Band-selection in spectroscopy information for vegetation health monitoring using explainable models

by Estrada, J.S. and Cheein, F.A.

Estrada, J.S. and Cheein, F.A. (2025) 'Band-selection in spectroscopy information for vegetation health monitoring using explainable models', *IFAC-PapersOnLine*, 59(23), pp.108-113.

Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 59-23 (2025) 108–113

Band-selection in spectroscopy information for vegetation health monitoring using explainable models ⋆

Juan Sebastian Estrada * **Fernando Auat Cheein** **

* *Department of Electronic Engineering, Universidad Tecnica Federico Santa María, Valparaiso, Chile (e-mail: juan.estradac@usm.cl).*
** *Harper Adams University, England, UK (e-mail: FAuat@harper-adams.ac.uk)*

Abstract: Health monitoring of vegetation can be achieved through the use of hyperspectral cameras and spectrometers. However, both types of equipment are expensive, and in the case of spectrometers, the data collection process is time- and resource-consuming. Even though the information from these instruments is comprehensive, for specific tasks, it is often redundant, with only a portion of the bands providing useful information for applications such as leaf water prediction.

In this context, we propose the identification of such bands using the GRAD-CAM algorithm and 1D convolutional neural networks for predicting leaf water content. The input data consists of the spectral signatures of avocado, olive, and grape leaves in the range of 350 to 2500 nm at different drying stages. To evaluate the identified set of bands, various vegetation indices were predicted using convolutional neural networks and the bands selected by the GRAD-CAM algorithm. The results demonstrate that the prediction of vegetation indices can achieve a correlation factor of up to 0.94 in some cases within the testing dataset.

Keywords: Plant health monitoring, vegetation indices, explainable AI, deep learning.

1. INTRODUCTION

The use of instruments that record the spectral reflectance of vegetation has helped researchers in phenotyping and vegetation health monitoring tasks, including yield prediction (Longfei et al., 2023; Teodoro et al., 2021; Messina et al., 2021), chlorophyll and nitrogen content estimation (Lu et al., 2021; Eugenio et al., 2023; Narmilan et al., 2022; Messina et al., 2021), leaf water content assessment (Villacrés et al., 2019; Villacrés et al., 2021), and pest and disease identification (Santos et al., 2022; dos Santos et al., 2022; Simões and do Amaral, 2023). These studies cover a wide range of crops, including maize (Lu et al., 2021), rice (Longfei et al., 2023), wheat (Liu et al., 2022), cotton (Marang et al., 2021), potato (Tedesco et al., 2021), onion (Messina et al., 2021), sugarcane (Narmilan et al., 2022), soybean (Teodoro et al., 2021), almonds (Chakraborty et al., 2025), grapes (Peanusaha et al., 2024) among others.

From spectral reflectance values, vegetation indices are derived to maximize their response to biophysical parameters while minimizing external disturbances such as atmospheric interference, variations in lighting, and background effects (Villacrés et al., 2021). Such indices as used as features to predict

⋆ The authors thank ANID AFB240002, basal center AC3E, ANID SCIA-ANILLO ACT210052, and ANID national doctorate scholarship, folio N° 21231129, Universidad Técnica Federico Santa María and the Direction of Post-grade programs DPP the direction of graduate programs.

For various applications, particularly leaf water content prediction, regions in the electromagnetic spectrum ranging from 1000 to 2500 nm, also known as the shortwave infrared (SWIR) region, are the most sensitive to water content (Estrada et al., 2025). Studies such as those conducted by Arevalo-Ramirez et al. (2020) and Villacrés et al. (2021) suggest that for tasks like leaf water content prediction in vegetation, there is a fundamental set of wavelengths. Identifying these key wavelengths could facilitate the development of more affordable sensors that record reflectance at specific wavelengths rather than capturing the entire spectrum (Villacrés et al., 2019).

Furthermore, band or wavelength selection methods have been widely studied for various reasons. The finer spectral resolution of hyperspectral devices enhances performance in tasks such as detection; however, it also results in a large volume of data, leading to longer processing times. Additionally, adjacent bands are highly correlated, and some bands may not contain relevant information for the desired task (Sun and Du, 2019). Therefore, selecting only the necessary features for model training becomes an essential step when working with hyperspectral narrow bands.

In recent years, artificial intelligence (AI) has become a valuable tool for assessing the health status of vegetation (Estrada et al., 2023). However, such models have the disadvantage of lacking transparency and explainability (Contreras and Bocklitz, 2024). With the rise of explainable AI (xAI), deep learning models can now be better

10.1016/j.ifacol.2025.11.772

understood, revealing which input features are important for a specific task (Contreras and Bocklitz, 2024).

Gradient-weighted class activation maps (Grad-CAM) (Selvaraju et al., 2017) offer a way to explain how deep learning models make decisions by visualizing activation maps. These models have been extensively used in other fields, such as medical imaging (Oliveira et al., 2024; Ayano et al., 2024; Ge et al., 2023) and time series prediction (Choi et al., 2022). However, their application to spectral data remains relatively unexplored (Contreras and Bocklitz, 2024).

In this context, we propose the use of a convolutional neural network to predict leaf water content from spectral reflectance values in the range of 350 to 2500 nm. Then, using the Grad-CAM algorithm, we identify the regions of the spectrum that contribute to the prediction. Subsequently, using only these regions as input features, we train several new models to predict common vegetation indices used in tasks such as water content estimation and chlorophyll and nitrogen prediction. The models are evaluated using mean squared error (MSE), mean average error (MAE) and correlation coefficient (R^2). This approach was tested in a dataset composed of leaves of olive, avocado and grape, which were dehydrated at five different stages (Estrada et al., 2025).

2. MATERIALS AND METHODS

The general architecture of this work is presented in Fig. 1. First, we train a simple 1D convolutional neural network to predict leaf water content. From the trained model, we extract the most important features using the Grad-CAM method. Then, using the features identified by the explainable model, we train additional 1D convolutional neural networks to predict several vegetation indices commonly used for assessing vegetation status.

2.1 Dataset

The dataset is obtained from (Estrada et al., 2025). It consists of 106 samples of avocado leaves, 111 samples of olive leaves, and 106 samples of grape leaves. For each leaf, reflectance values in the range of 350 nm to 2500 nm were recorded. Additionally, each sample underwent a dehydration process, resulting in five different leaf moisture content levels, each with its corresponding spectral measurement.

Figure 2 shows the average reflectance values at each band for the five dehydration stages, while Figure 3 presents the scatter plot of leaf water content for all samples.

2.2 Convolutional neural network for leaf water content prediction

For the initial task of leaf water content prediction using the full spectral signature, a 1D convolutional neural network is designed. 1D convolutional neural networks are suitable for this task and datatype due to their ability to capture features in sequential data (Kiranyaz et al., 2021). The proposed architecture is shown in Table 1. The model follows a common architecture, consisting of convolutional layers with a ReLU activation function, followed by pooling layers. Afterward, a flatten layer is applied, followed by a dense layer for final data processing. The output layer consists of a single neuron with a linear activation function, as this is a regression task.

Table 1. Layers and parameters of the proposed 1-D convolutional neural network for the leaf water prediction task

Layer	**Parameters**
Input	Size: (2151,1)
1-D convolution	Kernel Size: 3 Filters: 32 Activation: ReLU
Max Pooling	Stride: 2
1-D convolution	kernel Size: 3 Filters: 64 Activation: ReLU
Max Pooling	Stride: 2
1-D convolution	kernel Size: 3 Filters: 64 Activation: ReLU
Flatten	N/A
Dense	Neurons: 128 Activation: ReLU
Dense (output)	Neurons: 1 Activation: Linear

2.3 Identification of important wavelengths through xAI

The interpretation of results from deep convolutional models can be challenging due to the black-box nature of the model (Ayano et al., 2024). Grad-CAM is an interpretation method based on the gradients of the network at the last convolutional layer. It is capable of generating localization maps that highlight the contribution of each band to the final prediction result (Selvaraju et al., 2017; Ayano et al., 2024).

In our case, we propose using the most important bands or sets of bands identified by the Grad-CAM algorithm as input features for the general assessment of vegetation health. These wavelengths can be used to predict other vegetation parameters, not just leaf water content. The other vegetation parameters are represented by common vegetation indices.

2.4 Vegetation Indices

In this study, we selected three different vegetation indices used for various purposes in agriculture: Leaf water index (LWI) is used to asses the water content of leaves and canopy (Villacrés et al., 2019; Arevalo-Ramirez et al., 2020), Shortwave Infrared Water Stress Index (SIWSI) is used to assess water stress in canopy (Villacrés et al., 2019) and Chlorophyll Absorption Reflectance index (TCARI) which is used to assess chlorophyll status in vegetation (Estrada et al., 2023). Table 2 shows the equations for the selected indices.

For the prediction of the vegetation indices in this study, we again used the architecture presented in section 2.2, and trained different models to predict the selected VI's, using as input the identified regions by Grad-CAM. We evaluated model performance using common metrics for regression tasks, including root mean squared error (RMSE),

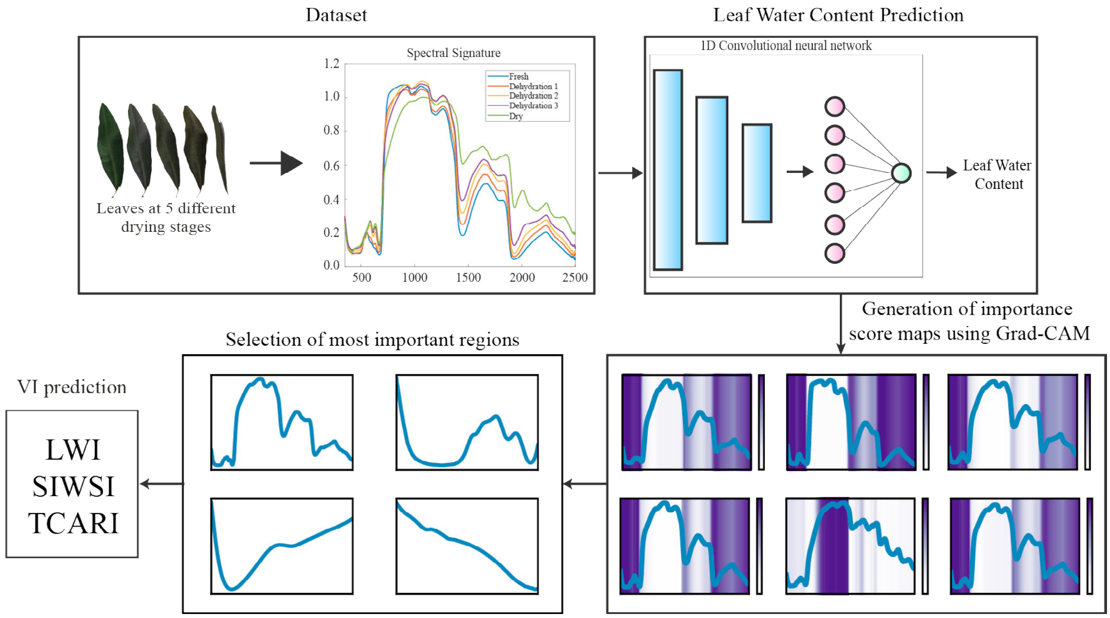

Fig. 1. General overview of the implemented methods, starting from the dataset, the leaf water content prediction using 1D CNN, the generation of importance score maps, the selection of the most important regions of the spectrum and finally the prediction of vegetation indices.

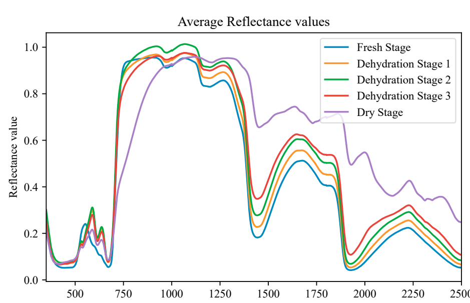

Fig. 2. Average reflectance values at each wavelength for all the samples in the dataset at the different drying stages

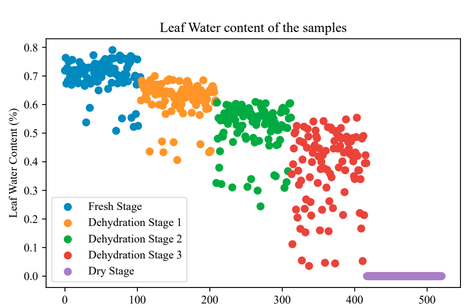

Fig. 3. Leaf water content of the samples in the dataset

Table 2. Vegetation indices used in this study

Name	Equation
LWI	R_{1300}/R_{1450}
SIWSI	$\dfrac{R_{1640} - R_{858}}{R_{1640} + R_{868}}$
TCARI	$3(R_{700} - R_{670}) - 0.2\left(R_{700} - R_{550}\frac{R_{700}}{R_{670}}\right)$

mean absolute error (MAE), and correlation coefficient (R^2).

3. RESULTS

This section presents the results of training the 1D convolutional neural network, the identification of most important regions in the spectrum and the prediction of vegetation indices using as input the reduced set of wavelengths.

3.1 Leaf water content prediction using 1D convolutional neural networks

The model was implemented in a Python 3.10.9 environment, using the TensorFlow-Keras framework. The training was conducted on a computer with an Intel Core Ultra 9 Processor CPU, an NVIDIA GeForce GTX 4080 Ti 8 GB GPU, and 32 GB of RAM, running the Windows 11 operating system. Other software tools utilized include CUDA 11.7 and cuDNN 4.0.

The dataset was partitioned with 70% of the samples for training, and 20% for validation and 10% for testing purposes. The model was trained using the 'Adam' optimizer for 100 epochs. The loss function used was the mean squared error (MSE) function.

The training results can be seen in Fig. 4. It is observed that the model did not overfit and converged around 30 epochs. Additionally, Fig. 5 shows the regression results compared with the leaf moisture content ground truth. The training results achieved a loss of 0.0013, a MAE of 0.02, and a correlation factor of 0.979.

3.2 Grad-CAM results

The Grad-CAM algorithm was applied to the trained model from the previous section to identify which reflectance bands or groups of bands are most important for

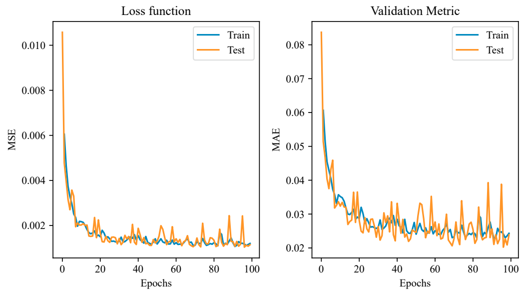

Fig. 4. Training history of the 1D convolutional model used for water content prediction.

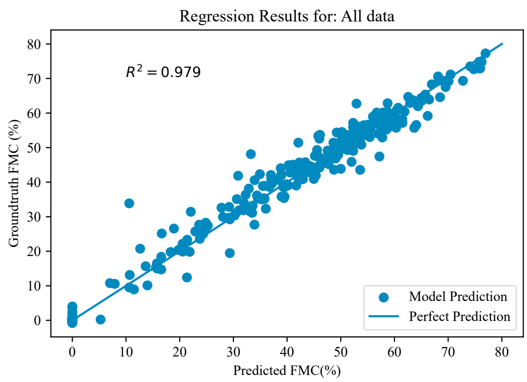

Fig. 5. Results for the prediction of leaf water content in the testing dataset.

the task of leaf water prediction. Figure 6 shows the average importance score for the dataset. The figure indicates that the most important regions are between 350 to 688 nm, 1886 to 2180 nm, and 2260 to 2500 nm. Additionally, we present the importance map for the completely dry stage in Fig. 7, as this stage has a leaf water content value of 0, and it presents a new completely different region from the maps for other stages. This map highlights a region with a high importance score, ranging from 1000 to 1450 nm.

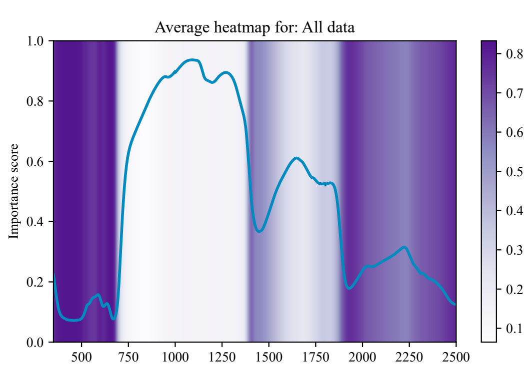

Fig. 6. Average importance score of the reflectance values for all the data in the testing dataset

From the average importance score, we selected three different regions to train the models used to predict the various vegetation indices. We chose the regions that presented an importance score above 0.7. These regions

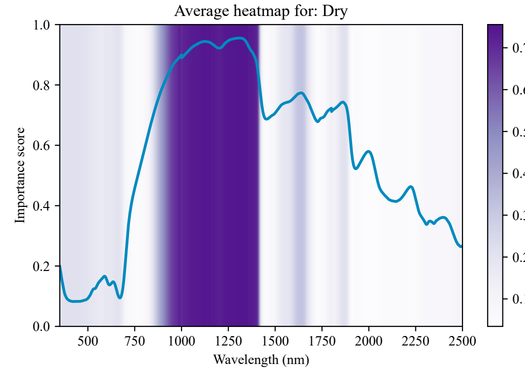

Fig. 7. Average importance score of the reflectance values for the samples in the completely dry stage.

are the reflectance values between 350 to 688 nm, 1886 to 2180 nm, and 2260 to 2500 nm.

3.3 Vegetation index prediction using the selected regions

For the vegetation index (VI) prediction, we trained several models using the regions identified by the Grad-CAM algorithm. First, three models were trained using a single region. Then, additional models were trained using the combined regions. The training resulted in a total of seven models per vegetation index: three for each individual region and four for all possible combinations of the regions.

The architecture of the model is the same as for the leaf water content prediction task (see Section 2.2), with the same hyperparameters as in Section 3.1. The evaluation metrics are shown in Table 3. The naming convention for the results is as follows: Region R0 ranges from 350 to 688 nm, Region R1 ranges from 1886 to 2180 nm, and Region R2 ranges from 2260 to 2500 nm. Regions R01 is the combination of regions 0 and 1, Region R02 is the combination of regions 0 and 2, Region R12 is the combination of regions 1 and 2, and Region R012 is the combination of regions 0, 1, and 2.

Table 3. Evaluation metrics of the models for predicting vegetation indices, using as input the most important regions identified by the Grad-CAM algorithm

Region	LWI		SIWSI		TCARI	
	R^2	RMSE	R^2	RMSE	R^2	RMSE
R0	0.710	0.123	0.867	0.078	0.795	0.077
R1	0.978	0.038	0.660	0.117	-0.824	0.180
R2	0.973	0.042	0.956	0.047	-0.264	0.160
R01	0.973	0.042	0.943	0.053	0.930	0.049
R02	0.961	0.050	0.956	0.047	0.842	0.068
R12	0.978	0.038	0.718	0.109	0.160	0.145
R012	0.977	0.039	0.946	0.051	0.847	0.070

4. DISCUSSION

In this study, we first predicted the leaf water content at five different dehydration stages using a 1-D convolutional neural network. This type of network is useful when dealing with sequential data, as it can detect features without prior pre-processing (Contreras and Bocklitz, 2024; Kiranyaz et al., 2021). The water content prediction task was completed with an MSE of 0.001, an MAE of 0.020, and an R^2 of 0.979. These results are comparable to other methods that use only vegetation indices (VIs), such as those presented by (Estrada et al., 2025) and (Villacrés et al., 2019), which used samples from *eucalyptus globulus* and *pinus radiata* . Our model achieved better metrics than Estrada et al. (2025) and results comparable to Villacrés et al. (2019); however, this study tested a more complete dataset including more vegetation species.

The main objective of this study is to identify which regions of the electromagnetic spectrum contribute most to the task of leaf water content prediction. Then, using these regions, we aim to predict other vegetation indices related to different vegetation parameters. The most important regions were identified through the use of Grad-CAM, an explainable AI algorithm that allows for the exploration of convolutional neural networks.

Using Grad-CAM, we were able to identify three regions that are most important for leaf water content prediction. These regions range from 350 to 688 nm, 1886 to 2180 nm, and 2260 to 2500 nm. It is important to note that the region from 350 to 688 nm corresponds to the visible spectrum, which aligns with the study presented by Arevalo-Ramirez et al. (2020), which predicted other bands in the spectrum using the visible and near-infrared regions at different dehydration levels.

Using the three individual regions and their combination, various models were trained to predict vegetation indices. In this case, the indices were: LWI, SIWSI, and TCARI. These indices were chosen due to their various applications in vegetation phenotyping. Additionally, to compute these indices, the reflectance values span a large region of the spectrum, showcasing the capabilities of the models to predict features even if the selected wavelengths are not a part of the identified regions.

The evaluation metrics of the models are shown in Table 3. This table demonstrates that predicting different VIs is possible using only a portion of the spectrum. It is important to note that the models using the first region, ranging from 350 to 688 nm, were able to retrieve all the indices with correlation factors over 0.7. This result suggests that it is possible to predict vegetation traits most sensitive to the infrared spectrum using only equipment capable of measuring in the visible spectrum, such as a regular camera.

By combining different regions, it was possible to retrieve all the vegetation indices with correlation factors over 0.9, suggesting that it is not necessary to employ the full spectrum from 350 to 2500 nm, but only a few selected regions; which may lead to the development of devices focused only in specific regions of the electromagnetic spectra.

5. CONCLUSION

In this study we proposed the use of important regions identified by xAI algorithms, namely Grad-CAM, to predict vegetation indices related to the health status of vegetation. For this purpose we trained a 1D convolutional network to predict the leaf water content. Then, using Grad-CAM, we identify the most important regions in the 1D convolutional network. Finally, using these regions as inputs we trained models for predicting the vegetation indices.

The results show that there are mainly three different regions that contribute the most to the task of leaf water content prediction, and that these regions can be used to predict other vegetation traits through the use of vegetation indices.

ACKNOWLEDGEMENTS

The authors thank ANID AFB240002, basal center AC3E, ANID SCIA-ANILLO ACT210052, and ANID national doctorate scholarship, folio N° 21231129, Universidad Técnica Federico Santa María and the Direction of Postgrade programs DPP the direction of graduate programs.

REFERENCES

Arevalo-Ramirez, T., Villacrés, J., Fuentes, A., Reszka, P., and Auat Cheein, F.A. (2020). Moisture content estimation of pinus radiata and eucalyptus globulus from reconstructed leaf reflectance in the swir region. *Biosystems Engineering*, 193, 187–205. doi: 10.1016/j.biosystemseng.2020.03.004.

Ayano, Y.M., Schwenker, F., Dufera, B.D., Debelee, T.G., and Ejegu, Y.G. (2024). Interpretable hybrid multichannel deep learning model for heart disease classification using 12-lead ecg signal. *IEEE Access*, 12, 94055–94080. doi:10.1109/ACCESS.2024.3421641.

Chakraborty, M., Pourreza, A., Peanusaha, S., Farajpoor, P., Khalsa, S.D.S., and Brown, P.H. (2025). Integrating hyperspectral radiative transfer modeling and machine learning for enhanced nitrogen sensing in almond leaves. *Computers and Electronics in Agriculture*, 234, 110195. doi:10.1016/j.compag.2025.110195.

Choi, H., Jung, C., Kang, T., Kim, H.J., and Kwak, I.Y. (2022). Explainable time-series prediction using a residual network and gradient-based methods. *IEEE Access*, 10, 108469–108482. doi: 10.1109/ACCESS.2022.3213926.

Contreras, J. and Bocklitz, T. (2024). Explainable artificial intelligence for spectroscopy data: a review. *Pflügers Archiv - European Journal of Physiology*. doi: 10.1007/s00424-024-02997-y.

dos Santos, L.M., e Silva Ferraz, G.A., Marin, D.B., de Figueiredo Carvalho, M.A., Dias, J.E.L., de Oliveira Alecrim, A., and de Lourdes Oliveira e Silva, M. (2022). Vegetation indices applied to suborbital multispectral images of healthy coffee and coffee infested with coffee leaf miner. *AgriEngineering*, 4(1), 311–319. doi:10.3390/agriengineering4010021.

Estrada, J.S., Demarco, R., Johnson, C.M., Zañartu, M., Fuentes, A., and Auat Cheein, F. (2025). A multispectral and hyperspectral image dataset for evaluating chemical traits and the water status of avocado, olive and grape through leaf dehydration under laboratory conditions. *Scientific Reports*, 15(1). doi: 10.1038/s41598-025-85714-8.

Estrada, J.S., Fuentes, A., Reszka, P., and Cheein, F.A. (2023). Machine learning assisted remote forestry health assessment: a comprehensive state of the art review. *Frontiers in Plant Science*, 14. doi: 10.3389/fpls.2023.1139232.

Eugenio, F.C., Grohs, M., Schuh, M., Venancio, L.P., Schons, C., Badin, T.L., Mallmann, C.L., Fernandes, P., da Silva, S.D.P., and Fantinel, R.A. (2023). Estimated flooded rice grain yield and nitrogen content in leaves based on RPAS images and machine learning. *Field Crops Research*, 292, 108823. doi: 10.1016/j.fcr.2023.108823.

Ge, C., Xu, J., Hu, J., Liu, P., Tang, R., Wang, J., and Ren, H. (2023). Mdma: Multimodal data and multi-attention based deep learning model for alzheimer's disease diagnosis. In *2023 8th International Conference on Cloud Computing and Big Data Analytics (ICCCBDA)*, 120–127. doi:10.1109/ICCCBDA56900.2023.10154636.

Kiranyaz, S., Avci, O., Abdeljaber, O., Ince, T., Gabbouj, M., and Inman, D.J. (2021). 1d convolutional neural networks and applications: A survey. *Mechanical Systems and Signal Processing*, 151, 107398. doi: 10.1016/j.ymssp.2020.107398.

Liu, J., Zhu, Y., Tao, X., Chen, X., and Li, X. (2022). Rapid prediction of winter wheat yield and nitrogen use efficiency using consumer-grade unmanned aerial vehicles multispectral imagery. *Frontiers in Plant Science*, 13. doi:10.3389/fpls.2022.1032170.

Longfei, Z., Ran, M., Xing, Y., Yigui, L., Zehua, H., Zhengang, L., Binyuan, X., Guodong, Y., Shaobing, P., and Le, X. (2023). Improved yield prediction of ratoon rice using unmanned aerial vehicle-based multitemporal feature method. *Rice Science*, 30(3), 247–256. doi:10.1016/j.rsci.2023.03.008.

Lu, J., Cheng, D., Geng, C., Zhang, Z., Xiang, Y., and Hu, T. (2021). Combining plant height, canopy coverage and vegetation index from UAV-based RGB images to estimate leaf nitrogen concentration of summer maize. *Biosystems Engineering*, 202, 42–54. doi: 10.1016/j.biosystemseng.2020.11.010.

Marang, I.J., Filippi, P., Weaver, T.B., Evans, B.J., Whelan, B.M., Bishop, T.F.A., Murad, M.O.F., Al-Shammari, D., and Roth, G. (2021). Machine learning optimised hyperspectral remote sensing retrieves cotton nitrogen status. *Remote Sensing*, 13(8), 1428. doi: 10.3390/rs13081428.

Messina, G., Praticò, S., Badagliacca, G., Fazio, S.D., Monti, M., and Modica, G. (2021). Monitoring onion crop "cipolla rossa di tropea calabria IGP" growth and yield response to varying nitrogen fertilizer application rates using UAV imagery. *Drones*, 5(3), 61. doi: 10.3390/drones5030061.

Narmilan, A., Gonzalez, F., Salgadoe, A.S.A., Kumarasiri, U.W.L.M., Weerasinghe, H.A.S., and Kulasekara, B.R. (2022). Predicting canopy chlorophyll content in sugarcane crops using machine learning algorithms and spectral vegetation indices derived from uav multispectral imagery. *Remote Sensing*, 14(5), 1140. doi: 10.3390/rs14051140.

Oliveira, B., Lobo, A., Costa, C.I., Fontes-Carvalho, R., Coimbra, M., and Renna, F. (2024). Explainable multimodal deep learning for heart sounds and electrocardiogram classification. In *2024 46th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 1–4. doi: 10.1109/EMBC53108.2024.10782371.

Peanusaha, S., Pourreza, A., Kamiya, Y., Fidelibus, M.W., and Chakraborty, M. (2024). Nitrogen retrieval in grapevine (vitis vinifera l.) leaves by hyperspectral sensing. *Remote Sensing of Environment*, 302, 113966. doi: 10.1016/j.rse.2023.113966.

Santos, L.B., Bastos, L.M., de Oliveira, M.F., Soares, P.L.M., Ciampitti, I.A., and da Silva, R.P. (2022). Identifying nematode damage on soybean through remote sensing and machine learning techniques. *Agronomy*, 12(10), 2404. doi:10.3390/agronomy12102404.

Selvaraju, R.R., Cogswell, M., Das, A., Vedantam, R., Parikh, D., and Batra, D. (2017). Grad-cam: Visual explanations from deep networks via gradient-based localization. In *2017 IEEE International Conference on Computer Vision (ICCV)*, 618–626. doi: 10.1109/ICCV.2017.74.

Simões, I.O. and do Amaral, L.R. (2023). UAV-BASED MULTISPECTRAL DATA FOR SUGARCANE RESISTANCE PHENOTYPING OF ORANGE AND BROWN RUST. *Smart Agricultural Technology*, 4, 100144. doi:10.1016/j.atech.2022.100144.

Sun, W. and Du, Q. (2019). Hyperspectral band selection: A review. *IEEE Geoscience and Remote Sensing Magazine*, 7(2), 118–139. doi:10.1109/MGRS.2019.2911100.

Tedesco, D., de Oliveira, M.F., dos Santos, A.F., Silva, E.H.C., de Souza Rolim, G., and da Silva, R.P. (2021). Use of remote sensing to characterize the phenological development and to predict sweet potato yield in two growing seasons. *European Journal of Agronomy*, 129, 126337. doi:10.1016/j.eja.2021.126337.

Teodoro, P.E., Teodoro, L.P.R., Baio, F.H.R., da Silva Junior, C.A., dos Santos, R.G., Ramos, A.P.M., Pinheiro, M.M.F., Osco, L.P., Gonçalves, W.N., Carneiro, A.M., Junior, J.M., Pistori, H., and Shiratsuchi, L.S. (2021). Predicting days to maturity, plant height, and grain yield in soybean: A machine and deep learning approach using multispectral data. *Remote Sensing*, 13(22), 4632. doi:10.3390/rs13224632.

Villacrés, J., Arevalo-Ramirez, T., Fuentes, A., Reszka, P., and Cheein, F.A. (2019). Foliar moisture content from the spectral signature for wildfire risk assessments in valparaíso-chile. *Sensors*, 19(24), 5475. doi: 10.3390/s19245475.

Villacrés, J., Fuentes, A., Reszka, P., and Cheein, F.A. (2021). Retrieval of vegetation indices related to leaf water content from a single index: A case study of eucalyptus globulus (labill.) and pinus radiata (d. don.). *Plants*, 10(4), 697. doi:10.3390/plants10040697.