



Review Article

Comparative Evaluation of Ground-based, Manual, and Remote Sensing Approaches for Crop Stress Detection: A Review between Malaysia and China

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ABSTRACT

This study presents a comparative evaluation of manual inspection, ground-based sensors, and UAV-based remote sensing for detecting crop stress in paddy, maize, and coconut fields across Malaysia and China. Although sensing technologies have advanced considerably, cross-country comparisons between regions with differing levels of technological maturity remain limited. China, recognised for its advanced adoption of UAV and sensor-based agriculture, provides a benchmark against Malaysia's developing digital agriculture landscape. Each method was assessed based on accuracy, responsiveness, scalability, and cost-effectiveness under field conditions. UAV-based remote sensing achieved the highest overall accuracy (mean 92%) and demonstrated superior scalability, enabling rapid large-area monitoring using vegetation indices such as NDVI and NDRE.

Ground-based sensors, including soil moisture probes and chlorophyll meters, showed moderate accuracy (mean 81%) and were suitable for plot-level monitoring with real-time feedback. Manual inspection recorded the lowest accuracy (mean 68%) and limited scalability due to labour dependency and subjective assessment. UAV methods were particularly effective in early stress detection, with thermal imaging identifying canopy temperature anomalies 3–5 days before visible symptoms, especially in

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maize and coconut fields. Integrating UAV and ground-based sensing provided more comprehensive and timely assessments than individual approaches. These findings support the development of scalable precision agriculture frameworks tailored to tropical and subtropical systems.

Keywords: AI, China, crop stress, ground sensing, Malaysia, manual inspection, NDVI, remote sensing

INTRODUCTION

Early and accurate detection of crop stress is critical for sustainable agriculture, efficient resource use, and stable food production, particularly under increasing climatic pressures. Crop stress, whether from pests, diseases, drought, or salinity, can significantly reduce yields if not identified and addressed promptly (Bela, 2023). In large-scale farming systems, timely monitoring remains a challenge due to limited accessibility and field size, often delaying effective management decisions (Umutoni & Samadi, 2024). Traditional methods such as manual inspection are widely used but are labour-intensive, subjective, and lack scalability (Mylonas et al., 2022).

In response, sensing technologies are gaining prominence in precision agriculture. Ground-based tools like chlorophyll meters and soil probes provide accurate, site-specific data (Soussi et al., 2024), while Unmanned Aerial Vehicles (UAVs) and satellite platforms deliver rapid, spatially extensive monitoring using indicators like Normalised Difference Vegetation Index (NDVI) and canopy temperature (Sharma et al., 2025). The integration of multispectral imaging with Artificial Intelligence (AI) analytics has further enhanced detection accuracy and decision-making efficiency (Cho et al., 2024).

Figure 1 presents a conceptual framework that outlines the integration of various sensing technologies for detecting crop stress and supporting farm-level decision-making. The process begins with environmental inputs such as climate, soil, and topography, which significantly influence crop growth and stress conditions, including water scarcity, nutrient deficiencies, pest infestations, and temperature extremes.

Monitoring these stress factors involves manual methods like visual inspections and leaf colour charts, and ground-based sensors that measure soil moisture, electrical conductivity, and chlorophyll content. These are complemented by remote sensing tools, including UAVs, satellites, and hyperspectral or thermal imaging systems, which enable large-scale and detailed monitoring.

The gathered data is transmitted through IoT networks and cloud platforms for acquisition and fusion, where it is processed using machine learning, artificial intelligence, and crop models to provide actionable insights. Ultimately, this information supports adaptive farm management strategies such as precise irrigation scheduling, fertigation, and pest control, enhancing crop productivity and sustainability through informed and timely interventions.

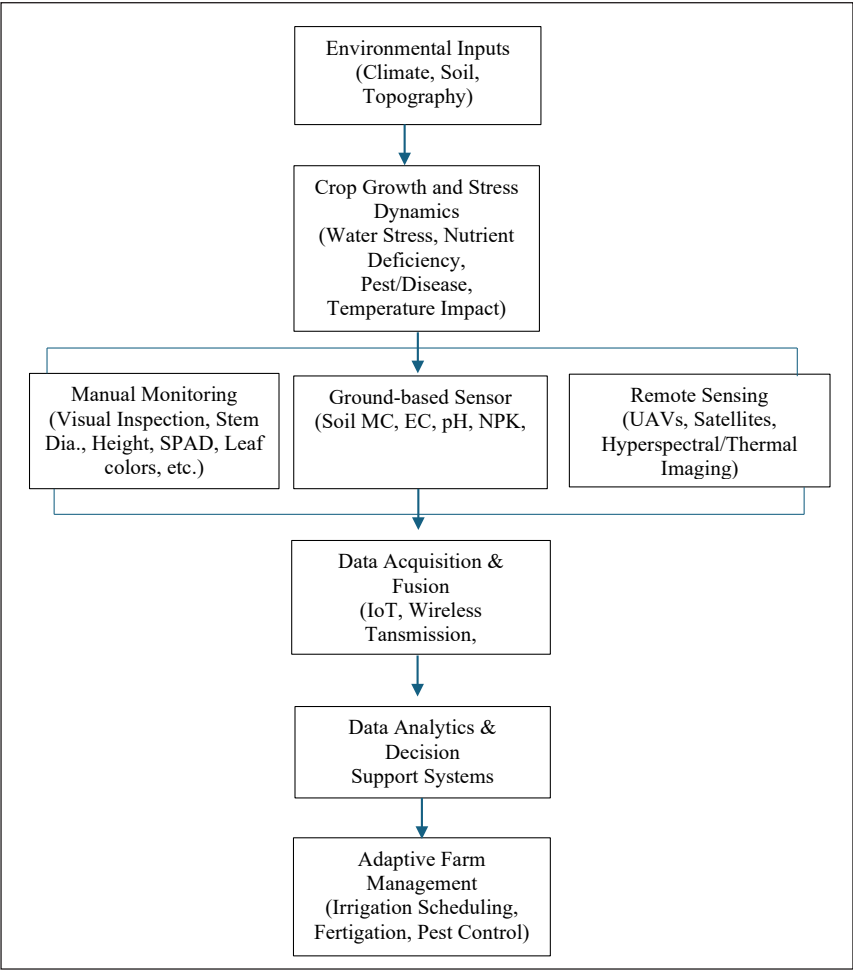


Figure 1. Conceptual framework of sensing technologies for crop stress detection

Despite rapid advancements in agricultural sensing technologies, their adoption across many parts of Asia, particularly in developing regions, remains limited (Gamage et al., 2024). Challenges such as high initial costs, insufficient technical training, and inconsistent infrastructure continue to hinder large-scale implementation. As a result, many farmers still depend on manual crop monitoring, which is labour-intensive, subjective, and often unreliable in complex field environments (Tian et al., 2020). Moreover, there is a scarcity of comparative field-based studies assessing the effectiveness and practicality of different sensing methods across diverse agroecological zones like Malaysia and China.

This study addresses that gap by evaluating the performance of manual inspection, ground-based sensors, and UAV-based remote sensing for detecting crop stress in paddy, maize, and coconut fields. It examines each method’s accuracy, responsiveness, and practical

usability under real-world conditions. The research also considers limitations posed by factors such as cloud interference in Moderate Resolution Imaging Spectroradiometer (MODIS) satellite imagery and variations in sensor calibration. By highlighting both the strengths and constraints of each approach, this study aims to inform more targeted and scalable precision agriculture practices tailored to tropical and subtropical farming systems.

Crop Stress: Definition and Indicators

Crop stress can be defined as any condition that adversely affects the growth, development, and yield of crops. Stress can arise from both biotic and abiotic factors. Biotic stresses are those caused by living organisms, such as pathogens, pests, and weeds, which damage crops directly or indirectly (Kour et al., 2025). These stresses can result in diseases like fungal or bacterial infections, insect damage, and competition for resources. On the other hand, abiotic stress is caused by environmental factors like temperature extremes, drought, soil salinity, and pollution, which directly or indirectly impact plant physiology (Sanaeifer et al., 2023).

Among the various abiotic stress factors, water stress remains the most significant challenge for crop production. Water scarcity during key growth stages of crops leads to reductions in yield and quality (Guo et al., 2025). Temperature stress, particularly heat stress, can cause cellular damage, reduce photosynthesis, and compromise overall plant health (Saewong et al., 2024). Salinity stress interferes with plant water uptake and nutrient absorption, leading to stunted growth and poor productivity (Hualpa-Ramirez et al., 2024). Crops that are subjected to multiple stresses simultaneously may exhibit compounded negative effects, making early detection critical for intervention (Pascual et al., 2022).

To effectively manage crop stress, a range of indicators can be monitored, including Normalised Difference Vegetation Index (NDVI), canopy temperature, moisture levels, and chlorophyll content. NDVI is a widely used remote sensing indicator that helps assess plant health based on the reflection of sunlight from vegetation (Zhao and Qu, 2024). NDVI values typically increase with healthy vegetation, while decreases indicate stress conditions (Essaadia et al., 2022).

Canopy temperature, which can be monitored through infrared thermometers or thermal cameras, rises in response to water stress and heat stress, providing a reliable indication of crop health (González-Dugo et al., 2010). Moisture levels are essential to understanding drought stress and are often assessed through soil moisture sensors or vegetation water content measurements (Tangjialeke et al., 2024). Chlorophyll content, which can be assessed through leaf tissue analysis or optical sensors, is a key indicator of plant photosynthetic capacity and health (Wang et al., 2024). Table 1 provides a summary of various crop stress indicators and the sensing methods used for their detection.

Table 1
Summary of various crop stress indicators and the sensing methods used for their detection

Stress Indicator	Physiological Basis	Sensing Method	Sensor Type / Platform	Reference(s)
NDVI (Normalised Difference Vegetation Index)	Changes in chlorophyll content and canopy structure	Spectral reflectance	Multispectral sensors (UAV, satellite, handheld)	Zhao & Qu (2024); Essaadia et al. (2022)
Canopy Temperature	Elevated leaf temperature due to reduced transpiration	Thermal infrared imaging	Infrared thermography (ground-based, UAV)	Jones et al. (2009); Prashar & Jones (2014)
Leaf Moisture Content	Dehydration of leaf tissue under stress	NIR and SWIR spectroscopy	Proximal hyperspectral sensors	Sanaeifar et al. (2023)
Chlorophyll Fluorescence	Disruption in photosynthetic electron transport	Fluorometry	Fluorescence sensors (e.g., PAM fluorometres)	Kour et al. (2025)
Soil Moisture	Availability of water to plant roots	Dielectric sensing	TDR/Capacitive probes, IoT soil sensors	Saeed et al. (2022); Tangjialeke et al. (2024)
Relative Water Content (RWC)	Degree of cell hydration	Gravimetric and pressure chamber methods	Manual/laboratory techniques	Guo et al. (2025)
SPAD (Chlorophyll Index)	Total leaf chlorophyll content	Leaf transmittance	SPAD handheld metres	Saewong et al. (2024)
Vegetation Indices (e.g., SAVI, EVI)	Enhanced detection under sparse vegetation or varied light	Spectral reflectance	Satellite or UAV-based multispectral imaging	Essaadia et al. (2022); Li et al. (2023)
Stomatal Conductance	Closure of stomata under water stress	Porometry	Porometres (leaf-level)	Hualpa-Ramirez et al. (2024)
Leaf Colour Changes	Anthocyanin or senescence-induced discolouration	RGB imaging	Cameras (ground-based or UAV)	Pascual et al. (2022)

Manual Methods for Crop Stress Detection

While modern technologies are reshaping crop stress detection, manual methods continue to play a vital role, especially in resource-limited settings. Visual inspection remains one of the most traditional and widely used techniques, involving the direct observation of symptoms such as leaf discolouration, wilting, or reduced growth (Lau & Tov, 2023).

Although such observations are quick and inexpensive, they are often subjective and highly dependent on the observer’s expertise. Nonetheless, visual assessments are still

valuable for initial stress identification and are frequently used in conjunction with more advanced diagnostic tools (Chakhvashvili et al., 2024).

Complementary manual methods include leaf and soil sampling, both of which provide deeper insights into plant health. Leaf analysis through laboratory testing can reveal nutrient deficiencies or detect pathogens, making it useful for identifying both abiotic and biotic stress factors (Kou et al., 2024; Zhang et al., 2023). For instance, low nitrogen levels in leaves may indicate nutrient stress (Francis et al., 2023).

Similarly, soil testing can identify underlying issues like pH imbalance or salinity, which often contribute to stress symptoms (Faqir et al., 2024; Tarolli et al., 2024). Despite their diagnostic accuracy, both approaches are time-consuming, require laboratory infrastructure, and lack scalability for large-scale real-time monitoring, limiting their broader application in precision agriculture.

Table 2 summarises the advantages and limitations of various manual crop management methods, highlighting their practical relevance. Manual harvesting ensures high-quality produce with minimal crop damage and environmental impact, but is labour-intensive and less scalable, making it suitable for high-value or organic crops. Manual weeding allows precise, chemical-free weed control, yet requires significant labour, limiting feasibility in large fields or regions with scarce labour.

Hand cultivation, such as hoeing, is low-cost and effective for small or irregular plots but physically demanding and inefficient at scale. Manual pruning and thinning improve plant health and yield by selectively removing diseased or crowded parts, though it demands skilled labour and time. Hand pollination is essential for controlled breeding and greenhouse environments, ensuring pollination where natural pollinators are absent, but it is impractical for large-scale operations. Collectively, these methods remain critical in specialised, smallholder, or organic farming systems where precision and crop quality are prioritised.

Table 2
The advantages and limitations of these manual methods offering insights into their relevance for crop management

Manual Method	Advantages	Limitations	Relevance for Crop Management
Manual Harvesting	• Allows precise selection of ripe produce, enhancing quality. • Reduces crop damage compared to mechanical methods. • Environmentally friendly; no fuel use.	• Labour-intensive and time-consuming. • Higher labour costs. • Limited scalability for large operations.	• Suitable for high-value crops where quality is critical. • Beneficial in regions with abundant labour. • Preferred in organic systems with minimal mechanical intervention.

Table 2 (continued)

Manual Method	Advantages	Limitations	Relevance for Crop Management
Manual Weeding	•Precise weed removal without harming crops. •No chemical residues; environmentally safe.	•Labour-intensive, especially for large fields. •Not feasible where labour is scarce or costly.	•Effective for small-scale or organic farming. •Useful where chemical herbicides are restricted or undesirable.
Hand Cultivation (e.g., hoeing)	•Simple tools; low cost. •Effective in small or irregular plots. •Minimal soil disturbance.	•Physically demanding. •Inefficient for large-scale operations.	•Ideal for smallholder farms and gardens. •Useful for spot treatments and hard-to-reach areas inaccessible to machinery.
Manual Pruning and Thinning	•Enhances air circulation and sunlight penetration. •Allows selective removal of diseased or damaged parts.	•Requires skilled labour. •Time-consuming.	•Important for crop health and yield optimisation. •Common in fruit orchards and vineyards.
Hand Pollination	•Ensures pollination when natural pollinators are absent. •Allows control over genetic crosses.	•Labour-intensive. •Not practical for large-scale crops.	•Essential in controlled breeding programs. •Useful in greenhouse or isolated environments.

**Source: Amanullah (2024a and 2004b)*

Ground-based Sensing Techniques

Ground-based sensing techniques have gained significant traction in recent years due to their ability to provide continuous, real-time data on crop health. Technologies such as IoT devices, handheld NDVI sensors, and soil moisture probes have become integral to precision agriculture (Zhang et al., 2024). These systems enable farmers to closely monitor crop conditions and manage resources efficiently, thus optimising productivity. IoT-based systems, for example, offer high spatial and temporal resolution, allowing continuous tracking of various environmental parameters such as soil moisture, temperature, and humidity (Dhanaraju et al., 2022). By providing real-time data, these systems allow for precise adjustments in irrigation and fertilisation, helping mitigate stress and improve crop yields (Mba et al., 2025; Rajak et al., 2023).

Handheld NDVI sensors, known for their affordability and portability, are also widely used in the field to assess plant health. These sensors measure light reflection at specific wavelengths, enabling early detection of stress before visible symptoms appear (Le et al., 2023). However, their effectiveness can be influenced by environmental factors such as light intensity and soil type, which can impact their accuracy (Zhang et al., 2024). Additionally,

soil moisture probes play a crucial role in managing water stress, one of the most common stressors in agriculture. These probes provide direct measurements of soil water content, which can be used to optimise irrigation schedules and prevent water wastage (Rasheed et al., 2022).

Figure 2 illustrates a typical setup of ground-based sensors in crop monitoring systems, including a leaf wetness sensor, which measures the duration and presence of moisture on leaf surfaces. This is critical for predicting the onset of foliar diseases, scheduling irrigation, and assessing microclimatic conditions that influence crop health. By providing real-time, site-specific information, the leaf wetness sensor enhances decision-making for disease management and irrigation planning, particularly in high-value crops where timely interventions can significantly impact yield and quality.

Table 3 compares various sensing methods based on accuracy, cost, advantages, and limitations. Soil moisture sensors offer high accuracy at a low to moderate cost but are limited to moisture measurement and require calibration. Leaf Area Index (LAI) is effective for vegetation analysis, but may need multiple sensors for larger areas. Electromagnetic Induction (EMI) is good for soil analysis, but is expensive and energy-intensive. Thermal infrared sensing provides non-invasive stress data, though it's sensitive to environmental factors. Portable chlorophyll meters are fast and non-destructive, but limited to leaf analysis. Drone-based imaging offers large-scale coverage, but requires skilled operators and has high costs. Ground Penetrating Radar (GPR) is useful for soil structure, but it is costly and specific to certain soil types.

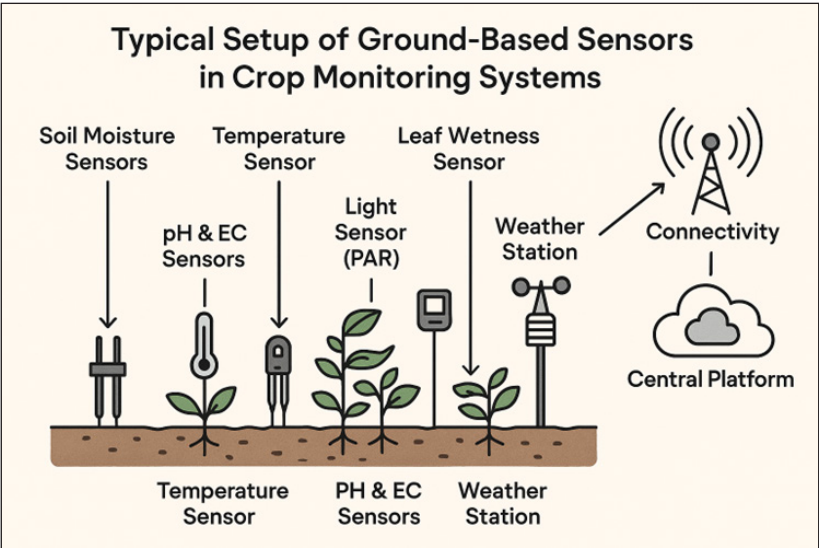


Figure 2. Typical setup of ground-based sensors used in crop monitoring systems

Table 3
Comparison of the accuracy and cost of different ground-based sensing methods

Sensing Method	Accuracy	Cost	Advantages	Limitations
Soil Moisture Sensor	± 2-5%	Low to Moderate (\$50-\$500)	High accuracy for moisture content measurement in soil	Limited to soil moisture; calibration required
Leaf Area Index (LAI)	± 2-3%	Moderate (\$300-\$2000)	Effective for vegetation analysis; non-destructive	May require multiple sensors for large areas
Electromagnetic Induction (EMI)	± 5-10%	High (\$1000-\$5000)	Good for soil salinity and texture analysis	Expensive; high energy consumption
Thermal Infrared Sensing	± 1-3%	Moderate (\$500-\$3000)	Non-invasive; provides information on plant water stress	Requires clear sky conditions; sensitive to environmental factors
Portable Chlorophyll Meter	± 1-2%	Moderate (\$100-\$1000)	Fast and non-destructive chlorophyll measurement	Limited to leaf analysis only
Drone-Based Imaging	± 3-5%	High (\$2000-\$10000)	Provides large-scale coverage with detailed imagery	Requires skilled operator; high initial cost
Ground Penetrating Radar (GPR)	± 10-15%	High (\$3000-\$15000)	Suitable for soil structure and depth analysis	High cost; limited to specific soil conditions

*Source: Prasad et al. (2021)

Ground Vehicle Mounted Sensing Technologies

Ground vehicle-mounted sensing platforms (GVMS) have rapidly gained attention as an intermediate approach between handheld tools and aerial remote sensing for crop stress detection. Typically mounted on tractors, ATVs, or small autonomous vehicles, GVMS integrate multispectral and hyperspectral cameras, thermal imagers, LiDAR scanners, chlorophyll meters, and soil probes to capture high-resolution data along crop rows (Sharma et al., 2025). Operating close to the canopy, these systems provide finer spatial detail and more stable signal quality than UAVs, even under cloudy, windy, or restricted-flight conditions (Unde et al., 2025).

Modern GVMS units leverage improvements in vibration damping, real-time processing, and machine learning based classification to detect subtle physiological changes such as early water stress, nutrient imbalances, canopy temperature anomalies, and biomass variations well before they are visually apparent (Wu et al., 2025). Moreover, their deployment alongside routine field operations such as fertiliser application or weeding allows continuous monitoring without additional labour, enhancing operational feasibility in large-scale and high-intensity farming systems (Mansoor et al., 2025).

Despite these strengths, practical constraints influence GVMS adoption across diverse farming systems. Field accessibility remains challenging in flooded paddy fields, steep

terrains, or perennial crop plantations with narrow inter-row spacing, while sensor fouling, vibration-induced signal noise at higher speeds, and reduced GNSS accuracy under dense canopies can limit data reliability if not carefully managed (Mat Lazim et al., 2020). International comparisons indicate that highly mechanised systems, such as those in China, achieve greater throughput and precision due to better road access, wider row spacing, and widespread use of RTK-equipped tractors (Jensen et al., 2025).

A growing consensus in the literature emphasises the benefits of integrating GVMS with UAV reconnaissance for a hybrid stress-monitoring approach, UAVs for rapid field-wide scanning and GVMS for detailed, row-level diagnostics while highlighting the ongoing need for affordable, standardised sensor modules and harmonised data-processing workflows to support broader adoption, particularly in tropical environments (Munasinghe et al., 2024).

Remote Sensing Technologies

Remote sensing technologies, such as satellite imagery and UAV-based platforms, offer powerful tools for monitoring crop stress on a large scale. Satellite systems like MODIS and Sentinel provide continuous, wide-area coverage, making them ideal for assessing crop health over large agricultural regions (Karmakar et al., 2024). MODIS, for instance, can capture data on vegetation indices such as NDVI, which provides a quantitative assessment of plant health. Sentinel satellites, with their higher spatial resolution, are particularly useful for monitoring smaller-scale agricultural areas (Heiss et al., 2025).

UAVs provide an alternative to satellite imagery, offering high-resolution, real-time data that can be tailored to specific fields (Rahman et al., 2024). UAVs are equipped with multispectral or hyperspectral cameras that capture detailed images of crop canopies, which are then analysed to assess plant health. UAVs offer the advantage of being able to capture data at a much higher frequency than satellites, providing farmers with more frequent updates on crop conditions. However, UAVs are limited by their flight range and battery life, making them suitable for smaller, more localised areas (Kramarić et al., 2025).

Vegetation indices such as NDVI, SAVI (Soil Adjusted Vegetation Index), and EVI (Enhanced Vegetation Index) are commonly used in remote sensing to assess plant health and stress (Fadl et al., 2024). These indices are calculated based on the reflectance of light at different wavelengths and are sensitive to changes in vegetation cover, chlorophyll content, and canopy structure (Gu et al., 2025). NDVI, in particular, is widely used to detect crop stress due to its simplicity and effectiveness in differentiating between stressed and healthy plants (Balasundaram et al., 2024). Figure 3 provides an example of NDVI imagery captured from satellite or UAVs, highlighting its utility in large-scale crop monitoring.

Table 4 compares different technologies for crop monitoring based on cost, spatial resolution, frequency of data acquisition, and key characteristics. Satellite imagery (e.g., Sentinel-2) is cost-effective and suitable for large-scale monitoring, with a spatial resolution



Figure 3. NDVI imagery captured from satellite or UAVs in large-scale crop monitoring

Table 4
Key characteristics of each technology, including cost, spatial resolution, and frequency of data acquisition

Technology	Cost	Spatial Resolution	Frequency of Data Acquisition	Remarks
Satellite (e.g., Sentinel-2)	Low (free access)	10-20 m	Every 5-10 days	Suitable for regional to global scale monitoring (Sothe et al., 2017).
Satellite (e.g., Planet Scope)	High (subscription)	3-5 m	Daily	Commercial service with high revisit and finer details (le Roux et al., 2021).
UAV (multispectral camera)	Medium-High (initial setup)	1-10 cm	On-demand (manual flight missions)	High flexibility and detail; limited by battery/labour (Deng et al., 2018).
Ground-based sensors (e.g., handheld NDVI, chlorophyll meters)	Low-Medium	Point-based/local	Continuous or user-defined intervals	High accuracy; useful for calibration and ground truthing (Zhao et al., 2025).
IoT soil/water sensors	Medium (installation + maintenance)	Point-based/local	Real-time/continuous	Good for micro-environment monitoring (soil/temp/moisture) (Comegna et al., 2024).
Manned aircraft (with hyperspectral sensors)	Very high	1-5 m	Scheduled (limited due to cost/logistics)	Effective for larger farms; not cost-efficient for smallholders (Tsouros et al., 2019).

of 10-20 meters and data available every 5-10 days. In contrast, commercial services like Planet Scope offer higher spatial resolution (3-5 m) with daily data acquisition but come at a higher cost. UAVs with multispectral cameras provide high flexibility and detail with a resolution of 1-10 cm, though they are limited by battery life and manual operation.

Ground-based sensors, such as handheld NDVI and chlorophyll meters, offer high accuracy and are useful for calibration, with continuous or user-defined data intervals. IoT sensors offer real-time, continuous monitoring of micro-environmental conditions but require medium-level investment. Manned aircraft with hyperspectral sensors provide detailed data for larger farms but are costly and less suitable for small-scale operations.

Role of AI in Sensing

The role of artificial intelligence (AI) in crop stress detection has been growing rapidly, with machine learning techniques being applied to a variety of sensing data sources. AI models have shown great promise in improving the accuracy and efficiency of crop monitoring systems by integrating data from multiple sources, such as remote sensing platforms, IoT devices, and ground-based sensors (Parra-López et al., 2025). These models are capable of classifying crop conditions, predicting stress, and optimising resource management strategies, making them invaluable tools for precision agriculture (Aarif et al., 2025).

Machine learning algorithms are particularly effective in processing large datasets from various sensing technologies. For example, convolutional neural networks (CNNs) have been used for image classification, allowing for the identification of stress symptoms from UAV or satellite imagery (Upadhyay et al., 2025). These algorithms can detect subtle changes in vegetation health that may be missed by traditional methods, providing early warnings of stress conditions (Lee et al., 2025).

AI models can also integrate data from multiple sources, such as soil moisture sensors and weather data, to create predictive models for stress events (Pandey and Mishra, 2024). This allows for more proactive management of crop health, reducing the need for reactive measures like emergency irrigation or pesticide application (Taha et al., 2025).

Evaluation Criteria and Comparative Metrics

The reviewed studies were assessed based on four primary criteria: accuracy, cost, scalability, and ease of use, which are key to determining their applicability in real-world agricultural practices across diverse agro-ecological zones in Malaysia and China. Accuracy is critical in ensuring the reliability of crop stress detection methods. Vegetation indices such as NDVI and EVI, derived from satellite and UAV imagery, are commonly used to assess plant health, with strong correlations to physiological stress indicators. However, factors like atmospheric interference, sensor type, and image calibration can influence the accuracy of remote sensing data. On the other hand, ground-based IoT sensors offer high

precision at a local scale but may lack the broad spatial representation provided by remote sensing technologies.

Cost is another important factor, particularly in resource-constrained settings. While satellite imagery from open-access platforms like Sentinel is free, high-resolution UAV imagery and commercial satellite services like PlanetScope come with considerable expenses. Ground-based sensors are relatively affordable, though they incur installation and maintenance costs. The cost-effectiveness of each method depends on farm scale and the availability of technical support.

Scalability is also vital for widespread adoption; satellite imagery works well for regional monitoring but may miss small-scale stress patterns, whereas UAVs offer detailed insights but are limited by coverage area, weather conditions, and battery life. IoT sensors are modular and adaptable for both smallholder and large commercial farms. Finally, ease of use is influenced by system complexity and required user training. While manual inspections are simple, they are less effective for early detection. In contrast, IoT and remote sensing technologies require specialised knowledge for deployment and interpretation, making user-friendly interfaces and automated analytics essential for adoption by farmers with limited technical expertise.

Comparative Analysis Framework

To facilitate a structured comparison, a multi-criteria decision-making (MCDM) approach was adopted, enabling the ranking of crop stress detection methods based on predefined criteria such as accuracy, cost, scalability, and usability. Studies such as Gunawan et al. (2024) have successfully applied MCDM frameworks to identify optimal stress monitoring solutions tailored to specific cropping systems.

Additionally, regression and statistical modelling were used in select studies to quantitatively compare technologies. For instance, Zhang et al. (2019) conducted a regression-based evaluation of UAV imagery and IoT soil data to identify water stress in maize, revealing that UAVs were superior for detecting large-scale variability, while IoT sensors were better suited for identifying localised nutrient-related stress.

Figure 4 presents different crop stress detection technologies, visualising their strengths and trade-offs. The integration of multi-source data using machine learning techniques has also emerged as a promising trend. Rashid et al. (2025) combined UAV, IoT, and satellite data using a deep learning architecture to improve detection accuracy and contextual interpretation. This integrated approach enhances prediction reliability and allows a holistic view of crop health under varying climatic and soil conditions.

Ultimately, the comparative evaluation outlined in this methodology supports evidence-based decision-making for selecting suitable stress detection methods in diverse agricultural landscapes across Malaysia and China. Future studies should focus on hybrid systems that

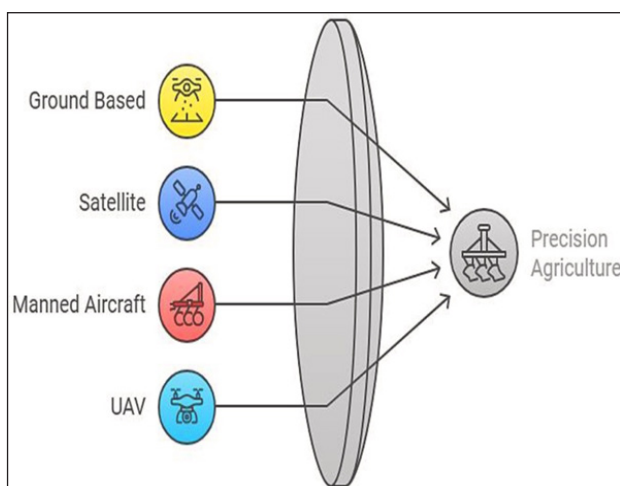


Figure 4. Different crop stress detection technologies (Rashid et al., 2025)

combine ground-based and remote sensing data within unified machine learning platforms for intelligent, real-time crop stress monitoring.

Performance of Manual Methods

Manual inspection remains one of the most commonly used methods for stress detection in crops. While this method is simple and inexpensive, it is often limited by its subjective nature and dependency on the skill of the observer. In terms of accuracy, manual observation is generally less reliable compared to more advanced technological methods. Studies have reported a high degree of variability in accuracy, with field inspectors often missing subtle signs of crop stress, particularly in the early stages (Tian et al., 2011).

The time required for manual inspection is another key consideration. Typically, manual observation can take hours or even days to cover large areas, depending on the crop type and field size (Sun et al., 2024). This is particularly challenging for large-scale farming operations, where the time and labour required can significantly impact productivity. Additionally, environmental conditions such as weather can affect the accuracy and efficiency of manual inspections, as rain, high winds, or excessive heat can obscure visual symptoms of stress.

Despite these limitations, manual inspection does have its advantages in providing a quick and relatively low-cost method for identifying overt stress symptoms, especially in cases where high-tech solutions may not be feasible (Walsh et al., 2024). Table 5 summarises the observed stress detection accuracy for manual inspection across different crop types and environments, highlighting the challenges in accuracy and the factors influencing it.

Ground-based Sensor Performance

Ground-based sensors have gained significant attention for real-time crop monitoring due to their ability to measure environmental parameters continuously. These sensors are typically placed in the field to monitor key variables such as soil moisture, temperature, and nutrient levels, which directly affect crop health (Shahab et al., 2025). In terms of real-time data quality, ground-based sensors provide a high level of reliability, with measurements that are frequently updated and capable of reflecting short-term changes in the crop environment (Velazquez-Chavez et al., 2024).

Figure 5 presents time-series data for soil moisture, NDVI, and temperature measurements collected from a set of ground sensors. The data highlights the temporal fluctuations in crop health indicators over a growing season, demonstrating how ground-based sensors can be used to track stress over time.

Table 5
Stress detection accuracy for manual inspection across different crop types and environments

Crop Type	Environment	Stress Detection Accuracy (%)
Wheat	Field (Dry Conditions)	85
Wheat	Field (Wet Conditions)	78
Corn	Greenhouse	92
Corn	Field (Dry Conditions)	88
Soybean	Field (Dry Conditions)	80
Soybean	Field (Wet Conditions)	76
Rice	Paddy Field	95
Rice	Greenhouse	91
Tomato	Field (Dry Conditions)	89
Tomato	Greenhouse	90

*Source: Walsh et al. (2024)

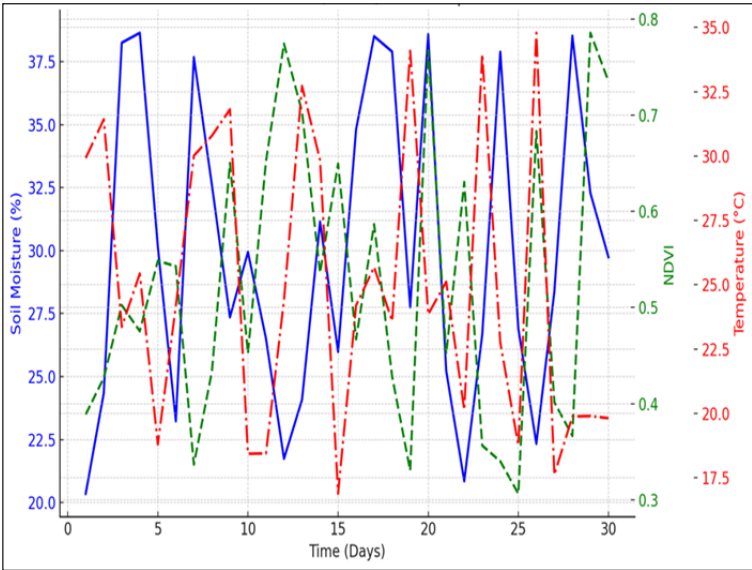


Figure 5. Time-series data for soil moisture, NDVI, and temperature measurement (Olawade et al.,2024)

Table 6 provides a comparison of sensor performance across different study locations, offering insight into how environmental factors influence the reliability and accuracy of the data.

Table 6
Comparison of sensor performance across different study locations

Country	Sensor Type	Environmental Factors	Sensor Accuracy	Reliability	Key Observations
Malaysia	Soil Moisture Sensor	High humidity, fluctuating temperatures, heavy rainfall	±2%	High	Performed well in tropical field conditions (Ahmad and Hashim, 2007).
Malaysia	Soil Temperature Sensor	High ambient temperatures, low humidity	±3%	Moderate	Performance slightly reduced due to sensor heating (Sulong et al., 2023).
China	pH Sensor	Dry inland climate, low rainfall, stable temperatures	±1.5%	Very High	Reliable for long-term deployment in drylands (Wang et al., 2024).
China	EC Sensor	Coastal zone, saline soil, high wind exposure	±5%	Low	Accuracy compromised by saline interference (Zhou et al., 2024).
Malaysia	NPK Sensor	Mixed lowland climate, moderate rainfall, occasional fog	±4%	Moderate	Sensor readings varied with environmental moisture (Ahmad and Hashim, 2007).

Remote Sensing Results

Remote sensing technologies, including UAVs and satellite imagery, have become increasingly popular for large-scale crop monitoring. These technologies provide the advantage of extensive spatial coverage, making them ideal for assessing crop stress over large agricultural areas (Dong et al., 2024). However, the resolution of the imagery plays a significant role in the effectiveness of stress detection. High-resolution imagery from UAVs allows for detailed observations of the crop canopy, enabling the detection of subtle stress symptoms that may be missed in low-resolution satellite images (Iheaturu et al., 2024).

In addition to resolution, weather conditions can also impact the reliability of remote sensing data. Cloud cover, for example, can obstruct satellite imagery, leading to incomplete data and gaps in monitoring (Chen et al., 2025). UAV-based imagery, while less affected by weather conditions, may face limitations such as reduced flight time and range, particularly when covering large areas (Yadav et al., 2024). To improve the accuracy of stress detection, artificial intelligence (AI) models have been applied to process remote sensing data, providing more accurate classifications of crop health.

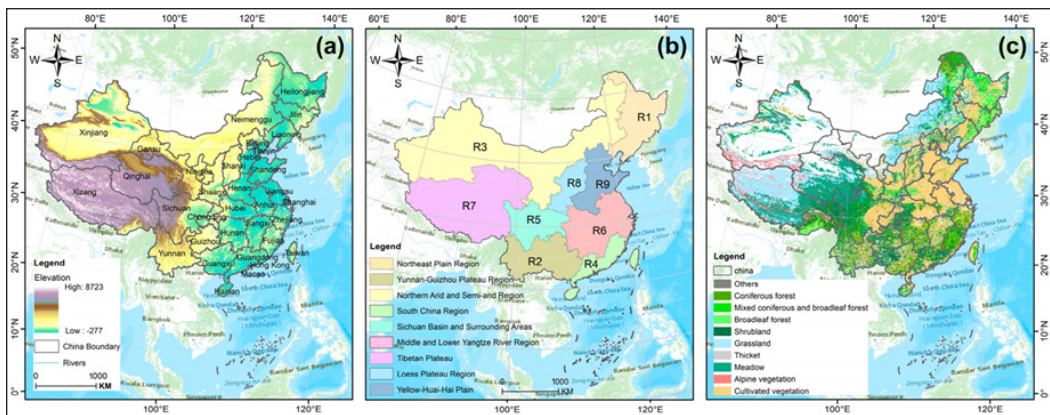


Figure 6. Spatial distribution of (a) elevation, (b) subregions of China and (c) vegetation types. (Ma et al., 2025)

Figure 6 illustrates the spatial distribution of key geographical and ecological attributes across China. Subfigure (a) presents the elevation map, highlighting topographic variations where the western regions, such as the Tibetan Plateau, feature higher elevations, while the eastern areas are characterised by lower altitudes. Subfigure (b) shows the subregional divisions of China, commonly used in environmental and agricultural studies, capturing ecological and climatic diversity across the country. Lastly, subfigure (c) depicts the distribution of vegetation types, illustrating dominant plant cover such as forests, grasslands, croplands, and barren lands.

Figure 7 illustrates remote sensing-based stress detection in four major crop types cultivated in Malaysia: paddy, oil palm, rubber, and vegetables. The multispectral or infrared satellite images show spatial patterns of crop stress, with red areas indicating stressed zones due to factors like drought, nutrient deficiency, or disease, while green areas signify healthy vegetation. In the paddy field quadrant, patchy red zones suggest irregular irrigation or pest infestations (Shaharum et al., 2020).

The oil palm quadrant displays circular plantation arrangements, with stress visible in scattered patches, possibly due to uneven soil moisture or disease. The rubber plantation appears mostly green, indicating minimal stress, likely due to uniform management and stable canopy health. In the vegetable quadrant, alternating red and green bands highlight variations in plant health across rows, which could be linked to differences in fertilisation, irrigation, or crop type diversity.

Table 7 compares AI models used for crop stress detection in Malaysia and China, showing how advanced algorithms improve detection accuracy with high-quality remote sensing data. Deep learning models (CNN) lead in accuracy (92%), while other models like Random Forest (RF) and XGBoost also perform well for large-scale monitoring.

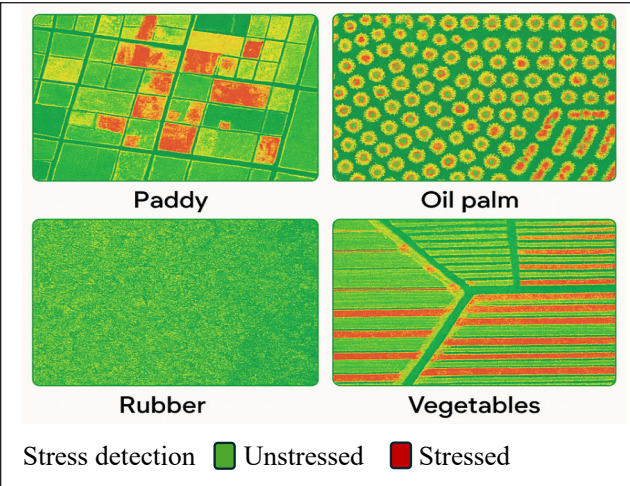


Figure 7. Stress detection in various crop types in Malaysia using remote sensing imagery

Table 7
Comparison of AI model classification accuracy for crop stress detection using remote sensing data in Malaysia and China

AI Model	Data Source	Remote Sensing Data	Region	Classification Accuracy	Notes
Support Vector Machine (SVM)	UAV (Unmanned Aerial Vehicle) imagery	High-resolution multispectral imagery	Malaysia	85%	Performs well with high-resolution data for stress detection (Zhang and Zhu, 2023)
Random Forest (RF)	Satellite imagery, field data	Landsat 8, Sentinel-2	China	88%	Robust for large-scale crop stress monitoring, with excellent feature importance handling (Zhang et al., 2022)
Deep Learning (Convolutional Neural Networks - CNN)	UAV and satellite data	Multispectral and hyperspectral data	Malaysia/ China	92%	High accuracy due to deep feature extraction and handling complex patterns (Saleh et al., 2024)
K-Nearest Neighbours (KNN)	Drone and field data	High-resolution RGB imagery	Malaysia	80%	Effective for simpler datasets but struggles with complex stress patterns (Phang et al., 2023)
Gradient Boosting Machines (GBM)	UAV and field data	High-resolution multispectral	China	89%	Highly accurate and efficient in detecting stress, especially with noise-reduced data (Bui et al., 2021)

Table 7 (continued)

AI Model	Data Source	Remote Sensing Data	Region	Classification Accuracy	Notes
Artificial Neural Networks (ANN)	Satellite imagery and field data	MODIS, Landsat	Malaysia/ China	87%	Performs well with non-linear relationships between remote sensing data and stress (Ni et al., 2025)
Decision Trees (DT)	Remote sensing data and field data	Sentinel-2, UAV imagery	Malaysia	83%	Simple to implement but less accurate for complex stress patterns (Xie, 2022)
XGBoost	Remote sensing data	High-resolution multispectral imagery	China	90%	Advanced boosting algorithm that offers a good balance of accuracy and computational efficiency (Samat et al., 2020)

Comparative Matrix Results

Table 8 compares manual inspection, ground-based sensors, and UAV-based remote sensing technologies for crop stress detection in Malaysia and China, highlighting their performance in terms of accuracy, scalability, and cost. UAV-based remote sensing outperforms the other methods with the highest accuracy (92%) and scalability, making it the most effective for large-scale monitoring (Su et al 2019). While manual inspection offers lower accuracy (70%) and is limited in scalability, it is cost-effective for small-scale observations. Ground-based sensors, with 80% accuracy, provide medium scalability and cost, offering a good balance between accuracy and application. UAV systems, though more expensive, are preferred for efficient, large-area coverage.

Crop stress monitoring can be achieved using ground-based, manual, and remote sensing methods, each with distinct advantages and limitations. Ground-based platforms, such as vehicle or trolley-mounted sensors, provide high-resolution, row-level data and can detect subtle physiological changes, while manual methods, including leaf sampling or SPAD measurements, are accurate but labour-intensive and limited in spatial coverage. Remote sensing approaches, such as UAV or satellite-based imaging, allow rapid, field-wide monitoring but may be affected by weather or canopy obstruction. To evaluate these approaches quantitatively, cost (C) can be calculated as:

The total system cost (C) is expressed as:

$$C = N \cdot P + L + M + E + I$$

[1]

where each component is defined as follows:

- N = number of sensors deployed (unitless)
- P = unit price per sensor (RM sensor⁻¹)
- L = labour cost associated with installation, calibration, operation, and data handling (RM)
- M = maintenance cost, including routine servicing, sensor replacement, and system upkeep over the study period (RM)
- E = energy cost, covering electrical power, batteries, charging, or fuel consumption during operation (RM)
- I = installation cost, including mounting structures, wiring, communication setup, and initial system configuration (RM)

Thus, Equation (1) represents the total capital and operational cost (RM) of the monitoring system for a given deployment period.

Scalability Metric

System scalability (S) is defined as:

$$S = \frac{A}{T \cdot f}$$
 [2]

where:

- A area monitored (ha or m²)
- T time required to complete one monitoring cycle (hours or days)
- f operational constraint factor (unitless), representing limitations such as the number of field passes, sensor density, or sampling frequency

A higher S value indicates greater scalability, reflecting the system’s ability to cover larger areas within shorter time frames under given operational constraints (Änäkkälä et al., 2022).

Table 8
Comparison of performance metrics for manual inspection, ground-based sensors, and UAV-based remote sensing technologies in crop stress detection in Malaysia and China

Method	Accuracy	Scalability	Cost	Application	Region
Manual Inspection	70%	Low	Low	Field-based observation	Malaysia/China
Ground-based Sensors	80%	Medium	Medium	Soil and plant monitoring	Malaysia/China
Remote Sensing (UAV-based)	92%	High	High	Aerial monitoring	Malaysia/China

Application and Implications

Applying these cost and scalability criteria demonstrates that mechanised Chinese farming systems achieve higher scalability and measurement precision through ground-based automated platforms. In contrast, Malaysian farms, which are typically smaller and mixed-crop, benefit more from lightweight ground sensors integrated with UAV reconnaissance.

While manual monitoring approaches incur lower initial costs, they exhibit limited scalability. Conversely, UAV-based systems provide rapid large-area coverage but involve higher operational and energy costs. Overall, this framework clarifies the trade-offs between spatial resolution, cost, and coverage, supporting the adoption of hybrid monitoring strategies according to local farm size and management conditions.

Figure 8 presents a comparison of method which include manual inspection, ground-based sensors, and UAV-based remote sensing, across three evaluation criteria: accuracy, scalability, and cost. UAV-based remote sensing stands out with the highest accuracy (92%) and scalability, while manual inspection has lower accuracy and scalability. Ground-based sensors strike a balance between cost and accuracy, with moderate scalability. Data are adapted from comparative performance metrics reported in UAV remote sensing and ground-based monitoring studies conducted in Southeast Asia and East Asia (Bui et al., 2021; Su et al., 2019; Xie, 2022).

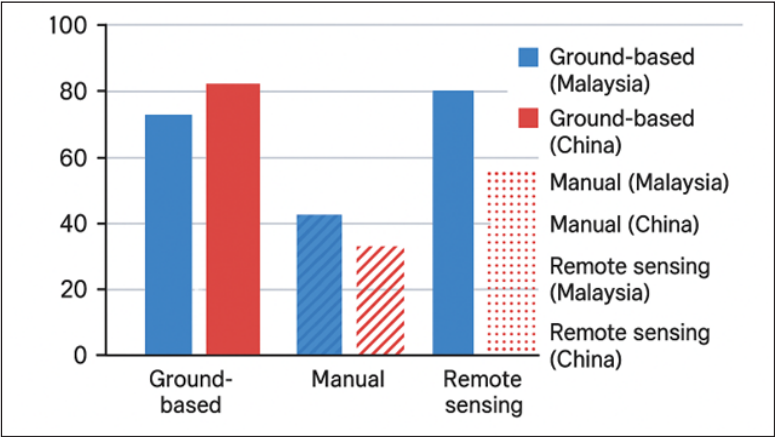


Figure 8. Comparison of methods for crop stress detection in Malaysia and China

Practical Implications for Farmers and Researchers

The practical implications of these findings depend heavily on the context of the farming operation. For smallholder farmers, the simplicity and low cost of manual inspection may make it the preferred choice, despite its limitations in accuracy (Amertet et al., 2024). However, for large-scale farms, remote sensing technologies, particularly UAV-based

systems, offer significant advantages in terms of coverage and accuracy. These methods, though costly, allow for more comprehensive monitoring of crop health, enabling farmers to detect stress across large areas in a relatively short time. Ground-based sensors, while more affordable than UAVs, provide highly reliable and accurate data on localised crop conditions. These sensors are particularly useful for monitoring variables like soil moisture, temperature, and nutrient content, which are critical for managing irrigation and fertilisation (Reza et al., 2025).

China vs Malaysia Comparison

The agricultural contexts in China and Malaysia offer unique challenges and opportunities for implementing crop stress detection technologies. China has made significant investments in agricultural infrastructure, which has facilitated the widespread adoption of advanced technologies such as UAVs and satellite-based remote sensing (Shah et al., 2024).

In contrast, Malaysia's smaller farm sizes and varying levels of infrastructure across regions may limit the widespread use of high-cost technologies like UAVs, although IoT-based sensors and manual inspection remain viable options for many farmers (Tiwari, 2022). Table 10 summarises the comparative national context of China and Malaysia, highlighting differences in infrastructure, policy support, and the availability of training for farmers.

Integration and Hybrid Systems

Recent research has emphasised the potential for integrating multiple sensing methods to improve crop stress detection. By combining remote sensing data with ground-based sensor information, it is possible to create hybrid systems that offer both broad-area monitoring and localised insights. Machine learning models can further enhance these hybrid systems by processing data from multiple sources to produce more accurate predictions of crop health.

Challenges and Limitations

Despite the advancements in crop stress detection technologies, several challenges remain. One of the primary technical barriers is the need for accurate and consistent ground truth data, which is essential for validating remote sensing and sensor-based measurements. Additionally, the cost of high-resolution sensors and UAV systems remains a significant limitation for smallholder farmers in developing regions.

Furthermore, data quality is influenced by environmental factors such as weather conditions, which can affect the accuracy of both remote sensing and ground-based sensor data. Addressing these challenges requires ongoing research and the development of more robust and affordable technologies.

CONCLUSION

This review has evaluated multiple methods for crop stress detection, including manual inspection, ground-based sensors, and remote sensing technologies. The findings indicate that remote sensing, particularly Unmanned Aerial Vehicle (UAV) based systems, provides the highest accuracy and scalability, making it most suitable for large-scale farms. Ground-based sensors offer reliable, site-specific data but require improvements in affordability and long-term reliability, especially for smallholder adoption. Manual inspection remains valuable for smallholder farms; however, it is less accurate and scalable. Consequently, manual methods and low-cost ground-based sensors are identified as needing urgent enhancement to improve usability and sustainability. Policy support, including subsidies and technical training, has been shown to significantly influence adoption rates of precision agriculture tools. For smallholder farmers, combining manual inspection with improved low-cost sensors can provide an affordable means of detecting stress, whereas larger farms benefit from integrating remote sensing with Internet of Things (IoT) sensors to achieve comprehensive, real-time crop monitoring.

Future research should focus on improving the accuracy and affordability of crop stress detection technologies. Policy support in the form of subsidies or incentives for adopting these technologies could help smallholder farmers, particularly in developing regions. Additionally, the integration of AI and machine learning models with hybrid sensing systems shows promise in improving detection accuracy and facilitating early intervention for crop stress management.

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CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

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