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Application of remote sensing and AI algorithms for crop stress detection: A case study between China and Malaysia

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Abstract

This review explores how remote sensing and artificial intelligence (AI) are being used to detect crop stress, focusing on recent research from Malaysia and China. The findings show that China is leading the way, with widespread use of advanced AI models like convolutional neural networks (CNNs), Vision Transformers (ViTs), and attention-based systems. These models are supported by large datasets and strong government backing, making it possible to detect crop stress early and accurately across large areas. Malaysia, on the other hand, is still in the early stages. Most studies are limited to small-scale trials using drone imagery and more traditional machine learning models such as Support Vector Machines (SVM) and Random Forest (RF). Despite these limitations, the results have been promising, especially for key crops like oil palm and rice. However, Malaysia faces challenges including a lack of localised data, limited AI infrastructure, and minimal policy support. To move forward, future efforts should focus on developing locally relevant models, using multiple types of data together, and fostering collaboration between researchers, policymakers and farmers. There's also a need to make sensing technologies more affordable and accessible to those working on the ground. In summary, while China has already laid a strong foundation for AI-powered crop stress detection, Malaysia has the potential to catch up provided that there is strategic investment in research, infrastructure and farmer engagement. With the right support, both countries can strengthen their agricultural resilience and better prepare for climate-related challenges.

Keywords: *remote sensing, crop stress detection, AI algorithms, precision agriculture*

Introduction

Crop stress, driven by environmental, biological, or nutritional factors, remains a major cause of yield loss in agriculture worldwide. As global food demand rises and climate variability intensifies, timely and accurate detection of crop stress has become increasingly critical. Traditional field-based stress assessment methods are labour-intensive, time-consuming, and spatially limited, making them impractical for large-scale monitoring (Ihuoma & Madramootoo, 2017).

Remote sensing, using satellite or drone imagery, enables continuous monitoring by capturing key data such as vegetation reflectance, thermal signatures, and canopy structure. Vegetation indices like the Normalised Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI) and Normalised Difference Water Index (NDWI) are commonly employed to assess plant health, water stress and biomass (de la Iglesia Martinez & Labib, 2023).

Recent advancements in sensor technology and increased temporal data availability through platforms like Sentinel-2 (S-2), Landsat 8 (L-8), and Unmanned Aerial Vehicles (UAVs) provide high-resolution data that enhances crop stress monitoring. The integration of Artificial Intelligence (AI), including Machine Learning (ML) and Deep Learning (DL), further improves data analysis and decision-making in precision agriculture. models, allows for better interpretation of remote sensing data.

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These AI models are adept at detecting subtle stress patterns and classifying stress types, often outperforming traditional threshold-based methods (Janga et al. 2023). Algorithms such as Random Forest, Support Vector Machines, and Decision Trees are effective for classifying crop stress based on diverse data sources.

Furthermore, advanced models like Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks have gained popularity for their ability to capture both spatial and temporal dependencies in the data (Lindemann et al. 2021). By combining remote sensing with AI, these methods enhance stress detection accuracy and support real-time decision-making in precision agriculture.

Despite growing research, comparative analyses of these techniques across different agroecological zones remain limited. China and Malaysia offer contrasting agricultural environments: China's temperate regions feature intensive cropping systems, while Malaysia's tropical climate supports year-round cultivation. Evaluating how remote sensing and AI-based methods perform in detecting crop stress in these regions is crucial for developing adaptable, transferable models.

This review aims to address this gap by examining the application of remote sensing and AI in detecting crop stress in China and Malaysia. It will assess the data sources, algorithmic approaches, and classification methods used in recent studies, evaluate their effectiveness, and identify key challenges and future directions. The review seeks to contribute to the development of accessible, intelligent monitoring tools to enhance agricultural resilience amidst growing climatic and environmental challenges.

Literature review

Remote sensing techniques for crop stress detection

Remote sensing (RS) has emerged as a pivotal technology for monitoring crop stress, offering non-destructive, real-time, and large-scale observation capabilities. Satellite platforms, including Sentinel-2 (S-2), Landsat 8 (L-8), and the Moderate Resolution Imaging Spectroradiometer (MODIS), are commonly used for their ability to capture continuous spectral data across broad geographic areas. These sensors measure reflectance in Visible (VIS), Near-Infrared (NIR), and Shortwave Infrared (SWIR) bands, which can be used to derive vegetation indices such as the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Normalized Difference Water Index (NDWI). These indices are highly correlated with various plant health indicators, including vigor, chlorophyll content, and water status (Ma et al. 2019). For instance, Zhang et al. (2023) found that NDWI was more effective than NDVI in detecting early drought stress in maize fields in eastern China. Alongside satellite-based platforms, unmanned aerial vehicles (UAVs) equipped with multispectral and thermal cameras have gained popularity for high-resolution, field-level stress detection. UAVs provide precise spatial details, making them invaluable for detailed crop stress analysis. In Malaysia, UAVs have been successfully used to monitor nutrient deficiencies and disease stress in oil palm and rice fields, achieving sub-meter accuracy in detecting symptoms such as chlorosis and canopy degradation (Rendana et al. 2015). However, operational challenges related to UAVs include their limited flight range and dependence on favourable weather conditions.

Artificial intelligence algorithms in stress classification

The integration of artificial intelligence (AI) algorithms has significantly transformed the analysis and interpretation of remote sensing data. Traditional machine learning (ML) models such as Random Forest (RF), Support Vector Machines (SVM), and Gradient Boosting (GB) have been extensively used for crop stress classification tasks. These models excel at handling multivariate input from different sensors and are often effective with moderate-sized labelled datasets (Haider et al. 2024). For example, RF was applied in northern China to classify wheat fields under varying drought stress levels, achieving an impressive classification accuracy of 88% using multispectral imagery and soil moisture data.

Deep learning (DL) models, particularly Convolutional Neural Networks (CNNs), offer enhanced performance by automatically extracting spatial and spectral features from imagery data, which improves stress detection accuracy. Long Short-Term Memory (LSTM) models, on the other hand, are used to capture temporal dynamics, which are crucial for monitoring stress progression throughout the growing season (Paul et al. 2025).

In Malaysia, Convolutional Neural Networks (CNN) trained on UAV imagery achieved 94% accuracy in distinguishing between fungal disease and nutrient stress in rice fields (El Sakka et al. 2025). However, deep learning methods are computationally intensive and require large, labelled datasets, which may limit their applicability in regions with fewer resources.

Comparative studies and regional applications

While there has been progress in using AI and remote sensing technologies for crop stress detection, comparative studies across different regions are still limited. In China, significant strides have been made in satellite data assimilation and operational crop monitoring. Meanwhile, Malaysia has leaned more toward UAV-based approaches, driven by smaller field sizes and persistent cloud cover in the region. The varying agroecological conditions, such as soil type, crop variety, and climate, significantly impact the performance of AI models, highlighting the need for localised calibration (Bracho-Mujica et al. 2023).

The gap between regional applications, transfer learning and domain adaptation have been proposed as potential solutions. For instance, a CNN model trained on maize data from China was successfully adapted to Malaysian corn fields with minimal retraining, demonstrating the feasibility of cross-country stress detection models when appropriate adjustments are made (Zou et al. 2024).

Despite these promising results, challenges remain in ensuring standardised ground truth data collection and achieving interoperability between different sensors and platforms. These issues need to be addressed to improve the effectiveness and applicability of remote sensing and AI-based stress detection systems globally.

Materials and method

This review systematically synthesises recent advances in remote sensing and artificial intelligence (AI) for crop stress detection, with a particular focus on studies conducted in China and Malaysia. The methodology included structured literature searches, classification of technological approaches, and comparative regional analysis to capture current trends and applications.

Literature collection and selection

A total of 785 documents were initially retrieved through a comprehensive search conducted across five major scientific databases such as Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar, spanning the period from January 2014 to March 2024. The search strategy incorporated combinations of keywords related to remote sensing, artificial intelligence, and crop stress, linked using Boolean operators such as AND, OR, and NOT. For example, search strings included: "remote sensing" AND "crop stress", "UAV" OR "satellite imagery" AND "AI", and "machine learning" AND "plant stress" AND (Malaysia OR China). The retrieved literature comprised peer-reviewed journal articles, conference proceedings, and technical reports.

Ensuring relevance and quality, a two-stage screening process was implemented. The first stage involved title and abstract screening to eliminate duplicates and irrelevant studies, narrowing the selection to 312 records. The second stage involved a full-text review, applying specific inclusion criteria: (i) use of remote sensing platforms such as Unmanned Aerial Vehicles (UAVs), Sentinel-2, or Landsat 8; (ii) application of AI or machine learning techniques including Support Vector Machines (SVM), Random Forest (RF), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM); and (iii) empirical field trials or experiments conducted in Malaysia or China. Ultimately, 40 studies were included in the final review. The entire selection process is visually summarised in *Figure 1* to enhance transparency and reproducibility.

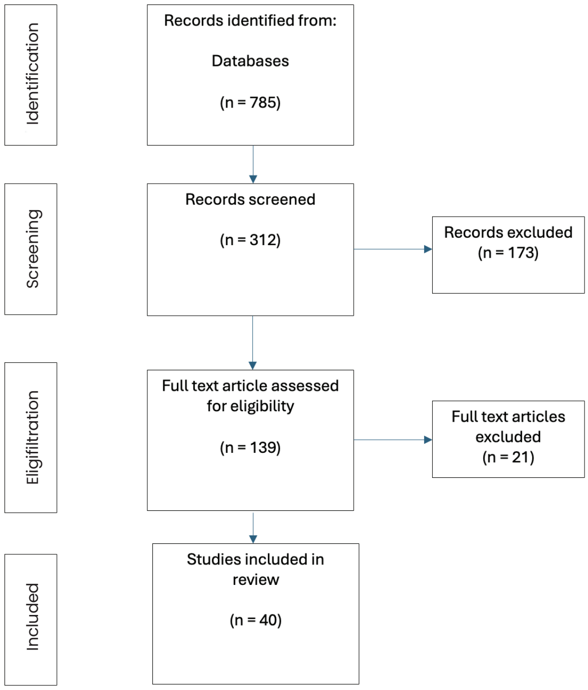

Figure 1. A flowchart to visually represent entire systematic literature review

Data extraction and review parameters

Each study was analysed for crop stress types (e.g., water stress, nutrient deficiency, pest/disease, salinity), remote sensing platforms (satellites like Sentinel-2, Landsat 8; UAVs; ground-based sensors), and vegetation indices such as NDVI, NDRE, CWSI, and PRI. AI techniques including Random Forest (RF), Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) models were documented, with performance evaluated using metrics such as classification accuracy, F1-score, RMSE, and AUC (Adugna et al. 2022). The dataset was then categorised by stress type, sensor, AI method, and region for cross-comparison (Martinez-Rios et al. 2021).

Regional contextualisation

Regional agricultural contexts were factored into the analysis. In China, large, mechanised farms often use satellite-based remote sensing for large-scale stress detection, while Malaysia's smallholder farms and tropical conditions (e.g. cloud cover, high rainfall) favour UAV-based solutions (Nahiyoon et al. 2024). Agroclimatic data from national meteorological agencies added environmental context to interpret crop stress variability across both regions.

Limitations of the reviews

This review is confined to stress detection during active crop growth and excludes studies on yield prediction or genomic research. English-language publications were prioritised, potentially excluding region-specific studies in other languages. Despite this, the review presents a useful representation of advancements in remote sensing and AI for crop stress monitoring in the two countries.

Results and discussion

Remote sensing combined with AI has transformed crop stress detection, offering precise, real-time assessments of drought, nutrient imbalance, disease, and salinity impacts. The reviewed studies from China and Malaysia reveal a consistent increase in the use of both satellite and UAV platforms integrated with AI algorithms for improved stress monitoring.

Figure 2 highlights the growth in studies using AI and imaging sensors from 2014 to 2024. Initial research was limited (3 studies in 2014, 6 in 2015), with notable growth from 2017 onwards. The field expanded significantly in 2019 (26 studies) and surged in 2020 (65) and 2021 (61), likely due to improved AI tools and heightened demand for high-throughput agricultural monitoring. This trend continued post-pandemic, peaking at 76 studies in 2024. The data underscore increasing reliance on AI and imaging technologies to address climate-driven stress factors and precision agriculture needs.

Figure 3 summarises the total number of studies retrieved from four major scientific databases Springer (SPR), ScienceDirect (SD), PubMed (PM), and Web of Science (WOS)before and after screening using the Automated Systematic Review (ASReview) tool. The figure provides insight into the efficiency of the screening process in identifying relevant studies for inclusion in the review. Initially, 974 articles were retrieved from SPR, out of which 434 were deemed relevant after ASReview screening, while 540 were categorised as irrelevant.

Similarly, SD yielded 122 articles, with 68 retained and 54 excluded. PM returned the highest number of initial records, with 1,114 studies retrieved; after screening, 567 were identified as relevant and 547 as irrelevant. Lastly, WOS contributed 494 articles, of which 321 were considered relevant and 173 were excluded. These results reflect the high volume of literature available in this field and underscore the importance of using systematic and semi-automated screening tools like ASReview to efficiently manage and curate large datasets during the review process.

Crop stress detection in China: Satellite and AI integration

Table 1 provides a comprehensive comparison of studies conducted in China that utilised Satellite Imagery (SI) for Crop Stress Detection and Classification (CSDC), highlighting the diversity of satellite sensors, methodologies, and accuracy metrics involved. Jiang et al. (2020) employed Sentinel-2 (S2) multispectral data for large-scale crop mapping, achieving an overall accuracy (OA) of 94%, demonstrating the effectiveness of high-resolution multispectral imagery in agricultural monitoring. Similarly, Liu et al. (2023) enhanced temporal information by leveraging time-series S2 images to produce a cropping intensity map at 10 m resolution, attaining an even higher OA of 96.68% and Kappa Coefficient (KC) of 0.90, indicating strong model reliability.

In contrast, Zhai et al. (2020) utilised an improved Linear Isometric Mapping (L–ISOMAP) dimensionality reduction approach combined with Random Forest (RF) on Landsat 8 (L8) imagery to automatically classify crops in Northeast China. While slightly lower, their reported OA of 83.68% is still acceptable, given the methodological complexity and spatial scale.

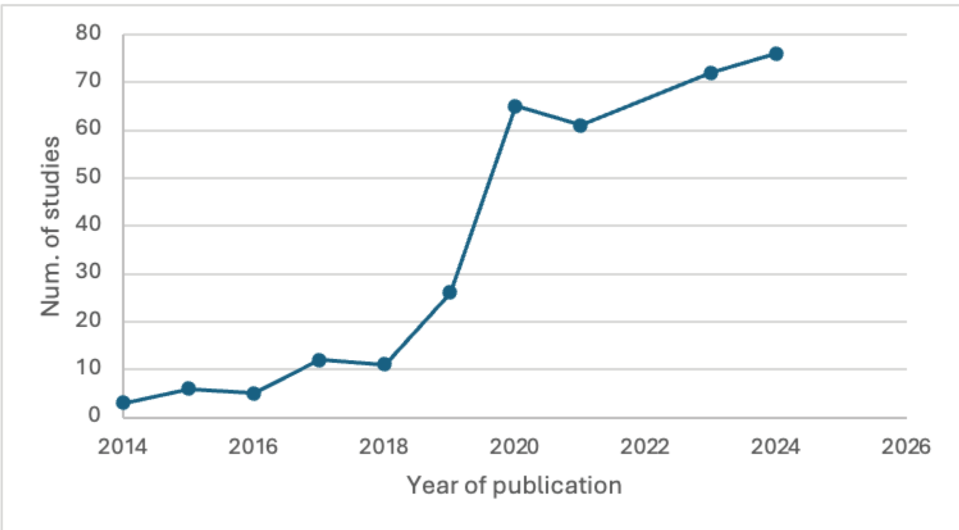

Figure 2. Overview of the total number of studies published by year using AI and imaging sensors to investigate plant stress responses.

Source: Walsh et al. 2024

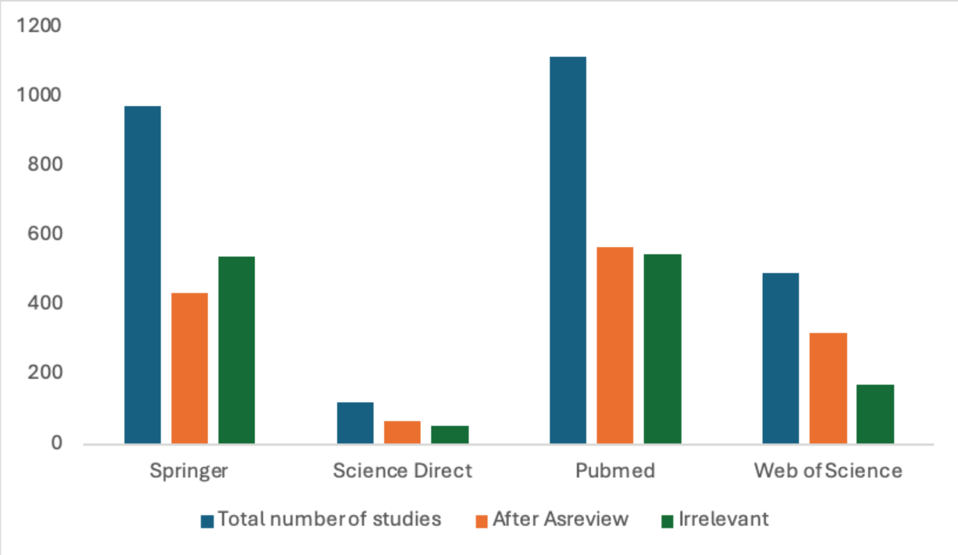

Figure 3. Summary of the total number of studies retrieved by SLR, which targeted AI and imaging sensors investigating plant stress.

Source: Walsh et al. 2024

Table 1. Comparison of crop stress detection accuracy in China using satellite imagery

Study	Satellite sensor	Method / Model	Accuracy metrics	Reference
Large-Scale and High-Resolution Crop Mapping in China	Sentinel-2	Multispectral image classification	Overall accuracy: 94%	Jiang et al. 2020
Cropping Intensity Map of China (10 m resolution)	Sentinel-2	Time-series analysis	Overall accuracy: 96.68%; Kappa: 0.90	Liu et al. 2023
Automatic Crop Classification in NE China	Landsat 8	Improved L–ISOMAP + Random Forest	Overall accuracy: 83.68%	Zhai et al. 2020
CIrrMap250: Annual Irrigated Cropland Maps	MODIS & Landsat	Multi-source fusion and annual mapping	Accuracy compared with existing datasets (value not explicitly stated)	Zhang et al. 2020
Crop Mapping with Combined Use of European and Chinese Satellite Data	Sentinel-2 & GF-1	Adapted ESA approach; classification algorithms	Overall accuracy: 94–97%	Fan et al. 2021
Improving the Accuracy of Satellite-Based High-Resolution Yield Estimation	Sentinel-2 & ZY-1 02D	LSTM, RF, GBDT, SVR	LSTM RMSE: 0.201 t/ha; RF RMSE: 0.260 t/ha	Jin et al. 2017
Evaluation of Crop Type Classification with Different High Resolution Satellite Data Sources	GF-1, Sentinel-2, Landsat 8	Random Forest	GF-1: 93–94%; Sentinel-2: 96–98%; Landsat 8: 97–98%	Fan et al. 2021
A Refined Crop Drought Monitoring Method Based on the Chinese GF-1 Wide Field View Data	GF-1 WFV	EVI2-based MPDI	Accuracy above 95%	Chang et al. 2018
Comparative Analysis of Chinese High-Resolution Satellite Data for Sugarcane Classification Based on U-Net Model	GF-1 & GF-2	U-Net deep learning model	GF-2 outperformed GF-1 in OA and Kappa coefficient	Chen et al. 2022
Categorisation by Leveraging CNNs and Remote Sensing Satellite Imagery for Crop Analysis in Arid Environments	Landsat-8	CNN architectures (ResNet, EfficientNetV2)	ResNet and EfficientNetV2 achieved highest classification accuracy	Malhan et al. 2024

A broader mapping effort was presented by Zhang et al. (2024) through the Cropland Irrigation Map 250 (CIrrMap250) dataset, which integrates data from Moderate Resolution Imaging Spectroradiometer (MODIS) and L8 for annual irrigated cropland monitoring. Although specific accuracy values were not reported, the approach emphasised multi-source data fusion, underscoring the importance of combining medium- and high-resolution datasets for enhanced spatial–temporal analysis.

Fan et al. (2021) explored two aspects: first, they compared S2 and China's Gaofen-1 (GF-1) satellite data in crop classification, applying an adapted European Space Agency (ESA) methodology and achieving a notable 94 – 97% OA, showcasing the effectiveness of combining European and Chinese satellite technologies. Second, they evaluated classification performance across different satellites using an RF classifier, reporting GF-1 (93 – 94%), S2 (96 – 98%), and L8 (97 – 98%), reinforcing the superior accuracy of high-resolution platforms.

Jin et al. (2017) evaluated yield estimation performance using S2 and Ziyuan-1 02D (ZY-1 02D) satellites and multiple machine learning models. The Long Short-Term Memory (LSTM) model produced the best result with a Root Mean Square Error (RMSE) of 0.201 t/ha, outperforming RF, Gradient Boosted Decision Trees (GBDT), and Support Vector Regression (SVR), emphasising the value of deep learning in capturing yield variability. In terms of drought detection, Chang et al. (2018) used GF-1 Wide Field View (GF-1 WFV) data with a refined Enhanced Vegetation Index 2 (EVI2)-based Modified Perpendicular Drought Index (MPDI), reporting over 95% accuracy in monitoring drought stress, proving the potential of vegetation indices in detecting abiotic stress conditions.

A more focused crop-specific analysis by Chen et al. (2022) involved sugarcane classification using GF-1 and Gaofen-2 (GF-2) images, implementing a U-Net deep learning model. The results showed that GF-2 imagery yielded better classification outcomes in terms of OA and KC, highlighting the role of spatial resolution in deep learning-based segmentation tasks.

Finally, Malhan et al. (2024) applied Convolutional Neural Networks (CNNs) such as Residual Network (ResNet) and EfficientNetV2 on L8 for crop stress analysis in arid environments. Both CNN models delivered the highest classification accuracies among tested architectures, reaffirming the emerging importance of advanced deep learning models in crop monitoring.

This comparative analysis underscores the diversity of approaches in crop stress detection research across China. High-resolution satellite platforms such as Sentinel-2 (S2), Gaofen-2 (GF-2), and Landsat-8 (L8) consistently deliver strong classification results, particularly when paired with Machine Learning (ML) and Deep Learning (DL) techniques. Moreover, the fusion of multi-source data and temporal information further improves accuracy, as observed in studies leveraging time-series or multi-sensor approaches. These findings support continued investment in high-resolution Earth Observation (EO) systems and algorithmic innovation to enhance agricultural monitoring and decision-making under changing climate conditions.

Table 2 presents a comparative overview of various Artificial Intelligence (AI) models applied in the detection and classification of crop stress across different agricultural contexts in China. These studies highlight the integration of ML and DL algorithms with diverse imaging sources such as satellites, drones, and Red-Green-Blue (RGB) sensors. A range of crop types such as cotton, rice, wheat, maize, potato and multiple mixed crops—were targeted using a combination of Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and transformer-based architectures.

For example, the detection of cotton water stress employed DL models like Visual Geometry Group 16 (VGG16), Residual Network 18 (ResNet-18), and MobileNetV3 (MNv3), using thermal imagery to identify physiological stress signatures associated with water deficits (AZO AI News, 2024). Similarly, time-series data from Sentinel-1A Synthetic Aperture Radar (SAR) was processed using sequential models like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) to support early classification of multiple crop types, demonstrating the effectiveness of temporal data in monitoring early phenological changes (Zou et al. 2019).

In the case of rice and potato crops, more specialised models such as the Attention-Based Depthwise Separable Neural Network with Bayesian Optimisation (ADSNN-BO) and Retina-UNet-Ag were employed to detect disease and stress symptoms using close-range leaf or aerial imagery (Chen et al. 2022 and Khan et al. 2021). These models were tailored to handle the complexity of fine-grained image features, allowing for more precise detection. Likewise, the Vision Transformer (ViT) and EfficientNetB0 (ENB0) architectures were successfully used with RGB images to identify nitrogen stress in maize, reflecting the growing trend of applying transformer models in agricultural computer vision tasks (Li et al. 2024).

While satellite-based systems such as those using S2, GF-2, and L8 offer the advantage of wide spatial coverage and frequent monitoring at relatively lower costs, they are not without challenges. Limitations such as cloud interference, relatively low spatial resolution, and temporal gaps between satellite passes may restrict their effectiveness in capturing rapid or highly localised stress events. In contrast, drone-based and proximal sensing technologies offer higher resolution data but are often constrained by scalability and operational complexity.

Overall, the table emphasises the growing diversity of AI approaches tailored for specific imaging modalities and crop stress scenarios in China. It underscores the need for a balanced consideration of resolution, coverage, cost, and model complexity when designing AI-powered crop stress detection systems for precision agriculture.

Table 2. AI model comparison for crop stress detection in China

Study	AI model(s)	Satellite/Imaging source	Target crop/ Stress type	Reference
Deep learning for cotton water stress detection	VGG16, ResNet-18, MobilenetV3, DenseNet-201, CSPdarknet53	Thermal imagery	Cotton water stress	AZO AI News, 2024
Early crop classification using sentinel-1A	1D CNN, LSTM RNN, GRU RNN	Sentinel-1A SAR time series	Multiple crops	Zou et al. 2019
Crop monitoring with pre-trained CNNs	DenseNet121, ResNet50	Satellite imagery	Various crops	Yang et al. 2024
CropQuant-Air for wheat trait analysis	YOLOv7, XGBoost	Drone imagery	Wheat	Zhao et al. 2023
Rice disease detection with ADSNN-BO	Attention-based depthwise separable neural network with Bayesian optimisation	Rice leaf images	Rice diseases	Chen et al. 2022
Potato crop stress identification	Retina-UNet-Ag	Aerial images	Potato crop stress	Khan et al. 2021
Nitrogen stress detection in maize	Vision Transformer (ViT), EfficientNetB0	RGB images	Maize nitrogen stress	Li et al. 2024

The advantages of satellite-based systems are clear, offering the ability to monitor vast areas with relatively low operational costs. However, satellite systems also face limitations such as cloud cover, coarse spatial resolution, and longer revisit times, which may hinder their ability to detect sudden or localised stress events in crops.

Crop stress detection in Malaysia using remote sensing and AI

In Malaysia, the adoption of UAV-based remote sensing technologies is more prevalent than satellite systems due to smaller farm sizes and persistent cloud cover in the tropical climate. These conditions limit the usability of satellite imagery, making UAVs a practical alternative for timely crop monitoring. For instance, Rahman et al. (2023) used UAV-mounted multispectral sensors combined with SVM (Support Vector Machines) to detect water stress and pest damage in oil palm plantations, achieving 95% classification accuracy.

Recent studies have applied various remote sensing platforms and AI algorithms to detect a range of crop stresses. Chong et al. (2017) demonstrated that spectral reflectance analysis could effectively identify nutrient deficiencies across different crops using vegetation indices. Rudiyanto et al. (2023) integrated SVM models with Sentinel-1 SAR (Synthetic Aperture Radar) imagery to track rice growth stages, highlighting the potential of satellite radar data for crop stress monitoring.

In oil palm plantations, Baharim et al. (2023) applied SVM and RF (Random Forest) classifiers to detect Ganoderma basal stem rot using UAV multispectral imagery, emphasizing the role of early disease diagnosis. Similarly, Lau et al. (2023) used deep learning models such as YOLOv4 and YOLOv4-Tiny to detect stress symptoms in chili and eggplant, showing the practicality of UAV-based monitoring in small and medium-scale farming.

Zainuddin et al. (2023) utilised CNN (Convolutional Neural Networks) with RGB images to identify diseases like rust and blight in maize. Anuar et al. (2022) compared the performance of CNN, KNN (K-Nearest Neighbors), and SVM models for detecting stress in various crops using RGB imagery, underscoring the adaptability of AI in agricultural diagnostics.

Nazsoft Tech (2024) further demonstrated the integration of deep learning in real-time agricultural monitoring by employing GoogLeNet and ResNet-101 models to detect nutrient deficiencies and diseases using camera-based imaging. Together, these studies reflect Malaysia's growing emphasis on leveraging remote sensing and AI technologies for precise, early detection of crop stress, which is essential for sustainable agricultural practices.

Table 3. Recent studies on crop stress detection and AI applications in Malaysia using remote sensing

Crop type	Stress type/Application	AI methodology	Remote sensing platform	Reference
Various crops	Nutrient stress	Spectral reflectance analysis	Remote sensing	Chong et al. 2017
Rice	Growth stages (stress indicator)	Support Vector Machine (SVM)	Sentinel-1 SAR	Rudiyanto et al. 2023
Oil palm	Ganoderma basal stem rot	ML classifiers (SVM, RF)	UAV multispectral imagery	Baharim et al. 2023
Chili, Eggplant	General stress proxy	YOLOv4, YOLOv4-Tiny	UAV imagery	Lau et al. 2023
Maize	Common rust and blight diseases	CNN	RGB imaging	Zainuddin et al. 2023
Various crops	General plant disease (stress proxy)	CNN, KNN, SVM	RGB imaging	Anuar et al. 2022
Various crops	Nutrient deficiency, disease	GoogLeNet, ResNet-101	Camera-based imaging	Nazsoft Tech, 2024

Challenges and future directions in crop stress detection using remote sensing and AI in Malaysia and China

One of the key limitations in crop stress detection in both Malaysia and China is the quality and consistency of remote sensing data. In Malaysia, persistent tropical cloud cover disrupts optical satellite imaging, reducing its effectiveness for timely crop monitoring (Zhao et al. 2023). In contrast, China's more advanced satellite infrastructure is constrained by inconsistent coverage and insufficient spatial resolution in certain regions, making it difficult to detect localised stress conditions (Zhang et al. 2024). Furthermore, current temporal resolutions often fail to capture rapid changes in crop health, which are critical for timely management interventions (Li et al. 2024).

Data integration presents another major challenge, particularly in fusing data from satellites, unmanned aerial vehicles (UAVs), and ground-based sensors. Variations in spatial and temporal resolution across these platforms complicate data fusion efforts. In Malaysia, where smallholder farms dominate, linking remote sensing outputs with ground-based agronomic measurements, such as soil moisture and canopy temperature, remains limited (Chong et al. 2017). In China, ongoing efforts to integrate synthetic aperture radar (SAR) and optical satellite data are still under development, restricting the precision of monitoring systems (Zhang et al. 2024).

The deployment of artificial intelligence (AI) models, such as convolutional neural networks (CNNs) and You Only Look Once (YOLO), faces additional barriers. These models require significant computational resources and large, high-quality annotated datasets, which are often scarce in tropical agricultural systems. In particular, datasets targeting specific stressors, such as nutrient deficiencies or crop diseases, are limited, increasing the risk of overfitting and reducing the models' adaptability across diverse agroecosystems (Anuar et al. 2022).

A further constraint is the limited availability of ground-truth data for model calibration and validation. In Malaysia, small-scale farms typically lack sensor infrastructure for systematic field data collection (Chong et al. 2017). In China, the sheer scale and variability of agricultural landscapes make consistent in-field validation resource-intensive, thus limiting the scalability of AI-driven monitoring platforms.

Finally, cost and scalability remain significant obstacles. In Malaysia, smallholder farmers often cannot afford UAVs, high-resolution satellite imagery, or AI-based analysis platforms (Lau et al. 2023). Even in China, despite stronger technological infrastructure, the operational costs of large-scale, high-frequency monitoring limit accessibility for smaller producers (Li et al. 2024). Overcoming these economic and technical barriers is essential to enable broader adoption and improve the effectiveness of remote sensing and AI-based crop stress detection systems.

Future direction and suggestion

Addressing current limitations will require advances in remote sensing technologies. Emerging low-cost, high-resolution satellites and UAVs, including those equipped with Synthetic Aperture Radar (SAR) and microwave sensors, can overcome issues like cloud cover and low spatial resolution, improving the reliability of crop stress monitoring in Malaysia and China (Zhao et al. 2023). These tools promise better temporal and spatial coverage for more accurate and timely assessments.

A major direction is the integration of multisource data from satellites, drones, and ground sensors combined with agronomic inputs such as soil moisture and weather conditions. AI-powered data fusion will be vital for merging these diverse datasets and delivering real-time insights to farmers (Anuar et al. 2022). Yet, developing robust algorithms for this purpose remains a key research priority.

Optimising AI models to reduce computational demands is also critical. Efforts are underway to make models lighter and compatible with smartphones or edge devices, improving access for smallholders in Malaysia and enabling broader scalability in China's large-scale farms (Lau et al. 2023).

The development of real-time decision support systems (DSS) using remote sensing and AI could also transform crop management. In Malaysia, such systems could support timely irrigation decisions, while in China, early detection of disease outbreaks could help minimize crop losses (Chen et al. 2020). Integrating DSS into existing farming practices would enhance both sustainability and productivity.

Collaborative, open-source platforms could accelerate progress by encouraging data and model sharing among researchers and farmers. This approach would support continuous refinement and wider adoption of stress detection systems in both countries (Zhang et al. 2024).

Localised, region-specific models offer another promising avenue. By accounting for unique soil and climate conditions, these models can deliver more targeted stress management. Such personalisation is especially relevant for Malaysia's small farms and China's diverse agricultural zones (Chong et al. 2017).

Finally, capacity building is essential. In Malaysia, extension services should train smallholders in digital farming tools, while in China, rural education programs could promote adoption on a national scale (Lau et al. 2023). Empowering farmers with knowledge and access to these technologies will be key to improving crop resilience and yield outcomes.

Key findings and insights

A review of recent studies highlights both progress and challenges in crop stress detection efforts in Malaysia and China. In both countries, remote sensing tools particularly satellite imagery, UAVs, and multispectral imaging have shown strong potential in detecting stress caused by nutrient deficiencies, water shortages and diseases. In China, advanced AI models like Convolutional Neural Networks (CNN), Vision Transformers (ViT), and attention-based architectures have significantly improved classification accuracy and enabled earlier detection, supporting large-scale precision agriculture systems (Zhang et al. 2024 and Zhao et al. 2023).

In comparison, Malaysia's research efforts remain at an earlier stage. While there is growing interest, studies have primarily focused on combining multispectral and thermal UAV data with machine learning methods such as Random Forest and Support Vector Machines (SVM), especially in crops like oil palm and paddy (Anuar et al. 2022 and Baharim et al. 2023). These approaches have successfully identified early signs of water and nutrient stress, though implementation is largely limited to research settings rather than field-scale applications.

A key trend in both countries is the use of multisource data fusion. Integrating UAV imagery with satellite and ground sensor data has led to more robust models and improved spatial and temporal resolution, helping overcome limitations of individual data sources like cloud cover or low resolution (Li et al. 2024 and Chong et al. 2017). Incorporating weather and soil data into AI-driven decision support systems has further improved the precision of stress detection and enabled more site-specific recommendations.

Importantly, localised model development has emerged as a critical factor. AI models trained on region-specific datasets tend to outperform generic ones, especially in tropical environments like Malaysia. In China, there is increasing focus on building tailored models based on crop types and agroecological zones, a strategy that could significantly enhance accuracy and usability in Malaysia's diverse farming contexts (Wang et al. 2016).

Despite technical advancements, practical challenges remain, particularly in Malaysia. High costs of data collection, limited infrastructure, and a lack of farmer training continue to hinder adoption. In contrast, China's progress has been supported by government-backed initiatives and scaled-up implementations, highlighting the importance of policy support and funding for technology uptake (Lau et al. 2023).

Limitations and challenges

Despite promising outcomes, several key limitations persist. The performance of AI-based crop stress detection is highly dependent on the availability of high-quality ground-truth data, which remains fragmented or outdated in many developing regions. UAVs provide detailed imagery but are constrained by limited spatial coverage, reducing their utility for large-scale monitoring unless used in tandem with other platforms. Furthermore, models trained in one crop or region often lack generalisability due to differences in environmental and phenotypic conditions, requiring frequent retraining. A lack of standardised protocols for stress classification also poses challenges for model reproducibility and inter-study comparisons.

Conclusion and recommendations

This review has examined recent developments in AI-integrated remote sensing for crop stress detection, focusing on Malaysia and China. China has demonstrated significant advancement through the use of deep learning models like CNNs, Vision Transformers, and attention mechanisms, supported by large datasets and strong government initiatives. These systems have enabled early and accurate detection of stress across broad agricultural landscapes.

In Malaysia, progress is emerging, though largely confined to experimental plots. Applications of multispectral drone imagery combined with classical machine learning algorithms such as SVM and Random

Forest have shown encouraging results, particularly for oil palm and paddy. However, broader implementation remains limited by a lack of localised datasets, infrastructure, and policy support.

Future work should prioritise the development of localised and crop-specific models, integration of diverse data sources, and multi-stakeholder collaboration. Promoting affordable sensing technologies and improving farmer training will be essential for scaling adoption. While the technological foundation is well-established especially in China realising its full potential in Malaysia will require targeted investment in capacity building, infrastructure and policy frameworks. Addressing these gaps will be critical for advancing digital agriculture and enhancing resilience in food production systems.

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