral imaging collects a few discrete spectral bands, typically less than 10, typically near- and short-infrared. Multispectral imagery can be used to identify stresses in crops early. Hyperspectral Imaging consists of continuous narrow bands with a 10-20 nm spectral resolution. Hyperspectral images can contain hundreds of electromagnetic spectrum bands and have more informational content than multispectral imaging, but complexity is escalated due to redundant information. Hyperspectral imaging is mainly used for crop classification and weed identification. Thermal imaging senses infrared radiation emitted by an object to produce a thermal image of the corresponding object. It can be used to detect water stress in crops, considering that the temperature for the plants under water stress is higher than that of unstressed plants [19].

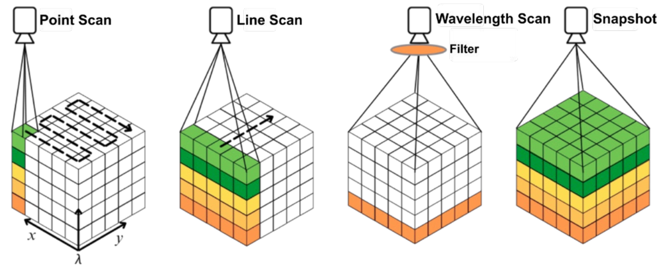


Figure 5: Different modes of image acquisition based on the hyperspectral camera [24].

All four camera types can be further classified into point scan, line scan, and snapshot systems. The different modes of image acquisition based on the hyperspectral camera are illustrated in Figure 5. Each acquisition mode has advantages and disadvantages for real-time applications, data collection, analysis, and management. While a point scan sensor collects data at discrete points, providing very high spectral resolution, a line scan sensor acquires data in a push-broom pattern and requires either the sensor or the observed object to move to capture a complete image. Line scan sensors are known to record distorted images once vibrations are introduced in the sensor or the object while data capture is in process, particularly when mounted on autonomous platforms such as aerial drones. Wavelength scan sensors require an additional filter that distributes specific wavelengths. Snapshot sensors acquire data simultaneously over the entire scene, requiring large amounts of data storage, which can be a limitation in real-time applications. The choice of image acquisition mode can impact the data volume, processing complexity, and the type of analysis that can be performed. Selecting the appropriate method depends on the specific application requirements, available hardware, and computational resources [24].

PlantSens (Prototype)

The R&D PlantSens project was one of the initiatives funded by Germany's Federal Ministry of Food and Agriculture (ger: Bundesministerium für Ernährung und Landwirtschaft, BMEL). This study was driven by the lack of a decision-support system for remotely monitoring crop water status in real time. The primary objective was to develop an automated monitoring system for remote water stress detection.

The system consists of three components: (1) a measuring robot for parallel image acquisition in different wavelengths, (2) a central server for data storing, analysis, and alarming functions, and (3) a meteorological station recording environmental parameters [10].

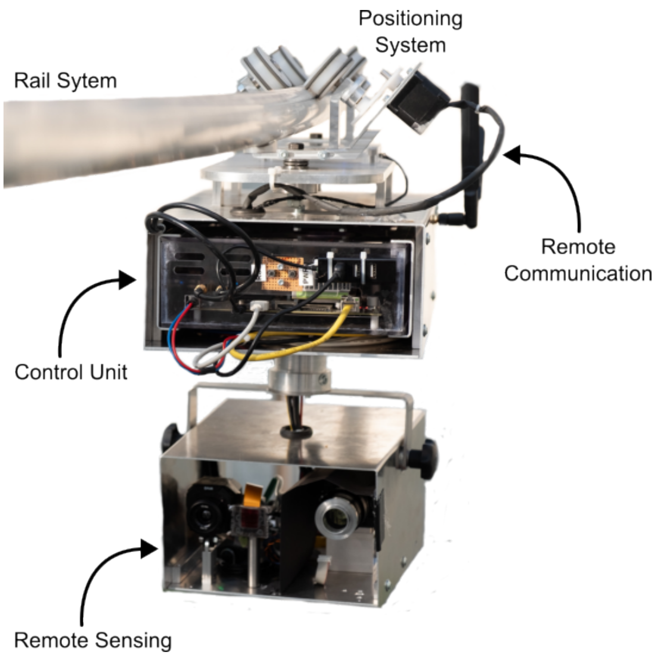


Figure 6: Prototype of the remote sensing system mounted on a self-driving platform.

The core of the PlantSens monitoring system is the multi-sensor measuring robot. The system was initially developed as a rail-based construction for kinematic measurements. The measuring unit is mounted on a self-driving platform, moving over the crops and acquiring images of the top leaves of plants. As illustrated in Figure 6, the prototype is divided into the operating and control unit, located in the upper and the measuring head in the lower part of the housing. The measuring head integrates three camera sensors: Xenics Bobcat for short-wave-infrared imagery, FLIR Vue Pro for thermal imagery, and Raspberry PI NoIR for visible and near-infrared image acquisition. These sensors operate across a wavelength range of 400 to 13,500 nm, enabling redundant water stress detection by combining thermal-based and absorption-based measuring methods. The acquired image data are transmitted in real-time to the central server, where they are analyzed to predict optimal crop irrigation timing [25]. PlantSens project is a good example of integrating advanced multi-sensor technology with automated image processing. By enabling real-time water stress detection in crops, the PlantSens system provides an efficient solution for optimizing irrigation management, ultimately supporting sustainable agriculture.

References

[1] H. Navarro-Hellín, J. Martínez-del-Rincon, R. Domingo-Miguel, F. Soto-Valles, and R. Torres-Sánchez, "A decision support system for managing irrigation in agriculture", Computers and Electronics in Agriculture, Elsevier, vol. 124, 121-131, 2016.

[2] M. P. González-Dugo, M. S. Moran, L. Mateos, and R. Bryant, "Canopy temperature variability as an indicator of crop water stress severity", Irrigation Science, vol. 24, 233-240, 2006.

[3] S. K. Srivastava, "Drip and surface irrigation methods: irrigation scheduling of onion, cauliflower, and tomato" in: A. Singh and M. R. Goyal (Eds.), "Micro Irrigation Engineering for Horticultural Crops", Taylor & Francis, 53-111, 2017.

[4] Y. Dong, "Irrigation Scheduling Methods: Overview and Recent Advances" in: M. Sultan and F. Ahmad (Eds.), "Irrigation and Drainage", IntechOpen, 2023.

[5] B. Xi, B. Clothier, M. Coleman, J. Duan, W. Hu, D. Li, N. Di, Y. Liu, J. Fu, J. Li, L. Jia, and J.-E. Fernández, "Irrigation management in poplar (Populus spp.) plantations: A review", Forest Ecology and Management, vol. 494, 119330, 2021.

[6] L. Bo, W. Tieliang, and S. Jian, "Crop water stress index for off-season greenhouse green peppers in Liaoning, China", Int. J. Agric. Biol. Eng., vol. 7, 28-35, 2024.

[7] W. R. DeTar, J. V. Penner, and H. A. Funk, "Airborne remote sensing to detect plant water stress in full canopy cotton", Am. Soci. Agric. Biol. Engineers, vol. 49, 655-665, 2006.

[8] E. Bwambale, F. K. Abagale, and G. K. Anornu, "Smart irrigation monitoring and control strategies for improving water use efficiency in precision agriculture: A review", Agricultural Water Management, 107324, 2022.

[9] S. S. Virnodkar, V. K. Pachghare, V. C. Patil, and S. K. Jha, "Remote sensing and machine learning for crop water stress determination in various crops: a critical review", Precision Agriculture, vol. 21, 1121-1155, 2020.

[10] L. Rojek, M. Möller, M. Richter, M. Bischoff-Schaefer, and K. Hehl, "PLANTSENS: A rail-based multi-sensor imaging system for redundant water stress detection in greenhouses", vol. 4, 100223, 2023.

[11] M. K. Nanda, U. Giri, and N. Bera, "Canopy Temperature-Based Water Stress Indices: Potential and Limitations" in: S.K. Bal, J. Mukherjee, B.U. Choudhury, and A.K. Dhawan (Eds.), "Advances in Crop Environment Interaction", Springer, 365–385, 2018.

[12] Y.-R. Chen, K. Chao, and M. S. Kim, "Machine vision technology for agricultural applications", Computers and Electronics in Agriculture, vol. 36, 173-191, 2002.

[13] N. Fahlgren, M. A. Gehan, and I. Baxter, "Lights, camera, action: high-throughput plant phenotyping is ready for a close-up", Curr. Opin. Plant Biol., vol. 24, 93–99, 2015.

[14] A. Elvanidi, N. Katsoulas, K. P. Ferentinos, T. Bartzanas, and C. Kittas, "Hyperspectral machine vision as a tool for water stress severity assessment in soilless tomato crop", Biosyst. Eng., vol. 165, 25–35, 2018.

[15] J. W. Rouse, R. H. Haas, J. A. Schell, D. W. Deering, and J. C. Harlan, "Monitoring the vernal advancement and retrogradation (green wave effect) of natural vegetation", NASA/GSFC Type III Final Report, 1974.

[16] J. Penuelas, J. Pinol, R. Ogaya, and I. Filella, "Estimation of plant water concentration by the reflectance Water Index WI (R900/R970)", Int. J. Rem. Sens., vol. 18, 2869–2875, 1997.

[17] H.-D. Seelig, A. Hoehn, L. S. Stodieck, D. M. Klaus, W. W. Adams, and W. J. Emery, "Plant water parameters and the remote sensing R1300/R1450 leaf water index: controlled condition dynamics during the development of water deficit stress", Irrig. Sci., vol. 27, 357–365, 2009.

[18] B. Gao, "NDWI – a normalized difference water index for remote sensing of vegetation liquid water from space", Rem. Sens. Environ., vol. 58, 257–266, 1996.

[19] S. Ghazal, A. Munir, and W. S. Quershi, “Computer vision in smart agriculture and precision farming: Techniques and applications”, Artificial Intelligence in Agriculture, vol. 13, 64-83, 2024.

[20] J. G. P. W. Clevers, L. Kooistra, and M. E. Schaepman, “Canopy water content retrieval from hyperspectral remote sensing”, in: S. Liang, N.E. Groot, and M.E. Schaepman (Eds.), 264-269, 2007.

[21] L. Rojek, K. Hehl, M. Möller, M. Richter, and M. Bischoff-Schaefer, “Strategy for the development of a photogrammetric monitoring system for a resource-saving and automated irrigation of crops in open field and protected environment (PLANTSENS)”, AGIT – Journal für Angewandte Geoinformatik, vol. 5, 87-99, 2019.

[22] S. B. Idso, R. D. Jackson, P. J. Pinter, R. J. Reginato, and J. L. Hatfield, “Normalizing the stress-degree-day parameter for environmental variability”, Agric. Meteorol., vol. 24, 45–55, 1981.

[23] R. D. Jackson, S. B. Idso, R. J. Reginato, and P. J. Pinter, “Canopy temperature as a crop water stress indicator”, Water Resour. Res., vol. 17, 1133–1138, 1981.

[24] B. G. Ram, P. Oduor, C. Igathinathane, K. Howatt, and X. Sun, “A systematic review of hyperspectral imaging in precision agriculture: Analysis of its current state and future prospects”, Computers and Electronics in Agriculture, vol. 222, 109037, 2024.

[25] L. Rojek, K. Hehl, M. Möller, M. Richter, and M. Bischoff-Schaefer, “Multi-sensor network-based measuring system for automatic irrigation of crop stands in greenhouses (PLANTSENS)”, AGIT – J. Angew. Geoinform. vol. 6, 146–160, 2020.

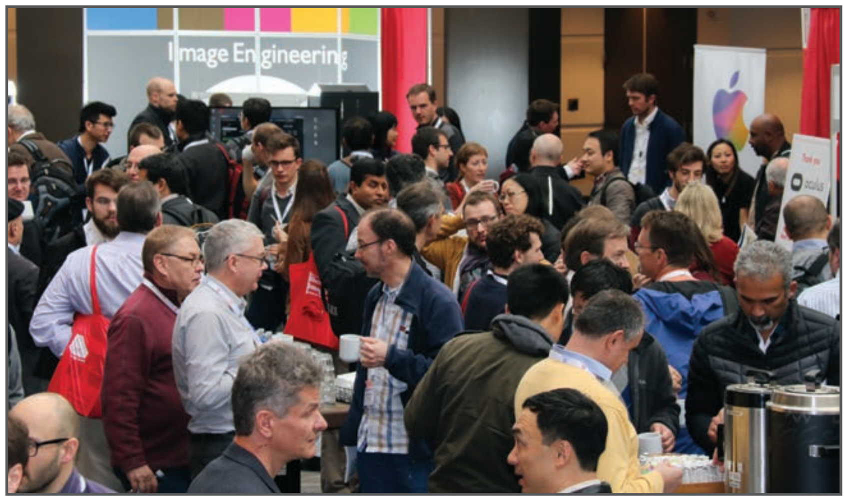
Author Biography

Lukasz Rojek holds a Master of Science in Geodata Acquisition and Visualization and is completing his Ph.D. at Bamberg University. With a strong background in software development and network administration, he gained practical experience in these fields alongside his academic journey. He is lecturing in Geoinformatics at the Berlin University of Applied Sciences and in Sensor Technologies at the SRH Berlin School of Technology. A certified Siemens and KNX instructor, Lukasz is deeply passionate about automation and robotics, infusing his enthusiasm into both his teaching and research projects.

Prof. Dr. Reiner Creutzburg is a retired Professor for applied computer science at the Technische Hochschule Brandenburg in Brandenburg, Germany. Since 2019 he is a Professor of IT Security at the SRH Berlin University of Applied Sciences, Berlin School of Technology. He is a member of the IEEE and SPIE and chairman of the Multimedia on Mobile Devices (MOBMU) conference at the Electronic Imaging conferences since 2005. In 2019, he was elected a member of the Leibniz Society of Sciences to Berlin e.V. His research interest is focused on Cybersecurity, Digital Forensics, Open Source Intelligence (OSINT), Multimedia Signal Processing, eLearning, Parallel Memory Architectures, and Modern Digital Media and Imaging Applications.

JOIN US AT THE NEXT EI!

Imaging across applications . . . Where industry and academia meet!



• SHORT COURSES • EXHIBITS • DEMONSTRATION SESSION • PLENARY TALKS •
• INTERACTIVE PAPER SESSION • SPECIAL EVENTS • TECHNICAL SESSIONS •

www.electronicimaging.org