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Artificial Intelligence in Indian Agriculture: Adoption Pathways, Data Systems, and Sustainability Outcomes

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ABSTRACT

Artificial Intelligence (AI) is another technology that is starting to be seen as a game changer in Indian agriculture and it could be implemented in the areas of crop management, pests and disease detection, irrigation schedules, market intelligence and livestock systems. The article focuses on a literature review of the academic investigations of the significance of AI applications in Indian agriculture, the data and digital infrastructure about the applications, the sustainability of the AI application use and the policy/governance tools of the AI application uptake. The review points out that the AI has provided hopeful outcomes on productivity enhancement, input-use productivity, pest management, and climate-sensitive decision-making, specifically in the pilot-based advisory regimes. Simultaneously, this is limited by its larger scale, disaggregated data, inequality in digital facilities, lack of interoperability, data regulation problems, and inequalities in access to various farmers. Another finding of this discussion is that AI in the Indian agricultural sector cannot be measured in terms of technical values, and the value of AI will be determined by the level to which it is integrated into the inclusive institutions, trusted and dependable digital infrastructure of the country and responsible governance procedures. The paper finds that AI can be used in transforming agriculture in India to be sustainable significantly, but it must come with the following conditions: working with the help of farmer-centred design, ethical use of data, and implementational models scalable, without references to specific pilot success stories.

1. INTRODUCTION

The digital revolution is changing the appearance of the agricultural sector of the whole world, and Artificial Intelligence (AI) is becoming one of the factors that define the productivity of the food production system, its effectiveness, and sustainability. Some of the artificial intelligence (AI) systems that could support farmers in making better, timely decisions in cases where they do not know about the climatic and market conditions are farm advisory systems, predictive pest and weather

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analytics and supply-chain optimisation. In this respect, AI has been frequently presented with a more generalised change in technology to facilitate the increasing food production without exerting heavy burdens on land water and other natural resources (Dhal and Kar, 2024). Even though the developed economies have already proven the advances of the accuracy and data-driven agriculture, the application of the technologies in the developing economies is not evenly distributed yet, and India is one of the largest prospects to examine the opportunities of AI and agriculture and to familiarise oneself with their constraints.

Farming in India is at the middle phase of the economy and livelihood in the nation. The reason is that it consumes an enormous proportion of the labour force and is also the reason of food security, country employment, and social stability. Simultaneously, the industry is also struggling with structural limitations that are long-term in character e.g. low productivity areas, fragmented land tenures, susceptibility to climatic factors, lack of efficiency in utilising inputs, weak connection to the market and the increasing strain on soil and water resources. This has increased the quest to search for technologies that can aid in decision making of the systems of production, risk management and post-harvest. One of such enablers has been regarded as AI since this technology will be able to combine weather, soil, crop, price, and remote-sensing data into practical recommendations to farmers, extension agencies, agribusinesses, and policymakers (Sowmya et al., 2025). It is the most promising, particularly in India, where rainfed farming is mostly practised, and the use of resources is inefficient and hence it is impeding sustainability. The agri-tech and AI-based farming interest is increasing, yet the evidence base in India is still disjointed. Most of the projects still remain focused on pilots, start-up ecosystem or localised partnerships and do not synthesise what actually worked, on what scale, and under what institutional conditions. Simultaneously, the agricultural AI governance is in its development. Even as digital agriculture platforms are on the rise, full attainment of the data availability, interoperability, inclusion, responsibility, digital literacy and public controls is still not achieved (Aggarwal et al., 2026). This renders that the gap that exists is between optimism and the reality of the availability of technology implementation. Nevertheless, even being sold as a new solution to the existing problems, the practical usefulness of AI will be determined by the available data systems, digital infrastructure, organisation of operations in institutions, and the confidence of AI technologies by farmers and rural individuals (Badavath et al., 2025).

Based on this ground, the current study will undertake a synthesis of secondary data to provide answers to four interconnected questions in the following manner; what are the AI consumption-uses that have been realised in Indian agriculture and how are these consumption-uses mediated; what are the public and open datasets or digital infrastructures which support such consumption-uses; what are the evidence of sustainability indicators in terms of productivity, resilience, environmental performance, and inclusion; and what are the policy and governance constructs which currently mediate AI consumption-use in Indian agriculture. The paper will synthesise the evidence on the technological, institutional, and sustainability levels to offer applied knowledge to researchers, policymakers, and practice professionals who can seek to apply AI to create more sustainable and inclusive agricultural development in India (Gul & Banday, 2024).

2. METHODOLOGY

The proposed research followed a secondary data synthesis methodology to understand the adoption of AI in Indian agriculture, the data ecosystems enabling its use, the sustainability of AI, and its regulatory aspects. Instead of creating original data, the research systematically examined and synthesised the evidence of reputable secondary sources to create a cohesive knowledge of the world. The method is congruous to an integrative literature review where the technological, socioeconomic, and policy-oriented pieces of evidence can be put together in the same analytical framework (Singh and Singh, 2025). The review relied on peer-reviewed journal articles, reports of international bodies, Government of India publications and a selective category of high-quality institutional or industry sources, which contained verifiable information that was pertinent to Indian agriculture.

Keywords that were used to conduct searches included: AI in agricultural systems in India, digital agriculture in India, precision farming in India, agricultural open data in India, agri-tech outcomes in India and AI agricultural policy in India. Specific searches were carried out in the materials of the organisations like FAO, World Bank, OECD, ITU, and GSMA, as well as official Indian documents such as NITI Aayog, publications by the Ministry of Agriculture, and publications of the Press Information Bureau. Peer-reviewed literature was incorporated to reinforce the evidence base especially when they had empirical evidence, case studies, or systematic observations on Indian agri-tech applications. The inclusion criteria were that the source needed to focus on the topic of agriculture in India, or offer directly application-relevant information applicable to the Indian context, and the sources needed to cover the aspects of AI, digital agriculture or similar data-driven technologies that had identifiable outcomes, pathways of implementation, or policy implications. Speculative and weakly-evidenced sources and those that were relatively more concerned with non-digital agricultural innovations were filtered out. Where needed, credible news or industry coverage was utilised only to the extent of certain factual information, e.g., pilot recovery or adoption rates, and these were approached with reservations.

The selection was done in a sequence. Follow-up searches were done as important themes came to light in the course of the review to better cover particular use-cases, datasets, and policy developments. The evaluation system was structured with four research questions. The use cases of AI in Indian agriculture were first located and clustered into the key areas that included crop management, pest and disease diagnosis, irrigation and input optimisation, market intelligence, and livestock or fisheries applications. Second, the paper mapped both publicly available datasets and digital infrastructure to support AI implementation, focusing on its openness, interoperability, quality, and data readiness in general. Third, there was a synthesis of evidence on sustainability outcomes under productivity and income effects, climate resilience, environmental sustainability, and social inclusion. Fourth, the political environment and governance were analysed based on national AI policies, digital agriculture, data governance, and partnership schemes. Narrative qualitative synthesis was applied to find convergences, inconsistencies, and gaps among sources, and quantitative numbers and facts were cross-validated where feasible with multiple references. This triangulated methodology allowed a contemporary and academically sound synthesis of the AI-agriculture situation in India, which was developing.

3. APPLICATIONS OF AI TO INDIAN AGRICULTURE

The value chain of Indian agriculture is becoming more digitally extended because AI is now used in crop planning and production management, pest monitoring, irrigation scheduling, marketing, and livestock support. According to the analysed literature, such applications can be divided into five large areas: crop management, pest and disease diagnostics, precision irrigation and input optimisation, market intelligence and price forecasting, and livestock and fisheries control. In these areas, there is still an uneven distribution of evidence base. Others are experimental or poorly documented, but there are applications which have shown quantifiable benefits in pilot applications, particularly advisory tools in crop planning and pest control. On the whole, it is evident that AI has already left the concept-stage debate in agricultural India, but the majority of uses remain in the pilot-test phase of deployment.

One of the most advanced fields of AI application in the Indian agriculture sector is crop management. In this case, machine learning systems will integrate weather predictions, past rainfall agenda, soil, satellite images, and farm management data to assist in making choices like sowing schedule, crop choice, nutrient plan, and yield prediction. They are especially useful in rainfed systems, where timing and risk management become essential issues. The most common example here is the Microsoft-ICRISAT project in Andhra Pradesh, in which AI-based sowing recommendations were based on long-term rainfall predictions and real-time weather forecasts to advise groundnut farmers on the best time to plant. The initial pilot reported positive yields, which proved that AI advisories can enhance the quality of decisions when presented through locally available resources, e.g., SMS messages in regional languages. Indian agri-tech companies like Aibono and CropIn are also building similar systems under the name of decision support. Although a lot of these interventions are still pilot-based, the consistent occurrence of yield and management improvements across crops and states gives this use case a moderate evidence base, particularly regarding advisory uses associated with weather, crop development, and yield predictiveness (Mansoor et al., 2025; Akter et al., 2024).

Another field of AI implementation of the greatest significance and comparative sophistication is pest and disease diagnostics. Such systems generally depend on images recognition-based on smartphones, disease datasets labelled by experts, pest surveillance data, and agro-meteorological data to detect stress in crops at an initial stage and enable a specific reaction. The image-based tools can be used to take images of crop symptoms and get quick diagnostic advice to farmers or the extension personnel, cutting delays in pest and disease control. In addition to diagnosis, predictive pest advisories, as predicted by the number of traps, weather conditions, and field-level observations, are also being offered using AI. The most notable one is the Wadhwani AI project on cotton pest control, especially of pink bollworm, which demonstrated promising outcomes in several states. Outcomes reported were better yields, increased profits and a decrease in the use of pesticides among the participating farmers.

Table 1. Major application areas of AI in Indian agriculture

AI application domain	Typical use cases	Data inputs used	Illustrative context	Reported outcomes	Evidence strength	Citations
Crop management	Sowing advisories, crop planning, nutrient scheduling, yield prediction	Weather forecasts, historical rainfall, soil data, satellite imagery, farm management records	Microsoft–ICRISAT groundnut advisory; decision-support platforms such as CropIn and Aibono	Improved timing of sowing, better crop planning, potential yield improvement, better decision-making under climatic uncertainty	Moderate	Mansoor et al. (2025); Akter et al. (2024)
Pest and disease diagnostics	Image-based disease detection, pest surveillance, predictive pest advisories	Smartphone images, expert-labelled disease datasets, pest trap counts, agro-meteorological data	Wadhwani AI cotton pest advisory, especially for pink bollworm	Better pest control, reduced delays in diagnosis, lower pesticide use, yield and profit gains in pilots	Moderate	Kumar et al. (2025); Chen (2025); Ryan et al. (2023)
Precision irrigation and input optimization	Irrigation scheduling, fertilizer optimization, input-use advisories	Soil moisture data, remote sensing, weather forecasts, evapotranspiration models, crop water requirement data	Pilot-scale AI irrigation and nutrient management interventions in controlled or region-specific settings	Water savings, improved input-use efficiency, possible yield maintenance or increase, improved resource management	Emerging to moderate	Manogna et al. (2025)
Market intelligence and price forecasting	Price prediction, crop marketing decisions, mandi intelligence, supply-chain analytics	Agmarknet mandi prices, arrivals data, production trends, trade data, time-series datasets	Experimental forecasting systems using digital market datasets such as Agmarknet and eNAM	Potential reduction in information asymmetry, better market planning, but limited verified evidence of direct farmer income gains	Limited	Manogna et al. (2025)
Livestock and fisheries management	Animal health monitoring, dairy management, predictive disease alerts, aquaculture monitoring	Sensor data, wearable data, milk collection records, machine vision, stock monitoring data	Stellapps and similar dairy technology initiatives; exploratory fisheries and aquaculture pilots	Early signs of improved herd monitoring and operational management, but limited large-scale evaluation	Low	Pandey & Mishra (2024)

The importance of such findings is that they imply not only the technological novelty but also the economic and environmental benefits. Nevertheless, scale evidence in the long-term is underrepresented, and a high rate of adoption is determined by access to smartphones, trust in recommendations, and last-mile advisory support (Kumar et al., 2025). That is why this category has moderate evidence, more powerful than most of the emerging use-cases but not yet completely implemented within the Indian farming systems (Chen, 2025; Ryan et al., 2023).

Optimisation of inputs and accurate irrigation is also a promising modelling and is underutilised and less scaled in India. They also generally integrate the information provided by soil moisture monitors, remote sensors, evapotranspiration models, weather forecasts, and crop water requirement models to provide irrigation warnings or schedule advice on input. These systems are particularly relevant to the areas where water stress is on the rise since the Indian agriculture remains, to a great extent, groundwater-oriented, and often squanders it. The article relies on pilot experiments, which show that AI-based irrigation scheduling may generate water savings without cutting or worsening crop yields. The identical thing can be stated regarding fertiliser optimisation because AI may utilise soil and crop data to prevent excess usage and maximise the yield of inputs. However, the evidence here is still evolving, unlike in crop advisory and pest diagnostics. Most of the interventions target the controlled pilot, greenhouse, orchard settings, or region-specific trials, with the barriers to adoption being critical since the price of sensors, their integration into data, and insufficient digital infrastructure in much of the rural areas. In spite of this, this type holds strategic interests because it puts AI directly in the course of water conservation, resource utilisation, and climate change (Manogna et al., 2025).

Some of the most discussed and yet unproven AI applications in Indian agriculture are market intelligence and price forecasting. These systems rest on mandi price records, arrivals, production patterns, trade records and time-series forecasting models such as ARIMA or LSTM in order to predict future price movements and improve market choices made by farmers. Hypothetically, these tools would enable the reduction of information asymmetry, improved planning of crops and farmers would sell produce at an opportune time and place. The ever-growing availability of digital market data on such websites as Agmarknet and eNAM provides an effective foundation to such analytics. However, the evidence which will be summarised in the draft shows that there is a minimal actual deployment. To a great degree, the sphere is still experimental and does not have much verified evidence of concrete gains in farmer income which could be traced to AI-established forecasts of prices. Some initiatives and start-ups already operate in this direction and policy papers are already inclined to refer to its potential, but compared to agronomic advisories, market forecasting is a young, poorly supported field of practice. The improved data atmosphere is accessible yet operative value to the ordinary farmers is just possible by reaching, recognising, and responding to forecasts on the premise of local market constraints (Manogna et al., 2025).

The least developed area of Indian agriculture has the potentially important frontier with AI, livestock and fisheries management. The underdeveloped applications include animal health monitoring with images and sensors, dairy management built on wearable and collection information, predictive disease models and machine vision in fisheries and aquaculture. The example of how AI and IoT are beginning to help monitor the herd and control milk is Stellapps and other Indian dairy technology companies. AI-based video monitoring and stock monitoring in small-scale fisheries have been piloted. This is promised, but the present evidence base is low and very little of the published large-scale evaluations have been done and much of the discussion has been anecdotal or exploratory in character. This is a real limitation. This area needs to be retained in the paper as it enables further expansion of the field of AI beyond crop agriculture, though it also should not be overstated. Today, livestock and fisheries usage ought to be perceived as a promising domain in the future with significant potential instead of a validating aspect in the sustainability performance in Indian agriculture (Pandey and Mishra, 2024).

4. DIGITAL INFRASTRUCTURE AND PUBLIC DATA

The success of AI in agriculture relies essentially on the fact that the appropriate data should be available and on the digital infrastructure that can be used to gather, unite, and apply AI. This ecosystem has grown significantly in India due to the open government data programs, satellite observation, weather and market databases, and the new digital platforms that farmers are being connected to. The combination of these resources is a foundation in AI applications in crop advisory, pest monitoring, irrigation scheduling, yield estimation and market intelligence. Simultaneously, the usability of these systems is limited by the poor quality of data, the lack of cohesion in ownership, and the insufficient interoperability. The open data architecture in India has also gained relevance of agricultural AI. There are many datasets available in the agriculture sector at the Open Government Data Platform (data.gov.in) with the support of the National Data Sharing and Accessibility Policy. One of the most helpful is Agmarknet, which reports the prices of thousands of mandis published daily and their arrivals in India. Due to the frequent updates of these records and their availability as machine-readable data, they offer a solid foundation to AI-based models of price trends analysis, market predictions, and supply-chain decision support. Equally, the statistics of crop area, production and yield published on government portals are becoming increasingly available in a structured format, allowing researchers and developers to develop historical trend models and regional prediction systems. Macro-level analysis can also be done using international open databases like FAOSTAT, but they are not as helpful in farm-level advisory systems because of their national-level aggregation. Some other Indian research institutes like ICAR and ICRISAT have also produced useful datasets but not all of them are regularly updated and easily accessible.

The second pillar of AI in agriculture in India is the accessibility of remote sensing and climate data. The earth observation systems of ISRO, as well as the Bhuvan platform, give imagery and geospatial data about crop surveillance, land utilisation, drought evaluation, and vegetation well-being. These are complemented by globally open sources, including MODIS, Landsat and Sentinel, which are well used by Indian researchers and agri-tech companies to develop AI models. These datasets are particularly useful as they can be monitored on a continuous basis on large scales, as well as locations where field-level data are weak or even non-existent. On the climate front, the India Meteorological Department (IMD) offers historical rainfall and temperature data, which are crucial in weather-related crop alerts, drought analysis and climate-risk analytics. Even though the availability of real-time weather feeds is not completely open, historical climate data are already a significant source of AI with regard to training agricultural systems.

A move in the right direction has been the attempt to make these various streams of data into coherent digital systems. Krishi Decision Support System (KDSS) is one such system that includes satellite, weather, soil and market data to support both macro-level planning and localised advice. More importantly, the suggested AgriStack within the framework of the Digital Agriculture Mission is an effort to establish a federated agricultural data infrastructure, which is based on farmer identity, land records, and crop survey data. The potential of such architecture was that any single farm might be connected to soil testing results, previous insurance claims, local weather conditions and other data, allowing a far more comprehensive information base to be used by AI applications. The Unified Farmer Service Interface (UFSI), which goes hand in hand with it is designed to act as a universal digital access point so that farmers can access the services and partners can access the value-added applications to which they are authorised. When properly implemented, this infrastructure can significantly eliminate data fragmentation, enable high-value agricultural data to be easier to process by AI systems, and can still need realistic protection and management (Balkrishna et al., 2024).

The new interest of India in AI-ready publicly available data can also be seen in how India has created AI-ready platforms like AI Kosh, which take machine-ready forms of datasets. The fact that the datasets are related to agriculture, including daily prices of various commodities and information about soils, can be viewed as an acknowledgement that the raw public data are oftentimes required to be cleaned and reorganised prior to being utilised in the AI training and deployment process. It is a good thing since the Indian agriculture sector has been limited not necessarily by the complete absence of data, but by the unavailability of standardised interoperable and analysis-ready data.

With these developments, there are still critical loopholes. Even at the plot level, yield data are not regularly gathered at the scale required to support a powerful machine learning application. The traditional pest and crop management practices involving local knowledge systems are hardly digitised. A number of areas of inconsistency can be seen in the real-time data flows and variation in terms of format, codes, and times of update still presents a challenge in integration. Linking land records with databases of farmers under AgriStack has already revealed the experience that institutional coordination and data cleaning are equally important as technical architecture. These concerns are relevant to the performance of AI directly: inadequately high-quality, incomplete, or mismatched information may lead to inaccurate recommendations and a lack of trust in the user.

The balance between openness and privacy is another significant problem. Although open data may contribute to innovation, other types of agricultural data, in particular, personally identifiable information of farmers and accurate records of land-based information, are sensitive. With the growth of the data protection system in India due to the Digital Personal Data Protection Act, 2023, anonymization, access through consent, and the definition of accountability will become the mechanisms of agricultural data governance. In the absence of them, digital agriculture will be extractive instead of empowering. Therefore, further developments will not be limited to the increase of data sets, but the development of reliable regulations that would allow access, use, and benefit sharing.

5. SUSTAINABILITY OUTCOMES

The sustainability implications of AI in Indian agriculture is now becoming increasingly apparent, although the empirical evidence can still be found mostly in pilots and initial deployments, rather than in major longitudinal studies. Literature reviewed in the present study indicates that AI can be used to support four key areas of outcomes, including productivity and income growth, climate resilience, environmental sustainability, and social inclusion. But the rewards of such advantages are very conditional. In cases where the AI tools are incorporated into powerful advisory systems, underpinned by quality data, and localised to local farming conditions, those results are positive; where implementation is disjointed or access is uneven, the benefits are significantly lower. Therefore, the value of AI sustainability in Indian agriculture should not be understood as an automatic one, but rather as determined by the institutional design, the delivery mechanisms, and inclusion protection (Pokhariyal et al., 2023).

The most documented effects are productivity and income effects. Multiple AI-based advisory and prediction systems have demonstrated increase in yields, input-use efficiency and farm profitability. A good example of this is the Microsoft-ICRISAT sowing advisory pilot in Andhra Pradesh; farmers were reported to have obtained approximately 30 percentage points more groundnut yields when they used historical rainfall pattern and real-time weather forecasts to make sowing decisions as compared to comparison groups. Similarly, the Wadhwani AI cotton pest advisory also showed that data-driven recommendations can enhance the agronomic and economic outcome, with reported 11 percent yields and 20-25 percent farmer profit enhancements, in part due to farmers being able to reduce unnecessary pesticides usage and protect the quality of crops (Akter et al., 2024; Chen, 2025). These examples suggest that AI has the potential to enhance the level of farm-level decision-making that can be converted into a real livelihood benefit. Nevertheless, evidence is focused in specific pilot settings and it is yet to be determined how well these results will be replicated in more extensive scaling across other agro-ecological and institutional settings.

Another area of AI usage that has good prospects of improvement is enhancing climate resilience, especially in a nation where agriculture is still very vulnerable to changes in rainfall, extreme temperatures, and pest attacks. The use of AI systems based on the integration of weather predictions, remote sensors, and field observing could assist farmers in predicting climate stresses and react faster. This comes with adaptive sowing advisories, early warning of pests and disease and irrigation scheduling tools, which enhance timing in ambiguous rainy seasons. These types of systems are particularly applicable in areas receiving rainfall, where any slight change in time can have a negative impact on exposure to crop loss. The general suggestion that AI can enhance adaptive capacity through the quicker, data-driven reaction to the variability of climatic conditions is aligned with the literature on digital agriculture and food-system resilience (Dhal and Kar, 2024). This contribution of resilience in the Indian case is not as evident in the dramatic standalone interventions but in the cumulative efficiency of a forecasting nightmares less uncertainty in decision-making. Simultaneously, the literature is yet to provide sufficiently long-term studies that can determine whether AI is significantly beneficial to resilience in response to recurrent climate shock, as opposed to merely on a single agricultural seasonal level.

Environmental sustainability is a third notable field of the impactful consequences of AI, where the technology can be used to mitigate the environmental impact of agricultural intensification. Accuracy with irrigation, optimized fertilization and use of AI to manage pests can reduce the excessive use of water, agrochemicals and other inputs. As an example, the AI-based irrigation pilot mentioned in the article reported approximately 20 percent water savings and a 15 percent increase in yield and indicated that resource conservation and productivity growth need not be at odds when advisories are in a timely and context-sensitive manner (Kumar, 2024). Equally, pest advisories, when assisted by AI, in cotton decreased pesticide application, through enhancing a more specific and timely intervention, which has direct environmental advantages in chemical load and non-target effects (Chen, 2025).

Table 2. Sustainability outcomes of AI in Indian agriculture

Sustainability dimension	Expected contribution of AI	Illustrative evidence	Risks and limitations	Overall implication	Citations
Productivity and income	Better farm decisions, improved input-use efficiency, higher yields, greater profitability	Microsoft–ICRISAT sowing advisory; Wadhwani AI pest advisory in cotton	Evidence concentrated in pilots; uncertain generalizability across agro-ecologies and institutions	AI can improve farm performance where data quality, localization, and delivery systems are strong	Akter et al. (2024); Chen (2025)
Climate resilience	Improved response to rainfall variability, pest outbreaks, and weather-related risk through early warning and predictive analytics	Weather-linked sowing advisories, pest alerts, irrigation scheduling support	Limited long-term evidence across repeated climate shocks; many findings remain seasonal or pilot-based	AI has strong potential as a resilience-support tool, especially in rainfed agriculture	Dhal & Kar (2024)
Environmental sustainability	Reduced excessive water use, more targeted agrochemical application, improved resource-use efficiency	AI-guided irrigation with water savings; pest advisories reducing unnecessary pesticide use	Sustainability claims often rely on project reports and early-stage evidence rather than independent long-term validation	AI may contribute to more sustainable intensification, but the evidence base is still maturing	Kumar (2024); Chen (2025)
Social inclusion	Improved access to advisory services through mobile, local-language, and voice-enabled systems; potential to reach underserved farmers	Mobile-based and digitally mediated advisories; policy discourse around inclusive digital agriculture	Unequal smartphone access, digital literacy gaps, land-linked exclusion, risks for women, tenants, and marginal farmers	Inclusion is possible, but not automatic; governance and delivery design determine who benefits	Ghosh et al. (2025); Meena et al. (2025)
Institutional sustainability	Better coordination of data, services, and farmer-facing delivery through digital public infrastructure	AgriStack, UFSI, KDSS, public-private partnerships under Digital Agriculture Mission	Fragmented implementation, weak interoperability, limited conversion of pilots into durable public systems	Long-term impact depends on trusted institutions, interoperability, and accountable governance	Balkrishna et al. (2024); Aggarwal et al. (2026); Nautiyal et al. (2025)

Since Indian agriculture is under a severe sustainability strain that is associated with groundwater depletion, nutrient imbalance and pesticides abuse. AI can thus operate as an empowering instrument of the more effective management of resources. Nonetheless, the existing evidence still leaves much to be desired: most of the arguments regarding sustainability are still founded on project reports or start-up stories as opposed to being based on studies that have been validated independently and across seasons. Consequently, the environmental argument in favor of AI is convincing yet immature as opposed to the scale-based decisive argument.

The fourth and the most disputed area is the social inclusion. Hypothetically, AI has the potential to decrease the asymmetry of information and offer advisory services to previously under-served farmers through the traditional extension systems. Mobile-based interfaces, local-language advisories, and voice-enabled tools could assist in reaching remote farmers, women, and smallholders in a more effective way, and particularly in combination with trusted intermediaries (Ghosh et al., 2025). The wider scope of India of which the AI for All vision explicitly envisages inclusive growth as a fundamental goal, recent policy directions and pilot playbooks are beginning to view metrics related to inclusion, including access to women farmers and smallholders, as measures of success. But inclusion cannot be presupposed. Smartphone access, connectivity, and digital literacy, and land-linked digital records are not evenly distributed, and inequalities influence who can benefit in fact using AI services.

There is a threat of being locked out digitally, thus, among the most severe issues in the assessment of the sustainability outcomes. The non-registered farmers in the digitalized database of the agricultural services or in the updated land records may be the losers since most of the agricultural services have been digitalized in mediation. It is especially concerning the AgriStack arguments and the digital farmer IDs. It has been feared that if subsidies or access to service digital identity system is not provided with adequate protection, then tenant farmers, sharecroppers, and women who have no formal title to land may be left behind, too. This would constitute a straight sabotage of digital agriculture sustainability and equity advocacies. The threat of possible bias in the algorithm will also remain unknown and probably equally significant in the sense that AI systems trained on biased data will have greater success in the well-documented regions, plants, or types of agriculture, but will generate more biased data on a marginal environment or a marginalized group. This is a projected design and governance issue though the Indian books have not put much in reference to this. Social sustainability of AI is not a mere case of diffusing technology; it entails non-technological datasets, predictability systems, interfaces with local languages and long-term human mediation via expansion and community institutions (Meena et al., 2025).

The opportunities of AI sustainability in the Indian agriculture are promising, yet remain hypothetical. There is pilot evidence that AI can be used to increase productivity and incomes, improve adaptability capacity, reduce the amount of resources wasted, and partially address information gaps. However, these benefits are neither structural nor confined any further to scale, inaccessibility and transformative governance. The point is that AI cannot be referenced as a sustainable solution itself, it can be only made sustainable when it is a part of large data systems, inclusive delivery, and sustainable governance structures (Ghosh et al., 2025). Such a case means that AI can assist with an Indian agricultural transformation by making it more productive, resilient, and fairer, whereas it should not be expected to erase them and instead, it might only widen existing divisions (Pokhariyal et al., 2023).

6. POLICY AND GOVERNANCE ENVIRONMENT

The policy and institutional framework, which would define the introduction of technologies, their access, and communication between governmental and non-governmental entities, is directly related to the development of AI in Indian agriculture. However, in the recent years, India has changed towards a more explicit policy encouragement of AI in agriculture. Nevertheless, the governance structure is incomplete. Its policy path is desirable, but it is still lagging behind its aspirations, especially in regards to standards, interoperability, safeguards to farmers and expansion of successful pilots beyond localized piloting (Agarwal et al., 2023).

In the AI strategy of India, agriculture is found to be a high priority area at the national levels. National Strategy on Artificial Intelligence has put agriculture among the sectors that AI has been found to play an important social value, which otherwise may not be realized in a privately driven market incentive. What is significant about that framing is that it is a rationale to have the government invest in agricultural AI as a developmental and public-good intervention, rather than leaving the industry solely to the privatized start-up or the divided experimentation. Later policy documents and governmental communication have reinforced this orientation with the emphasis on AI-enabled advisories, productivity maximization, climate-oriented risk management, and the market intelligence being the primary priorities of agricultural transformation. Meanwhile, the broader Responsible AI debate in India has focused on inclusion, transparency, and positive implementation of the AI in society and has created a policy framework according to which agricultural AI is expected to serve efficiency and equity goals.

The Digital Agriculture Mission (2021-2025) pursuant to which AI, remote sensing, blockchain, and digital platforms have been developed through partnerships and pilot projects has been among the largest institutional mechanisms of this change. The logic of the policy is clear in this instance: first, it is necessary to build digital public infrastructure and then it is possible to innovate the services around the infrastructure. This is also the reason why the mission gives a high priority to AgriStack, digital identities of farmers, crop documentation, geospatial data, and interoperability in delivering services. This, in the first place, can enable guided subsidies, consultancy services, insurance services, and customized AI tools based on proven and linked agricultural datasets. The corresponding Unified Farmer Service Interface (UFSI) is especially noteworthy that it is directed towards a platform model instead of a collection of fragmented schemes. With the possibility of enhancing duplication, providing innovation through APIs, and building up services on a similar backbone by several stakeholders in case it is implemented successfully, such an architecture can be significantly helpful (Balkrishna et al., 2024).

The partnerships between the government and the business have also played very significant roles within the policy framework. The government ministries have also contracted technology firms and agri-tech players to collaborate with them in testing AI-powered solutions in crop forecasting, advisory services, and in digital service delivery. The strong points of this model include the following: the state will be able to exploit the technical capacity privately, and the state will be able to preserve the direction of the policy to the populace. It has also improved accelerated testing in areas such as yield prediction, accuracy advisory and provision of services using digital identity. This is one of the very real weaknesses. Pilot-heavy models of partnership visibility are likely to be not institutionalized over time (Das et al., 2025). Majority of projects operate in a controlled setting and do not become part of the normal agriculture governance systems or extension (Saha et al., 2025). As a result, India has many prospective pilots, but only relatively a small number that have climbed, created and publicly responsible AI services in agriculture. This is one of the primary aspects of the weaknesses of governance in the current situation.

The data governance is now the most critical policy concern. Along with the digitalization of agriculture, it is not just the presence of data, but the access to the data, the permission to access data, the conditions of the permission, and the good. Farmer data like identity, land records, crop preferences, soil status and production patterns are highly sensitive data particularly when they have cross linkages between systems. The sector-specific agricultural data law in India is yet to be set, thus, at the moment, the field of governance is regulated by the bigger legal and policy instruments, the most notable among them is the Digital Personal Data Protection Act, 2023. It is a general description of consent, correction, deletion, and obligations on data fiduciaries and directly applies to such platforms as AgriStack and databases (Nautiyal et al., 2025). The policy intention in the form of the article is voluntary sharing of the data i.e. farmers consent to share their records to avail some of the services. That is the appropriate conceptual direction. Still on the operational front, lots to be sorted out: how meaningful the consent will be sought in the low-literacy setting, how the permissions will be followed-up, how the redress of grievances will be established, how the asymmetry between the farmers on the one hand and the big digital service providers on the other will be addressed.

Another governance issue is connected to the distinction of open data and personal data. The market prices, weather series and aggregate crop statistics are likely to be shared freely, and these are useful sources of information, which ought to be appreciated as valuable public goods in the context of AI innovation. In comparison, the information on the plot level, the correct land-linked data, and the personal identifiable data of the farms should be put under strict stricter control. The issue is that the agricultural AI could be the most efficient only in case multiple datasets are integrated on the farm level. That poses a policy dilemma; the more it is assimilated the more technical it is the more likely to be useful, but surveillance, marginalization, abuse or commercial exploitation of others. This stress is evident in the civil society concerns regarding the problem of individual access to governmental-related farm information on pilot arrangements. This could indeed threaten the integrity of digital agriculture in the absence of apparent safety nets and accountability systems who will soon question its validity even by the very individuals it is meant to protect.

It also has an inclusion dimension of governance. As the electronic identities and linked databases emerge as the stakeholders in the service delivery, there is a possibility that farmers who were not fully recorded or those who did not have all the land history would be locked out in the benefits. It is not a conceptual matter. The discussion of digital farmer IDs and subsidy connection has already proven the disadvantaged position of tenantry farmers, sharecroppers and women who do not even have a formal title to their land in case the systems will prove to be too inflexible. It means that the governance cannot be quantified by only the efficiency indicators of such aspects as accuracy of targeting or speed of transaction. It must also be evaluated on the premises as to whether it meets Indian agrarian fact on the ground, which includes informal tenure, gender disparity in access, and uneven access to digital access. The technical elegance in a system in being able to lock out the vulnerable users is a failure in governance, and is not a policy triumph.

It possesses a strategic policy commitment, an emerging digital public infrastructure architecture as well as an augmented experimentation of public-private partnerships in the country. Nevertheless, a complete development of governance systems in the sense of standards, privacy, inclusion, accountability and scale has not yet had pace with such improvements. The second one must change the promotion policy to the operational governance: stricter regulatory data protection in reality, inter-operable electronic environment, more clear recommendations on what to do with the data with citizens, and organizational methods of transforming pilot success into long-term agricultural service. Without this kind of change, AI in Indian agriculture will remain an industry of partial potential, and not a systemic change (Aggarwal et al., 2026; Balkrishna et al., 2024; Nautiyal et al., 2025).

7. CONCLUSIONS

Artificial intelligence is also becoming an important agent of change in Indian agriculture and more applications are being implemented in crop advice, pest and disease management, irrigation prediction, market intelligence, and so on. It is also proved that AI has great opportunities of increasing productivity, resource usage efficiency, climate adaptability and decision making in the agricultural systems. In the meantime, this also has an unequal impact of its own since it is still being applied in pilots, startup ecosystems, and small institutional settings rather than being applied in scaled up public systems. This is also brought out by the fact that technological capability is inadequate in itself. The implementation of AI will be successful in the Indian agricultural sector in the long term, provided that there is good digital infrastructure, reliable and interoperable data systems, non-discriminatory access, and clear how governance privacy, consent and accountability can be applied. Without knowing these foundations, AI has the potential of escalating the differences among individuals instead of reducing them. AI cannot be regarded as a solution but should be regarded as a part of the greater idea of agricultural transformation that involves innovation with the government policy, institutional support, and farmer-centered design. Through enabling governance and effective implementation, AI would have a significant role to play in a more productive, sustainable, and resilient agricultural future in India.

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