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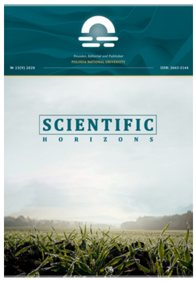

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State-of-the-art technologies for remote sensing of crops water status and nutrients in agriculture: A review

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Abstract. The research relevance is predetermined by the need to introduce effective methods and tools for monitoring water resources and tracking soil nutrient levels to improve agricultural production and sustainable use of natural resources. The research aims to provide a comprehensive overview of the latest technologies and techniques used in RS for accurately assessing water status and nutrient levels in crops, aiming to enhance agricultural productivity and sustainability. The latest advancements in remote sensing techniques that enable precise monitoring and assessment of water levels and nutrient conditions in crops, crucial for optimizing agricultural practices, were studied. The literature research was conducted by adapting the Preferred Reporting Items for Systematic Reviews and Meta-Analysis Methods. The current study provides an overview of RS technology, with a special focus on establishing crops' water and nutrient status in agriculture. A thorough review of research focused on the applications and technologies of RS in agriculture, using a broad-to-narrow approach, was also conducted. The scientific studies analysed provide the following: RS crops on a large scale level, RS crops on a field level, RS crops on a greenhouse level, RS on a plant level and RS on a leaf level. Current cutting-edge technologies are also presented. The findings of this study could be beneficial to those involved in sustainable agriculture, such as researchers, academics, and aspiring students

Keywords: review; precision agriculture; precision irrigation; smart farming; remote sensing; crop monitoring; plant water response; non-invasive; non-destructive

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INTRODUCTION

The timely and reliable information on crops' water and nutrient status is of critical importance in the conditions of modern precision agriculture and smart farms. By 2050, the world population is expected to increase to almost 10 billion people, and to feed them, existing food production must be increased by 59-98% according to estimates by the Food and Agriculture Organization (FAO, 2023). It is also estimated that agriculture will use over 70% of the world's freshwater reserves, with about half of it being lost or wasted. Up to 95% of the world's food production depends on soil. As a result of unsustainable agricultural practices, overexploitation of natural resources, and growing populations, one-third of the soils have already degraded, and experts estimate that soil erosion could lead to a 10% loss of crop yields by 2050. Soils are also full of life and contain approximately 25% of the world's biodiversity. Globally, remote sensing (RS) has been supporting decision-making in the field of agriculture for many years.

Several previously published literature reviews partially examine the application of the RS in the crops' water status and nutrients determined in agriculture. M. Weiss *et al.* (2020) conducted a meta-review of agronomical variables and plant traits that can be estimated from remote sensing. They described different methodological approaches to retrieve them, discussed how these variables are employed by different stakeholders for specific applications and concluded with an overview of caveats and future challenges. A. Konings *et al.* (2019) presented a review of microwave remote sensing observations sensitive to plant water content. They introduced the principles behind microwave remote sensing observations to illustrate how they are sensitive to plant water content and discussed how various sensor types can be leveraged for specific applications depending on the spatiotemporal resolution needed. M. Bacco *et al.* (2019) provided a survey of the most recent research activities in the area of digitalization of agriculture, in the form of both research projects and scientific literature, to show the already achieved results, the current investigations, and the still open challenges, both technical and non-technical. G. Lassalle (2021) conducted a meta-review about the advances achieved in monitoring natural and anthropogenic plant stressors by hyperspectral remote sensing over the last 50 years. He presented advances in hyperspectral monitoring of plant stress with a total of 466 peer-reviewed articles.

N. Katsoulas *et al.* (2016) conducted a review of crop reflectance monitoring as a tool for water stress detection in greenhouses. They presented challenges of detecting water status in greenhouses by remote sensing, discussed sensors available for reflectance sensing and applications, effects of environmental, canopy structure and other parameters and proposed possible solutions to mitigate the effects of those parameters. U. Ahmad *et al.* (2021) conducted a review on crop reflectance monitoring as a tool for water stress detection in greenhouses. They reviewed past research and recent advances regarding the sensors and approaches used for crop reflectance measurements and the indices used for crop water and nutrient status detection. A. Damm *et al.* (2018) conducted a review of remote sensing of plant-water relations. They reviewed suitable remote sensing approaches to assess plant-water relations ranging from pure observational to combined observational-modelling approaches. They used a combined energy balance and radiative transfer model to assess the explanatory power of pure observational approaches focusing on plant parameters to estimate plant-water relations, followed by an outline for a more effective use of remote sensing by their integration into soil-plant-atmosphere continuum (SPAC) models. It is possible to conclude that there are similar studies, but they are not categorized as in this publication – from the general to the particular, from the global scale to the leaf level.

The research aims to present a thorough examination of contemporary technologies and methodologies employed in remote sensing to precisely evaluate the water conditions and nutrient concentrations in crops. The ultimate goal is to improve agricultural efficiency and promote sustainable practices.

REMOTE SENSING CROPS ON LARGE SCALE LEVEL

Improved satellite data resolution from platforms like Landsat 8 and Sentinel-2 has opened up new possibilities for monitoring crop conditions and mapping yields on a larger scale in agriculture. J. Clevers *et al.* (2017) utilized Sentinel-2 satellite images to estimate LAI, LCC, and CCC of potato crops using vegetation indices (VIs). Their study found that Sentinel-2 bands with a 10 m spatial resolution were sufficient, eliminating the need for red-edge bands with a 20 m resolution. J. Miao *et al.* (2022) employed machine learning models to estimate leaf nutrient levels in mangrove forests using Sentinel-2 images. They compared XGBoost, RF, and LightGBM models and mapped nutrient levels for multiple seasons, highlighting the importance of monitoring seasonal changes. A. Hama *et al.* (2022) introduced a low-cost LiDAR approach to estimate leaf water content (LWC) by measuring reflectance in the 905 nm band, which was found to be closely related to leaf structure. T. Dong *et al.* (2020) utilized Landsat 8 and Sentinel-2 data to estimate crop biomass in Manitoba, Canada, by parametrizing a crop growth model using remotely sensed LAI. Lastly, I. Sanches *et al.* (2014) used spectral feature analysis to detect plant stress in visible/near-infrared wavelengths, identifying a new index, PSDI, effective for detecting stress in hydrocarbon-impacted plants based on field and airborne data. Table 1 presents the above data in a summarized form:

Table 1. Examples of RS crops on large scale level				
Source	**Sensor**	**Crop**	**Estimation**	**Results**
(Clevers *et al.*, 2017)	Sentinel-2 satellite images	Potato	LAI; LCC; CCC	At 10 m spatial resolution: WDVI estimating LAI with R^2=0.80, RMSEP=0.36; CVI estimating LCC: R^2=0.656; RMSEP=0.066 g·m^{-2}); CI_{green} linear estimator of CCC: R^2=0.818; RMSEP=0.29 g·m^{-2}; At 20 m spatial resolution: TCARI/OSAVI linear estimator of LCC: R^2=0.696, RMSEP=0.062 g·m^{-2}
(Miao *et al.*, 2022)	Sentinel-2 image	Mangrove	Seasonal leaf nutrients: carbon (C), nitrogen (N) and phosphorus (P)	XGBoost demonstrates high accuracy in estimating leaf C, N, and P levels with R^2 values of 0.655, 0.799, and 0.829 in spring, summer, and winter for leaf C, and R^2 values of 0.668, 0.743, and 0.704 for leaf N, and R^2 values of 0.539, 0.622, and 0.596 for leaf P
(Hama *et al.*, 2022)	LiDAR and hyperspectral data	leaves of sweet potatoes	LWC by LiDAR reflectance	Using LiDAR reflectance, the estimation of LWC (Liquid Water Content) achieves a high level of accuracy, with an R^2 value of 0.950, an RMSE (Root Mean Square Error) of 6.78%, and a MAPE (Mean Absolute Percentage Error) of 18.6%
(Dong *et al.*, 2020)	Landsat 8 and Sentinel-2 data	Anola, soybean, wheat, corn, oats and beans	Crop biomass using remotely sensed LAI	The accurate estimation of above-ground dry biomass for these six crops is achieved by assimilating LAI data obtained from satellite sources. The estimation yielded favourable results, with an R^2 value of 0.81, an RMSE of 135.4 g/m^2, a normalized RMSE (nRMSE) of 37.9%, and a relative per cent difference (RPD) of 2.26
(Sanches *et al.*, 2014)	ProSpecTIR-VS airborne imaging spectrometer for far-range field hyperspectral RS data	Forages brachiaria grass and perennial soybean	Plant stress in hydrocarbon-contaminated soil, true leaf data	Among the leaf data, the PSDI and chlorophyll feature area demonstrated the highest proportion (67-70%) of plants exhibiting signs of stress

Source: *developed by the author*

REMOTE SENSING CROPS ON THE FIELD LEVEL

T. Silva *et al.* (2022) conducted on-site measurements of chlorophyll levels in grapevines to assess their nitrogen status. The study established a relationship between chlorophyll meter readings and actual leaf nitrogen contents. C. Araújo-Paredes *et al.* (2022) evaluated the accuracy of using an aerial sensor to estimate plant water status (PWS) through the Crop Water Stress Index (CWSI). They compared CWSI values derived from aerial thermographic and portable thermal cameras with measurements of stem water potential and demonstrated the feasibility of estimating CWSI and generating spatial maps using aerial thermography. H. Zheng *et al.* (2018) assessed the performance of three sensors on an unmanned aerial system (UAS) for estimating nitrogen status in rice. They employed various Vis to estimate leaf and plant nitrogen accumulation and evaluated their integration with field data. P. Rosso *et al.* (2022) compared ground-based LAI data with remote sensing information using VIs, machine learning, and radiative transfer models in barley experiments. They determined that machine learning algorithms and VIs performed well, indicating the potential of using satellites and remotely piloted aircraft in precision agriculture. Du *et al.* (2022) used a multi-rotor UAV equipped with image sensors to gather maize canopy data and developed models for LAI estimation using different algorithms. N. Katsoulas *et al.* (2016) utilized ML algorithms to estimate NDVI in Arabica coffee cultivars using a passive RGB sensor in a UAV. They derived an NDVI equation based on RGB bands and found satisfactory agreement compared to in situ data, providing a simple method for evaluating vegetative vigour. Table 2 presents the above data in a summarized form:

Table 2. Examples of RS crops on field level				
Source	**Sensor**	**Crop**	**Estimation**	**Results**
(Silva *et al.*, 2022)	Chlorophyll hand-held meter	Wine grape "Chardonnay"	Chlorophyll	The generated models produced estimations for chlorophyll a, b, and total with calibration errors of 0.98, 0.58, and 1.47μg ml^{-1} cm^{-2}, respectively. For prediction, the errors are 1.03, 0.67, and 1.49 μg ml^{-1} cm^{-2}. In terms of leaf nitrogen content, the calibration error is 1.49 g kg^{-1}, while the prediction error is 3.39 g kg^{-1}

Table 2, Continued

Source	Sensor	Crop	Estimation	Results
(Araújo-Paredes *et al.*, 2022)	Thermal Imagery	Grape vine	CWSI	Among the two models analysed, it is observed that for CWSITair, CWSIS demonstrated better evaluation of crop water stress compared to stem water potential, with an R^2 value of 0.55. Additionally, CWSIS exhibited a strong correlation with the portable sensor, with an R^2 value of 0.58, indicating its potential for practical application in field measurements
(Zheng *et al.*, 2018)	RGB, colour-infrared and multispectral cameras	Rice	Nitrogen status	The findings indicated that the red edge (VIs) derived from multi-spectral (MS) images achieved the highest level of accuracy in estimating Leaf Nitrogen Accumulation (LNA) with R^2 values ranging from 0.79 to 0.81 and RMSE values of 1.43 to 1.45 g m^{-2}. Similarly, for Plant Nitrogen Accumulation (PNA), the red edge VIs demonstrated strong performance with R^2 values ranging from 0.81 to 0.84 and RMSE values of 2.27 to 2.38 g m^{-2}
(Rosso *et al.*, 2022)	Sentinel-2, Landsat and Sen2-Agri	Barley	LAI	The coefficients of determination obtained from all approaches ranged from approximately 0.7 to 0.9. When only four Sentinel-2 bands are utilized instead of the full set of 12, the top-performing ML algorithms achieve even higher levels of accuracy
(Du *et al.*, 2022)	CMOS sensors (RGB bands of spectral and spatial information of image pixels	Maize	LAI	There is a strong correlation between RGB-based VIs and LAI. The (RF model outperformed other models across the entire observation period as well as during specific growth stages. It exhibited the highest coefficients of determination (R^2) ranging from 0.71 to 0.88 and the lowest RMSE values ranging from 0.12 to 0.25 on the test datasets. Following the RF model, the BPNN (Backpropagation Neural Network) model and LR models also showed good performance
(de Oliveira *et al.*, 2022)	Passive RGB sensor on UAS	20 Arabica coffee cultivars	Foliage level	A high ratio between the foliage level and the NDVI can be observed (r=0.97, p-value < 0.01)

Source: *developed by the author*

REMOTE SENSING CROPS ON THE GREENHOUSE LEVEL

Q. Li *et al.* (2022) investigated the relationship between soil water content (SWC), drought stages of wheat, canopy temperature, and spectral response characteristics. They found that red-valley position (RVP) and red-edge position (REP) parameters showed significant shifts during certain drought stages of wheat, while vegetation water indexes effectively distinguished different levels of water stress across various growth stages. A. Bianchi *et al.* (2017) developed a water balance model based on the FAO-56 method to schedule irrigation for greenhouse spinach crops. They found that nitrogen treatment had minimal impact on crop development and irrigation requirements. C. Ru *et al.* (2020) examined the effectiveness of using the CWSI based on leaf temperature to assess the water status of grapevines. They determined the optimal time and conditions for observing CWSI values and concluded that CWSI was more effective than Tc-Ta (canopy temperature minus air temperature) in monitoring plant water stress, with stomatal conductance (gs) showing the strongest correlation with CWSI. Table 3 presents the above data in a summarized form:

Table 3. *Examples of RS crops on the greenhouse level*

Source	Sensor	Crop	Estimation	Results
(Li *et al.*, 2022)	Ground hyper-spectral RS	Wheat	Water stress during tillering, jointing and milk maturity.	The presence of water stress at various growth stages resulted in noticeable variations in spectral characteristics. Notably, there are significant differences in SWC and canopy temperature across different stages of wheat drought, with the jointing stage experiencing the most pronounced changes in canopy temperature
(Bianchi *et al.*, 2017)	RGB images	Spinach (Spinacia oleracea)	Water requirements	The FAO-56-GH model demonstrated favourable performance during both the validation and calibration periods, as indicated by the evaluation metrics. In the validation period, the model exhibited a coefficient of determination (R^2) of 0.80, an RMSE of 0.41 mm day^{-1}, and an NSE of 0.78. Similarly, during the calibration period, the model achieved an R^2 of 0.84, an RMSE of 0.21 mm day^{-1}, and an NSE of 0.83

Table 3, Continued

Source	Sensor	Crop	Estimation	Results
(Ru *et al.*, 2020)	Infrared thermometer	Grapevines	Leaf temperature, Water status – water stress	The correlation between the leaf-air temperature difference (T_c-T_a) and indicators of PWS (φ_s, g_s, E) is statistically significant (P<0.05). Among these indicators, the relationship between g_s, E, and T_c-T_a is particularly strong, with R^2 values ranging from 0.530 to 0.604 and from 0.545 to 0.623, respectively. Additionally, there is a reliable linear correlation between the CWSI value and soil moisture at depths of 0-40 cm, with statistical significance (P<0.05)

Source: *developed by the author*

REMOTE SENSING ON PLANT LEVEL

N. Chandel *et al.* (2022) developed a non-invasive method using computer vision and thermal-RGB imagery to detect water stress in winter wheat crops. Deep learning models and function-approximation models are utilized to classify crops as stressed or non-stressed based on thermal-RGB images and various input parameters. P. López-García *et al.* (2022) conducted experiments to assess the impact of different water qualities and irrigation start times on crop growth. LR techniques and ANN models are trained using multispectral and RGB data to simulate water stress. J. Fernández-Novales *et al.* (2021) focused on assessing the water status of grapevines using leaf water potential and canopy temperature measurements. Spatial-temporal maps are generated to analyse variations in water status. S. Zhuang *et al.* (2017) developed a model for early identification of water stress in maize using image analysis. A two-stage detection model based on gradient-boosting decision trees is used to distinguish between adequate water supply and water stress conditions in maize fields. Table 4 presents the above data in a summarized form.

Table 4. *Examples of RS crops on the plant level*

Source	Sensor	Crop	Estimation	Results
(Chandel *et al.*, 2022)	RGB and thermal imagery plus computer vision	Winter wheat	Crop water stress	Different irrigation treatments significantly affect measurements of canopy temperature (Tc), relative water content (RWC), SMC, and RH concerning crop and soil responses. The 100% ETc treatment resulted in the lowest Tc (22.5±2°C), highest RWC (90%), and highest SMC (25.7±2.2%), while the 25% ETc treatment had the highest Tc (28±3°C), lowest RWC (74%), and lowest SMC (20.5±3.1%). ResNet50 performed the best among feature extraction models, achieving a discriminant accuracy of 96.9% with RGB inputs and 98.4% with thermal imagery inputs. Thermal imagery generally provided higher classification accuracy compared to RGB imagery. Among function approximation models, the DL-LSTM model achieved the highest discriminant accuracy of 96.7% and displayed lower errors in stress/non-stress classification
(López-García *et al.*, 2022)	Multispectral and RGB UAV Imagery	Vineyard	Water Status	Utilizing ML techniques, such as ANN models, is an efficient approach to analysing data obtained through UAV remote sensing for the estimation of S_ψ. These models outperform LR models and using RGB bands and GCC as inputs leads to satisfactory outcomes. High-resolution RGB cameras are a cost-effective alternative to multispectral and thermal sensors, with promising results. To avoid soil effects and obtain precise GCC values, accurate vegetation segmentation is essential
(Fernández-Novales *et al.*, 2021)	Ground drone; Thermal infrared radiometry and multispectral sensor	Grapevine	PWS	The researchers employed Partial Least Squares (PLS) regression to develop calibration and prediction models. The findings revealed that the most effective prediction models for grapevine water status achieved a cross-validated determination coefficient (r^2_{cv}) of 0.57 in the morning and 0.42 at midday. The RMSE of cross-validation ($RMSE_{cv}$) was determined to be 0.191 MPa in the morning and 0.139 MPa at midday
(Zhuang *et al.*, 2017)	RGB outdoor camera	Maize	Early water stress detection	The accuracy of identifying three different water treatments is found to be 80.95%, while the accuracy of detecting water stress is 90.39%

Source: *developed by the author*

REMOTE SENSING ON LEAF LEVEL

In 2015, Dhillon introduced the "Leaf Monitor," a continuous leaf monitoring system specifically designed for measuring the PWS of almond and walnut trees. The Leaf Monitor system utilized a thermal infra-red sensor to measure leaf temperature and integrated additional sensors to monitor various environmental factors such as air temperature, relative humidity, photosynthetically active radiation (PAR), and wind speed. To optimize its performance, the system included a leaf holder, a solar radiation diffuser dome, and a wind barrier. These systems were interconnected in a wireless mesh network, allowing data collection and transmission every 16 minutes through the internet.

In a subsequent study published in 2019 by the same research team led by Dhillon, they developed a methodology to predict PWS in almond and walnut trees using the continuous leaf monitoring system. The researchers collected data on leaf temperature and environmental conditions using the Leaf Monitor system. These data were then utilized to calculate a Modified CWSI, which served as an indicator of the plant's water status. Before an irrigation event, MCWSI values were estimated and used to determine the appropriate irrigation amount for low-frequency variable rate irrigation (VRI). The irrigation amounts were based on the correlation between MCWSI and Drought Stress Water Potential (DSWP). By implementing variable rate irrigation, the researchers achieved a significant average reduction of 39% in water consumption compared to the fixed 100% evapotranspiration (ET) replacement irrigation method for all the trees.

Analysing strawberry leaf colour can effectively help evaluate soil status and protect against excess environmental nutrients and financial losses in strawberry crops (Madhavi *et al.,* 2022). The objective of this study was to create ML models, specifically multiple linear regression (MLR) and gradient boost regression (GBR), that can simulate variations in strawberry leaf colour. These colour changes are based on soil physicochemical properties and plant age, using mean values of the RGB channels. Accurate measurements of soil physicochemical components were obtained from the largest and most diverse coloured leaves of the strawberry plants using a multifunctional soil sensor in the rooting zones. Additionally, 400 strawberry leaflets were sampled at different stages of vegetative and reproductive growth, and individual leaves were captured using a digital imaging system. The RGB mean values of the coloured leaf images were extracted using image segmentation algorithms incorporated into image processing techniques. Subsequently, MLR and GBR models were developed to predict the RGB mean values of the leaves based on the soil physicochemical measurements and plant age. The GBR model demonstrated superior performance compared to the MLR model, achieving high-performance metrics.

Several other studies have explored the use of advanced techniques for assessing PWS and health in various crops. F. Hahn *et al.* (2021) focused on mango trees and employed dendrometers and capacitors with Teflon clamps to measure LWC and examine the influence of water on mango production. H. Skoneczny *et al.* (2020) investigated the potential of non-invasive proximal hyperspectral remote sensing (RS) to distinguish between healthy, infected, and dry leaves of apple trees using spectral bands and indices. F. Rojo *et al.* (2016) proposed a new method for calculating CWSI and Modified CWSI using continuous leaf monitor data in almond orchards and vineyards to implement site-specific irrigation management. J. Rodriguez-Perez *et al.* (2018) compared ordinary least squares regression (OLSR) and functional linear regression (FLR) models to predict LWC using reflectance data and wavelengths in grapevines. T. Zhao *et al.* (2020) used hyperspectral imaging to evaluate water status in tomato leaves and computed vegetation indices (VIs) to assess LWC in different parts of the plants. These studies highlight the potential of advanced techniques in monitoring PWS and health for improved crop management. Table 5 presents the above data in a summarized form.

Table 5. *Examples of RS crops on leaf level*

Source	Sensor	Crop	Estimation	Results
(Dhillon, 2015; Dhillon *et al.,* 2019)	Thermal infrared sensor for continuously monitor the temperature of leaves, as well as the ambient temperature, relative humidity, photosynthetically active radiation (PAR), and wind speed	Almond and walnut	PWS	In almond: MCWSI and DSWP linearly related, r^2=0.67; In walnuts, MCWSI and DSWP in quadratic relationship R^2=0.75
(Madhavi *et al.,* 2022)	RGB camera with a pixel resolution of 5472 × 3648	Strawberry	Leaf Colour Using RGB Mean Values Based on Soil Physicochemical Parameters Using Machine Learning Models	GBR model, utilizing RGB mean values throughout the growth stage, demonstrated a good fit with R^2 and RMSE values of (R=0.77, 7.16, G=0.72, 7.37, and B=0.70, 5.68), respectively. On the other hand, the MLR model performed moderately, with R2 and RMSE values of (R=0.67, 8.59, G=0.57, 9.12, and B=0.56, 6.81), when predicting RGB mean values consecutively in strawberry leaves
(Hahn *et al.,* 2021)	Inductive and Capacitive Sensors	Mango	Leaf Monitoring	The capacitance and Hall effect sensors can produce signals that can be used for scheduling irrigation based on predetermined thresholds.
(Skoneczny *et al.,* 2020)	Non-invasive proximal hyperspectral RS	Apple	Hyperspectral Analysis of Healthy, Infected and Dry Leaves	The 1450 nm band in the SWIR range effectively separates infected (I) and healthy (H) leaves, while the 1900 nm SWIR band distinguishes all three leaf types. Pearson correlation tests revealed that ARI, MSR, and QFI showed the strongest correlations with the progression of infection

Table 5, Continued

Source	Sensor	Crop	Estimation	Results
(Rojo *et al.*, 2016)	Continuous WSN leaf temperature monitoring system and soil and pressure sensors, latching solenoid valves	Almond orchards and Vineyards	PWS	In grapes: MCWSI and DSWP are linearly related, with R^2=0.70; In almonds, CWSI and DSWP strongly correlated with a second-order relationship and R^2=0.78
(Rodriguez-Perez *et al.*, 2018)	Hyperspectral	Four grape varieties	LWC expressed as equivalent water thickness	The most accurate model is achieved by utilizing functional linear regression (FLR) within the spectral range centred around 1465 nm, resulting in a coefficient of determination (R^2) of 0.70 and a percentage root mean squared error (%RMSE) of 8.485
(Zhao *et al.*, 2020)	Portable hyperspectral camera	Tomato	Leaf Water Status	The most successful regression model for evaluating water content (WC) is obtained by utilizing TBI regression with DIFF data at 1410 nm and 1520 nm wavelengths. Similarly, the most efficient regression model for determining moisture content (MC) is achieved through NDVI regression with RAW data at 1300 nm and 1310 nm wavelengths. The models used for the MC assessment showed better performance compared to those used for the WC assessment

Source: *developed by the author*

CUTTING-EDGE TECHNOLOGIES

Industries are moving towards smart factories, and the agricultural sector should also embrace the concept of smart farms. Unmanned ground vehicles (UGVs) play a vital role in the development of smart farms (Gonzalez-De-Santos *et al.,* 2020). While there are similarities between smart factories and smart farms, specific research is needed to address the unique characteristics of UGVs designed for outdoor agricultural tasks. Multi-drone systems consisting of smaller or medium-sized drones can perform tasks with greater accuracy, tolerance, and safety compared to larger machines. Autonomous drones, whether operating alone or in fleets, are essential for the precise application of herbicides and fertilizers. This approach reduces chemical usage, resulting in benefits such as lower costs, improved operator safety, enhanced community health, and higher food quality with reduced toxicity.

The Research Centre for High Technology Greenhouse Plant Production at Ehime University is working on a project called "Intelligent Greenhouse Systems," in which the main concept is the "Speaking Plant" approach (Hiroshige, 2015). The SPA approach suggests that the best way to grow crops is by considering the plants' physiological status. To implement SPA, a chlorophyll fluorescence imaging drone is developed to measure the photosynthetic activity of tomato plants in greenhouses. This drone is designed to be low-cost, easy to use, and suitable for commercial tomato production. The researchers also studied how storage temperature affects tomato fruit colour using multiple regression analysis to improve postharvest management.

This study (Kalaitzoglou *et al.,* 2021) aims to investigate how blue light affects plant growth by measuring light absorption and photosynthesis in tomato plants. The experiment involved growing tomato plants in six different combinations of artificial solar and blue LED light, with varying levels of blue light. The results showed that increasing the blue light fraction led to a decrease in plant growth, which is related to a more compact plant morphology and lower light absorption. However, the blue light did not affect the plants' maximum photosynthetic capacity. The study suggests that increasing blue light in a solar light environment can hinder plant growth, but further research is needed to confirm this in high-light growth environments typically used in tomato production.

A digital twin refers to a virtual representation of a farm that offers benefits such as increased productivity, improved efficiency, and reduced energy consumption and losses. A. Nasirahmadi and O. Hensel (2022) presented a comprehensive overview of digital twin concepts and technologies in the field of agriculture. It covers various aspects including soil management, irrigation, robotics, farm machinery, and post-harvest processing. The review explores data recording, modelling, artificial intelligence, big data, simulation, analysis, prediction, and communication aspects of digital twin systems in agriculture. By continuously monitoring the farm in real time and updating the virtual model to reflect changes in the physical environment, digital twins provide valuable support to farmers. This technology represents the cutting-edge advancement in the digital transformation of the agricultural sector.

C. Pylianidis *et al.* (2021) used a combination of qualitative and quantitative methods to explore the advantages of digital twins in the agricultural domain. The study begins with a comprehensive literature review focusing on digital twins in agriculture between 2017 and 2020. By examining 28 use cases and comparing them with examples from other fields, the researchers assess the extent of digital twin implementation in agriculture. They analysed reported benefits, service categories, and technology readiness levels to evaluate the adoption of digital twins in the agricultural sector. Furthermore, the study identifies specific characteristics of digital twins that can be beneficial in agriculture and proposes a roadmap for their implementation, considering increasing levels of complexity. Ultimately, the research underscores the distinctive attributes of digital twins that make them particularly valuable in the context of agriculture.

"Agri-Food 4.0" is a term used to describe the latest developments in the agriculture sector, which includes the integration of digital technologies and the Internet of Things. Similar to the concept of "Industry 4.0", Agri-Food 4.0 aims to optimize efficiency and productivity through the use of these technologies. While the agriculture sector has already incorporated electronic controls and data collection methods through sensors and drones, there is still a need to improve supply chain performance and decision-making processes. This survey (Lezoche *et al.,* 2020) reviews over a hundred papers on new technologies and supply chain methods to understand the future of Agri-Food 4.0.

According to the United Nations Development Programme (2021), global agriculture and food systems are under constant enormous pressure. It is estimated that by 2050 the world population will grow to almost 10 billion people and to feed it, current food production must be increased by 59-98% (Domingues *et al.,* 2022). It is also estimated that agriculture uses over 70% of global freshwater supplies, with around half of this being lost and wasted. Globally, about one-third of the food produced is wasted or thrown away. Agri-food is at the heart of the United Nations 2030 Agenda and impacts all 17 Sustainable Development Goals.

In 2019, the twenty-six EU member states signed a declaration of cooperation to support the successful digitization of agriculture and rural areas in Europe. In it, they recognize the potential of digital technologies to help tackle important and pressing economic, social, climate and environmental challenges facing the EU's agri-food sector and rural areas. In 2022, FAO calls for an end to soil degradation. Up to 95% of the world's food production depends on soil. As a result of unsustainable farming practices, overexploitation of natural resources and a growing population, one-third of soils have already been degraded, and experts estimate that soil erosion could lead to 10% crop loss by 2050. Soils are also full of life and contain approximately 25% of the world's biodiversity (FAO, 2023).

The introduction of so-called precision agriculture (PA) and digital technologies in the field of agriculture are ways to optimize and improve the processes in it. New digital technologies make farming more accessible, using a combination of different technologies working together to improve the precision of farming, including high-speed internet (5G) mobile phones, high-resolution RS technologies through images from satellites and unmanned aerial vehicles (UAVs), sensors connected to the Internet of Things (IoT), wireless sensor networks (WSN), robotics and 3D printing (Kalaitzoglou *et al.,* 2021).

The use of PA is primarily driven by WSN, which consists of interconnected wireless nodes that monitor environmental conditions (Shafi *et al.,* 2019). These nodes are equipped with components, such as transmitters, microcontrollers, sensors, antennas, and electronic circuits to collect and transmit data to a gateway. Nodes are categorized as either data sources or receivers/gateways, with receivers having more computing power. In agriculture, different plants have varying needs even within the same farmland, and sensors are employed to monitor the changing behaviour of plant parameters, including soil properties, plant characteristics, weather conditions, fertilization options, and water requirements. The most commonly used wireless communication protocols in agricultural IoT applications are Cellular, 6LoWPAN, ZigBee, RFID, Wi-Fi, and LoRaWAN (Avşar & Mowla, 2022).

The combination of ML, HPC, and big data technologies opens up new opportunities for data-intensive science in the interdisciplinary field of agrotechnologies. ML algorithms applied to sensor data transform farm management systems into real-time AI-driven programs that offer valuable recommendations to support farmers' decision-making (Liakos *et al.,* 2018). ML approaches were successfully applied in various areas, such as classifying plant diseases from plant images using CNNs for different plant species and diseases, detecting insects on leaves through object segmentation and deep learning techniques (Domingues *et al.*, 2022), and predicting soil moisture levels (Atanasov *et al.,* 2023). In a global context, RS has been supporting decision-making in agriculture for over 45 years (Ammoniaci *et al.,* 2021; Domingues *et al.,* 2022).

CONCLUSIONS

Remote sensing technologies offer valuable insights for improving agricultural productivity and efficient water resource management. Soil moisture sensors provide accurate and consistent data, enabling objective observations of plant water status, although they have limitations in capturing field-wide moisture variations. Handheld remote sensing devices offer better temporal, spectral, and spatial resolution for on-site monitoring, but their effectiveness is limited for evaluating larger areas compared to sensors on planes and satellites. Proximal sensors require location-specific calibration and may pose data analysis challenges. Leaf physiology methods provide objective assessments of crop water stress but are time-consuming, destructive, and not suitable for real-time monitoring. Modern imaging techniques such as fluorescence, thermography, and multispectral imaging enable fast and non-destructive phenotyping for early detection of water stress. Satellite-based remote sensing has significant potential but can be constrained by spatial and temporal resolution limitations and cloud cover. To overcome these challenges, unmanned aerial vehicles (UAVs) equipped with remote sensing sensors offer a cost-effective alternative, providing high-resolution imagery with flexibility in flight and mission timing. UAVs surpass satellite resolution and offer quick and repeatable deployment. Combining multispectral and hyperspectral images enhances the comprehensive understanding of crop conditions. By integrating these technologies, agriculture can benefit from improved practices and sustainable resource management.

Prospects for future research in state-of-the-art technologies for remote sensing of crop water status and nutrients in agriculture include advancing sensor technologies for improved accuracy and resolution, integrating data from multiple sources for comprehensive analysis, and exploring the integration of remote sensing with precision agriculture techniques for site-specific management.

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CONFLICT OF INTEREST

The author has no conflict of interest to declare.

REFERENCES

[1] Ahmad, U., Alvino, A., & Marino, S. (2021). A review of crop water stress assessment using remote sensing. *Remote Sensing*, 13(20), article number 4155. doi: 10.3390/rs13204155.
[2] Ammoniaci, M., Kartsiotis, S.P., Perria, R., & Storchi, P. (2021). State of the art of monitoring technologies and data processing for precision viticulture. *Agriculture,* 11(3), article number 201. doi: 10.3390/agriculture11030201.
[3] Araújo-Paredes, C., Portela, F., Mendes, S., & Valín, M.I. (2022). Using aerial thermal imagery to evaluate water status in Vitis vinifera cv. Loureiro. *Sensors,* 22(20), article number 8056. doi: 10.3390/s22208056.
[4] Atanasov, S., Harizanova-Petrova, B., & Petrova, R. (2023). Tomato leaf colour as predictor of soil moisture level using machine learning techniques. *Scientific Horizons,* 26(2), 31-42. doi: 10.48077/scihor.26(2).2023.31-42.
[5] Avşar, E., & Mowla, M.N. (2022). Wireless communication protocols in smart agriculture: A review on applications, challenges and future trends. *Ad Hoc Networks*, 136, article number 102982. doi: 10.1016/j.adhoc.2022.102982.
[6] Bacco, M., Barsocchi, P., Ferro, E., Gotta, A., & Ruggeri, M. (2019). The digitisation of agriculture: A survey of research activities on smart farming. *Array*, 3-4, article number 100009. doi: 10.1016/j.array.2019.100009.
[7] Bianchi, A., Masseroni, D., & Facchi, A. (2017). Modelling water requirements of greenhouse spinach for irrigation management purposes. *Hydrology Research,* 48(3), 776-788. doi: 10.2166/nh.2016.079.
[8] Chandel, N.S., Rajwade, Y.A., Dubey, K., Chandel, A.K., Subeesh, A., & Tiwari, M.K. (2022). Water stress identification of winter wheat crop with state-of-the-art ai techniques and high-resolution thermal-rgb imagery. *Plants,* 11(23), article number 3344. doi: 10.3390/plants11233344.
[9] Clevers, J.G., Kooistra, L., & Van den Brande, M.M. (2017). Using Sentinel-2 data for retrieving LAI and leaf and canopy chlorophyll content of a potato crop. *Remote Sensing*, 9(5), article number 405. doi: 10.3390/rs9050405.
[10] Damm, A., Paul-Limoges, E., Haghighi, E., Simmer, C., Morsdorf, F., Schneider, F.D., van der Tol, C., Migliavacca, M., Rascher, U., & Rascher, U. (2018). Remote sensing of plant-water relations: An overview and future perspectives. *Journal of plant physiology*, 227, 3-19. doi: 10.1016/j.jplph.2018.04.012.
[11] Dhillon, R. (2015). *Development and evaluation of a continuous leaf monitoring system for measurement of plant water status* (PhD Dissertation, Department of Biological Systems Engineering, University of California, Davis).
[12] Dhillon, R., Rojo, F., Upadhyaya, S.K., Roach, J., Coates, R., & Delwiche, M. (2019). Prediction of plant water status in almond and walnut trees using a continuous leaf monitoring system. *Precision Agriculture,* 20, 723-745. doi: 10.1007/s11119-018-9607-0.
[13] Domingues, T., Brandão, T., & Ferreira, J.C. (2022). Machine learning for detection and prediction of crop diseases and pests: A comprehensive survey. *Agriculture,* 12(9), article number 1350. doi: 10.3390/agriculture12091350.
[14] Dong, T., Liu, J., Qian, B., He, L., Liu, J., Wang, R., Jing, Q., Champagne, C., McNairn, H., Powers, J., Shi, Y., Chen, J.M., & Shang, J. (2020). Estimating crop biomass using leaf area index derived from Landsat 8 and Sentinel-2 data. *ISPRS Journal of Photogrammetry and Remote Sensing,* 168, 236-250. doi: 10.1016/j.isprsjprs.2020.08.003.
[15] Du, L., Yang, H., Song, X., Wei, N., Yu, C., Wang, W., & Zhao, Y. (2022). Estimating leaf area index of maize using UAV-based digital imagery and machine learning methods. *Scientific Reports,* 12, article number 15937. doi: 10.1038/s41598-022-20299-0.
[16] FAO. (2023). Retrieved from https://www.fao.org/home/en.
[17] Fernández-Novales, J., Saiz-Rubio, V., Barrio, I., Rovira-Más, F., Cuenca-Cuenca, A., Santos Alves, F., Valente, J., Tardaguila, J., & Diago, M.P. (2021). Monitoring and mapping vineyard water status using non-invasive technologies by a ground robot. *Remote Sensing,* 13(14), article number 2830. doi: 10.3390/rs13142830.
[18] Gonzalez-De-Santos, P., Fernández, R., Sepúlveda, D., Navas, E., & Armada, M. (2020). Unmanned ground vehicles for smart farms. *Agronomy – Climate Change & Food Security*, 6, article number 73. doi: 10.5772/intechopen.90683.

[19] Hahn, F., Espinoza, J., & Zacarías, U. (2021). Mango leaf monitoring with inductive and capacitive sensors and its comparison with trunk dendrometer measurements. *Engineering Proceedings,* 9(1), article number 28. doi: 10.3390/engproc2021009028.
[20] Hama, A., Matsumoto, Y., & Matsuoka, N. (2022). Estimating leaf water content through low-cost LiDAR. *Agronomy,* 12(5), article number 1183. doi: 10.3390/agronomy12051183.
[21] Hiroshige, N. (2015). Development of speaking plant approach technique for intelligent greenhouse. *Agriculture and Agricultural Science Procedia*, 3, 9-13. doi: 10.1016/j.aaspro.2015.01.004.
[22] Kalaitzoglou, P., Taylor, C., Calders, K., Hogervorst, M., van Ieperen, W., Harbinson, J., de Visser, P., Nicole, C.C.S., & Marcelis, L. F. (2021). Unraveling the effects of blue light in an artificial solar background light on growth of tomato plants. *Environmental and Experimental Botany,* 184, article number 104377. doi: 10.1016/j.envexpbot.2021.104377.
[23] Katsoulas, N., Elvanidi, A., Ferentinos, K.P., Kacira, M., Bartzanas, T., & Kittas, C. (2016). Crop reflectance monitoring as a tool for water stress detection in greenhouses: A review. *Biosystems Engineering*, 151, 374-398. doi: 10.1016/j.biosystemseng.2016.10.003.
[24] Konings, A.G., Rao, K., & Steele-Dunne, S.C. (2019). Macro to micro: Microwave remote sensing of plant water content for physiology and ecology. *New Phytologist*, 223(3), 1166-1172. doi: 10.1111/nph.15808.
[25] Lassalle, G. (2021). Monitoring natural and anthropogenic plant stressors by hyperspectral remote sensing: Recommendations and guidelines based on a meta-review. *Science of the Total Environment*, 788, article number 147758. doi: 10.1016/j.scitotenv.2021.147758.
[26] Lezoche, M., Hernandez, J.E., Díaz, M.D.M.E.A., Panetto, H., & Kacprzyk, J. (2020). Agri-food 4.0: A survey of the supply chains and technologies for the future agriculture. *Computers in Industry,* 117, article number 103187. doi: 10.1016/j.compind.2020.103187.
[27] Li, Q., Gao, M., & Li, Z.L. (2022). Ground hyper-spectral remote-sensing monitoring of wheat water stress during different growing stages. *Agronomy,* 12(10), article number 2267. doi: 10.3390/agronomy12102267.
[28] Liakos, K., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors,* 18(8), article number 2674. doi: 10.3390/s18082674.
[29] López-García, P., Intrigliolo, D., Moreno, M.A., Martínez-Moreno, A., Ortega, J.F., Pérez-Álvarez, E.P., & Ballesteros, R. (2022). Machine learning-based processing of multispectral and RGB UAV imagery for the multitemporal monitoring of vineyard water status. *Agronomy,* 12(9), article number 2122. doi: 10.3390/agronomy12092122.
[30] Madhavi, B.G.K., Basak, J.K., Paudel, B., Kim, N.E., Choi, G.M., & Kim, H.T. (2022). Prediction of strawberry leaf color using RGB mean values based on soil physicochemical parameters using machine learning models. *Agronomy,* 12(5), article number 981. doi: 10.3390/agronomy12050981.
[31] Miao, J., Zhen, J., Wang, J., Zhao, D., Jiang, X., Shen, Z., & Wu, G. (2022). Mapping seasonal leaf nutrients of mangrove with Sentinel-2 images and XGBoost method. *Remote Sensing,* 14(15), article number 3679. doi: 10.3390/rs14153679.
[32] Nasirahmadi, A., & Hensel, O. (2022). Toward the next generation of digitalization in agriculture based on digital twin paradigm. *Sensors,* 22(2), article number 498. doi: 10.3390/s22020498.
[33] Pylianidis, C., Osinga, S., & Athanasiadis, I.N. (2021). Introducing digital twins to agriculture. *Computers and Electronics in Agriculture*, 184, article number 105942. doi: 10.1016/j.compag.2020.105942.
[34] Rodriguez-Perez, J.R., Ordóñez, C., González-Fernández, A.B., Sanz-Ablanedo, E., Valenciano, J.B., & Marcelo, V. (2018). Leaf water content estimation by functional linear regression of field spectroscopy data. *Biosystems Yngineering*, 165, 36-46. doi: 10.1016/j.biosystemseng.2017.08.017.
[35] Rojo, F., Kizer, E., Upadhyaya, S., Ozmen, S., Ko-Madden, C., & Zhang, Q. (2016). A leaf monitoring system for continuous measurement of plant water status to assist in precision irrigation in grape and almond crops. *IFAC-PapersOnLine*, 49(16), 209-215. doi: 10.1016/j.ifacol.2016.10.039.
[36] Rosso, P., Nendel, C., Gilardi, N., Udroiu, C., & Chlebowski, F. (2022). Processing of remote sensing information to retrieve leaf area index in barley: A comparison of methods. *Precision Agriculture,* 23(4), 1449-1472. doi: 10.1007/s11119-022-09893-4.
[37] Ru, C., Hu, X., Wang, W., Ran, H., Song, T., & Guo, Y. (2020). Evaluation of the crop water stress index as an indicator for the diagnosis of grapevine water deficiency in greenhouses. *Horticulturae,* 6(4), article number 86. doi: 10.3390/horticulturae6040086.
[38] Sanches, I.D.A., Souza Filho, C.R., & Kokaly, R.F. (2014). Spectroscopic remote sensing of plant stress at leaf and canopy levels using the chlorophyll 680 nm absorption feature with continuum removal. *ISPRS Journal of Photogrammetry and Remote Sensing*, 97, 111-122. doi: 10.1016/j.isprsjprs.2014.08.015.
[39] Shafi, U., Mumtaz, R., García-Nieto, J., Hassan, S.A., Zaidi, S.A.R., & Iqbal, N. (2019). Precision agriculture techniques and practices: From considerations to applications. *Sensors,* 19(17), article number 3796. doi: 10.3390/s19173796.

[40] Silva, T.M.M.D., Costa, B.R.S., Oldoni, H., Mitsuyuki, M.C., & Bassoi, L.H. (2022). Calibration of chlorophyll hand-held meter based on vineyard NDVI zones for estimation of leaf N content. *Ciência e Agrotecnologia*, 46, article number e006222. doi: 10.1590/1413-7054202246006222.
[41] Skoneczny, H., Kubiak, K., Spiralski, M., Kotlarz, J., Mikiciński, A., & Puławska, J. (2020). Fire blight disease detection for apple trees: Hyperspectral analysis of healthy, infected and dry leaves. *Remote Sensing,* 12(13), article number 2101. doi: 10.3390/rs12132101.
[42] United Nations Development Programme. (2023). Retrieved from https://www.undp.org/.
[43] Weiss, M., Jacob, F., & Duveiller, G. (2020). Remote sensing for agricultural applications: A meta-review. *Remote Sensing of Environment*, 236, article number 111402. doi: 10.1016/j.rse.2019.111402.
[44] Zhao, T., Nakano, A., Iwaski, Y., & Umeda, H. (2020). Application of hyperspectral imaging for assessment of tomato leaf water status in plant factories. *Applied Sciences,* 10(13), article number 4665. doi: 10.3390/app10134665.
[45] Zheng, H., Cheng, T., Li, D., Zhou, X., Yao, X., Tian, Y., Cao, W., & Zhu, Y. (2018). Evaluation of RGB, color-infrared and multispectral images acquired from unmanned aerial systems for the estimation of nitrogen accumulation in rice. *Remote Sensing*, 10(6), article number 824. doi: 10.3390/rs10060824.
[46] Zhuang, S., Wang, P., Jiang, B., Li, M., & Gong, Z. (2017). Early detection of water stress in maize based on digital images. *Computers and Electronics in Agriculture*, 140, 461-468. doi: 10.1016/j.compag.2017.06.022.

Сучасні технології дистанційного зондування водного режиму та поживних речовин у сільському господарстві: огляд

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Анотація. Актуальність дослідження зумовлена необхідністю впровадження ефективних методів та інструментів моніторингу водних ресурсів та відстеження рівня поживних речовин у ґрунті для покращення сільськогосподарського виробництва та сталого використання природних ресурсів. Метою дослідження є надання комплексного огляду новітніх технологій та методів, що використовуються в ДЗЗ для точної оцінки стану водних ресурсів та рівня поживних речовин у сільськогосподарських культурах з метою підвищення продуктивності та сталості сільського господарства. Були вивчені останні досягнення в методах дистанційного зондування, які дозволяють проводити точний моніторинг і оцінку рівнів води і поживних речовин у посівах, що має вирішальне значення для оптимізації сільськогосподарських практик. Дослідження літератури проводилося шляхом адаптації методів систематичних оглядів і мета-аналізу, яким надається перевага при складанні звітів. У цьому дослідженні представлено огляд технології ДЗЗ з особливим акцентом на визначенні водного та поживного статусу сільськогосподарських культур у сільському господарстві. Також було проведено ретельний огляд досліджень, присвячених застосуванню та технологіям ДЗЗ у сільському господарстві, з використанням підходу «від широкого до вузького». Проаналізовані наукові дослідження свідчать про наступне: ДЗЗ на великомасштабному рівні, ДЗЗ на рівні поля, ДЗЗ на рівні теплиць, ДЗЗ на рівні рослин та ДЗЗ на рівні листків. Також представлені сучасні передові технології. Результати цього дослідження можуть бути корисними для тих, хто займається питаннями сталого сільського господарства, таких як дослідники, викладачі та студенти-початківці

Ключові слова: огляд; точне землеробство; точне зрошення; розумне землеробство; дистанційне зондування; моніторинг посівів; реакція рослин на воду; неінвазивний; неруйнівний