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The use of artificial intelligence and remote sensing in today's pest management in farming

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Abstract

There are a lot of issues happening right now, like the world's population increasing really fast, natural resources being used up quickly, there's not as much land left for growing food, the climate is changing a lot faster than before, and people are getting sick from diseases such as Ebola, Lassa, Zika, Nipah, and most recently, the COVID-19 outbreak. Technological advances help us learn more about how farming works, starting from tiny cells up to entire farms, which helps people all over the world. Using remote sensing, artificial intelligence, and machine learning helps create accurate data sets that are useful for developing better management tools and models. These technologies help understand different types of soil, use water more wisely, give plants the right nutrients, predict and warn about weather and issues, protect crops from diseases and insects, and detect dangers like locusts. Using RS, AI, and ML algorithms is a good way to help agriculture deal with issues from living and non-living factors, and it supports sustainability, which is important to meet the increasing needs of the human population. This article talks about how using AI algorithms and remote sensing data can help monitor pests in real time, detect issues early, and predict pest problems more accurately. Even though there are issues with data quality and getting access to technology, using AI along with remote sensing can make a big difference in how pests are controlled

Keywords: Canopy measurement, weed infestation mapping, abiotic stress monitoring, pest monitoring, insect taxonomy, pest damage

Introduction

In every area, whether it's something as complex as rocket science or as simple as farming, people are always looking for better and smarter tools that can take over different tasks. This can only happen if machines can quickly grasp how humans think and make decisions. Agriculture, which means growing food crops, is a hard work job that is very important because it helps support life on Earth. Moreover, the world is dealing with a serious problem because of growing population, changing climate, using up natural resources, fewer farm workers, and new diseases like the COVID-19 outbreak. Managing agricultural fields to meet food needs and reach the second sustainable development goal, which is to end hunger, is a tough task (Martos *et al.*, 2021) [88]. Over the past ten years, there have been big changes in technology across many industries around the world. The European Commission has named 2021 as the start of a new era of industrial innovation, called Industry 5.0 (Martos *et al.*, 2021). Wooden and metal farming tools were grouped into the first two stages of the agricultural revolutions. During the third and fourth stages, big technological improvements like robotics, machines, communication systems, and understanding genetic codes were the main accomplishments. The fifth agricultural industrial revolution includes modern technology like artificial intelligence, machine learning, and remote sensing, as mentioned in Martos *et al.*, 2021. AI and RS tools help farmers take better care of their fields by making it simpler to check how well crops are growing and how healthy they are. This means taking care of insect pests, diseases, and weeds on time, along with using water wisely, giving plants the right nutrients, and keeping the soil healthy (Kim *et al.*, 2008) [72].

Agriculture-linked robots are made to help bring AI into farming more smoothly, offering possible answers to many different problems that farmers face. With the help of AI, farmers can use chatbots as their virtual guides to get timely advice and recommendations on different parts of crop management. Drones, which are like flying robots, can be controlled from a distance and use GPS to navigate.

They help in doing different farming jobs without needing people to do them by hand, such as checking if crops are healthy, deciding when to water them, applying chemicals, spotting weeds and pests, and even predicting future conditions (Mogili and Deepak, 2018; Ahirwar *et al.*, 2019) ^[2, 91]. AI is always changing and growing in new ways because of improvements in how computers work. At the same time, many areas of the economy are also seeing benefits from AI, including the agriculture industry. It has made big progress in agriculture, like helping with removing weeds, managing how water is used, keeping track of diseases, and controlling insects and pests. It also gives good times to plant and harvest different crops and helps sell them in the right market when they are most valuable (Javaid *et al.*, 2023) ^[54].

AI has greatly helped farmers use different technologies, and looking at farm activities before making decisions helps ensure that crops are produced in good amounts and high quality (Vijayakumar and Balakrishnan, 2021; Subeesh and Mehta, 2021) ^[122, 126]. AI can help solve many problems in farming, like a lack of workers, by providing tools such as self-driving tractors, smart watering systems, devices that apply fertilizer and pesticides, and robots that pick crops (Wongchai *et al.*, 2022; Bu and Wang, 2019) ^[20, 129]. Many AI and machine learning models use different sets of data, like temperature and soil moisture, to help farmers decide the best times to plant, choose which crops to grow, apply fertilizer, and harvest crops. This helps them make better decisions for growing healthy crops. (Singh *et al.*, 2022; Sabrina *et al.*, 2022) ^[109, 117]. AI algorithms can help find different kinds of insects, whether they are big or small, and how they eat. These algorithms can quickly let farmers know if harmful insects are attacking their crops, right on their phones. This way, farmers can act fast to stop the insects from causing damage to their crops. In this review, we look at how AI and recommendation systems are used to control insect pests. We look at how well these technologies work and the difficulties faced when using them for controlling pests. We also offer a detailed look at AI and RS as strong tools for helping with sustainable and effective pest control in farming and ecological settings.

Remote sensing (RS)

Right now, the approach for finding, spotting, sorting, and handling different insect pests and disease-causing organisms is changing. Instead of using old ways, people are now using new tools and methods like remote sensors, geographic information systems, and GPS to collect information. RS is the process of collecting information about an object, area, or event by using data from a device that does not touch the object being studied (Lillesand *et al.*, 2015) ^[79]. De Jong and Van der Meer (2007) ^[28] explain that the remote sensing process, as shown in Figure 1, has several steps. Each step is important for getting and using data collected through remote sensing. RS refers to a wide range of technologies including satellites, GIS, Internet of Things (IoT), cloud computing, sensors, Decision Support Systems (DSS), and autonomous robots. The RS process is mostly affected by the features of electromagnetic radiation (EMR), which is used to gather data and understand it. Depending on

where the EMR comes from, RS is divided into two kinds: passive remote sensing and active remote sensing. Active remote sensors use a source of radiation, like RADAR, and work both during the day and at night because they don't rely on light to function. Passive remote sensors don't have their own light source. Instead, they rely on light from outside to see the object, which means they can only work during the day.

The air around us is important for remote sensing because electromagnetic radiation goes through it before hitting the things on the ground. When radiation hits gas molecules or tiny particles like aerosols, it can bounce off in many different directions, including back toward the sensor. When electromagnetic radiation, like visible light, infrared, or microwaves, from a remote sensing device such as a satellite or drone hits an object, different things can happen. These interactions mostly depend on the natural qualities of the object and the features of the radiation coming in. The three most common ways something interacts are by absorbing, emitting, and reflecting. RS instruments are made to find and measure the radiation that is reflected back. By looking at this reflected radiation at various wavelengths, scientists can learn important things about the object being studied and use that information to make good choices for many different uses (Pellikka and Rees, 2009) ^[102]. When the incoming radiation interacts with the object being studied, a sensor like a digital camera, electromagnetic scanner, radar system, multispectral scanner, or hyperspectral scanner gathers and records the information. This information is captured as either reflected or emitted electromagnetic radiation, as mentioned by Yang and Everitt in 2011. Radiation can be saved in two main ways: either as analog, such as aerial photos, or as digital, like signal values, which are kept on a magnetic CD or DVD. After using a remote sensor to record the EMR from the target objects, the data is sent electronically to a receiving station where it is processed later. For looking at images, there are different software choices you can use, like Imagga, Hive, and Anyline. These programs use smart tools to look at pictures and get useful information from them. When looking at an image, there are three main types of information that are considered. These are: giving different labels to separate parts of the image, figuring out the characteristics of the object being studied, and keeping track of how those characteristics change over time (Jensen, 2007) ^[55, 136]. The last result from a remote sensing process can sometimes be used as a starting point for more analysis, like in a GIS system. At the same time, this information can also be combined with other kinds of data for different research uses.

Integrated pest management is a thorough method used to control pests, helping to lower the need for chemical pesticides on crops and soil, and supporting a healthier, more natural environment. However, implementing IPM requires ongoing monitoring and watching over crops can be a tough job. So, AI can be used to solve this problem, as mentioned in Murmu *et al.*, 2022. AI can look at big amounts of data and make conclusions based on past reports, which helps farmers take action on pests at the right time (Katiyar, 2022) ^[66, 94]. Many research studies have been done showing that using RS and AI is really helpful in managing insect pests. Prabhakar and his team in 2012 ^[102] showed how using satellite data from remote sensing can help track and forecast the movement of a big insect pest, the fall armyworm, in corn fields. In another study, Smith and their team in 2020 showed how drones with multispectral sensors were used to check for pest damage in vineyards. They did this by looking at the different light patterns reflected by the vines. The improvements in the RS process allow for quick and precise

collection of broad-scale data, even from hard-to-reach areas (Malinowski *et al.*, 2015) ^[101, 87, 119]. The timeline shows a short overview of the progress made in RS technology.

Remote sensing platforms

The place where remote sensors are attached, called RS platforms, is divided into three kinds depending on how high up from the Earth's surface the sensors are placed: ones on the ground, ones in the air, and ones in space (Johnson *et al.*, 2001) ^[57]. Ground-based platforms are placed close to or on the Earth's surface to look at certain features of the environment, plants, or things being studied. They are especially helpful for doing close-up and detailed research on individual plants or small groups of plants. Airborne platforms are airplanes that carry RS equipment for doing surveys from the air. These platforms can fly lower than satellites, which lets them capture more detailed images and collect data focused on specific areas. Aerial survey missions use various tools such as airplanes, helicopters, and unmanned aerial vehicles. Spaceborne platforms are sensors and tools mounted on satellites, like geostationary and sun-synchronous satellites, that fly around Earth. These satellites collect data from space, allowing them to keep a continuous watch over the entire Earth's surface and regularly capture images or information from different areas. The information gathered by these satellites is very useful for many purposes, such as predicting the weather, tracking changes in the climate, creating maps of land use, supporting farming activities, and helping during emergencies like natural disasters (Roy *et al.*, 2022) ^[105]. The latest example of space-based remote sensing is India's Chandrayaan-3 lander, Vikram, which landed gently on the Moon's South Pole on August 23, 2023. The rover Pragyan has done research on the moon's atmosphere and found that oxygen and other minerals are present (Kanu *et al.*, 2024) ^[62].

Applications of remote sensing and artificial intelligence in agriculture

Modern agriculture and food production, which are meant to support the increasing global population, face ongoing challenges due to global climate change. This change adds more stress to crops from both non-living and living factors, causing problems for both economic and environmental sustainability (Bakala *et al.*, 2020) ^[12]. AI and RS appear to offer hope because they can measure and analyze crop characteristics using different tools, as shown in Jung *et al.*'s 2021 study. Besides being used in other areas, RS and AI are also very important in agriculture and gardening (Figure 3) ^[60]. Using AI through unmanned aircraft systems has given a big advantage in doing advanced data analysis for managing farm fields, which makes the whole system more resilient and efficient (Coble *et al.*, 2018) ^[24]. Many companies, including AGEYE Technologies, a Where, Blue Reiver Technology, Farm Shots, Fasal, Harvest CROO Robotics, Helio Pas AI, Hortau Inc., Ibex Automation, PEAT, Root AI, Trace Genomics, and Vine View, have created different AI tools for agriculture. These tools do many things like predicting the weather and how it affects pests, managing weeds, picking and packaging fruits and vegetables, and keeping track of watering and fertilizing crops (Dutta *et al.*, 2014) ^[31]. Remote sensing is a very helpful technology that lets us collect information about crops continuously without harming them and at a low cost, as mentioned in Barbedo's 2019 work. Images are taken by sensors that are far away, and using deep learning machine models, these images are sorted into different categories. By looking at the image, we check if the plant is in good condition or if it has a sickness. Convolutional neural

networks, which are a type of artificial intelligence, were used to find the pathogen that causes disease in plants. This was done by looking at images of leaves that had lesions and spots (Barbedo, 2019) ^[13].

Crop identification

The RS and AI help in identifying and classifying crops by studying the spectral features of different plant covers, especially when the crops are similar and hard to tell apart. Compared to old ways of identifying crops, AI gives a big benefit by making things more accurate and faster. It can look at a lot of data quickly, find small differences in plants, and keep track of crops as they grow in real time. This helps make better decisions and use resources smarter for different types of crops. With the help of optical remote sensing, Low and Duveiller (2014) ^[82] set out the needed level of detail for recognizing a particular type of crop and found that there isn't a single pixel size that works equally well for all crops. However, the size of the pixels and the purity needed for identifying crops can be different depending on the type of crop and the type of landscape. Also, not all sensors work well for detecting most crops. For example, MODIS with a 250-meter resolution can spot most crops in a field, but Landsat with a 30-meter resolution can classify objects more clearly. Zhang and their team in 2016 ^[140] used two types of consumer cameras an RGB camera that captures red, green, and blue colors, and a modified near-infrared camera and attached them to an aerial remote sensing system to help identify crops in Texas. Images taken by NIR cameras give better classification results compared to images taken by RGB cameras and other non-spectral features.

AI-based crop identification is now easy to use for recognizing various field crops by looking at images using convolutional neural networks. These networks can spot, sort, and find different objects by studying the features in the images, as shown by Ranjithkumar *et al.* in 2021 ^[103]. Ibatullin and their team in 2022 ^[53] used remote sensing and artificial intelligence to track different types of crops. They were able to correctly identify crops with accuracy between 85% and 95% by using satellite images from Sentinel-1 and Sentinel-2. The *Ficus genus* includes almost 1,000 different plant species around the world, which makes it really hard for an average person to tell them apart completely without making a mistake. In this case, Kho and their team in 2017 ^[70] created a basic automatic system that uses an artificial neural network and a support vector machine to recognize and sort images of three types of *Ficus* plants: *F. benjamina*, *F. pellucidopunctata*, and *F. sumatrana*, achieving an accuracy of about 83%.

Crop acreage estimation

The need for different types of crops used in farming and gardening changes over time because their prices or value in the market are not always steady. So, it's really important to figure out exactly how much space you need to grow certain crops based on what's in demand in the market and what you can sell abroad. Estimating the amount of land needed to grow enough crops to feed a big population is one of the hardest things for decision-makers to handle. Right now, satellite technology along with GIS and machine learning is being used to estimate how much land is used for growing crops in large areas. Meraj and others in 2022 calculated how much wheat was grown and how much was produced in Uttar Pradesh, India. They used data from satellites and a model called CASA, which is developed by Carnegie, Ames, and Stanford. Another satellite, SPOT-5, uses multispectral imagery data to figure out what type of crop is

growing and also to guess how big the crop area is at the same time (Yang *et al.*, 2006) ^[134, 90]. Kshetrimayum *et al.* (2024) ^[75] combined machine learning algorithms with data from the Sentinel-1A satellite's SAR system to find out how much pearl millet is grown in India and to forecast the yield of pearl millet in the areas of Agra and Firozabad.

Canopy measurement

Canopy structure and volume are key factors in crops, especially when it comes to accurately applying fertilizers, pesticides, and water in growing plants like fruits and vegetables (Sharma *et al.*, 2022) ^[112]. Trout and their team in 2008 suggested that remote sensors can be used to evaluate the canopy features in horticultural crops by measuring the amount of photosynthetically active radiation that the plant canopy absorbs. Ayyalasomayajula and others in 2009 measured the volume and height of an automated citrus tree with 85% accuracy by using slanted or straight images. Checking the temperature at the top layer of plants helps show if they are not getting enough water. One way to check if crops need more water is by using thermography. This method measures the temperature of the plant leaves from a distance. Giménez-Gallego and their team in 2021 created a device that automatically measures the temperature of almond crop canopies. They used a cheap thermal camera and image analysis tools based on artificial intelligence. To analyze the data collected by drones, a simple and easy-to-use app named Agrovieview was created. This app uses the cloud and AI to count plants in the field, find where they are, tell if they're alive or dead, measure different parts of the plant canopy, and make maps showing where there might be disease or pest problems. Ampatzidis *et al.* (2020) ^[5, 38, 8, 125] used the Agrovieview app to check the phenotypic features of citrus fields, such as tree height, canopy size, and pest detection in both regular and highdensity plantations.

Harvest time assessment: Because markets around the world are changing a lot, it's more important than ever to have correct and detailed information. This helps people make smart choices at every stage, like when making products, managing resources, understanding the market, and getting funding. Because RS can predict things, farmers can now rely on it to get information about the factors that influence when to plant and when to harvest crops. Using traditional imaging methods, spectroscopy, and hyperspectral imaging systems together can help gather spatial and spectral information from fruits, vegetables, and other crops. This helps in figuring out important quality factors, as mentioned by Singh *et al.* in 2009. Hahn (2004) ^[44, 115] says that tomatoes can be grouped into three types hard, soft, and very soft with 90% accuracy, using remote sensors. Temporal RIS-AWiFS data was used to find the best times to harvest apples from orchards. Before, people used regular statistical methods to guess when the harvest would happen, but these methods usually made mistakes. A new model was created to predict the best time to harvest using LSTM, which is a type of AI, and it uses real-time data about production and weather conditions (Liu *et al.*, 2022) ^[81]. AI has been combined with UAVs to create a basic design for olive harvesting drones. This is meant to replace the old, slow ways of picking and collecting olives, which required a lot of manual work and were very tiring (Khan *et al.*, 2024) ^[69]. Dates, which are from the *Phoenix dactylifera* L. plant, come in many different types. Each type looks a bit different on the outside and also has different chemicals inside. Because of this variety, it's hard to know exactly when to pick each type and how to take care of it after

picking. This makes it challenging to make sure all the types are good for selling in the market. Today, to handle this issue, AI and computer vision technology are being used more and are seen as accurate, safe, quick, and effective tools (Noutfia and Ropelewska, 2024) ^[97]. Today, people use better AI models, such as ResNet-59, to predict when potatoes will be ready to harvest. These models help make predictions more accurate, allowing for better planning of resources, less waste, and improved food security (Abdelhamid *et al.*, 2024) ^[1]. AI-driven harvest time assessment of a crop is more effective than traditional manual methods because it offers better accuracy in timing the harvest to reach the best possible moment. It takes into account various factors such as how evenly the crop ripens, current market conditions, how long the crop can stay fresh, and how to reduce waste. By finding the exact time to harvest, AI helps prevent fruits from being too ripe or not ripe enough, which improves the quality of the crops and reduces waste after harvest. This helps keep the income of farmers and related people stable. In contrast, traditional methods depend only on what farmers see with their eyes, which can be wrong because it's hard to check big areas evenly, and weather changes can also make it tricky to get accurate information.

Crop yield estimation: Growers can use the RS approach to check the final amount of crop they expect to get and see the differences in production between fields that are growing the same crop. Vegetation indices, which are based on the different colors of light captured in multispectral images, can be used. The two most commonly used indices are the ratio of near-infrared to red light (Jordan, 1969) ^[59] and the Normalized Difference Vegetation Index (NDVI) (Rouse *et al.*, 1973) ^[104]. Zaman *et al.* (2006) ^[139] used an automatic ultrasonic system and a remote sensing-based yield monitoring system, and they found that there was a straight-line relationship between the size of the tree and the amount of fruit it produced. Another part of remote sensing, called thermal imaging, has been used to figure out how many fruits are in orchards and groves. This works because there's a difference in temperature between the fruit and the air around it. Crop yield is affected by how different factors related to the plant and its environment work together, including temperature, rainfall, the type of plant, how well the seeds germinate, how much the plant flowers, and how much pesticide is used. It is very important to understand how much each factor affects the amount of crops produced. Al-Adhaileh and Aldhyani (2022) ^[4] used the ANN model in Saudi Arabia to precisely forecast crop yields by analyzing data sets that included various factors affecting potato, rice, sorghum, and wheat production. Babae and their team in 2021 used an artificial neural network to predict how much rice crops would produce. In a similar situation, Hara and their team in 2021 highlighted how choosing the right variables to predict crop yield is important when using artificial neural networks along with data collected from remote sensing. A big integration between AI and data from the Sentinel-2 satellite is helping precision agriculture, especially for estimating crop yields in different types of crops such as maize, wheat, and rice (Aslan *et al.*, 2024) ^[7, 46, 9]. Vegetation indices are made from images taken by satellites and are used to predict crop yields very accurately by combining AI algorithms like machine learning and deep learning models. To check how well AI-based models predict crop yields, people often use several measures like mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and R-squared (R²). These metrics help evaluate how accurate and exact the data collected from different models is.

Stress due to pests and diseases

Now, people are using remote sensing and artificial intelligence to identify different insect pests and diseases that affect farmland, as well as to gather information on the best ways to control these pests and diseases. Remote sensing and AI/ML techniques are very good at tracking changes in plant biomass, pigments, color, and how well plants are growing during times of abiotic stress in crops, as shown in a study by Pinter *et al.* in 2003. Small *et al.* (2015) ^[118, 99] found that using past weather information can help in forecasting possible outbreaks of late blight in tomatoes and potatoes. They suggested creating a web-based decision support system. RS can detect changes in plants like yellowing leaves, dying cells, slow growth, drooping, and curling of leaves. Fluorescence spectroscopy, fluorescence imaging, and NIR spectroscopy were used to find fire blight disease in pear plants that didn't show any symptoms. A newer method called electronic nose systems is used to detect plant diseases. The E-nose and fluorescence imaging have been used in a new way to check for stress in plants caused by insect pests and diseases. This is done by finding small changes in the volatile organic compounds (VOCs) that plants release through smell and by looking at changes in the way plant tissues glow under light. This helps in finding insect pests and diseases early, even before any signs are visible. E-noses were used to identify and tell apart fire blight and blossom blight diseases in apple trees in a lab setting (Fuentes *et al.*, 2018) ^[36]. Lins and their team did a study in a field setting in 2009 ^[80] to tell the difference between leaves that had citrus canker and leaves that were healthy but had chlorosis. The SVM performs better than other machine learning methods when it comes to predicting when and how much plant diseases and pests will occur. Bhatia and their team in 2020 ^[15] used a mix of two methods, SVM and logistic regression, to find out if tomatoes have powdery mildew disease. Xiao and their team in 2019 ^[131] talked about using LSTM networks to connect weather information with how population numbers of insects change and how often they attack crops. A useful smartphone app has been created to help detect and recognize pests and diseases on time, which can reduce big economic losses. This app uses a Python-based REST API, PostgreSQL, and Keycloak, and has been tested in real-world scenarios against different pests, such as *Tuta absoluta* in tomato plants, as described in Christakakis *et al.*, 2024 ^[23].

Weed infestation mapping

RS techniques are a better and faster way to map weeds compared to traditional ground surveys, especially when dealing with big areas. Weeds were divided into two groups broad-leaved and grass-weeds based on their leaf texture. This helped in creating more effective selective herbicides. The methods used included Gabour wavelets and neural networks. Digital color photos were used to find areas with no plants in blueberry fields, as shown by Zhang *et al.* in 2010. Backes and Jacobi (2006) ^[10, 141] used high-resolution satellite images from the QuickBird satellite to find weeds in sugarbeet fields. They found a big and thick patch of Canadian thistle growing as a weed. Costello and their team in 2022 ^[25] created a new way to find and show where *Parthenium* is growing. They used regular color images and images that capture more detailed light information, along with AI technology to help.

Using herbicides too much around the world has made many weeds resistant to them, so new strategies that use AI are needed to deal with this problem. Several AI-powered tools are sold for managing weeds, such as robotics, remote sensing, and spectral analysis. Even though AI tools have a lot of potential to help

control weed resistance to herbicides, they aren't widely used yet (Ghatrehsamani *et al.*, 2023) ^[37]. It is important to correctly detect and identify different types of weeds in order to manage them effectively. These days, AI and drone technology are often used to help control weeds in rice fields, as mentioned in Ahmad *et al.*'s 2023 study. Su (2020) ^[121, 3] used drones with hyperspectral cameras to recognize weed types by taking many pictures of various spectral bands. Machleb and their team in 2020 ^[85] showed how autonomous mobile robots can be used to watch over areas, find different types of weeds, create maps of where the weeds are, and manage them in a smart and effective way. Many machine learning methods, including Random Forest Classifier, Support Vector Machine, and Convolutional Neural Network, are used to sort different kinds of digital images and find weeds in crops such as rice, as mentioned by Kamath *et al.* in 2020 ^[61].

Abiotic stress monitoring

Crop plants often face different environmental influences, like light, temperature, and water, which can lead to non-living stresses such as drought, salinity, soil acidity, and high heat. Keeping an eye on non-living stress factors in plants is important for better farming practices and understanding how healthy crops are doing. RS techniques offer useful ways to identify and figure out different kinds of abiotic stresses. A common sign that plants are under nonliving stress is when they have less chlorophyll. When plants face stress, like not enough water or too many harmful minerals, their chlorophyll breaks down, which changes how they reflect light.

A new method has been created to detect stress levels, especially in tree and row crops, where the shaded part of the tree canopy is also considered (Jones *et al.*, 2002) ^[58]. However, it has a problem where the stomata often stay closed in shady areas and there is not much change in temperature. In a similar way, the presence of surface water can be detected by looking at how plants reflect light, whether or not there is actually water on the surface (Pinter *et al.*, 2003) ^[99].

By using spectral reflectance data along with advanced analysis methods like vegetation indices and machine learning algorithms, researchers can measure stress levels and track the health of crops and plants over time. This helps in finding abiotic stress early on, allowing for timely actions and improved ways to manage crops. In addition, AI and ML-based algorithms can be used to help crops grow better even when they face tough conditions. Using machine learning in QTL mining can help find different genetic factors that make legumes more tolerant to stress, as shown in Singh *et al.*'s 2021 study. Different vegetation indices are used to analyze stress levels, especially water stress in plants. These include NDVI (Karnieli *et al.*, 2010) ^[64, 114], PRI (Photochemical Reflectance Index) (Ryu *et al.*, 2021) ^[107], and MSI (Moisture Stress Index) (Hunt *et al.*, 1987) ^[51]. NDVI helps in planning irrigation by showing which parts of the field are more likely to dry out, which makes it easier to plan water use for crops more accurately. PRI measures how well a crop uses the sunlight it gets and checks if the plants are under water stress, as well as how much carbon dioxide the plants take in. MSI measures how much water is in the leaves of plants and is used to check for stress in plant canopies, assess fire risks, understand how ecosystems function, and forecast productivity. Navarro and their team in 2022 used images of leaves taken with special equipment that captures detailed light information, along with an artificial intelligence program, to find out what causes various types of stress in plants. An artificial neural network was used to analyze the reflection patterns of

light in the visible and near-infrared regions, which were the primary indicators of stress. Advances in AI have led to the creation of high-speed tools that help manage plant problems caused by living and non-living factors. These tools also generate large amounts of data, such as the transportable array used for agriculture that collects data from far away, and the phenotyping reference platform (TERRA-REF) ^[96] that helps predict stress in plants early on (Gou *et al.*, 2024) ^[42].

Irrigation water requirement

RS can tell if the water level in a field is changing, like when it's too wet or too dry, using technology that adjusts watering amounts, such as the center pivot system (Mc Dowell, 2017) ^[89]. A more detailed land data assimilation system was used as a tool to create maps showing soil moisture and temperature. The system was designed to give details about how wet the soil is at a certain depth and the temperature of the soil at different levels, including the area around plant roots. There is a strong need to use AI and machine learning models to figure out how much water crops need for irrigation. Mohammed and his team in 2023 studied how to use AI models to figure out the best amount of water needed for micro-irrigation systems that are controlled by sensors and powered by solar panels. Four machine learning algorithms logistic regression (LR) ^[92], support vector regression (SVR), long short-term memory (LSTM) neural network, and extreme gradient boosting (XGBoost) were used and checked to predict water needs. Out of these, LSTM and XGBoost gave more accurate results for predicting how much water is needed for irrigation compared to SVR and LR. When there isn't much water available, an automatic irrigation decision support system can help in smartly planning when to water crops. This makes

water usage more efficient and helps grow better crops. Katimbo and their team in 2023 looked at how well different AI-based algorithms and models work for predicting crop evapotranspiration and the crop water stress index. They did this by checking the soil's wetness, the temperature of the plant leaves, and the NDVI value from maize plants that were being watered. After looking at how well each model performed and their scores, it was found that Cat Boost is the best model for calculating the crop water stress index, and Stacked Regression is the best for calculating crop evapotranspiration. To deal with the issue of water scarcity in growing legumes in Uttar Pradesh, India, AI was combined with precision farming to grow peas. The use of AI-based precision irrigation helped in using water more effectively, increasing crop yield, lowering greenhouse gas emissions, and cutting down the cost of farming (Kim and Al Zubi, 2024) ^[71, 65].

Applications of remote sensing and artificial intelligence in insect pest management

The wavelength of electromagnetic radiation changes depending on how it interacts with the plant's surface. So, the health and strength of a plant can greatly influence how leaves reflect light, as found by Luo and others in 2013. Scientists have used RS to check how much plants are damaged by insect pests, chlorosis, and necrosis by looking at how light reflects off the plants, as done by Franklin in 2001. Many research studies have looked into how RS, AI, and ML can be used to identify insect species, check how much they are present and how bad the damage is, find new places where insects live and breed, and spot signs of diseases (Tables 1-3) ^[35, 83].

Table 1: Application of remote sensing techniques in insect pest research

Insect	Crop	Research parameter	Remote sensing technology used	Reference
Fruitfly	-	Species identification	RGB camera	Faria <i>et al.</i> (2014)
Stored grain pests	Wheat	Species identification	Proximal RS and hyperspectral reflectance profile	Singh <i>et al.</i> (2010)
Fruitfly	-	Species identification	Proximal RS	Dowell and Ballard (2012)
Tobacco bud worm and corn ear worm	Cotton	Species identification	Proximal RS	Jia <i>et al.</i> (2007)
Ants	-	Cryptic Species identification	Imaging Spectroscopy	Klarica <i>et al.</i> (2011)
Evacanthine Leafhopper	Jujubes	Species classification	Hyperspectral Imaging	Wang <i>et al.</i> (2016)
Vespa vellutina	-	Flight monitoring	Harmonic RADAR	Maggiora <i>et al.</i> (2019)
Leafhopper	Cotton	Infestation	Hyperspectral RS	Prabhakar <i>et al.</i> (2012) ^[102]
Leaf miner	Tomato	Damage and incidence	Leaf reflectancespectroscopy	Xu <i>et al.</i> (2007)
Cyst nematode	Beet root	Mapping of symptoms	Combined use of remote sensing and GIS technique	Hillnhütter <i>et al.</i> (2011)
Cotton leaf worm	Cotton	Management timing	Satellite RS	Yones <i>et al.</i> (2012)
Mite	Cotton	Early infestation detection	Multispectral RS	Fitzgerald (2000)
Desert locust	-	Habitat detection and breeding zones	Remote sensing and GIS technique	Latchinsky and Sivanpillai (2010)
Brown plant hopper (BPH)	Rice	Changes in spectral characteristics due to brown plant hopper	Hyperspectral RS	Yang <i>et al.</i> (2007)
Mountain pine beetle	Pine	Infestation dynamics	NDMI Multispectral (Landsat) RS	Goodwin <i>et al.</i> (2008)
Aphid (Diuraphisnoxia)	Wheat	Quantification of stress level	Multispectral RS	Backoulou <i>et al.</i> (2011)

Table 2: Applications of remote sensing techniques in plant disease research.

Disease	Crop	Research parameter	Remote sensing technology used	Reference
Scald	Apple	Detection of scald induced browning in stored apples	Hyperspectral RS	Chivkuno va <i>et al.</i> (2001)
Yellow rust	Wheat	Early disease detection	Hyperspectral RS	Bravo <i>et al.</i> (2003)
Orange rust	Sugarcane	Detection of disease	DWSI Hyperspectral (Hyperion) RS	Apan <i>et al.</i> (2004)
Powdery mildew and	Wheat	Identification of diseases caused by Erysiphe graminis and	Hyperspectral RS	Graeff <i>et al.</i> (2006)

take all disease		Gaeumannomyces graminis		
Soft rot	Broccoli	Early detection of disease	Hyperspectral RS	Datt (2006)
Late leaf spot	Peanut	Change in spectral characteristics	Multispectral RS	Prabhakar <i>et al.</i> (2006)

Disease	Crop	Research parameter	Remote sensing technology used	Reference
Leaf rust	Wheat	Disease detection and identification	Hyperspectral (HyMap) RS	Franke and Menz (2007)
Bacterial leaf blight	Rice	Disease severity	MLR Hyperspectral RS	Yang (2010)
Wheat streak mosaic	Wheat	Disease severity	Multispectral (Landsat TM) RS	Meraj <i>et al.</i> (2022)
Stem rot	Oil Palm	Mapping and identification	Multispectral (QuickBird) RS	Santoso <i>et al.</i> (2011)

Table 3: Examples of application of artificial intelligence and machine learning in insect research.

Insect	Crop	Research parameter	Reference
Major pests	Coffee	Detection and identification	Lee and Tardaguila (2023) ^[77]
Diamond back moth	Cabbage	Abundance forecasting	Kaur <i>et al.</i> (2022) ^[67]
Major pests	Tomato	Prediction of pest outbreak	Holzinger <i>et al.</i> (2023) ^[49]
Thrips	Tomato	Management	González <i>et al.</i> (2022) ^[39]
Whitefly	Tomato	Life stages assessment and identification	Lutz and Coradi (2022) ^[84]
Fruit fly	-	Species detection and identification	Murmuet <i>et al.</i> (2022)
Aphid	Soybean	Population dynamics	Murmuet <i>et al.</i> (2022)
Insect pests	-	Pest classification	Xia <i>et al.</i> (2023) ^[130]
Insect pests	-	Insect activity	Rydhmer <i>et al.</i> (2022) ^[106]
Whitefly	Cotton	detect crop symptoms, environmental conditions, and physical characteristics	Toscano-Miranda <i>et al.</i> (2022) ^[24]
Aphid		Pest forecasting	Bourhis <i>et al.</i> (2021)
Brinjal shoot and fruit borer, Epilachna beetle	Brinjal	Detection, identification, and classification	Saikumar <i>et al.</i> (2023) ^[110]
Aphid	-	Monitoring and forecasting	Batz <i>et al.</i> (2023) ^[14]
Riptortus pedestris	Soybean	Detection and forecasting	Park <i>et al.</i> (2023)
Locust	-	Monitoring and management	Klein <i>et al.</i> (2021) ^[74]
Stored grain pest	Wheat	Grain damage	Sabancı (2020) ^[108]

Using artificial intelligence and remote sensing in managing insect pests

AI algorithms have been really helpful in finding diseases and pests that harm cotton. They can automatically look for signs in the crops, check the surroundings, and notice features that point to the presence of pests or diseases. In a study, Gopinath and others in 2022 created an automatic system that uses a lot of data to classify plant leaf diseases. They used a special type of algorithm called CRNN, which is a mix of convolutional and recurrent neural networks. This system helped tell the difference between healthy and sick leaves from various plants like bananas, peppers, potatoes, and tomatoes. Sujithra and Ukrit (2022)^[123, 41] used several types of deep neural networks, including CNN, Radial Basis Neural Network (RBNN), and Feed-Forward Neural Network (FFNN), to identify leaf diseases in banana and sugarcane plants. The way different AI models and deep learning algorithms work together to make good decisions for managing insect pests is shown in Figure 5. A method that uses drones to detect pests involves flying robots equipped with different types of sensors and imaging tools like regular cameras, cameras that capture multiple colours, heat sensors, and cameras that capture a wide range of light wavelengths. These tools help in spotting insect pests in crops. This method helps find pests early and use pesticides wisely to control them, which helps keep the ecosystem in balance. The IoT-based UAVs (Yadav *et al.*, 2024)^[133] use AI methods and Python programming to send images of different rice pests to the Imagga Cloud, offering useful and timely information that helps take the right action (Bhoi *et al.*, 2021)^[16].

Insect taxonomy and systematics: People are getting more worried every day about invasive pest species, which are becoming a serious biosecurity problem. This happens because of things like tourism, trade between countries, and changes in the world's climate (Hulme, 2009)^[50]. So, we need to be very careful with quarantine and inspections to stop harmful non-native pests from spreading. Using automatic inspection and detection methods helps cut down on costs and time needed to check for invasive pest species in goods, and using proximal RS is a good way to do this. Using data from an RGB camera that measures reflected light, researchers looked at the wings and stinger of three fruit fly species that look very similar. They were able to tell them apart and identified them as *Anastrepha fraterculus*, *A. oblique*, and *A. sororcula* (Faria *et al.*, 2014)^[32]. Researchers used a near-infrared and hyperspectral imaging system to tell the difference between healthy wheat kernels and those that were damaged by insects while they were stored. They did this by looking at the reflected light patterns from the wheat, which helped them identify the damage (Singh *et al.*, 2010)^[116]. Using the same method, two fruit fly species (Dowell and Ballard, 2012)^[30], the tobacco budworm, and the corn earworm (Jia *et al.*, 2007)^[56] were also found. Klarica and others in 2011^[73] used imaging spectroscopy to find two hidden ant species, *Tetramorium caespitum* and *T. impurum*. Wang and their team in 2016^[128] used a type of imaging called hyperspectral imaging, which captured 37 different color bands between 41.1 and 87 nanometers, to help classify insects. They also looked at DNA from the mitochondria and measured the physical features of the insects. Through this, they found and identified seven

different species within the leafhopper genus *Bundera* from the Evacanthine group.

Even though species are considered the basic units in all research, they can sometimes be unreliable in identifying organisms, especially when complex evolutionary processes such as hybridization, polyploidy, and mutation are happening. Combining taxonomy with AI under one idea of what a species is can help bring together data and automatically find features that make species identification less dependent on personal opinions (Karbstein *et al.*, 2024) ^[63]. A machine learning algorithm was created to find the most common insect pests in coffee fields by looking at pictures, and it worked better than old ways of finding and recognizing pests (Lee and Tardaguila, 2023) ^[77]. Deep learning, which is a part of machine learning, was used to find and track the number of whiteflies on tomato plants by recognizing them at different stages of their life cycle, as mentioned in Lutz and Coradi's study from 2022 ^[84]. Saikumar and his team in 2023 ^[110] did tests to find and sort out different insect pests that attack eggplant using artificial intelligence. They used Python along with Keras and TensorFlow, and the model they used was CNN-VGG-16. Throughout the study, 204 images of insect pests were collected and used as input data to automatically identify and classify different types of insect pests, including Brinjal shoot and fruit borers and the Epilachna beetle, as reported by Saikumar *et al.* in 2023 ^[110].

Insect movement and migration: The monitoring of migrant insect species can be done using entomological radar. RS technology can automatically track the height, how fast insects are moving sideways, which way they are going, their position, their weight, and their shape. Recent improvements in radar technology have led to the creation of new harmonic radar systems that can track certain insect species, like *Vespa vellutina*, which fly at heights of up to 500 meters (Maggiore *et al.*, 2019) ^[86]. AI-based pest surveillance and monitoring systems use cameras and sensors to gather data and can correctly predict when a specific pest is likely to infest an area. Researchers from California University created an AI system that helps detect the reasons for pest problems and follow where the pests are moving (Sharma *et al.*, 2022) ^[112]. The computer vision system and ICT algorithm suggested here seem to work well as an automatic way to track insects, and they can be a helpful tool along with other methods used to watch nocturnal insects, as mentioned in Bjerger *et al.*, 2021. AMMODs, which are Automated Multisensor Stations used to monitor Species Diversity, work like weather stations and function as selfoperating devices that collect data on various species such as plants, birds, mammals, and insects (Wägele *et al.*, 2022) ^[127].

Detection of biotic stress

Biotic stresses, like diseases and insect pests, can seriously harm how well crops grow. Crop stress from pests and diseases can be found using remote sensing. This works because when plants are under stress from living things like insects or pathogens, they change in color, look, and how they do photosynthesis. These changes affect how much energy the plants take in and how they reflect light, which can be detected from a distance (Prabhakar *et al.*, 2012) ^[101]. Prabhakar and his team in 2012 ^[102] checked how much stress and damage leafhopper attacks caused to cotton plants. They looked at the chlorophyll levels and how much water the leaves were holding, using ground-based hyperspectral remote sensing. Based on these measurements, they divided the plants into five groups, from 0 to 4, showing from healthy plants

to those with serious damage. The damage to the leaves in a tomato field was checked using leaf reflectance spectra (Xu *et al.*, 2007) ^[132, 101], and the symptoms of cyst nematode in beet were tracked by using both remote sensing and GIS methods (Hillnhütter *et al.*, 2011) ^[48]. Scientists used a part of deep learning in machine learning to predict how many diamondback moths are in cabbage crops. This method was shared by Kaur and others in 2022. To detect and recognize various pests in tea plantations in Yunnan and stop the tea leaves from losing quality, transfer learning with CNN was used (Li *et al.*, 2024) ^[78, 67].

Pest monitoring, forecasting, and early warning

Knowing how old the larvae are in the field helps predict when pests will first appear and when they might come back, and it also helps decide the best time to use insecticides for controlling pests. RS is important because it gives information about the current stage of insect pests in the field, using the total number of degree days that have built up (Yones *et al.*, 2012) ^[138]. The best time to manage the cotton leafworm (*Spodoptera littoralis*) was found by using degree days, which are based on air temperature between 174.85 and 197.59, as calculated from satellite data (Yones *et al.*, 2012). A study by Nansen and others in 2015 looked at two types of insects, the maize weevil and the large flour black beetle. The study found that changes in how their bodies reflected light over time were connected to how they reacted to two ways of killing them: using harmful worms called entomopathogenic nematodes and using a plant-based insecticide. Colour infrared photography was used to check for black fly and brown spot scale problems in citrus orchards, as well as to look at white fly issues in cotton fields. Scientists looked at mite problems in cotton fields early on by checking how the plants looked, changed color, and how their leaves covered the ground over time. They used multispectral remote sensing for this study, as mentioned by Fitzgerald in 2000.

Machine learning models can be used to predict pest problems, like the main pests affecting tomato plants. These models were able to predict pest outbreaks with much more accuracy than older statistical methods, as shown in a study by Holzinger *et al.* in 2023 ^[49]. Machine learning can help create decision support systems that connect how pest populations change with environmental factors, which supports better management strategies. A decision support system was created using machine learning to help control thrips in tomato crops, which led to a clear decrease in the number of insecticides used (González *et al.*, 2022) ^[39]. AI-based algorithms, like machine learning, help in predicting and warning about pests early on. In the case of fruit flies, various species were identified and grouped according to the patterns on their wings, as reported by Murmu and others in 2022. Machine learning algorithms can predict how pest populations change based on environmental factors like temperature and rainfall. Deep learning algorithms can help predict when and how many aphids will appear on soybean plants, as shown in the study by Murmu *et al.* in 2022. AI can help improve predictions about aphid pests by making monitoring systems better and enhancing the models used to forecast their spread (Bourhis *et al.*, 2021) ^[18].

It takes a lot of time to analyze many samples collected using traditional insect catching methods like suction traps. A knowledgeable taxonomist is required for accurate sample handling, which can slow down the tracking of insect numbers. AI-powered image recognition and machine learning algorithms have become a more promising solution for this. Aphids can lead to significant damage in crop production either by eating

the plants directly or by spreading plant viruses. Batz and their team in 2023 ^[14] looked into how AI, machine learning, and image recognition can be used to watch for and predict insect pests in a structured way. A key pest, *Riptortus pedestris*, that causes significant damage to soybean pods and leaves was identified through a monitoring system that uses an unmanned ground vehicle with a GoPro camera. The machine learning models used to study this pest were part of a group of deep learning algorithms, including MRCNN, YOLOv3, and Detectron2 (Park *et al.*, 2023) ^[98]. As the world's population continues to grow, it's becoming increasingly important to get early warnings about new pests, like locusts, entering areas where they don't normally exist. Halubanza (2024) ^[45] created a sophisticated AI model based on a CNN called MobileNet version 2. This model is used to automatically recognize different types of locusts. It was able to correctly identify *Locusta migratoria* with 91% accuracy and *Nomadacris septemfasciata* with 85% accuracy.

Detection, identification, and classification of insect habitats

Using multispectral scanners on satellites like Landsat, remote sensing images can be collected to help find where a certain insect lives. In the states of Nebraska and South Dakota, mosquito larvae were found in Lewis and Clarke Lake using a multispectral scanner. This lake was found to have seven types of mosquitoes: *Aedes dorsalis*, *A. vexans*, *Culex tarsalis*, *C. restuans*, *C. silinarius*, *Culiseta annulate*, and *Anopheles walker* (Hayes *et al.*, 1985) ^[47]. Using RS and GIS methods has helped find locust habitats and breeding areas in Africa, southern Europe, and southwest Asia, as shown by Latchininsky and Sivanpillai in 2010 ^[76].

Infrared sensors can find out when flying insects are active by using lights that emit nearinfrared light and fast sensors that pick up light (Rydhmer *et al.*, 2022) ^[106]. Different features like how fast wings beat, the dark color on wings, and the size of wings compared to the body can be measured in the field. These measurements can be sent automatically to a cloud database and then studied using machine learning and artificial intelligence. Xia and their team in 2023 checked how well Vision Transformer models work for identifying different types of pests. The researchers used ResNet50, MMNet, DNV, and a group of models that combined the predictions from these three models to make the final decision through a vote. MMNet used an attention mechanism to find important parts of the image. The areas that were found were then used to train more detailed CNN-based classification models at various levels of resolution. Every year, locusts appear in various areas around the world. This is because it's hard to track and watch locust areas, which are mostly in hard-to-reach parts of countries that are experiencing conflict. Since the 1980s, remote sensing has been used to track and control locust swarms. Today, drones are offering new ways to manage locusts more efficiently and quickly. The studies have used AVHRR, SPOT-VGT, MODIS, and Landsat to track locust outbreaks (Klein *et al.*, 2021) ^[74, 130].

Pest damage and yield forecast

You can check how much crops are damaged by pests by looking at how they reflect light, using drones, and also by knowing what percentage of the crops can be harvested when there is pest damage, as shown in the study by Hunt and Rondon from 2017. The crop yield forecast was made by looking at how vegetation indices relate to actual crop yield, using data from remote sensors, as described by Casa and Jones in 2005. Crop yield depends on many things, especially pests and diseases,

which makes it hard to predict accurately. But using field sensors to monitor different growth patterns has made it easier to forecast how much crops will produce. Sharma and their team in 2020 used a combination of CNN and LSTM models on raw image data to predict wheat crop yields. The new model showed a big improvement in accuracy, reaching 74% better than traditional methods used for predicting crop yields. It also performed much better than other deep learning models, improving by 50%. Dharani and their team in 2021 compared three methods ANN, CNN, and RNN with LSTM to see which one works best for predicting crop yields. The findings showed that CNN was more accurate than ANN, and the RNN with LSTM performed best among all methods, reaching an accuracy of 89%. A CNN-RNN model was suggested to forecast soybean and corn production in the United States by Khaki *et al.* in 2020. Sabanci (2020) ^[108, 68, 29, 113, 21, 52] applied AI methods like artificial bee colony optimization, artificial neural networks, and extreme learning machine to identify damage caused by Sunn pest in wheat grains in Turkey. Toscano-Miranda and their team in 2022 ^[124] did a study on cotton plants by using AI methods like classification, image segmentation, and feature extraction. They used algorithms like support vector machines, fuzzy inference, back-propagation neural networks, and CNNs. The study looked at the most common pests, like whiteflies, and diseases such as root rot.

Challenges and future trends

The ability of AI and remote sensing in managing insect pests depends on developing accurate and up-to-date monitoring systems that can predict pest problems and help in targeting pest control efforts more effectively. However, important issues such as poor data quality and lack of data, difficulty in getting technology, high costs of computation, challenges in identifying different species, rules about using AI in pest control, and adjusting to changes in the environment, especially from climate change, need to be solved to make sure pest management is done in a responsible and sustainable way. The bright future in this area could include better image analysis, combining data from multiple sensors, using models to predict problems, targeting pests more accurately, monitoring with drones, using smart traps and attractants, and building easy-to-use platforms for everyone involved to share information, which helps in managing pests more effectively.

Conclusion

Agriculture depends a lot on getting the right information at the right time, and remote sensing and AI are very important in giving that information. RS and AI can quickly collect data and cover big areas of farmland, helping farmers and those making decisions to choose the best times and methods for growing crops, giving water where it's needed, and dealing with pests. One particular area where RS and AI have shown a lot of promise is managing insect pests. These methods help in keeping track of pests, finding out when pest problems start, giving early warnings, and figuring out the best time to use pest control measures. This way, farmers can stop crops from getting damaged and keep their money from being lost because of insects. Recent improvements in spectroscopy and other remote sensing methods have created new chances for creating different and creative ways to manage crops. Using data from remote sensing with regular farming methods can help use resources like water, fertilizers, and pesticides more accurately and effectively, making the whole process better and more productive. We need to work on making data collection and

processing faster so we can quickly react to changes happening on the ground. This would make the information more useful and relevant for people who make decisions in agriculture, and it could help increase productivity and the ability to cope with changing environmental conditions.

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