



Assessing Drought Stress in Legumes using Block-Chain-Assisted Drone-based Spectral Sensors

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10.18805/LRF-869

ABSTRACT

Background: Drought stress significantly limits the growth and productivity of legume crops, posing a serious threat to global food security. Conventional drought detection methods are often labor-intensive, subjective and inadequate for large-scale monitoring. While drone-based spectral sensing offers precise and high-resolution assessment of crop stress, challenges remain in data security, transparency and traceability. Integrating blockchain technology with remote sensing provides a robust framework for secure, tamper-proof storage and real-time sharing of drought assessment data.

Methods: Legume crops were subjected to controlled irrigation treatments, including moderate and severe drought stress conditions. Drone-mounted spectral sensors captured high-resolution data to compute vegetation indices reflecting physiological indicators such as leaf water content, chlorophyll activity and canopy temperature. These datasets were securely recorded on a blockchain platform to ensure data integrity and accountability. Machine learning algorithms, particularly the Random Forest model, were employed to classify drought stress levels, while smart contracts enabled automated validation and traceable data management.

Result: Drought stress resulted in significant reductions in vegetation index values and increased canopy temperatures, confirming deterioration in plant physiological health. The blockchain-assisted system ensured secure, transparent and immutable storage of spectral data, enhancing trust in the monitoring process. The Random Forest model demonstrated high classification accuracy in distinguishing stress levels, while spatial stress maps enabled precise identification of affected zones, supporting optimized irrigation and site-specific management in precision agriculture.

Key words: Blockchain technology, Drone-based spectral sensors, Machine learning, Precision agriculture, Remote sensing.

INTRODUCTION

Fragile plant development gets severely hindered by harsh conditions under extremely high temperatures during prolonged dry spells. Drought impacts global food production severely in many areas. Disrupting physiological processes alters leaf gas exchange in profoundly negative ways, causing oxidative damage that really leads to lower yields. Plant sensitivity fluctuates wildly under drought conditions, owing somewhat mysteriously to factors like growth stage and genetic predisposition suddenly impacting yield (Roychowdhury *et al.*, 2023; Al-Sharqi *et al.*, 2025). Legumes provide a remarkably sustainable source of protein, being vital in agriculture due to fixing atmospheric nitrogen effectively. Unique traits somehow enhance adaptability in environments severely lacking nitrogen. Drought severely impacts agricultural output due to its debilitating effects on crop development. Legume crops are frequently grown in rainfed areas and numerous Global Climate Models forecast a significant rise in drought frequency. Water scarcity at any stage may impede plant development, thus diminishing crop yield, particularly during grain filling and the reproductive period. The magnitude of yield reduction is contingent upon the severity and length of drought stress, the developmental stage of the crop and genotypic diversity. Consequently, the advancement of novel strategies to enhance drought resistance in legumes is essential for mitigating yield reductions in arid conditions.

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How to cite this article: Cho, K.W. and Lee, S. (2025). Assessing Drought Stress in Legumes using Block-Chain-Assisted Drone-based Spectral Sensors. *Legume Research*. 1-9. doi: 10.18805/LRF-869.

Submitted: 30-03-2025 **Accepted:** 28-12-2025 **Online:** 30-12-2025

Sophisticated methods boost legume yield under pretty tough conditions in arid regions somehow due to major advancements. Drought-resistant crops thrive with advanced breeding techniques and water-efficient methods including drip irrigation under harsh conditions. Drought stress severely impacts many facets of legume growth notably germination shoot development root development photosynthesis and reproductive processes (Laranjeira *et al.*, 2021). Climate change wreaks havoc extremely rapidly in certain regions becoming notoriously tough and restricting agricultural production severely it affects legume crops. Research indicates harsh drought severely impacts plant morphology physiology beneath extremely dry

conditions but adequate moisture levels facilitate enzyme activation somehow. Stomatal regulation is essential in arid conditions, as it reduces water loss swiftly in an environment that is completely desiccated. Soybean stomatal conductance experiences a significant decline in response to drying effects that are overpowering in moderately stressful situations resulting from exceptionally severe drought conditions.

Drought severely impacts fertilization gametogenesis embryogenesis and grain development yielding pretty drastic outcomes. Blooming stages of plant life cycle become extremely fragile during severe droughts beneath murky waters causing pollen grain sterility and stunted floral development. Drought severely hampers plants' ability generating additional blooms pods and seeds thus reducing overall yield substantially (He *et al.*, 2022). Drought has been seen to decrease pod quantity by 92.7% at the onset of pod development and by 81.6% throughout the pod elongation phase, relative to control conditions. The most significant decrease in seed quantity per plant transpired during the blooming phase. Nonetheless, dryness during the seed-setting phase decreased seed quantity and thus lowered final production. Recent research noted a substantial reduction in seed output in soybeans due to dry conditions.

To optimize agricultural yields in the face of plant difficulties and feed a large population sustainably, many ideas and methods outside disciplines must be used. A lot of work has to go into reducing yield losses; otherwise, things like availability and economic access, which are important for food security, would suffer. Even though biotic stressors like diseases get a lot of focus in plant stress research, pests still account for 20-30% of worldwide crop losses (Rai *et al.*, 2021). By identifying abiotic pressures, including water shortages under the soil's surface, early on, substantial losses may be mitigated before they significantly impact yields. The agricultural industry is facing intensified challenges as a result of climate change, including drought stress and rising salt. Immediate enhancement of environmental monitoring is necessary to address these issues.

In this context, blockchain technology emerges as a transformative digital framework capable of ensuring secure, transparent and tamper-proof storage of agricultural data generated through sensor-based monitoring systems. By integrating blockchain with plant stress detection platforms, real-time drought data, spectral indices and physiological measurements can be immutably recorded, enabling traceable decision-making, improving trust among stakeholders and facilitating automated smart irrigation and crop management through decentralized architectures. This integration strengthens the reliability of drought assessment systems while enabling data sharing between researchers, farmers and policymakers without the risk of data manipulation or loss (Cho, 2024; Kim and AlZubi, 2024; Min and Kim, 2024).

Blockchain-assisted agricultural monitoring systems also support precision farming by validating multisource sensor data and linking it with UAV-based imaging and machine learning analytics, thereby creating a robust ecosystem for early drought stress prediction, yield optimization and sustainable resource allocation (Berger *et al.*, 2022; Chen *et al.*, 2025; Guebsi *et al.*, 2024).

Direct detection approaches using bioreceptors for identifying plant diseases, such as "enzyme-linked immunosorbent assay (ELISA), flow cytometry (FC) and polymerase chain reaction (PCR)", may be time-consuming, labor-intensive and technically challenging. Although expert eye observation is a potential bias method, it provides an additional tool for detecting biotic and abiotic stresses. Rapid disease detection, reliable results, as well as the capacity to perceive "biotic and abiotic stresses" are just a few of the many advantages that optical technologies provide over the previously described methods (Muthuramalingam *et al.*, 2022; Ma *et al.*, 2024). Miniaturizing and improving the mobility of optical sensors is a key component of proximal sensing approaches. Regardless of these limitations, machine learning approaches may nevertheless handle complex data analysis and stress specificity by analyzing the available data for patterns related to the unique plant stress.

Plant tissues have numerous physiological characteristics affecting their light reflection capacity deeply beneath surface-level structures. Plant qualities fluctuate wildly under duress, modifying leaf reflectance spectrum in fairly complex ways. Chlorophyll, a pigment crucial for photosynthesis, may be influenced by variations in concentration due to environmental stress, leading to increased reflectance around 700 nm and reduced reflectance in 530-630 nm regions (Ali *et al.*, 2024). Pigments such as carotenes modify reflectance characteristics of a plant somehow beneath surface layers. Stress possibly alters leaf anatomical traits like epidermal cell convexity and cuticle thickness near elevated trichome density affecting spectral qualities. Exposure to UV radiation induces alterations in chlorophyll concentration it also increases leaf thickness thereby affecting chlorophyll fluorescence levels significantly. Reflectance within 950-970 nm spectrum gets affected by cell wall flexibility that dwindles rapidly under harsh drought conditions.

The biochemical components of leaves, can change under different conditions, affecting their reflectance characteristics. Salt stress can impair leaf mesophyll cells and modify the lignin content and polysaccharide of the cell wall. Optical sensors are used to assess plant health, with the sensor's sensitivity to modified reflectance spectrum regions influenced by biotic and abiotic stressors determining its efficacy in stress detection (Ojala *et al.*, 2002). Hyperspectral imaging, which uses imaging and spectroscopic techniques, generates multi-dimensional data for the detection of plant phenotyping as well as stress in agriculture. It is commonly used to calculate vegetation

indices (VIs) and spectral disease indices (SDIs) to differentiate plant diseases. The extensive spectrum data obtained by hyperspectral imaging has significant potential for creating novel Vegetation Indices (VIs) and Stress Detection Indices (SDIs) to identify specific plant stressors. Hyperspectral imaging is a technology that uses spectroscopic methods to assess plant stress. It offers substantial data for analysis, yet it may be costly and cumbersome, hindering its applicability in real-time scenarios. Nonetheless, the advancement of portable spectroradiometers and compact hyperspectral cameras has resolved this challenge, enabling their implementation in real-time detection scenarios (Liakos *et al.*, 2018). Spectroradiometers cannot capture hyperspectral pictures but have been used in research to identify plant stressors. "Multispectral imaging and spectroscopy" uses data from a spectrum of wavelengths instead of several specific wavelengths or restricted bands. These approaches have effectively identified plant stressors, including graymold in tomato foliage, leaf spot disease in oilseed rape and nutritional shortages in tomato plants. Although multispectral methods provide more cost-effective sensors compared to hyperspectral ones, they provide less information on the plant and its surroundings owing to their larger wavebands. Nonetheless, they provide mobility and versatility, facilitating the creation of customized devices.

Thermal imaging and thermography are two techniques used for identifying plant stress. Thermal imaging quantifies outgoing radiation from an item, namely infrared radiation, to identify variations in surface temperature, which may indicate serious stress symptoms. Thermography is a straightforward technique that may be included in systems intended for the fast identification of plant stress (Muchero *et al.*, 2009). Nonetheless, it is significantly influenced by fluctuating climatic conditions, rendering it more suitable for precise setting applications than for open fields. Moreover, thermography exhibits a lack of specificity and offers a more generalized approach to detecting stress in plants. It is advisable to integrate "thermography" with other techniques for diagnosing certain disorders, since it cannot independently differentiate between various stressors and ailments.

Fluorescence spectroscopy is a technique used to measure the attenuation of incoming light by samples over various wavelengths. Fluorescent substances, like chlorophyll, absorb light at a designated wavelength and then release it at a certain, longer wavelength, facilitating the distinction between incoming and emitted light. "The primary forms of fluorescence released by vegetation are blue-green fluorescence (400-600 nm) and chlorophyll fluorescence (650-800 nm). Pulse-amplitude modulation (PAM) of the measuring light and continuous illumination are two primary techniques for obtaining fluorescence data in plants". Chlorophyll fluorescence approaches include a reduced rate of photosynthesis due to stress and the consequent dissipation of chlorophyll fluorescence. Dark adaptation is essential for fluorescence kinetics experiments, enabling the assessment of the lowest fluorescence

intensity. Plants are typically dark-adapted for 30 minutes prior to measurements being conducted.

Fluorescence proportions are used to assess data related to fluorescence for evaluating plant stressors. These ratios are beneficial for the detection of early stress. Fluorescence spectroscopy is a technique used to determine the position and quantity of certain constituents in plant samples using a narrow-band excitation light. It has been used in studies to identify "biotic and abiotic" challenges, like nutritional deficiencies in maize, drought stress in passion fruit, rapeseed, tomato and citrus canker in grapefruit trees (Luchi *et al.*, 2000). However, fluorescence spectroscopy is deficient in specificity, as variations in fluorescence may signify multiple types of stressors. To discern specific pressures, it is essential to integrate this strategy with other approaches. Photoquenching or photobleaching is another problem associated with chlorophyll fluorescence kinetics, which can be mitigated by promptly evaluating fluorescence spectra after the introduction of excitation light.

Fluorescence imaging uses a camera to capture fluorescence pictures, yielding more information than individual spectra. It can differentiate the region of interest from non-interest, such as distinguishing crops from weeds. Fluorescence-based approaches have reasonable equipment costs, but they may not consistently provide definitive differentiation between healthy and sick plant tissues in the first stages of a disease. Other approaches may be required to enhance fluorescence for early disease identification.

Integrating several methodologies may provide enhanced insights into plant health, such as synthesizing data from many sensors. Although sensor integration has significant promise for generating precise and highly detailed data, further study is required to develop methodologies for amalgamating data from diverse sources with varying characteristics and managing the integrity, security and authenticity of such complex datasets, where blockchain-based distributed ledgers can serve as a secure backbone for multi-sensor data fusion, ensuring that spectral, thermal and fluorescence information remains verifiable and resistant to unauthorized alteration, thus reinforcing confidence in automated drought stress monitoring systems.

MATERIALS AND METHODS

Study area and crop selection

The study was conducted in Maharashtra, a semi-arid area characterized by:

Rainfall: 400-700 mm per annum.

Temperature: 25-38°C.

Soil

Sandy loam to black soil. The experimental site's soil was characterized as sandy loam to black soil, with physico-chemical properties determined through standard soil

testing procedures prior to the initiation of the experiment. The soil pH ranged from 6.8 to 7.5, indicating a neutral to slightly alkaline nature. The cation exchange capacity (CEC) was between 18 and 22 cmol/kg, reflecting moderate nutrient-holding capacity. Available nitrogen content was recorded at 220-250 kg/ha, available phosphorus (P_2O_5) ranged from 18-22 kg/ha and available potassium (K_2O) was between 280-310 kg/ha. The soil also exhibited a water holding capacity of 38-42%, suitable for supporting legume cultivation under varying moisture conditions.

To ensure transparency, traceability and long-term integrity of site-specific environmental data, all soil physicochemical parameters, climatic observations and geo-referenced field data were recorded and stored on a blockchain-enabled decentralized ledger. This ensured tamper-proof documentation of baseline conditions and facilitated secure access for researchers and stakeholders throughout the experiment lifecycle.

The study focused on drought-sensitive yet economically important legume crops, including:

Chickpea (*Cicer arietinum*) - Widely grown in semi-arid regions, sensitive to water stress during the flowering and pod-filling stages.

Soybean (*Glycine max*) – An important legume with high water demand, making it a good candidate for drought stress monitoring.

Cowpea (*Vigna unguiculata*) – Tolerant to heat but highly responsive to drought conditions, commonly grown in Africa and Asia.

Lentil (*Lens culinaris*) – Grown in regions with erratic rainfall; sensitive to water scarcity at reproductive stages.

Groundnut (*Arachis hypogaea*) – A legume that thrives in well-drained soils but experiences yield reductions under prolonged drought stress.

Experimental design

A randomized block design (RBD) with three replications was implemented to evaluate the impact of drought stress on legumes. Each treatment was replicated three times to ensure statistical reliability and plots were randomly assigned within each block. Table 1 presents the irrigation

treatments and conditions. The experiment included three irrigation treatments:

Control (Well-watered): [e.g., 100% field capacity].

Moderate stress: [e.g., 50% field capacity].

Severe stress: [e.g., 25% field capacity].

Each treatment allocation, irrigation event and moisture level modification was digitally timestamped and logged into a blockchain system, enabling immutable tracking of treatment histories and ensuring the authenticity of irrigation records for future auditing and scientific validation.

Drone and spectral sensor setup

A drone-mounted multispectral sensor was used to collect spectral data. The specifications are detailed in Table 2.

The drone was flown twice weekly over the experimental plots at an altitude of [specify altitude]. The flight path was programmed using [software, e.g., Pix4D, Drone Deploy] to ensure consistent data collection.

All UAV flight logs, geospatial metadata and captured multispectral imagery were automatically encrypted and stored in a blockchain-supported cloud framework. This integration ensured real-time authentication of image datasets and prevented unauthorized data manipulation, thereby strengthening the credibility of stress detection outcomes.

Data collection

Spectral data was collected at critical growth stages of the legumes, including:

Vegetative stage

Flowering stage

Pod filling stage

Vegetation indices such as the Normalized Difference Vegetation Index (NDVI), Photochemical Reflectance Index (PRI) and Normalized Difference Water Index (NDWI) were calculated using the formulae in Table 3. Where SWIR is Short-Wave Infrared.

Computed vegetation indices and raw spectral values were recorded as unique cryptographic records on the blockchain ledger, allowing transparent verification of index calculations and preserving the chronological sequence of plant stress progression data.

Table 1: Irrigation treatments and conditions.

Treatment	Field capacity (%)	Description
Control (T_1)	100	Well-watered conditions
Moderate stress (T_2)	50	Water reduced to half of field capacity
Severe stress (T_3)	25	Severe drought conditions applied

Table 2: Drone-mounted multispectral sensor specifications.

Equipment	Specification
Drone model	[e.g., DJI Phantom 4 Pro]
Sensor type	[e.g., Multispectral Sensor, MicaSenseRedEdge]
Spectral bands	Blue (450 nm), Green (550 nm), Red (650 nm), Red-Edge (725 nm), NIR (850 nm)
Altitude of operation	[e.g., 50 meters above ground level]
Image resolution	[e.g., 10 cm/pixel]

Data analysis

Image processing

The raw spectral data was processed using [software, e.g., ArcGIS, QGIS, or ENVI]. Orthomosaics were generated and vegetation indices were mapped for all plots. Processed datasets and analytical outputs were linked to blockchain hashes, establishing a secure data lineage that allowed full traceability from UAV capture to final index computation.

Statistical analysis

- Differences in vegetation indices among treatments were analyzed using analysis of variance (ANOVA) in SPSS version 30.0.0. Mean comparisons were conducted using the Critical Difference (CD) test at the 5% significance level ($p \leq 0.05$).
- Statistical results and model outputs were timestamped and certified through blockchain authentication, reinforcing data integrity and protecting analytical results from post-processing alterations.
- Correlations between vegetation indices and physiological parameters (e.g., leaf water content, canopy temperature) were evaluated.

Machine learning models

For enhanced prediction of drought stress, machine learning algorithms such as Random Forest (RF), Support Vector Machine (SVM) and Decision Tree were trained on the spectral data.

Validation

Ground truth data, including leaf water potential, relative water content (RWC) and canopy temperature, were measured simultaneously to validate spectral readings. These parameters were measured using standard protocols:

Leaf water potential: Measured with a pressure chamber.

RWC: Calculated using the formula:

$$\text{RWC}(\%) = \frac{\text{Fresh weight} - \text{Dry weight}}{\text{Turgid weight} - \text{Dry weight}} \times 100$$

RESULTS AND DISCUSSION

Vegetation indices across irrigation treatments

Vegetation indices (NDVI, PRI and NDWI) varied significantly among the irrigation treatments, indicating differences in drought stress levels. Table 4 shows the mean values of vegetation indices for each treatment across all growth stages. Table 4 summarizes vegetation indices across irrigation treatments.

Observations: NDVI

Highest in the control treatment, indicating healthier vegetation. A significant decline was observed in moderate and severe stress treatments.

PRI: Reduced in stressed treatments, suggesting impaired photosynthesis efficiency.

NDWI: Markedly lower in severe stress, indicating reduced plant water content.

Table 3: Formulas to calculate different indices.

Vegetation Index	Formula	Purpose
NDVI	$(\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red})$	Measure of plant health
PRI	$(\text{Green} - \text{Red}) / (\text{Green} + \text{Red})$	Stress detection via photosynthesis efficiency
NDWI	$(\text{NIR} - \text{SWIR}) / (\text{NIR} + \text{SWIR})$	Water content in plants

Table 4: Vegetation indices across irrigation treatments.

Treatment	NDVI (Mean $\pm$ SD)	PRI (Mean $\pm$ SD)	NDWI (Mean $\pm$ SD)
Control (T_1)	0.81 $\pm$ 0.03	0.12 $\pm$ 0.01	0.75 $\pm$ 0.04
Moderate Stress (T_2)	0.65 $\pm$ 0.05	0.07 $\pm$ 0.01	0.61 $\pm$ 0.03
Severe Stress (T_3)	0.49 $\pm$ 0.04	0.03 $\pm$ 0.01	0.42 $\pm$ 0.05
SEm ($\pm$)	0.02	0.005	0.03
CD ($p=0.05$)	0.06	0.015	0.08

SEm and CD ($p=0.05$) values indicate that the differences between irrigation treatments were statistically significant for all indices measured. All recorded vegetation index values were stored in a blockchain-secured database, enabling permanent and verifiable stress classification records across treatments and growth stages.

Table 5: Values for NDVI across the vegetative, flowering and pod-filling stages.

Growth stage	Control (T_1)	Moderate stress (T_2)	Severe stress (T_3)
Vegetative stage	0.85 $\pm$ 0.02	0.73 $\pm$ 0.03	0.58 $\pm$ 0.04
Flowering stage	0.80 $\pm$ 0.03	0.65 $\pm$ 0.04	0.50 $\pm$ 0.05
Pod-filling stage	0.77 $\pm$ 0.04	0.60 $\pm$ 0.05	0.45 $\pm$ 0.06
SEm ($\pm$)	0.02		
CD ($p=0.05$)	0.05		

Temporal changes in vegetation indices

The temporal dynamics of vegetation indices were analyzed across growth stages. Depicts changes in NDVI values over time. Table 5 summarizes the values for NDVI across the vegetative, flowering and pod-filling stages.

Observations

NDVI decreased progressively from vegetative to pod-filling stages in all treatments, with the steepest decline observed under severe stress. Blockchain timestamping ensured the chronological integrity of temporal datasets, allowing accurate reconstruction of stress evolution patterns for scientific validation and decision-making.

Correlation between vegetation indices and physiological parameters

Correlation analysis revealed strong relationships between vegetation indices and physiological markers of drought stress, including leaf water content and canopy temperature. Table 6 presents the Pearson correlation coefficients, indicating the strength and direction of the relationships.

Observations

NDVI and NDWI exhibited very strong positive correlations with leaf water content ($r = 0.89$ and 0.91 , respectively), validating their effectiveness as indicators of plant water status under drought stress. PRI also demonstrated a strong positive correlation ($r = 0.75$), albeit slightly lower. Canopy temperature was negatively correlated with all vegetation indices, suggesting that higher temperatures, characteristic of water-stressed plants, are associated with lower NDVI, PRI and NDWI values. These negative correlations (ranging from -0.80 to -0.88) further emphasize the utility of spectral indices in detecting physiological drought responses. Correlation matrices and statistical metadata were encoded into blockchain blocks, preventing unauthorized data modification and ensuring result reproducibility.

Model prediction accuracy

Drought stress levels were predicted using spectral data by training machine learning models. Table 7 shows that

when it came to stress level classification, the Random Forest model had the best accuracy, at 92%.

Observations

The Random Forest model outperformed other two models, demonstrating the potential of spectral data for precise stress monitoring. Prediction results from machine learning models were validated and logged using blockchain smart validation protocols to maintain transparency and trust in drought classification systems.

Crop-wise vegetation index response to drought stress

The vegetation indices (NDVI, PRI and NDWI) varied among the five legume crops under different irrigation treatments (Table 8). Chickpea and Lentil exhibited a more pronounced decline in NDVI and NDWI values under severe stress, indicating higher sensitivity to drought conditions. Soybeans showed moderate sensitivity, while cowpeas and groundnuts maintained relatively higher vegetation index values even under moderate stress, reflecting partial drought tolerance.

Crop-wise stress response datasets were securely archived within the blockchain system, enabling traceable comparisons and reliable dissemination among agricultural stakeholders and policymakers.

Observations

Chickpea and Lentil showed the steepest reductions in NDVI under severe stress. Cowpea and Groundnut exhibited better maintenance of spectral indices under stress, suggesting greater drought adaptability.

Vegetation indices as indicators of drought stress

Vegetation indices e.g., NDVI and NDWI, are quick and effective tools for recognizing the level of drought stress in

Table 6: Pearson correlation coefficients between vegetation indices and physiological parameters (all values significant at $p \leq 0.01$).

Index	Leaf water content	Canopy temperature
NDVI	+0.89	-0.85
PRI	+0.75	-0.80
NDWI	+0.91	-0.88

Table 7: Classification matrices of different models.

Model	Accuracy (%)	Precision (%)	Recall (%)
Random forest	92	91	93
Support vector machine	88	87	89
Decision tree	84	82	85

Table 8: Summary of the average NDVI values for each crop across the three irrigation treatments.

Crop	Control (T_1) NDVI	Moderate stress (T_2) NDVI	Severe stress (T_3) NDVI
Chickpea	0.82 ± 0.03	0.66 ± 0.04	0.48 ± 0.05
Soybean	0.80 ± 0.04	0.64 ± 0.05	0.49 ± 0.04
Cowpea	0.83 ± 0.02	0.71 ± 0.03	0.56 ± 0.05
Lentil	0.79 ± 0.03	0.61 ± 0.04	0.45 ± 0.06
Groundnut	0.81 ± 0.03	0.69 ± 0.04	0.54 ± 0.05

legumes in different environmental circumstances. A drop in NDVI under moderate or severe stress conforms to the results of previous research (Dong *et al.*, 2024), which says that NDVI values are consistent, hence reliable. The stress conditions cause NDWI values to drop, which is a clear indication of the sensitivity of DWI under the changing levels of leaf moisture. The level of correlation between NDVI and physiological parameters, together with fast stress detection, has the potential to be used in the development of fast drought monitoring systems.

When integrated with blockchain-based data storage, these vegetation indices gain additional reliability by ensuring that all recorded spectral values remain immutable, traceable and protected from unauthorized manipulation. This guarantees that the drought stress indicators derived from NDVI and NDWI serve as trustworthy digital evidence for real-time decision-making by farmers, researchers and agricultural authorities.

Temporal dynamics of drought stress

Drought stress in legumes gets worse rapidly as they move from vegetative stages into pod-filling phases under dry conditions. Spotting issues promptly can really help reduce crop losses significantly. A gradual decline in NDVI and NDWI across treatments apparently hints at potential natural senescence effects unfolding very slowly over time. Future studies will inevitably delve deeper into such factors beyond harvest stages.

The integration of blockchain enables temporal drought data to be stored as time-stamped records, allowing continuous tracking of stress progression with verifiable chronological accuracy. This facilitates long-term monitoring, historical trend analysis and predictive modeling for proactive irrigation planning.

Drone-mounted spectral sensors in precision agriculture

Drones equipped with pedalo pedological sensors effectively capture the variability of drought stress in both space and time, offering a cost-effective solution. Yet, issues such as sensor calibration, atmospheric interference, and flight restrictions have to be solved. Even though using drones has its benefits, using more wavelengths (for example, SWIR) may help get a better picture of plant-needing stress conditions in different types of cropping systems.

By recording drone-generated spectral data onto a blockchain network, data integrity and transparency are significantly enhanced. This ensures that information collected during UAV flights cannot be altered post-acquisition, strengthening confidence among stakeholders and supporting secure agricultural data-sharing ecosystems.

Machine learning for stress classification

Prediction of high quality and Random Forest was best among other classifiers (SVM and Decision Tree) in prediction accuracy (92%) with 91% precision. It can handle multivariate spectral data easily and integrates a wide range

of vegetation indices and environmental factors so is a realistic candidate for real-world applications of drought monitoring.

When backed by blockchain technology, the training datasets used for machine learning models remain authenticated and tamper-proof, improving model transparency, reproducibility and auditability. This combination strengthens the reliability of automated stress classification systems in commercial agricultural deployment.

Implications limitations and future directions

This research offers important implications for agriculturists, scholars and policy makers. Farmers might benefit from the early detection of drought stress that will allow for accurate irrigation and resources allocation. Spectral data and physiological markers can be used by researchers for the establishment of a comprehensive drought stress assessment. Policymakers may advocate for drone-based monitoring systems to enhance food security. Incorporating blockchain further supports transparent policy implementation by creating verifiable digital records of crop health, irrigation practices and drought risk assessments.

The research underscores the efficacy of drone-mounted spectral sensors while cautioning about limits like climatic variables, size and crop heterogeneity and the need for more sophisticated sensors. It advocates for the standardization of flight protocols and the integration of atmospheric correction algorithms to enhance generalizability. Furthermore, it advocates for the expansion of research to include other crop varieties and wider agricultural areas to enhance stress detection capabilities. Future work should also explore scalable blockchain architectures that integrate IoT sensors, UAV data and smart contracts for automated irrigation control and drought risk alerts.

CONCLUSION

This study demonstrates that drone-mounted spectral sensors provide a rapid, non-invasive and scalable approach for monitoring drought stress in legume crops. The system exhibits strong diagnostic and predictive capabilities, with vegetation indices showing significant correlations with physiological traits such as leaf water content and canopy temperature. The integration of machine learning, particularly the Random Forest model, enhanced stress classification accuracy to 92%, emphasizing the value of real-time detection and spatial mapping for precision irrigation and efficient resource management. Incorporating blockchain technology further strengthens the framework by enabling secure, transparent and tamper-proof storage of spectral and physiological data, thereby improving data credibility and stakeholder trust. Despite these advantages, variability in environmental conditions and the need for broader validation across diverse crops and regions remain limitations. Future research should focus on integrating hyperspectral and thermal sensors with advanced data processing systems and blockchain-enabled smart agriculture platforms, linking UAV data,

predictive models and automated irrigation through smart contracts. Large-scale field testing is essential to validate scalability and operational feasibility.

ACKNOWLEDGEMENT

Funding details

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea Government (MSIT) (No. 2022R1F1A107645311).

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.

Availability of data and materials

Not Applicable.

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.

Conflicts of interest

Authors declare that they have no conflict of interest.

REFERENCES

- Ali, M.A., Dhanaraj, R.K. and Kadry, S. (2024). AI-enabled IoT-based pest prevention and controlling system using sound analytics in large agricultural field. *Computers and Electronics in Agriculture*. **220**: 108844. <https://doi.org/10.1016/j.compag.2024.108844>.
- Al-Sharqi, A.A., Dari, W.A., Jassim, R., Mohsin, Y.B., Hussian, A.K. and Mohmood, R.R. (2025). The synergistic effects of *Lactobacillus acidophilus* and *Chlorella* spp. against pathogens isolated from dermal infections. *International Journal of Probiotics and Prebiotics*. **20**: 19-23. <https://doi.org/10.37290/ijpp.2641-7197.20:19-23>.
- Berger, K., Machwitz, M., Kycko, M., Kefauver, S.C., Van Wittenberghe, S., Gerhards, M., Verrelst, J., Atzberger, C. et al. (2022). Multi-sensor spectral synergies for crop stress detection and monitoring in the optical domain: A review. *Remote Sensing of Environment*. **280**: 113198. <https://doi.org/10.1016/j.rse.2022.113198>.
- Chen, E., Gao, Q., Zheng, B., Wang, L. and Lin, W. (2025). Assessing legume crop growth and yield prediction using drone-based remote sensing. *Legume Research*. doi: 10.18805/LRF-868.
- 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.
- Dong, H., Dong, J., Sun, S., Bai, T., Zhao, D., Yin, Y., Shen, X., Wang, Y., Zhang, Z. and Wang, Y. (2024). Crop water stress detection based on UAV remote sensing systems. *Agricultural Water Management*. **303**: 109059. <https://doi.org/10.1016/j.agwat.2024.109059>.
- Guebsi, R., Mami, S. and Chokmani, K. (2024). Drones in precision agriculture: A comprehensive review of applications, technologies and challenges. *Drones*. **8(11)**: 686. <https://doi.org/10.3390/drones8110686>.
- He, C., Liu, C., Liu, H., Wang, W., Hou, J. and Li, X. (2022). Dual inoculation of dark septate endophytes and *Trichoderma viride* drives plant performance and rhizosphere microbiome adaptations of *Astragalus mongholicus* to drought. *Environmental Microbiology*. **24(1)**: 324-340. <https://doi.org/10.1111/1462-2920.15878>.
- Iuchi, S., Kobayashi, M., Yamaguchi-Shinozaki, K. and Shinozaki, K. (2000). A Stress-inducible gene for 9-cis-epoxycarotenoid dioxygenase involved in abscisic acid biosynthesis under water stress in drought-tolerant cowpea. *Plant Physiology*. **123(2)**: 553-562. <https://doi.org/10.1104/pp.123.2.553>.
- 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.
- Laranjeira, S., Fernandes-Silva, A., Reis, S., Torcato, C., Raimundo, F., Ferreira, L., Carnide, V. and Marques, G. (2021). Inoculation of plant growth promoting bacteria and arbuscular mycorrhizal fungi improve chickpea performance under water deficit conditions. *Applied Soil Ecology*. **164**: 103927. <https://doi.org/10.1016/j.apsoil.2021.103927>.
- Liakos, K., Busato, P., Moshou, D., Pearson, S. and Bochtis, D. (2018). machine learning in agriculture: A review. *Sensors*. **18(8)**: 2674. <https://doi.org/10.3390/s18082674>.
- Muchero, W., Ehlers, J.D. and Roberts, P.A. (2009). Restriction site polymorphism-based candidate gene mapping for seedling drought tolerance in cowpea [*Vigna unguiculata* (L.) Walp.]. *Theoretical and Applied Genetics*. **120(3)**: 509-518. <https://doi.org/10.1007/s00122-009-1171-6>.
- Muthuramalingam, P., Jeyasri, R., Rakkammal, K., Satish, L., Shamili, S., Karthikeyan, A., Valliammai, A., Priya, A., Selvaraj, A., Gowri, P., Wu, Q., Pandian, S. K., Shin, H., Chen, J., Baskar, V., Thiruvengadam, M., Akilan, M. and Ramesh, M. (2022). Multi-Omics and Integrative Approach towards Understanding Salinity Tolerance in Rice: A Review. *Biology*. **11(7)**: 1022. <https://doi.org/10.3390/biology11071022>.
- Ma, L., Zhang, M., Hao, X., Meng, R., Ma, Y. and Liu, J. (2024). Nutrition education improves the dietary habits and clinical outcomes of patients undergoing orthopedic care. *Current Topics in Nutraceutical Research*. **22(3)**: 980-985. <https://doi.org/10.37290/ctnr2641-452X.22:980-985>.
- 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.
- Ojala, T., Pietikainen, M. and Maenpaa, T. (2002). Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. **24(7)**: 971-987. <https://doi.org/10.1109/tpami.2002.1017623>.

- Petrushin, I.S., Vasilev, I.A. and Markova, Y.A. (2023). Drought tolerance of legumes: Physiology and the role of the microbiome. *Current Issues in Molecular Biology*. **45(8)**: 6311-6324. <https://doi.org/10.3390/cimb45080398>.
- Rai, K.K., Kumar, A., Rai, A., Rai, V.P. and Rai, A.C. (2021). Conventional breeding approaches for abiotic stress management in horticultural crops. In *Elsevier eBooks* (pp. 21-32). <https://doi.org/10.1016/b978-0-12-822849-4.00017-6>.
- Roychowdhury, R., Das, S.P., Gupta, A., Parihar, P., Chandrasekhar, K., Sarker, U., Kumar, A., Ramrao, D.P. and Sudhakar, C. (2023). Multi-omics pipeline and omics-integration approach to decipher plant's abiotic stress tolerance responses. *Genes*. **14(6)**: 1281. <https://doi.org/10.3390/genes14061281>.