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REVIEW ARTICLE

Information and communication technologies in sustainable crop protection: advancing towards sustainable agriculture

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Abstract

Conventional pest management strategies that predominantly rely on chemical pesticides present considerable environmental and health hazards, thereby underscoring the urgent need for sustainable alternatives. The deployment of Information and Communication Technologies (ICT) in agriculture provides robust approaches to sustainable pest and disease management, effectively reducing dependency on chemical inputs. Advanced technologies—including remote sensing, Geographic Information Systems, and machine learning are fundamentally transforming precision agriculture by facilitating real-time monitoring and enabling data-driven decision-making processes. This review examines recent advancements in ICT for pest and disease management, with a focus on innovations such as remote sensing, automated smart traps, and decision support systems. The convergence of artificial intelligence and the Internet of Things further illustrates the potential to enhance crop protection. Additionally, early warning systems, such as the Food and Agriculture Organization's Fall Armyworm Monitoring and Early Warning System, are redefining strategies for real-time monitoring and timely intervention. The discussion also addresses challenges including limited ICT access in rural and developing regions, as well as concerns related to data privacy and cybersecurity. Overall, integrating ICT with sustainable farming practices offers significant potential to reduce chemical inputs, improve pest control efficiency, and enhance global food security. Future developments in AI-driven analytics, cloud-based data-sharing platforms, and digital farmer extension services will be essential for scaling ICT adoption in sustainable crop protection.

Keywords Sustainable agriculture · Precision crop protection · Smart pest management · Remote sensing · Decision support systems · Internet of Things (IoT)

Introduction

The agricultural sector faces numerous challenges, including increasing food demand, climate change, and the depletion of natural resources. Among these, pest and disease management remain a critical issue, threatening crop production and food security (Ahmad et al. 2013, 2015, 2017a, 2017b; Ekwomadu and Mwanza 2023; Rameez et al. 2024). Cereal crops provide a major food source for humans and animals, yet they are heavily attacked by pest and diseases. These diseases are often insidious, without obvious symptoms at first, and are extremely difficult to control (Ekwomadu and Mwanza 2023). Traditional methods of pest control, relying heavily on chemical pesticides, pose significant environmental and health risks, contributing to soil degradation, water contamination, and biodiversity loss. Innovative integrated management techniques are crucial in reducing the reliance on chemical inputs (Abbas et al. 2022). In recent years, Information and Communication Technologies (ICT) have emerged as transformative tools in promoting sustainable pest and disease management, aligning with global goals of sustainable agriculture (Franck et al. 2024; Aithal and Aithal, 2024). By incorporating advanced technologies like remote sensing, Geographic Information Systems, and machine learning, precision agriculture is entering a transformative new era that allows for more precise and flexible management of agricultural systems. Remote sensing, particularly when integrated with artificial intelligence and machine learning, has proven to be highly effective in monitoring agricultural health and facilitating informed

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decision-making in integrated pest management (IPM) (Rajabpour and Yarahmadi 2024).

ICT's integration into agriculture allows for the development of precision farming techniques, real-time monitoring, data-driven decision-making, and reduced reliance on chemical inputs. The rapid expansion of ICT in rural areas of developing countries presents new opportunities to deliver timely, cost-effective information services to farmers and support better coordination among agricultural agents (Aker et al. 2016). Advancements in digital technology provide a valuable opportunity to analyze crop pest and disease data across and within farms, allowing for a deeper understanding of variability (Tonnang et al. 2022). Tools such as the Open Data Kit (ODK), Research Electronic Data Capture (REDCap), Fall Armyworm Monitoring and Early Warning System (FAMEWS), and remote sensing technologies have significantly improved the efficiency, accuracy, and scope of data collection in agriculture, particularly for pest and disease management. These tools streamline the gathering of diverse types of data—such as text, geographic locations, images, audio, and video—allowing researchers, farmers, and agricultural agents to access and analyze critical information in real-time. This review explores the advancements in ICT for pest and disease management, highlighting key technologies, their applications, and the broader implications for sustainable agriculture (Tonnang et al. 2022).

The role of ICT in crop protection

ICT encompasses an extensive array of digital tools, ranging from mobile applications, sensors, drones, and Geographic Information Systems (GIS) to remote sensing technologies and machine learning models (Table 1 and Fig. 1). These pioneering technologies are being progressively employed to enhance the monitoring of pest populations, predict disease outbreaks, and optimize pest control strategies in agriculture. They are reshaping traditional agricultural practices by offering real-time data, precision, and a more efficient, sustainable approach to pest and disease management. The key areas where these technologies are making a significant impact include:

Real-time monitoring and early warning systems

Early detection of pest and disease outbreaks is essential for minimizing crop damage and reducing the dependency on chemical pesticides (Fig. 2). Timely identification allows farmers to take targeted action before the problem escalates, thus preserving both crop health and the environment. ICT solutions, such as remote sensing and IoT-based (Internet of Things) monitoring systems, are revolutionizing this process by providing farmers with real-time data on pest and disease activity (Tonnang et al. 2022). These technologies facilitate more precise and informed decision-making, helping farmers intervene at the right moment, rather than resorting to blanket pesticide applications.

Case studies

Artificial Intelligence technologies are revolutionizing agricultural pest management by providing efficient and effective solutions to challenges like time-consuming manual pest detection and rising pest populations (Vidya et al. 2025). Case studies such as the PACMAN SCRI project, which focuses on apple crop load management, and Project PANTHEON's SCADA system for hazelnut orchard management illustrate the transformative impact of artificial intelligence and IoT in enhancing agricultural practices (Sharma and Shivandu, 2024). Liu et al. (2022) developed a deep learning model for improved pest identification. After removing image backgrounds, their ResNet V2 model achieved 96% accuracy on a test set of reared insects. Exploring model updates with a new dataset (Dataset 2), they found transfer learning with the T_ ResNet V2 model yielded 84.6% accuracy. Further optimization using Particle Swarm Optimization to optimize the parameters of a Support Vector Machine (SVM) and Back Propagation Neural Network increased accuracy to 73.9% and 75.0%, respectively. However, training with a mixed dataset reduced accuracy to 65.5%. One more example of successful case study is the real-time monitoring of fall armyworm, *Spodoptera frugiperda* in Kenya by Buchaillot et al. (2022). They developed and tested a monitoring algorithm using Sentinel 2A and 2B satellites, employing optimized first-derivative Normalized Difference Vegetation Index (NDVI) time series analysis through Google Earth Engine. Their observations confirmed a loss of green biomass during the vegetative growth stages of maize, attributed to the presence of *S. frugiperda*, which was consistent with the signals indicating a decline in leaf area index (LAI) and total green biomass (as measured by NDVI). They also investigated commercial nanosatellite constellations, such as PlanetScope, which may provide advantages in terms of higher spatial resolution and more frequent data returns.

One of the most impactful applications of ICT in early detection is the use of smart traps integrated with sensors (Aslam et al. 2024). These smart traps are deployed across fields and continuously monitor pest populations by capturing and identifying pests in real time. For example, in one case study, Welsh et al. (2022) created a smart trap utilizing simple optoelectronic beam break circuits to monitor disruptions in light between a series of infrared emitters and photodiode receivers. When an insect interrupts the light beam, it results in a reduction of the photocurrent generated by the receivers, which is proportional to the extent

Table 1 Recent information and communication technologies solutions in sustainable crop protection, along with the recent research insights

ICT Solution	Application in Crop Protection	Sustainability Impact	Recent Research Insights	References
Remote Sensing & Geographical Information System (GIS)	Monitoring crop health, soil conditions, pest outbreaks	Reduces pesticide use, early pest detection, and site-specific treatments	Research shows reduction in chemical inputs due to precision monitoring	Sishodia et al. (2020)
Drones & Unmanned Aerial Vehicles (UAVs)	Aerial surveillance of crop conditions and pest infestations	Minimizes environmental impact by applying precise pest control measures	Studies demonstrate savings in pesticide application	Karthik et al. (2021)
Support Vector Machine (SVM) and Convolution Neural Networks (CNNs)	The SVM method is utilized to classify and predict specific diseases	Reduces environmental impact	Average correct recognition rate of the rice disease recognition model based on deep learning and SVM is 96.8%	Jiang et al. (2020)
Internet of Things (IoT) Sensors	Real-time data on soil moisture, weather, and pest activity	Enables targeted irrigation and pest control, reducing resource wastage	Research suggests IoT reduces water usage in pest-prone areas	Dhanaraju et al. (2022)
Artificial Intelligence (AI) and Machine Learning	Predictive modeling for pest outbreaks, disease spread, and yield forecasts	Optimizes resource use, reducing chemical and energy inputs	Machine Learning predicts prevalent tea pest *Empoasca onukii* through a random forest algorithm and a bivariate map	Li et al. (2024)
Mobile Apps and Platforms	Farmers' access to crop protection advisories and best practices	Improves smallholder decision-making and promotes sustainable practices	Farmers who grew cooking bananas and raise livestock were more likely to know about and use mobile phone-based agricultural services	Kabirigi et al. (2022)
Decision Support System (DSS)	These tools integrate a combination of pest population models and process models	Improving the timing and methods of crop protection interventions	The effectiveness of DSS in various situations depends on the availability of adequate data to quantify the joint distribution between predicted and actual pest intensity, as well as information to assess the impact of control measures at a specific level of disease	Helps et al. (2024)

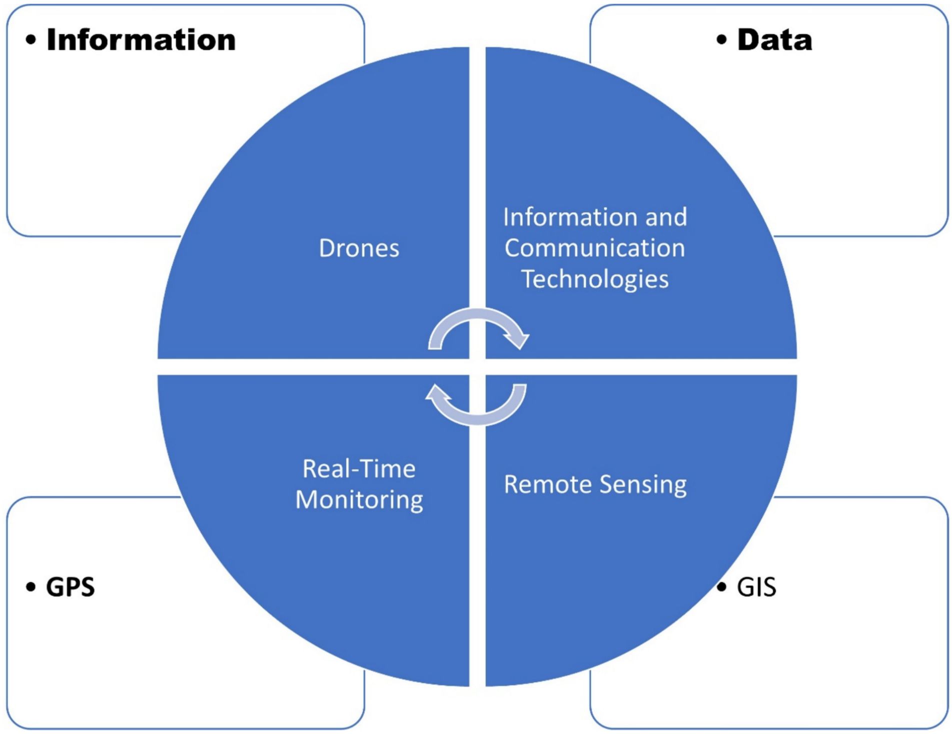

Fig. 1 Information and communication technologies in crop protection. *GPS* Global Positioning System, *GIS* Geographic information system

of the disruption. This decrease in photocurrent, caused by an insect breaking the emitter beam, is then converted into a readable voltage using a current-to-voltage converter, typically configured as a trans-impedance amplifier. Once a pest is detected, the system automatically sends actionable insights to farmers through mobile alerts, dashboards, or cloud-based platforms. This immediate feedback allows farmers to assess the level of pest activity and decide on targeted interventions, such as biological controls or localized pesticide application, rather than treating the entire field. The Food and Agricultural Organization's FAMEWS app provides farmers with a powerful tool to monitor and report pest infestations, allowing them to share valuable data with a global database (Anonymous 2024). This collaborative approach not only aids in real-time tracking of fall armyworm populations but also facilitates communication between local authorities and farmers, ensuring that control measures are well-coordinated. the app promotes proactive management by providing farmers with timely alerts and guidance on pest control options. This empowers farmers to act quickly and efficiently, implementing measures that are both effective and sustainable. Mwenda et al. (2023) assessed the impact of ICT-based pest information services (IBPIS) on the adoption of integrated pest management (IPM) and compliance with pre-harvest intervals (PHI). They used the average treatment effect on the treated (ATET) method to analyze their data. A logit model was used to calculate a score, with T = 1 for IBPIS adopters and T = 0 for non-adopters. The study found that 48.2% of farmers adopted at least one IBPIS. Overall, 51.2% of farmers adopted IPM, but this rate was significantly higher among IBPIS adopters (64.6%) compared to non-adopters (38.6%).

Remote sensing and GIS for pest mapping

Remote sensing technologies, combined with GIS, provide large-scale monitoring of crop health and pest or disease spread across wide geographic areas (Chithambarathanu and Jeyakumar 2023). Satellite imagery and drone-based systems capture real-time data on vegetation indices, which can indicate stress from pests or diseases (Abdullah et al. 2023; Rajabpour and Yarahmadi 2024). Current satellite sensors are not adequately capable for spatially resolving individual plants or tracking pathogenesis because of low temporal resolution. Unmanned Aerial Vehicles (UAVs) are improved option (Barbedo et al. 2019a, 2019b). UAVs can manoeuvre through challenging and rough terrain to capture high-quality images. These images help identify pests and guide pest control efforts. Equipped with cameras, UAVs can address many crop protection challenges that traditional pest management tools cannot (Maslekar et al. 2020; Subramanian et al. 2021) (Table 2). Qin et al. (2016) provided a strong data set that supports the optimized design, enhanced performance, and rational use of UAVs for insecticide spraying in rice fields. The study demonstrated that varying the drone's flying height (between 0.8 and 1.5 m) and flight

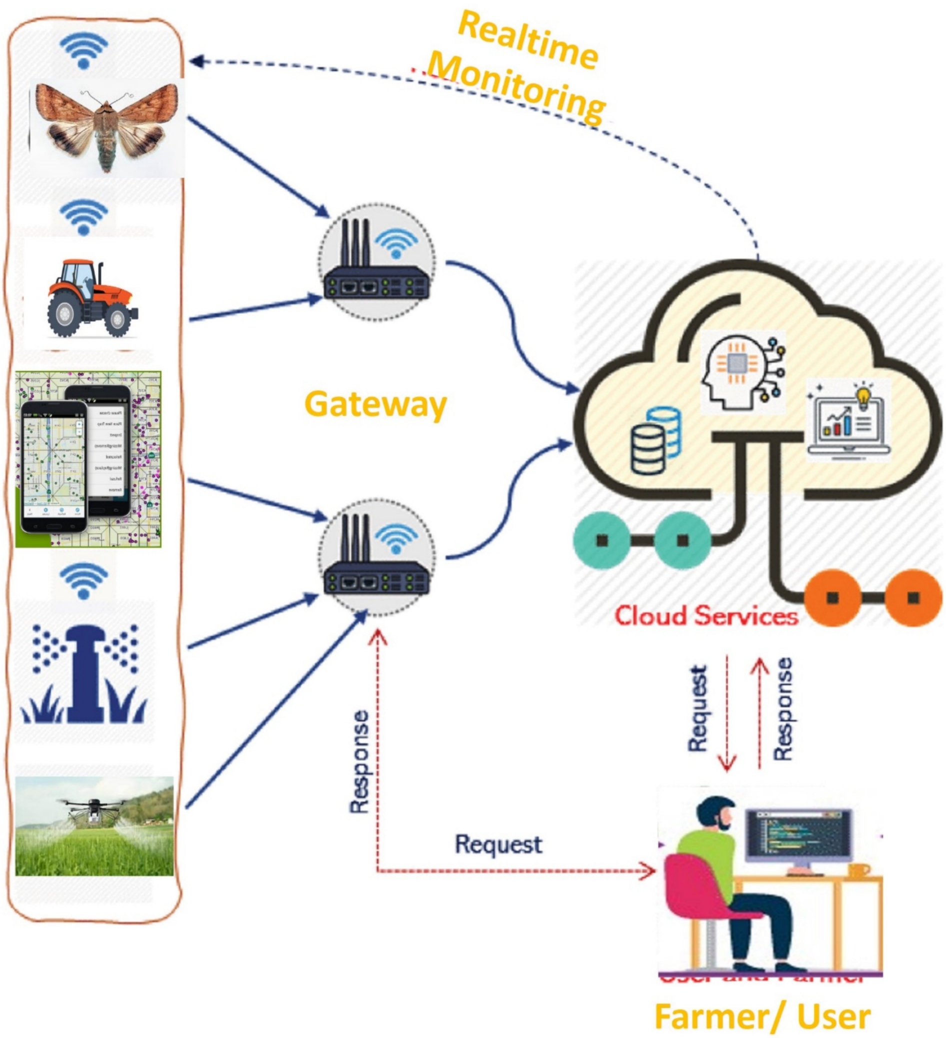

Fig. 2 Smart agriculture and realtime monitoring of pests and diseases (Modified from Gupta et al. 2020)

speed (3 to 5 m/s) significantly impacted droplet deposition. Drones are also used to release beneficial insects (e.g., *Trichogramma* spp.) in specific pest-infested areas (Zhang et al. 2024). The problem of pest detection using digital images shares several similarities with disease detection, as insects are primary vectors for many of the most important plant diseases. Thus, it is no surprise that factors such as illumination, angle of capture, and shadows have also been shown to have a significant impact on pest detection (Otsu et al. 2018; Barbedo et al. 2019a, 2019b). GIS mapping allows for spatial analysis, helping farmers and policymakers design localized intervention strategies. Qing et al. (2020) developed an autonomous system for managing pests in rice fields using machine vision technology. This system, which combines a desktop unit with a cloud server, integrates a light trap that kills and disperses insects while simultaneously capturing images of the trapped pests. These images are then transmitted to a cloud server for further analysis. By automating pest monitoring, this system provides an efficient and real-time solution for pest management, allowing for faster interventions and more precise control strategies.

Klein et al. (2023) successfully utilized satellite imagery from Sentinel-2 and Landsat to develop a highly precise land cover map aimed at enhancing locust management. By integrating this map with a user-friendly hexagonal grid system, they facilitated efficient monitoring of locust populations across different scales, ultimately improving control strategies. The land use /land cover map derived from Sentinel-2 imagery for 2021 achieved an overall accuracy of 86.02% with a Kappa coefficient of 0.824. Meanwhile, the binary cropland classification demonstrated a higher accuracy of 96.48%, with a Kappa coefficient of 0.877. Jiang et al. (2020) demonstrated the successful application of deep learning techniques combined with Support Vector Machine (SVM) algorithms to identify four distinct rice leaf diseases using image data. Their approach involved the use of Convolutional Neural Networks (CNN) to extract detailed features from images of diseased rice leaves. The SVM method was then employed to classify and predict the

Table 2 Use of drones/ unmanned aerial vehicles (UAVs) in pest and disease management

Category	Use of Drones/UAVs in Pest Management	Key Benefits	Reference
Monitoring and Surveillance	Drones equipped with multispectral, hyperspectral, and thermal cameras to monitor crop health, detect pest infestations, and assess Normalized Difference Vegetation Index (NDVI)	Equipped with cameras, UAVs can address many crop protection challenges	Maslekar et al. (2020)
Precision Spraying	Targeted application of pesticides, insecticides, or biological control agents via drone systems	Reduced chemical use, minimized human exposure, precise targeting of pest hotspots. A comprehensive database for optimizing UAV design, improving performance, and ensuring efficient insecticide application	Qin et al. 2016; Subramanian et al. 2021
Field Mapping	Generation of detailed pest and disease distribution maps and monitoring using UAV-Based Data	Accurate decision-making, better pest and disease control planning, Conserving battery life, shortening mapping time, or flying at higher altitudes to reduce overlap percentage	Barbedo 2019a, b; Duarte et al. 2022
Thermal Imaging	Use of drones with thermal cameras to detect temperature variations in plants affected by pests or diseases	Multispectral (3 to 6 bands, 0.4 to 1.0 μm) and thermal cameras (7–14 μm) on drones detect crop diseases, monitor vigor, estimate biomass and yield, and identify abiotic and biotic stress symptoms	Yang et al. 2014; Abbas et al. 2023
Biological Control	Drones used to release beneficial insects (e.g., *Trichogramma*) in specific pest-infested areas	Environmentally friendly, reduces reliance on chemical pesticides	Filho et al. 2020; Zhang et al. (2024)
Aerial Trapping	Deploying drone-mounted traps for pest population sampling and monitoring	Remote trapping, labor-saving, covers hard-to-reach areas	Filho et al. 2020; Lucas et al. 2024
Pest and Disease Damage Assessment	Drones equipped with high-resolution cameras to assess pest-induced damage to crops	Quick damage assessment, supports insurance claims and compensation processes	Maslekar et al. (2020)
Fertilizer and Seed Dispersal	Using drones to apply fertilizers or disperse seeds in areas affected by pest damage or where pest management activities are underway	Restores damaged crop areas, enhances soil health	Kariyanna and Sowjanya (2024)
Data Analysis and Reporting	UAVs collect data that can be analyzed using AI and machine learning to predict pest outbreaks and recommend management actions	Data-driven decisions, improves efficiency	Helps et al. 2024

presence of specific diseases. This combination of CNN for feature extraction and SVM for classification enabled accurate disease recognition, showcasing the potential of machine learning in plant disease diagnostics. Wang et al. (2022) introduced a different application of modern technology in agriculture by proposing the use of UAVs for remote sensing in cotton farming. Their system was designed to estimate cotton habitats and detect potential problem areas at the farm level using GIS. The GIS network tool was utilized to determine cotton transit routes and to pinpoint and display potential sites where volunteer cotton (cotton plants growing unintentionally outside designated areas) might thrive. Through the combination of UAVs and image processing techniques, they were able to accurately identify the locations of volunteer cotton, enabling targeted removal along transit routes and reducing the risk of crop contamination or spread of pests.

The ability to use satellite data to follow the movement of locust swarms across East Africa showcases the immense potential of remote sensing technology in managing large-scale pest outbreaks. The FAO has been instrumental in monitoring locust invasions and breeding activity through its global Desert Locust Information Service (DLIS) (http://www.fao.org/ag/locusts/en/activ/DLIS/index.html). Researchers like Wang et al. (2021) mapped changes in a vegetation health index (NDVI) across East Africa from December 2019 to May 2020. This analysis helped assess the impact of the locust swarms on local plant life. According to FAO investigations (http://www.fao.org/ag/locusts/en/info/info/index.html), locust swarms began forming and multiplying rapidly in the mid-2019 within the breeding area near the border of India and Pakistan. NDVI anomalies from July 2019 to May 2020 revealed that the most severely damaged vegetation was concentrated in the summer locust breeding grounds, where NDVI values were significantly lower compared to typical years. Ishengoma et al. (2021) and Sheema et al. (2022) both used CNN-based models (VGG16, VGG19, InceptionV3, and MobileNetV2) to detect fall armyworm (FAW) infestations in maize. Ishengoma et al. used drones and image analysis to achieve up to 100% accuracy, while Sheema et al. combined odor detection with image analysis, reaching up to 99.2% accuracy. Both studies significantly improved accuracy through image modification techniques. To combat greenhouse pests, Rustia et al. (2022) created I2PDM, a smart system using edge computing devices. I2PDM accurately identifies thrips and whiteflies, common threats to tomatoes and orchids. After over three years of collecting pest and environmental data, the system proved effective, helping farm managers implement IPM strategies and reduce pest numbers by up to 50.7% annually.

These examples demonstrate how cutting-edge technologies like machine vision, deep learning, and UAV-based remote sensing are revolutionizing crop protection. By automating the detection and classification of pests and diseases and improving the precision of habitat monitoring, these systems contribute to more sustainable, data-driven approaches to crop management. They not only enhance the efficiency of pest and disease control but also reduce the reliance on chemical inputs, promoting healthier and more environmentally friendly farming practices.

Decision support systems (DSS)

In the context of Integrated Pest Management (IPM), the use of information and data-driven models can be extended to form comprehensive "decision systems" or "decision management tools." These tools incorporate a combination of pest population models and process models, where applicable, to guide more effective management actions (Damos and Karabatakis 2013; Franck et al. 2024). By integrating such models, farmers and agricultural managers can make more informed decisions, improving the timing and methods of interventions, and ensuring that pest control measures are both targeted and efficient. A major benefit of these DSS tools is their ability to minimize the unintended consequences of pesticide use (Damos 2015). Traditional pest control practices often rely on broad-spectrum pesticide applications, which can lead to issues such as pesticide resistance, harm to non-target organisms, and environmental contamination. However, with the help of these forecasting and decision-making tools, farmers can adopt a more precise and integrated approach to pest management. For instance, these systems can indicate the best time to apply biological controls or eco-friendly pesticides, significantly reducing chemical use and promoting more environmentally sustainable agriculture. One of the key advancements in this area is the development of computer-aided forecasting systems and DSS, which play a critical role in enhancing the sustainability of pest control efforts (Helps et al. 2024). These systems utilize data from pest monitoring and environmental factors, such as weather conditions, to predict potential pest outbreaks and suggest appropriate management actions. By providing early warnings and recommendations, they enable farmers to take preventative measures or apply control treatments at optimal times, reducing the risk of crop damage. DSS can provide customized advice based on local conditions, helping farmers choose the best management practices to combat pest and disease threats. These systems often integrate GIS tools to deliver spatially explicit advice. The economic value of DSS can be measured by comparing the cost of using a standard pesticide spray program to the cost of following the DSS's recommendations. In other words, the value of a DSS is the difference between these two costs. According to Helps et al. (2024), the DSS equation is

$$V = C_S - C_{Dss}$$

where, V is economic value of a DSS, C_S is standard pesticide spray programme and C_{DSS} is the cost of DSS guidance.

These systems allow for adaptive management, where real-time data feeds into ongoing decision-making processes. As pest populations fluctuate and environmental conditions change, these tools provide dynamic recommendations, ensuring that pest control strategies are continuously optimized. In this way, the use of population and process models in decision support not only improves pest control efficiency but also aligns with the principles of IPM, which emphasizes long-term, sustainable solutions that balance economic, environmental, and social factors. Ananias et al. (2021) created a user-friendly AI system to help predict the optimal storage time for peaches. Users input the initial quality of the peaches and the storage conditions (temperature and humidity). For example, if peaches have a hardness of 5.07 kg/0.5cm2, acidity of 8.16 gmalic acid/L, and soluble solids content of 10.63°Bx, and are stored at 1.95 °C and 93.74% relative humidity, the system predicts they can be stored for 23 days before reaching peak quality, after which they have a 5-day shelf life for marketing.

Farmer field schools (FFS)

Developed in the late 1980s by FAO in response to brown rice leafhopper outbreaks in Indonesia (Van de Fliert et al. 1995; Tonle et al. 2024). FFS, or Farmer Field School, is an educational method that helps farmers make informed decisions based on their understanding of their local agricultural systems. It's a different approach compared to simply transferring technology to farmers. Pontius et al. (2002) explain that FFS focuses on empowering farmers to make choices that are right for their specific fields and situations. FFS is a different approach compared to simply transferring technology to farmers (Röling 2002). FFS is undoubtedly one of the most effective tools for disseminating IPM technologies in general and biocontrol technologies in particular (van den Berg et al. 2020; Tonle et al. 2024). The FFS approach to biocontrol is based on Agro-Ecosystem Analysis (AESA). In AESA, farmers first observe their crops and then take note of factors like soil health, water availability, and the presence of pests, beneficial insects, diseases, or weeds. This helps them understand the whole farming system and make informed decisions about pest control (Tonle et al. 2024).

Challenges and future directions

While ICT offers substantial benefits in sustainable pest and disease management, several challenges remain. In many rural and developing regions, farmers face barriers to accessing advanced ICT tools due to a lack of infrastructure, affordability issues, and limited digital literacy (Deichmann et al. 2016; Ayim et al. 2022; Kumar 2023). A digitalization report (Anonymous 2019) found that 33 million smallholder farmers in Africa were using digital applications. This number is expected to grow to 200 million by 2030. Bridging this digital divide is essential to ensure the widespread adoption of ICT in agriculture. In one case study, Kabirigi et al. (2022) studied how smallholder banana farmers in Rwanda use mobile phones. They found that farmers who grew cooking bananas were more likely to know about and use mobile phone-based agricultural services. Those who raised livestock were also more comfortable with technology. Surprisingly, male farmers often faced challenges with using mobile phones, such as not knowing how to use them, finding them too expensive, or not understanding the language. However, farmers with more education were less likely to have these problems. Remote sensing techniques applying hyperspectral or multispectral cameras mounted on drones are still expensive (Lucas et al. 2024).

Protecting data privacy and security is a major concern when collecting large amounts of agricultural data (Gupta et al. 2020). Farmers need to trust that their data will be used responsibly and safely, especially when working with businesses. As more farmers and communities use technology on their farms, researchers and government agencies are studying the risks of cyberattacks. The U.S. Department of Homeland Security released a report (Mutschler 2018) that emphasizes the importance of precision agriculture and the need to protect against cyber threats. Jahn (2020) argues that the lack of cyber insurance will have a significant impact on agriculture businesses. They also call for regulations to protect farmers who use smart devices.

Conclusions

This review discusses the sustainable crop protection with the help of ICT and their advancements towards sustainable agriculture. ICT is playing an increasingly vital role in advancing sustainable crop protection, offering solutions that align with the principles of sustainable agriculture. From real-time monitoring systems to AI-driven predictive analytics, digital technologies are helping farmers reduce their reliance on chemical inputs, enhance crop yields, and protect the environment. However, realizing the full potential of ICT in pest management will require overcoming challenges related to access, affordability, and scalability. Moving forward, a collaborative effort between governments, researchers, and the private sector will be crucial in ensuring that ICT continues to drive innovation in sustainable agriculture, leading to resilient and productive farming systems globally. Future research and development efforts should focus on addressing these challenges and exploring new ICT-based solutions, such as artificial intelligence, machine learning, and blockchain technology, to further advance sustainable pest and disease management.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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