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AI-Driven Pest Control Strategies for Sustainable Cotton Cultivation in Developing Regions

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Abstract

Among the best economically important agricultural crops in Global South, cotton farming has been a repeat victim of pests and has been witnessed to pose a threat to both, the stability of yield and the income of farmers as well as ecological viability. Conventional methods of pest control based on the large use of chemical pesticides have caused the increased costs of inputs, pest resistance, and environmental deterioration. This case study will discuss how we will roll-out an Artificial Intelligence (AI) based pest management system to offer early detection, predictive modeling and real-time decision support to cotton farmers in the developing countries. The system provides pest surveillance and minimises chemical inputs by combining satellite imagery, sensor readings and machine learning algorithms. The paper outlines the potential of AI to fill knowledge gaps, to provide the small holder farmer with the affordable means to achieve digital accessibility and also help in sustainable practices in cotton farming. In addition, it explores issues like access to data, Internet and digital literacy, and the constraints of infrastructure that affect adoption in low-resource environments. The results indicate that AI-enhanced pest control does not only enhance food crop productivity and mitigate environmental hazards but proves to be a scalable solution, which can be readily customised to various global agricultural environments of the Global South.

Keywords: ***Artificial Intelligence, Pest Management, Cotton Farming, Precision Agriculture, Global South, Sustainable Agriculture, Machine Learning, Smallholder Farmers, AgriTech, Digital Farming.***

1.Introduction

The cotton, commonly called the white gold of agriculture, has traditionally been the chief economic resource in the lives of millions of families in the Global South. In the present day, more than 100 million homes that exist in every part of the world have relied almost directly or indirectly on cotton production to earn them livelihood, income and social-economic safety. Albeit its economic importance, cotton agriculture is highly susceptible to attacks by pests especially bollworms that have turned out to be one of the greatest threats to farmers. This growth cycle is particularly sensitive to pest damage as compared to a crop such as cereal or pulse crops, which are more robust to changes in our environment leading to massive losses of economic benefit to the environment. In the case of very smallholder farmers in developing countries much of whom work on marginal landholdings with limited access to modern technology, pest outbreaks can be disastrous and fuel a cycle of poverty and debt and even in some cases the desperately tragic phenomenon of farmer suicides(1). As an example, reports after the pink bollworm epidemic in Maharashtra, India in 2017 emphasized the role of pest-caused crop failure as a key factor that contributed to an outbreak in cotton farmer suicides. This grim picture can demonstrate that pest management is not one of the agronomic problems, but one of the urgent socio-economical and humanitarian challenges.

Cotton farm pest control measures have been based primarily on use of chemical pesticides. Pesticides have the potential of being successful in managing the pests when used in the right way but the wrong usage or excessive use has led to undesired outcomes. Such irrational sprays usually kill helpful insects, destroy the ecological balance, and hasten the evolution of the resistant population of pests towards the pesticides thereby ending up diminishing the success of the used chemical control mechanisms. Moreover, pesticide intensive agriculture, is expensive, poor on environmental sustainability, and a source of potential health hazards to the farmers and their families with regard to toxic exposure. The timing and mode of application of pesticides has thus emerged as the determining factor of farm output and farm life. The sad thing is that, the smallholder farmers often do not have sufficient timely, reliable, and localized information to be able to make these kinds of decisions. The uncertainty, the complexity of ecology and financial vulnerability that occur together makes the environment where farmers can choose to spray too late, too early or even at a wrong frequency and all of those practices reduces the sustainability of cotton production.

Technology solutions that have been made possible in this context provide a transformational option to rethinking and redesigning pest management practices. Setting up such a system was recently enabled by advances in artificial intelligence (herein abbreviated AI), machine learning and mobile computing, enabling systems to assist in pest control decisions at a substantially higher degree of precision than formerly(2). The combined use of AI with inexpensive devices like pheromone traps and smartphones has offered emerging possibilities of making real-time insights accessible to smallholders farmers without incurring prohibitive costs that would be used to construct groundbreaking facilities. Farmers can now use automated and scalable systems that can offer instant recommendations, replacing an approach that depended only on visits by agriculture extension workers, who already have limited resources. The trend is compatible with the worldwide transition to precise agriculture, the focus of which is the effective utilization of inputs, low environmental burden, and better decision-making based on data-driven analytics.

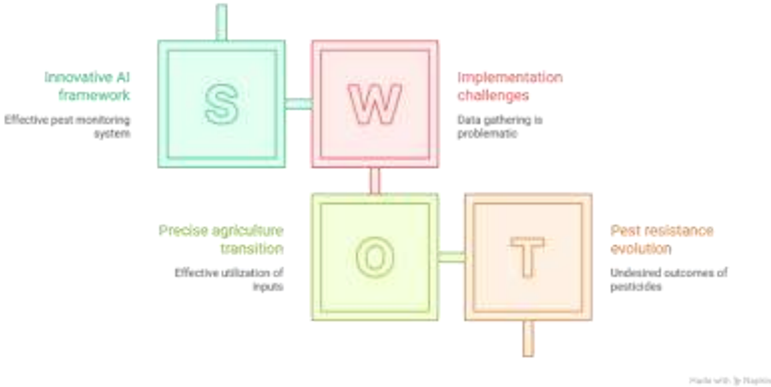

FIGURE 1 AI-Powered Pest Control for Cotton Farming

The AI-powered pest control system described in the case study under consideration can be deemed as a creative effort to deploy a solution to the exclusive problems of cotton farming in the Global South. Trained and tested during the growing seasons in India over several years, the system is based on deep learning models that have been conditioned to examine photographs of pests that are gathered in pheromone traps. These models identify, characterize, and estimate pest populations, to come up with actionable guidelines as to whether it is prudent to spray pesticides or not. Its design is also explicitly optimized (design): by its introduction of inexpensive critical traps and its reliance on the ubiquitous smartphone camera (especially the built-in camera), it provided a realistic app to small-scale farmers(3). Furthermore, the system has been implemented in pre-existing digital pipelines and extension worker schemes, allowing growth to occur through existing farming systems, thus not necessitating the need to have entirely new infrastructure. Integrating AI in the current environment, the method allows closing the gap between technological development and local ways, as well as social-economic realities.

The outstanding aspect of this undertaking is the environment under which it is carried out. AI implementation in smallholder farming communities is orders of magnitude different than implementing AI solutions within environments that have an abundance of resources. Cotton cultivation is not all year round, and the dynamics of the outbreaks of pests is very uncertain, making data gatherin and model training very problematic. Images of pests captured in actual field settings cannot be compared to the high-quality laboratory images encountered in entomological studies and it is challenging to annotate and ground-truth even to expert analysts. Network availability in the countryside can be very poor and it is not practical to expect heavy duty cloud-based computers to be carried out in the countryside, this means that something relatively lightweight to be run on low bandwidth devices should happen. Moreover, the farmers and extension workers do not necessarily enjoy the level of digital literacy, and these resources demand user-simple, interpretable, and user-friendly solutions. This is not to say that the limitations of AI-based agricultural applicability are bound only by technical reasons; rather, they are even more structurally based on the social contexts of deployment and support of agricultural solutions on which the nature of AI-based solutions depends.

This case study has thus contributed in two folds. On the one hand, it presents a diverse and technologically innovative AI-powered framework of pest monitoring and pesticide management but it is also rooted in the reality of the experience of farmers in the Global South. Second, it summarizes important lessons on field deployment, where issues included the diversity of data, the complexities in data annotation, the metrics of model evaluation, infrastructure constraints, as well as adoption issues. Such lessons are not specific to cotton cultivation; they provide a guide that can aid in the use of AI-driven interventions by researchers and practitioners of other areas of global development. The study demonstrates the value of research at the nexus of artificial intelligence, agriculture, and socio-economic resilience to show the possibility of technology in poverty alleviation, promoting sustainability, and strengthening the empowerment of smallholder communities.

2.Background

The need to place the problem in a network of agronomic, technological, socio-economic, and environmental dimensions justifies the need to understand the issue of pest control in cotton farms within the broader context of that issue. Whereas traditional background studies have focussed on pests, pesticides and farmer behaviour, in a broader interpretation, cotton production in the Global South is embedded in systemic interconnections that can be characterised by the ecological vulnerability, climate change, rural development and digitalisation of agriculture. Four emerging themes are discussed in the section that give a more comprehensive context to the case study: climate variability and pest dynamics, economics of smallholder cotton production, digital agriculture ecosystems and social aspects of adoption of technology(4).

2.1 Pests and Climate Variability

The current issue of climate change on pest behavior is one of the characterizing problems of cotton growing nowadays. Changing climatic conditions such as rainfall patterns, prolonged dry periods and abnormal temperature variation have changed the reproductive cycles and pest behavior mainly in pink bollworms and whiteflies. Warm temperatures tend to increase the pace of pests whose life cycle allows several generations to crop the crops in the course of a single season thus compounding the damage. Meanwhile, uneven precipitation may destroy cotton plants and they become more exposed to strikes by pests. In situations of smallholder farmers, who have no irrigation schemes and survive on rain-fed farming, these climate-based processes increase risk and uncertainty. Herein, the role of AI-driven pest control monitoring systems is beyond the context of a technological innovation but as a mechanism of climate adaptation, which farmers could use to get warnings in advance and counteract the exacerbating effects of the planetary instability. Combining the use of climate models with pest prediction algorithms has great potential in the development of resilience in the cotton sector.

2.2 Smallholder Economic Cotton Production

There is no ease of divorcing pest management and the economics of cotton production. In much of the Global South, cotton cultivation is an input-intensive, risky activity. The money that farmers put into seeds, fertilisers, pesticides and labor investments do not greatly pay off because of the unstable prices on the market and the need to rely on intermediaries in order to make sales. Economic weaknesses compounded by pest boom usually trap farmers into debt cycles when they take loans to repeatedly sprinkle the pesticides. In addition, the increase in the prices of transgenic cotton seeds and little bargaining power of smallholder growers in international cotton market further reduces profitability. It is in this context that AI based pest management has a possible economic lifeline with the use of such systems. With less unnecessary pesticide sprays and more effective decision making, such systems are capable of reducing production costs, stabilise yields and eventually enhance net farm income. The economic aspect also highlights the relevance of affordability and scalability:een solutions have to be low cost, require simple deployment, and to be capable of showing visible economic returns in order to win farmer acceptance.

2.3 The Global South Digital Agriculture Ecosystems

Artificial intelligence in cotton cultivation is not used in a vacuum but rather as a franchise of a larger wave of rural digital agricultural endeavors that are changing rural economies. The mobile phones became a source of knowledge dispersion as the farmers became linked with the government schemes and weather forecasts as well as to agricultural advisories. As a case in point, in India, where cheap smartphone devices are widely available and rural internet penetration continues to grow, digital farming solutions have a thriving environment. But digital agriculture is more than connectivity; strong ecosystems that build on the hardware (e.g., pest traps, sensors), software (e.g., AI algorithms, apps), and people (e.g., extension workers, local cooperatives) are needed. In this vein, AI-powered pest surveillance may be seen as a part of a broader ecosystem of digitalized agricultural R&D, as well as precision irrigation infrastructure, mobile-powered crop-advisory services, and blockchain-powered supply chain services. Placing pest management in this ecosystem shows the prospects of cross-technology and vertical scalability.

2.4 Redemption in the Social Aspects of Technology Adoption

The end result is that technology innovation in agriculture should be finally anything that comes out in the hands of the farmer. Nevertheless, the process of the implementation of new tools depends on a sophisticated system of socio-cultural and institutional factors(5). The digital literacy rates, the level of trusting technology, the role of genders in farming families, access to institutional support, all these factors determine the possibility of farmers accepting AI-based solutions. As an example, women and their role in pest monitoring and pesticide application are important in most cotton growing areas but formal extension activities often do not reach them. It is thus important to have systems of designing inclusive AI, which accommodate both men and women farmers. Likewise, the credibility of automated recommendations belonging to farmers hinges on the concepts of transparency and explainability. Provided that farmers see AI as a black box that gives almost imperceptible prescriptions, they might not be willing to act as per its instructions. Developing trust involves participatory design strategies where farmers are included in testing, feedback and development of adaptations. Moreover, the institutional ecosystem, in its turn, composed of cooperatives, NGOs, and privately owned agritech companies as well as government agencies, represents an intermediary between technology developers and the farming communities. This is done so that the synergy of cross-sector actors can be guaranteed in order to scale solutions in a sustainable manner.

2.5 Moving to a Whole picture of Background

When taken together, these themes imply that the practice of pest management in cotton farms is more than a technical issue of merely identifying and subduing insects. It is a complex phenomenon existing at the crossroad of ecology, economics, technology and the society. Increased pest pressures due to climate variability, increased economic vulnerability to crop damage, newly available digital ecosystems to intervene, and the settings of social contexts will define adoption and trust. Any AI based solution would hence have to be enveloped under such a comprehensive picture of the farming landscape. In setting the stage of pest management in the multi-dimensional context, the case study reveals how technology could transcend beyond single-dimensional interventions as a platform towards integrated approach of agricultural resilience, poverty alleviation and sustainable development, in the Global South.

3.Alternative Solutions

To overcome the pest-management crisis of cotton farming one should proceed not only to a multitechnology approach but through scaling up artificial intelligence in order to identify synergetic synergies. Although image analysis of pests on the smartphone with the help of AI is an interesting advance, the vision is to implement solutions that are dynamic, contextually responsive and scalable. Here, we describe synergistic strategies, even though they are distinct, that can be implemented as potentially effective means to mitigate pest risks and, concurrently, to increase the resilience of cotton farmers.

3.1 Forecasting Predictive Pest Models

Conventional pest management is usually on a reactive basis- farmers take action once an infestation is realized or causes loss. Nevertheless, the further development of data science allows introducing the transition to predictive pest control. This integration of history-based pest data, space-based weather, and on-site agro-climatic indices in AI systems, predicts weeks in advance whether and where pest emergence is likely (6). Climatic conditions like rainfall, humidity, temperature variation, which control the cycle of pests can be included in the predictive models. As an example, pink bollworms are adapted to warm, arid conditions; an AI model with real-time weather feeds could be used to forecast the risk of increased infestation rates and warn the farmers, accordingly. These forecast-based advisory would enable the farmers to deploy early interventions limiting the loss of crops and avoid the overuse of pesticides. More importantly, those systems can be incorporated into government extension systems or mobile technology, by which early-warnings can be sent to farmers in bulk.

3.2 IPM AI-Assisted

Integrated Pest Management (IPM) has been proven to be a sustainable method of pest control over the years, together with biological, mechanical, cultural and chemical strategies. Nevertheless, reduction in implementation of IPM effectively at smallholder level has in most instances been a challenge because of the requirements in narrowing down, contingent, knowledge. In this case, the application of AI can become a strong enabler, as this technology can guide farmers through the adoption of the most appropriate combination of pest control measures.

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The IPM platform assisted with an AI solution can, in fact, make suggestions on releasing natural predators when the population of pests does not reach economic concentration, crop rotation, depending on the pest cycle according to the seasons, and selective, but only when the infestation exceeds dangerous levels, pesticide spraying could be used. That would be a way of balancing environmentally sensitivity and economic feasibility to use less chemicals and still maintain the productivity of the farm. Notably, integrating IPM recommendations with AI systems would mean that the advice given to the farmer is in context with what is happening in real-time and not abstract generalizations that do not make much sense in the field.

FIGURE 2 AI pest management strategies range from reactive to proactive

3.3 Targeted Spraying and Drone Based Surveillance

A third frontier of cotton pest control would be with the incorporation of unmanned aerial vehicles (UAVs), or drones. Drones, which are developed using high-resolution cameras and artificial intelligence-based image recognition technologies, are capable of covering vast cotton fields in a considerably shorter time as compared to the human scouts. Unlike Static pheromone traps drones, in contrast, are able to monitor stress indicators due to pests of plants early, including a change in the color of leaves or the density of the canopy and intervene actively. In addition to the detection, one can equip drones with precision spraying systems in order to eliminate the use of blanket spraying in fields to disperse pesticides to the entire field when it is only infected in a specific location. Such selective practice will not only save input costs and the smallest risk of environmental pollution, but also save useful insects. As far as smallholder farmers pot not have their personal drones, cooperinitive approaches or community drone services may offer affordable access. A closed feedback loop of drone-collected information into an AI-based decision platform would make sure that monitoring drives an immediate response.

3.4 Digital advisory systems that are farmer-centric

Technological remedies cannot make their desired changes unless they are farmer-friendly. Barriers to digital literacy, lack of confidence in automatized tools, and dependence on trusted social networks (as the sources of agricultural advice) apply to many smallholders. In order to close such a gap, AI based pest management systems should be incorporated into the system of farmer-centric advisory(7). These ecosystems might integrate AI knowledge with the humans who act as intermediaries e.g. extension workers, farmer producer organizations / village level entrepreneurs etc. who are able to interpret the technical suggestions in ways that is locally intelligible. Further, more illiterate farmers could access pest management information in their own languages using conversational AI agents that are provided via voice-based mobile interface. Such systems might be used to also share knowledge in peer-to-peer fashion, where farmers might be able to upload field photos, share their experience, and get AI recommendations to be verified across the crowd. Advisory systems emphasis on human-centered design allows ensuring that the technology is used as a complement to the experience of the farming communities but not an alternative.

3.5 Multi-Stakeholder cooperation on Deployment

One of the keys that can lead to successful implementation of AI-based management of pests is the need to involve various stakeholders. Governments are able to offer institutional support, information infrastructure, and policy inducement of sustainable pest control. Agritech start-ups and AI research institutions can develop innovative algorithms and digital systems and NGOs and cooperatives can be used as transmission belts of community involvement. Seed companies and cotton purchasers that are actors of the private sector have a vested interest in quality cotton production and can invest in pest management technologies as a means of value chain sustainability efforts. Last but not least, international development agencies are able to provide funding and technical assistance in piloting and scaling of interventions. Sharing the burden of pest management makes the collaborative deployment models in this case greater adoption and sustainability as the solutions do not have to be siloed in the development of agriculture solutions.

3.6 On a path to resilient cotton farming systems

Together, the solutions hereby proposed put a totally different lens on pest management: no longer as a specialized purely technical issue, but as a redesigning of cotton farming as resilient and sustainable. Farmers are getting empowered with predictive forecasts, AI-assisted IPM is bringing a sense of balance between ecological health and production, drone surveillance is helping provide precision interventions, and farmer-friendly advisory systems are driving usability and trust (8). These solutions are rooted in the understanding that farmers exist in smallholder operating contexts that are defined by uncertainty and a lack of resources, as well as complex socio-economic forces. Effective strategies to control pests should thus be technology advanced, being accessible, affordable and culturally appropriate.

4. Examining the Difficulties

The potential of using AI-enabled pest management in cotton production is tremendous, but there are many pitfalls on the road of research prototypes to practical application. The agricultural settings in the Global South, in contrast to hermetically belted laboratory situations, are agri-environmentally multidimensional and are technically, socio-economically, environmental, and institutionally circumscribed. In our section, we review four essential issues that condition the applicability and survivability of AI-based solutions in pest management: insufficient data and data quality, infrastructure and accessibility issues, farmer trust and behavioral hindrance, and governance and ethical issues.

4.1 Lack and Quality of Data Data lack and quality gaps

AI requires data to perform, but in the case of cotton farming applications, quality and representativeness of inputs are unlikely to be encountered. Whereas systematic pest data may be accumulated in advanced agricultural research stations, in smallholder farms, there is rarely uniform recording of pest attacks, man use or even yields. This has been the case with majority of AI systems used to detect pests via small, fragmented or region-specific data that lacks generalisation when applied in different geographies. Furthermore, the resolution of the field-collected images is frequently bad or the lighting inhomogeneous, or some irrelevant noise is present and makes both manual annotation and accuracy of the algorithms questionable. The issue is further compounded by climate variability where lifecycles of pests and patterns of infestation alter from season to season and therefore static datasets are not so secure over time. Training of strong AI models thus necessitates pipelines of data collection, participatory annotation by locals with the help of local experts, and adaptive learning systems that can continually revise predictions. In the absence of solutions to these data-related issues, AI-driven pest management will not be very reliable and scalable.

4.2 Restrictions of infrastructure and accessibility

Farmer Outreach The most sophisticated AI algorithms will never work so long as farmers lack the infrastructure to access them. Unreliable electricity, ineffective internet access and low smartphone penetration are characteristics of many cotton- growing areas in the Global South. In distant villages, network outages are frequent, and cloud-based-based computation tools made with digital tools are impractical. Likewise, the smartphones with the ability to operate complex AI models can be considered unaffordable to smallholder farmers that commonly tend to focus on primary subsistence needs rather than made-up investments in technology(9). The accessibility also reaches language and literacy: the applications that have been developed in English or the urban dialects might be meaningless to the farm people. Systems which can operate in an offline setting as well as on low-cost devices and provide the recommendation in the local language via voice are hence important to design. Also, physical infrastructure like road network, extension offices and input supply chain have a bearing on whether farmers are able to act on the digital advisories. Consider an AI system suggesting the use of a pesticide, the system is not of much value when the farmer cannot buy or get these supplies in time. These infrastructural constraints are the reasons why context-sensitive frugal innovation is warranted when it comes to AI implementation.

4.3 Opportunity Costs of Trust and Behavioral Obstacles in Farmer

Use of technology in agriculture is not only technicalities as to the performance but also depends on human application in terms of perceptions and trust. People who are the most critical about automated systems are farmers, especially in cases when the given recommendations go against all the common training of the age or against the folk wisdom. As an example, AI-recommended decision: stopping the pesticide spraying can be disregarded when a farmer feels that there are pests on the field which have to be dealt with urgently by means of chemicals. On the same note, farmers might also view the use of AI technologies as black box prescribers that do not explain the logic behind the prescribed decisions. How it is constructed, developing trust involves transparency, explainability, and participatory design. These recommendations need to be visible to farmers as well as the evidence underpinning them (e.g. annotated pest images or probability scores) so that farmers can make their own informed decisions. Behavioral aspects are also important: farmers can be risk averse and they could opt to over-spray instead of taking the risk of losing the entire crop to under-spraying, despite AI recommending otherwise. These barriers, and the ones with no change, and that must be overcome within the process include constant training, involvement of the community, and the provision of the recommendations of the AI into the trusted advisory channels, extension workers or farmer cooperatives. Even technically competent AI systems will not get optimum use unless they have farmer trust.

4.4 Governance and Ethics

Among critical issues of AI-based pest management which remains underdiscussed, there is a problem of the governance and ethics of applying technology. Frequently this data is published in centralized databases run by agritech companies or research organizations based on data gathered in the fields of farmers, pest traps, and through mobile applications. Farmers can lose ownership of their agricultural data without the relevant protection and these data can be sold out or used to manipulate the input sales without the consent of the farmer. Equal ethics Likewise, there are ethical issues of equity: will smallholder farmers get an equal benefit of the AI innovations, or will the benefits be smelled by more-fortunate farmers with more resources? Lack of accountability is another question pertaining to the introduction of AI. What happens when an erroneous recommendation by an AI system causes loss of crops crop, who should take the blame the developer, the extension agency or the farmer? Moreover, to the extent that traditional ecological knowledge breaks down and farmers develop a total dependence on digital admonitions, AI tools threaten to cement dependency. The solution to these governance and ethical issues lies in the articulation of policies regarding data ownership, transparent measures of accountability, and the needs to be inclusive and lays emphasis on the rights and agency of the small-scale farmers.

4.5 Moving to the Solutions to the Challenges

These technical difficulties; that cut across data, infrastructure, trust, and governance demonstrate that AI-based pest management is not a plug-and-play technology. It takes a many sided approach to overcome them. Technically, scientists will have to make an investment in data augmentation, federated learning and adaptive models that can work well in low-data and low-connectivity settings. On the infrastructure front, collaborations with telecom deployers and governments can help to expand connectivity to rural areas and companies that produce devices must make smartphones that are cost efficient and agriculture friendly. On the human side, co-design and validation, that is, participatory, should be able to create trust and the feeling of relevance in the minds of farmers. Ethical AI systems on the governance front should be designed to suit agricultural conditions where the use of digital tools in agricultural fields should only benefit farmers but not exploit them. Finally, all these efforts have to be aligned to one vision where technology integrates to supplement the ecological knowledge, empower farmers and improve resilience of cotton farming systems.

5.Conclusion

The issue of pest control in cotton growing provides the location not only to the fragilities but also to the restructuring prospects of Global South agriculture. Over past decades, pests have caused low yields and farm profits, reduced the incomes of households and promoted unsustainable farms relying on chemical insecticides. Smallholders conditionally, cotton farmers producing very weak livelihoods, have been the biggest burden bearers of these challenges. The combination of artificial intelligence, digital agriculture ecosystems and participatory innovation however now gives a new opportunity to redesign pest control as an aspect of a more complete system of agricultural resilience.

As the present analysis in this case study shows, AI-based solutions should not be conceptualized as discrete technological interventions, but as elements of the socio-technical systems. Artificial intelligence can be applied to a farm at the technical level, with predictive pest forecasting, AI-assisted integrated pest management (IPM), drone-based surveillance and farmer-friendly advisory systems representing the sort of depth of innovation that can be achieved when artificial intelligence meets agriculture. Such innovations have the potential to minimize unneeded pesticide applications, decrease input costs, and increase seasonal intervention to appropriate times, a factor that can benefit farmers tremendously, not to mention propelling the aspect of environmental sustainability. But the influence they have is dependent on much more than the accuracy of algorithms.

Among the key lessons that this discussion teaches us is the instruction of centrality of the context. Smallholder farmers in the Global South work in landscapes that are structurally-limited with regard to infrastructure, climatic insecurity, and socio-economic insecurity. The limited amount of data, low connectivity, widespread lack of digital literacy, and lack of a coherent value chain are daunting challenges to wider deployment of AI systems. Such limits are not weaknesses of the farmers but structural realities that any technologies have to be patterned with. Solutions, which overlook these realities, run the risk of worsening inequalities or creating the tools that can be used on pilot projects but not in practice. On the other hand, tech created in that light weight model and for low-resource devices, as offline, interfaces in local languages and integration into already existing extension networks, will be most likely to be adopted, trusted and sustained.

Human and institutional aspects of pest management are also very important. Technology uptake is not only influenced through the personal preferences of individual farmers, but also through the dominant cultural practices, gender relations as well as institutional encouragement. People must agree with AI systems and they must be earned by transparency, participatory design, and providing evidence of tangible benefits. Innovations are more likely to be adopted when farmers can comprehend the consequences of the advice, when they realize a yield or cost-saving increase in the production process, and when they have trusted intermediaries to confirm the utility of the tools, say an extension worker or a farmer cooperative. Incorporation of women farmers who, although playing a crucial part in cotton production, are usually not engaged in any formal agricultural system another necessary aspect of equitable deployment. It will be necessary that AI systems become equally developed in terms of inclusivity and social trust as in terms of technical performance.

The other important lesson is the role of governance and ethics in advancing the future of AI in agriculture. Technical input is the data produced on fields that farmers cultivate but that data alone is not a technical input but rather a valuable asset that raises matters of privacy, equity and power. Transparent data ownership, data responsibility and consent agreements are crucial in ensuring that data ownership is a value added opportunity that does not leave the farmer as victims of digital technologies. Likewise, matters relating to the liability in case of such erroneous recommendations should be solved by institutional protections. Absent ethical and governance norms, the AI tools can further widen digital rifts and strengthen reliance instead of empowering farmers. In comparison, AI may support the independence of farmers in decision-making, reinforce decision-making, and foster sustainable agricultural transformation with principles of fairness, inclusivity, and transparency.

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Conflicts of interest

The authors have no conflicts of interest to declare

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