



REVIEW ARTICLE

Evolving pest management paradigms through information and communication technologies

Kavadana Sankara Rao¹, Ramanuj Vishwakarma^{1*}, Praveen Babu Rapaka², Bhupal Hatzade¹, Adarsha S K¹ & Sankarganesh E¹

¹Department of Entomology, Bihar Agricultural University, Sabour, Bhagalpur 813 210, Bihar, India

²Krishi Vigyan Kendra, Dr Y S R Horticultural University, Pandirimamidi 533 288, Andhra Pradesh India

*Correspondence email - entoramanuj@gmail.com

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Abstract

This review highlights the transformative potential of different information and communication technologies (ICTs) in advancing current pest management approaches in agriculture. Climate change, driven by altered weather factors, is seriously impacting crop growth and is found to act as a major determinant for the stagnation of yields. Dramatic shifts in climatic conditions are also escalating insect pest and disease problems. To address these escalating pest pressures, integrated pest management (IPM) has been widely promoted as a sustainable, multitactical management approach. However, improper pest identification, poor monitoring and a lack of tools for real-time information dissemination remain critical challenges among farmers. These limitations often lead farmers to rely on a single-tactic, chemical-based pest management approach. ICT tools can effectively bridge these gaps and support the modernisation of pest management systems. ICT tools such as remote sensing, geographical information systems (GIS), global positioning systems (GPS), internet of things (IoT) sensors, artificial intelligence (AI) and cloud-based technologies are equipped to provide services for pest identification, monitoring, prediction and management advisory systems. These technologies enable automated pest recognition, real-time data collection, population estimation, early warning and targeted management recommendations. ICTs have the potential to transform existing pest management paradigms and strengthen the adoption of integrated pest management.

Keywords: artificial intelligence; climate change; information and communication technologies; pest management; remote sensing; sustainability

Introduction

Agriculture underpins global food security, yet it is increasingly threatened by climate-related shifts in temperature, rainfall and extreme weather events. These changes have contributed to stagnating yields in several major crops (1, 2). Altered microclimatic conditions have also created more favourable environments for insect pests and diseases, intensifying their impact on crop production. Insect pests and diseases are responsible for substantial yield losses ranging from 17 to 41 % in major food crops and these losses are expected to increase under a changing climatic scenario (3). Beyond reduced yields, pest and disease outbreaks generate significant socio-economic and environmental consequences (4). Integrated Pest Management (IPM) has been promoted worldwide as a sustainable, multitactical approach that combines cultural, biological, mechanical and chemical tools. Owing to the complexity of integrating all these tactics, the majority of farmers in developing countries are again switching to chemical pesticides (5). Despite the technological developments, the timely identification of pest organisms, assessment of their population levels and taking timely pest management action have remained as persistent challenges. Limited literacy rates, unfavourable socioeconomic conditions, insufficient environmental awareness, irrational decision-making by

farmers, a lack of ethical principles among all stakeholders, ineffective regulatory frameworks and government policies, restricted access to IPM technologies, challenges in accessing extension services and fluctuating consumer preferences alongside retail market demands are reported to be the primary factors hindering the adoption of IPM (6). Economic pressures, market demands and the perceived risk of crop losses further discourage farmers from adopting IPM. Limited access to timely and location-specific pest information forces many growers to rely on pesticide dealers, leading to an overdependence on chemical control (7, 8). Hence, the timely availability of pest management information is crucial for sustainable pest management and reducing the farmers' dependence on pesticide dealers. Furthermore, this information empowers farmers to make informed choices that can have significant economic and environmental implications. In this context, information and communication technologies (ICTs) play an indispensable role in pest diagnosis, monitoring and management in agriculture.

Pest management tools have evolved through traditional, digital and AI-driven phases (Fig. 1). ICT tools act as catalysts for evolving pest management approaches. They bridge the gaps among the existing pest management tools and play a vital role at each step of pest management. These tools facilitate services such

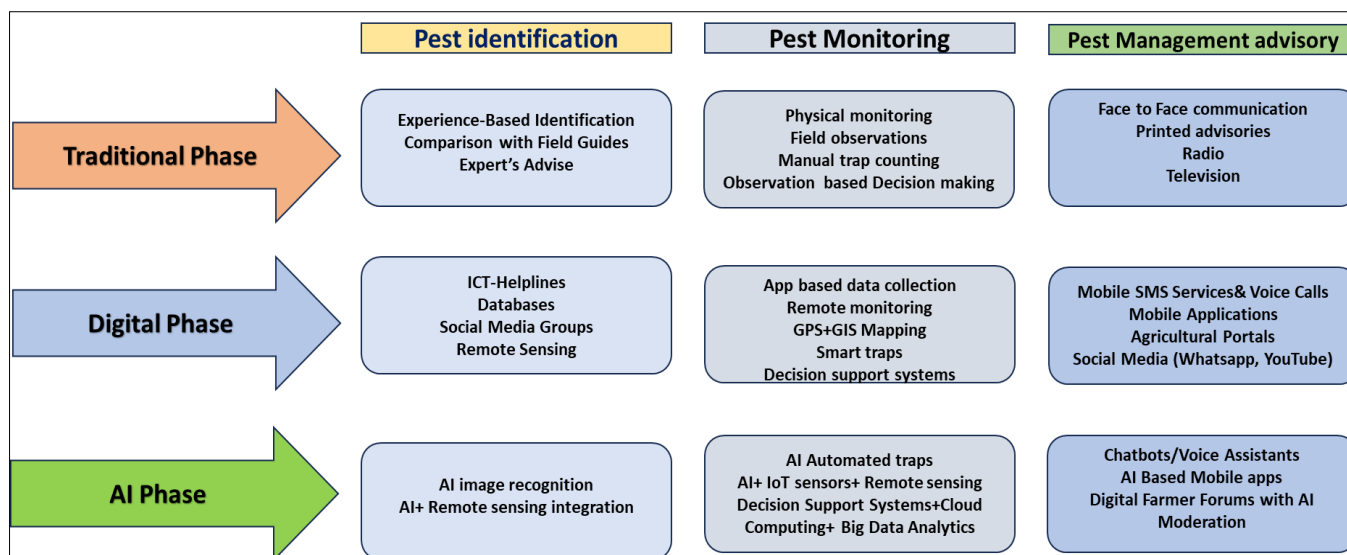


Fig. 1. Phase wise evolution of pest identification, monitoring and management advisory tools.

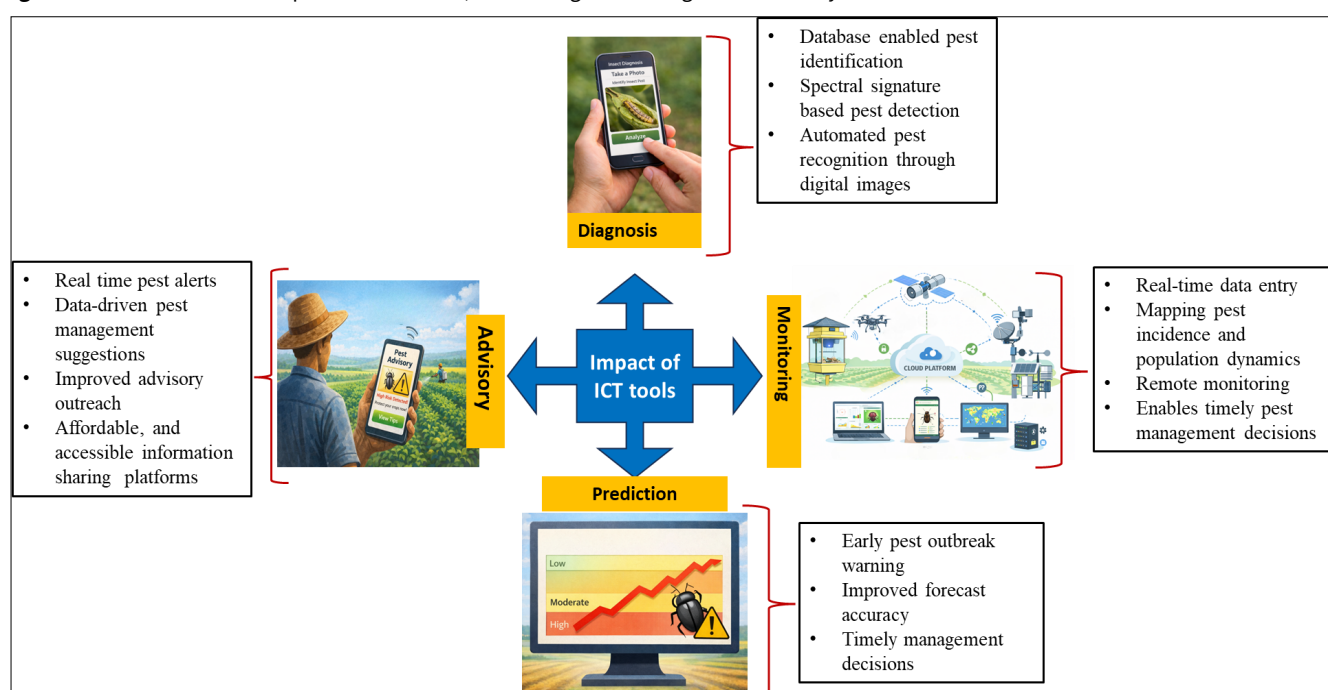


Fig. 2. Transformative potential of ICTs in pest management.

as pest identification, pest monitoring, data collection, storage and analysis, pest prediction and provision of management advisories (Fig. 2). Mobile apps, websites and remote consultation platforms support farmers by providing the resources to identify pests and diseases affecting their crops. They facilitate remote access to expert advice and utilise the power of image recognition technology (9).

ICT-enabled sensor networks, remote sensing technologies, IoT devices and data analytics platforms allow continuous pest surveillance and predictive modelling (10, 11). ICT platforms pave the way for intelligent plant protection solutions by offering IPM tools, decision support systems and precision application technologies. By harnessing ICTs, farmers can optimise pest management practices, mitigate risks and sustainably improve crop yields. There is substantial scope to leverage ICT tools in developing economies of the world, particularly in Southeast Asia and Sub-Saharan Africa. Given these emerging opportunities, this review critically evaluates how ICT innovations can transform pest identification, monitoring, prediction and management in agriculture. In this review, literature from multiple international sources was examined to understand global trends in the

application of ICT tools, organised under appropriate subheadings.

ICTs for Pest Identification

Accurate identification is fundamental for understanding the biology, ecology and behaviour of insect pests and disease-causing organisms. Traditionally, growers have relied on expert consultation, diagnostic keys, field guides, leaflets and printed manuals. However, these methods are often time-consuming, inconsistent in accuracy and difficult to access in remote regions (12). ICT tools have been evolving as promising options to overcome these limitations. Web-based platforms such as web portals, databases and spreadsheets are some of the basic ICT-based digital tools available for pest identification purposes. These tools allow users to search for morphological characteristics of insect or disease symptoms and match species or infested parts using interactive keys and image galleries. Some of the important web portals and databases being used for taxonomic identification of insect pests and diseases in India and abroad are included in Table 1 (13-20). Recent advances in remote sensing have enabled the use of multispectral and

Table 1. Some of the prominent web portals/databases being used for insect pests/diseases identification in India and abroad

Sl.No.	Web portals/database name	Reference
1.	NBAIR Insect Database (India)	(13)
2.	TNAU AgriTech Portal (India)	(14)
3.	EPPO Database (Europe & Mediterranean)	(15)
4.	BugGuide.Net (North America)	(16)
5.	USDA APHIS – Plant Pests & Diseases (North America)	(17)
6.	Pest Identification Tool (Australia)	(18)
7.	CABI Pest and Disease Image Database (Global)	(19)
8.	iNaturalist (Global)	(20)

hyperspectral imagery for detecting crop stress associated with insect feeding and pathogen infection (21). These sensors capture subtle physiological and biochemical changes in plants, allowing early identification of fungal, bacterial, viral diseases and certain insect pests. Image-based spectral signatures have shown high accuracy in diagnosing disease severity across crops such as rice, wheat, maize, citrus and banana. Representative examples of remote-sensing-based pest and disease detection studies are summarised in Table 2 (22-34). Artificial intelligence (AI) has recently revolutionised pest identification by enabling automated recognition of insects and disease symptoms from digital images. Using computer vision techniques, AI systems extract visual features from photographs and classify pests through machine learning and deep learning algorithms. Convolutional Neural Networks (CNNs) and advanced architectures such as YOLO (You Only Look Once) have significantly improved detection of small, complex targets, addressing challenges posed by limited taxonomic expertise (35). A selection of AI-based studies on insect and disease identification is presented in Table 3 (36-47).

Web portals and databases cannot be considered standalone ICT tools for pest identification. They primarily function as reference repositories and rely heavily on user expertise. In the absence of expert interpretation, the likelihood of misidentification remains high. Moreover, their practical utility at the field level is limited because most platforms are not optimised for offline access or rapid, in situ pest diagnosis. Spectral signatures derived from remote sensing tools also have limited utility for direct pest

identification. They reflect indirect crop stress responses rather than pest-specific signals. Similar spectral patterns can result from nutrient deficiencies, diseases, or abiotic stresses, which reduces identification accuracy. Among ICT tools, AI-powered image recognition systems show the greatest promise for pest identification. They enable rapid and automated diagnosis using field-acquired images. These systems reduce dependence on expert knowledge and support farmers and extension workers in achieving accurate, real-time identification. However, the integration of these tools into actionable IPM recommendations is still evolving. Their wider adoption is constrained by limited training datasets, dependence on image quality, morphological similarities among pest species and connectivity and infrastructure limitations in rural areas.

ICTs for Pest Monitoring

Pest monitoring is an essential aspect of Integrated Pest Management (IPM). Collecting pest data, analysing it and making informed decisions are its main objectives. Traditionally, methods such as field scouting and traps have been employed for monitoring purposes. Nevertheless, these techniques can be time-consuming, labour-intensive and constrained by a shortage of trained personnel (48). They also fail to adjust to an altered climate. ICTs can promote real-time data collection, analysis and decision-making and are likely to be the most feasible solutions for monitoring activities. Trained field scouts or users can directly enter real-time pest data into ICT-based datasheets or mobile applications. This data is then processed and analysed through centralised databases, enabling timely

Table 2. Multispectral and hyperspectral image-based pest detection in different crops

Crop	Pest	Remote sensing method	Imaging system	Detection accuracy	Reference
Rice	Brown planthopper	Hyperspectral	Spectroradiometer	73.0 %	(22)
	Leaf folder	Hyperspectral	Imspector spectral camera	98.0 %	(23)
	Leaf blast	Hyperspectral	Imspector v10e Imager	92.2-97.8 %	(24)
	Bacterial leaf blight	Hyperspectral	Spectroradiometer	88.9 %	(25)
	Brown spot	Hyperspectral	Spectroradiometer	95.7% (Leaf) 64.4% (Canopy)	(26)
Wheat	Yellow rust, Powdery mildew, Aphid	Hyperspectral	Imspector v10e-qe	83.0 %	(27)
Maize	Grey leaf spot	Multispectral	Satellite imagery	84.0 %	(28)
	Phaeosphaeria leaf spot	Multispectral	Satellite imagery	84.0 %	(29)
Cotton	Aphid	Multispectral	Satellite imagery	80.0 %	(30)
Potato	Late blight	Hyperspectral	Handheld spectroradiometer	95-98 %	(31)
Citrus	Canker	Hyperspectral	Electro-multiplying charge coupled Device	95.7 %	(32)
Banana	Fusarium wilt	Multispectral	Uav with a multispectral camera	80.0 %	(33)
Oil palm	Ganoderma	Hyperspectral	Spectroradiometer	80.0 %	(34)

Table 3. AI-based pest detection in different crops

Crop/pest	Images used	Number of categories	Framework /modal used	Accuracy	Reference
Rice Insect Pests	7868	14	RP-DETR	76.9 %	(36)
Rice Stored grain pests	3154	2	YOLO v8	97.7%	(37)
Maize Insect Pests	4533	13	YOLOv7	76.3 %	(38)
Maize fall armyworm and Mango fruit flies	36822	4	YOLOv8x	94.0 %	(39)
Cotton insect pests and diseases.	6358	7	Improved YOLOv8n	88.1 %	(40)
Tomato diseases and pests	15000	12	YOLOv3	92.4 %	(41)
Chilli diseases	5100	5	SE-CNN	99.1 %	(42)
Potato diseases	1700	5	DenseNet-201	97.2 %	(43)
Cucumber diseases	940	5	VGG-19, VGG-M	98.1 %	(44)
Insect species	2526	17	InsectNet	96.0 %	(45)
Insects of different orders	15000	7	YOLO v5	93.0 %	(46)
Grasshopper, mosquito, armyworm, beetle, bollworm and aphids	15000	6	CNN	93.7 %	(47)

advisories to be delivered directly to registered farmers. In India, CROPSAP and HORTSAP in Maharashtra and e-SAP in Karnataka, serve as exemplary e-surveillance systems for pest monitoring and management at the state level (49, 50).

ICTs also enable the remote observation of pests through various methods, including Internet of Things (IoT) sensors, drones and satellite imagery. IoT sensors are intelligent devices that gather environmental data (temperature, humidity, light, moisture and CO₂) and biological information (indicators of crop stress, duration of leaf wetness, presence of spores or insect stages and insect activity) from the microclimate of the crop. This data is transmitted wirelessly to cloud platforms for further analysis. Ultimately, this analysed information aids in monitoring crop health and generating alerts and management suggestions (51). These IoT sensors can either be installed directly in the field or combined with traps. Several researchers have developed sensor-based prototypes for

monitoring pest infestations in agricultural and horticultural crops. Case examples illustrating the integration of different sensors with various devices are presented in Table 4 (52-68). Multispectral and hyperspectral image-based monitoring of insect pests and diseases has been considered as a viable option with the help of satellites, aircraft and drones. By analysing the spectral signature of targeted crop or pest, these tools allow us to identify and track the incidence levels of pest (69). Besides these tools, Geographical positioning systems (GPS) provide precise location tagging of pests, trap placements and infested areas. This assists in geographical mapping and monitoring the target pest in real-time. Further, Geographical information systems (GIS) can be utilised to gather, store, analyse and visualise spatial information related to pest distribution and environmental factors. It aids in identifying areas of high pest activity, infestation patterns and trends in outbreaks in a location-specific manner. Integrated use of GPS and GIS enables real-time monitoring, forecasting and spatial planning in Integrated Pest

Table 4. Sensor-based monitoring of insect pests and diseases

Sensor type	Integrated device	Target pest	Crop	Reference
Optical sensors	Sex-Pheromone trap	Codling moth	Apple	(52)
	Sex-Pheromone trap	European Grapevine Moth	Grape	(53)
	Fruit fly trap	Fruit flies	Peach, cherry, Olive, Melons	(54)
	Yellow sticky trap	Aphids	Green houses	(55)
Acoustic Sensors	Robot vehicle	Pyralid moths	Rice, Maize	(56)
	Acoustic device	Rice weevil, Lesser grain borer, Red flour beetle	Rice	(57)
	Acoustic device	Red palm weevil	Coconut	(58)
	Acoustic device	Stem and root borer	Cashew	(59)
	Acoustic device	Termites	Soil	(60)
	Acoustic device	Northern Leaf Blight	Maize	(61)
Temperature and humidity sensors	IoT-enabled system	Powdery mildew, Anthracnose, Root rot	Mango	(62)
	IoT-enabled system	Early blight, Light blight, Powdery mildew	Tomato, Potato	(63)
	IoT-enabled system	Leaf spot	Groundnut	(64)
	IoT-enabled system	Powdery mildew, Downey mildew, Grey rot	Grape	(65)
Carbon dioxide sensors	CO ₂ sensor instrument	Grain deterioration by insects and diseases	Stored Grains	(66)
	CO ₂ Sensor instrument	Spoilage of stored grains by insects and fungi	Stored Grains	(67)
Integrated system with various Sensors (Temperature, Humidity, CO ₂ , Light intensity, Optical sensor)	IoT-enabled system	Insect pests and diseases	Field and greenhouse crops	(68)

Management (IPM) programmes (70). Recent advances in Artificial Intelligence and Machine Learning have introduced automated species recognition and population estimation systems, which are expected to significantly improve pest surveillance efficiency (71).

Smart traps, e-surveillance systems, GIS, GPS, IoT sensors and multispectral and hyperspectral remote sensing constitute advanced ICT tools for insect pest monitoring. Each technology contributes complementary information on pest abundance, spatiotemporal dynamics and crop stress responses. The future direction lies in their seamless integration with AI-driven analytics and decision-support systems. Such convergence can facilitate real-time field-level surveillance, enhance predictive accuracy and enable timely, precise and cost-effective pest management interventions.

ICTs for Pest Data Storage and Analysis

Recent advances in pest monitoring have enabled the collection of extensive pest-related data. Field observations, IoT sensors, mobile applications and remote sensing technologies now generate large volumes of data. Manual handling of these datasets is inefficient and prone to errors. Effective storage and analysis of these data have become essential for proper analysis, early warning and pest predictions. ICTs help bridge these limitations by supporting informed decision-making, precision agriculture and timely pest management actions. Cloud computing services like Amazon's AWS, Microsoft's Azure and Google Cloud offer scalable storage options (72). Apache Hadoop and Apache Spark are prime examples of big data analysis frameworks that facilitate the processing of large and complex datasets (73). Cloud computing and big data analytics remain at an early stage of adoption in IPM programmes. Nevertheless, sustained investments in digital infrastructure and data integration frameworks could significantly strengthen pest surveillance, forecasting and evidence-based decision-making.

ICTs for Early Warning Systems and Pest Prediction

Proactive measures to manage crop pests before they cause significant damage are of immense value in agriculture. Early warning systems and pest prediction models have gained prominence for forecasting pest incidence and their outbreaks under field conditions. These tools help conserve plant-protection resources by reducing unnecessary time, labour and cost. ICT tools such as GIS, remote sensing, machine learning, artificial intelligence, satellite imagery and predictive modelling are playing an exceptional role in this aspect (74). These systems process collected data on weather, crops and pest populations and more reliably predict pest outbreaks. Such predictions support the development of timely management advisories for farmers and extension workers (75). Notable examples include FAMEWS and eLocust3, which are reliable systems designed for early warnings of fall armyworm and locust invasions, respectively (76).

Analysing real-time crop-pest-weather interactions is

inherently complex. Accurate pest prediction, therefore, requires the integration of multiple digital tools within a unified framework. Pest population data and crop stress information must be captured through digital technologies such as smart traps, satellite imagery and drone-based sensing and subsequently aggregated on cloud-based platforms. These datasets can then be utilised for GIS and GPS-enabled spatial mapping and analysed using advanced AI and machine learning algorithms. Such an integrated digital approach holds significant promise for addressing pest-related challenges at the field level and enabling proactive pest management.

ICTs for Pest Management Advisories and Information Sharing

Timely access to pest management advisories is crucial for farmers. Any delay may lead to a waste of farmers' resources and crop loss. Traditionally, farmers have relied on in-person communication and printed extension materials to access pest management information. These extension services often face challenges due to their limited reach and delays. To address this issue, radio and television have been instrumental in disseminating pest-related information. However, these broadcast-based tools are limited by one-way communication, generic content and minimal location-specific relevance.

In response to these limitations, significant work has been done in developing ICT-based platforms for information sharing. These include mobile-based tools such as short messaging services (SMS), voice calls and smartphone applications, as well as web portals, expert systems, cloud-based platforms, GIS-supported advisories, AI-driven recommendation systems and social-media channels such as WhatsApp and YouTube. SMS and voice calls have been providing essential services by connecting plant protection experts with farmers. Several national agencies, State Agricultural Universities and private input providers continue to utilise these platforms to deliver pest management information, particularly to rural and illiterate farmers. Examples of prominent SMS and voice call-based agricultural pest information service providers in India are mentioned in Table 5 (77-82). In recent years android smartphones have become a core component of ICT-driven agricultural interventions. These devices enable the integration of multiple communication technologies within a single, affordable and accessible platform. They also support AI-enabled image recognition, remote-sensing inputs, IoT-based sensor data and expert-system recommendations for pest diagnosis and management. Representative Android-based mobile applications used for pest management in various countries are presented in Table 6 (83-92).

Mobile applications integrated with AI-based chatbots and cloud computing platforms are emerging as highly effective ICT tools for pest management advisories. They enable the real-time collection, integration and analysis of available data. AI chatbots provide interactive, personalised recommendations, while cloud platforms support large-scale data processing and continuous

Table 5. Some of the important SMS and voice call providers for agriculture/pest related information in India

S.No.	ICT tool	Operating agency	Reference
1.	Kisan call centre (KCC)	Ministry of Agriculture & Farmers Welfare, Government of India	(77)
2.	Kisan help line	Bihar Agricultural University, Bihar	(78)
3.	PAU kisan app and helpline	Punjab Agricultural University, Punjab	(79)
4.	Farmers call center	Acharya N.G. Ranga Agricultural University andhra Pradesh	(80)
5.	e-SAP	University of Agricultural Sciences, Raichur, Karnataka	(81)
6.	Farmer.Chat	Digital Green	(82)

Table 6. Android-based mobile applications widely used in different countries for plant protection

S.No.	Mobile application name	Developer	Technology used	Available country	Capabilities					Reference
					Automatic pest identification	Pest monitoring	Management advisory	Weather data recording	Pest prediction	
1.	Plantix	Progressive Environmental & Agricultural Technologies, Germany	AI + Image recognition + Cloud	Worldwide	P	x	P	P	P	(83)
2.	Agrio	Saillog Ltd, Israel	AI + Computer Vision+ Satellite Data	India, Israel, Africa, South America and parts of Europe	P	x	P	P	P	(84)
3.	Taranis	AAA Taranis Visual Ltd, Israel	Drones + Computer vision + Remote sensing+ Cloud computing+ Big data analytics	Worldwide	P	P	P	P	P	(85)
4.	CropIn SmartFarm	CropIn Technology Solutions, India	Satellite imaging + AI + IoT	India	x	x	P	P	P	(86)
5.	Fasal	Wolkus Technology Solutions Pvt. Ltd, Bengaluru, India	IoT sensors + AI + Microclimate data	India	x	x	P	P	P	(87)
6.	Nuru	FAO and Penn State Univ., USA	AI+ Computer vision + Offline ML	Worldwide	P	x	P	x	x	(88)
7.	FAMEWS	FAO, Rome	AI+ Computer vision+ GIS Mapping + Cloud	Worldwide	P	x	P	P	P	(89)
8.	Bighaat	BigHaat Agro Pvt Ltd, Bengaluru, India	Computer vision+ Satellite Data	India	P	x	P	P	P	(90)
9.	Granoscan	National Research Council (CNR), Italy	AI+ Computer vision+ GPS+ Cloud computing	Italy	P	x	x	x	P	(91)
10	Cropalyzer	Bejo Zaden B.V. & Webuidapps, Netherlands	Image Data Base+ Expert Knowledge Base	Netherlands Germany and France	P	x	P	x	x	(92)

model updates. Together, these tools enhance the timeliness, accuracy and scalability of advisories. However, translating complex model outputs into simple, actionable advisories for smallholder farmers remains a critical barrier to their effective utility.

Challenges in ICT-enabled Pest Management.

ICTs have increasingly been integrated into agriculture, but their widespread adoption in pest management has been limited by various constraints. Broadly, these constraints can be classified as general constraints and specific constraints. General constraints are more related to socio-economic, infrastructural and systemic issues that affect the overall use of digital technologies in agriculture. These mostly prevail among farmers with small holdings. They include limited digital literacy, internet connectivity issues and the affordability of mobile phones (93). In contrast, specific constraints relate to the technical and operational limitations of ICT tools themselves, which continue to evolve rapidly and often lack adequate adaptation to diverse agricultural contexts. Pest identification is challenged by the intricacy of pest morphologies and overlapping symptoms. Low-quality photos and a dearth of annotated datasets are also among the reasons for improper detection of targeted pests. Consequently, even advanced AI-enabled mobile applications often struggle to provide reliable pest identification, particularly under real-world field conditions (94).

ICT-based pest monitoring tools may fail to provide desired results because of limited real-time data acquisition, low spatial and temporal resolution of imaging tools and poor accuracy of sensors and automated identification systems, especially under variable field conditions. Early warning systems face critical challenges as new pests emerge and the dynamics of existing pests vary significantly due to climatic factors. These factors lead to misidentification and raise doubts about the credibility of pest prediction systems (95, 96). Moreover, early-warning platforms that integrate remote sensing, pest modelling and AI tools require extensive location-specific calibration to accurately reflect local agroecosystems. Inadequate communication channels and fragmented information flow among farmers, extension workers, researchers and other stakeholders further hinder the timely dissemination of pest-related information. These challenges disproportionately affect digitally excluded communities, limiting the equitable adoption of ICT-based pest management tools (97).

Future Perspectives

Addressing the constraints of ICT-based pest management calls for a comprehensive and vision-oriented approach. Rural digital infrastructure investment is essential, particularly in enhancing Internet connectivity and electricity supply. Access to ICT tools must be provided on an equal basis. Developing user-friendly applications in local languages, with voice-based interfaces and intuitive designs, will further enhance accessibility for elderly and low-literacy communities. Advances in AI and machine learning should be supported by the development of large, high-quality, open-source pest image datasets that represent diverse crops and agroecological regions. This will raise the accuracy of computerised pest identification systems in various farming systems. Sensor calibration and farmers training are key to addressing data quality challenges in pest monitoring. Additionally, predictive modelling systems must be continuously refined to incorporate evolving pest dynamics and climate variability. Stronger collaboration among ICT developers, extension agencies, research institutions and private-sector partners is essential for overcoming current limitations. Integrated digital platforms that consolidate pest advisories from multiple sources can

reduce contradictory recommendations and promote consistent, science-based guidance. Ensuring the timely dissemination of ICT innovations to farmers will further support the adoption of sustainable, ICT-enabled pest management practices.

Conclusion

Insect pests and diseases continue to threaten global food security, underscoring the need for timely identification, accurate monitoring, effective early-warning systems and reliable management advisories. Information and Communication Technologies (ICTs), including AI-driven image recognition, IoT sensors, GIS, GPS, cloud computing and mobile platforms, offer powerful tools to support real-time, data-informed pest management. These technologies provide farmers with timely, location-specific guidance, thereby enhancing the effectiveness of integrated pest management (IPM). Nevertheless, the full potential of ICTs can only be realised by addressing infrastructural, technical and socio-economic barriers. As agriculture moves toward more sustainable and resilient systems, ICT-enabled, precision-based pest management will play an increasingly pivotal role.

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Authors' contributions

KSR conceived, designed and wrote the manuscript. RV was responsible for technical guidance and manuscript review. PR and BH were helped in planning and interpretation of collected literature. ASK and SE reviewed the manuscript. All authors read and approved the final manuscript.

Compliance with ethical standards

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