

High-Resolution Stress Detection in Crops: Integrating Satellite and Drone Remote Sensing for Resilient Agriculture

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Abstract

Satellite and drone-based remote sensing technologies are transforming how we detect plant stress by offering wide-area, non-contact monitoring tools. These systems can identify early signs of drought, heat, salinity, and nutrient stress using vegetation indices like NDVI, NDWI, and red-edge reflectance. In many developing regions, food systems remain vulnerable, yet field-based monitoring continues to be the standard, often too slow and limited to fully capture what is occurring across farms. The review is based on a structured synthesis of peer-reviewed studies and technical reports published between 2007 and 2025, selected through targeted keyword searches across Scopus, Web of Science, and Google Scholar, with emphasis on field-level applications in stress-prone agricultural systems. It examines how remote sensing is currently being applied to track abiotic stress across major crops, using case studies from India, China, Mali, and Sudan. These case studies help illustrate what is effective and where gaps still exist. Notably, NDVI and canopy temperature indices have shown strong correlations with drought severity and crop losses. Key challenges include the lack of stress indices tailored to local crops and soils, a limited connection between detected stress and yield outcomes, and the high costs or technical barriers associated with drone use. The review also outlines specific future research needs, such as how to detect multiple stressors simultaneously, enhance drought detection in drylands, and develop low-cost, accessible remote sensing tools that can assist smallholder farmers. These findings underscore the need for localized, affordable remote sensing solutions to bridge the gap between research and practice.

Keywords: Remote Sensing Technologies, NDVI and Vegetation Indices, Food System Resilience, Drone and Satellite Monitoring, Stress Detection in Crops, Developing Country Agriculture.

Introduction

The frequency, severity, and prevalence of abiotic stresses, including but not limited to drought, heat, salinity, and nutrient deficiency, pose major threats to global food security

(Ecke et al., 2022). These environmental impediments hinder plant growth, diminish crop yields, and destabilize agroecosystems, particularly in regions that are already susceptible to these constraints (Sharma et al., 2025). Therefore, enhancing plant resilience to these stresses is critical for sustaining agricultural productivity and ensuring adaptive capacity in the face of ongoing environmental challenges.

Remote sensing has emerged as a powerful, non-invasive tool for monitoring and assessing plant responses to abiotic stress at multiple spatial and temporal scales (Berger et al., 2022). Unlike traditional ground-based methods, remote sensing offers scalable and repeatable observations that are essential for precision agriculture, crop modeling, and resilience planning (Sharma et al., 2025).

Both satellite-based and drone-based (unmanned aerial vehicle, UAV) platforms have been increasingly deployed for plant stress detection. Satellite systems such as Sentinel-2, Landsat, and MODIS offer large-scale, temporal monitoring (Ecke et al., 2022), while drones equipped with multispectral, hyperspectral, and thermal sensors allow high-resolution imaging at the field level (Sharma et al., 2025). These complementary approaches have revolutionized the mapping, quantification, and interpretation of stress-related traits across diverse cropping systems.

This review synthesizes current knowledge on the use of satellite and drone-based remote sensing for detecting and managing abiotic stress in plants. It highlights key sensing technologies, vegetation indices, and spectral methods used for monitoring drought, heat, salinity, and nutrient-related stress. The paper also examines case studies, identifies technological limitations, and discusses future research priorities for leveraging remote sensing to enhance plant resilience in both research and agricultural practice.

Statement of the Problem

Across numerous farming systems, particularly in areas under climate pressure, crops are facing severe challenges such as drought, heat, inadequate soil nutrients, and salinity stress. These obstacles diminish yield and jeopardize food security. In many instances, stress is only recognized once damage has already occurred. Traditional methods of assessing crop health, such as walking through fields or depending on farmer reports, are slow, costly, and often cover limited areas. Remote sensing tools, like satellite and drone imagery, present a more effective means of monitoring crops over vast regions without causing harm. However, despite their potential, these tools are not yet widely adopted where they are needed most. Many farmers and researchers lack access to reliable data, training, and resources suitable for local conditions. Additionally, various studies are dispersed, and there is no definitive guide on the most effective practices. To advance, there is a pressing need for a thorough review that consolidates key knowledge, identifies gaps, and illustrates how remote sensing can genuinely aid in the early detection of crop stress and support improved decision-making on the farm.

Objectives of the Review

- This review looks into how satellite and drone-based remote sensing is being used to detect abiotic stress in crops and improve resilience.
- It explains the main tools, platforms, and vegetation indices used to monitor drought, heat, salinity, and nutrient-related stress.
- It also presents selected case studies to show how these tools are applied in real farm conditions.
- Beyond just showing what is possible, the review points out where the gaps still lie, especially in terms of local relevance and practical use.
- The aim is to give a clear picture of what has been done, what is missing, and how remote sensing can be better used to support stress detection and crop management going forward.

Materials and Methods

This review was developed through a structured synthesis of peer-reviewed journal articles, technical reports, and field-based case studies focused on the application of satellite and drone-based remote sensing technologies for the detection and management of abiotic stress in crops. Literature was retrieved from major scientific databases including Web of Science, Scopus, PubMed, Google Scholar, and ScienceDirect, covering studies published between 2007 and 2025. A combination of search terms was used to identify relevant sources, including "remote sensing and crop stress," "NDVI and drought," "thermal imaging and agriculture," "UAV and abiotic stress," and "vegetation indices and plant resilience." Boolean operators and truncation techniques were applied to maximize coverage while retaining specificity to the core research questions.

The selection of materials followed a relevance-based screening strategy that prioritized empirical studies examining abiotic stress in crop systems through satellite or UAV platforms. Studies were considered suitable if they presented original data, validated sensing methods, or comparative evaluations of vegetation indices such as NDVI, NDWI, PRI, EVI, and LST, particularly in relation to drought, heat, salinity, or nutrient stress. Emphasis was placed on those involving active crop monitoring or resilience assessment under real-world field conditions, including both large-scale farms and smallholder plots. Publications were excluded if they focused exclusively on biotic stress, forest or land cover classification, or ecosystem monitoring without a clear link to agricultural productivity. Further exclusions applied to opinion pieces, conference abstracts without full texts, or studies lacking methodological clarity.

Each selected article was reviewed in full to extract critical details, including geographic context, crop type, stress condition assessed, platform and sensor used, spatial and temporal resolution, index performance, and validation strategy. Particular attention was paid to the scale of application, with studies ranging from regional satellite monitoring (e.g., Sentinel-2, MODIS, Landsat) to field-scale UAV imaging using thermal, multispectral, or hyperspectral cameras. The goal was to evaluate how each sensing approach contributed to detecting early stress signals, supporting precision agriculture, or improving resilience

outcomes. Studies from arid and semi-arid regions, including India, Sudan, and parts of China and Africa, were prioritized to reflect the contexts where early stress detection is most critical for yield preservation.

To ensure scientific rigor, a quality appraisal framework adapted from agricultural and environmental review protocols was applied. This involved assessing whether the study clearly defined objectives, used appropriate sensing tools and indices, incorporated ground-truthing or field validation, and presented findings relevant to practical crop management. Several high-resolution UAV studies (e.g., Berni et al., 2009; Zhang et al., 2019; Guo et al., 2024) and multi-sensor satellite applications (e.g., Berger et al., 2022; Drusch et al., 2012; Roy et al., 2014) met these criteria and were therefore integrated into the final synthesis.

Case studies were also included to highlight how remote sensing tools are already being used in real farm settings. Examples from wheat and maize systems in India and China, drought monitoring in sorghum-producing regions of Sudan, and salinity mapping in the Netherlands were selected to provide geographical and methodological diversity. These cases not only illustrate the potential of remote sensing in stress-prone environments but also serve to ground the review in application-focused outcomes. By combining insights from both satellite and drone platforms across varying resolutions and crop types, this review aims to provide a consolidated view of the current state of remote sensing for abiotic stress detection in agriculture, while identifying methodological gaps and areas where further research is needed to support resilience in climate-affected farming systems. To enhance transparency, a PRISMA-style flow diagram (Figure 1) was developed to summarize the screening and selection process. A total of 83 studies were initially retrieved from five databases. After removing duplicates and screening titles and abstracts for relevance to abiotic stress detection in crops, 63 full-text articles were assessed in detail. Of these, 55 studies met all inclusion criteria and were incorporated into the final synthesis. Exclusion reasons included methodological ambiguity, lack of ground-truthing, or insufficient focus on validated remote sensing tools.

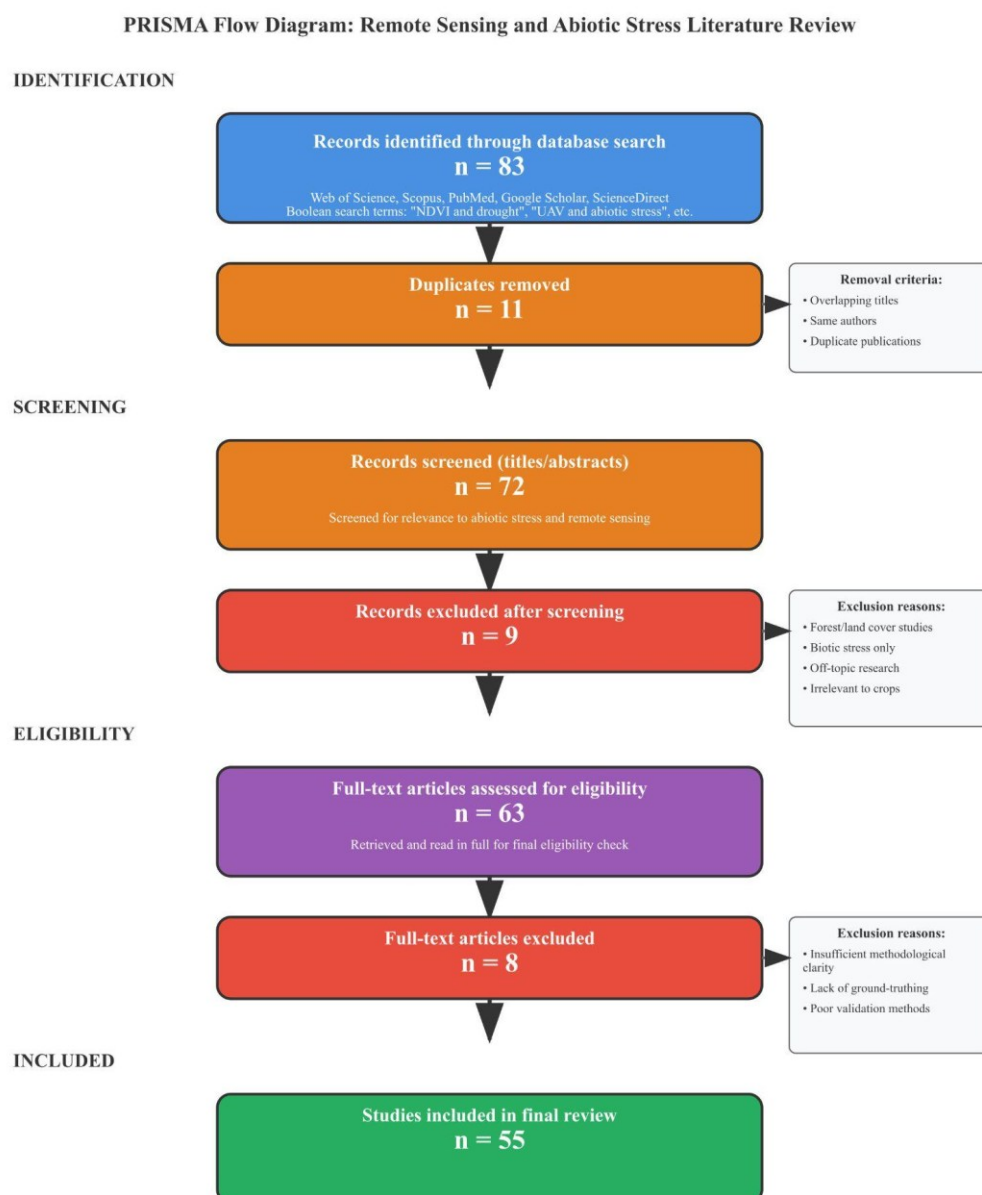


Figure 1 presents the PRISMA flow diagram detailing the systematic review methodology
Source: Adapted from Page et al. (2021).

Discussion

Remote Sensing Technologies

Satellite-Based Remote Sensing

Satellite-based remote sensing entails the gathering of electromagnetic data of the surface of the Earth through sensors that are placed on orbiting platforms around the Earth. This technology facilitates consistent, large-scale monitoring of vegetation condition and stress responses across broad geographic regions (Thenkabail, 2016). It has also become a major instrument of agricultural research and environmental monitoring, especially when it comes to detecting and measuring the abiotic stress of crops (Berger et al., 2022).

Well-known satellite platforms are the MODIS (Moderate Resolution Imaging Spectroradiometer), Sentinel-2, Landsat 8 and 9, and PlanetScope. MODIS has characteristics such as a moderate-spatial-resolution global map, meaning that it covers the globe nearly daily and has a spatial resolution of between 250 and 1000 meters. It is therefore appropriate to monitor the health of the vegetation at regional and continental levels (Hemati et al., 2021). Sentinel-2 offers higher spatial resolution (10–60 meters) and includes red-edge and short-wave infrared bands that are highly responsive to plant stress indicators (Drusch et al., 2012). The Landsat satellites give multi-spectral and thermal information on a long-term record, which has a 30-meter resolution and is retrieved once in 16 days, enabling historical stress trends (Roy et al., 2014). Its high-resolution imagery (about 3-5 meters), revisited frequently (up to several times an hour), provided by a commercial constellation of CubeSats named PlanetScope, will allow detailed monitoring of crop phenology and local stress situations (McCabe et al., 2017).

The key strength of satellite remote sensing is in the direct information being produced as they generate repeat and synoptic coverage of wide areas, which is critical in their role in determining stress trends, modelling crop responses, and making management decisions (Zipper et al., 2016). Satellite data also support the calculation of vegetation indices such as NDVI, NDWI, and LST, which are widely used for diagnosing drought, heat, and salinity stress (Delegido et al., 2013).

However, limitations include the relatively coarse resolution of many public satellites, which may not capture fine-scale variability within smallholder or fragmented fields (Delaney et al., 2025). Additionally, passive optical sensors are susceptible to cloud cover, atmospheric interference, and illumination issues, which can reduce data availability during critical growth stages (Zhang et al., 2023). For accurate interpretation, satellite-based stress detection often requires ground validation and, in some cases, complementary data from higher-resolution sources such as drones (Zarco-Tejada et al., 2012).

Drone-Based Remote Sensing (UAVs)

Drones or Unmanned Aerial Vehicles (UAVs) are a useful instrument in stress monitoring on plants since they have the capability of delivering site-specific information with a very high resolution (Guo et al., 2024). UAVs can fly low and have many different sensors, such as RGB (visible light), multispectral, hyperspectral, thermal infrared, LiDAR (Light Detection and Ranging) (Zhao et al., 2024). The sensors provide the possibility to accurately estimate the canopy structure, chlorophyll concentration, surface temperature, and elevation, which are all significant factors in monitoring early symptoms of abiotic stress (Al-Najadi et al., 2025).

The most prominent benefit of remote sensing with UAVs is that it provides an ultra-high spatial resolution of the measurement, which is usually between 2 and 10 cm, allowing accurate mapping of stress distribution down to individual fields (Berni et al., 2009). UAVs can also be eminently one-off in design: they can be allowed to fly when needed, according to a particular growth period, even suited to different crops and terrain. This renders them

particularly valuable to research studies, phenotyping platforms, and precision agriculture applications where they need to control the time and specifically focus their local knowledge (Berni et al., 2009).

Also, the cost of UAV systems is comparatively affordable in individual or preliminary studies, and they require minimal infrastructure with minimal logistical constraints than satellite tasking or manned aircraft surveys. Their modular design allows having multiple sensors on a flight simultaneously and acquiring data on different wavelengths (Jang et al., 2020).

Nevertheless, there are several operational limitations on UAV-based remote sensing. They have short battery life and flight endurance, and usually the coverage per flight is small to medium-sized fields. Deployment may also be limited by regulatory structures that limit access to airspace, particularly around cities or other sensitive sites. In addition, high-resolution UAV imagery is computationally demanding and one that needs special technical skills to process its data, especially hyperspectral or LiDAR data (Krause & Sanders, 2023). Because of this, UAV systems are generally applied complementary to satellite-based systems, that is, they serve as a validation of the ground truth (from the ground) or as high-resolution checks, where necessary.

Table 1: Comparison of Satellite-Based and Drone-Based Remote Sensing for Plant Stress Monitoring

Feature	Satellite	Drone (UAV)
Coverage	Global to regional	Local (field-level)
Spatial Resolution	Medium to coarse (10–1000 m)	High to ultra-high (2–10 cm)
Temporal Frequency	Frequent (e.g., MODIS daily, Sentinel-2 every 5 days)	On-demand (user-controlled flight)
Common Sensors	MODIS, Landsat, Sentinel-2, PlanetScope	RGB, multispectral, thermal, LiDAR
Limitations	Affected by cloud cover, limited spatial detail	Short flight duration, regulatory constraints

The comparison outlined in Table 1 summarizes the distinct strengths and limitations of satellite- and drone-based platforms. To further illustrate this contrast, Figure 2 presents a spatial resolution comparison between Sentinel-2 satellite imagery and UAV-derived data from vineyard parcels in the Piedmont region of Italy (Khaliq et al., 2019). While the satellite imagery provides valuable broad-scale coverage, it lacks the spatial detail needed to capture within-field variability. In contrast, the UAV imagery distinctly highlights fine-scale differences in canopy vigor and parcel boundaries. This visual comparison reinforces the complementary nature of the two platforms: satellites are optimal for consistent, large-area monitoring, whereas drones offer the ultra-high resolution necessary for localized stress detection and precision agriculture.

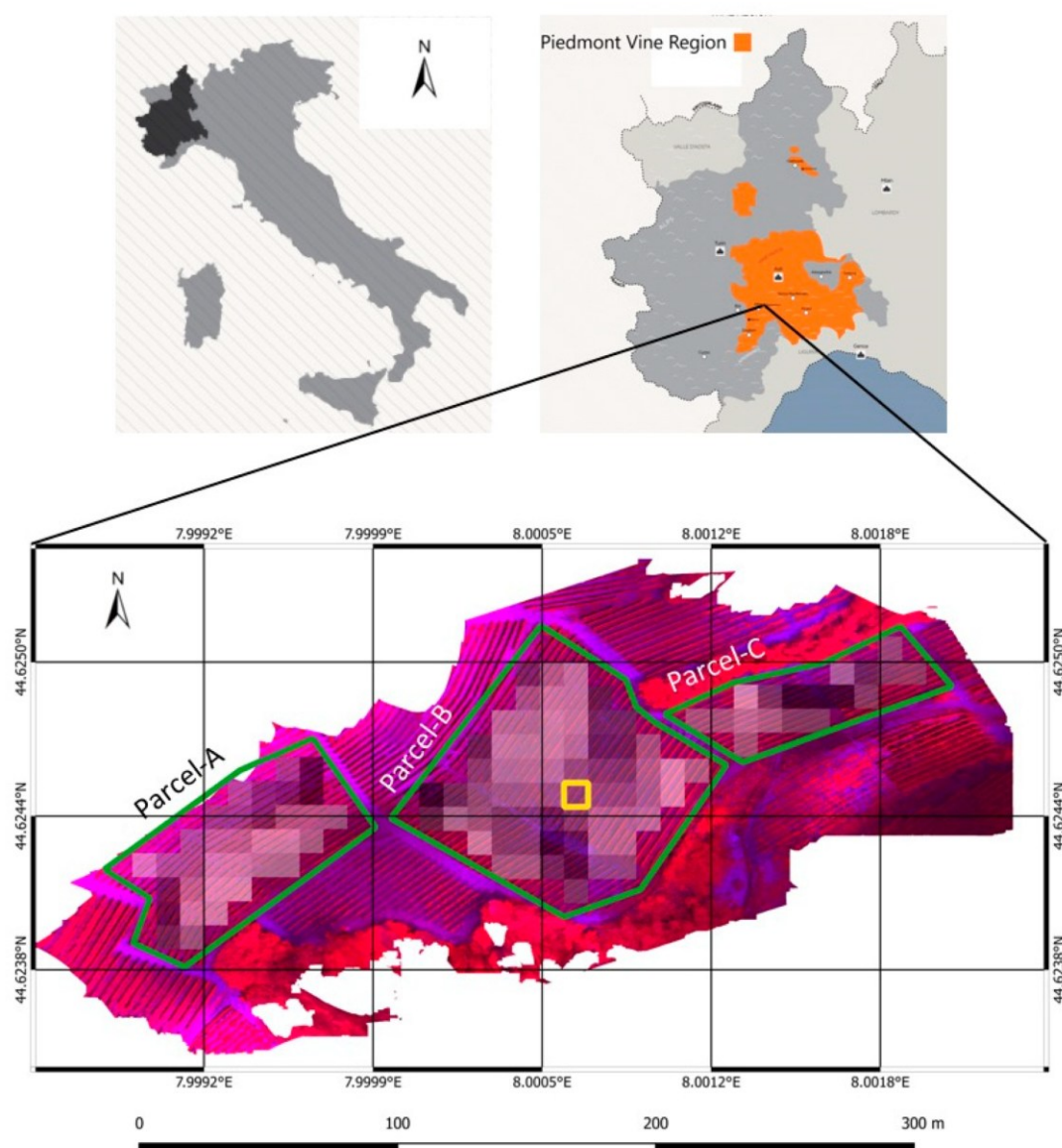


Figure 2. Spatial resolution comparison between Sentinel-2 satellite imagery and UAV-derived data in vineyard parcels of the Piedmont region, Italy.

Adapted from Khaliq et al. (2019).

Spectral and Thermal Indices for Stress Detection

Remote sensing spectral and thermal indices have turned out to be invaluable in the diagnosis of abiotic stress on plants. These indices take advantage of specific reflectance traits of vegetation to measure stress-related elements of canopy water status, chlorophyll content, and canopy temperature. The satellite- and UAV-based platforms foster the retrieval of these indices, allowing the detection of stress on diverse spatial and temporal scales.

NDVI (Normalized Difference Vegetation Index) is one of the most widely used indices, calculated using near-infrared (NIR) and red wavelengths. NDVI effectively captures

chlorophyll content and photosynthetic activity, making it a reliable proxy for overall plant vigor. In conditions of drought or nutrient stress, the decrease in NDVI usually shows canopy reductions or senescence (Wang et al., 2016).

NDWI (Normalized Difference Water Index), derived from NIR and shortwave infrared (SWIR) bands, is used to estimate vegetation water content. A declining NDWI indicates reduced plant water availability or turgor loss, which is particularly important for early drought detection (Das et al., 2023). Recent UAV applications, including mapping crop water stress with thermal and multispectral aircraft systems, validate their usefulness (Dong et al., 2024).

EVI (Enhanced Vegetation Index) improves sensitivity in high biomass regions by incorporating blue reflectance and correction for atmospheric and canopy background noise. It is more responsive than NDVI under dense canopy conditions and can reveal subtle stress signals masked in NDVI data (Matsushita et al., 2007).

PRI (Photochemical Reflectance Index) is sensitive to changes in xanthophyll pigment activity and reflects the efficiency of light use in photosynthesis. It provides insights into short-term physiological responses to environmental stress, particularly heat and light stress (Yang et al., 2020).

LST (Land Surface Temperature), derived from thermal infrared bands, is a key thermal indicator of plant stress. Elevated canopy temperature, especially under low soil moisture conditions, reflects stomatal closure and reduced transpiration, signaling drought or heat stress (Neinavaz et al., 2021).

UAV-based thermal imaging enhances stress detection by capturing canopy temperature variations with high spatial fidelity. For example, strategies for estimating crop water stress (via CWSI) from UAV platforms have recently evolved to include daily-scale continuous monitoring using multispectral-thermal fusion (Sharma et al., 2025) and sophisticated UAV field systems (Ariante & Core, 2025).

These indices have been applied across a range of crop-stress scenarios. In walnut orchards, high-resolution UAV-based NDVI and LST successfully mapped water stress gradients (Sharma et al., 2025). This aligns with recent pilot work in Athens, Georgia, where UAV-based thermal imaging was used to monitor urban surface temperatures with sub-meter resolution, highlighting the potential of drone thermal sensing beyond agriculture and emphasizing the importance of sensor calibration and altitude considerations for accurate interpretation (Henn & Peduzzi, 2024).

Table 2: Key Vegetation Indices Used in Remote Sensing for Abiotic Stress Detection

Index	Full Name	Primary Purpose	Sensor Requirement	Targeted Stress Type(s)
NDVI	Normalized Difference Vegetation Index	Assesses vegetation greenness and vigor	Multispectral (Red & NIR)	Drought, salinity, and general vegetation stress
NDWI	Normalized Difference Water Index	Estimate vegetation water content	Multispectral (NIR & SWIR)	Drought, water deficiency
LST	Land Surface Temperature	Detects canopy temperature anomalies	Thermal infrared	Heat stress
PRI	Photochemical Reflectance Index	Evaluates photosynthetic efficiency and light-use dynamics	Hyperspectral or narrowband multispectral	Nutrient stress, heat stress
EVI	Enhanced Vegetation Index	Improves the vegetation signal in dense canopies	Multispectral (Blue, Red, NIR)	General stress, canopy structure changes

Remote Sensing Applications in Abiotic Stress Detection

Drought Stress

Drought stress is one of the most extensively studied abiotic stressors in remote sensing, owing to its wide-reaching effects on plant productivity, water use efficiency, and ecosystem function (Chaiyana et al., 2024). Remote sensing technologies have proven particularly effective in detecting drought-induced physiological changes through spectral, thermal, and structural signals at multiple scales (Brewer, 2012).

Indicators of canopy reflectance and emissivity can be used to infer the soil moisture availability, which is a significant data point in the meteorology of drought. Normalized Difference Vegetation Index (NDVI), Land Surface Temperature (LST), and Normalized Difference Water Index (NDWI) are the multispectral and thermal indices most often used to estimate vegetation water status (Zarco-Tejada et al., 2012). Due to the fine resolution of the spatially variable data, high-resolution drone-based imagery supplements the capability of detecting within-field water deficiencies to alleviate this issue (Guo et al., 2024).

The Vegetation Health Index (VHI) or the Crop Water Stress Index (CWSI) are some examples of satellite-derived drought measures, which combine thermal and vegetative indicators to measure the degree of drought (Karnieli et al., 2010). The indices will be especially relevant in regional monitoring with platforms that can provide the temporal construction required to monitor stress development during the growing season (Zipper et al., 2016).

Time-series analysis of vegetation indices allows for early detection and forecasting of drought conditions by capturing temporal deviations from phenological baselines (Vicente-Serrano et al., 2010). UAV-derived NDVI and thermal metrics have proven effective in

tracking moisture stress dynamics across arid agricultural zones, supporting timely irrigation decisions and yield risk mitigation (Zhao et al., 2024).

In remote sensing, the presence of drought stress can be assessed spatially and temporally resolved by assessing vegetation condition, to provide a scalable alternative to in situ measurements. Once calibrated using ground-truth data, these methods increase both the accuracy and responsiveness of drought monitoring systems in research and practical agriculture (Li et al., 2024).

Heat Stress

Heat stress significantly disrupts plant physiological processes, particularly during flowering and grain-filling stages, leading to reduced yield and impaired reproductive success (Barnabás et al., 2008). Remote sensing enables the early detection and quantification of heat-induced stress through thermal and spectral measurements, especially via canopy temperature monitoring (Jones et al., 2009).

Thermal infrared (TIR) data are central to heat stress detection. Elevated canopy temperature, typically measured as Land Surface Temperature (LST), indicates reduced transpiration due to stomatal closure, an early physiological response to excessive heat (Agarwal et al., 2025). When soil moisture is sufficient, plants transpire actively to cool their leaves. However, under heat stress, reduced stomatal conductance limits evaporative cooling, resulting in canopy warming that can be captured by thermal sensors (Jones, 2002). Unmanned aerial vehicles (UAVs) equipped with thermal cameras offer a high-resolution, site-specific method for monitoring these temperature changes. Their ability to capture spatial variability in canopy temperature at critical growth stages enables precise assessment of heat sensitivity across genotypes or field plots (Zhang et al., 2019). This has made UAVs particularly valuable for heat tolerance phenotyping in breeding programs (Al-Najadi et al., 2025).

By providing rapid, non-invasive measurements of thermal responses under field conditions, UAV-based platforms support the identification of heat-resilient cultivars and inform targeted management interventions. When integrated with spectral data and ground observations, thermal remote sensing offers a powerful tool for characterizing plant responses to extreme temperatures across diverse cropping systems (Katrina Ariel Henn & Peduzzi, 2024).

Salinity and Nutrient Stress

Salinity and nutrient imbalances drastically affect the metabolism of the plants. This results in chlorosis, stunted growth, and low yield. The application of these stressors employs specific spectral alterations, which could be identified/resolved through the remote-sensing platforms. Salinization normally results in the change of surface reflectance patterns as the reflectances in visible and near-infrared bands increase with the increase in the number of salts (Nawar et al., 2014). Such variations are often recorded through multispectral imagery, which allows early diagnosis of saline patches in a field (Jones et al., 2024).

Due to nutrient deficiency, especially nitrogen and phosphorus, chlorophyll production and leaf arrangement are impacted. It leads to decreased red and blue absorption and a change in vegetation index response, especially NDVI and PRI (Al-Najadi et al., 2025). UAV-mounted multispectral sensors are effective for detecting these physiological changes at high resolution. Chlorophyll-related indices can help distinguish between nutrient-stressed and healthy plants, especially during critical growth stages (Yu et al., 2024).

Remote sensing tools also facilitate spatial mapping of affected zones, supporting targeted fertilization or remediation strategies. This site-specific insight is particularly valuable in precision agriculture, allowing resource optimization and minimizing environmental impacts from over-application of inputs (Zhao et al., 2024). A practical example of remote sensing-based abiotic stress mapping is illustrated in Figure 3. The bivariate maps generated for the Netherlands demonstrate how satellite-derived data can be used to assess the spatial overlap of drought and salinity stress across agricultural landscapes. Such visualizations support site-specific decision-making by identifying high-risk areas and guiding adaptive management strategies.

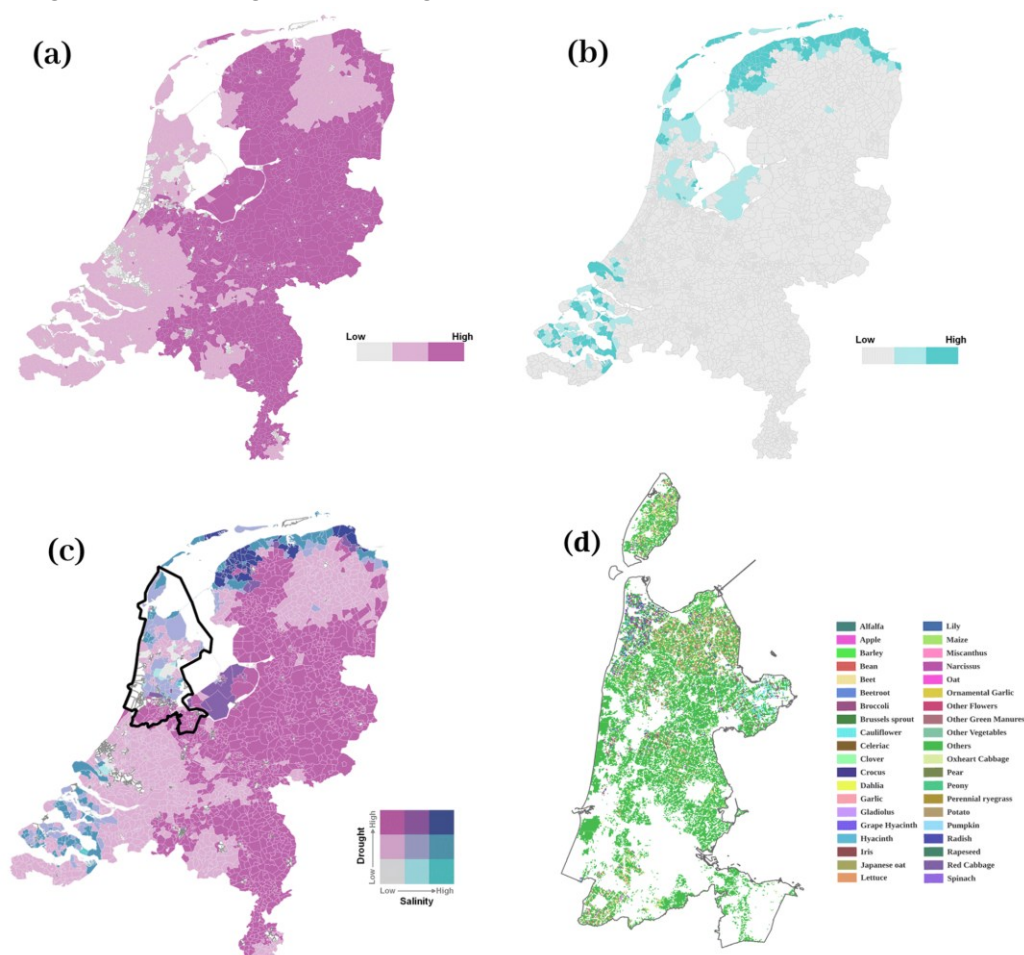


Figure 3. Mapping of abiotic stress factors using remote sensing in the Netherlands: (a) salinity distribution, (b) drought hazard, (c) bivariate map of salinity and drought co-occurrence, and (d) crop type distribution overlay.

Source: Adapted from Wen et al. (2022).

To address the contextual effectiveness of remote sensing tools across various crop-stress scenarios, Table 3 summarizes optimal combinations of platforms, sensors, and stress targets, with an emphasis on field validation and relevance to both advanced and resource-limited settings.

Table 3. Remote Sensing Applications in Abiotic Stress Detection Across Crop Types

Crop	Stress Type	Platform	Sensor / Index	Key Insight	Reference
Wheat	Drought	Sentinel-2	NDVI, NDWI	NDVI consistently tracks within-field drought and yield variability	Marino, 2022
Maize	Heat	UAV (Drone)	Thermal (Land Surface Temp.)	Canopy temperature mapping validated for heat/drought stress	Zhang et al., 2019
Tomato	Salinity	UAV (Drone)	Multispectral (PRI, NDVI)	The PRI-based index accurately detected early salinity-induced chlorophyll changes	Tang et al., 2023
Rice	Nitrogen Deficiency	UAV (Drone)	Multispectral (CI_red-edge)	Differentiated N-deficient from well-fertilized plots	Carracelas et al., 2024
Potato	Drought	UAV	Multispectral	Yield prediction improved significantly when combining UAV-derived vegetation indices at the tuber initiation stage with cultivar data using machine learning	Li et al., 2021
Grapevine	Water Stress	UAV vs Sentinel-2	NDVI, canopy structure	UAV imagery revealed fine-scale canopy variation missed in satellite data	Khaliq et al., 2019
Soybean	Drought	UAV	Multispectral (Red-edge, NIR, SWIR)	Early detection of canopy wilting and pre-visual drought stress symptoms using high-throughput phenotyping	Jones et al., 2024

The Role of Remote Sensing in Plant Resilience

Remote sensing supports plant resilience by providing timely, spatially explicit information that guides agricultural decision-making (Sishodia et al., 2020). Its value lies in translating stress observations into actions that reduce losses and maintain productivity under environmental constraints (Lausch et al., 2017).

In crop management, remote sensing enables targeted irrigation and fertilization. Field-level variability in water and nutrient demand can be identified early, allowing interventions to be applied precisely (Sishodia et al., 2020). This reduces input waste and improves plant recovery during stress periods. This sequence, from data acquisition to outcome, can be visualized in Figure 4, which provides a conceptual workflow outlining how remote sensing information is processed and applied. The figure captures the transformation of raw satellite and UAV data into calculated indices, followed by stress classification, management intervention, and resilience outcomes. It highlights the multi-stage value chain by which remote sensing supports both precision decisions and long-term adaptability.

Early warning systems built on remote sensing detect anomalies before visible symptoms appear (Satapathy et al., 2024). These alerts support prompt responses, especially in drought- or salinity-prone regions, where delayed action can lead to irreversible damage. In plant breeding, remote sensing data assist in identifying stress-tolerant genotypes. High-throughput field assessment using spatial and temporal metrics enables consistent

evaluation across large populations and environments (Jones et al., 2024; Carracelas et al., 2024).

At broader scales, remote sensing informs regional risk mapping and planning. It enables identification of vulnerable zones, monitoring of environmental trends, and supports resilience strategies through evidence-based allocation of resources.

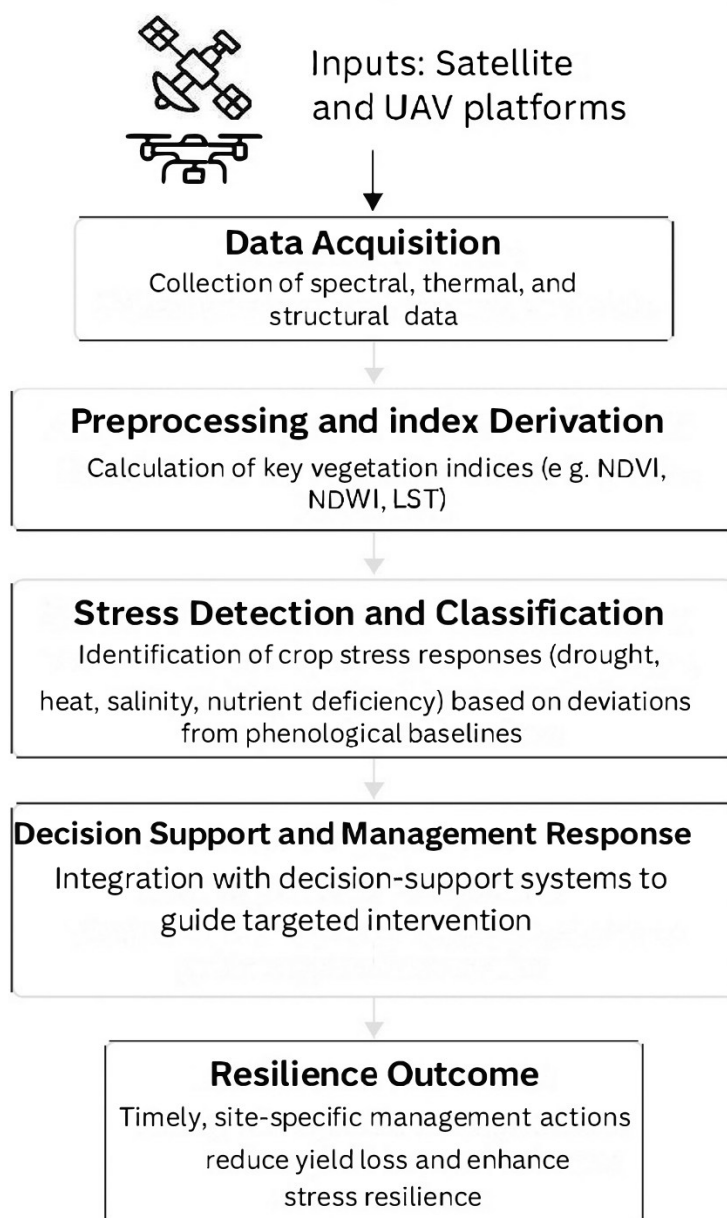


Figure 4. Conceptual Workflow for Enhancing Plant Resilience Using Remote Sensing

Case Studies

Remote sensing has become an important tool in agriculture, especially in regions where access to consistent ground-based data is limited. In many parts of the world, including India, China, and across Africa, farmers and researchers are using satellite and drone

technologies to monitor plant health, manage drought risks, and improve crop yields. These examples show how such tools are making a real impact under field conditions.

Table 4. Case Studies on Remote Sensing Applications for Abiotic Stress Monitoring

Location	Crop	Stress Type	Platform	Sensor / Index Used	Key Outcome
India	Wheat	Drought	Satellite	NDVI, NDWI, NDDI (Landsat-8)	Detected seasonal stress differences and enabled early drought assessment.
China	Maize & Wheat	Heat & Water	UAV (Drone)	Thermal imaging, canopy temperature	Enabled early identification of heat-stressed plots for rapid response.
Sudan	Sorghum	Drought	Satellite	DSI (TRMM, MODIS)	Mapped long-term drought severity and linked it to yield trends.

These case studies demonstrate how remote sensing technologies offer scalable, location-specific solutions to abiotic stress detection, especially in developing-country settings where traditional monitoring methods are limited. Success factors include the ability to deliver early stress indicators, enhance decision-making, and overcome data infrastructure gaps through satellite and UAV-based monitoring. The technologies are especially impactful in regions with limited infrastructure and low ground data availability. Satellite and UAV data provide timely, spatially explicit information through dashboards or direct alerts, supporting better planning and yield protection. However, challenges such as cost, regulatory constraints, data processing complexity, and sensor access must be addressed for broader adoption, particularly in resource-limited settings.

Limitations of the Review

This review was limited to English-language, peer-reviewed sources. As such, it may not fully capture emerging findings from grey literature, non-indexed regional reports, or research published in other languages, particularly from low-resource settings. These omissions may introduce bias and limit the global generalizability of conclusions.

Future Research Directions

Future research needs to address certain gaps that still hinder adoption and accuracy.

Identifying More Than One Stress at Once

In most farms across developing regions, crops often face more than one challenge at the same time, including drought, heat, nutrient deficiency, or even salinity. But current models tend to focus on just one issue. There is a real need for systems that can detect and separate multiple stress signals so farmers and researchers get the full picture.

Adjusting Vegetation Indices for Local Conditions

Most stress-detection indices were built using data from outside Africa or Asia. But crops, soils, and weather conditions in these regions are different. Remote sensing tools must be tested and adjusted to work well with local crops like cassava, sorghum, yam, or tomato.

Connecting Stress to Likely Yield Loss

It is not enough to say a crop is under stress; what farmers need is an idea of how bad it is and how much harvest might be lost. Future work should focus on models that link remote stress readings to expected yield outcomes, so timely and cost-effective interventions can be made.

Building Better Tools for Drylands

Dryland areas like northern Nigeria, parts of East Africa, or the Sahel have unique conditions, less vegetation, more exposed soil, and short rainy seasons. Many remote sensing indices fail in such areas. New drought-monitoring indicators that are tailored to these environments and sensitive enough to pick up early warning signs should be developed.

Making Drone Technology More Accessible

Drones provide very accurate field-level data, but the high cost and technical know-how involved often keep them out of reach. Research should focus on cheaper hardware, simpler processing software, and ways extension workers can use these tools directly without needing advanced training.

Monitoring What Happens After Stress

Most systems stop after identifying a stress event. But what happens next? Some crops bounce back, others do not. We need better ways to track how crops recover after drought, flooding, or heat, so farmers know if their rescue efforts, such as watering, fertilizing, and pruning, are paying off or not. These priorities can be broadly grouped into two categories: technological improvements, including better multi-stress detection, local calibration of indices, and development of dryland-specific indicators; and accessibility and usability challenges, such as the high cost of drones, lack of local capacity, and the need to connect stress signals to actionable yield predictions.

Conclusion

Remote sensing has shown real potential in helping researchers and farmers detect crop stress early and understand how different environmental conditions affect yield. Across studies in India, China, and parts of Africa, tools like NDVI, thermal imaging, and deep learning models have been used to monitor drought, nutrient stress, and water shortage. These methods have proven useful not just for identifying when crops are under pressure, but also for linking those stress signals to eventual yield loss.

This review highlights clear strengths in the use of satellite and UAV-based technologies, particularly in their ability to provide timely, spatially rich data that enhances decision-making. However, major challenges remain. Most studies are still concentrated on large-scale farms or test plots in better-resourced regions. In many developing areas, fields are smaller, stress factors are combined, and farmers lack access to the tools, training, or infrastructure needed to act on remote sensing insights.

Closing this gap requires more than just better technology. It demands locally led, context-specific innovation. Research must increasingly focus on dryland and mixed-farming systems, on lowering costs, simplifying usage, and ensuring that tools are designed with the realities of smallholder farmers in mind. This is where the real future of crop stress monitoring lies, not only in higher resolution or more complex models, but in making sure those models work in the environments where resilience is needed most.

Recommendations

Remote sensing tools should be redesigned to reflect field realities in underdeveloped regions, where internet access, infrastructure, and technical capacity are limited. Effective systems must function offline, update automatically when reconnected, and communicate insights through SMS, radio, or lightweight mobile apps in local languages. Vegetation indices must be tailored to local crops and intercropping systems. Models based on maize or wheat often fail when applied to crops like cassava, cowpea, or sorghum grown under different conditions. Open-access calibration datasets built on locally grown varieties are essential. Detection alone is not enough. Farmers need tools that offer clear guidance, whether the stress is reversible, what action is needed, and how severe the impact might be. Converting complex data into simple, decision-ready outputs improves usefulness in the field. All tools should be co-designed with local farmers, extension agents, and agronomists. Validation must happen during development, not after. Delivering outputs in formats that align with users' contexts, such as audio summaries, printed visuals, and local language alerts, ensures uptake and practical value.

For broader implementation, cost-effective drone integration should focus on cooperative ownership, community-level training, and plug-and-play technology. Simplified apps and open-source platforms can make aerial monitoring feasible beyond research pilots. In addition, monitoring efforts must include structured follow-up to capture crop recovery or continued stress. Without timely feedback, opportunities for effective intervention are often lost.

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