South Asian Journal of Agricultural Sciences

E-ISSN: 2788-9297
P-ISSN: 2788-9289
Impact Factor (RJIF): 5.57
www.agrijournal.org
SAJAS 2025; 5(2): 103-109
Received: 12-05-2025
Accepted: 15-06-2025

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Early detection of crops with UAVs utilizing deep learning techniques: A Review

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DOI: https://www.doi.org/10.22271/27889289.2025.v5.i2b.196

Abstract
Various biotic and abiotic stressors are applied to crops. The biotic factors in this situation are weeds, bacteria, fungi, and pests, while the abiotic stresses are soil pH, water salinity, temperature, humidity, and weather. Unmanned Aerial Vehicles (UAVs) provide a practical way to diagnose stress early and treat it quickly, increasing the yield of crops. Applications of deep learning and computer vision during plant surveillance can help achieve these goals more quickly and precisely by collecting data and comparing it to an existing dataset.
Multispectral sensors employed on gimbles can be used in the future, which have been verified and trained with a range of datasets, and should be used for UAV-based crop detection. Because of their ability to measure soil fertility, identify crop diseases, increase productivity, and uncover a range of crop-affecting factors, drones are helpful in the management of natural resources and agricultural operations. UAVs can identify areas that need more attention. In the agricultural sector, unmanned aerial vehicles can be used to reduce the time and potentially hazardous effects of fertilizer and pesticide spraying. This study provides a brief overview of the usage of UAVs for agricultural surveillance.

Keywords: UAVs, Deep learning technique, technique of computer vision, crop analysis, area, disease detection

Introduction
Despite accounting for 20.2% of India's GDP, the agriculture industry is dangerous [1]. Lack of employees, erratic monsoons, production problems, limited productivity, etc., are some of the limitations. Agriculture is the main industry that provides jobs in rural villages. According to the FAO report on India at a Glance, 2022, 70% of rural households still rely on agriculture, and about 82% of agricultural households are tiny and marginal. All those who work in agriculture must think carefully about this issue and create creative solutions to guarantee sustainability for the coming generations.
India is still developing the technique, but drones are being utilized for crop security there. The Council for Agricultural Research in India (ICAR) initiated a network project in September 2021 that investigated the use of drones and AI methods for quick analysis of agricultural health, growth, and for more efficient input management. With a drone and artificial intelligence, crop health can be monitored almost instantly. Additionally, drones are utilized to map aquaculture management practices, map macrophyte infestation, sample water, and apply liquid pesticides and fertilizers at varying rates [1]. In precision livestock husbandry, AI and drone technologies are being used, especially to check the health of the animals.
The objective of increasing farmers' incomes is to adopt a holistic strategy that prioritizes increasing production through creation. Making better use of resources for irrigation, enhancing the use of inputs, decreasing post-harvest losses, adding value, transforming agricultural markets, minimizing risk, offering security and support, and encouraging related activities. The government has put in place a number of programs, policies, initiatives, and changes to raise farmer earnings [2]. Each policy and program is aided with additional monetary and nonmonetary funding, like the introduction of endowment funds like the Agricultural Infrastructure Fund. India's agricultural sector could undergo a revolution due to drone technology. To create low-cost drone technology for customers, including farmers.
Along with the predicted cost for the demonstration of a drone in the field, various participants from industry, like Indian Council of Agricultural Research, State Agricultural

University etc., are offering financial aid at hundred percent (up to ten lakh rupees) of the UAV's cost [2]. Additionally, farmers can make decisions about raising agricultural output by using real time applications and informative channels like as the Farm-o-pedia and agrismart app, which provide stakeholder with real time information and guide for advices.

Numerous stresses that are generally categorized as biotic and abiotic stressors are experienced by agricultural crops. Figure 1 illustrates these data.

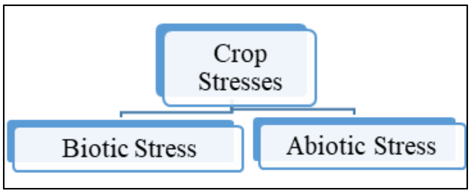

Fig 1: Crop stresses

As seen in Figure 2, biotic stressors include diseases brought on by bacteria and viruses, nematodes like worms that cause fruit to rot, and insects that consume different plant parts such roots, leaves, stems, and fruits. Therefore, in order to improve crop production and management, these stresses should be identified early on and minimized or eliminated to increase output.

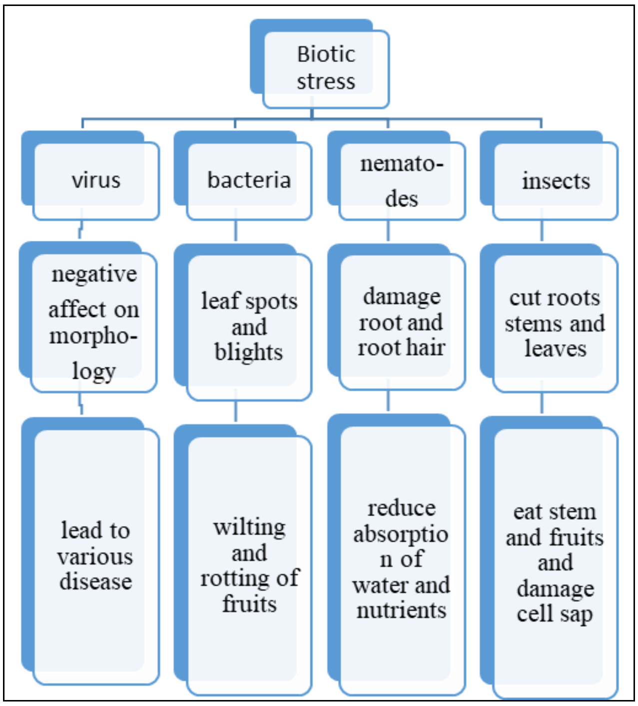

Fig 2: Biotic Stress

Abiotic stresses as shown in Figure 3 like cold stress which lead to cell damage and enzyme inhibition, drought which lead to reduction in rate of photosynthesis and cell expansion, various nutrient deficiency which lead to chlorosis and presence of any kind of toxic material leads to ion imbalance. Abiotic stressors lead to reduced potential of nutrient absorption and affect the crop negatively.

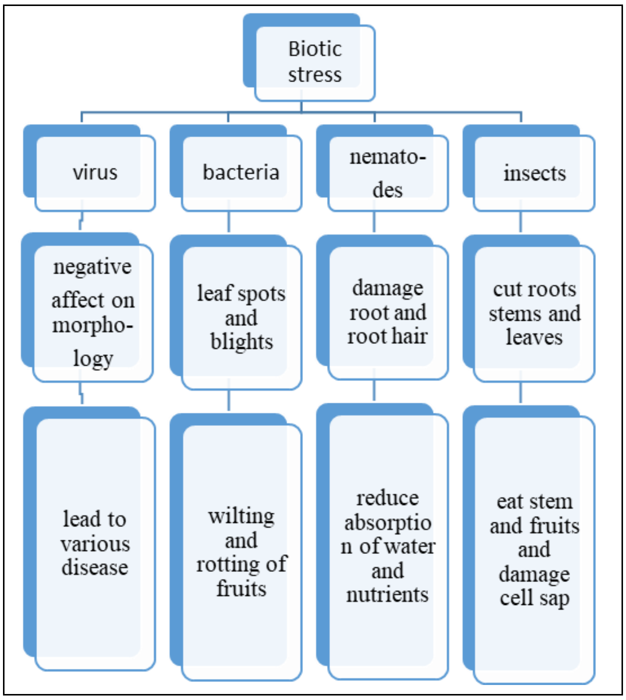

Fig 3: Abiotic Stress

Applications of UAVs in agriculture

Using apps on their smartphones, kisan and other contributors can view the information collected by drones remotely from cloud-based services. This information can be used to estimate agricultural productivity and requirements, including sowing and fertilizer and pesticide use.

- **Chemical spraying:** UAVs can be employed to apply chemicals like pesticides and weedicides due of the vast heterogeneity of the soil and crops. Different doses of chemicals may be required as per the crop conditions and the amount of the insect-pest infestation.
- **Agricultural monitoring:** Throughout the growing season, drones can be used to keep an eye on crop health and make timely, suitable interventions. An appropriate timely action can help in crop improvement.
- **Crop irrigation:** Using multispectral indices, UAVs equipped with different kinds of sensors that may locate dry areas in the field.
- **Aerial mapping:** Based on the reflection pattern at different wavelengths in the aerial mapping image, a number of multispectral indices can be computed using a range of sensors, including thermal visual and near-infrared. These indicators can be used to evaluate crop issues like disease, insect-pest attack, and water stress. Even before symptoms appear, the drones' sensors can detect the prevalence of diseases or deficiencies.
- **Management of livestock:** The massive herd of animals can be managed with the help of drones. Based on their heat signatures, the drones with high-resolution sensors and infrared cameras can quickly identify sick animals. After being identified, the affected animal can be isolated from other animals and given prompt medical attention.

- **Analyzing topography and soil:** Drones can be fitted with sensors that can perform analysis. The topography and the evaluation of the soil's fertility, moisture, and nutrient levels can be used to organise sowing pattern of crop, managing irrigation, and regulate application of fertilisersin addition with accounting for field circumstances and yield variations of the crop.
- **Control of pests:** Drones may identify and notify farmers of field regions affected by weeds, diseases, and insect pests in addition to soil conditions.
- **Weed identification:** Drones can be employed to recognise the class of weeds that are growing in particular area. To prevent them from comptetinging for resources with the main crop, we may eradicate these weeds from the field as soon as possible.
- **Surveying land:** Estimating the general condition of crops over wide areas is practically impossible. Farmers can determine which field areas need maintenance and stay updated on plant health by using drone mapping to map agricultural landscapes.

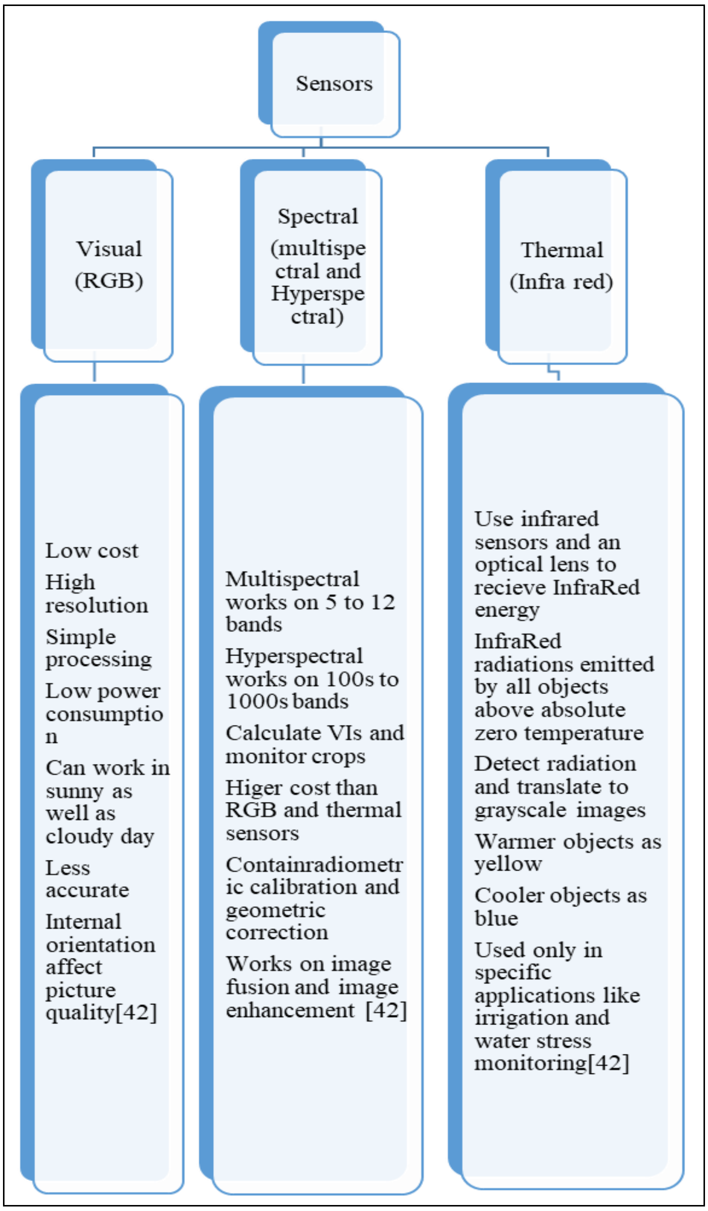

Fig 3: Sensors with their features

Table 1: Types of Drones and their UAVs

Types of UAVs	Features
One rotor drone	Robust and long lasting Like a helicopter
Multi rotor drones	Commercial drone that is stable Employed with four rotors Almost 30 minutes of flight time Used for aerial Imagery
Fixed wing drones	Utilised in aeroplane style rigid wings and gas powered Upto 16 hours continuousl flight Not able to hover like helicopter

Robust wing Hybrid drones	Combination of rotor based design and Fixed wing designs Intricate technology Rotation is made possible by fixed wings and make vertical landing
Non-combat drones	Not expensive rather more complex Used for large reconnaissance
GPS drones	Connected to satellite Map flights and generate data Map large topography
Photography drones	Use automatic flight modes Precise and stable in capturing images across large area

Sensors

One of the key components of a UAV is its sensors, which enable it to carry out a variety of tasks with little to no human assistance using sophisticated algorithms. These tasks include navigation, the recognition and geolocation of possible crop abnormalities based on visual data, and the provision of a crop status map that may be useful to farmers or other machines collaborating with the UAV. By automating certain tasks that need a team to complete, drones employed with latest sensors and cameras can uplift crop output while reducing cost and time ffor the farmers. The most popular camera sensors for tracking crop diseases are:

- RGB cameras
- Multispectral cameras
- Hyperspectral cameras
- Thermal infrared cameras

Related works

In order to investigate how different biotic and abiotic factors affect crops, a comprehensive review of the given works is overseen to see which methods are currently being employed to ascertain the impact of frameworks and their efficiency.

Author's name and year	Computer Vision Techniques employed	Objective and place of work	Outcomes
Kim *et al*. (2023) [3]	High-resolution DSM model photogrammetry using UAVs	To precisely determine deformation on soil surface (SSD) in the South Corean timber harvesting zone	• Acquired 2D photos (VPFs) and used the DSM of various SSDs, which were calculated using DSMs from different months. DoD • July through June: -3 cm • From September to June, 11 cm • From October to June, 4 cm • 7 centimeter of erosion • 9 cm of deposition in the first month
Karthikeyan D, *et al*. (2023) [4]	Triboelectric nano generator with sensors and IoT	To map and track soil properties to determine whether they are suitable for agricultural practices	• Examine how sensors and IoT combine to collect information and execute orders for intelligent irrigation. Make use of contemporary hardware and software tools to map and monitor soil properties. • In order to anticipate soil pH, it is important to use linear regression to fit data on a quasi-prediction.
Majur P, *et al*. (2023) [5]	Precision agricultural remote sensing using RGB spectral reflectance generated from UAVs	To assess nutritional status of crop and soil variability on winter rye in the field	• RGB and available soil potassium had a negative correlation. • Near IR and red edge revealed a positive correlation. • Phosphorus and potassium shortfalls are generally less severe and harder to find using RGB sensing methods than nitrogen shortages.
Haltorf *et al*. (2023) [6]	UAV with sensor node and ground station communication capabilities	Creating a suitable system architecture to collect information from scattered sensor nodes in agriculture	• The range was between 300 and 1000 meters. • As UAVs flight height and sensor node depth increased, the signal strength declined. • The drone and sensor node's maximum readout distance was found to be 550 meters. • Consistency in measuring LoRa signal strength supports validity.
Nguyen *et al*. (2023) [7]	Pre diagnose of yellow rust in wheat and estimating the final Yield by the Use of Multi-Spectral UAV Imaging	Yellow rust detection in spring wheat using characteristics like temporal dimension and spectral texture	• Disease-focused VIs are created using spectral dimensions and grey level occurrence matrices. SVM, RF, and MLP machine learning pipelines are employed to detect infections, and 3D CNN is created and employed for diagnosis.
Kumar M. *et al*. (2023) [8]	Drone with sensors and AI	Pre prediction of disease and precisely managing amount of pesticides in cashew cultivation keeping in mind soil air and temperature factors	• MobileNet V2, training classifier, can classify seedling blight with an accuracy of ninety five percent. • 99% accuracy in identifying healthy leaves
Kunkunuri ANJ, *et al*. (2022) [9]	Sentinel 1A SAR data and drone	Combining drones and satellites to deliver high-resolution data for PA over a broad scale	• Carried out analysis of quality as well as analysis of quantity for the class of wheat and compared it with high-resolution captured images. • Use medium to low-resolution satellite data to distinguish between barren and ploughed areas in order to identify early-stage wheat.
Aderson de S, *et al*. (2022) [10]	Multispectral camera-equipped unmanned aerial vehicle	To identify abiotic stressors in soybeans, such as hydrodeficiencies and nutrient deficiencies, temperature-dependent radiometric calibration of thermal data is being monitored.	• 35 Green Red Vegetation Indices were extracted and correlated with presence of nitrogen and conductance of stomata in leaf.
Jackuline *et al*. (2022) [11]	Image analysis using DL and machine learning	Sort plant disease signs, paying particular attention to	• To calm the photos, the Gaussian filter was used to eliminate background noise.

		environmental elements that influence rainfall.	• Plant disease is automatically identified and categorized using image segmentation.
Stutsel B, *et al.* (2021) [12]	UAVs use thermal and optimal cameras.	To monitor how plants react to soil salinity stress by changing their temperature	• GRVI vegetation index based on RGB data that has been calibrated
Mim T.T. *et al.* (2021) [13]	Model of Convolutional Neural Network and Alexnet-based on processing of images	Sought to identify infections by identifying leaf and bloom diseases in sponge gourds.	• To detect gourd disease, a popular pretrained AlexNet model with several CNN 2D layer layers and a multilayer ReLU activation function is used.
Habib MT, *et al.* (2021) [14]	Machine learning employed	To determine papaya disease	• The disease-affected area is first separated using k-means clustering, and then Support Vector Machine is utilized for classification. • Ten feature sets and 126 entries make up the dataset. • The accuracy of the method was almost 90%.
Saha R, *et al.* (2020) [15]	Techniques of Deep learning	To determine whether orange fruit is unwell	• Using the CNN Method, eight sets of character and a dataset of size sixty eight were classified. • Around 93% accuracy was achieved.
Habib MT, *et al.* (2020) [16]	An expert agro medical system based on Machine vision.	To use an agromedical expert system to detect jackfruit disease	• The k-means clustering technique employed to categorise 480 photos by converting them from RGB space to l*a*b. • With 89.52% accuracy, the ten features extracted Random Forest classifier produced the best results when compared to others.
Majumder, *et al.* (2019) [17]	A machine learning approach	Recognizing carrot disease	• Segmenting the illness prone area with K-means clustering technique • After that, an SVM classifier will classify two hundred two photoss and eleven character sets. • The accuracy of the method was 96%. • Poor quality and filtering backdrop make it difficult to acquire accurate findings.
Sasirekha, *et al.* (2019) [18]	Support Vector Machine analysis of images	Analysing images for recognition and categorize carrot vegetable diseases.	• Began by changing the RGB photos to l*a*b. • Next, segmentation is done with k-means clustering. • SVM is used for texturing and classification in order to find thirteen characteristics.
Zhu H, *et al.* (2019) [19]	approach based on deep learning	Determine the carrots' visual quality.	• Used AlexNet to determine the grade of carrots and extract characteristics from their images. • To identify diseases, a binary classification algorithm is employed. • 98.70% accuracy was attained.
Gaikwad S.A. *et al.* (2017) [20]	Using SVM classifiers in image processing	To identify fruit diseases	• system of classification based on image processing methods • Photos were separated using k-means clustering, characterstics were obtained from segmented images, and an Support Vector Machine classifier was utilized for classification.
Islam M, *et al.* (2017) [21]	Image analysis with ML	To provide a comprehensive method for identifying potato plant disease	• Using an SVM classifier, an area of consideration containing features of illness was identified over images with 95% accuracy. In l*a*b color space, an area of consideration containing disease symptoms is identified in images. • Ten characters were recovered. • 95% accuracy was attained using SVM classifier disease in over pictures.
Rozassio LJ, *et al.* (2016) [22]	The Otsu method and k-means clustering are used.	To find several kinds of flaws in fruits and veggies	• Applied Color-based image segmentation to four different types of fruits and vegetables. • There were sixty-three images utilized. • No classification was made.
Samajpati B.J. *et al.* (2016) [23]	Segmenting images with k-means clustering	To identify three different common apple disease	• Out of 80 photographs, a total of 13 features were recovered. • Diseases classified using the Radio Frequency classifier. • The overall accuracy varies as a result of the fusion of several features.
Khadabadi, *et al.* (2015) [24]	Neural network-based probabilistic classification system	To recognize and classify carrot vegetable diseases	• With the use of DWT, characteristics were extracted and the disease was categorized with 88% accuracy.

Challenges faced in Indian scenario: Even though India is an agricultural country, the majority of its rural residents still make their living from farming. Indian stakeholders encounter a few difficulties, including:

Payload limitation [25]. Consumer drones are limited in what they can transport. As a result, they cannot afford to install large, expensive sensors. But many consumers, mainly in underdeveloped countries, simply cannot afford the expenditure of such sensors. Nonetheless, it is anticipated that, similar to consumer drones, the cost of lightweight sensors would decrease in the upcoming years.

Cheap sensors with low resolution capability and expensive sensors with high resolution capability [25]. The value of sensors with great spectrum resolving power is a significant deterrent to extensive utilisation of UAVs in farming. Many people were consequently constricted in their options for using consumer-grade digital cameras. Pixel distortion, overlapping wavebands, and severe vignetting are problems with consumer digital cameras. These sensors may therefore have certain specialized applications, such as weed identification.

Environmental sensitivity [25] Cloud cover has no effect on drone photos taken. However, other weather conditions including rain, storm, humidity, evaporation and temperature variance may have a negative effect on its utility. However, with appropriate schedule of flight administration and, to certain value, the use of image pre-processing techniques, these issues can be fixed.

Insufficient stamina while flying [25] Despite the versatility that multi-rotor drones offer in terms of sensor installation and flight time, monitoring a larger region remains a significant challenge. However, fixed-wing drones can help with mapping and examining the wider region. Nevertheless, they can only be equipped with lightweight sensors.

The high expense of purchasing a house [25] Although consumer drones are less costly, they use consumer-made optical sensors that aren't appropriate for many agricultural uses. With a hyperspectral sensor, cereal crop analysis has a lot of possibilities. However, many people are unable to afford them. The cost of ownership is also increased by the fact that these sensors still weigh a lot, requiring larger carrier drones. Thus, the initial cost of ownership continues to be a major obstacle to the broader deployment of drones. In addition to the sensors' size and weight, we can expect their price to drop in the future.

Crop irrigation requires specific training for farmers [25]. Drones using thermal, multispectral, or hyperspectral sensors may use multispectral indices to find dry areas of the field.

- **Aerial mapping:** A variety of sensors, such as thermal visual and near-infrared, can be used to calculate a number of multispectral indices based on the aerial mapping image's reflection pattern at various wavelengths. These indicators can be used to assess crop problems such as water stress, disease, and insect-pest attack. The drones' sensors can recognise the prevalence of diseases or deficiency which may occur in near future.
- **Animal Farms management:** UAVs can be employed in managing the enormous clusters of animals. Drones equipped with infrared cameras and high-resolution sensors can detect unfit among them rapidly on the basis of their body temperature. Once discovered, the impacted individuals utilize the technology appropriately; moreover, farmers' trust and knowledge must be bolstered. The main challenge to the successful application of drones in agriculture may be cultivating the abilities and drive of a wide variety of farmers. Despite being a profession that younger generations choose, farming is a reasonably easy chore to complete. But in order to implement the entire process, training is essential.

Insufficient technical know-how [25] for maintenance and repairs, together with a scarcity of spareparts. Although consumer drones are easy to operate, maintaining and repairing them calls for technical know-how. Moreover, a shortage of components (for replacing the damaged component) may be an issue in various localities.

Conclusion

It may be concluded from the aforementioned studies that agricultural technology has developed at an exceptionally fast pace in recent years. Several deep learning and computer vision techniques have made it possible for farmers and other stakeholders to evaluate and resolve a range of problems more swiftly, easily, and laboriously. They would benefit more, though, if these early projections of sickness or nutrient levels were made so that they could be avoided before they manifest.

In order for farmers to use Drones (UAVs) on their cultivable land to increase productivity and enhance fertile power of soil with less use of chemicals, more frequent training and awareness campaigns are also required.

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