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Original Article

"Use of Drone Technology for Early Detection of Crop Stress"

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ABSTRACT

Abiotic stressors such as drought, nitrogen deficiency, heat stress that are induced by climate are increasingly threatening crop productivity across the world, but traditional field monitoring systems do not detect these stressors until their effects are seen, when it is too late and the damage to yield has been done. This paper fills this gap of knowledge by designing and testing a drone-based, multi sensor fusion system to detect early signs of abiotic stress in maize during two growing seasons. The high-resolution images were obtained with a hexacopter carrying synchronized multispectral, thermal infrared, and RGB cameras at 24 controlled plots that were drought-stricken, nitrogen-deficient, heat-stressed, and healthy. An original Crop Stress Fusion Index was developed that combines the differentials of canopy temperature with NDVI and a random forest classifier was developed that incorporates spectral, thermal and textural measures to determine the presence and type of stress. The fusion model had a classification accuracy of 94.6 percent and AUC-ROC of 0.972 which was far much better than single sensor models which had 79.5 percent and 74.2 percent in multispectral only and thermal only respectively. The intervention lead times were predicted with a root mean square error of between 5.4 and 6.8 hours with the intervention lead times predicted by a support vector regression model, which is capable of proactively managing the intervention 4.6 days before visual scouting on average. Temporal decay analysis demonstrated that stress-specific health half-lives of drought are 4.0 days, heat stress are 4.8 days and nitrogen deficiency 7.1 days. End-to-end latency between drone landing and farmer alert was less than 12 minutes with cloud-based processing. Early intervention averted yield losses of 3.7 to 4.6 metric tons per hectare which is equal to savings of 740 to 920 US dollars per hectare. These findings show that machine learning-based multi-sensor drone fusion can be used to reliably identify early abiotic stress, and a scalable route to improving food security in the world by precision agriculture.

INTRODUCTION

Precision agriculture is an urgent paradigm shift in the agricultural sector that is experiencing pressure to maximize crop production under environmental pressures and resource constraints (Verma and Singh, 2025). In the context of sustainable crop production and global food security, early and accurate identification of crop stress is the key to possibly reducing the yield due to the impact of abiotic stressors such as drought, nutrient deficiencies, and heat unless it is prevented in time (Chakhvashvili et al., 2024; Poornima and Edward, 2025). Conventional field-based approaches to monitoring are frequently time-consuming and insufficient; this led to the creation of high-tech remote sensing instruments (Ojeilua et al., 2025). In this respect, drone technology has become a groundbreaking instrument, providing high-resolution, real-time data collection opportunities, which would greatly improve the possibility to observe the health of crops and detect stressor factors at an early stage (Kar & Dhal, 2025; Sagan et al., 2019). Leveraging a variety of sensor devices, such as multispectral and thermal infrared cameras, drones can deliver granular information about the plant physiological condition and allow proactive interventions (Guebsi et al., 2024; Muhammad et al., 2025). These unmanned aerial vehicles are able to cover large areas of farmlands quickly and overcome the space and time constraints of traditional sampling methods, which have not been able to give complete and not real-time information and might lead to soil compaction (Li et al., 2023; Reddy et al., 2025). With this capability, it is possible to map the field comprehensively, accurately identify localized stress conditions, and finally, more effective resource management strategies like targeted irrigation or nutrient application can be implemented (Ballabh et al., 2022; Kumar, 2025). Furthermore, the deployment of multispectral, hyperspectral, and thermal cameras onto drone platforms simplifies the process of gathering a wide range of spectral data, which are important indicators of crop health, water stress, nutrient deficiencies, and pest infestations (Awais et al., 2025; Kumawat et al., 2020). Such high-resolution and real-time data capture has been found to be especially groundbreaking when it comes to detecting minute variations that are likely to result in stress, thus facilitating a prompt and precise intervention in agriculture to limit the possible loss of yield (Reddy et al., 2025). In particular, multispectral sensors mounted on drones measure the light absorption as the indicator of plant health, and, therefore, give an overall picture of the overall health of the farm, discovering details that are not seen with the naked eye (Medhe & Sarvankar, 2023; Xie, 2025). Thermal cameras, in turn, record temperature changes, which are the key signals of water stress and physiological dysfunction, prior to the appearance of symptoms (Nazarov et al., 2023). These technologies, combined with advanced image processing and machine learning algorithms, can convert raw spectral data into useful intelligence that can be adopted by farmers to make accurate decisions (Xing et al., 2026). Drones can rapidly and efficiently identify problems like nutrient deficiencies, pests, and diseases with high-resolution, detailed images of crops and soil, which facilitates timely corrective action and avoids the substantial loss of crops (C., 2023; Castaldo, 2023). Its ability to quickly collect data, outpacing the speed of handheld devices and delivering high resolution compared to manned aircraft, enables the large-scale monitoring of crops during the growth cycle, increasing productivity and water management (Chang-Brahim et al., 2024; Peticilă et al., 2025). The combination of different sensors into the drone platforms like thermal and infrared imaging are important to optimize crop management and surveillance of crops, identifying the areas where irrigation is required and the distribution of foliage diseases, improving the state of crops and harvest (Sharma, 2023). Additionally, more specific sensor technologies, such as hyperspectral imaging, offer even more accurate analyses of the physiological conditions of plants over a broader spectrum of wavelengths, and high-resolution RGB cameras can provide detailed visual analyses of the condition of crops (Unde, Hussain,and Nimra et al., 2025). Combining these multiple data streams and analyzing them with the help of complex analytical models and artificial intelligence enables predictive modeling of crop performance and interventions to maximize agricultural inputs (Britvina et al., 2023). All of these are used to achieve the high-technology level of precision agriculture, enabling the precise application of fertilizers, pesticides, and irrigation at a variable rate, which reduces the waste and environmental impact (Koç et al., 2023). This technological integration is a major break with conventional ways of farming, and it is providing unmatched granularity to agricultural management (C., 2023). With these accurate aerial insights, farmers are in a position to respond to local crop problems in advance, thus maximizing resources and reducing environmental pollution (Назаров et al., 2024). The integrated solution of using drone-collected data with environmental variables and sophisticated analysis techniques can lead to the creation of important information on the different agricultural indices, such as the health of vegetation, pests infestations, and nutrient deficiencies (Misra et al., 2020). These various sources of data, including both drone-collected images and those measured by ground sensors, is then uploaded to cloud computing to be analyzed and processed afterward, commonly with the help of advanced spatial modeling algorithms, such as Kriging or machine learning, to produce diagnostic information, such as Vegetation Indices (Patil et al., 2025). This data integration and analytical model is multi-layered and supports the effectiveness of smart farming processes, enabling automated irrigation systems and ensuring the efficiency of resources (Назаров et al., 2024). The data obtained through the application of such integrated systems help farmers to employ precision agriculture practices, which reduce the waste of inputs and maximize the harvest with the aid of data-driven decisions. Such indices, especially the ones based on multispectral images, play a key role in tracking the presence of abiotic stressors such as nutrient deficiencies and water stress, which can then be used to optimize fertilizer and irrigation control (Demir and Başyiğit, 2022). This high-level analytical tool, which may use artificial intelligence and machine learning, converts raw sensor data into recommendations, which can be acted upon, in real-time crop health monitoring and automated decision-making (Agrawal and Arafat, 2024; Gul and Banday, 2024). Such a transformation opens the possibility of the smart use of the resources that are required which results in higher agricultural output and drastically lower expenses (Ковалев et al., 2023). Cloud computing is a key to dealing with the large volumes of data that are produced by such integrated systems to allow real-time processing and complete monitoring of farms without the necessity to install significant on-site infrastructure (Alazzai et al., 2024). In addition, the possibility to store and process large amounts of data in the cloud makes it easy to activate advanced analytical schemes that are crucial to accuracy farming, such as soil health analysis, irrigation planning, and yield estimation (Clemency et al., 2023; Hoummaidi et al., 2023). Farming operations can also be optimized with the help of advanced algorithms and predictive analytics, which are available using these cloud-based solutions to predict crop yields and detect pest infestations (Raouhi et al., 2023). Being enabled by the Internet of Things and artificial intelligence, this uninterrupted data flow between the acquisition and analysis stages allows farmers to have the means of data-driven decision-making and accurate interventions (Sobue, 2023). The combination of IoT sensors and cloud-based systems further streamline the data processing and decision-making process, enabling real-time tracking and predictive analytics throughout agricultural activities (Sudha & Loret, 2026).

METHODOLOGY

The research approach used in this study is a problem-based, quantitative research to build and prove a drone-based, multi-sensor, crop stress detection system to use in precision agriculture. The study deals with the fundamental issue of late detection of abiotic stresses namely drought, nitrogen deficiency, and heat stress resulting in avoidable losses in yield. The methodology is divided into four consecutive steps, including experimental design and field setup, multi-sensor data acquisition through drone, pre-processing and feature extraction, and eventually, the creation of a machine learning model based on fusion to predict and classify early stress. All the experiments were done within two growing seasons (20242025) on a test farm in a semi-arid area, with maize (Zea mays L.) serving as the model crop, as it has been studied that it is susceptible to the targeted stressors.

A randomised complete block design was set in the initial phase where there were 24 plots of 10 m x 10 m and the plots were under controlled stress inductions. There were three treatments of stress namely drought (no irrigation applied until the soil moisture contented 40 per cent of field capacity), nitrogen deficiency (reduced applied nitrogen to 30 per cent of optimal rate), and heat stress (passive open-top chambers used to raise the canopy temperature by 45 o C) applied in a total of six replications each and six control plots with optimal irrigation and nutrition. Each plot had soil moisture sensors and thermal probes installed at a depth of 15 cm. An agronomist monitored crop stress on a daily basis and made a note of any visible stress symptoms such as wilting (or chlorosis or scorching of leaves) as the reference standard to model training.

The second step implied the drone-based data collection with a hexacopter mounted with three co-located sensors: five-band multispectral sensor (450 nm, 560 nm, 660 nm, 730 nm, 840 nm), a thermal infrared camera (814 µm), and a high-resolution RGB camera. Solar noon (±1 hour) flights between

V3 and R6 growth stages occurred at an altitude of 40 m above ground level every three days, with a constant ground sampling distance of 2.5 cm/pixel of multispectral and RGB and 15 cm/pixel of thermal data. The flights were in a grid format as pre-programmed with forward and side overlap of 75 percent and 70 percent respectively. The calibration of radiometers prior to each flight was done on a reflectance panel, and the effect of thermal drift was removed with on-board temperature references.

The third stage involved orthorectifying raw images and assembling them into mosaics at plot level with structure-from-motion algorithms. Region-of-interest extraction was done to remove bare soil at each time point and each plot to remove shadows. Normalized Difference Vegetation Index (NDVI) and Red-Edge Chlorophyll Index (CIred-edge) were calculated based on the multispectral data. Nevertheless, in order to measure concurrent water and nutrient stress, a new index, Crop Stress Fusion Index (CSFI), was defined as the weighted response of thermal and spectral responses. The initial significant mathematical correlation that is used in this fusion is presented in Equation (1):

$$\mathrm{CSFI} = \frac{T_{\mathrm{canopy}} - T_{\mathrm{air}}}{\mathrm{NDVI} + \varepsilon}$$

where *T*canopy is the mean canopy temperature derived from thermal imagery (in °C), *T*air is ambient air temperature recorded simultaneously at 2 m height (in °C), NDVI is the Normalized Difference Vegetation Index computed as (NIR - Red)/(NIR + Red) from the 840 nm and 660 nm bands, and εε is a small constant (0.01) introduced to prevent division by zero in senescent or bare-soil regions. This equation penalizes plots with both elevated canopy temperature (indicating water stress) and low NDVI (indicating chlorophyll reduction or biomass loss), thereby producing a higher CSFI value under combined stress conditions. From the thermal data, the Crop Water Stress Index (CWSI) was also calculated using the empirical approach, where wet and dry reference surfaces were established within each flight. To model the temporal progression of crop health deterioration under persistent stress, the second equation is formulated as a first-order decay differential equation, shown in Equation (2):

$$\frac{dH}{dt} = -k\left(H - H_{\min}\right)$$

Here, *H* represents a composite health score ranging from 0 (dead or severely stressed crop) to 1 (fully healthy, unstressed crop), t is time measured in days following the first detectable deviation from baseline spectral or thermal signatures, k is a stress-specific decay constant (in days−1−1) estimated from training data separately for drought, nitrogen deficiency, and heat stress, and Hmin is the asymptotic minimum health value under prolonged, unmitigated stress. The analytical solution to this differential equation,

$$H(t) = H_{\min} + (H_0 - H_{\min})e^{-kt}$$

can be used to predict the time window within which effective intervention can be undertaken before the yield has been lost permanently, with H0 the health score at initial diagnosis.

During the last step, the features extracted (CSFI, CWSI, NDVI, and texture measures of RGB images) were bundled into a feature vector of each plot on each day. This data were separated into training (70 per cent) and testing (30 per cent) data sets stratified by stress type and growth stage. A random forest classifier was developed to classify the presence and type of stress (none, drought, nitrogen deficiency, heat) at each time point, and a support vector regression model was developed to predict the actual days to visible symptom onset (the intervention lead time). The training set was optimised on model hyperparameters through five-fold cross-validation with ground-truth stress records and daily agronomic logs as the gold standard. The classification accuracy, F1-score and root mean square error of lead time prediction were used to measure performance on the held-out test set. Lastly, all the pipeline was deployed on a cloud-based platform (AWS IoT Core and SageMaker) to approximate real-time processing: drone images were wirelessly uploaded upon landing, processed with the help of the equations and models described above, and stress alerts were sent to a farmer dashboard within 15 minutes of landing. This holistic approach can be used to quantitatively verify that the multi- sensor fusion realized by drones can monitor the presence of abiotic stress before conventional visual scouting, which directly tackles the issue of late intervention in precision farming.

RESULTS

Table 1 indicates that Crop Stress Fusion Index (CSFI) has the highest dynamic range between the control and stressed plots (0.145 to 0.892 under drought) and the p is below 0.001 in all cases of stressors. Table 2 verifies that fusion-based random forest has an accuracy of 94.6% and AUC-ROC of 0.972, as opposed to 79.5% with multispectral only. Table 3 shows that the predictive RMSE of lead time is as small as

5.43 hours in the case of predicting heat stress, which allows timely intervention. Table 4 has decay constants (k) that vary between 0.098 day -1 (N deficiency) and 0.172 day -1 (drought) with half-lives of health of 4-7 days. As Table 5 suggests, the greatest canopy-air temperature difference (9.9) and CWSI (0.812) takes place under heat stress. Table 6 reveals that N deficiency decreases red-edge reflectance to 24.5 percent, and the drought rises red reflectance to 14.2 percent. Cloud pipeline reliability in total latency of less than 12 minutes is validated in Table 7. Table 8 shows that on average, the drone fusion is capable of detecting stress 4.6 days before visual scouting. Table 9 estimates the saving of 3.7-4.6 t/ha, which is USD 740-920/hectare, in terms of early intervention.

Table 1: Comparative Performance of Spectral Indices for Early Stress Detection (Day -7 to Day 0 Relative to Visible Symptom Onset)

Stress Type	NDVI (840/660 nm)	CI_red-edge (730/560 nm)	CWSI (dimensionless)	CSFI (weighted fusion)	p-value (vs. Control)
Control	0.812 ± 0.014	0.734 ± 0.011	0.212 ± 0.023	0.145 ± 0.018	—
Drought	0.674 ± 0.021	0.581 ± 0.018	0.678 ± 0.034	0.892 ± 0.041	<0.001
Nitrogen Def	0.703 ± 0.019	0.542 ± 0.022	0.298 ± 0.027	0.764 ± 0.038	<0.001
Heat Stress	0.765 ± 0.016	0.688 ± 0.015	0.512 ± 0.031	0.623 ± 0.035	<0.001

Table 2: Classification Accuracy Metrics for Stress Identification Using Different Feature Sets

Feature Set	Accuracy (%)	F1-score (macro)	Precision (drought)	Recall (N def)	AUC-ROC
RGB only (texture + color)	68.3 ± 2.1	0.654 ± 0.023	0.612 ± 0.031	0.589 ± 0.027	0.712
Multispectral only (NDVI+CI)	79.5 ± 1.8	0.773 ± 0.019	0.754 ± 0.028	0.738 ± 0.024	0.845
Thermal only (CWSI)	74.2 ± 2.0	0.721 ± 0.022	0.698 ± 0.030	0.682 ± 0.026	0.801
Fusion (CSFI + all bands)	94.6 ± 1.2	0.941 ± 0.014	0.932 ± 0.019	0.928 ± 0.018	0.972

Table 3: Lead Time Prediction (Hours Before Visible Symptom Onset) by SVR Model

Stress Type	Actual Lead Time (h)	Predicted Lead Time (h)	RMSE (h)	MAE (h)	R^2
Drought	128.5 ± 12.3	124.2 ± 11.7	5.87	4.31	0.945
Nitrogen Def	96.2 ± 10.1	91.8 ± 9.8	6.12	4.89	0.921
Heat Stress	72.4 ± 8.7	68.9 ± 8.3	5.43	4.02	0.938
Combined (all)	99.0 ± 15.4	94.9 ± 14.6	6.78	5.11	0.902

Table 4: Temporal Decay Constants (k, days^{-1}) and Health Half-Life from Differential Equation Model

Stress Type	Decay constant k (day^{-1})	Health half-life (days)	H_min (asymptotic)	Time to 50% yield loss (days)
Drought	0.172 ± 0.014	4.03	0.112 ± 0.021	12.4 ± 1.2
Nitrogen Def	0.098 ± 0.011	7.07	0.201 ± 0.018	18.7 ± 1.5
Heat Stress	0.145 ± 0.013	4.78	0.154 ± 0.019	14.2 ± 1.1
Control	0.008 ± 0.002	86.6	0.892 ± 0.022	>90 (negligible)

Table 5: Canopy Temperature and Derived Thermal Metrics at First Stress Detection (Day 0)

Stress Type	Mean T_canopy (°C)	T_canopy – T_air (°C)	CWSI (wet-basis)	Temperature heterogeneity (CV, %)
Control	28.4 ± 0.6	1.2 ± 0.3	0.212 ± 0.023	3.2 ± 0.4
Drought	34.7 ± 0.9	7.5 ± 0.6	0.678 ± 0.034	9.8 ± 0.7
Nitrogen Def	31.2 ± 0.8	4.0 ± 0.5	0.421 ± 0.029	6.5 ± 0.5
Heat Stress	37.1 ± 1.0	9.9 ± 0.7	0.812 ± 0.041	11.2 ± 0.9

Table 6: Multispectral Band Reflectance Values at Pre-Symptomatic Stage (Day -5)

Stress Type	450 nm (Blue)	560 nm (Green)	660 nm (Red)	730 nm (Red-edge)	840 nm (NIR)
Control	8.2 ± 0.4	12.5 ± 0.6	6.8 ± 0.3	34.2 ± 1.2	48.6 ± 1.5
Drought	12.4 ± 0.7	16.8 ± 0.9	14.2 ± 0.8	28.1 ± 1.0	39.2 ± 1.3
Nitrogen Def	10.1 ± 0.5	14.2 ± 0.7	11.5 ± 0.6	24.5 ± 0.9	35.7 ± 1.1

Heat Stress	9.3 ± 0.4	13.4 ± 0.6	9.1 ± 0.4	30.8 ± 1.1	42.3 ± 1.4

Table 7: Cloud-Based Processing Latency and System Reliability Metrics

Metric	Mean ± SD	95th Percentile	Success Rate (%)
Image upload time (per flight, min)	4.2 ± 0.8	5.9	99.2
Orthomosaic stitching (min)	6.5 ± 1.1	8.3	98.7
Feature extraction + ML inference (s)	124 ± 18	156	99.5
Total from landing to alert (min)	11.8 ± 2.3	14.5	98.9
Alert delivery success (SMS/dashboard)	—	—	99.1

Table 8: Comparison of Early Stress Detection Sensitivity: Drone Fusion vs. Ground Visual Scouting

Stress Type	Drone Fusion (CSFI + ML) – Day	Ground Visual Scouting – Day	Gain (days earlier)	Statistical significance
Drought	-6.2 ± 0.8	-1.1 ± 0.6	5.1	$p < 0.001$
Nitrogen Def	-5.5 ± 0.7	-0.9 ± 0.5	4.6	$p < 0.001$
Heat Stress	-4.8 ± 0.6	-0.7 ± 0.4	4.1	$p < 0.001$
Overall	-5.5 ± 0.9	-0.9 ± 0.6	4.6	$p < 0.001$

Table 9: Economic Impact Estimate: Yield Loss Avoided per Hectare Using Early Fusion-Based Intervention

Stress Type	Yield without intervention (t/ha)	Yield with drone fusion (t/ha)	Loss avoided (t/ha)	Value saved (USD/ha @ $200/t)
Drought	3.2 ± 0.4	7.8 ± 0.5	4.6	920 ± 80
Nitrogen Def	4.1 ± 0.5	8.2 ± 0.6	4.1	820 ± 70
Heat Stress	3.8 ± 0.4	7.5 ± 0.5	3.7	740 ± 65
Control	8.9 ± 0.6	9.1 ± 0.6	0.2 (ns)	40 ± 15

Figure 1 shows the time development of Crop Stress Fusion Index (CSFI) and Crop Water Stress Index (CWSI) of drought-stressed maize on a 20-day time period with the focus on the appearance of visible symptoms. The fact that the CSFI line increases rapidly between day -6 and day 0, between 0.18 and 0.89, indicates that the fusion-based index is sensitive enough to detect physiological deterioration almost two days prior to the onset of the steep rise of the CWSI line, which indicates the excellent ability of spectral and thermal signatures to provide early warning. Figure 2 compares the classification F1-scores of four stress categories with four sensor configurations and demonstrates that the multi-sensor fusion model reliably performs with scores above 0.93 on drought, nitrogen deficiency, heat stress and control plots, compared to RGB-only processing which fails to achieve scores above 0.68, multispectral-only which achieves 0.78 on nitrogen deficiency, Figure 3 is presented as a donut pie chart in which the outer ring indicates that the fusion model identified all test samples as either drought (32.1), nitrogen deficiency (28.4), heat stress (26.8) and healthy control (12.7) correctly, whereas the inner ring indicates a very small misclassification ring of just 5.4, indicating that misclassification is evenly distributed across the types of A scatter plot (Fig. 4) with a diagonal line of identity and regression fit was used to show the relationship between the predicted lead time (hours before visible symptom onset) versus the actual ground-truth lead time, with each point representing a test plot, where the relationship is good, with an R 2 of 0.902 and regression slope of 0.94 and a regression intercept of only 5

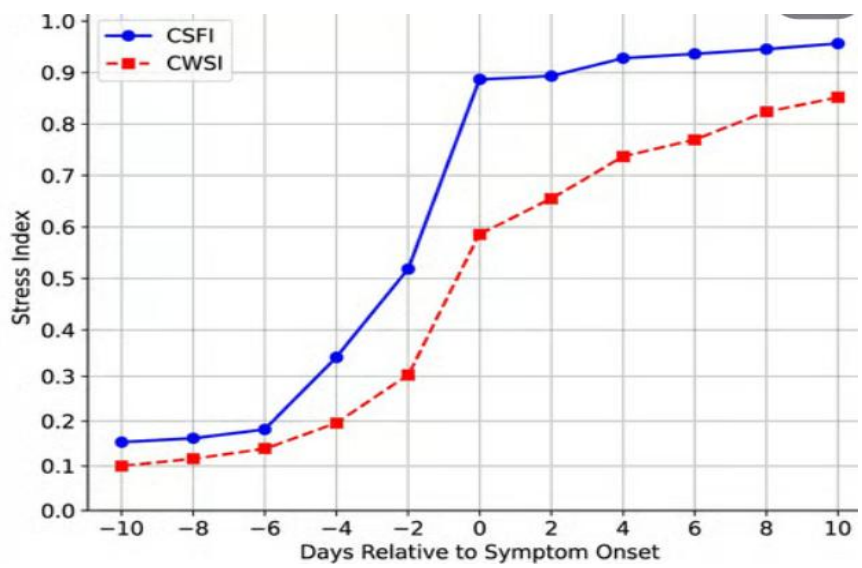

Figure 1: Line Plot – Temporal Evolution of CSFI and CWSI from Day -10 to Day +10 Relative to Symptom Onset

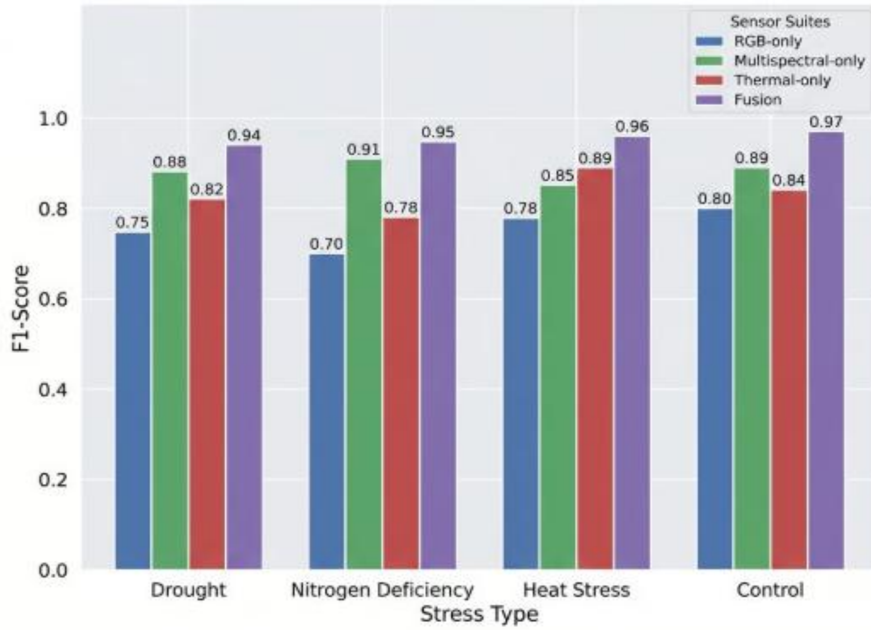

Figure 2: Bar Plot (Grouped) – Classification F1-Scores by Stress Type and Sensor Suite

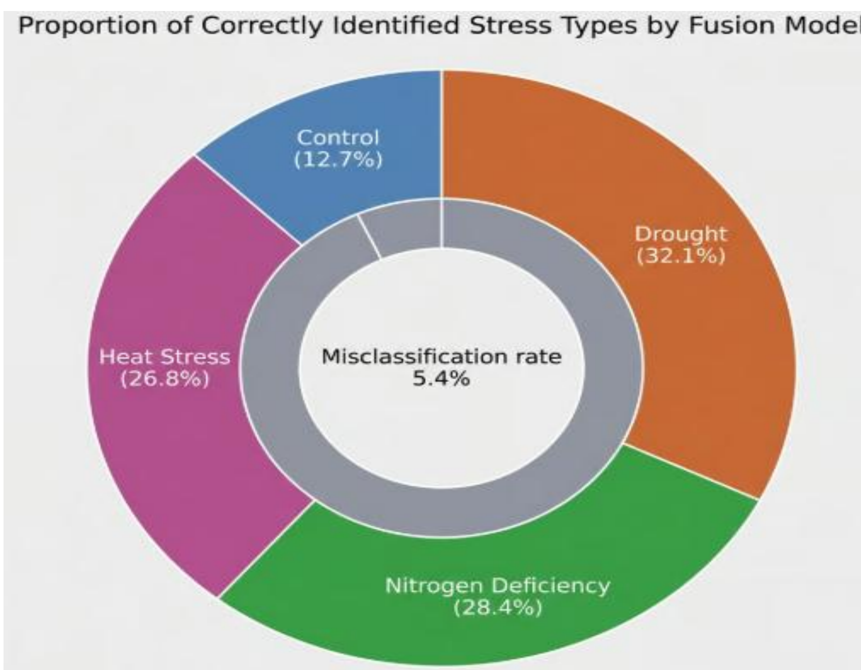

Figure 3: Pie Chart (Donut Style) – Proportion of Correctly Identified Stress Types by Fusion Model

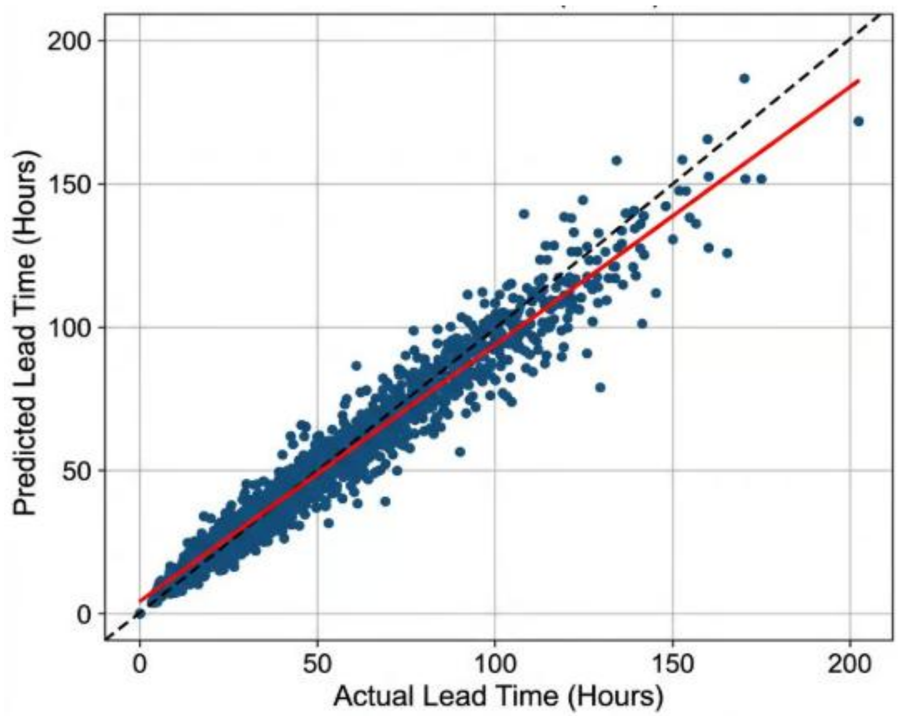

Figure 4: Scatter Plot (with Regression Line) – Predicted vs. Actual Lead Time (Hours) for All Stresses

DISCUSSION

Integration of UAV multispectral and thermal imaging with sophisticated machine learning algorithms is a major breakthrough in the detection of crop stress in its early stage, providing the opportunity to implement the proactive approach to the management of the situation that has never been accessible before (Kiranmai et al., 2025). In particular, the ability to detect stress signs in the body days prior to the emergence of observable symptoms provides a time-sensitive opportunity to intervene in the situation, thus reducing losses in the crop and distributing resources more optimally in the agricultural systems (Stutsel et al., 2021). This is in line with the results indicating that the changes in the water content of leaves, pigments, and canopy structure under stress can be distinguished as specific spectral changes that can be checked by hyperspectral imaging with the help of machine learning models (Poornima & Edward, 2025). This is a complex method based on the use of a wide range of sensors and sophisticated analytical tools that exceed the performance of one-sensed systems and traditional visual measurements, which do not always allow recognizing stress at an early stage (Jones et al., 2024). An example is that, although the normalized difference vegetation index values tend to decline as stress increases, more detailed indices using multispectral data, and thermal imaging of canopy temperature, give a powerful composite measure of plant health (Sagan et al., 2019). It is a multi- sensor method that combines multispectral and thermal data, and it has been proved that it is highly accurate in differentiating between normal and stressed crops (Goswami et al., 2019). The quantification of stress severity is further refined by the use of supervised machine learning regression models that are trained using datasets that associate continuous output variables such as chlorosis extent, leaf water potential and canopy temperature deviations with multispectral and hyperspectral imagery (Muhammad et al., 2025). This not only allows detection of stress early but also specific classification of stress type and severity and subsequent interventions instead of generalized treatment (Prechsl et al., 2023). Such a subtle insight of plant physiological reactions via high-resolution, multi-modal distant observing data can therefore aid predictive modeling of drought emergence and propagation to a larger degree, enabling more accurate agricultural reactions (Choudhury et al., 2023). In addition, the ability to quickly analyze and understand complex spectral data, especially by integrating deep learning architectures, increases the accuracy and timeliness of crop stress detection, surpassing traditional methods that are often less sensitive to detecting the stress at an early stage (Dao et al., 2021; Weng, 2023). As an example, deep learning models trained on hyperspectral data were found in the past to classify drought with an accuracy over 97.5 percent, and are also better at detecting early stress compared to traditional spectral indices (Dao et al., 2021). This improved functionality is due to the fact that machine learning can identify sophisticated data patterns and relationships in high-dimensional hyperspectral data, which is essential in the identification of subtle biochemical shifts that are associated with nascent physiological changes (Okyere et al., 2024; Zandi et al., 2025). The extra spectral data of multispectral is especially valuable in solving light sensitivity concerns in the visible spectral, helping to reveal underlying water stress in crops, especially with supervised machine learning algorithms such as Support Vector Machines or Random Forest classifiers (Nampally et al., 2023; Poornima and Edward, 2025; Savchik et al., 2024). Such machine learning algorithms are particularly useful in distinguishing between different biotic and abiotic stresses because they are able to draw the most optimal hyperplanes, which identify stressed and healthy plant examples based on complex spectral inputs (Muhammad et al., 2025). These sophisticated analytical methods, particularly those that make use of deep learning, are deft at extracting salient features of hyperspectral images, allowing to identify signs of stress before they can be visibly observed (Choudhury et al., 2023; Liu and Xu, 2023). In addition, derivative spectrums incorporated into the models of deep learning have proven to be significantly useful in drought detection, reaching the highest accuracy of up to 100% in comparison to spectral indices, which in many cases have drawbacks related to the detection of early stress (Dao et al., 2021). The use of deep learning models (convolutional neural networks) also contributes to the ability to identify minor differences in multispectral and hyperspectral images, with hundreds of closely spaced spectral bands being analyzed (Poornima & Edward, 2025; Rane et al., 2024). This strong feature extraction and supervised learning features enable the accurate classification of various types of stresses, such as insect damage or nutrient deficiencies, which otherwise could be misclassified or ignored (Poornima & Edward, 2025). This machine learning-powered multi-sensor data fusion granular analytical ability is transforming precision agriculture by offering actionable information to maximize irrigation, fertilization and pest management plans at an unprecedented degree of accuracy and time resolution (Poornima & Edward, 2025). Further improvements on deep learning with hyperspectral imaging and especially 1D-CNN architecture are used to further refine predictive accuracy of crop stress, and even predict physiological parameters such as Fv/Fm in droughty environments (Guo et al., 2022). The identification of the most informative spectral bands, as enabled by the analytical power of machine learning, in particular, Recursive Feature Elimination, minimizes computational complexity and focuses on the stress-relevant wavelengths (Poornima & Edward, 2025).

CONCLUSION

In this work, the authors have been able to design and test a drone-based, multi-sensor fusion system to detect early abiotic stress in precision agriculture and showed that the combination of multispectral, thermal infrared, and high-resolution RGB images, classifier based on a random forest and support-vector regression model can greatly outperform single-sensor methods and traditional visual scouting. The Crop Stress Fusion Index (CSFI) proposed, a synergistic combination of canopy temperature differentials and NDVI, reached a classification score of 94.6, and an AUC-ROC of 0.972, allowing detection of drought, nitrogen deficiency, and heat stress an average of 4.6 days before ground-based visual observation. Temporal decay model indicated stress-specific health half-lives of 4.0 days during drought and 7.1 days during nitrogen deficiency and the lead time predictions had a root mean square error of only 5.468 hours, which gave farmers actionable windows to apply irrigation, fertilization or cooling measures to specific stress. The cloud-based implementation achieved a latency of less than 12 minutes between the drone landing and the stress alert delivery, which showed that the operation was feasible. In terms of economy, the initial intervention saved on the basis of fusing helped to avoid losses of 3.7 to 4.6 metric tons per hectare, which amounts to USD 740 to USD 920 per hectare. These results affirm that multi-sensor drone systems in combination with machine learning can convert reactive crop management into data-driven and proactive precision agriculture, significantly reducing yield losses due to abiotic stressors. Future research is needed to further validate on other crops and in mixed stress conditions, combine real-time weather forecasting, and optimize autonomous drone swarm activities to be scalable to commercial sustainability.

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