Analysis of the Potential of Remote Piloted Aircraft in the Detection of Damage by Frost in Coffee Plants

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***Abstract*— The current methods for monitoring and evaluating the frost damage of coffee plants are not only costly but also impractical in areas of extensive cultivation. Therefore, remote sensing using Remotely Piloted Aircraft (RPA) can be a feasible alternative, providing coffee producers with a fast, continuous, and accessible method to identify and evaluate the frost damage in coffee plants. Therefore, the objective of this study was to evaluate the frost damage in coffee plantations using multispectral images obtained from RPA. For the analysis of frost on the coffee plants, 18 sampling points were selected in the field. Each sampling point consisted of 5 plants, 1 central plant and 2 sets of 2 plants in the east-west direction from the main plant. The evaluations of the frost damage were performed visually through scores. Subsequently, 3 levels were defined according to the percentage of damage to the plant. The images were obtained with a multispectral camera coupled to an RPA with rotating wings. The spectral signatures of each of the 3 levels of frost damage were determined. The spatial distribution of the frost damage on the plantation allowed the identification of the plantation regions most susceptible to the effects of frost. The spectral signatures made it possible to differentiate coffee plants with different levels of frost damage. The Modified Photochemical Reflectance Index (MPRI) showed the most significant variation in the different levels of frost damage, during the Green Normalized Difference Vegetation Index (GNDVI) had the slightest deviation..**

Keywords*— *Remotely piloted aircraft, vegetation indices, precision agriculture, climate change

I. INTRODUCTION

Brazil is the largest producer and exporter of coffee; Brazil accounts for approximately 36% of the world's production and 29% of the exports, and coffee generates a turnover of approximately USD 6.2 billion per year for the country. This economic importance of Brazilian coffee production at the international level is also reflected in the domestic market, since Brazil, in addition to being the largest coffee producer and exporter, is the second-largest consumer market in the world [1]. In addition, coffee production has relevant social importance as an activity that generates jobs and secures labour in the field [2].

Most of the national production comes from the South and Southeast regions, which have climatic conditions that can limit the development and productivity of coffee plantations. Among the climatic conditions, frost causes the most significant damage to crops and, consequently, the greatest damage to producers, as coffee plants are susceptible to low temperatures [3]. The damage caused by frost on coffee plants can cause the death of plant tissue by a physicochemical process. In this process, there is cell dehydration, loss of turgidity potential, increase in solute concentration, reduction in cell volume and rupture of the plasma membrane. The result is a reduction in income in the year of occurrence, with impacts in the following years [4].

Despite the knowledge of the negative effects of frost on coffee crops and its frequent occurrence over the last few years, there is still no precise and defined methodology for assessing damage to coffee trees affected by frost. Therefore,

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developing new techniques or methods that can accurately evaluate the effects of frost is essential for maintaining and developing the coffee plantation in regions susceptible to frost.

In this context, Remotely Piloted Aircraft (RPA) can be a viable tool in collecting and assessing frost damage in coffee plantations. RPA is an emerging technology that has gained increasing popularity in the remote sensing community in recent years, mainly due to its ability to continuously obtain high spatial resolution images [5]. Unlike remote sensing based on orbital or airborne sensors, RPAs are operated at low altitudes and therefore are less constrained by weather conditions, involve lower cost and complexity in operations, and enjoy high deployment flexibility for repeated missions [6,7]. In addition, they can be applied to smaller areas and specific locations with the ease of obtaining data in less time, such as monitoring and identifying frost damage.

RPA has been successfully used to evaluate different conditions of coffee plants, such as nitrogen content [8,9], disease [10], biophysical parameters [11], planting errors [12] and fruit detection and maturation [13,14]. However, assessing frost damage, there is still a considerable gap to be filled.

Therefore, based on the hypothesis that the use of RPA can solve the problems of data collection regarding the occurrence of frost, the objective of this work was to evaluate the damage caused by frost in coffee plantations through multispectral images obtained by RPA.

II. Material and Methods

A. Description of the study area

A field experiment was performed on a commercial farm on the Bom Jardim farm, located in the municipality of Santo Antônio do Amparo, Minas Gerais, Brazil, with geographical coordinates 21°01′11.93″ S, 44°55′24.46″ W and an altitude of 927 m (Fig. 1). The region's climate, according to the Köppen climate classification, is Cwa (humid subtropical), with hot and humid summers and cold and dry winters, with an annual average air temperature of 19.8°C and average annual total rainfall of 1,670mm [15]. The area has an approximate 3.5 ha, cultivated with coffee crop (*Coffea arabica* L.), of the cultivar Catucaí Vermelho IAC 144, with 6 years since initial planting, with a spacing of 3.5m between rows and 0.5m between plants, totalling 5,700plants.ha^{-1} (Fig. 1). The occurrence of frost was observed on July 8 and 9. The minimum temperatures on these days were 1.8 and 0.3°C, respectively. An automated weather station on the property measured the minimum temperature on those days. For the in situ analysis of the frost damage of coffee plants, 18 sampling points were marked at the plantation. Each sampling point consisted of 5 plants, 1 central plant, and 2 sets of 2 plants in the east-west direction from the main plant.

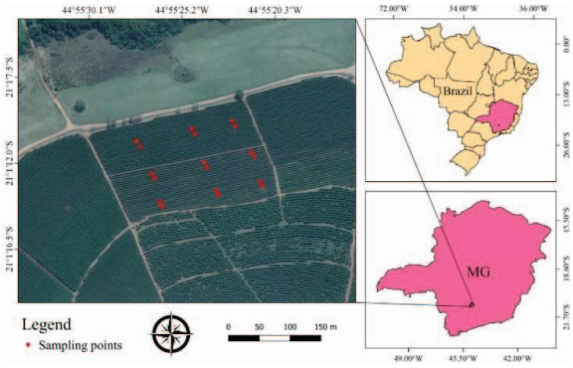

Fig. 1 Geographical location of the study area.

B. Evaluation of the frost damage

The evaluations of the frost damage were performed visually by the attribution of scores. For this, three experts in the field of agriculture and with experience in the area of coffee production went to the field for evaluation and assigned scores (percentage of the plant with damage to the leaves, branches, and stems) to the previously selected plants. After this, the data were compiled, and the mean of the three observers was calculated. Subsequently, 3 levels were defined according to the percentage of damage to the plant: healthy = 0% (or no damage), moderate = up to 50% of the plant was damaged, and severe = more than 50% of the plant was damaged.

C. Image acquisition and processing

Sequoia multispectral camera (MicaSense, Seattle, WA, United States) was embedded in commercial RPA 3DR Solo. The camera has four 1.2-megapixel monochrome sensors that collect global shutter imagery along four discrete spectral bands: green (530–570 nm), red (640–680 nm), red-edge (730–740 nm) and near-infrared (770–810 nm). The horizontal (HFOV), vertical (VFOV) and diagonal (DFOV) fields of view of the multispectral camera are 61.9º, 48.5º and 73.7º, respectively, with a focal length of 4mm. Additionally, to transform the digital numbers (grey levels) from the sensors to reflectance values, a calibrated reflectance panel (MicaSense, Seattle, WA, United States was used before and after the flight.

The flights were performed between 12h and 14h local time to obtain good lighting conditions and avoid shadows. Flight planning was performed by using the free software Mission Planner [16], which was executed on a portable computer. The parameters adopted were an altitude of 60m, a mean speed of 3 m.s^{-1}, and a frontal and lateral overlap of 80%, which resulted in a spatial resolution of 6.44 cm.

Image processing was performed using Pix4Dmapper, version 4.4.12 (Pix4D, Lausanne, Switzerland). Pix4d follows a 3-step workflow [17]. Initially, the software calculates the key points in the images and uses them to find correspondences between them. From these initial correspondences, the software performs several automatic aerial triangulation (AAT), bundle block adjustment (BBA), and iterative steps of camera autocalibration until ideal reconstruction is achieved. Next, a densified point cloud is generated to obtain a highly detailed digital surface model

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(DSM). Subsequently, based on the DSM, reflectance maps and vegetation indices are generated.

The spectral signature was obtained in the software QGIS 2.18.13by using the semi-automatic classification plugin (SCP) developed by [18]. The reflectance at the wavelengths of green, red, red-edge, and near-infrared was measured at each sampling point referring to the levels of frost damage. For this, the mean reflectance at each wavelength in the pixels present in a 0.20m radius was calculated from the center of each plant, totalling 90 measurements.

The vegetation indices used in this study were based on the combination of reflectance values in the green, red, red-edge and near-infrared spectral bands (Table 1). The choice of vegetation indices was based on the ability of these indices to assess and identify frost damage in different crops since, for coffee, only the Normalized Difference Vegetation Index (NDVI) was previously analyzed.

Table 1. Vegetation indices obtained from reflectance in the green, red, red-edge and near-infrared spectral bands

Vegetation indices	Equation	Reference
GNDVI (Green Normalized Difference Vegetation Index)	$\frac{\rho_{nir}-\rho_{green}}{\rho_{nir}+\rho_{green}}$	[19]
NDVI (Normalized Difference Vegetation Index)	$\frac{\rho_{nir}-\rho_{red}}{\rho_{nir}+\rho_{red}}$	[20]
NDRE (Normalized Difference Red Edge)	$\frac{\rho_{nir}-\rho_{edge}}{\rho_{nir}+\rho_{edge}}$	[21]
MPRI (Modified Photochemical Reflectance Index)	$\frac{\rho_{green}-\rho_{red}}{\rho_{green}+\rho_{red}}$	[22]

ρblue: reflectance in the blue band; ρgreen: reflectance in the green band; ρred: reflectance in the red band; ρnir: reflectance in the near-infrared band; ρedge: reflectance in the red-edge band

The Raster Calculator tool in the QGIS software was used to calculate the indices. Subsequently, to assess the potential of vegetation indices to differentiate levels of frost damage (severe, moderate and healthy), the mean values of each vegetation index within a 20 cm radius from the center of each sampled plant were extracted using the Zonal Statistics plugin, also present in QGIS.

III. RESULTS AND DISCUSSION

A. Spatial distribution of the frost damage

The spatial distribution of the frost damage in the plantation is shown in Fig. 2. It was observed that the plants in the southern region of the plantation showed no frost damage. In contrast, the plants in the northern region of the plantation showed severe damage. The plants in the central region of the plantation showed moderate damage.

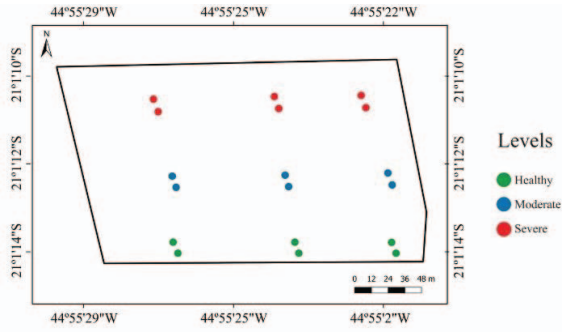

Fig. 2. Spatial distribution of the frost damage on the plantation

Knowing the spatial distribution of frost damage is essential for producers adequately managing plantations. Thus, producers have sought alternatives that replace the current methods of assessing frost damage, which in addition to being costly, are not viable in extensive cultivation areas. Given this, [23] used the orbital images to evaluate the impact of frost on a state scale. The results demonstrated the potential of orbital images to evaluate the impact on coffee plants per frost event. However, orbital images have limitations compared to suborbital images through RPA.

B. Spectral signature of coffee plants with frost damage

The mean reflectance of coffee plants at the wavelengths of green, red, red-edge, and near-infrared for different levels of frost damage is shown in Fig. 3.

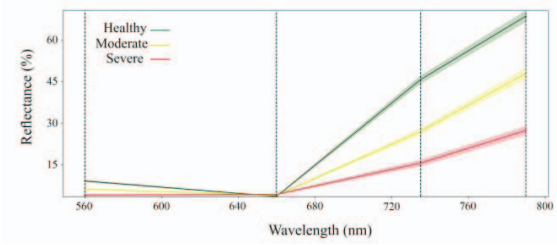

Fig. 3. Spectral signatures of coffee plants at different levels of frost damage

As expected for the vegetation, the spectral signatures showed greater reflectance in the near-infrared region than in the visible region. Coffee plants and vegetation generally reflect more energy in the near-infrared spectral region. This is due to the interaction of energy with the internal structures of the leaves and the structure of the canopy itself through the absorption of energy in large quantities due to the photosynthetic pigments of plants such as chlorophyll and anthocyanin [24-26].

Regarding the plantation regions with the occurrence of frost, the plants with more severe damage had higher reflectance values at the red and red-edge wavelengths. In comparison, the plants with no damage had higher reflectance values at the green and near-infrared wavelengths. Frost damage can cause physiological changes in plant leaves, such as decreases in photosynthesis and chlorophyll content in the

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leaves, dehydration, and decreases in biomass, and consequently, modify the spectral characteristics of the vegetation by reducing reflectance in the near-infrared region and increasing reflectance in the visible spectral region [27]. Similar to this study, [26] monitored the impact of frost on winter wheat and observed that the reflectance in wheat with no damage was lower in the visible spectral region and higher in the near-infrared region than that of the wheat affected by frost. [28] also observed that the reflectance in oilseed rape leaves gradually decreased according to frost freezing time. Therefore, multispectral images obtained by RPA can differentiate coffee plants affected by the frost from healthy coffee plants.

C. *Vegetation indices*

The average values of vegetation indices in plants with different levels of frost damage can be seen in Table 2.

Table 2. Mean values of vegetation indices in plants with different levels of frost damage

Vegetation indices	Healthy	Moderate	Severe
MPRI	0.42	0.19	-0.02
NDVI	0.89	0.82	0.72
NDRE	0.21	0.28	0.28
GNDVI	0.76	0.76	0.73

The MPRI showed the most significant variation (0.44) between plants considered healthy and plants with severe frost damage. On the other hand, the GNDVI had a minor variation (0.03). Regarding the variation between plants with moderate and severe damage, the MPRI also presented the most significant variation (0.21), while the NDRE did not show variation. It is worth mentioning that only the NDVI and MPRI indices showed variation between the levels of frost damage. The other indices, GNDVI and NDRE, could not differentiate all levels of frost damage.

Gabrielli et al. [29], evaluating frost damage in White Mustard from vegetation indices obtained from Sentinel-2 images, found different results from this study. The NDRE index presented the highest value of R^2 (0.46) compared to the NDVI (0.21).

Although the MPRI, an indice that uses only the reflectance in the visible bands, showed the most significant variation, a greater variation was expected for the NDVI, GNDVI and NDRE indices, indices that use the combination of the near-infrared with the visible bands, because as shown in Figure 3, the variation in near-infrared reflectance at different levels of frost damage to plants is more pronounced when compared to reflectance in the visible bands. This relationship can be observed in Gabrielli et al. [29]. The authors demonstrate that the VIs calculated from the reflectance values in the red and red-edge regions were the most correlated with frost damage in White Mustard.

The variation in the values of vegetation indices due to frostbite on leaves could also be observed in other studies and cultures. Feng et al. [30] reported that the NDVI value of winter wheat drops dramatically after frostbite, and therefore NDVI can be used to monitor frostbite in winter wheat over large areas. XXX [23] demonstrated that the NDVI values in coffee plantations vary soon after the frost, allowing us to visualize the extension of the affected area. Gabrielli et al. [29] observed that vegetation indices decrease as the frost index in White Mustard increases.

In this context, the VI can be used as another tool to support the producer in the management of their coffee plantations as a result of the damage caused by frost. However, for the methodology proposed in this study to be consolidated, other studies must be carried out exploring other regions, different species of coffee trees and different RPA and multispectral sensors.

IV. CONCLUSIONS

This study showed that producers could use RPA to monitor and evaluate frost damage in coffee plantations. The spatial distribution of frost damage and the DSM of the plantation allowed the identification of the plantation regions most susceptible to the effects of frost. The spectral signatures made it possible to differentiate coffee plants with different levels of frost damage. The Modified Photochemical Reflectance Index (MPRI) showed the most significant variation in the different levels of frost damage. The Green Normalized Difference Vegetation Index (GNDVI), had a minor deviation.

The monitoring and evaluation of frost damage in coffee plantations with the use of RPA are essential to optimize and facilitate decision-making by the producers. This can significantly reduce production costs and minimize frost damage.

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REFERENCES

[1] United States Department of Agriculture (2022). *Coffee: world markets and trade Foreign Agricultural Service/USDA*. Available: https://apps.fas.usda.gov/psdonline/circulars/coffee.pdf

[2] B. B. Ribeiro, L. M. V. L. Mendonça, G. A. Assis, J. M. A. Mendonça, M. R. Malta, and F. F. Montanari, "Evaluation of the Chemical and Sensory Characteristics of *Coffea canephora* Pierre and *Coffea arabica* L. BLENDS," *Coffee Science*, vol. 9, no. 2, p. 178-186, June 2014.

[3] J. B. Matiello, and S. R. Almeida. (2016*) Deu geada no cafezal, não façam podas já.* Available:: http://www.cccrj.com.br/revista/839/24.pdf

[4] J. C. Ramalho, F. M. DaMatta, A. P. Rodrigues, P. Scotti-Campos, I. Pais, P. Batista-Santos, et al., "Cold impact and acclimation response of *Coffea* spp," *Plants Theoretical and Experimental Plant Physiology*, vol. 26, no. 1, pp. 5-18, Feb. 2014.

[5] A. Rango, A. Laliberte, C. Steele, J. E. Herrick, B. Bestelmeyer, T. Schmugge, et al., "Using unmanned aerial vehicles for rangelands: current applications and future potentials," *Environmental Practice, Abingdon*, vol. 8, no. 3, pp. 159-168, July 2006.

[6] E. R. Hunt, W. D. Hively, S. J. Fujikawa, D. S. Linden, C. S. T. Daughtry, and G. W. McCarty, "Acquisition of NIR-green-blue digital photographs from unmanned aircraft for crop monitoring," *Remote Sensing*, vol. 2, no. 1, pp. 290-305, Jan. 2010.

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[7] A. S. Laliberte, M. A. Goforth, C. M. Steele, and A. Rango, "Multispectral remote sensing from unmanned aircraft: Image processing workflows and applications for rangeland environments," *Remote Sensing*, vol. 3, no. 11, pp. 2529-2551, Nov. 2011.

[8] D. B. Marin, G. A. S. Ferraz, P. H. S. Guimarães, F. Schwerz, L. S. Santana, B. D. S. Barbosa, et al. "Remotely Piloted Aircraft and Random Forest in the Evaluation of the Spatial Variability of Foliar Nitrogen in Coffee Crop," *Remote Sensing*, vol. 13, no. 8, pp. 1471, Apr. 2021.

[9] T. C. Parreiras, G. H. E. Lense, R. S. Moreira, D. B. Santana, and R. L. Mincato, "Using unmanned aerial vehicle and machine learning algorithm to monitor leaf nitrogen in coffee," Coffee Science, vol. 15, pp. 1-9, 2020.

[10] D. B., Marin, L. S. Santana, B. D. S. Barbosa, R. A. P. Barata, L. P. Osco, A. P. M. Ramos, et al., "Detecting coffee leaf rust with UAV-based vegetation indices and decision tree machine learning models," *Computers and Electronics in Agriculture*, vol. 190, pp. 106476, Nov. 2021.

[11] L. M. Santos, G. A. S. Ferrazm B. D. S. Barbosa, A. V. Dioto, M. T. Andrade, L. Conti, et al., "Determining the Leaf Area Index and Percentage of Area Covered by Coffee Crops Using UAV RGB Images," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, v. 13, p. 6401-6409, 2020.

[12] L. S. Santana, G. A. S. Ferraz, J. P. B. Cunha, M. S. Santana, R. O. Faria, D. B. Marin, D. B. et al., "Monitoring errors of semi-mechanized coffee planting by remotely piloted aircraft," *Agronomy*, vol. 11, no. 6, pp. 1224, Jun. 2021.

[13] G. L. A. Carrijo, D. E. Oliveira, G. A. Assis, M. G. Carneiro, V. C. Guizilini, and J. R. Souza, "Automatic detection of fruits in coffee crops from aerial images," *in 2017 Latin American Robotics Symposium (LARS) and 2017 Brazilian Symposium on Robotics (SBR)*, Curitiba, PR, 2017, pp. 1-6.

[14] R. N. Martins, F. A. C. Pinto, D. M. Queiroz, D. S. M. Valente, and J. T. F. Rosas, "A Novel Vegetation Index for Coffee Ripeness Monitoring Using Aerial Imagery," *Remote Sensing*, vol. 13, no. 2, pp. 263, Jan. 2021.

[15] A. F. Freitas, D. H. S. Nadaleti, H. R. O. Silveira, G. R. Carvalho, R. P. Venturin, V. A. Silveira, et al., "Productivity and beverage sensory quality of arabica coffee intercropped with timber species," *Pesquisa Agropecuária Brasileira*, vol. 55, 2020.

[16] M. Oborne (2018). *Mission Planner*. Available: http://ardupilot.org/planner/index.html

[17] J. M. Fernández-Guisuraga, E. Sanz-Ablanedo, S. Suárez-Seoane, and L. Calvo, "Using unmanned aerial vehicles in postfire vegetation survey campaigns through large and heterogeneous areas: Opportunities and challenges," *Sensors*, vol. 18, no. 2, pp. 586. Feb., 2018.

[18] L. Congedo (2016). Semi-Automatic Classification Plugin Documentation. Available: https://plugins.qgis.org/plugins/SemiAutomaticClassificationPlugin/

[19] A. A. Gitelson, Y. J. Kaufman, and M. N. Merzlyak, "Use of a green channel in remote sensing of global vegetation from EOS-MODIS," *Remote sensing of Environment*, vol. 58, no. 3, pp. 289-298. Dec. 1996.

[20] J. W. Rouse, R. H. Haas, D. W. Deering, J. A. Schell, and J. C. Harlan, "Monitoring the Vernal Advancement and Retrogradation (Green Wave Effect) of Natural Vegetation," Greenbelt: NASA/GSFC, Type III, Final Report, 1974.

[21] A. Gitelson, and M. N. Merzlyak, "Quantitative estimation of chlorophyll-a using reflectance spectra: Experiments with autumn chestnut and maple leaves," *Journal of Photochemistry and Photobiology B: Biology*, vol. 22, no. 3, pp. 247-252, Mar. 1994.

[22] Z. Yang, P. Willis, and R. Mueller, "Impact of band-ratio enhanced AWIFS image to crop classification accuracy," in *Proceedings of the 17th William Pecora Memorial Remote Sensing Symposium*, Denver, CO, USA, 2008, pp. 1-11.

[23] D. R. Rafaelli, M. A. Moreira, and R. Farias, "Análise do potencial de dados MODIS para monitorar o impacto de geada em nível estadual e em lavouras de café," *Agricultura em São Paulo*, vol. 53, no. 1, pp. 5-15, Jan. 2006.

[24] M. R. Slaton, E. R. Hunt Jr, and W. K. Smith, "Estimating near‐infrared leaf reflectance from leaf structural characteristics,' *American Journal of Botany*, vol. 88, no. 2, pp. 278‐284, Feb. 2001.

[25] P. J. Pinter Jr, J. L. Hatfield, J. S. Schepers, S. James, E. M. Barnes, M. S. Moran, et al., "Remote sensing for crop management," *Photogrammetric Engineering & Remote Sensing*, vol. 69, no. 6, pp. 647-664, June 2003.

[26] H. Wang, Z. Huo, G. Zhou, L. Wu, and H. Feng, "Monitoring and forecasting winter wheat freeze injury and yield from multi-temporal remotely sensed data," *Intelligent Automation & Soft Computing*, vol. 22, no. 2, pp. 255–260, Nov. 2015.

[27] K. Prabhakara, W. D. Hively, and G. W. McCarty, "Evaluating the relationship between biomass, percent groundcover and remote sensing indices across six winter cover crop fields in Maryland, United States," *International Journal of Applied Earth Observation and Geoinformation*, vol. 39, pp. 88-102, July 2015.

[28] C. Wei, J. Huang, X. Wang, G. A. Blackburn, Y. Zhang, S. Wang, et al., "Hyperspectral characterization of freezing injury and its biochemical impacts in oilseed rape leaves," *Remote Sensing of Environment*, vol. 195, pp. 56-66, June 2017.

[29] M. Gabbrielli, M. Corti, M., Perfetto, V., Fassa, V, and L. Bechini, L, "Satellite-Based Frost Damage Detection in Support of Winter Cover Crops Management: A Case Study on White Mustard," *Agronomy*, vol. 12, no. 9, pp. 1-16, Aug. 2022.

[30] M. Feng, W. Yang, L, Cao, and G. Ding, "Monitoring winter wheat freeze injury using multi-temporal MODIS data," *Agricultural Sciences in China*, vol. 8, no. 9, pp. 1053-1062, Sept. 2009.

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