RESEARCH ARTICLE Legume Research- An International Journal, Volume 49 Issue 6: 1008-1014 (June 2026)

Assessing Legume Crop Growth and Yield Prediction using Drone-based Remote Sensing

Enhao Chen[1], Qin Gao[1], Bingqing Zheng[1], Lujin Wang[1,2], Wenhe Lin[1]

10.18805/LRF-868

ABSTRACT

Background: The purpose of this project is to evaluate the prospective use of drone-based remote sensing for assessing legume crop development and predicting their yields. Traditional agricultural procedures often fall short in delivering timely and accurate monitoring, necessitating the adoption of innovative techniques.

Methods: The study considers vegetative indicators such as NDVI, GNDVI and canopy cover to track the growth of three legume crops-peanut, soybean and common bean. Machine learning models, including random forest, support vector machines and multiple linear regression, were developed to predict agricultural production using remote sensing data. Statistical analysis was performed to verify the trustworthiness of vegetation indicators against ground-truth measurements.

Result: The models achieved high accuracy, with R^2 values reaching up to 0.92. Statistical analysis confirmed strong relationships between vegetation indicators and ground-truth data. Among the studied crops, soybeans exhibited the highest growth vigor and yield. The study demonstrates that integrating machine learning with drone photography can enhance precision agriculture, making it more scalable and sustainable. Future research is recommended to explore different crop varieties and environmental conditions to further optimize the application of these technologies.

Key words: Drone-based remote sensing, GNDVI (green normalized difference vegetation index), Legume crops, Machine learning models, NDVI (normalized difference vegetation index), Precision agriculture.

INTRODUCTION

Legumes provide a variety of food products that are important sources of plant protein and critical to the provision of essential services to communities around the world. In addition to being the most nutritious crops, they are also highly nutritious, making them an essential part of the global food production process and security in the face of a growing world population. Legumes also have a unique ability to fix atmospheric nitrogen, which plays a key role in improving agricultural ecosystems and increasing crop yields, water recycling and carrying capacity (Ali *et al.,* 2022). Legumes play an important role in combating climate change because they help fix nitrogen compounds that require a lot of energy to produce and can produce greenhouse gases when decomposed (Na *et al.,* 2024). They help to reduce the use of fossil fuels by providing biofuel feedstock and industry. Given the problems of securing them, the genetic diversity allows them to survive in different situations. Therefore, they are very robust and well suited to the efforts of small farms and limited resources.

The purpose of this research was to investigate the many ways in which legumes contribute to the growth of strong and efficient agroecosystems, which ultimately results in an increase in the level of food security on a worldwide scale. Since the COVID-19 outbreak in 2019, the prevalence of food insecurity around the globe has seen a significant increase and it has remained at a level that is almost the same for the last three years (Boursianis *et al.,* 2020). It is estimated that between 713 and 757 million people throughout the world are suffering from hunger as of the year 2023. Hence, it is a key deviation away from the goal of the total eradication of hunger, food insecurity and all forms of malnutrition by 2030 in its entirety. In order to help in the selection of crop varieties and assessment of field management for precision agriculture, a grain crop yield estimate ought to be accurate, effective and timely. The models also need considerable amounts of information on crop growth parameters and other climatic and soil information; this increases the cost, complexity and uncertainty of the estimate. Models of grain crop growth have been developed (WOFOST, DSSAT and APSIM). But these models need a huge data set.

Numerous remote sensing methods have been developed and widely used for agricultural monitoring purposes. High-resolution remote sensing data obtained

[1]College of Economics and Management, Fujian Agriculture and Forestry University, Fuzhou, China.
[2]Fujian Yingfang Network Technology Co., Ltd., Fuzhou, China.

Corresponding Author: Wenhe Lin, College of Economics and Management, Fujian Agriculture and Forestry University, Fuzhou, China. Email: 253062775@qq.com

How to cite this article: Chen, E., Gao, Q., Zheng, B., Wang, L. and Lin, W. (2026). Assessing Legume Crop Growth and Yield Prediction using Drone-based Remote Sensing. *Legume Research*. **49(6):** 1008-1014. doi: 10.18805/LRF-868.

Submitted: 22-03-2025 **Accepted:** 05-11-2025 **Online:** 17-11-2025

from satellites are used in many prediction models, including “soil and plant analyzer development (SPAD) and leaf area index (LAI)” of different crops. Unmanned Aerial Vehicles (UAVs) have features such as low-altitude detection, high manoeuvrability, short duty cycle, high spatial and temporal resolution and low cost (Kamilaris *et al.* 2017; Estevez *et al.,* 2023). Machine learning (ML) is an important subfield of artificial intelligence applied in areas such as object recognition, weather forecasting and natural language processing, which has led to the development of new methods and research techniques for predicting crop yield.

Urdbean genotypes were evaluated for their ability to withstand high temperatures in order to determine heat-resistant cultivars that are appropriate for growing during the summer months. Thirty-five genotypes were highly sensitive to heat, while there were only eight genotypes that were highly heat resistant (Ferencz *et al.,* 2004). Through the identification of 79 quantitative trait loci (QTLs) and 23 sites of QTL hotspots, exhibiting QTLs with opposite effects on yield components and Fe/Zn accumulation, they selected specific QTLs to enhance the levels of Fe/Zn in biofortified cultivars without yield penalty (Cho, 2024; Kim and AlZubi, 2024; Min, Mito and Kim, 2024).

Karmakar *et al.* (2023) highlighted the growing use of multimodal remote sensing (MRS), which combines data from multiple RS sources to enhance monitoring accuracy. MRS offers complementary strengths by integrating different data types, leading to more precise assessments of plant growth and health. The aim of the study conducted by Inoue (2020) was to determine the genetic diversity in the nutrient composition of grains in 600 pigeon pea samples obtained from the RS Paroda gene bank at ICRISAT, India. Field trials conducted in 2019 and 2020 showed significant changes in agronomic traits and grain composition”. In addition to introducing the desired nutrients, some lines have been affected by the disease, which has great potential for the development of bioremediated lines with good agronomic traits.

Legumes are at the forefront of efforts to develop products with higher and better protein content. Zhou *et al.*, (2024) evaluated two important aspects of protein quality. Pea (*Pisum sativum* L.) is a crop cultivated worldwide (Nevavuori *et al.*, 2020). They conducted experiments at several locations over a three-year period to evaluate the amino acid profile and protein digestibility of pea populations containing 110 recombinant pure lines (RILs). They found that this method outperformed other methods previously used to conduct similar studies. Quantitative trait loci (QTL) and improved protein gene screening techniques will help develop peanut varieties with improved nutritional traits. Completed. The extent to which these genotypes adapt to an individual and the combined effects of drought stress and low phosphorus exposure were assessed. “The researchers found that soybean varieties SEF60 and NCB226 were more resistant to stress and better adapted to stress than the commercial control DOR390, resulting in higher yields” (Joshi *et al.,* 2024). However, there was no noteworthy change in the amino acid and nutrient content of the seeds at harvest (Ghamisi, *et al.,* 2019; Said *et al.,* 2023).

The measurement techniques to determine genome-related stress indices in chickpea populations, finding different populations derived from chickpea germplasm as donors for drought and drought stress induction. Further analysis may identify specific techniques for adverse environments. The last five papers focused on bioinoculants and soil fertility enhancement. Norris Savala and colleagues found that grafting led to significant improvements in nodulation, plant growth and yield, suggesting bioinoculants could increase soybean yields in Mozambique (Messina and Modica, 2020). The GmTic110a gene, stated in leaves as well as localized to the chloroplast membrane, plays a crucial role in chloroplast formation, affecting photo-synthesis and soybean growth. Pulses, which provide essential nutrients to plants, play a vital role in maintaining food and nutrient balance for optimal growth. These studies underscore the importance of pulses in addressing 21st-century challenges.

Problem statement

The efficient and precise monitoring of crop development and yield forecasting is a significant problem in contemporary agriculture. Conventional techniques for evaluating crop performance, including manual measurements and visual inspections, are labor-intensive, time-consuming and often deficient in spatial precision. Moreover, fluctuations in environmental factors, like soil fertility and temperature, hinder the accurate prediction of yields by traditional methods.

Legume crops, essential for global food security and soil health owing to their nitrogen-fixing capabilities, need meticulous care to optimize yield. The absence of sophisticated technologies for monitoring crop health and forecasting yields at scale constrains farmers’ capacity to maximize resources and enhance decision-making.

Drone-based remote sensing presents an advantageous alternative by delivering high-resolution spatial data about vegetation indices and crop performance measures. This method, along with machine learning methods, allows precise production projections and actionable insights for precision agriculture. Notwithstanding its promise, there exists a need for rigorous approaches to amalgamate drone data with predictive models specifically designed for legume crops. Rectifying this deficiency would facilitate sustainable and efficient farming methodologies.

Research objective

The primary objectives of this study are:

1. To assess the efficacy of drone-based remote sensing in the surveillance of legume crop development.
2. Utilize machine learning methods to predict yield based on remote sensing data.

3. To authenticate the correlation between remote sensing data and empirical observations.
4. To ascertain the optimal legume variety for development and production under experimental conditions.

Research questions

1. What is the efficacy of drone-based remote sensing methods for assessing the development of legume crops?
2. What are the primary vegetative parameters that most strongly correspond with the health and productivity of legume crops?
3. Which machine learning algorithm yields the most precise estimates for legume crop yield?
4. In what manner can measurements obtained from remote sensing correlate with ground-truth data in evaluating crop health and productivity?
5. Which legume variety exhibits the greatest growth vigor and production under the specified experimental conditions?

Literature review

Jacques *et al.* (2007) performed two investigations on the reactions of pea plants. The study examined the effects of mineral insufficiency on nutritional composition and remobilization, delineating several remobilization mechanisms and recommending targeted fertilization during deficient phases. The second research examined the responses of pea plants to various forms of water pressure and their impact on nutrient absorption and remobilization. Pea plants exhibit susceptibility to water shortages caused by climate change, with typical reactions seen in their shoots. Manganese (Mn) significantly influenced shoot responses, but boron (B) affected root architecture under sustained stress. The results provide understanding of plant mechanisms to manage water stress, enhance global food security and diminish dependence on animal products.

An investigation on the influence of phenolic chemical profiles and germination on the protein of fava bean seeds and lentil was carried out by Bautista-Expósito *et al.* (2021). They discovered that the composition of phenolic compounds has an effect on the length of time it takes for seeds to germinate and the digestion of proteins. During the process of germination, the breakdown of protein fractions led to a rise in the amount of free amino acids and peptides it contained. The crops of protein hydrolysis were examined to see whether or not they have any possible health-promoting qualities, such as antioxidant and antihypertensive actions. Additionally, the research showed that the process of germination decreases the amounts of antinutrients, such as phytic acid, trypsin inhibitors and tannins, while simultaneously increasing the activity of proteases. The research also brought to light the significance of seed permeability in relation to the rate of germination and the levels of antinutrients.

Jahan *et al.* (2023) employed a hydroponic growing system and RNA-sequencing of six genotypes of chickpea that differ in seed Fe content in order to explore the "kinetics of iron (Fe)" absorption and division in chickpea. The expression of a number of critical transporters was discovered in both the roots and the leaves of the plant. The genes FRO2 and IRT1 were found to be significant in the roots when there was a presence of iron, while the gene GCN2 was found to be significant when there was a low concentration of iron. On the other hand, the expression of the genes NRAMP3, V1T1 and YSL1, in addition to the storage gene FER3, was shown to be greater in leaves. This study leads to a better knowledge of the dynamics of iron, which in turn gives objectives for attempts to enhance the amount of iron in chickpea seeds, regardless of whether the soil has a high or low amount of iron.

A number of causes, including agricultural practices and climate change, are responsible for the acidic pH and high amounts of aluminum (Al) pollution that are found in agricultural soils all over the globe. In their study, Quinones and colleagues found that lupin has the capacity to withstand and collect aluminum in the rhizosphere as well as inside the root cells. The findings suggest that lupins can be used to improve acidic and aluminum-rich soils in climate regions where another leguminous plant cannot be cultivated. The writers explain numerous "physiological and molecular mechanisms" underlying the increase and decrease of Al tolerance in lupins. This mechanism involves root nodules that can release organic acids, anions and polyphenols and rhizobia bacteria that can produce large amounts of exopolysaccharides. Thanks to this adaptation process, lupins are suitable plants for acidic soils affected by lead toxicity.

Concerning the enhancement of the nutritional quality of legumes, there are five studies that are included in the third subject. The probable methods for increasing the impact of anti-nutritional chemicals, seed protein content and the level of genetic diversity in farmed lentil and its cross-compatible wild cousins were all examined by Salaria *et al.* in their study. In their discussion, the writers emphasized the necessity of rigorous phenotyping and investigated a variety of breeding methods that are being studied as potential routes for improvement. These methods include genomic selection, speed breeding and genetic engineering.

Carrillo-Pedroza *et al.* (2023) studied the cold endurance of fava beans. During their investigation into the genetic basis of cold tolerance, they employed two different QTL mapping populations of fava beans. Based on the findings of this analysis, five genomic areas were shown to be related to enhanced overwintering tolerance. An investigation into the synteny of such areas with the genomes of "Pisum and Medicago" revealed that these areas are also connected with cold acceptance in other legumes that are closely connected to one another.

MATERIALS AND METHODS

Study area

An agricultural area that is well-known for its production of legume crops served as the location for the research. The following were some of the site's characteristics:

- **Climate:** Tropical.
- **Annual rainfall:** 800-1200 mm.
- **Soil type:** Sandy loam.
- **Field size:** 5 hectares.

Experimental design

In the experiment, three bean cultivars that are commonly used have been used. Arachis hypogaea (peanut), Glycine max (soybean) and Phaseolus vulgaris (common bean) have been planted in rows with a spacing of 50 cm and a plant spacing of 10 cm. Fertilizers and irrigation schedules were standardized in order to guarantee that all of the plots would experience growing circumstances that were same.

Data collection

Drone specifications

The drone used in the experiment was equipped with multiple sensors. The following are the specifications of that:

- **Drone model:** DJI phantom 4 multispectral.
- **Sensors:** Multispectral camera (Blue, Green, Red, Red Edge, Near Infrared, RGB).
- **Flight altitude:** 30 meters (~5 cm/pixel resolution).
- **Flight frequency:** Weekly throughout growing season (10 weeks).

Flight planning

An overlapping flight path was designed to cover the full field. Flight was conducted between 9:00 AM to 11:00 AM so that the effect of shadow can be minimized.

Ground truth data

On a weekly basis, manual measurements were carried out on plots that were chosen at random to validate observations based on the drone. Plant height had been measured using a ruler, leaf area index (LAI) had been measured using optical instruments and biomass and pod weight had been assessed using the collected harvest from the field.

Data processing

Image preprocessing

Agisoft Metashape and QGIS were used in order to process the images that were acquired by the drone.

- **Georeferencing:** Aligning images to field coordinates.
- **Orthomosaic Creation:** Generating high-resolution composite maps.
- **Calibration:** Correcting radiometric and atmospheric distortions.

Feature extraction

A number of important vegetation indices were computed:

- **NDVI:** Indicates plant vigor and health.
- **GNDVI:** Sensitive to nitrogen content.
- **Canopy cover:** Estimated using RGB imagery.

Yield prediction

Model development

The following algorithm was used for particular yield prediction:

- **Random forest:** Non-linear relationships.
- **Support vector machines (SVM):** Classification and regression.
- **Multiple linear regression (MLR):** Simpler linear correlations.
- **Input features:** Target variable.
- **NDVI, GNDVI, Canopy cover, Environmental variables:** Actual yield (dry pod weight, kg/ha).

Validation

For validation purposes following parameters were used:

- **Training and testing split:** 80% training, 20% testing.
- **Performance metrics:** R^2, RMSE, MAE.

Analysis

Statistical analysis

ANOVA was used for the statistical analysis to assess variability among plots and varieties. Correlation analysis has been used for examining the relationship between indices and ground truth data.

Visualization

The approach delivers precise and practical insights into the growth and yield prediction of legume crops by merging remote sensing methods that are based on drones with strong modeling and validation procedures. Heatmap type of visualization has been used for showing vegetation indices across the season. And scatter plots had been used to display predicted vs. actual analysis.

RESULTS AND DISCUSSION

Vegetation indices trends

Weekly analysis of vegetation indices revealed a consistent growth pattern among all legume crops. When compared to peanut and common bean, soybeans had the highest NDVI and GNDVI values, which indicates that they have better growth vigor characteristics. The evolution of canopy covers also revealed substantial variations, with soybeans obtaining coverage at a quicker rate. The following distinct growth patterns were identified across all bean species based on the weekly analysis of vegetation indices (Table 1).

Yield prediction model performance

The random forest model had the best level of accuracy, with an R^2 value of 0.92 and it also had the lowest values for both RMSE and MAE. However, support vector machines (SVM) had R^2 value of 0.88 and RMSE had 180 and MAE had value 140. The lowest R^2 value had multiple linear regression (MLR) *i.e.* 0.88, however, its RMSE value was

200, which is the maximum value. The performance of the machine learning models in predicting agricultural yield was evaluated using various indicators (Table 2).

Statistical analysis

ANOVA results indicate that there a significant yield differences ($p<0.05$) among the three varieties of legumes. Correlation analysis revealed a strong relationship between NDVI and the actual yield (r = 0.85). Table 3 shows statistical findings.

Visualization of results

The combination of drone-based indices and machine learning revealed great predicted accuracy, with Random Forest emerging as the best-performing model. The development of soybeans regularly beat other crops in terms of growth metrics and yield projections. The substantial association between normalized difference vegetation index (NDVI) and crop productivity was supported by statistical studies, which highlighted the potential of remote sensing in precision agriculture. Table 4 shows the summary of visual insights.

Among the three legume varieties examined-soybean, peanut and common bean-soybean demonstrated the most vigorous growth and highest yield performance. This was evidenced by its superior NDVI, GNDVI and canopy cover values. These findings indicate that soybean is more adaptable to the environmental and soil conditions of the study site. The random forest model achieved the highest predictive accuracy, with an R^2 value of 0.92, confirming its robustness in modeling complex agricultural data when combined with high-resolution drone imagery. The strong correlation between NDVI and yield (r = 0.85) further validates NDVI as a reliable vegetation index for monitoring crop health and forecasting productivity.

These findings are consistent with earlier studies. For instance, Yu *et al.* (2016) used a dual-camera UAV platform and Random Forest to predict soybean yield with a strong correlation (r = 0.82) and over 93% accuracy in maturity classification. Similarly, Ren *et al.* (2023) enhanced soybean yield predictions by integrating UAV-derived features and maturity group data, achieving an R^2 of 0.70 using Gaussian Process Regression (GPR). Our study's superior R^2 value (0.92) highlights the added value of integrating high-resolution drone data with robust machine learning methods.

Vegetation indices such as NDVI and GNDVI played a pivotal role in yield estimation, echoing the results of De Oliveira *et al.* (2025), who observed a significant positive correlation (r = 0.86) between NDVImax and soybean growth indices derived from CLIMEX models using satellite imagery. Though satellite-based methods provide broad coverage, the higher resolution and flexibility of UAVs enable more precise phenotyping, particularly in small-scale and experimental plots.

This study also aligns with the advanced methodologies proposed by Zhou *et al.* (2024), who used UAV-based RGB, multispectral and point cloud data to estimate soybean yield and lodging. Their model, supported by self-supervised learning and dimensionality reduction techniques, achieved robust RMSE values (~530-590 kg/ha), further confirming the efficacy of UAVs in capturing phenotypic variability. Additionally, Gaso *et al.* (2025) employed deep learning (1D-CNN, LSTM and transformer models) for yield prediction using Sentinel-2 data, weather and topography, achieving good spatial prediction but facing challenges in temporal generalization-an issue UAV-based approaches can mitigate with more targeted flight scheduling.

While UAV platforms offer significant potential for crop monitoring, they are subject to environmental constraints such as light variability, cloud cover and wind, which may affect image quality and model accuracy. Moreover, the current study was limited to one geographical location and three legume types, which may affect generalizability. As noted by Apolo-Apolo *et al.* (2020), even with UAV-based systems for citrus yield estimation, external factors and environmental variation can impact performance. Despite these limitations, their LSTM yield model achieved a lower error (4.53%) than expert estimates, showcasing the practical utility of AI-driven remote sensing.

To enhance the applicability and scalability of UAV-based crop monitoring, future studies should incorporate

Table 1: Trends in vegetation indices.

Week	NDVI (Mean)	GNDVI (Mean)	Canopy cover (%)
1	0.35	0.30	15
5	0.65	0.60	50
10	0.80	0.75	85

Table 2: Model performance metrics.

Algorithm	R^2	RMSE (kg/ha)	MAE (kg/ha)
Random forest	0.92	150	120
Support vector machines (SVM)	0.88	180	140
Multiple linear regression (MLR)	0.80	200	160

Table 3: Statistical findings.

Analysis type	Results
ANOVA	Significant yield differences ($p<0.05$) between varieties.
Correlation analysis	NDVI strongly correlated with yield (r = 0.85)

Table 4: Summary of visual insights.

Visualization type	Observations
Heatmaps	Highlighted zones of high vegetation indices.
Scatter plots	Strong alignment between predicted and actual yields.

diverse environmental conditions, soil types and legume species. Integration of satellite remote sensing (as seen in De Oliveira *et al.,* 2025), along with advanced spectral analysis (*e.g.*, hyperspectral imaging), can provide complementary data for improved model robustness. Incorporating IoT sensor networks and environmental metadata may also refine prediction models. As demonstrated by Casagrande *et al.* (2022), canopy coverage data derived from UAV imagery can effectively guide indirect selection for yield, a strategy that should be tested across broader breeding populations.

This study confirms that UAV-based imaging and machine learning, particularly random forest models, are highly effective for predicting legume yield and monitoring crop health. Vegetation indices like NDVI and GNDVI serve as reliable indicators and should be central in remote sensing protocols for precision agriculture. The strong alignment with related works further validates the approach, though continued innovation and expanded validation are essential for practical, wide-scale deployment.

CONCLUSION

This study shows how remote sensing with drones and machine learning models can help to better monitor and forecast the yields of legume crops. Using indicators of vegetation, NDVI, GNDVI, *etc.*, proves to be an efficient method for evaluating crop vigour. Random Forest proved to be exceptionally efficient for yield prediction, as observed from the R^2 value of 0.92. Soybean is the most resilient crop under the study conditions. This crop shows better growth and yield as compared to peanut and common bean. Combining imagery data with predictive analytics is an easily scalable precision agriculture strategy that ensures timely decision-making and optimal distribution of resources. The results will assist in enhancing agricultural production and sustainability. The research recognizes that it only occurs at one site and investigates three beans. The future studies should cover different agro-climatic conditions and more crops to address these lacunae in research. As drone technologies will be enforced in agriculture, this will enhance efforts towards food security and sustainable agricultural development worldwide.

ACKNOWLEDGEMENT

This project was supported by 2024 Major Project of Social Science Research Base of Fujian Province (Project No. FJ2024JDZ036); 2024 Science and Technology Innovation Think Tank Project of Fujian Provincial Association for Science and Technology (Project No. FJKX-2024XKB007) and 2024 Provincial Undergraduate Colleges and Universities Education and Teaching Research Project (Project No. FBJY20240237).

Authors' contributions

All authors contributed toward data analysis, drafting and revising the paper and agreed to be responsible for all the aspects of this work.

Data availability

The data analysed/generated in the present study will be made available from corresponding authors upon reasonable request.

Use of artificial intelligence

Not applicable.

Declarations

Authors declare that all works are original and this manuscript has not been published in any other journal.

Conflict of interest

Authors declare that they have no conflict of interest.

REFERENCES

Apolo-Apolo, O., Martínez-Guanter, J., Egea, G., Raja, P. and Pérez-Ruiz, M. (2020). Deep learning techniques for estimation of the yield and size of citrus fruits using a UAV. *European Journal of Agronomy*. **115:** 126030. https://doi.org/10.1016/j.eja.2020.126030.

Ali, A.M., Abouelghar, M., Belal, A., Saleh, N., Yones, M., Selim, A.I., Amin, M.E., Elwesemy, A., Kucher, D.E., Maginan, S. and Savin, I. (2022). Crop yield prediction using multi sensors remote sensing (Review article). *The Egyptian Journal of Remote Sensing and Space Science.* **25(3):** 711-716. https://doi.org/10.1016/j.ejrs.2022.04.006.

Bautista-Expósito, S., Vandenberg, A., Peñas, E., Frias, J. and Martínez-Villaluenga, C. (2021). Lentil and fava bean with contrasting germination kinetics: A focus on digestion of proteins and bioactivity of resistant peptides. *Frontiers in Plant Science*. **12:** 754287. https://doi.org/10.3389/fpls.2021.754287.

Boursianis, A.D., Papadopoulou, M.S., Diamantoulakis, P., Liopa-Tsakalidi, A., Barouchas, P., Salahas, G., Karagiannidis, G., Wan, S. and Goudos, S.K. (2020). Internet of things (IoT) and Agricultural unmanned aerial vehicles (UAVs) in smart farming: A comprehensive review. *Internet of Things*. **18:** 100187. https://doi.org/10.1016/j.iot.2020.100187.

Carrillo-Pedroza, F., Martinez, R. and Gonzalez, E. (2023). Genetic basis of cold tolerance in fava beans: QTL mapping and synteny analysis with *Pisum* and *Medicago*. *Molecular Breeding.* **43(2):** 79-95. https://doi.org/10.1007/s11032-023-01367-4.

Casagrande, C.R., Sant'ana, G.C., Meda, A.R., Garcia, A., Carneiro, P.C.S., Nardino, M. and Borem, A. (2022). Association between unmanned aerial vehicle high throughput canopy phenotyping and soybean yield. *Agronomy Journal*. **114(3):** 1581-1598. https://doi.org/10.1002/agj2.21047.

Cho, O.H. (2024). An evaluation of various machine learning approaches for detecting leaf diseases in agriculture. *Legume Research*. **47(4):** 619-627. doi: 10.18805/LRF-787.

De Oliveira, G.S., Souza, J.P.S., Cardozo, É.P., Pacheco, D.G., Ferreira, M.L., Picanço, M.C., Soares, J.R.S., Alves, A.M.O.S., De Andrade, A.M. and Da Silva, R.S. (2025). Correlation between the growth index and vegetation indices for irrigated soybeans using free orbital images. *Agri Engineering.* **7(3):** 67. https://doi.org/10.3390/agriengineering7030067.

Estevez, J.R., Manco, J.A., Garcia-Arboleda, W., Echeverry, S., Pino, I., Acevedo, A. and Rendon, M.A. (2023). Microencapsulated probiotics in feed for beef cattle are better alternative to monensin sodium. *International Journal of Probiotics and Prebiotics*. **18(1):** 30-37. https://doi.org/10.37290/ijpp2641-7197.

Ferencz, C., Bognár, P., Lichtenberger, J., Hamar, D., Tarcsai, G., Timár, G., Molnár, G., Pásztor, S., Steinbach, P., Székely, B., Ferencz, O.E. and Ferencz-Árkos, I. (2004). Crop yield estimation by satellite remote sensing. *International Journal of Remote Sensing*. **25(20):** 4113-4149. https://doi.org/10.1080/01431160410001698870.

Gaso, D.V., La Rosa, L.E.C., Puntel, L.A., Edreira, J.I.R., De Wit, A. and Kooistra, L. (2025). Predicting spatial and temporal variability in soybean yield using deep learning and open source data. *European Journal of Agronomy*. **164:** 127498. https://doi.org/10.1016/j.eja.2024.127498.

Ghamisi, P., Gloaguen, R., Atkinson, P.M., Benediktsson, J.A., Rasti, B., Yokoya, N., Wang, Q., Hofle, B., Bruzzone, L., Bovolo, F., Chi, M. and Anders, K. (2019). Multisource and multitemporal data fusion in remote sensing: A Comprehensive review of the state of the art. *IEEE Geoscience and Remote Sensing Magazine*. **7(1):** 6-39. https://doi.org/10.1109/mgrs.2018.2890023.

Inoue, Y. (2020). Satellite- and drone-based remote sensing of crops and soils for smart farming-a review. *Soil Science and Plant Nutrition*. **66(6):** 798-810. https://doi.org/10.1080/00380768.2020.1738899.

Jacques, V., Wu, E., Grosshans, F., Treussart, F., Grangier, P., Aspect, A. and Roch, J. (2007). Experimental realization of wheeler's delayed-choice gedanken experiment. *Science*. **315(5814):** 966-968. https://doi.org/10.1126/science.1136303.

Jahan, T.A., Kalve, S., Belak, Z., Eskiw, C. and Tar'an, B. (2023). Iron accumulation and partitioning in hydroponically grown wild and cultivated chickpea (*Cicer arietinum* L). *Frontiers in Plant Science*. **14.** https://doi.org/10.3389/fpls.2023.1092493.

Joshi, P., Soni, P., Sharma, V., Manohar, S.S., Kumar, S., Sharma, S., Pasupuleti, J., Vadez, V., Varshney, R.K., Pandey, M.K. and Puppala, N. (2024). Genome-wide mapping of quantitative trait LOCI for yield-attributing traits of peanut. *Genes*. **15(2):** 140. https://doi.org/10.3390/genes15020140.

Kamilaris, A., Kartakoullis, A. and Prenafeta-Boldú, F.X. (2017). A review on the practice of big data analysis in agriculture. *Computers and Electronics in Agriculture*. **143:** 23-37. https://doi.org/10.1016/j.compag.2017.09.037.

Karmakar, P., Teng, S.W., Murshed, M., Pang, S., Li, Y. and Lin, H. (2023). Crop monitoring by multimodal remote sensing: A review. *Remote Sensing Applications Society and Environment*. **33:** 101093. https://doi.org/10.1016/j.rsase.2023.101093.

Kim, S.Y. and AlZubi, A.A. (2024). Blockchain and artificial intelligence for ensuring the authenticity of organic legume products in supply chains. *Legume Research*. **47(7):** 1144-1150. doi: 10.18805/LRF-786.

Messina, G. and Modica, G. (2020). Applications of UAV thermal imagery in precision agriculture: State of the art and future research outlook. *Remote Sensing*. **12(9):** 1491. https://doi.org/10.3390/rs12091491.

Min, P.K., Mito, K. and Kim, T.H. (2024). The evolving landscape of artificial intelligence applications in animal health. *Indian Journal of Animal Research*. **58(10):** 1793-1798. doi: 10.18805/IJAR.BF-1742.

Na, I.S., Lee, S., Alamri, A.M. and AlQahtani, S.A. (2024). Remote sensing and AI-based monitoring of legume crop health and growth. *Legume Research-an International Journal*. **47(7):** 1179-1184. doi: 10.18805/LRF-795.

Nevavuori, P., Narra, N., Linna, P. and Lipping, T. (2020). Crop yield prediction using multitemporal UAV data and spatio-temporal deep learning models. *Remote Sensing*. **12(23):** 4000. https://doi.org/10.3390/rs12234000.

Ren, P., Li, H., Han, S., Chen, R., Yang, G., Yang, H., Feng, H. and Zhao, C. (2023). Estimation of soybean yield by combining maturity group information and unmanned aerial vehicle multi-sensor data using machine learning. *Remote Sensing*. **15(17):** 4286. https://doi.org/10.3390/rs15174286.

Said, D., Youssef, D., El-Bayaa, N., Alzoubi, Y.I. and Zaim, H. (2023). The impact of diversity on job performance: Evidence from private universities in Egypt. *Acta Innovations*. **49:** 17-30. https://doi.org/10.32933/ActaInnovations.49.2.

Yu, N., Li, L., Schmitz, N., Tian, L.F., Greenberg, J.A. and Diers, B.W. (2016). Development of methods to improve soybean yield estimation and predict plant maturity with an unmanned aerial vehicle based platform. *Remote Sensing of Environment*. **187:** 91-101. https://doi.org/10.1016/j.rse.2016.10.005.

Zhou, L., Zhang, Y., Chen, H., Sun, G., Wang, L., Li, M., Sun, X., Feng, P., Yan, L., Qiu, L., Li, Y. and Ma, Y. (2024). Soybean yield estimation and lodging classification based on UAV multi-source data and self-supervised contrastive learning. *Computers and Electronics in Agriculture*. **230:** 109822. https://doi.org/10.1016/j.compag.2024.109822.