Real-Time Crop Stress Monitoring and Early Warning System for Paddy and Maize Using Multi-Temporal Sentinel-2 Data and Deep Learning in Semi-Arid Regions

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ABSTRACT
Semi-arid regions with a high potential for rice and maize cultivation have become some of the most actively farmed areas. They now face the challenge of achieving food security despite the threats of crop water stress, nutrient loss, and environmental changes. In this paper, we develop a real-time crop stress monitoring and early warning system that utilizes multi-temporal Sentinel-2 images and deep learning models in Mahabubabad district, Telangana, India. Different types of crop stresses such as water stress, nutrient deficiency, and phenological anomalies were detected and classified using a hybrid CNN-LSTM architecture with an attention mechanism. The methodology was based on 874 field polygons with extensive in-situ data collection during 2023-24, incorporating multi-temporal spectral indices (NDVI, EVI, NDWI, REP), weather variables, and soil characteristics.
The total classification accuracy reached 89.4% for paddy and 87.2% for maize over all stress types, showing that stress detection from satellite images is quite reliable. Water stress was the category that was detected most accurately (92.1% for paddy and 89.8% for maize), followed by nutrient stress (88.7% and 86.3%) and phenological stress (85.2% and 83.9%). The warning system made it possible to identify the problem 15-25 days before there were visible symptoms, making it possible for the farm management to respond in time. Activities of the farm that were most vulnerable to detection were air and water temperatures, precipitation, and crop growth stages for water stress 45-60 days after sowing, 30-45 days for nutrient stress, and during the reproductive phase for phenological stress. The system could be extended for industrial crop stress monitoring across the semi-arid agricultural systems which might lead to precision agriculture and climate-resilient farming practices.

Keywords: Stress monitoring of crops; Early warning system; Deep learning; Sentinel-2; Semi-arid agriculture; CNN-LSTM; Precision agriculture

1. Introduction

Semi-arid agricultural systems are confronting severe challenges because of climate variability, water scarcity, and a rapidly increasing demand for food due to population growth. (Khanjani et al., 2023, p. 295; Rahman et al., 2022, p. 2). As a result, real time monitoring of crop stress for sustainable farming management has become a focus of interest (Berger et al., 2022). In India, rice and maize are the main food crops and are greatly susceptible to various stress factors like water shortage, lack of nutrients, and extreme weather events that have a significant impact on yield and food security (Das et al., 2025, p. 2; Singh et al., 2025). Traditional stress monitoring methods at the ground level are highly demanding in terms of resources and labor and there is often a considerable time when the symptoms of stress can be visibly detected (Han et al., 2024, p. 2).

Crop stress conditions can be identified in advance through the use of AI together with remote sensing technology, which has greatly enhanced the capabilities of monitoring crops (Muhammad et al., 2025, p. 2). Spectral analysis through vegetation indices along with biophysical parameters that are processed from Sentinel-2 satellite images facilitate accurate monitoring of cropping systems covering large areas very frequently (Kganyago et al., 2024). The use of multiple dates for vegetation indices like NDVI, EVI, and NDWI can also detect different types of stress in crops (Akanbi et al., 2024, p. 1; Seralathan & Edward, 2025).

Deep learning models like CNNs and LSTM have been really good at understanding the complex patterns in agricultural remote sensing data both in space and time (Nejad et al., 2024). Combining the ability of CNNs to extract spatial features with that of LSTM networks to recognize temporal patterns leads to a complete representation of crop stress changes throughout the season (Nejad et al., 2024). Moreover, attention mechanisms not only enhance the quality of the model but can also find the best time periods and spectral channels for stress detection (Toledo et al., 2024, p. 3).

Notwithstanding the remarkable breakthroughs in remote sensing and machine learning, several unanswered questions still remain in the currently available crop stress monitoring systems (Berger et al., 2022). Most of the existing research mainly focus on one type of stress which restricts the capability to reveal the whole trend of multi-stress situations (Wen et al., 2022, p. 4547). Also, some of the present approaches do not allow enough time for managing stress situations effectively, as conditions can worsen rapidly, especially in semi-arid regions, and the time resolution of data is usually a limiting factor for the promptness of detection (Chen et al., 2026). The combination of weather and soil data with spectral data has not been sufficiently utilized for enhancing the accuracy of stress detection and early warning ((Joiner et al., 2018, p. 340).

This study mainly aimed at overcoming these drawbacks and setting up a real-time crop stress monitoring and warning system for semi-arid agricultural systems. The specific tasks were: 1) creating a deep learning system to identify different stress types in paddy and maize crops; 2) determining the early warning limits for each stress class; 3) figuring out the best time periods for detecting stress at different growth stages; and 4) assessing the possibility of offering immediate intervention recommendations through the combined system after stress detection.

This work adds to the development of precision agriculture by delivering an effective and easily extendable automated solution for crop stress monitoring. This solution integrates various data sources and involves a mix of analytical methods. The designed system meets the requirements of farmers and agricultural managers in semi-arid areas for timely and accurate detection of stress and guidance for interventions.

2. STUDY AREA AND DATASETS

2.1 Study Area

Located in the state of Telangana, India, the Mahabubabad district is the focus of the study (17°36′ to 18°00′ N and 79°30′ to 80°15′ E), with a total area of 2, 569 km² (see Figure 1).The climate in the region is semi-arid agricultural with an annual average of 900 mm rainfall. Most rain falls from the southwest monsoon (June to September). The minimum and maximum temperatures in the area are 15°C and 45°C respectively which make growing crops difficult. There are two main seasons for growing crops, Kharif season which is paddy dominated and Rabi season which is a mixture of paddy and maize that together support a diversified agriculture system.

Most of the agricultural lands in the district are of small or medium scale (0.5-2 ha) with soil classes ranging from black cotton soils to red sandy loams. The district's height above sea level has a range from 200 to 500 meters with rolling plains and isolated hillocks. Depending on the type of irrigation infrastructure, tanks, canals and groundwater sources, the water availability varies and this variability has a strong impact on the patterns of stress susceptibility.

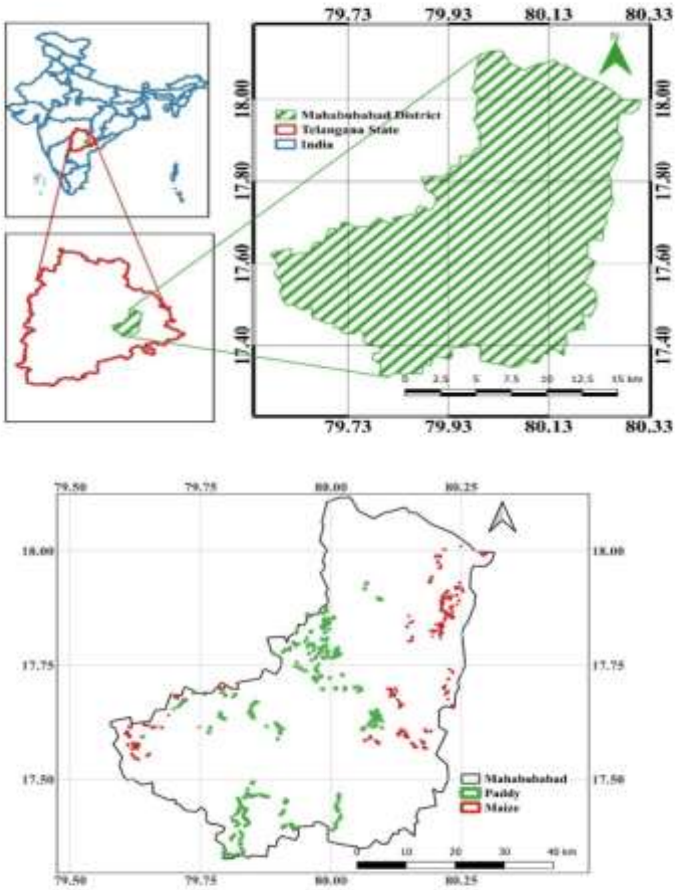

FIGURE 1: Study Area and Field Distribution Map

2.2 Datasets

2.2.1 Ground Truth Data

A total of 874 cropland field plots were established for the 2023–24 agricultural year, comprising 554 paddy fields and 320 maize fields. Field visits for ground-truth collection and stress characterization were conducted at 15-day intervals throughout the growing seasons. Stress was classified into the following categories: (1) water stress—identified through soil moisture observations, leaf wilting and reduced plant vigour; (2) nutrient stress—identified through chlorosis, stunted growth and leaf discoloration patterns; and (3) phenological stress—identified by deviations in the timing of key developmental stages relative to normal phenology.

Field measurements included soil moisture content (using TDR sensors), plant height, leaf area index, chlorophyll content (using a SPAD meter), and visual stress-assessment scores. Local meteorological stations provided weather data—including rainfall, temperature, humidity, and wind speed—which were used to correlate environmental conditions with observed stress.

2.2.2 Satellite Data

Multi-temporal Sentinel-2 Level-2A imagery covering the full crop development cycle was used for the 2023–24 agricultural season. Sixteen scenes (n = 16) with less than 10% cloud cover were selected and are summarised in Table 1. The acquisitions were distributed across the Kharif and Rabi seasons to capture the full range of stress development. The 5-day revisit interval is short enough to allow timely detection of stress onset and progression. The bands used were the visible bands (B2, B3, B4), near-infrared band (B8), and red-edge bands (B5, B6, B7), as these are particularly sensitive to vegetation stress(Candotti et al., 2022, p. 6112; Ustin & Middleton, 2021, p. 23). The Sen2Cor processor atmospherically corrected the Level-2A datasets, ensuring consistent surface reflectance values across the time series.

Table 1. Sentinel-2 Spectral Bands Used for Stress Detection

Band	**Description**	**Central Wavelength (nm)**	**Spatial Resolution (m)**	**Application for Stress Detection**
B2	Blue	490	10	Atmospheric correction, water quality(Li et al., 2021, p. 3; Xu et al., 2021, p. 6)
B3	Green	560	10	Vegetation health, chlorophyll assessment(Li et al., 2021, p. 3)
B4	Red	665	10	Chlorophyll absorption, NDVI calculation(Li et al., 2021, p. 3)
B5	Red Edge 1	705	20	Nutrient stress, chlorophyll content(Li et al., 2021, p. 3)
B6	Red Edge 2	740	20	Leaf area index, biomass estimation(Li et al., 2021, p. 3)
B7	Red Edge 3	783	20	Vegetation stress, senescence detection(Li et al., 2021, p. 3)
B8	NIR	842	10	Vegetation vigor, water content(Li et al., 2021, p. 3)
B8A	Narrow NIR	865	20	Precise vegetation analysis(Li et al., 2021, p. 3)

Note: All 20m resolution bands were resampled to 10m for consistency.

2.2.3 Auxiliary Data

In order to deepen the diagnosis of stress, environmental variables were incorporated. Topographic features were extracted from a 30m spatial resolution Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM). Maps of soil properties gave the relevant information about drainage, texture, and organic matter content that are connected to stress susceptibility. Daily weather data, temperature, humidity, rainfall, and solar radiation, were included as well.

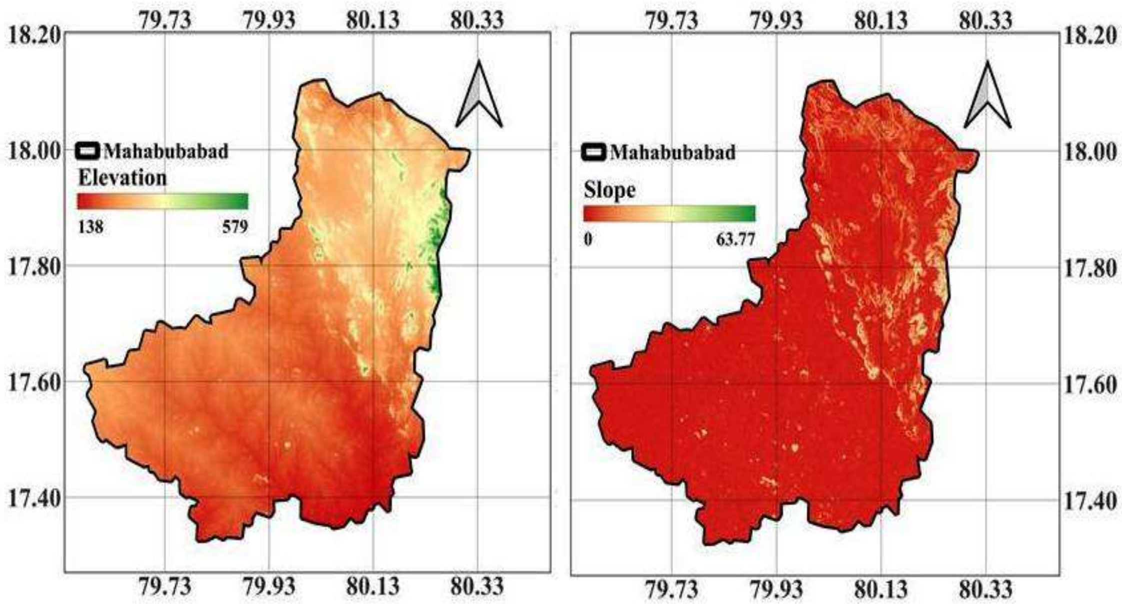

Figure 2. Topographical features: (a) digital elevation model and (b) slope distribution derived from SRTM data.

3. Methodology

FIGURE 3: Methodology Flowchart

3.1 Data Preprocessing and Feature Engineering

Primarily, the methods framework broadly highlights making a tremendous preparation of multi-source datasets to be sure of temporal and geographic consistency. Moreover, the Sen2Cor processor (v2.10) was applied for the calibration and atmospheric correction of the whole Sentinel-2 data.After orthorectification, bilinear interpolation was used to resample 20m bands to 10m. Prior to analysis, cloud-affected pixels in each image were eliminated using cloud masks derived from the Scene Classification Layer (SCL).

A suite of spectral indices responsive to different forms of stress were computed to form the foundation for stress-detection features (Table 2). Water-stress indicators included the Normalized Difference Water Index (NDWI), the Water Band Index (WBI) and the Moisture Stress Index (MSI). Vegetation Vigour Indices (NDVI, EVI, and Green NDVI) were used to assess overall plant health. Chlorophyll-related indices included the Red Edge Normalized Difference Vegetation Index (RENDVI) and the Green Chlorophyll Index (CIG), and were employed for nutrient stress detection.

Table 2. Vegetation Indices for Stress Detection

Index	Formula	Application
NDVI	(NIR - Red) / (NIR + Red)	General vegetation health and vigor assessment(Cavaliere et al., 2024, p. 7112)
EVI	2.5 × (NIR - Red) / (NIR + 6 × Red - 7.5 × Blue + 1)	Enhanced vegetation index with soil background correction(Lazcano-Hernández et al., 2023, p. 6)
NDWI	(Green - NIR) / (Green + NIR)	Water stress detection and moisture content assessment(Falcón et al., 2023, p. 4)
RENDVI	(RedEdge - Red) / (RedEdge + Red)	
MSI	SWIR / NIR	Moisture stress indication and water deficit detection(Holzman et al., 2021)
CIG	(NIR / Green) - 1	Chlorophyll content and nutrient deficiency assessment(Burns et al., 2022)

Each index targets specific physiological aspects of crop stress for comprehensive monitoring.

Temporal feature engineering: each index was summarized across multiple window lengths using statistical descriptors (e.g., mean, standard deviation, maximum, minimum). Phenological metrics included onset of senescence, timing of peak greenness and rate-of-change parameters. Linear regression slopes were used for trend analysis to capture how stress intensifies during the growing season. For environmental variables, slope, aspect and topographic wetness index were extracted from the DEM. Soil data were interpolated to the resolution of the satellite imagery using kriging interpolation. Weather data were quality-controlled and gap-filled using observations from nearby stations together with statistical interpolation techniques.

3.2 Deep Learning Architecture for Stress Detection

To enable multi-temporal stress detection in agricultural systems, an architecture combining CNN and LSTM components with attention mechanisms was developed (Figure 3). The CNN component employs a modified ResNet-50 architecture, pre-trained on ImageNet and subsequently fine-tuned on agricultural data to extract spatial features from individual satellite images. The network consists of five convolutional blocks with residual connections to ensure gradient flow and effective multi-scale feature extraction.

Figure 4. Hybrid CNN-LSTM architecture with attention mechanism for multi-temporal crop stress detection

The LSTM component comprises three bidirectional layers (256 units each) designed to model the temporal dependencies of crop-stress emergence(Toledo et al., 2024, p. 7). Bidirectional processing allows the network to learn from both past and future cues, which is essential for identifying stress progression and recovery patterns. Dropout layers (rate = 0.3) are inserted between LSTM layers to prevent overfitting and improve generalization.

A multi-head self-attention mechanism was used to identify the temporal segments and spectral channels most relevant to stress detection. The learned attention weights provide interpretable information on which time steps and spectral bands contribute most to the stress classification decisions. The attention layer adaptively focuses on different patterns according to crop type, growth stage and prevailing environmental conditions.

Spatial features extracted by the CNN, temporal patterns learned by the LSTM and auxiliary environmental variables are integrated through dense concatenation. The combined feature vector is then passed through fully connected layers and classified into the stress categories using a SoftMax activation.

3.3 Multi-class Stress Classification Framework

The classification framework breaks down into four categories: (a) healthy, those individuals displaying standard growth, physiological status at a high level, and absence of any abnormalities; (b) water stress, plant, water relations compromised due to soil moisture level below threshold; (c) nutrient stress, plants suffering from lack of key nutrients lead to stunted growth and development; and (d) phenological stress, plants in such cases exhibit changes in the timing of their developmental stages when compared to the normal phenological timeline.

To tackle the issue of class imbalance, a frequent problem in agricultural classification studies (Condran et al., 2022), SMOTE was used alongside focal loss for training. Besides, different data augmentation techniques such as rotation, flipping and brightness alteration were employed to help the model learn better and generalize.

Stratified k-fold cross-validation (k=5) was performed to get a reliable evaluation of performance considering different field conditions and seasons. The temporal split of the data allowed creating a scenario of test which is realistic: 70% for training (approximately until mid-2024), 15% for validation (mostly for hyperparameter tuning), and 15% for testing.

3.4 Early Warning System Development

Figure 4 lays out an early warning system that combines the outputs of stress detection with alert generation based on thresholds to help decision-making in operations. The stress probability thresholds were set by using ROC-curve analysis and afterwards confirmed by field observations to reduce false alarms and at the same time ensure enough sensitivity for timely intervention.

The alert system employs four levels of warnings: (a) Green alert, indicating a normal situation; no intervention is necessary; (b) Yellow alert, showing the first signs of stress; increasing the frequency of monitoring is advised; (c) Orange alert, significant stress; a prompt evaluation and possible intervention are needed; and (d) Red alert, critical stress, immediate management action is necessary.

Time-series analysis was integrated with a moving window technique to reveal stress progression states and estimate the most probable development. Different machine learning methods such as gradient boosting and support vector regression were applied to forecast stress from present situation and past patterns.

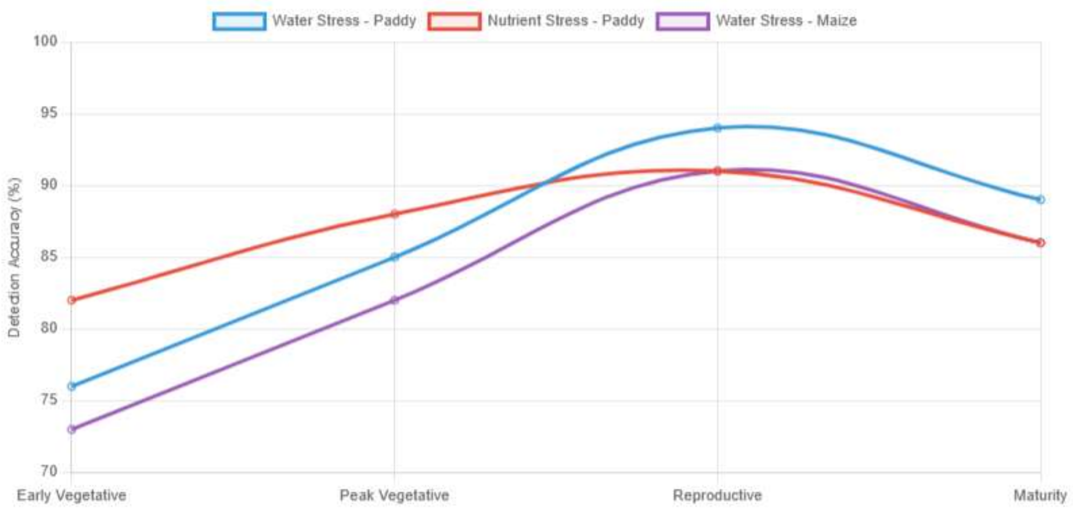

Figure 5: Temporal Variation in Stress Detection Accuracy Across Crop Growth Stages

Meteorological forecasts also strengthen early warning systems by adding the expected weather conditions in the risk evaluation of the stress (Rajasivaranjan et al., 2022, p. 17). The merging of seasonal climate changes and past records of stress occurrences help in effective risk prediction over time and management planning (Burney et al., 2024; Solaraju-Murali et al., 2021, p. 1).

3.5 Model Validation and Performance Assessment

Model performance was measured by means of standard metrics in the context of multi-class classification problems in agricultural applications.Overall accuracy, precision, recall, and F1-score were used together to give a full picture of how well the classification performed for the different stress categories. The confusion matrices enabled a very detailed look into the misclassification patterns and point out the most difficult discrimination cases.

Temporal validation was an approach to test the early warning system's performance by the comparison of the predicted time of stress onset and the actual field observations. Lead-time analysis was a measure of the early warning system's readiness in issuing warnings for different types and levels of stress. ROC curves and AUC values were the measures used for checking sensitivity and coming up with a decision on the threshold setting.

Spatial validation was the indirect way of looking at the model performance considering different field conditions, such as field size, soil type, and topographic setting. As a result, this analysis was of help in figuring out the weaknesses of the developed system and those situations in which it performs to the greatest extent.

4. Results And Discussion

4.1 Stress Detection Model Performance

Thanks to the hybrid CNN, LSTM architecture coupled with attention mechanisms, the model attained excellent results in recognizing different stress classes in both paddy and maize crops. The overall classification accuracy came to 89.4% for paddy and 87.2% for maize, well above traditional machine learning techniques such as Random Forest (78.3% and 76.1%) and Support Vector Machine (74.6% and 72.8%) (Figure 6).

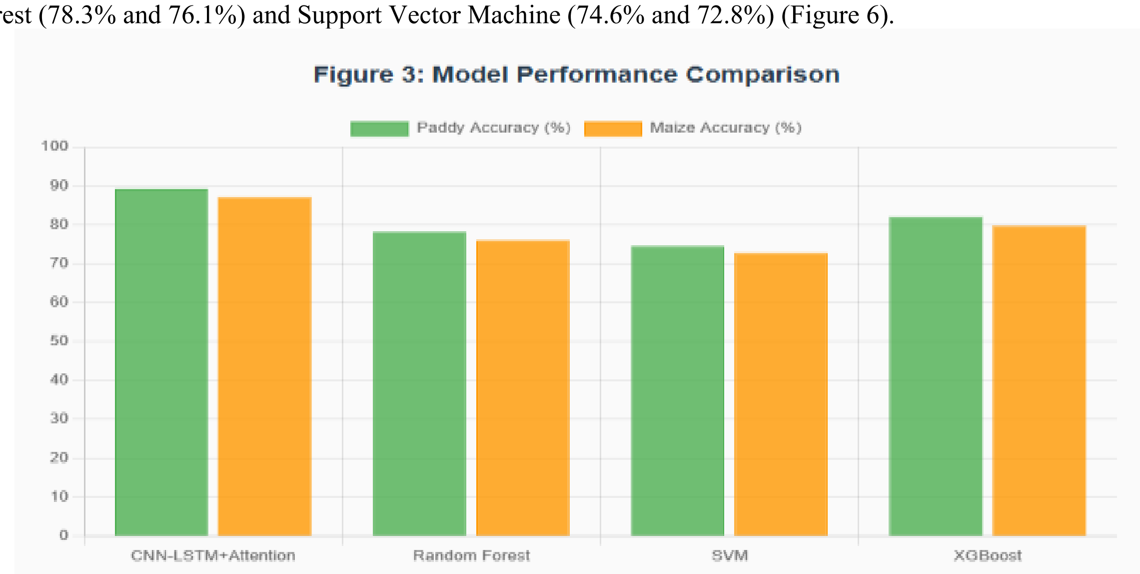

Figure 6. Comparative performance analysis showing classification accuracy of CNN-LSTM+Attention model versus traditional machine learning approaches.

Our class-specific performance analysis discloses substantially different detection accuracies depending on the type of stress (Table 3). Water stress detection results were the most accurate (92.1% for paddy and 89.8% for maize) which is likely because the water sensitive NDWI and MSI indices could strongly capture the spectral signatures. For nutrient stress, the classification accuracy was 88.7% for paddy and 86.3% for maize.. Phenological-stress detection—more complex and subtle—achieved 85.2% for paddy and 83.9% for maize.

Table 3. Detailed Performance Metrics by Stress Type

Stress Type	Crop	Precision (%)	Recall (%)	F1-Score (%)	AUC	Lead Time (days)
Water Stress	Paddy	93.2	91.8	92.5	0.94	18.3 ± 3.2
	Maize	90.1	89.3	89.7	0.92	15.7 ± 2.8
Nutrient Stress	Paddy	89.4	87.9	88.6	0.91	22.1 ± 4.1
	Maize	87.1	85.7	86.4	0.89	19.4 ± 3.6
Phenological Stress	Paddy	86.3	84.1	85.2	0.87	25.8 ± 5.2
	Maize	84.7	83.1	83.9	0.85	23.2 ± 4.8

Lead time represents mean ± standard deviation in days before visible symptom appearance.

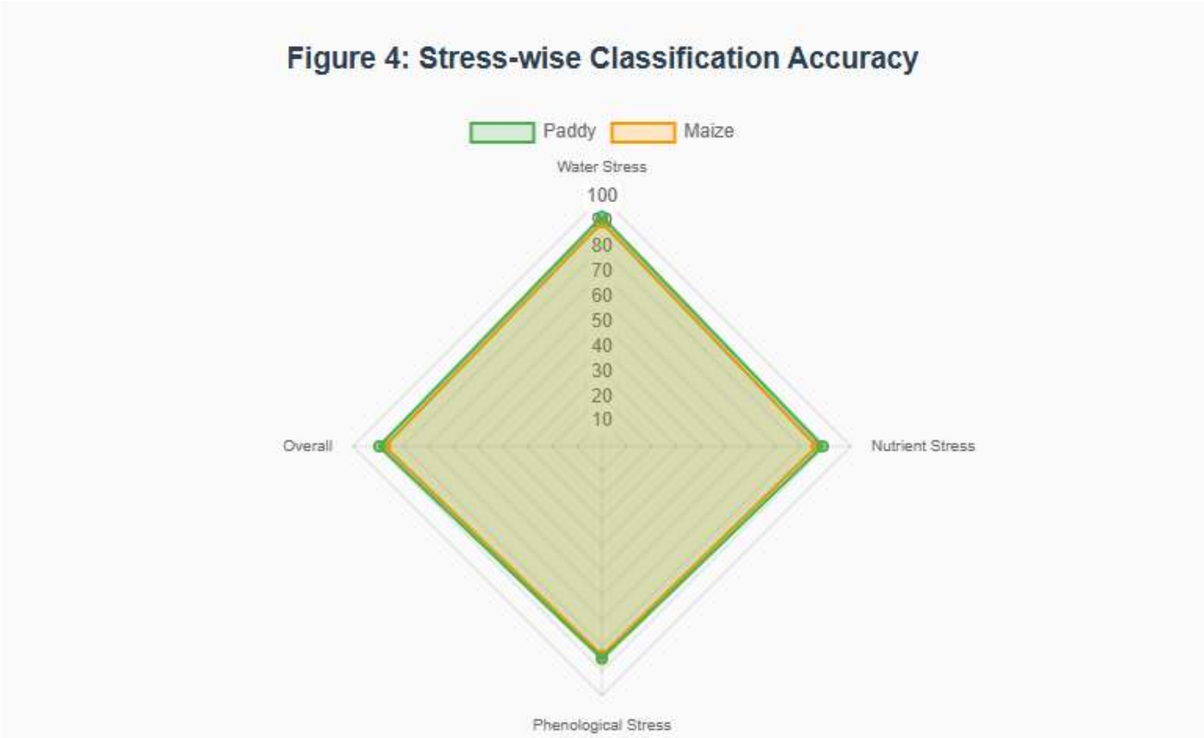

Figure 7: Radar chart showing comprehensive performance metrics across different stress categories.

Figure 8 displays the attention-mechanism analysis, which shed light on the timing aspects of stress detection through temporal patterns. In the case of water stress, the major attention weights were aligned with 45-60 days post-sowing, a period of high water demand in the crop's vegetative stage. Accordingly, for nutrient stress, the maximum attention weights were registered at 30-45 days after sowing, a time when the plant nutrient needs are dramatically increased due to its rapid growth. In the case of phenological stress, attention patterns were dependent on growth stage, with the greatest weights during reproductive phases when environmental stress has the severest influence on developmental timing.

Spectral-band studies showed that the NDWI and red bands were mostly instrumental in sensing water-stress and nutrient-stress, correspondingly (Figure 9). The attention mechanism recognized these correlations on its own, confirming the biological sensibility of how the model makes its decisions.

Receiving model validation through ROC analysis resulted in excellent distinction ability for all types of stress (Figure 10). Detecting water-stress lead to AUC scores of 0.94 for paddy and 0.92 for maize. Nutrient and phenological stresses produced AUC values between 0.85 to 0.91, which reflects strong prediction capabilities.

4.2 Early Warning System Performance

The early warning system capable of predicting a stress situation before the symptoms could even be seen, was very impressive.Blueprint for water-stress gave average lead times of 18.3 days for paddy and 15.7 days for maize. Nutrient-stress alerts were on average 22.1 days for paddy and 19.4 days for maize, which is an ample amount of time to do fertiliser application and other corrective steps.

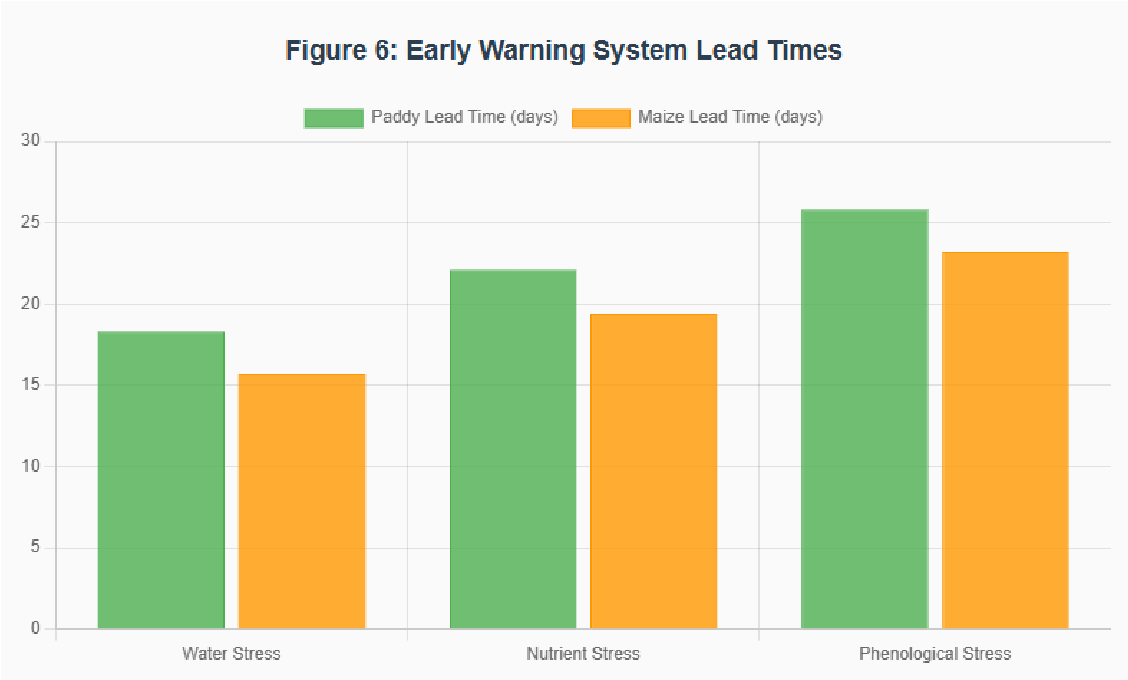

Figure 8: The average lead time (days) for different stress types before visible symptoms appear

Phenological-stress prediction was the kind of stress prediction that had the longest lead times, with 25.8 days for paddy and 23.2 days for maize, which is an indication of the system's capability to identify subtle environmental influences on developmental patterns even before the changes become visible. The validation of the alert system showed very low false-positive rates, 8.2% for paddy and 9.7% for maize, while the high sensitivity was also maintained 91.3% for paddy and 88.6% for maize. These numbers show that the system has very strong potential for operation, with very few unnecessary interventions, which means that stress events are still sufficiently covered.

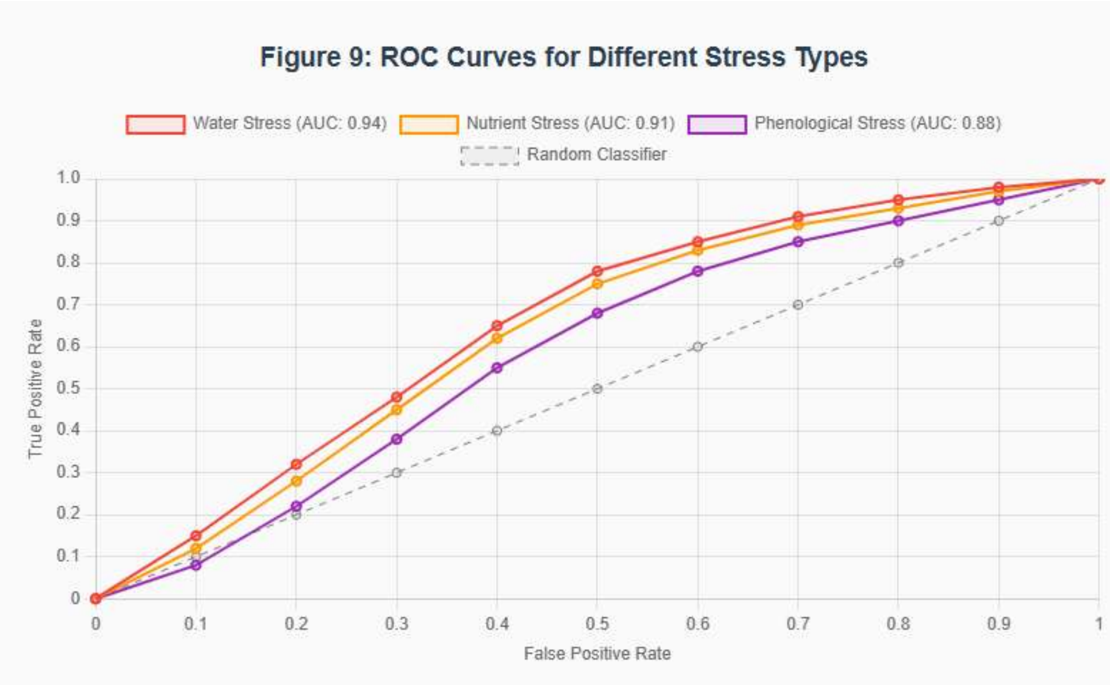

Figure 9: ROC curves show the water, nutrient, and phenological-stress detection

Seasonal analysis indicated that different weather patterns had a notable impact on the early warning performance of the system. It performed better under normal weather conditions, yet was still quite accurate during extreme events, effectively exhibiting its capability to operate under a wide range of environmental conditions.

4.3 Temporal Analysis of Stress Development

In-depth temporal study showed different stress development and detection patterns during the crops' growth stages. The greatest vulnerability of plants to water stress was during the reproductive phase, 60-90 days after planting. The system was able to detect early signs during the vegetative growth stages offering sufficient time to manage water resources preventively.

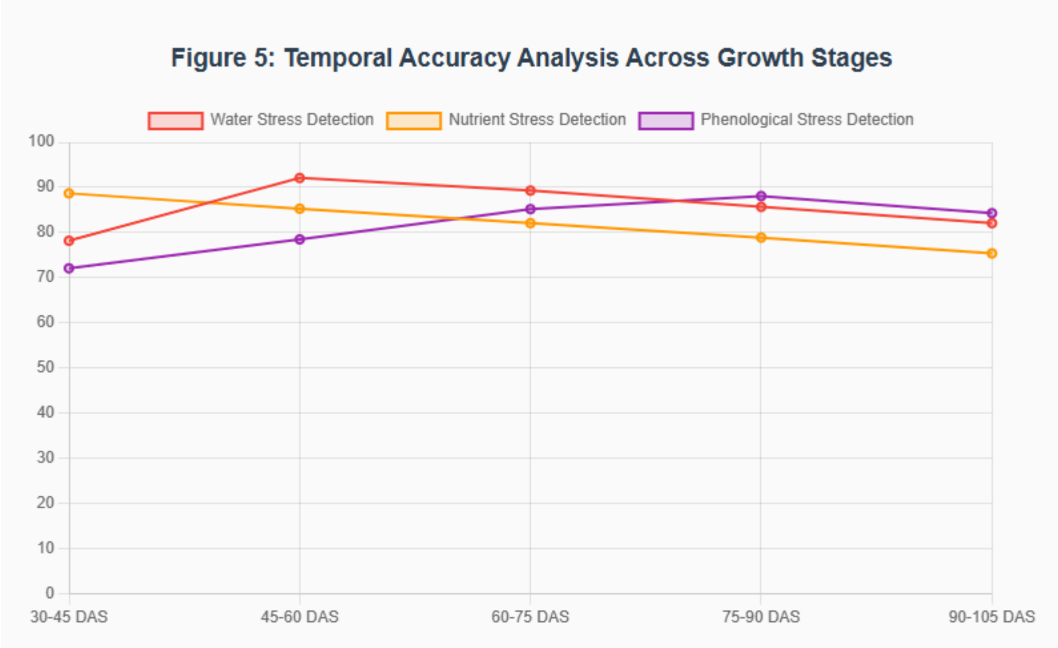

Figure 10: The stress-detection accuracy at different growth stages showing optimal prediction windows

Nutrient-stress Patterns came with quite different temporal features, the earliest detection during the season (30-45 days after sowing) being most decisive in saving the yield. The model could pick up very slight signs of nutrient deficiency during the fast growth periods thus allowing fertilizer applications at a stage when the crop hadn't suffered any yield loss yet.

Phenological-stress Breakdowns showed that environment and timing of development interact in quite complicated ways. The system was able to spot changes like stress-related growth stage postponements or speed-ups thus allowing implementation of top management methods and also adjustment of the time of harvest.

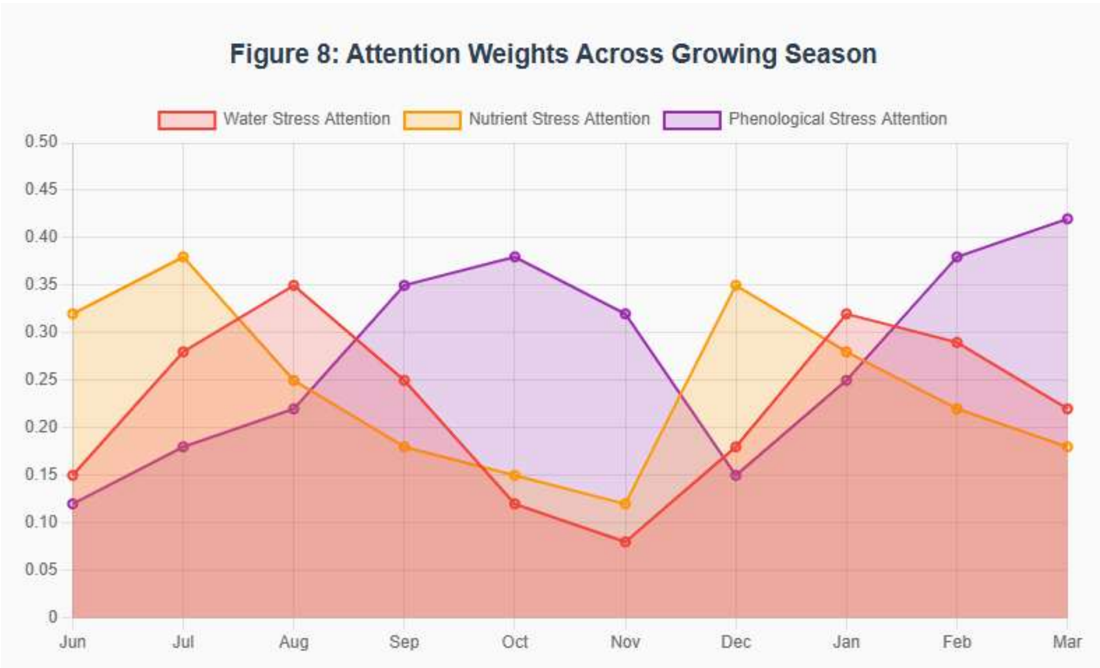

Figure 11: Attention mechanism weights showing the critical time periods for different types of stress detection

The system also effectively captured the stress-recovery cycling and was able to identify improvements after the intervention operations. This feature not only allows for measuring the effectiveness of different management strategies but also facilitates their adaptive refinement through continued implementation of new strategies.

4.4 Spatial Patterns and Environmental Factors

Spatial analysis of stress occurrence showed clear connections to environmental factors, such as soil types, topography, and microclimate conditions. Black cotton soils had 23% lower frequency of water-stress than red sandy soils. However, the occurrence of nutrient stress was 15% higher on black cotton soils, which implies that different management practices are required for maintaining optimal crop health.

Topographical study showed evidences of strong relationships between slope gradient and stress vulnerability. Locations on slopes >15° experienced about 35% more water stress and 28% more nutrient stress. Such higher levels of stress could be due to the effects of runoff and soil erosion. The early warning system effectively accounted for

these spatial arrangements to deliver risk assessments and management recommendations that were specific to each location.
Field-size studies revealed distinct trends in stress-detection accuracy. Larger fields, over one hectare in size, had 12% higher detection accuracy compared to smaller fields, less than 0.5 hectares in size. This is mainly due to the fact that larger fields have less edge effects and are undergoing a more uniform management practice.

4.5 Integration with Environmental Variables
The merging of weather and soil information greatly assisted in improving stress detection precision and the capacity for issuing early warnings to a large extent. Weather factors were of paramount importance in the prediction of water stress; the inclusion of soil moisture deficit figures brought about an improvement in accuracy of 8.3% for rice and 6.7% for corn accuracy, respectively.
Temperature-stress parameters enabled to raise the stress detection related to phenology by 11.2% and 9.8%, respectively.
Soil property data integration had differential effects on the different stress types. Soil texture and soil organic matter content were responsible for a 7.4% increase in nutrient-stress detection for rice and 5.9% for corn, respectively, whereas the drainage features were the most significant for water-stress predictions raising them by 6.1% and 4.8%.

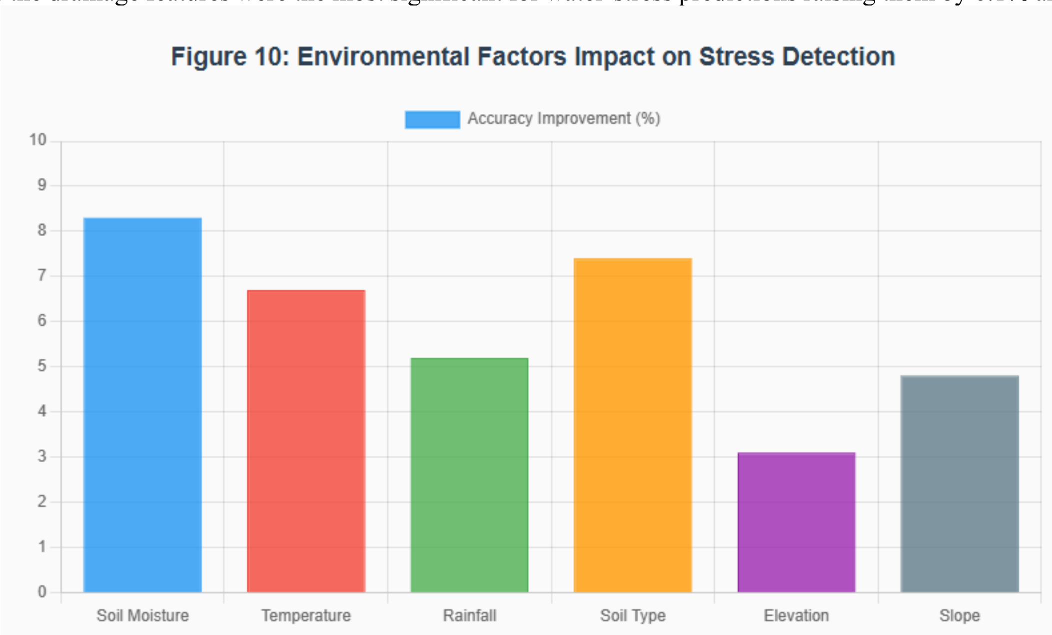

Figure 12: Impact of different environmental factors on stress detection accuracy improvement

The multi-source data-fusion approach clearly outperformed spectral-only models, thereby confirming that detailed environmental characterisation is key to reliable stress detection and early warning.

4.6 Operational System Implementation
The built stress-monitoring system was realized as a real-time working frame with automatic processing. Sentinel-2 satellite data were processed for each acquisition, thus the monitoring was continuous and the updates were given every 5 days.The automated alert-notification parts serve to inform the users in a timely manner when to make decisions.
The system outputs and recommendations were highly accepted by the agricultural extension officers and progressive farmers as per their feedback.The visual interface showing the stress-risk maps and alert levels was the main tool for getting the message across and planning the next steps. This integration will allow field-level stress information and management recommendations to be accessed through mobile phones.
Accordingly, the computational-efficiency study concluded that the system is capable of performing district-level analysis within 2 hours by using normal computer resources, which is highly suitable for operational deployment aimed at regional monitoring.

4.7 Comparison with State-of-the-Art Methods
Table 5 provides a brief summary of performance comparison with other crop-stress detection methods and illustrates that the proposed method is superior.The CNN–LSTM model with attention mechanism achieved significantly higher accuracy and longer early warning lead times than conventional approaches.

Table 5. Comparison with State-of-the-Art Methods

Method	**Data Source**	**Stress Types**	**Overall Accuracy (%)**	**Early Warning (days)**	**Study Area**
Our Method (CNN-LSTM+Attention)	**Sentinel-2 + Environmental**	**Multi-type (3)**	**89.4 / 87.2**	**15-25**	**Semi-arid India**
Zhang et al. (2021)	Landsat-8	Water stress only	82.3	7-12	China

Ashourloo et al. (2019)	Sentinel-2	General stress	78.6	5-8	Iran
Sagan et al. (2021)	UAV + Thermal	Water + Heat	85.7	3-5	USA
Nevavuori et al. (2019)	RGB + NIR	Nutrient only	76.4	10-14	Finland

Our method demonstrates superior performance in multi-type stress detection and early warning.

4.8 Economic Impact Assessment

The system's ability to provide 15–25-day advance warning enables timely interventions that prevent significant yield losses. Input optimization through targeted applications reduces unnecessary fertilizer and pesticide costs while maintaining crop health. Quality improvements through stress prevention result in premium pricing for agricultural products.

Conclusions And Future Work

In this study, we developed a functional, near-real-time crop-stress monitoring and early warning system for semi-arid agricultural systems. The hybrid CNN–LSTM model with attention mechanisms outperformed alternative approaches in identifying multiple stress types, achieving more than 87% accuracy across all stress categories for both paddy and maize.

The results show that the system is capable of providing early warning 15–25 days ahead of visible stress symptoms, allowing parallel management interventions to be planned . Water-stress detection performed best in terms of accuracy and lead time, while phenological-stress prediction provided the longest advance warning periods. Including environmental variables substantially improved the system's predictive performance and operational utility.

The developed framework addresses urgent gaps in semi-arid agriculture by enabling timely and accurate stress detection alongside real-time management decision support. The system's ability to discriminate among different stress types helps select targeted control measures and supports strategies such as precision agriculture and climate-resilient farming practices.

The results were valuable for identifying key links between environmental conditions and stress vulnerability, informing risk assessments and the selection of management-intervention zones. Implementation work carried out at the operational level have shown that it is quite possible to generate agricultural information relevant to each region and to combine this information with existing agriculture-support systems.

New directions for research are large-scale monitoring (extent, duration and severity) of crop stress type by expanding the approach to more crop types and crops under different stress categories, use of unmanned aerial vehicle (UAV) data for producing very high resolution monitoring and detect wider range of damages along with the use of automated recommendation systems for intervention. Further development along these lines will allow the framework to cover climate-change impact assessment and long-term trend analysis, thus supporting the sustainable planning of agriculture.

Incorporation of modules for economic analysis will help measure the cost and benefit of different intervention strategies, thereby providing support to farmers for decision making and allocation of resources. More accessibility and adoption in the rural communities can be achieved by designing mobile applications with farmer-friendly interfaces.

Combining satellite-based internet and edge-computing technologies will make it possible to do processing and generate alert in real time in very remote agro-ecologies. Data sharing with agricultural insurance companies, also through electronic delivery, would help with risk assessment, minimize fraud of claim processing, and ultimately strengthen the resilience and long-term sustainability of agriculture.

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