Agri Articles
(e-Magazine for Agricultural Articles)
Volume: 04, Issue: 01 (JAN-FEB, 2024)
Available online at http://www.agriarticles.com

Futuristic Farms: Smart Solutions for Abiotic Stress Using Proximal Hyperspectral Sensing

(*Aniket Sunil Gaikwad and Vaishnavi Pramod Kharbdakar)
Post Graduate Institute, Mahatma Phule Krishi Vidyapeeth, Rahuri, Ahmednagar, Maharashtra, India – 413722
*Corresponding Author's email: aniketgaikwad1963@gmail.com

Abstract

Abiotic stresses, including factors like nutrient deficiency, salinity, drought, heavy metals, herbicides, and extreme temperatures, pose a significant threat to crop production in India. Minimizing yield losses is crucial, emphasizing the importance of early detection to mitigate their impact on crop growth. Recent advancements in hyperspectral remote sensing offer a cost-effective and time-efficient solution for early abiotic stress detection over larger areas. Proximal hyperspectral sensing, positioned within 10 meters above plants, allows a comprehensive examination of plant physiology at sub-millimeter spatial resolution. This paper demonstrates the potential of hyperspectral techniques in real-time abiotic stress management, reducing yield losses.

Keywords: Abiotic stress, hyperspectral remote sensing, nutrient stress, salinity stress, non-destructive assessment and proximal sensing

Introduction

Regular crop monitoring is crucial for sustainable agriculture, minimizing plant stress and ensuring high yields. Abiotic stress factors, including nutrient deficiency, salinity, cold, drought, and heavy metals, significantly impact plant development and crop productivity. These stresses pose threats to food security amidst climate changes from human activities. Plants respond to abiotic stress through molecular, cellular, and physiological changes. Remote sensing techniques, offering timely and non-destructive monitoring of vegetation, surpass direct field techniques. However, multispectral broadband-based remote sensing has limitations in quantifying biochemical properties due to low spectral resolution, averaging critical details and losing specific narrow-band features, such as absorption features.

Adverse environmental conditions, including nutrition, salinity, temperature, and water, often hinder plant growth. Abiotic stresses, particularly nutrient deficiencies and water stress, significantly affect crop productivity (Li *et al.*, 2021). Precision agriculture relies on advanced techniques, including phenotyping for plant stress and breeding programs. Recent imaging technologies, especially hyperspectral sensing, offer non-destructive monitoring of plant characteristics (Mohd Asaari *et al.*, 2018). Hyperspectral imaging sensors combine spatial and spectral information, providing a detailed understanding of plant health (Mertens et al., 2021). The near-infrared and visible spectral ranges play a vital role in observing changes in leaf pigment, cellular composition, and water content (Zhang *et al.*, 2020) (**Figure 1**). Understanding plant-light interactions, sensors, imaging platforms, and processing algorithms is essential for successful plant phenotyping (Liu *et al.*, 2020).

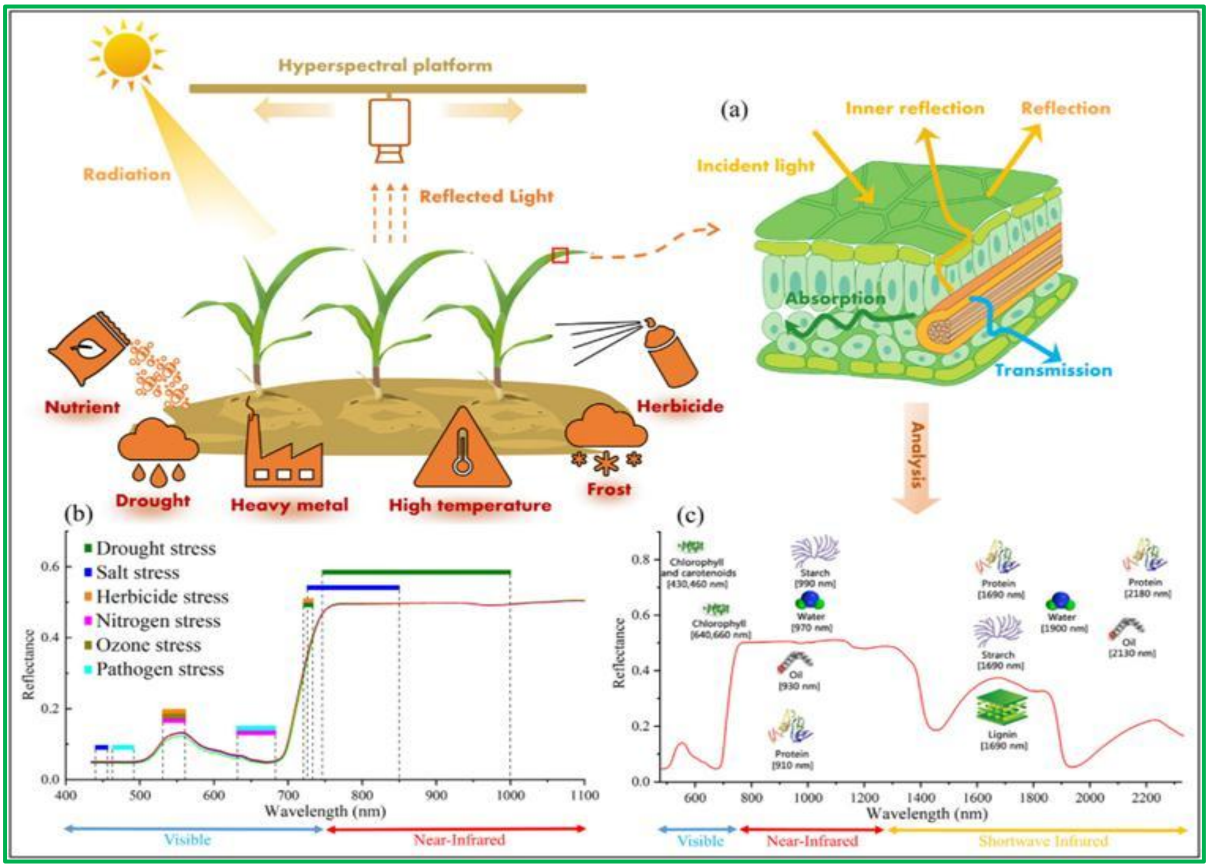

Figure 1: Plant tissue interaction for hyperspectral sensing of abiotic stresses

Reflectance and light absorption, influenced by physiological and chemical characteristics, change under stress, affecting the spectrum. Key stress indicators include chlorophyll levels, pigments, leaf traits, and stomatal behavior (Zubler and Yoon, 2020). Wavelength choice, like blue and red regions (**Figure 1b**), characterizes chlorophyll, photosynthesis, and cellular architecture (Zhu *et al.*, 2021). Severe drought and salt stress alter leaf water content and mesophyll structure, impacting near-infrared reflectance (Lowe *et al.*, 2017).

Proximal sensing

Hyperspectral tech for plant assessment faces setup, data, and sample challenges. Diverse hardware allows varied measurements. Sensor's role in detecting abiotic stress-induced spectral changes is vital. The visible spectrum assesses plant stress, with the same sensor used indoors or outdoors at varying distances. Portable and fixed spectrometers, for proximal sensing, capture leaf and canopy spectra. Proximal imaging analyzes leaf stress and spatial distribution. Proximal sensing calibrates methods for airborne or satellite imaging (Laroche-Pinel *et al.*, 2021). Non-imaging sensors (e.g., leaf-clip) with internal light avoid interference. Proximal hyperspectral tech at canopy scales links leaf and large-scale measurements.

Various areas acquire canopy reflectance data across scales, from single plants to multiples (Lassalle, 2021). Controlled environments stress plants for reproducible assessments of intensity and duration (Tirado *et al.*, 2021). Challenging stress replication may lead to field measurements adapting controlled methods or calibrating data for airborne and satellite imaging (Grieco *et al.*, 2022). Land-based device sensors in field applications provide high spatial resolution, measuring parameters at leaf or canopy scale. **Figure 2** illustrates setups for proximal hyperspectral sensing of abiotic stress.

Figure 2: Proximal hyperspectral sensor setups for abiotic stress monitoring in plants under laboratory and field conditions

Data processing

Reflectance differences reveal plant traits and genotype responses to abiotic stress through hyperspectral analysis. Hyperspectral data processing involves four steps: (i) preprocessing, (ii) segmentation, (iii) variable extraction, and (iv) data analysis (Liu *et al.*, 2020). Preprocessing enhances contrast, reduces interference, and aids analysis. Segmentation minimizes errors using cluster-based methods like k-means (Mishra *et al.*, 2021). Reflectance spectra, measured at multiple wavelengths, may convert into abstract variables, like principal components, for dimensionality reduction.

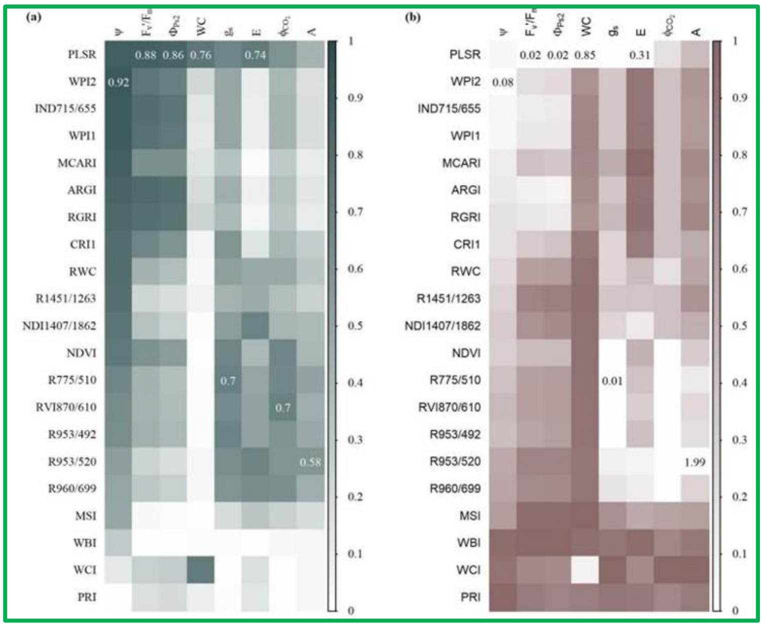

Figure 3: Heatmap of R^2 values (a) and scaled RMSE values (b) to compare the prediction accuracy of SRI and PLS-based models (Mertens et al., 2021)

Proximal hyperspectral studies use spectral reflectance indices (SRIs) directly related to plant traits (e.g., chlorophyll, water content). SRIs describe abiotic stress reactions by combining wavelengths related to specific physiological properties. **Figure 3** shows reflectance-physiology relationships for rapid phenotyping using SRIs and PLS predictive models. Index-based linear regression models assess SRIs for drought detection, comparing with PLS models. SRI-based models offer comparable accuracy to PLS for predicting traits based on hyperspectral data.

Monitoring plant stress involves evaluating the spectral signature to identify stress levels. Graphical analysis informs statistical, prediction, and classification models (Lassalle, 2021). Statistical analysis uses reflectance metrics. Prediction models calculate continuous variables, including stressors or symptoms. Classification models map data to categorical outputs, assessing health. Radiative transfer models, common in remote sensing, extract physiological parameters. However, this model lacks adaptability to proximal hyperspectral technologies' specific illumination issues.

Applications of Proximal Hyperspectral Sensing

Leaf-scale hyperspectral measurements show lower sensitivity to external conditions (e.g., lighting, climate, humidity) than canopy-scale measurements. Valuable for basic lab research, it provides insight into subtle plant changes during stress. However, leaf-level measurements lack practical field use due to low throughput. Proximal hyperspectral images at the canopy scale in the field offer high spatial resolution and increased throughput. Data accuracy is high, less influenced by environmental factors due to proximity. Yet, it has limited vegetation detection capacity, insufficient for large-scale plant stress detection. Different scales reveal various stress aspects. Leaf-scale reflects biochemical characteristics, while canopy-scale assesses plant structure effects. Leaf-scale spectral indices may be less effective for canopy-scale detection due to inherent bias. Multiscale spectral indices are generally more suitable for practical purposes. Stress-sensitive wavelengths at different scales share common characteristics, often in the green, red, and near-infrared ranges. Changes in leaf structure and moisture content, indicated by reduced NIR reflection, reliably predict canopy structure changes. Several cases of leaf and canopy-scale measurements under abiotic stress are discussed below.

1. **Nutrient deficiency:** Nitrogen limits crop growth, impacting photosynthesis and yields, with deficiencies in phosphorus, potassium, and micronutrients when absorption is challenging [Lassalle, 2021]. Nutrient scarcity affects leaves, constraining growth, causing discoloration, and deformation. Spectral reflectance, especially in the visible region, indicates nutritional status. Deficiencies, reflected in pigmentation changes and leaf yellowing, increase reflectance in the green-red region. Hyperspectral images detect necrosis linked to nutrient deficiencies, with increased reflectance in affected areas. Using hyperspectral images is effective for in situ crop nutrition assessment, considering spatial and temporal variability.

1.1. **Leaf scale:** Yu *et al.* (2020) demonstrated HSI's role in precise nitrogen testing for optimal rice fertilizer application. GAELM model with DWMD achieved R2 > 0.68 for training and validation. Shi *et al.* (2022) used PCA and ICA on cucumber leaf spectral images to detect phosphorus deficiency signals, enabling early diagnosis. Osco *et al.* (2020) proposed a random forest model for Valencia orange leaves, predicting nutrients with R2 between 0.912 and 0.727. In semi-arid regions, nitrogen measurement is crucial for olive tree fertilization. Rubio-Delgado *et al.* (2021) analyzed olive leaf spectral properties with hyperspectral data, preferring PLS models over vegetation indices. Yamashita *et al.* (2020) studied hyperspectral data to quantify nitrogen and chlorophyll in tea plants, revealing a nitrogen-specific wavelength range (1325–1575 nm) using regression models (**Figure 4**).

1.2. **Canopy scale:** Continuous Plant Monitoring Using HSI (Weksler et al., 2020) revealed correlations in spectral measurements and transpiration rates in pepper plants. Grieco et al. (2022) utilized HSI to predict nutrient concentrations in HEB-25 barley, achieving high predictability for N, P, and K (R2: 0.90, 0.75, 0.89). Nguyen et al. (2020) developed a night-based HSI system for bok choy and spinach, accurately determining fertilization levels (75%, 80%). Siedliska et al. (2021) used hyperspectral imaging for phosphorus analysis in wild celery, strawberry, and sugar beet crops, with accuracy increasing as plants grow.

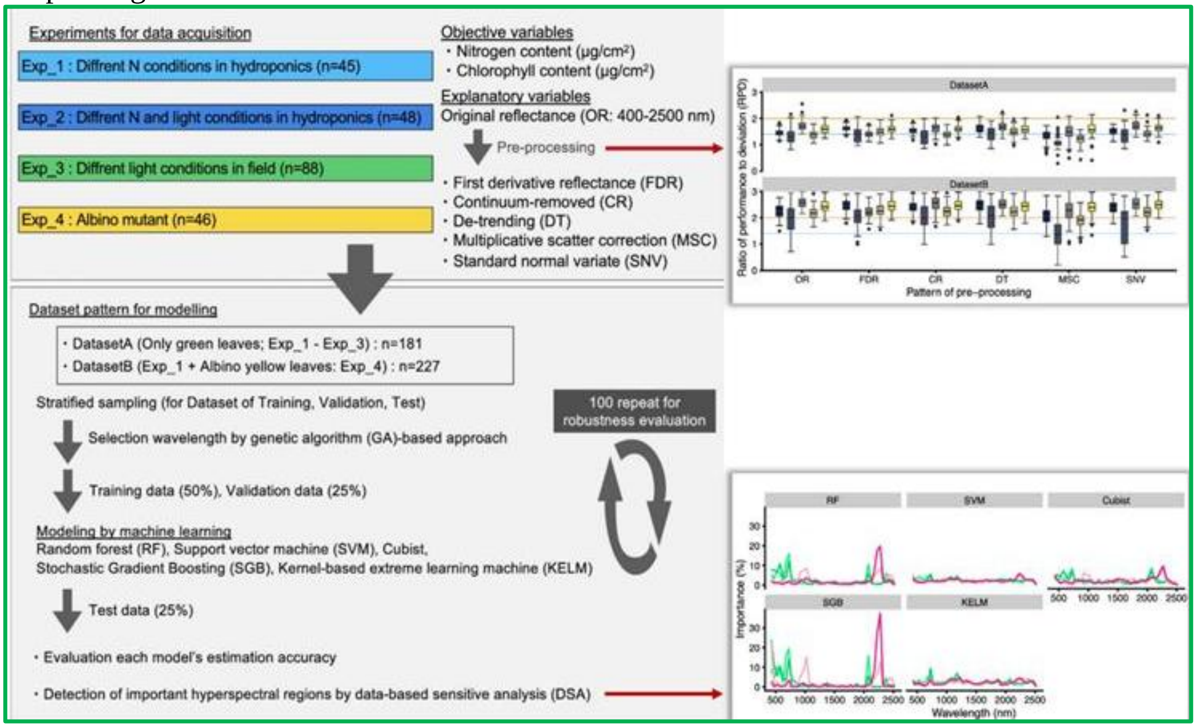

Figure 4: Hyperspectral Nitrogen Detection Procedure (Yamashita et al., 2020)

2. **Salinity:** Salinity stress limits plant productivity, causing significant yield losses. Mitigation involves selecting salt-tolerant crops for improved irrigation and reduced freshwater consumption (Morton *et al.*, 2019). Natural salt deposition, a global concern, affects most crops through leaf degeneration, altered plant interactions, reduced chlorophyll, and compromised disease resistance (Lassalle, 2021). Symptoms include leaf discoloration, observed as increased reflectivity in green areas due to reduced chlorophyll (Goldsmith *et al.*, 2020). Hyperspectral data are valuable for assessing salinity stress.

2.1. **Leaf scale:** Enhancing productivity in salty soils involves selecting salinity-tolerant varieties. Das *et al.* (2020) used hyperspectral tech to monitor salinity stress in 56 rice genotypes, employing PCA and PLS combined models for leaf nutrient prediction. PLSR-combined models outperformed simple ones, aiding in selecting salt-tolerant rice genotypes. Calzone *et al.* (2021) monitored two pomegranate varieties during a 35-day salt treatment, using PLS models to predict leaf parameters critical for plant-salinity relationships. Spectral signatures allowed analysis before visible symptoms, but tolerance levels between cultivars couldn't be determined. Cotrozzi and Couture (2020) explored HSI for crop leaf reactions to stresses before visible symptoms. Spectral data effectively predicted osmotic potential, chlorophyll, and phenol levels (validation R2 0.70 to 0.84). Lettuce yields improved under specific conditions. Boshkovski *et al.* (2022) studied olive plants under drought and salt, correlating spectral data with biochemical characteristics. Stressed plants showed reduced photosynthesis, increased enzyme activity, and specific vegetation indices highlighted significant wavelength ranges. The study aids farmers in identifying stress in large olive trees, optimizing growth, productivity, and sustainability.

2.2. **Canopy scale:** Soil salinity, influenced by factors like saltwater irrigation, varies along the profile, requiring measurements at different depths. An experiment on winter wheat plots correlated hyperspectral indices with salinity, revealing optimal indices for estimating soil salinity, especially at 30 cm depth (R2 = 0.81). Linear or quadratic models based on indices proved suitable for practical evaluation of local saline water irrigation systems (Zhu *et al.*, 2021). In coastal salt marshes facing environmental stressors, early detection is crucial. Goldsmith *et al.* (2020) used hyperspectral imagery to investigate stressors' effects on Spartina alterniflora, finding consistent spectral response models in greenhouse and field experiments. Challenges arise in adapting greenhouse findings to the field due to limited factors examined. Feng *et al.* (2020) used hyperspectral imaging to characterize 13 okra genotypes after salt treatment, developing algorithms for segmenting leaves and plants from RGB images. PLS models analyzed the relationship between leaf spectral reflectance data and physiological traits. El-Hendawy *et al.* (2021) assessed spectral indices for predicting grain yield (GY) and stress tolerance indices (STIs) in wheat genotypes under salinity and control treatments, identifying three significant spectral indices affecting GY.

Conclusion

This paper reviews recent advances in proximal hyperspectral remote sensing for monitoring abiotic stressors, emphasizing its utility in detecting various crop stresses. It identifies stresses by analyzing their impact on photosynthesis, plant structure, light absorption, and reflectance spectrum. However, remote sensing models for large areas are not suitable for proximal hyperspectral imaging due to atmospheric conditions. Proximal crop imagery should consider plant morphology, illumination, and leaf characteristics. Remote sensing, not a standalone system, requires validation through ground truth and integration with collateral information for decision support. The emerging applications of proximal hyperspectral technologies underscore their critical role in rapidly and nondestructively evaluating plant characteristics.

References

1. Boshkovski, B., Doupis, G., Zapolska, A., Kalaitzidis, C., and Koubouris, G. 2022. Hyperspectral imagery detects water deficit and salinity effects on photosynthesis and antioxidant enzyme activity of three Greek olive varieties. *Sustainability* (Switzerland) 14:1432.
2. Calzone, A., Cotrozzi, L., Lorenzini, G., Nali, C. and Pellegrini, E. 2021. Hyperspectral detection and monitoring of salt stress in pomegranate cultivars. *Agronomy* 11:1038.
3. Cotrozzi, L. and Couture, J.J. 2020. Hyperspectral assessment of plant responses to multi-stress environments: prospects for managing protected agrosystems. *Plants People Planet* 2:244–258.
4. Das, B., Manohara, K.K., Mahajan, G.R. and Sahoo, R.N. 2020. Spectroscopy based novel spectral indices, PCA- and PLSR-coupled machine learning models for salinity stress phenotyping of rice. *Spectrochimica Acta, Part A: Molecular and Biomolecular Spectroscopy* 229:117983.
5. El-Hendawy, S., Al-Suhaibani, N., Mubushar, M., Tahir, M.U., Refay, Y. and Tola, E. 2021. Potential use of hyperspectral reflectance as a high-throughput nondestructive phenotyping tool for assessing salt tolerance in advanced spring wheat lines under field conditions. *Plants* 10:2512.
6. Feng, X., Zhan, Y., Wang, Q., Yang, X., Yu, C., Wang, H., Tang, Z.Y., Jiang, D., Peng, C. and He, Y. 2020. Hyperspectral imaging combined with machine learning as a tool to obtain high throughput plant salt-stress phenotyping. *Plant Journal* 101:1448–1461.
7. Goldsmith, S.B., Eon, R.S., Lapszynski, C.S., Badura, G.P., Osgood, D.T., Bachmann, C.M. and Tyler, A.C. 2020. Assessing salt marsh vulnerability using high-resolution hyperspectral imagery. *Remote Sensing* 12:2938.

8. Grieco, M., Schmidt, M., Warnemünde, S., Backhaus, A., Klück, H.C., Garibay, A., Tandrón Moya, Y.A., Jozefowicz, A.M., Mock, H.P., Seiffert, U., Maurer, A. and Pillen, K. 2022. Dynamics and genetic regulation of leaf nutrient concentration in barley based on hyperspectral imaging and machine learning. *Plant Sci*ence 315:111-123.
9. Laroche-Pinel, E., Albughdadi, M., Duthoit, S., Chéret, V., Rousseau, J. and Clenet, H. 2021. Understanding vine hyperspectral signature through different irrigation plans: A first step to monitor vineyard water status. *Remote Sensing* 13:536.
10. 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* 788:147758.
11. Li, Z., Zhou, J., Dong, T., Xu, Y. and Shang, Y. 2021. Application of electrochemical methods for the detection of abiotic stress biomarkers in plants. *Biosensors and Bioelectronics 182*:113105.
12. Liu, H., Bruning, B., Garnett, T. and Berger, B. 2020. Hyperspectral imaging and 3D technologies for plant phenotyping: From satellite to close-range sensing. *Computers and Electronics in Agriculture 175*:105621.
13. Lowe, A., Harrison, N. and French, A.P. 2017. Hyperspectral image analysis techniques for the detection and classification of the early onset of plant disease and stress. *Plant Methods* 13:80.
14. Mertens, S., Verbraeken, L., Sprenger, H., Demuynck, K., Maleux, K., Cannoot, B., De Block, J., Maere, S., Nelissen, H., Bonaventure, G., Crafts-Brandner, S.J., Vogel, J.T., Bruce, W., Inzé, D. and Wuyts, N. 2021. Proximal hyperspectral imaging detects diurnal and drought induced changes in maize physiology. *Frontiers Plant Science* 12:240.
15. Mishra, P., Sadeh, R., Ryckewaert, M., Bino, E., Polder, G., Boer, M.P., Rutledge, D.N. and Herrmann, I. 2021. A generic workflow combining deep learning and chemometrics for processing close-range spectral images to detect drought stress in *Arabidopsis thaliana* to support digital phenotyping. *Chemometrics and Intelligent Laboratory Systems* 216:104373.
16. Mohd. Asaari, M.S., Mishra, P., Mertens, S., Dhondt, S., Inzé, D., Wuyts, N. and Scheunders, P. 2018. Close-range hyperspectral image analysis for the early detection of stress responses in individual plants in a high-throughput phenotyping platform. (ISPRS) *Journal of Photogrammetry and Remote Sensing* 138, 121–138.
17. Morton, M.J.L., Awlia, M., Al-Tamimi, N., Saade, S., Pailles, Y., Negrão, S. and Tester, M. 2019. Salt stress under the scalpel – dissecting the genetics of salt tolerance. *Plant Journal* 97:148–163.
18. Nguyen, H.D.D., Pan, V., Pham, C., Valdez, R., Doan, K. and Nansen, C. 2020. Night-based hyperspectral imaging to study association of horticultural crop leaf reflectance and nutrient status. *Computers and Electronics in Agriculture* 173:105458.
19. Osco, L.P., Ramos, A.P.M., Pinheiro, M.M.F., Moriya, É.A.S., Imai, N.N., Estrabis, N., Ianczyk, F., de Araújo, F.F., Liesenberg, V., de Castro Jorge, L.A., Li, J., Ma, L., Gonçalves, W.N., Marcato, J. and Creste, J.E. 2020. A machine learning framework to predict nutrient content in Valencia-orange leaf hyperspectral measurements. *Remote Sensing* 12:906.
20. Rubio-Delgado, J., Pérez, C.J. and Vega-Rodríguez, M.A. 2021. Predicting leaf nitrogen content in olive trees using hyperspectral data for precision agriculture. *Precision Agriculture* 22:1–21.
21. Siedliska, A., Baranowski, P., Pastuszka-Woźniak, J., Zubik, M. and Krzyszczak, J. 2021. Identification of plant leaf phosphorus content at different growth stages based on hyperspectral reflectance. *BMC Plant Biology* 21:1–17.

22. Tirado, S.B., Dennis, S.S., Enders, T.A. and Springer, N.M. (2020). Utilizing spatial variability from hyperspectral imaging to assess variation in maize seedlings. *The Plant Phenome Journal*, 4(1): e20013.
23. Weksler, S., Rozenstein, O., Haish, N., Moshelion, M., Walach, R. and Ben-Dor, E. 2020. A hyperspectral-physiological phenomics system: Measuring diurnal transpiration rates and diurnal reflectance. *Remote Sensing* 12:1493.
24. Yamashita, H., Sonobe, R., Hirono, Y., Morita, A. and Ikka, T. 2020. Dissection of hyperspectral reflectance to estimate nitrogen and chlorophyll contents in tea leaves based on machine learning algorithms. *Scientific Reports* 10:1–11.
25. Yu, F., Feng, S., Du, W., Wang, D., Guo, Z., Xing, S., Jin, Z., Cao, Y. and Xu, T. 2020. A study of nitrogen deficiency inversion in Rice leaves based on the hyperspectral reflectance differential. *Frontiers Plant Science* 11:1758.
26. Zhang, N., Yang, G., Pan, Y., Yang, X., Chen, L. and Zhao, C. 2020. A review of advanced technologies and development for hyperspectral-based plant disease detection in the past three decades. *Remote Sensing* 12(19):3188.
27. Zhu, K., Sun, Z., Zhao, F., Yang, T., Tian, Z., Lai, J., Zhu, W. and Long, B. 2021. Relating hyperspectral vegetation indices with soil salinity at different depths for the diagnosis of winter wheat salt stress. *Remote Sensing* 13:1–21.
28. Zubler, A. V. and Yoon, J. (2020). Proximal methods for plant stress detection using optical sensors and machine learning. *Biosensors* 10(12):193.