PLANT SCIENCE TODAY
Vol 12(sp1): 01–12
https://doi.org/10.14719/pst.9861

eISSN 2348-1900

REVIEW ARTICLE

Advances in assessing the impact of agricultural disasters through remote sensing applications

Shanmugam N[1*], Pazhanivelan S[2], Muthumanikam D[1], Tarun Kshatriya T[3], Raju M[4], Selvakumar S[2] & Aruneshwaran A[1]

[1]Department of Remote Sensing & Geographic Information System, Tamil Nadu Agricultural University, Coimbatore 641 003, Tamil Nadu, India
[2]Centre for Water and Geospatial Studies, Tamil Nadu Agricultural University, Coimbatore 641 003, Tamil Nadu, India
[3]Department of Soil Science & Agricultural Chemistry, Tamil Nadu Agricultural University, Coimbatore 641 003, Tamil Nadu, India
[4]Department of Agronomy, Tamil Nadu Agricultural University, Coimbatore 641 003, Tamil Nadu, India

*Correspondence email - shanmugam.npsk@gmail.com

Received: 07 May 2025; Accepted: 30 July 2025; Available online: Version 1.0: 27 August 2025; Version 2.0: 29 September 2025

Cite this article: Shanmugam N, Pazhanivelan S, Muthumanikam D, Tarun Kshatriya T, Raju M, Selvakumar S, Aruneshwaran A. Advances in assessing the impact of agricultural disasters through remote sensing applications. Plant Science Today. 2025;12(sp1):01–12. https:/doi.org/10.14719/pst.9861

Abstract

Remote Sensing (RS) technology, which harnesses electromagnetic radiation, has changed agricultural disaster management. By identifying spectral signatures generated various objects on the Earth's surface, it enables effective monitoring of crop health, soil conditions and environmental changes. RS linked with Geographic Information Systems (GIS), prioritizes response actions, anticipates damaged areas and simulates disaster scenarios, revolutionizing disaster management approaches. Integration with modern analytics, such as machine learning, enhances catastrophe impact assessments, agricultural production estimations and land cover classification, thereby boosting disaster preparedness and response. Recent innovations, such as Unmanned Aerial Vehicles (UAVs) and high-resolution satellite imaging systems, offer rapid mapping of flooded areas and accurate post-disaster damage assessment. The merging of remote sensing with artificial intelligence (AI) and big data analytics further enhances disaster response and management, lowering the dangers associated with socio-ecological vulnerability. However, obstacles remain, including the need to boost sensor capabilities, improve data delivery and address regulatory issues with UAVs. Future directions include combining hazard and disaster process models, developing user-centric solutions and utilizing IoT and big data for more accurate disaster prediction and mitigation. Overall, RS and GIS offer vital tools for mitigating agricultural disasters, delivering early information for decision-making and decreasing the impact on food security and agricultural output.

Keywords: agriculture disasters; drought assessment; flood assessment; remote sensing; UAV

Introduction

The agricultural sector is the most vulnerable to the impacts of climate change and natural disasters. Agricultural disasters, including droughts, floods and storms, have a major effect on food security, economic stability and rural life (1). The utilization of geospatial information and technology, such as RS and GIS, is increasingly adopted a means to enhance agricultural disaster response. This is mostly owing to the recent breakthroughs in spatial resolution, accessibility and cost (2).

RS collects data by detecting electromagnetic radiation reflected or emitted from objects, enabling the observation of Earth's surface features without direct contact. Differentiating between items is based on the different electromagnetic radiation wavelengths that interact with various surface materials, including bare earth, water and vegetation (3). Hyperspectral remote sensing, which collects data in small wavebands, is used to understand crop plant features and processes (4). To evaluate these traits and enhance crop management, the vegetation index, which is a set of waveband combinations associated with particular plant properties, is a useful tool (5). With the creation of new sensors and advancements in both spatial and temporal resolution, the application of RS in precision agriculture has made significant progress (6).

Technological developments in RS have greatly enhanced our capacity to track and respond to agricultural disasters. Timely delivery of real-time or near-real-time satellite data such as vegetation indices, thermal imagery and precipitation estimates is essential for effective agricultural monitoring and disaster response (7, 8). The specific applications of RS was outlined in detecting and quantifying agricultural challenges, including nutrient deficiencies and crop diseases (9, 10). These studies collectively underscore the critical role of RS in assessing the impacts of various agricultural disasters such as floods, droughts and cyclones on crop health and productivity.

RS platforms such as satellites and UAVs have significantly advanced the monitoring of agricultural disasters.

These tools play a crucial role in tracking key indicators of impending disasters, including changes in soil moisture, water availability and vegetation health (11, 12). The value of RS in detecting both biological and physical stresses that influence crop yield (9). Similarly, previous works highlighted the potential of microwave remote sensing for identifying drought occurrences throughout the crop growth cycle (13). Together, these studies demonstrate the effectiveness of RS in providing timely and spatially detailed insights critical for agricultural disaster preparedness and response.

Advancements in spectral sensor technologies and data processing methods have significantly enhanced the ability to assess damage resulting from agricultural disasters. Multispectral and hyperspectral sensors are increasingly applied in post-disaster assessments, not only for evaluating building damage but also for detecting and quantifying crop stress and losses. The role of RS in identifying agricultural stresses (9), while early works demonstrated the effectiveness of multitemporal satellite imagery in post-earthquake structural damage assessment methods that are increasingly being adapted for agricultural applications as well (14). These sensors can distinguish between stressed and healthy vegetation by analyzing their data and spectral changes suggestive of damage can be found. The importance of RS and GIS in agricultural disaster response, emphasizing the use of technology and geospatial information to improve data services and lower the risk of disaster (2, 15).

Disaster management techniques have been greatly enhanced by the integration of RS data with GIS (16). This integration enables the prioritization of response activities, prediction of affected areas and simulation of disaster scenarios (17). The speed and efficacy of response operations are further increased by the application of AI in disaster management, including RS and geographic analyses (18). However, for the effective gathering and distribution of spatial data during emergencies, user-friendly, Internet-based GIS systems must be created (19).

Disaster impact assessments in agriculture have greatly improved with the application of AI and machine learning techniques to analyze RS data (20). By predicting crop yields, detecting anomalies and classifying different types of land cover, these technologies improve disaster preparedness and response (21). Additionally, it has been demonstrated that automating the prediction of agricultural yield via the use of machine learning and RS is faster and more effective than conventional techniques (22).

Major agricultural disasters

Drought

RS technology is used to monitor agricultural droughts spatially and temporally to minimize losses. The dominant method is the drought index, which involves the variable land surface temperature (LST), vegetation index, land cover, wetness index and rainfall. Drought mapping using GIS and RS at the district scale provides detailed spatial information on climate and physiographic aspects, but it requires consistent temporal data to accurately track changes over time. This presents challenges due to cloud cover, limited revisit cycles and delays in data processing or delivery, which may hinder timely assessment during fast-evolving disasters (23).

The National Remote Sensing Centre, part of the Indian Space Research Organisation (ISRO), has established a satellite -based initiative for the evaluation of drought conditions, known as the National Agricultural Drought Assessment and Monitoring System (NADAMS) (24). NADAMS data from NOAA, MODIS and resources at 2 satellites were used for rainfall, soil moisture and irrigation crop sowing data to assess periodical drought situations.

Fig. 1 depicts the process of estimating drought or flood consequences based on rainfall data, specifically rainfall deviation (RFDev) and dry period circumstances. If no drought or flood trigger is discovered, a basic evaluation is carried out and the condition is reported as no drought or flood. If a trigger is detected, the method advances to analyzing impact indicators

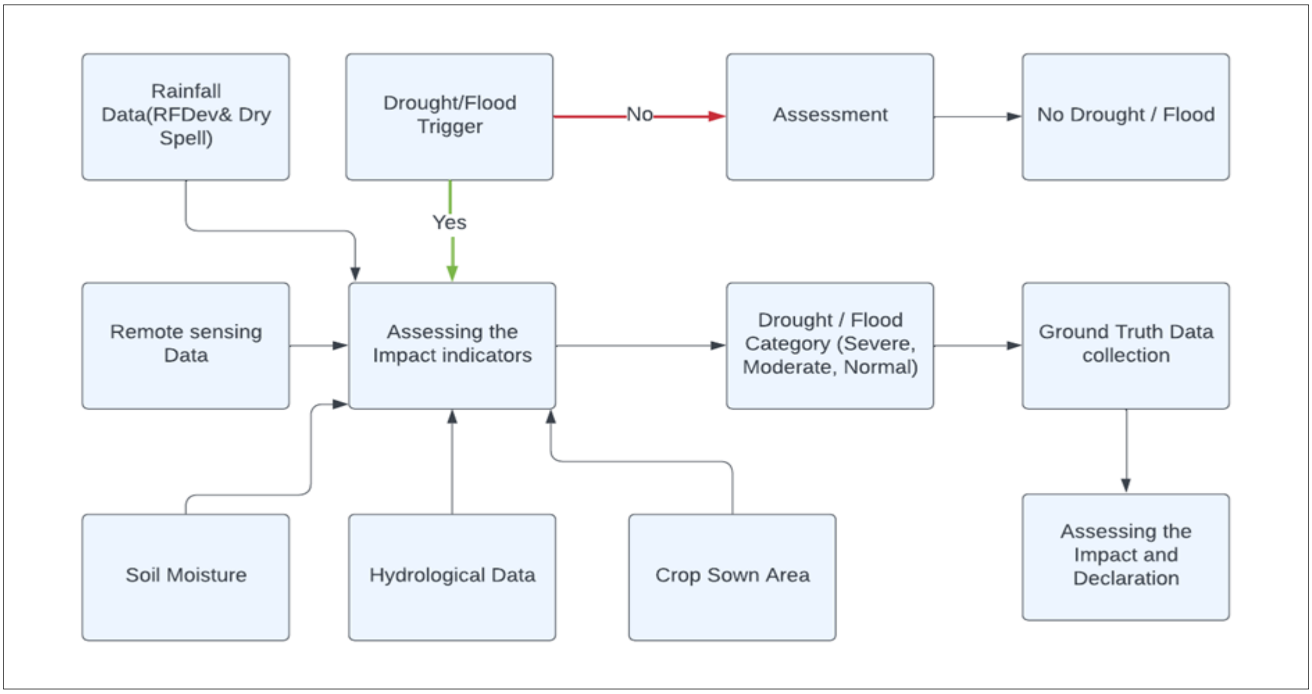

Fig. 1. Flow diagram of procedure of drought assessment as per new drought manual (25).

utilizing RS data, soil moisture, hydrological data and crop planted area. These signs assist characterize the event's intensity as severe, moderate, or normal. Ground truth data is then obtained to validate these determinations on the ground. Based on this verification, the final impact is appraised and an official declaration is produced (25).

Flood

Fig. 2 delineates the temporal sequence of activities associated with flood event management, underscoring the systematic integration of flood inundation models and risk data across four key phases: planning, pre-event, response and recovery. In the initial planning stage, flood risk models and historical datasets are employed to conduct rapid scenario planning, facilitating the development of simulations for flood events of varying magnitudes. This is subsequently augmented by detailed scenario planning, informed by domain experts to enhance the specificity and robustness of preparedness measures. In the lead-up to a potential flood event, the models are continuously refined using real-time forecast data, enabling updated rapid scenario planning that supports anticipatory decision-making. In the event of a flood, these pre-established scenarios guide immediate response strategies. The recovery phase is characterized by the integration of field-based observations to generate event-specific flood extent and damage maps, which are essential for impact assessment and informing future mitigation and adaptation strategies. The figure exemplifies a cyclical and adaptive framework for flood risk management, highlighting the dynamic interplay between predictive modeling, expert knowledge and empirical data in enhancing overall resilience to flood hazards.

Flood impact assessment and response tactics have been transformed by RS, especially high-resolution satellite imagery, Synthetic Aperture Radar (SAR) and LiDAR (26). These technologies allow for the quick mapping of flooded areas, early detection and monitoring of flood extents and accurate elevation mapping, all of which are essential for comprehending the dynamics of floods and potential damage (27). RS data and GIS are combined to create comprehensive flood risk maps and precise damage assessments. This helps with mitigation and recovery efforts (28). In urban sprawl contexts, flood risk management can be further improved through a multitemporal analysis of multispectral satellite imagery (29).

Cyclone

RS technologies, including satellite imagery and aerial photography, serve as essential tools for assessing the impacts of cyclones on agricultural landscapes. The value of RS in accurately mapping cyclone-induced changes, particularly highlighting its effectiveness in detecting terrain alterations and evaluating the extent of damage (30). The effectiveness of a multi-scalar technique is that it combines radar and optical RS to quickly estimate the extent of flooding and vegetation damage during cyclones (31).

Cyclones can have devastating impacts on agriculture, causing widespread crop damage, soil erosion and flooding. RS and GIS play an important role in assessing and mitigating the effects of cyclones on agricultural lands. Satellite imagery and aerial photography allow for rapid mapping of cyclone-affected areas, providing timely information on the extent of flooding, wind damage to crops and soil erosion (2). Multispectral and radar sensors can penetrate cloud cover to assess damage even during ongoing storms. Change detection techniques comparing pre- and post-cyclone imagery enable quantification of impacted agricultural areas (32). GIS integration of RS data with other spatial information like topography, land use and infrastructure allows for comprehensive damage assessment and prioritization of response efforts. Flood inundation modeling using digital elevation models and rainfall data helps predict at-risk agricultural zones. Vegetation indices derived from multispectral imagery track crop health and recovery in cyclone-affected regions over time (33).

RS technologies in disaster management

RS technologies have emerged as essential instruments for disaster assessment, providing precise and timely data that are essential for efficient response and mitigation (2). Developments in data processing algorithms and sensor technology have improved our capacity to track, evaluate and respond to a range of man-made and natural disasters (34). With an emphasis on current advancements and uses, this paper explores the functions of optical, microwave, radar, thermal and hyperspectral RS in catastrophe assessments (35).

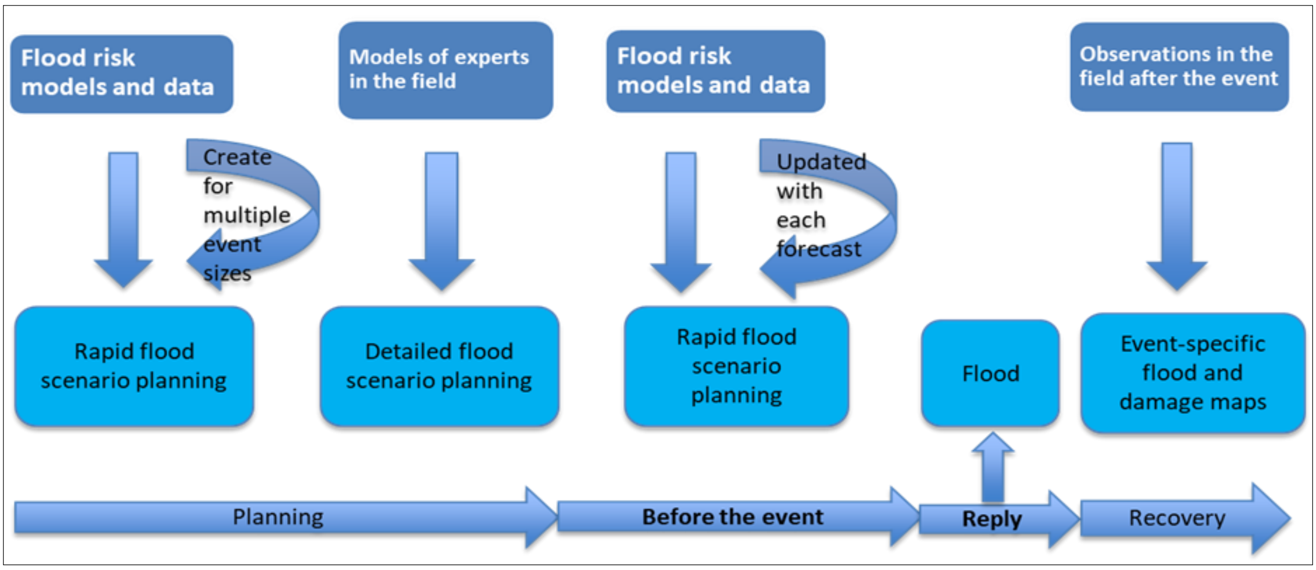

Fig. 2. Chronological framework of a flood event.

For example, SAR delivers high-resolution imagery capable of detecting subtle changes in Earth's surface, making it particularly effective in seismic monitoring. Techniques like InSAR enable the measurement of surface displacement over time, offering valuable insights into tectonic activity and structural damage (36). In flood management, the combined use of optical and microwave sensors enhances the accuracy of flood extent mapping. Optical sensors capture high-resolution images for visual interpretation, while microwave sensors provide all-weather, real-time data, even under cloud cover crucial for predicting and managing flood events (37).

Similarly, RS plays a vital role in landslide detection, especially in regions that are remote or difficult to access. Technologies such as LiDAR, SAR and optical imagery allow for the monitoring of slope stability and the mapping of geological hazards with high spatial accuracy (38). Drought monitoring relies heavily on vegetation indices (e.g., NDVI) and soil moisture data derived from satellite platforms, which can assess crop health and water stress over large areas, thereby aiding early warning systems (39). These applications highlight the versatility RS across different disaster types. Moreover, global collaboration in RS through frameworks like the International Charter on Space and Major Disasters further enhances disaster risk reduction by promoting the sharing of critical satellite data during emergencies (40, 41). Together, these technologies and cooperative efforts demonstrate how RS continues to revolutionize disaster assessment and management across the globe.

Optical RS

Several satellite sensors were used in optical RS satellites such as Landsat, Sentinel-2, SPOT which pick up reflected sunlight in a range of spectral bands, mostly in the visible and near-infrared (NIR) ranges. High-resolution imagery from these sensors is crucial for evaluating damage caused by natural disasters, including floods, landslides and earthquakes (2).

Optical imagery is crucial for landslide detection in post-earthquake situations. For example, one study used Sentinel-2 data to track landslides caused by earthquakes both manually and semi-automatically by examining variations in brightness values and vegetation indices. To find patches of bare earth suggestive of landslides, false-color composites were constructed and indices such as the Normalized Difference Vegetation Index (NDVI) were computed. This method aided hazard assessment and response planning by enabling the rapid creation of landslide inventories (42).

However, optical RS has limitations at night and under cloud cover, which may make it more difficult to collect data in a timely manner during some crisis scenarios. Integrating optical data with other RS modalities has become a standard practice to address these difficulties (2).

Microwave and radar RS

Microwave and radar RS, particularly SAR, offer all-weather, day-and-night imaging capabilities, making them invaluable for disaster assessment. SAR systems emit microwave signals and measure backscattered responses, enabling the detection of surface changes regardless of weather conditions (43). SAR has proven to be effective for flood monitoring. For example, companies such as Umbra utilize SAR data to track flooding events, providing real-time information crucial for emergency response. SAR's ability to penetrate cloud cover and darkness allows for the detection of flood extents, water levels and even distinctions between freshwater and saltwater intrusion. This capability is particularly beneficial in regions that are prone to frequent and severe flooding (44).

Moreover, SAR data can be integrated with optical imagery using advanced algorithms. A study demonstrated the use of a Generative Adversarial Network (GAN)-based model to translate SAR images into optical-like images, facilitating the assessment of wildfire impacts. By generating synthetic optical images from SAR data, researchers can calculate burn-sensitive spectral indices, achieving high accuracy in burned area detection and burn severity mapping (43). InSAR techniques further enhance disaster assessment by measuring the ground deformation. InSAR has been employed to monitor tectonic movements, volcanic activity and land subsidence, providing critical information for early warning systems and infrastructure planning (42).

Thermal RS

Thermal RS detects emitted infrared radiation and captures surface temperature variations that are indicative of various disaster-related phenomena. Thermal sensors are particularly useful for monitoring wildfires, volcanic eruptions and urban heat islands (44). Wildfire assessment and thermal imagery enable the detection of active fire fronts and the mapping of burned areas. The high sensitivity of thermal sensors to temperature differences allows for the identification of hotspots and monitoring of fire progression, even in the presence of smoke. This information is vital for directing firefighting efforts and assessing the post-fire impacts on ecosystems and infrastructure (43).

Thermal RS contributes to volcanic monitoring by detecting thermal anomalies associated with magma movement and eruptions. By analyzing thermal data, scientists can identify changes in volcanic activity, aiding hazard assessment and evacuation planning (35). Furthermore, thermal imagery can be used to assess urban heat islands, which can exacerbate the effects of heatwaves. By mapping the temperature distributions across urban areas, authorities can implement mitigation strategies to reduce heat-related health risks (45).

Hyperspectral imaging

Hyperspectral imaging captures data across numerous contiguous spectral bands, providing detailed spectral information for every pixel in an image. This rich spectral data enables the identification and characterization of materials including urban sediments, glacial tills and mineral substrates, pollutants and also crop types, making hyperspectral imaging a powerful tool for disaster assessment (35). In agricultural disaster response, hyperspectral imaging offers essential capabilities for identifying and assessing human-induced and environmental components influencing crop lands and soil. A unique hyperspectral RS method has been created to aid in monitoring afflicted regions by recognizing components such as soil pollutants, agricultural residue and synthetic inputs like fertilizers or plastics. The solution functions through a bespoke software extension for hyperspectral picture analysis, boosting situational awareness during droughts, floods, or chemical exposure incidents. Although promising, this instrument is still an emerging approach and continued validation is needed for its frequent implementation in agricultural monitoring and emergency response (35).

Hyperspectral imaging also contributes to environmental monitoring by detecting changes in vegetation health, soil properties and water quality. These applications are crucial for assessing the impact of disasters on ecosystems and guiding recovery and restoration efforts (2).

Advances in satellite and UAV RS

Recent developments in satellite and unmanned aerial vehicle, RS have greatly enhanced agricultural disaster monitoring. The potential of UAV RS in precision agriculture is particularly in identifying weed and pathogen infestations, drought stress and evaluating nutrient status and growth vigor (46). The use of satellite RS in disaster management, especially during the preparation and reaction phases is rapid and highly effective to create awareness (47). The importance of multi-scale imaging was highlighted through the fusion of UAV and satellite data, emphasizing its effectiveness for crop monitoring and early stress detection (48). The application of RS was examined in crop protection, focusing on the identification of biological and physical stresses that impact crop productivity (9). Collectively, these findings illustrate how satellite and UAV based RS technologies have transformed the monitoring and management of agricultural disasters.

Disaster management and agricultural monitoring have greatly benefited from satellite RS, especially with the use of multispectral and hyperspectral data. The use of satellite RS in disaster management. It is mainly used for planning mitigation strategies and hazard risk assessment particularly for its ability to cover large areas and cost-effectiveness (47, 49) (Table 1).

The accuracy and speed of disaster assessment and response can be further improved by integrating satellite data with cutting-edge analytical methods, such as machine learning algorithms (47). RS with UAVs has the potential to revolutionize precision agriculture, especially in drought stress, weed and pathogen detection, nutrient status assessment and yield prediction (46). In particular, the use of hyperspectral RS in agricultural management, includes crop yield estimation, insect pest monitoring and plant disease monitoring (50). All these studies highlight the importance of satellite RS for precision agriculture and disaster relief.

UAVs have been used in precision agriculture, disaster domains and agricultural landscapes that support biodiversity (51-53). Their multispectral sensors, thermal imaging capabilities and high-resolution cameras allow them to capture detailed information, which makes it easier to conduct targeted surveys and deploy them quickly in disaster-affected areas (51). The integration of UAV and satellite RS technologies has made agricultural disaster management more accurate, efficient and effective (51). Despite the potential for greater economic and environmental benefits, precision agriculture has not yet fully embraced these technologies (53).

Integrating RS with GIS for disaster assessment

Agricultural disaster assessment and management have greatly advanced as a result of the integration of RS and GIS, which offers a thorough method for comprehending, tracking and responding to a variety of hazards (16, 54-56). Through this integration, stakeholders including farmers, government agencies, disaster response teams, policymakers, insurance providers and researchers can effectively carry out targeted interventions during agricultural disasters. And by combining the strengths of RS technologies, such as drones and satellites, with GIS's spatial analysis capabilities of GIS they make informed decisions. Stakeholders can determine the extent and severity of the impacts of a disaster and prioritize response efforts by identifying vulnerable areas and analyzing spatial patterns (16, 54-56).

The integration of RS and GIS provides comprehensive disaster risk maps, visualizing disaster risk hotspots to monitor and enabling the development of focused mitigation strategies by combining RS data with GIS layers. Additionally, it facilitates early warning systems and real-time monitoring of agricultural disasters, allowing stakeholders to quickly identify changes in crop health and environmental conditions (57). Satellite RS has proven especially useful in agriculture because of its ability to provide information on soil moisture content, environmental conditions and crop health (58). Furthermore, crop identification, classification and yield estimation have been made possible by the integration of RS and GIS in land-use planning and decision support systems (59) (Table 2).

The integration of GIS and RS provides a powerful framework for post-disaster assessment and recovery in agriculture. These technologies enable the collection, analysis and visualization of spatial data, offering critical support in evaluating damage and guiding response efforts. The potential of GIS and RS to deliver near real-time data for effective disaster monitoring, prediction and decision-making in agricultural contexts (8, 60). In particular, for forestry applications, the importance of RS as a primary data source for GIS technologies enable improved mapping, inventory and decision-making processes. The value of GIS and RS in disaster management,

Table 1. Characteristics of UAVs for agricultural RS monitoring.

Category	Benefits	Limitations
Fixed-wing	Long endurance, Large load, Fast flight speed and Large operation range	Takeoff needs run-up Landing needs glide No hovering capability
Multirotor	Fly horizontally and vertically Vertical takeoff and landing Hovering at a given location Autonomous navigation Simple structure	Short endurance time Small load Poor resistance to harsh environment
Unmanned helicopter	Vertical takeoff and landing Hovering at a given location Flight stability	Complex wing structure High maintenance cost

Table 2. Types of RS with satellite products, resolutions and applications in agricultural disaster management

Type	Satellite	Spatial resolution	Spectral bands	Temporal resolution	Application in agricultural disaster management	Product source
Multispectral	Landsat-8/9 (OLI/TIRS)	30 m (VIS-NIR), 15 m (PAN)	11 bands	16 days	Monitoring flood extent, drought stress and land-use change	USGS Earth Explorer
	Sentinel-2A/B	10 m, 20 m, 60 m	13 bands	5 days	Detecting crop damage, mapping flood and cyclone-affected areas	Copernicus Open Access Hub
	MODIS (Terra/Aqua)	250 m - 1 km	36 bands	1-2 days	Large-scale drought monitoring and vegetation stress assessment	NASA LP DAAC
Hyperspectral	PRISMA (Italy)	30 m	239 bands	29 days	Mapping soil contamination, assessing crop biochemical stress due to disasters	ASI (Italian Space Agency)
	Hyperion (EO-1)	30 m	220 bands	16 days	Analyzing crop stress and detecting early signs of disaster impact	NASA Earth Observing System
Panchromatic	WorldView-3	0.31 m	1 band	<1 day	High-resolution assessment of flood damage and structural impact on agriculture	Maxar Technologies
	GeoEye-1	0.41 m	1 band	3 days	Field-scale monitoring post-disaster for recovery planning	Maxar Technologies
Thermal infrared	Landsat-8/9 (TIRS)	100 m (resampled to 30 m)	2 bands	16 days	Estimating evapotranspiration to detect drought and heat stress	USGS Earth Explorer
	MODIS (Terra/Aqua)	1 km	3 bands	1-2 days	Surface temperature monitoring and drought severity analysis	NASA LP DAAC
	ASTER	90 m	5 bands	On-demand	Thermal anomaly detection and water stress mapping	NASA Earth Data
Very high resolution	WorldView-2/3	0.31 m (PAN), 1.24 m (MS)	8 bands	<1 day	Detailed disaster impact analysis and damage estimation	Maxar Technologies
	Pleiades-1A/1B	0.5 m	5 bands	2 days	Change detection and monitoring of cyclone/flood impacts	Airbus Defence and Space

particularly in terms of supporting decision-making (16). Altogether, these studies highlight the importance of incorporating GIS and RS into agricultural disaster assessment and management so that stakeholders can better target aid, improve resilience and optimize response plans.

Vegetation indices analysis

Enhancing agricultural resilience is largely dependent on vegetation indices, such as the NDVI and EVI, which are obtained from RS data (61). These indices allow for the monitoring of important variables and early identification of anomalies by offering insights into the productivity, stress and health of vegetation (62). However, they are susceptible to external influences, such as topographic changes, which may affect their accuracy (63). Despite these difficulties, vegetation indices are widely used in many fields, such as disaster management, sustainable development and climate change studies (64) (Table 3).

Spatial-temporal change detection methods

Spatial-temporal change detection techniques are crucial for understanding how phenomena evolve and space (65). In land cover change analysis, environmental monitoring and disaster management, these techniques, which include pixel-based, object-based and change vector analyses, are frequently employed (65, 66). The accuracy and applicability of these techniques have been further improved by the integration of RS data and GIS (65). Land use and land cover changes can now be detected much more easily owing to recent developments in machine learning, especially when deep learning techniques are applied (67). It is still difficult to choose the best change detection technique and more investigation is required to resolve this problem (65, 68).

Vegetation health monitoring has been greatly enhanced by high-temporal-resolution satellite data. Often utilized for this purpose, MODIS, Sentinel-2 and VIIRS provide regular observations that allow for the near-real-time identification of drought symptoms. While MODIS delivers a clearer temporal evolution of damage, Sentinel-2 provides rich geographical information for monitoring the health of the forest canopy during drought periods (69). These satellites can measure the short-term and long-term effects of drought on forest development, identify vegetation stress stages and calculate forest resilience traits (70).

Integration of multi-source data

Enhancing the efficacy of agricultural applications through RS requires the integration of data from multiple sources (71-74). By enabling the extraction of complementary data, this integration enhances the precision and dependability of the evaluation of agricultural conditions (71). For example, improved calibration and validation of remote sensing products can be achieved by merging field data obtained from ground-based sensors with high-resolution satellite imagery (71). Moreover, the integration of weather data facilitates the comprehension of the impact of environmental factors on crop productivity and health (71). Effective forest management necessitates the utilization of all pertinent data and resources, including ancillary information, field measurements and data from RS (73). An area or phenomenon of interest can be better understood and more thoroughly described through the

Table 3. Common vegetation indices used in agricultural RS

Index	Full form	Formula	Purpose
NDVI	Normalized Difference Vegetation Index	(NIR - Red) / (NIR + Red)	Detects live green vegetation.
RVI	Ratio Vegetation Index	NIR / Red	Highlights vegetation by using a simple ratio between NIR and Red bands.
IPVI	Infrared Percentage Vegetation Index	(NDVI + 1) / 2	Scales NDVI to a 0-1 range for easier interpretation.
SAVI	Soil-Adjusted Vegetation Index	(NIR - Red) / (NIR + Red + L) * (1 + L)	Reduces soil brightness effects for areas with sparse vegetation.
VCI	Vegetation Condition Index	(NDVI - NDVI_min) / (NDVI_max - NDVI_min) * 100	Monitors drought by comparing current NDVI with historical extremes.
VHI	Vegetation Health Index	α * VCI + (1 - α) * TCI	Combines VCI and TCI to assess overall vegetation health.
TCI	Temperature Condition Index	(T_max - T) / (T_max - T_min) * 100	Identifies vegetation stress caused by temperature anomalies.

integration of multi-sensor RS data, such as multispectral optical data and radar imagery (74).

Geospatial analytics for risk modeling

Geospatial analytics is essential for risk modeling in many different fields, especially when combined with sophisticated analytical methods. By examining variables like elevation, land cover and proximity to water bodies, it can simulate flood risks in the context of natural disasters (75). In the field of epidemiology, variables like population density, travel patterns and healthcare infrastructure are taken into account to aid in the modeling of disease transmission. Within the finance industry, geospatial analytics is employed to simulate risks related to market dynamics, insurance claims and property values (75). Additionally, it makes it possible to evaluate environmental hazards like pollution and the effects of climate change on local communities (76). Decision-makers are better able to recognize, manage and reduce risks when they have access to spatially explicit insights from geospatial analytics, which eventually results in more resilient and sustainable societies (77).

Innovative approaches to uncertainty analysis

There have been many novel approaches put forth in the field of uncertainty analysis. Strong and flexible approaches are essential, especially when dealing with profound uncertainty, as is frequently the case in intricate and dangerous systems (78). Model outputs can vary significantly depending on uncertainty representation technique (79). The shortcomings of current approaches in managing uncertainty in model structure and variability in society and various approaches are proposed (80). Computationally effective methods for propagating the effect of uncertainty with a focus on probabilistic uncertainty analysis in multidisciplinary design (81). Together, these studies highlight the value of varied and thorough approaches to uncertainty analysis, especially when dealing with complex and uncertain systems.

High-resolution spatial modeling

Accurate mapping and environmental analysis depend on the application of high-resolution spatial modeling, made possible by cutting-edge RS technology (82). Because it can offer precise representations of land use dynamics, this is especially significant in urban and regional systems (83). The accuracy and applicability of these models are further improved by combining conventional geostatistics methods with cutting-edge approaches like support vector machines and artificial neural networks (84). However, as noted by previous researchers, the demand for higher-resolution global land cover mapping underscores the necessity for continued advancement and refinement of RS models to meet emerging agricultural and environmental monitoring needs (85).

Applications of machine learning (ML) in remote sensing

ML is a branch of artificial intelligence dedicated to creating algorithms that enable computers to learn from data and make decisions on their own, without specifically programming them (86). ML has become known as an efficient tool in RS for agricultural applications, delivering advanced capabilities for data interpretation and forecasting (87).

The agricultural industry has undergone a revolution thanks to ML techniques, especially in the early detection and assessment of natural disasters like wildfires, floods, droughts and pest outbreaks (88). Large amounts of sensor and satellite data can be processed by these methods to find patterns and anomalies related to these disasters, allowing for quick mitigation and response plans (89). Additionally, ML models are essential for determining the effects of agricultural disasters on crop health and productivity, forecasting yield losses, pinpointing areas of vulnerability and suggesting countermeasures to reduce financial losses for (88). Recent advancements in deep learning have significantly enhanced RS applications in disaster management. Unlike traditional ML pipelines that require manual feature extraction and post-processing, deep learning enables end-to-end learning, allowing models to simultaneously learn feature representations, processing rules and prediction outputs (90, 91). These models, particularly autoencoders, are effective in pixel-wise classification tasks such as land cover mapping, where each pixel is categorized into classes like forest, water, or urban areas. Meanwhile, object detection frameworks including Faster R-CNN and Mask R-CNN are used to identify discrete entities (e.g., buildings, vehicles) by generating bounding boxes and performing instance segmentation (92, 93). In disaster scenarios, such capabilities enable precise mapping of damaged structures or flooded zones. Applications of convolutional neural networks (CNNs) have also shown strong performance in high-resolution land cover classification (94) and scene classification (95). However, due to the data- and computation-intensive nature of training deep models, transfer learning is commonly used to adapt pre-trained networks to new RS tasks with limited labeled data (96). These deep learning methods collectively support improved accuracy and automation in disaster detection, damage assessment and resilience planning through satellite and UAV imagery analysis.

The resilience of agricultural systems has greatly increased as a result of recent developments in artificial intelligence and RS (97). By combining these technologies with big data strategies, disaster response and management can be improved, which reduces the effects and risks associated with socio-ecological vulnerability (98). Particularly, ML applications have been crucial in assisting with agricultural management choices, such as the identification and prediction of extreme events (89). Additionally, research on climate change and preparedness can benefit from the application of artificial intelligence and ML, which can improve alerts for impending weather phenomena, including extreme events (99).

Challenges and future directions in RS

Agriculture disaster management through RS presents a variety of challenges and opportunities for the future. When designing and developing RS systems, previous researchers highlights how important it is to put end users first, especially when it comes to disaster relief (100). Enhancing sensor capabilities and data dissemination are two ways that emphasizes the significance of timely data delivery (7). IoT, wireless sensor networks and big data analytics are examples of emerging technologies that have the potential to improve disaster management and prediction (101). Improved spatial and temporal resolution, data integration and interoperability are among the issues that addresses, when examining the benefits and drawbacks of using RS to monitor irrigated agriculture (102). The necessity of user-centric, timely and integrated remote RS for agricultural disaster management is highlighted by all of these studies combined.

The resilience of agricultural systems has greatly increased as a result of recent developments in artificial intelligence and RS (97). But by incorporating hazard and disaster process models into research, the potential of these technologies can be further realized (103). Planning and damage assessments can be improved, as well as hazard detection, identification, mapping and monitoring. Additionally, by utilizing current sensors and NASA's Earth Observing System's Data and Information System, the timely delivery of RS data for agricultural and disaster management applications can be enhanced (7). Additionally, the development of methods for large-scale surveillance and the dissemination of pertinent data to growers and consultants can improve the use of RS for crop protection, including the detection of disease, weed and insect infestations and nutrient deficiencies (9).

Benefits of RS and GIS in mitigating agricultural disasters

By delivering timely and precise information on crop health, soil moisture levels and weather patterns, RS and GIS play a critical role in reducing agricultural disasters (58). These tools are especially helpful in determining and understanding how topography, soil and climate affect agricultural output (33). Additionally, they facilitate decision-making in disaster management by offering real-time information and visualization capabilities (16). In addition, calamities like floods, droughts and pest infestations can be tracked and predicted with the use of RS and GIS (8). Due to their ability to provide precise and timely information, RS and GIS are essential tools for mitigating agricultural disasters (104). These technologies make it possible to recognize possible hazards, such as floods and droughts and to take preventative action to lessen their effects (105). Through the ability to overlay affected areas with available data sources, estimate the magnitude of the disaster and determine resource requirements, GIS also aids in disaster response and recovery (106).

RS technologies, including satellite imagery and UAVs, drones, manned aircraft sensor imagery, provide real-time data on crop health, soil moisture and weather patterns. This facilitates early detection of anomalies such as droughts, floods and pest infestations. For instance, the integration of RS data with GIS platforms enables the mapping of vulnerable areas, allowing for timely interventions and resource allocation (107). GIS offers spatial analysis tools that are crucial for risk assessment and disaster planning. By overlaying various data layers such as topography, land use and historical disaster occurrences GIS helps identify high-risk zones and informs the development of mitigation strategies. This spatial awareness is vital for policymakers and stakeholders in making informed decisions (45). After a disaster, RS and GIS are instrumental in assessing the extent of damage. High-resolution satellite images can quantify crop losses and infrastructure damage, providing essential information for recovery efforts and insurance claims. Such assessments enable a swift response, minimizing the long-term impacts on agricultural productivity (107).

The fusion of RS and GIS with advanced technologies like AI and ML has enhanced predictive modeling and decision-making processes. These integrations allow for more accurate forecasts of agricultural disasters and the development of automated response systems, thereby improving the efficiency of mitigation efforts (34). Data derived from RS and GIS analyses support the formulation of evidence-based policies and efficient resource management. By understanding the spatial distribution of risks and resources, governments and organizations can allocate aid effectively, plan for sustainable land use and implement practices that reduce vulnerability to future disasters (107). The integration of RS and GIS technologies plays a pivotal role in mitigating agricultural disasters. Their capabilities in early detection, risk assessment, impact analysis and policy support are essential for building resilient agricultural systems. As these technologies continue to evolve, their application will become increasingly vital in safeguarding global food security (32).

Technologies and techniques for RS

The advancement of high-resolution satellite imaging systems (e.g., Sentinel-2, WorldView, Landsat 9) has markedly improved the application of RS in agricultural catastrophe monitoring (9). Accurate monitoring of crop health, soil conditions and water availability is made possible by these systems' ability to take accurate pictures of agricultural environments. These platforms are made even more capable by the addition of multispectral and hyperspectral sensors, which enable the detection of minute variations in vegetation stress (46). Because technology makes it possible to identify and evaluate any issues early on, this has significantly transformed how agricultural disasters are assessed and handled. Furthermore, post-disaster damage assessment has made use of RS technology, mapping the impacted areas and identifying building damage through the use of satellite photos (108). The procedures for gathering, analysing and making decisions in disaster management have all been greatly enhanced by these developments.

UAV surveillance of agricultural disasters is a fast-developing topic that has great promise for improving resource allocation and response coordination (52). These tools have been effectively used in a variety of catastrophe contexts, such as critical infrastructure post-disaster monitoring (109). They are especially useful for tracking and mapping the consequences of natural hazards because of their affordability and adaptability (110). However, resolving privacy, safety and regulatory issues is necessary before they can be widely used (111).

Conclusion

RS technology has greatly enhanced the identification monitoring and assessment of agricultural calamities by using electromagnetic radiation to gather information about different objects on the Earth's surface. The combination of GIS with this technology has revolutionized disaster management techniques by enabling precise interventions, predictive modeling and continuous real-time monitoring. RS allows for the detection and analysis of characteristics and activities of agricultural plants, hence improving crop management using techniques such as vegetative indices. The integration of RS and GIS has revolutionized disaster management approaches by prioritizing response measures, forecasting impacted regions and modeling catastrophe scenarios. ML, a form of advanced analytics, has enhanced the accuracy of catastrophe impact assessments, estimations of agricultural output and categorization of land cover. As a result, disaster planning and response efforts have become more efficient. The combination of several data sources, semantic segmentation and spatial-temporal change detection methods has improved the precision and dependability of assessing agricultural conditions.

The use of advanced technology such as UAVs and high-resolution satellite imaging systems has significantly changed the way agricultural disaster monitoring is conducted. This technology allows for quicker mapping of flooded regions and precise evaluation of damage after a catastrophe. The integration of RS technology with AI and big data analytics has significantly enhanced the ability to respond to and manage disasters, therefore mitigating risks associated with socio-ecological vulnerability. Nevertheless, there are still obstacles that need to be overcome, such as enhancing the capabilities of sensors, optimizing the flow of data and resolving regulatory concerns associated with UAVs. Future advancements in RS for agricultural disaster management include integrating hazard and disaster process models, developing solutions that prioritize user (e.g., farmers, governments, agribusiness) needs and harnessing the potential of IoT and big data analytics to enhance the accuracy of catastrophe prediction and mitigation.

Acknowledgements

I would like to thank the Department of Remote Sensing & GIS and Center for Water and Geospatial Studies for their support and for funding this research.

Authors' contributions

SN and PS conceptualized the study. SN, PS and TKT developed the methodology and carried out the formal analysis. Investigation was conducted by SN and TKT. The original draft was written by SN, PS and TKT. PS, MD, RM and SS contributed to writing the review and editing of the manuscript. Supervision was provided by SP, MD, RM, TKT and AA. All authors read and approved the final manuscript.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interests to declare.

Ethical issues: None

References

1. FAO. The state of the world's land and water resources for food and agriculture - systems at breaking point. Rome: FAO; 2021.
2. Hu L, Zhang C, Zhang M, Shi Y, Lu J, Fang Z. Enhancing FAIR data services in agricultural disaster: a review. Remote Sensing. 2023;15(8):2024. https://doi.org/10.3390/rs15082024
3. Wójtowicz M, Wójtowicz A, Piekarczyk J, editors. Application of remote sensing methods in agriculture. 2015.
4. Sahoo RN, Ray SS, Manjunath KR. Hyperspectral remote sensing of agriculture. Current Science. 2015;108:848–59.
5. Hatfield JL, Prueger JH, Sauer TJ, Dold C, O'Brien PL, Wacha KM. Applications of vegetative indices from remote sensing to agriculture: past and future. Inventions. 2019. https://doi.org/10.3390/inventions4040071
6. Mulla DJ. Twenty five years of remote sensing in precision agriculture: key advances and remaining knowledge gaps. Biosystems Engineering. 2013;114:358–71. https://doi.org/10.1016/j.biosystemseng.2012.08.009
7. Kalluri SNV, Plante R, Mohamed M, Bergman R, Carr K. Remote sensing applications for operational decision making at local scales: current status and future opportunities for agriculture and disaster management applications. IGARSS 2001 Scanning the Present and Resolving the Future Proceedings IEEE 2001 International Geoscience and Remote Sensing Symposium (Cat No01CH37217). 2001;2:840–2. https://doi.org/10.1109/IGARSS.2001.976654
8. Nayak S, Zlatanova S, editors. Remote sensing and GIS technologies for monitoring and prediction of disasters. 2008. https://doi.org/10.1007/978-3-540-79259-8
9. Hatfield PL, Pinter P. Remote sensing for crop protection. Crop Protection. 1993;12:403–13. https://doi.org/10.1016/0261-2194(93)90001-Y
10. Abd El-Ghany NM, Abd El-Aziz SE, Marei SS. A review: application of remote sensing as a promising strategy for insect pests and diseases management. Environmental Science and Pollution Research. 2020;27:33503–15. https://doi.org/10.1007/s11356-020-09517-2
11. Wright T, Homer C, Yang L, Xian G, Ahl D. Conversion of image time series to categorical maps for monitoring cover change in the conterminous United States. Remote Sensing of Environment. 2010;114(8):1685–95. https://doi.org/10.1016/j.rse.2010.03.003
12. Thenkabail PS, Enclona EA, Ashton MS, Van Der Meer B. Accuracy assessments of hyperspectral waveband performance for vegetation analysis applications. Remote Sensing of Environment. 2004;91(3–4):354–76. https://doi.org/10.1016/j.rse.2004.03.013

13. Dadhwal VK, Parihar JS. Remote sensing applications in agriculture: Retrospect and prospect. Current Science. 2008;96 (7):1004–9.
14. Jackson TJ, Chen D, Cosh M, Li F Anderson M, Walthall C, et al. Vegetation water content mapping using Landsat data derived normalized difference water index for corn and soybeans. Remote Sensing of Environment. 2004;92(4):475–82. https://doi.org/10.1016/j.rse.2003.10.021
15. Rembold F, Oduori SM, Gadain H, Toselli P. Mapping charcoal driven forest degradation during the main conflict period in South Central Somalia (2000–2010). Energy for Sustainable Development. 2013;17(5):510–4. https://doi.org/10.1016/j.esd.2013.07.006
16. Bhandari S, Chawla I, Mishra V. A data-driven approach for accurate estimation of irrigated area using remotely sensed vegetation and climate datasets. Remote Sensing. 2022;14(1):142. https://doi.org/10.3390/rs14010142
17. Wulder MA, White JC, Goward SN, Masek JG, Irons JR, Herold M, et al. Landsat continuity: Issues and opportunities for land cover monitoring. Remote Sensing of Environment. 2008;112(3):955–69. https://doi.org/10.1016/j.rse.2007.07.004
18. Weng Q. Remote sensing of impervious surfaces in the urban areas: Requirements, methods and trends. Remote Sensing of Environment. 2012;117:34–49. https://doi.org/10.1016/j.rse.2011.02.030
19. Lillesand T, Kiefer RW, Chipman J. Remote sensing and image interpretation. John Wiley & Sons; 2014.
20. Chuvieco E, Huete A. Fundamentals of satellite remote sensing. CRC Press; 2009.
21. Rouse JW, Haas RH, Schell JA, Deering DW. Monitoring vegetation systems in the Great Plains with ERTS. In: Third ERTS Symposium. NASA SP-351 I. 1974:309–17.
22. Tucker CJ. Red and photographic infrared linear combinations for monitoring vegetation. Remote Sensing of Environment. 1979;8 (2):127–50. https://doi.org/10.1016/0034-4257(79)90013-0
23. Huete AR. A soil-adjusted vegetation index (SAVI). Remote Sensing of Environment. 1988;25(3):295–309. https://doi.org/10.1016/0034-4257(88)90106-X
24. Bannari A, Morin D, Bonn F, Huete AR. A review of vegetation indices. Remote Sensing Reviews. 1995;13(1–2):95–120. https://doi.org/10.1080/02757259509532298
25. Duchemin B, Maisongrande P, Boulet G, Benhadj I. A simple algorithm for yield estimates: Evaluation for semi-arid irrigated winter wheat monitored with green leaf area index. Environmental Modelling & Software. 2008;23(7):876–91. https://doi.org/10.1016/j.envsoft.2007.10.003
26. Salas WA, Ducey MJ, Rignot E, Skole DL. Assessment of JERS-1 SAR data for monitoring secondary vegetation in Amazonia. Acta Amazonica. 2002;32(4):613–28. https://doi.org/10.1590/1809-43922002324620
27. Wu B, Yan N, Liu H, Wang H, Huang J, Chen Z, et al. Estimating winter wheat yield using a hybrid approach from remote sensing and crop model data. Remote Sensing. 2014;6(2):1204–32. https://doi.org/10.3390/rs6021204
28. Bolton DK, Moffat I, Smith A, Davidson A, Millard K, Coops NC, et al. Forecasting crop yield using remotely sensed vegetation indices and crop phenology metrics. Agricultural and Forest Meteorology. 2021;308–9:108528. https://doi.org/10.1016/j.agrformet.2021.108528
29. Johansen K, Morton M, Malady C, Trotter M, Barclay C, Robson A, et al. Predicting grain yield and protein in wheat with multiscale remote sensing. Field Crops Research. 2022;286:108608. https://doi.org/10.1016/j.fcr.2022.108608
30. Zipper SC, Qiu J, Kucharik CJ. Drought effects on US maize and soybean production: spatiotemporal patterns and historical changes. Environmental Research Letters. 2016;11(9):094021. https://doi.org/10.1088/1748-9326/11/9/094021
31. You J, Li X, Low M, Lobell D, Ermon S. Deep Gaussian process for crop yield prediction based on remote sensing data. In: Proceedings of the AAAI Conference on Artificial Intelligence. 2017;31(1). https://doi.org/10.1609/aaai.v31i1.11266
32. Keerthi MG, Bhargavi R, Shikha R, Nithya S. Real time crop prediction based on climatic parameters using deep learning. In: 2021 2nd International Conference on Smart Electronics and Communication (ICOSEC). 2021:1435–9. https://doi.org/10.1109/ICOSEC51865.2021.9591900
33. Sathya P, Paulraj MP. Crop prediction system using hybrid deep learning model. In: 2022 8th International Conference on Advanced Computing and Communication Systems (ICACCS). 2022:1214–9. https://doi.org/10.1109/ICACCS54159.2022.9785071
34. Guan K, Wu J, Kimball JS anderson MC, Li B, Hain C, et al. The shared roles of meteorological drivers and satellite data in explaining global crop yield variability. Environmental Research Letters. 2017;12(10):104008. https://doi.org/10.1088/1748-9326/aa83bd
35. Wang Q, Zhong R, Ma Y, Chen S, Yang Y, Cheng Y, et al. Mapping and evaluating global yellow rust resistance in wheat using remote sensing and genome-wide association study. Remote Sensing. 2021;13(5):1026. https://doi.org/10.3390/rs13051026
36. Yuan C, Du W, Duan Y, Wang Z, Li M, Tan K, et al. Detecting wheat yellow rust with UAV-based hyperspectral imagery and machine learning. Remote Sensing. 2022;14(14):3312. https://doi.org/10.3390/rs14143312
37. Sankaran S, Khot LR, Espinoza CZ, Jarolmasjed S, Sathuvalli VR, Vandemark GJ, et al. Low-altitude, high-resolution aerial imaging systems for row and field crop phenotyping: A review. European Journal of Agronomy. 2015;70:112–23. https://doi.org/10.1016/j.eja.2015.07.004
38. Srivastava A, Misra A, Kumar A, Gupta R, Pandey S. Smart monitoring and controlling of agricultural environment using a wireless sensor network. In: 2018 4th International Conference on Computing Communication and Automation (ICCCA). 2018:1–4. https://doi.org/10.1109/CCAA.2018.8777500
39. Bala A, Kumari M, Arora A, Malik S. IoT-based precision agriculture: Using soil and environmental sensors. Materials Today: Proceedings. 2021;46:7804–8. https://doi.org/10.1016/j.matpr.2021.02.070
40. Basu S, Ghosh A, Mahapatra S, Roy K, Chakraborty C. Smart irrigation: An IoT-based system for weather-aware automated irrigation. Sustainable Computing: Informatics and Systems. 2022;35:100735. https://doi.org/10.1016/j.suscom.2022.100735
41. Sudharsan K, Vigneshwaran R, Prakash A. Internet of Things (IoT)-based smart agriculture: Towards building a smart Indian agriculture. In: 2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS). 2021:1196–201. https://doi.org/10.1109/ICACCS51430.2021.9441877
42. Sharma M, Kumar D, Vijeta D, Das B. Smart agriculture using IoT: A review. Materials Today: Proceedings. 2022;56:2145–9. https://doi.org/10.1016/j.matpr.2022.03.558
43. Lin CY, Fu CM, Lin SW, Huang YH, Chien JC. Integrating AI and IoT for smart agriculture: A comprehensive review. Applied Sciences. 2021;11(24):12062. https://doi.org/10.3390/app112412062
44. Golhani K, Balasundram SK, Vadamalai G, Pradhan B. A review of neural networks in plant disease detection using hyperspectral data. Information Processing in Agriculture. 2018;5(3):354–71. https://doi.org/10.1016/j.inpa.2018.05.002
45. Ashwini S, Nagaraja GS, Manikantan K, Lakshminarayan CP. Applications of artificial intelligence in agriculture: A review. International Journal of Current Microbiology and Applied

Sciences. 2020;9(2):2651–9. https://doi.org/10.20546/ijcmas.2020.902.303

46. Mahlein AK, Rumpf T, Welke P, Dehne HW, Plümer L, Steiner U, et al. Development of spectral indices for detecting and identifying plant diseases. Remote Sensing of Environment. 2013;128:21–30. https://doi.org/10.1016/j.rse.2012.09.019

47. Sladojevic S, Arsenovic M anderla A, Culibrk D, Stefanovic D. Deep neural networks based recognition of plant diseases by leaf image classification. Computational Intelligence and Neuroscience. 2016;2016:3289801. https://doi.org/10.1155/2016/3289801

48. Brahimi M, Boukhalfa K, Moussaoui A. Deep learning for tomato diseases: Classification and symptoms visualization. Applied Artificial Intelligence. 2017;31(4):299–315. https://doi.org/10.1080/08839514.2017.1315516

49. Zhang S, Wu X, You Z, Zhang L. Leaf image based cucumber disease recognition using sparse representation classification. Computers and Electronics in Agriculture. 2017;134:135–41. https://doi.org/10.1016/j.compag.2017.01.014

50. Singh V, Misra AK. Detection of plant leaf diseases using image segmentation and soft computing techniques. Information Processing in Agriculture. 2017;4(1):41–9. https://doi.org/10.1016/j.inpa.2016.10.005

51. Librán-Embid F, Klaus F, Tscharntke T, Grass I. Unmanned aerial vehicles for biodiversity-friendly agricultural landscapes - A systematic review. The Science of the Total Environment. 2020;732:139204. https://doi.org/10.1016/j.scitotenv.2020.139204

52. Glantz EJ, Ritter FE, Gilbreath D, Stager SJ, Anton A, Emani R, et al. UAV use in disaster management. International Conference on Information Systems for Crisis Response and Management; 2020.

53. Hunt ER, Daughtry CST. What good are unmanned aircraft systems for agricultural remote sensing and precision agriculture? International Journal of Remote Sensing. 2018;39:5345–76. https://doi.org/10.1080/01431161.2017.1410300

54. Archibald PD. GIS and remote sensing data integration. Geocarto International. 1987;2:67–73. https://doi.org/10.1080/10106048709354110

55. Ehlers M, Greenlee D, Smith TF, Star JL. Integration of remote sensing and GIS: Data and data access. Photogrammetric Engineering and Remote Sensing. 1991;57:669–75.

56. Colpaert A. Satellite and UAV platforms, remote sensing for geographic information systems. Sensors (Basel, Switzerland). 2022;22. https://doi.org/10.3390/books978-3-0365-5362-7

57. Hinton JC. GIS and remote sensing integration for environmental applications. Int J Geogr Inf Sci. 1996;10:877–90. https://doi.org/10.1080/02693799608902114

58. Katkani D, Babbar A, Mishra V, Trivedi A, Tiwari S, Kumawat RK. A review on applications and utility of remote sensing and geographic information systems in agriculture and natural resource management. International Journal of Environment and Climate Change. 2022. https://doi.org/10.9734/ijecc/2022/v12i430651

59. Vibhute AD, Gawali DBW, editors. Analysis and modeling of agricultural land use using remote sensing and geographic information system: A Review. 2013.

60. Bala P, Tom SL. GIS and Remote sensing in disaster management. Imperial Journal of Interdisciplinary Research. 2017:3.

61. Herring JW, David, editors. Measuring Vegetation (NDVI & EVI): Feature Articles. 2000.

62. Vélez S, Martínez-Peña R, Castrillo D. Beyond vegetation: A review unveiling additional insights into agriculture and forestry through the application of vegetation indices. J. 2023. https://doi.org/10.3390/j6030028

63. Matsushita B, Yang W, Chen J, Onda Y, Qiu GY. Sensitivity of the Enhanced Vegetation Index (EVI) and Normalized Difference Vegetation Index (NDVI) to Topographic Effects: A case study in high-density cypress forest. Sensors (Basel, Switzerland). 2007;7:2636–51. https://doi.org/10.3390/s7112636

64. Huete AR, Didan K, Leeuwen WJDv, Miura T, Glenn EP, editors. MODIS Vegetation Indices. 2010. https://doi.org/10.1007/978-1-4419-6749-7_26

65. Lu D, Mausel PE, Brondízio ES, Moran EF. Change detection techniques. International Journal of Remote Sensing. 2004;25:2365–401. https://doi.org/10.1080/0143116031000139863

66. Chen H, Liu P, Huang X. Remote sensing image change detection based on spatial neighborhood analysis. 2013 IEEE International Conference on Control System, Computing and Engineering. 2013:296–9. https://doi.org/10.1109/ICCSCE.2013.6719977

67. Kumar S, Arya S. Change detection techniques for land cover change analysis using spatial datasets: a review. Remote Sensing in Earth Systems Sciences. 2021;4:172–85. https://doi.org/10.1007/s41976-021-00056-z

68. Zi-fu H. A summary of change detection methods of remote sensing image. Remote Sensing Information. 2005.

69. West E, Morley P, Jump A, Donoghue D. Satellite data track spatial and temporal declines in European beech forest canopy characteristics associated with intense drought events in the Rhön Biosphere Reserve, central Germany. Plant Biology. 2022;24. https://doi.org/10.1111/plb.13391

70. Müller M, Olsson P-O, Eklundh L, Jamali S, Ardö J. Response and resilience to drought in northern forests revealed by Sentinel-2. International Journal of Remote Sensing. 2024;45:5130–57. https://doi.org/10.1080/01431161.2024.2372076

71. Mura MD, Prasad S, Pacifici F, Gamba P, Chanussot J, Benediktsson JA. Challenges and opportunities of multimodality and data fusion in remote sensing. Proceedings of the IEEE. 2015;103:1585–601. https://doi.org/10.1109/JPROC.2015.2462751

72. Swain PH, Richards JA, Lee T, editors. Multisource data analysis in remote sensing and geographic information processing. 1985.

73. Roller N, Bergen K. Integrating data and information for effective forest management. Journal of Forestry. 2000. https://doi.org/10.1093/jof/98.6.61

74. Kulo N. Multisensor remote sensing data integration. Geodetski glasnik. 2019. https://doi.org/10.58817/2233-1786.2019.53.50.71

75. Ivić M. Artificial intelligence and geospatial analysis in disaster management. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. 2019. https://doi.org/10.5194/isprs-archives-XLII-3-W8-161-2019

76. Henry DO, Majemite MT, Dada MA, Obaigbena A, Oliha JS, Biu PW. A review of data analytics techniques in enhancing environmental risk assessments in the U.S. Geology Sector. World Journal of Advanced Research and Reviews. 2024.

77. Musinguzi M, Asiimwe I. Application of geospatial tools for landslide hazard assessment for Uganda. South African Journal of Geomatics. 2014;3:302–14. https://doi.org/10.4314/sajg.v3i3.4

78. Cox LA. Confronting deep uncertainties in risk analysis. Risk Analysis. 2012;32. https://doi.org/10.1111/j.1539-6924.2012.01792.x

79. Helton JC, Johnson JD, Oberkampf W. An exploration of alternative approaches to the representation of uncertainty in model predictions. Reliab Eng Syst Saf. 2003;85:39–71. https://doi.org/10.1016/j.ress.2004.03.025

80. van Asselt MBA, Rotmans J. Uncertainty in integrated assessment modelling. Climatic Change. 2002;54:75–105. https://doi.org/10.1023/A:1015783803445

81. Du X, Chen W, editors. An efficient approach to probabilistic uncertainty analysis in simulation-based multidisciplinary design. 2000. https://doi.org/10.2514/6.2000-423

82. Ehlers M, editor. Remote sensing for GIS applications: new

sensors and analysis methods. SPIE Remote Sensing; 2004. https://doi.org/10.1117/12.514078

83. White R, Engelen G. High-resolution integrated modelling of the spatial dynamics of urban and regional systems. Computers, Environment and Urban Systems. 2000;24:383–400. https://doi.org/10.1016/S0198-9715(00)00012-0
84. Kanevski MF, Maignan M, editors. Analysis and modelling of spatial environment data. 2004.
85. Chao-ying H. Higher resolution global land cover mapping. Geomatics World. 2011.
86. Mitchell TM, Mitchell TM. Machine learning. McGraw-Hill New York; 1997.
87. Shaik AS, Shaik N, Priya D. Predictive modeling in remote sensing using machine learning algorithms. Int J Curr Sci Res Rev. 2024;7 (06).
88. Liakos KG, Busato P, Moshou D, Pearson S, Bochtis DD. Machine learning in agriculture: A review. Sensors (Basel, Switzerland). 2018:18. https://doi.org/10.3390/s18082674
89. Gaitan CF, editor. Machine learning applications for agricultural impacts under extreme events. 2020. https://doi.org/10.1016/B978-0-12-814895-2.00007-0
90. Zhu XX, Tuia D, Mou L, Xia G-S, Zhang L, Xu F, et al. Deep learning in remote sensing: A comprehensive review and list of resources. IEEE Geoscience and Remote Sensing Magazine. 2017;5(4):8–36. https://doi.org/10.1109/MGRS.2017.2762307
91. Zhang L, Zhang L, Du B. Deep learning for remote sensing data: A technical tutorial on the state of the art. IEEE Geoscience and Remote Sensing Magazine. 2016;4(2):22–40. https://doi.org/10.1109/MGRS.2016.2540798
92. Ren S, He K, Girshick R, Sun J. Faster R-CNN: Towards real-time object detection with region proposal networks. Advances in Neural Information Processing Systems. 2015;28.
93. He K, Gkioxari G, Dollár P, Girshick R, editors. Mask R-CNN. Proceedings of the IEEE International Conference on Computer Vision; 2017. https://doi.org/10.1109/ICCV.2017.322
94. Minetto R, Segundo MP, Sarkar S. Hydra: An ensemble of convolutional neural networks for geospatial land classification. IEEE Transactions on Geoscience and Remote Sensing. 2019;57 (9):6530–41. https://doi.org/10.1109/TGRS.2019.2906883
95. Zou Q, Ni L, Zhang T, Wang Q. Deep learning based feature selection for remote sensing scene classification. IEEE Geoscience and Remote Sensing Letters. 2015;12(11):2321–5. https://doi.org/10.1109/LGRS.2015.2475299
96. Hu F, Xia G-S, Hu J, Zhang L. Transferring deep convolutional neural networks for the scene classification of high-resolution remote sensing imagery. Remote Sensing. 2015;7(11):14680–707. https://doi.org/10.3390/rs71114680
97. Jung J, Maeda M, Chang A, Bhandari M, Ashapure A, Landivar-Bowles J. The potential of remote sensing and artificial intelligence as tools to improve the resilience of agriculture production systems. Current Opinion in Biotechnology. 2020;70:15–22. https://doi.org/10.1016/j.copbio.2020.09.003
98. Sarker MNI, Peng Y, Yiran C, Shouse RC. Disaster resilience through big data: Way to environmental sustainability. International Journal of Disaster Risk Reduction. 2020;51:101769. https://doi.org/10.1016/j.copbio.2020.09.003
99. Huntingford C, Jeffers ES, Bonsall MB, Christensen HM, Lees T, Yang H. Machine learning and artificial intelligence to aid climate change research and preparedness. Environmental Research Letters. 2019;14. https://doi.org/10.1088/1748-9326/ab4e55
100. Evans JD, Cappelaere P, Moe KL, Frye SW, Mandl D. Improving information standards and remote sensing support for disaster management. 2014 IEEE Geoscience and Remote Sensing Symposium. 2014:1397–400. https://doi.org/10.1109/IGARSS.2014.6946696
101. Adeel A, Gogate M, Farooq S, Ieracitano C, Dashtipour K, Larijani H, et al. A survey on the role of wireless sensor networks and IoT in disaster management. ArXiv. 2018;abs/1909.10353. https://doi.org/10.1007/978-981-13-0992-2_5
102. Ozdogan M, Yang Y, Allez G, Cervantes C. Remote sensing of irrigated agriculture: opportunities and challenges. Remote Sens. 2010;2:2274–304. https://doi.org/10.3390/rs2092274
103. Showalter PS. Remote sensing's use in disaster research: a review. Disaster Prevention and Management. 2001;10:21–9. https://doi.org/10.1108/09653560110381796
104. Buckle P, editor. Geographic information systems and hazard management. 1993.
105. Rajeev, Tanuja, editors. Role of remote sensing and its applications in disaster management like earthquake, flood and tsunamis. 2016.
106. Richardson TM, Renner RN. Geographic information systems supporting disaster response and recovery. Real Estate eJournal. 2008.
107. Giardina G, Macchiarulo V, Foroughnia F, Jones J, Whitworth M, Voelker B, et al. Combining remote sensing techniques and field surveys for post-earthquake reconnaissance missions. Bulletin of Earthquake Engineering. 2023;22:1–25. https://doi.org/10.1007/s10518-023-01716-9
108. Yamazaki F, Matsuoka M. Remote sensing technologies in post-disaster damage assessment. Journal of Earthquake and Tsunami. 2007;1:193–210. https://doi.org/10.1142/S1793431107000122
109. Adams SM, Friedland CJ, editors. A survey of unmanned aerial vehicle (UAV) usage for imagery. 2011.
110. Giordan D, Manconi A, Remondino F, Nex F. Use of unmanned aerial vehicles in monitoring application and management of natural hazards. Geomatics, Natural Hazards and Risk. 2017;8:1–4. https://doi.org/10.1080/19475705.2017.1315619
111. Kim KE, Davidson JM. Unmanned aircraft systems used for disaster management. Transportation Research Record. 2015;2532:83–90. https://doi.org/10.3141/2532-10

Additional information

Peer review: Publisher thanks Sectional Editor and the other anonymous reviewers for their contribution to the peer review of this work.

Reprints & permissions information is available at https://horizonepublishing.com/journals/index.php/PST/open_access_policy

Publisher's Note: Horizon e-Publishing Group remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Indexing: Plant Science Today, published by Horizon e-Publishing Group, is covered by Scopus, Web of Science, BIOSIS Previews, Clarivate Analytics, NAAS, UGC Care, etc
See https://horizonepublishing.com/journals/index.php/PST/indexing_abstracting

Publisher information: Plant Science Today is published by HORIZON e-Publishing Group with support from Empirion Publishers Private Limited, Thiruvananthapuram, India.