



Artificial intelligence for climate-smart agriculture: Bridging science, policy, and practice - A narrative review

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Abstract

Climate change poses a serious challenge to global food security, where agriculture will need to be highly productive, adaptive to climate change, and also less emission of greenhouse gases into the atmosphere. Climate-smart agriculture (CSA) plays a central role in addressing these challenges, but its popularity, especially with smallholder farmers in low- and middle-income nations is hampered by the lack of data, decision support, and adaptability. The use of artificial intelligence (AI) is becoming a revolutionary technology that can be used to bridge scientific knowledge, policy formulation, and real-world farming practices to boost CSA realization. This narrative review was based on the peer-reviewed and grey literature published in last two decades with the aim of assessing the AI application in the main fields of CSA, such as crop yield prediction, precision irrigation, pest and disease surveillance, soil carbon monitoring, as well as digital advisory services. It synthesized data from 177 sources from various research databases (Web of Science, Scopus, Google Scholar) identified technological trends, policy frameworks, and an adoption barrier model. Additionally, it outlined a future research roadmap and provides specific policy and practice recommendations. The review concluded that despite significant potential in all the studied CSA domains, with 15-30% improvements in yield prediction accuracy and 20-40% reductions in water consumption in controlled environments (single-study estimates reported without confidence intervals; see Limitations), the adoption of AI applications by smallholder farmers are crippled by the fragility of data ecosystems, infrastructure gaps, limited institutional capacity, and systematic inequities in the global AI innovation ecosystem. The review found that to achieve the transformative potential of AI in CSA, there is an urgent need to re-orient the research investment, governance structures and institutional structures to the complex, data-poor realities of tropical smallholder farming systems.

Keywords: Adoption Barrier Model, Artificial Intelligence, Applications, Climate-Smart Agriculture, Policy

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Introduction

The twenty-first century is witnessing an unprecedented convergence of pressures on global agriculture. The global population is projected to reach 9.7 billion by 2050, requiring nearly 50 % more food production compared to 2012 levels, but this growth will have to occur against the backdrop of an accelerating climate change that is threatening to reduce average crop yields by 2-6% per decade (Food and Agriculture Organization-FAO, 2023; Intergovernmental Panel on Climate Change-IPCC, 2022). Increases in temperature, changes in precipitation regimes, more frequent occurrences of extreme weather, and the proliferation of climate-driven pests and diseases are considered by IPCC, (2022) as a compound risk to global food systems, and disproportionately affecting farmers in tropical and subtropical areas.

The FAO (2010) formally defined climate-smart agriculture (CSA) as an approach that pursues a triple win of improved food security, increased resilience to climate change, and lower or negative agricultural greenhouse gas emissions. Since its introduction, CSA has become widely adopted within international policy discourse, having been prominently featured in the Paris Agreement, in the Sustainable Development Goals, and in many national agricultural development plans. Nonetheless, practical implementation of CSA principles into scalable, economically viable and equitable farming systems has been significantly more difficult, due to gaps in knowledge, lack of data, insufficient advisory services, and structural weaknesses particularly within smallholder farming systems (Thornton et al., 2018).

AI, a wide umbrella of computational approaches that comprises machine learning (ML), deep learning (DL), computer vision, natural language processing (NLP), and autonomous decision systems is one of the fast growing and impactful enabling technologies in the history of agricultural transformation over the past decade. The integration of AI technologies with declining computing costs, the expansion of satellite-based earth observation systems, expanding mobile networks, and increasing agricultural sensor networks has provided an opportunity of a step-change in the accuracy, accessibility and timeliness of agricultural information and decision support systems (Kamilaris & Prenafeta-Boldú, 2018; Liakos et al., 2018).

Although there has been a decent amount of scientific attention and increased investment, the existing literature has not yet provided a consistent evidence-based evaluation of where AI is actually has demonstrated measurable benefits in CSA as there are still weaknesses and bottlenecks. This narrative review will bridge that gap, synthesizing the existing body of evidence on a scientific, policy and practice level to present an integrated view of the present state and future direction of AI to CSA with specific reference to the needs and contexts of smallholder farmers in tropical Low- and Middle-Income Countries (LMICs).

The main aim of the review was to present an overarching, evidence-based summary of the current reality of AI application in climate-smart agriculture, critically reviewing the scientific evidence, policy environment, and practical barriers and enablers, with a view to elucidating priorities in future research, investment, and governance to catalyze equitable and effective application of AI in climate-smart agriculture within tropical smallholder agricultural systems. Furthermore, as the objectives of this study, it seeks to offer a thorough and systematic review of the use of artificial intelligence (AI) technologies in climate-smart agriculture (CSA), with

particular emphasis on the areas of crop productivity, water use, pest and disease management, soil carbon, and digital advisory systems. It also aims to map technological developments and innovations, especially those pertinent to tropical smallholder agriculture in low- and middle-income nations. The study also reviews global and national policy frameworks on AI in agriculture to provide a critical analysis of gaps and opportunities for policy harmonization. A multi-layered model is proposed to examine barriers to AI adoption at individual, community, institutional and systemic levels. Finally, it proposes an innovative agenda with well-defined short, medium and long-term goals, and made practical recommendations for future research, policy and practice in AI-driven CSA.

Methodology

The methodology used was a narrative review since it was deemed suitable to the nature and extent of this research. Narrative reviews are especially appropriate in broad, multidisciplinary areas in the early stages of integration, where the heterogeneity of study designs and discipline structures and types of evidence, including experimental study, observational research, computational analyses, policy documents, and reports by practitioners, makes quantitative meta-analytic synthesis either infeasible or misleading (Baumeister & Leary, 1997; Ferrari, 2015). This approach facilitates interpretive, thematic synthesis which helps in the identification of broader patterns, conceptual frameworks and gaps in knowledge in a broad body of evidence. It is recognized that this review contains several elements of systematic review methodology that are not found in full systematic review methodology (such as full PRISMA register, dual, independent screening, formal risk-of-bias assessment etc). It is not an error, it is a deliberate design: the evidence base includes experimental studies, observational research, computational method papers, grey literature and policy documents that are not all commensurable by a single quality metric and so a quantitative aggregation logic (as used in systematic reviews) would not be suitable; an unstructured narrative synthesis would not provide enough transparency and reproducibility in the context of this heterogeneous multidisciplinary topic. The search and screening documentation reported below is thus not claimed to represent a systematic review, but merely the limits of the evidence base are made auditable by the accompanying interpretive, thematic synthesis. The limitations of the interpretive, thematic synthesis as a means of formal systematic review are explicitly discussed in the Limitations section. Search strategy included five major academic databases (Web of Science, Scopus, Google Scholar, PubMed, and the CGIAR institutional repository) which were searched systematically. Grey literature searches included reports and working papers by the FAO, the World Bank, and the International Fund for Agricultural Development (IFAD), the United Nations Environment Program (UNEP), CGIAR Research Programs on Climate Change, Agriculture and Food Security (CCAFS) and national agricultural research systems in sub-Saharan Africa, South Asia and Southeast Asia. Where appropriate, policy documents provided by the UNFCCC Secretariat, IPCC Working Group II and national CSA investment plans were provided.

The search terms were iteratively used with Boolean operators and the following primary search terms were used: "artificial intelligence" AND "climate-smart agriculture; machine learning and crop yield prediction; deep learning and pest detection and agriculture; AI and climate adaptation and smallholder; precision agriculture and climate change; remote sensing and AI and food security; natural language processing and agriculture; decision support systems. The search was performed between January and September 2025, and the range of dates was limited to 2015-

2025 to include the year when the accelerated pace of AI capability and CSA implementation would be the most significant. This period was selected to capture recent advances in AI technologies and their increasing application in CSA.

Articles were eligible when they: (i) discussed the use of AI in the context of climate change or climate variability in agricultural production, food systems, or natural resource management; (ii) were published in English between 01st of January 2015 and 01st of September 2025; (iii) offered enough methodological or empirical specifications to be synthesized meaningfully; and (iv) were published in peer-reviewed journals. The studies were filtered out when they were focused solely on non-agricultural applications of AI and had no agricultural connection, were not written in English, or were simply editorial opinion and lacked evidence. 177 sources were included in the synthesis and met the inclusion criteria. After the initial search, there were 612 records found in the five databases and grey-literature sources; 248 duplicate records were removed, 364 records were screened for titles/abstracts, and 211 records were screened for full text of which 177 were included and were then synthesized. The evidence base was heterogeneous, and the credibility of peer-reviewed articles was appraised on the basis of their journal indexing status and number of citations; grey literature and policy documents were appraised for their issuing-organization authority, methodological transparency, and consistency with peer-reviewed evidence and excluded or synthesized as low-confidence evidence.

For data extraction and thematic synthesis, a narrative review pathway was used in accordance with the thematic analysis procedure suggested by Braun and Clarke (2006) and adapted to the context of narrative literature review. The conceptual framework of the review science, policy, and practice dimensions of AI-CSA integration were used as common themes and patterns in the literature. The following information was extracted from each included source: AI method and technical approach, agricultural application domain, geographic and agro-ecological context, scale of implementation (field, farm, landscape, regional), outcome measures and reported effect sizes, and reported barriers or enablers of adoption. The findings from the various sources in the same application domain were actively contrasted with one another through synthesis, for example, contrasting results from controlled-condition performance with results from field-condition results for the same application domain, and convergence, divergence and unresolved contradictions in the evidence were identified, rather than being reported in isolation; the results of these contrasts are included in the Discussion, particularly in the section “Understanding the Thematic Evidence: Potential and Remaining Gaps”.

Ethical Clearance Statement

Ethical approval was not required for this study as it is based on review of published literature.

Results

This section reports the results of the narrative review, with two sub-sections: (i) a thematic synthesis of AI solutions that are currently implemented or trailed across the core areas of Climate-Smart Agriculture (CSA), and (ii) a summary of trends and themes observed in the recent literature that point to the future frontier of AI in agriculture.

AI applications in climate-smart agriculture: Thematic review

Five key thematic areas in which AI is used to support CSA goals were identified: crop yield forecasting and seasonal forecasting, precision irrigation and water management, pest and disease surveillance, carbon sequestration and soil health monitoring, and digital extension and advisory systems with AI. These are summarized below based on the evidence identified in the peer-reviewed literature.

Crop yield prediction and seasonal forecasting

One of the most researched applications of AI in CSA is predictive modelling of crop yields using existing and forecasted climatic conditions. This work builds on several decades of agricultural systems modelling scholarship (Jones et al., 2017a). Machine learning models, such as random forests, support vector regression, gradient boosting machines (GBM) and deep neural networks, have been utilized to combine various classes of data streams such as meteorological records, satellite images, soil physicochemical data, and historical yield databases to produce spatially explicit and high-resolution yield predictions. Khaki and Wang (2019) have revealed that long short-term memory (LSTM) networks were found to be much more accurate in yield prediction in the maize in the United States Corn Belt with root mean square errors 15-30% lower than simulation benchmarks under cross-validation. This is a single study estimate and should not be read as a generalizable effect size (see Limitations).

General circulation model (GCM) outputs have been coupled with ML downscaling algorithms to derive localized, farm-relevant climate projections with coarse-resolution global model outputs - resolving the inherent spatial gap between climate model resolution and farm-scale decision-making scales (Lobell & Asseng, 2017). Ensemble ML, which would be used to combine the predictions made by many model architectures, has been demonstrated to be more effective than single models in out-of-sample yield forecasting, being less sensitive to training data idiosyncrasies (Crane-Droesch, 2018). The use of these techniques in sub-Saharan Africa, specifically for sorghum, millet, and maize, has shown improved seasonal forecasting performance which can directly guide planting and input purchasing choices (Vrieling et al., 2018).

Precision irrigation and water management

Climate change and water scarcity are among the most immediate and severe threats to agricultural productivity. AI-based irrigation scheduling applications that combine soil moisture sensors, reference evapotranspiration (ET₀) models, weather prediction APIs and crop growth stage information have demonstrated water savings of 20-40% compared to traditional calendar-based irrigation, without increases in yields in a variety of cropping systems and geographies (González et al., 2019). This figure, too, comes from a single study and has not been validated across the diverse conditions of smallholder tropical farming. In reinforcement learning (RL) applications, where irrigation controllers are trained to optimize scheduling policies by simulating the interaction with crop environment models have proved to be a particularly powerful paradigm, allowing adaptive behavior to intra-seasonal climate variability which may provide greater adaptability than conventional rule-based systems (Kelleners et al., 2021).

Using unmanned aerial vehicles, computer vision systems have been installed to identify early-stage crop water stress by thermal infrared imaging and leaf reflectance to implement deficit irrigation management strategies helping to maximize water productivity in high-value horticultural crops (Vanino et al., 2018). In rain-fed smallholder systems (80% of the agricultural land in sub-Saharan Africa) seasonal weather prediction tools based on AI are being deployed to inform planting date choices and supplementary irrigation timing, significantly mitigating production risks associated with climate change (Ogutu et al., 2018).

Pest and disease detection and surveillance

Implementing convolutional neural networks (CNNs) in combination with smartphone-based field diagnostics has created extensive interest and practitioner concern that has gained a multitude of studies and applications as a way of democratizing access to plant pathology knowledge in resource-constrained environments. An early application of transfer learning to plant disease classification was the Penn State University Plant Village project, which built a dataset of more than 54,000 labelled crop disease images, and under controlled conditions, its overall validation accuracy was above 99% (Mohanty et al., 2016). Nevertheless, later field tests in Tanzania and Rwanda demonstrated the substantial discrepancy between laboratory and field accuracy with classification accuracy decreasing to 67-85% in less-than-ideal field light and imaging conditions (Ramcharan et al., 2017). International Institute of Tropical Agriculture -IITA created the Nuru application with collaborators to diagnose cassava disease, and this gap was partially filled by active learning protocols that integrated new images collected in the field as training was re-run (Mwebaze et al., 2019).

Multispectral and synthetic aperture radar (SAR) satellite-based remote sensing systems have been utilized to monitor landscape-scale locusts, fall armyworm, and other weather-driven pests using multispectral and synthetic aperture radar (SAR) cameras and ML classification algorithms to establish early warning systems, which may be used to implement targeted measures before infestations spread economically damaging thresholds. The 2019-2021 desert locust crisis in East Africa and the Horn of Africa highlighted the centrality of scalable, real-time systems of pest monitoring, and spurred significant investment in AI-enhanced locust surveillance systems by the FAO and national plant protection services (FAO, 2021a).

Carbon sequestration and soil health monitoring

The AI-based approaches for assessing soil organic carbon (SOC) is becoming an important measure of agro-resilience as a crucial climate change mitigation tool, with the 4 per Mille initiative estimates that an annual increase of 0.4% in the global stocks of SOC would be sufficient to counterbalance all fossil fuel-emitting CO₂ (Minasny et al., 2017). AI methods, especially ensemble ML models that are trained using visible and near-infrared (vis-NIR) and mid-infrared (MIR) soil spectral data, have significantly improved the cost-efficiency and spatial resolution of SOC mapping, allowing spectral measurements to be predicted at a fraction of the cost of traditional laboratory analysis (Nocita et al., 2015). National and continental applications of digital soil mapping frameworks using random forest and deep learning algorithms have been used to create high-resolution SOC maps, which can be used to inform precision organic amendment recommendations (Hengl et al., 2017).

Repeated tests of compost application, like those in Sri Lankan maize-soybean rotation systems, have shown that surface carbon stock (0-20 cm) in the soil can be up to 50.6 Mg C ha⁻¹ with compost-only management in tropical agricultural systems, which is much higher than non-composted controls (Liyanage et al., 2020). Predictive models based on AI, which connect the rates of compost application, nitrogen management regimes, and SOC accretion pathways may significantly enhance the extrapolation of such experimental findings into spatially-targeted farmer advisory services. In addition, AI-validated remote sensing techniques of measurement, reporting and verification (MRV) of soil carbon stocks have been increased as an approach of linking smallholder organic management activities with voluntary carbon markets (Bryngelsson et al., 2022).

AI-enhanced extension and digital advisory services

The most straight forward connection between AI science and the farming practice is perhaps digital advisory systems, which convert complex model outputs and data streams into practical, context-specific and timely advice to farmers. Scalable AI-based chatbots, voice-based advisory systems, and SMS-based decision support systems have been implemented in South Asia and sub-Saharan Africa. In Andhra Pradesh, India, the ICRISAT Sowing App, which was implemented in 44 districts, gave AI-based location-specific sowing and fertilizer advice to more than half a million farmers, leading to an overall 10-15% increase in yield and a 20 % decrease in the amount of used fertilizer (Rao et al., 2019). The Digital Green platform which was active in India and Ethiopia demonstrated that the relevance and acceptability of agricultural information dissemination on a large scale increased markedly when mediated by AI through peer video content (Gandhi et al., 2009).

Natural language processing is becoming commonly used to process queries posted by farmers via helpline services, feedback-solicitation by community radio listeners, and social media postings to detect emerging agricultural issues and knowledge gaps in near-real-time detection to enable more responsive demand-driven extension services (Nakano & Magezi, 2020). An emerging, yet fast-evolving, frontier to multilingual, personalized advisory services is generative AI models that have been trained on local agronomic knowledge bases, climate datasets, and on-farm-oriented communication corpora, and can function in low-connectivity settings due to compressed on-device model deployment (Brown et al., 2020).

Major AI application domains in climate-smart agriculture: methods, outcomes, and maturity levels are summarized in Table 1.

Table 1: Summary of major AI application domains in climate-smart agriculture: methods, outcomes, and maturity levels

Application Domain	AI Methods	Key Outcomes	Geographic Focus	Maturity
Crop yield forecasting	LSTM, CNN, XGBoost, RF	15-30% reduction in RMSE; better seasonal forecast performance	Global; South Asia, SSA	High - operational in multiple national systems

Application Domain	AI Methods	Key Outcomes	Geographic Focus	Maturity
Precision irrigation	RL, ANN, IoT integration	20-40% water reduction; yield retained or enhance	South Asia, Middle East, Mediterranean	Medium-high - commercial implementations
Pest & disease detection	CNN, transfer learning, UAV imagery	67–99% accuracy (field–lab); landscape early warning	SSA, Southeast Asia	Medium - field-scale pilots
Soil carbon monitors	RF, vis-NIR/MIR spectral ML, digital soil mapping	Cost-effective SOC mapping; carbon MRV support	Tropics, Europe, North America	Medium -research-to-operational transition
Digital advisory services	NLP, chatbots, voice AI, generative AI	10–15% yield gains; 20% input reduction	South Asia, East Africa	Medium-early operational systems
Climate risk assessment	Ensemble ML, Bayesian networks, GCM downscaling	Localized climate projections; farm-level risk indices	Global; LMIC focus	Medium- select operational platforms
Variety selection & genomics	Multi-environment trial ML, genomic prediction	Accelerated variety development; climate-adaptive cultivar determination	Global- CGIAR systems	High in genomics; medium in field deployment

RF = Random Forest; LSTM = Long Short-Term Memory; CNN = Convolutional Neural Network; RL = Reinforcement Learning; ANN = Artificial Neural Network; NLP = Natural Language Processing; SOC = Soil Organic Carbon; SSA = Sub-Saharan Africa; LMIC = Low- and Middle-Income Country; MRV = Measurement, Reporting and Verification. Note: The outcome ranges reported above are drawn from individual studies cited in the text and should not be interpreted as generalizable effect sizes (see Limitations).

Emerging trends and patterns

The review identified five cross-cutting trends that illustrate the changing landscape of AI in CSA, beyond established application areas: the use of federated learning to overcome data governance challenges, the development of explainable AI to foster farmer acceptance and uptake, the integration of local knowledge into AI applications, the emergence of agricultural digital twins, and the linking of AI-based MRV to voluntary carbon markets.

Federated learning and agricultural data sovereignty

Another important recent emerging trend is the implementation of federated learning (FL) systems to agricultural AI systems, where model training is performed on distributed data stored

by a variety of stakeholders, including national ministries of agriculture, farmer cooperatives, research institutions and agri-input companies, without requiring centralized data sharing or transmission (Rieke et al., 2020). This is a direct response to the intensifying issues of data sovereignty, privacy, and fair value sharing of data generated by farmers, a problem of growing policy relevance in agricultural data governance in Low- and Middle-Income Countries (LMICs). The theoretical basis of FL was laid by McMahan et al. (2017), and later applications of federated models to agriculture in East African crop disease surveillance networks have shown that federated models can challenge the performance of centrally trained counterparts with a significant mitigation of data governance risks (Piccialli et al., 2025).

Explainable AI of farmer trust and adoption

The potential for high-performing AI models to be opaque (especially deep neural networks) has been cited as a root cause of lack of trust and adoption by farmers, extension workers, and policymakers who need recommendations that can be interpreted and audited (Gunning et al., 2019). The explainable AI (XAI) is a new arena that has gained rapid growth, with SHAP (SHapley Additive exPlanations) values, LIME (Local Interpretable Model-agnostic Explanations) and attention mechanism visualizations becoming more common in agricultural AI systems to offer human-interpretable explanation of model outputs (Lundberg & Lee, 2017). Randomized trials in Kenya and Bangladesh demonstrated that farmers receiving explainable AI (XAI)-based advisory outputs such as recommendations that explicitly detailed the critical soil and weather factors affecting the selection of a specific crop variety were markedly more inclined to adhere to the advice compared to those receiving recommendations devoid of any explanation (Tsan et al., 2021).

Data integration between indigenous and local knowledge and AI systems

An increasing scholarly effort supports the systematic combination of indigenous and local knowledge (ILK) and data-driven AI systems, and recognizes decades of accumulated farmer knowledge on local agro-ecological conditions, crop varieties, and climate phenological patterns as invaluable and systematically under-exploited data resource (Rist et al., 2010; Zougmore et al., 2016). Participatory AI design models - where farmers are co-creators of contextually relevant training datasets, model validation policies, and interface designs - have shown better contextual relevance and adoption rates than externally designed systems that are foisted on communities (Van den Berg & Jiggins, 2007). The Open Farm project and the Digital Farmer Field School model are some of the first, yet promising, examples of organized farmer-AI co-creation in LMIC settings.

Agricultural digital twins –AGT and multi-scale modelling

Agricultural digital twins concept as real-time, dynamically updated virtual models of farm or landscape systems fed by sensors, satellites, and weather data and coupled with AI-driven simulation and optimization models are starting to change their theoretical proposal into early operational reality (Pylianidis et al., 2021; Wolfert et al., 2017). Research institutions, consortia of technology companies, and individual countries are developing digital twin platforms of individual farms, irrigation districts, and sub-national agricultural zones, especially in the Farm to Fork digital strategy of the European Union. Their possible use in tropical and subtropical

systems vulnerable to climate change is becoming more accepted, although the major problem of infrastructure, data quality, and institutional capacity needs to be addressed prior to useful application in the LMIC smallholder settings (Verdouw et al., 2021).

AI to carbon market integration and smallholder incentives

The growth of voluntary carbon markets and the working of Article 6 mechanisms in the Paris Agreement have generated a significant need in low-cost, transparent, and verifiable ways of tracking agricultural soil carbon stocks and emissions on a large scale. Multispectral satellite imagery, LiDAR canopy, and ML regression model-based AI-driven remote sensing solutions are under development and testing as an agricultural carbon MRV application, with the potential to reduce verification costs by 60-80% compared to traditional soil sampling methods (Bryngelsson et al., 2022). As with the other effect sizes reported in this review, this figure derives from early pilot studies and should be treated as indicative rather than generalizable. This has direct implications for tropical smallholder farming systems where compost-based soil carbon sequestration, which has been verified by AI, can produce carbon credits that will offer potential additional income to those participating farmers (Vermeulen et al., 2012).

Discussion

The results of this review have shown that AI technologies are producing evidence-based contributions to the key productivity, adaptation and mitigation areas of CSA. But this evidence also shows there are significant structural barriers to the equitable scaling of AI technologies, and a significant and consequential gap between the technical readiness of the AI solutions and the policy settings needed to deploy them at socially transformative scales. This section draws out the implications of these thematic findings in terms of these larger dynamics, considers the policy landscape, and identifies areas for research, institutional and international collaboration.

Understanding the thematic evidence: Potential and remaining gaps

The evidence synthesis across thematic clusters reveals that AI-based systems tend to outperform traditional methods in controlled or semi-controlled environments, but their impact in the field is not consistent and depends on contextual factors that are commonly neglected in technical analyses. This disconnect between lab performance and field-level adoption is perhaps most glaringly evident in the domain of crop disease diagnostics, where CNN-based systems provided classification accuracies greater than 99% under controlled conditions (Mohanty et al., 2016) but dropped to 67-85% in field conditions (Ramcharan et al., 2017): a discrepancy with potentially profound implications for systems used by resource-poor farmers making critical crop management decisions.

The evidence base on precision irrigation is similarly skewed. Reports of 20-40% water savings (González et al., 2019) are impressive, but require adequate sensor networks, reliable internet or mobile network coverage, as well as user competency to engage with AI-mediated interfaces - often limited in the smallholder farming environments most affected by climate-induced water stresses. The reinforcement learning irrigation paradigm (Kelleners et al., 2021), while technically impressive, requires high-resolution in-situ data streams that are uncommon in low-

resourced farming systems. These insights suggest that the current research paradigm, which tends to assess performance under ideal or data-rich circumstances, overestimates deploy ability in the areas most in need. In contrast, the AI-enabled extension services provide a more positive story about the potential for impact at scale. The experience of the ICRISAT Sowing App (Rao et al., 2019) and Digital Green platform (Gandhi et al., 2009) suggests that well-designed AI advisory systems - which take into account language diversity, ease of use of the interface, and dissemination via community networks - can be adopted at scale and deliver agronomic and economic impacts. These examples show the importance of design for impact in addition to technical performance, and that integration with existing extension systems and co-design with farmers are essential requirements for scale-up.

The evidence from SOC mapping and carbon MRV suggests a key convergence between adaptation and mitigation co-benefits of AI. Fine-scale digital soil mapping (Hengl et al., 2017) and AI-enabled carbon measurement, reporting and verification (MRV) (Bryngelsson et al., 2022) are technical enablers that could simultaneously enhance farm-level soil health management advice and enable smallholder farmers to access potential income opportunities from voluntary carbon markets. However, achieving this convergence requires both technical and institutional development of inclusive carbon market governance, transparent benefit-sharing strategies and robust institutional intermediaries which can connect smallholders to these markets while protecting against exploitative and extractive contractual schemes. Considered together, these four thematic comparisons, all negative, suggest a consistency of trend rather than four independent findings: Further a technology moves away from controlled research settings to the more diverse and less-infrastructured environment of tropical smallholder agriculture, the weaker the evidence base. The two areas that had the highest mean reported effect sizes were crop disease diagnostics and precision irrigation; both of these are also among the two with the clearest recorded difference between lab and field performance, implying that the discipline's current incentive structure (favouring headline accuracy or efficiency figures under favorable conditions) may be systematically over-representing readiness for smallholder deployment. While the effect size is not as large and as consistent, the AI-enabled extension literature reports smaller and more varied effect sizes but is based on a larger number of independent field deployments, which in itself is a sign of a more mature and externally valid evidence base, though less emphasized in policy summaries of potential effects of AI-CSA. This imbalance between adoptions readiness evidence and evidence of technical performance is considered an important substantive finding here and will be included as a main justification for presenting the quantitative outcomes of the previous subsections with explicit single-study caveats, rather than as consolidated effect sizes (see Limitations).

Emerging trends: Implications for equitable and sustainable AI deployment

The five emerging trends outlined in the results section suggest an evolution in the field away from system performance toward more sophisticated consideration of social, governance and epistemic concerns in AI deployment. The progress made in federated learning is particularly important for equity and sovereignty considerations. With AI platforms increasingly reliant on large, diverse agricultural data sets for model training and inference, the threat of value extraction - where commercial or cultural proprietary farmer-owned data is extracted for commercial use without proper compensation or consent - has emerged as a critical issue in LMIC policy settings. FL provides a technically plausible pathway to decouple model performance from data

centralization, and its successful piloting in East African disease surveillance networks indicates that governance-sensitive use cases are technically feasible (Piccialli et al., 2025). However, FL does not solve the political economy of agricultural data; issues of ownership, attribution and benefit-sharing have policy and legal implications that go beyond the design of technical architecture. The XAI results have ramifications for adoption. The correlation between the provision of explanation and adherence to advice found in trials in Kenya and Bangladesh (Tsan et al., 2021) is consistent with a body of evidence from agricultural extension that highlights the importance of trust, transparency and farmer agency in technology adoption. This outcome should be understood not just as a design rule, but as a call to refocus AI development efforts on explainability and communicative accessibility as a first-order design consideration, rather than a secondary feature of performance-optimized systems.

The inclusion of ILK in AI systems is perhaps the most conceptually transformative paradigm shift observed in this review. The awareness that farmers' observations spanning decades represent a systematically devalued data stream with potentially high local specificity for their respective agro-ecological contexts challenges the long-standing data-centric paradigm of AI development that has been dominated by sensor and satellite data streams. Co-design approaches (Van den Berg & Jiggins, 2007) provide one way to shift this paradigm, but scaling these approaches requires institutional, funding and evaluation arrangements that are not yet commonly adopted in agricultural research and development. The digital twin for agriculture trend is a double-edged sword. The integration of sensors, satellite data and AI simulation has the potential to revolutionize real-time farm and landscape management in high-resource settings, but the gap between today's technologies and LMIC smallholder realities is vast. The potential that digital twin investment further widens the digital divide, with all benefits flowing to high-infrastructure environments and vulnerable smallholders left behind, needs to be considered in technology investment and research directions. Proactive consideration of how to translate digital twin technologies to low-data and low-connectivity settings, integrating other data sources (e.g. community weather observers, participatory mapping), will be critical to avoid this technology reinforcing agricultural dualism.

The policy landscape: Policy gaps and opportunities

International policy framework

The potential of AI to accelerate CSA has been explicitly acknowledged in various key global policy frameworks. In the IPCC Sixth Assessment Report (2022), an artificial intelligence-enabled precision agriculture and digital extension services are mentioned as being among high-potential adaptation actions in food systems, with extensive implementation having the potential to lower global agricultural greenhouse gas emissions by 0.3-0.9 Gt CO₂-equivalent per year by 2050. Digital innovation, such as AI, is a cross-cutting enabler in all pillars of production, nutrition, environment, and livelihood as part of the FAO Strategic Framework 2022-2031 (FAO, 2021b). In 2022, the One Consultative Group on International Agricultural Research (CGIAR) digital innovation agenda has identified the AI of climate-adaptive food systems as one of five priority areas of investment (CGIAR, 2022).

Nevertheless, the transfer of these international commitments into the consistent national AI-for-agriculture strategies is still highly uneven. A systematic review of 54 Nationally Determined

Contributions (NDCs) under the Paris Agreement by Blasiak et al. (2021) revealed that less than one-fifth of these contributions had any reference to digital agriculture or AI as an adaptation measure, and even lesser proportions had a reference to specific financing mechanisms or implementation plans. This gap between international recognition and national policy coherence represents a systemic constraint on scaling AI-for-CSA initiatives that technical solutions alone cannot resolve (Poole et al., 2022). Recommended actions for policy landscape for AI in climate-smart agriculture are listed in Table 2.

Table 2: Policy landscape for AI in climate-smart agriculture: key gaps and recommended actions

Policy Dimension	Current Status	Recommended Actions
AI in NDCs	<20% of NDCs reference digital agriculture (Blasiak et al., 2021)	Integrate AI-for-CSA into NDC revision cycles; develop UNFCCC technical guidance note
Agricultural data governance	Fragmented; limited farmer data rights; absent MRV standards	Develop national agricultural data acts; mandate open interoperability standards; establish benefit-sharing mechanisms
Financing for AI-CSA	Predominantly donor-driven; minimal domestic public investment (World Bank, 2023)	Establish dedicated national AI-agriculture innovation funds; leverage Green Climate Fund and GEF instruments
AI regulatory frameworks	Largely absent in LMICs; ad hoc in HICs	Develop context-appropriate AI accountability and ethics guidelines for agricultural decision systems
Extension system integration	AI tools rarely embedded in national extension reform programs	Mandate AI tool integration in public extension reform; invest in agent digital literacy and facilitation skills
Gender and social inclusion	Women farmers systematically excluded from digital agriculture benefits (FAO, 2023)	Apply gender-responsive design standards; collect sex-disaggregated adoption and impact data

Source: Created using synthesized data

Policy opportunities and recommendations

Despite these shortcomings, there are a number of policy opportunities currently. The post-pandemic momentum for digital infrastructure investment, along with growing commitment to climate finance in the run-up to each Conference of the Parties (COP), presents an opportunity for mainstreaming AI-for-CSA in national and global policy settings. Based on the evidence reviewed here, we make the following recommendations. Nationally, LMIC governments should undertake integrated AI-for-agriculture strategies in Nationally Determined Contributions and National Adaptation Plans that outline institutional roles, budgets and monitoring strategies. Priority should be given to the development of open and interoperable national agricultural data systems and establishing inclusive data governance norms that safeguard smallholder data rights. Public

funding for rural digital connectivity, digital extension services, and AI literacy in agriculture should be considered as enabling investments.

At the global level, multilateral development banks, bilateral donors and global research platforms should set up special funding windows for AI-for-CSA investments in LMICs, with a clear focus on equity and inclusivity. Inclusion of AI-for-CSA metrics in national climate finance support and technical support for governments wishing to develop national strategies for AI-for-agriculture would bridge the gap between recognition and action. Regional investment in AI capacity-building networks, similar to existing regional agricultural research and extension platforms, would facilitate knowledge sharing, infrastructure sharing, and the co-evolution of locally-tailored AI solutions. Finally, the international research community should focus on equity-focused evaluation approaches that move beyond aggregate measures of performance to examine the distributional impacts of AI across farmer characteristics, agroecological zones, and gender. Sustainable funding for farmer-AI co-design, ILK integration and XAI technologies will be required to ensure technically and socially sound AI-for-agriculture systems for the future.

Adoption barrier model for AI in climate-smart agriculture

Although the potential of AI apps in all of the areas of CSA has been demonstrated in the previous sections, smallholder farmers and national agricultural systems in LMICs are still limited in their adoption by an intricate multi-layered barrier to adoption. Based on the Technology Acceptance Model (Davis, 1989) and Rogers (2003) Diffusion of Innovations model, and sociotechnical systems views (Geels, 2004), the hierarchical barrier model below is proposed, classifying constraints into four levels nested around the individual to the systemic.

It is important to note that the four-level structure of the present model is not reported as such in any one of the reviewed literature but rather is a conceptual synthesis by the authors. It was built by identifying all of the barriers to AI adoption in the 177 synthesized sources and inductively categorizing them by the level at which they operate – either individually, community level, institutional level, or systemic level – and by mapping this categorization onto three theories of technology adoption (those mentioned above) to ensure that the structure was not the result of how the literature was organized, but rather theoretically coherent. The four-level architecture – and the classification of individual barriers within the four levels – is the interpretation of the authors based on the cited evidence, not the result of any direct evidence found in any of the cited studies.

Individual-level barriers

On the personal farmer level, the main barriers to AI adoption in CSA settings are a lack of digital literacy, access to affordable smartphones and stable internet connections, a lack of knowledge about existing tools, and insufficient trust in the recommendations offered by algorithms. Tsan et al. (2021) discovered that the trust mediated by social proximity, i.e., farmers are much more likely to use AI-based advisory tools when it is recommended by trusted peers or extension workers is a better predictor of adoption than the perceived technical accuracy. Moreover, cognitive load of probabilistic or unfamiliar with context recommendations is a consistent usability issue in across different farmer groups (Nyanga et al., 2011).

Community and social barriers

Community-level obstacles include the gender-differentiated access to digital technologies, the lack of land tenure security to encourage long-term investments in precision management, and social dynamics of information sharing that may either promote or suppress diffusion (Klerkx et al., 2019). Collective action problems - in which the effective implementation of landscape-scale AI systems, (like irrigation district management systems or pest surveillance networks) demand coordination between large groups of farmers - are a unique category of community barrier that cannot be addressed through technical solutions alone (Ostrom, 1990). Such difficulties are especially acute in tropical smallholder systems, which are characterized by a very fragmented landholding and a weak mechanism in institutional coordination.

Institutional barriers

On the institutional front, in most LMICs the disjointedness and perennial ineffective coordination of national agricultural innovation systems is a root cause of fundamental impediments to AI deployment at scale (Klerkx & Jansen, 2010). National Agricultural Research and Extension Systems (NARESS) do not generally have the technical capacity, computational infrastructure and interdisciplinary expertise to develop, validate and maintain locally adapted AI tools. The institutional access and adaptation of AI technologies is further limited by intellectual property arrangements and restrictive licensing models that govern most of the commercially developed AI tools (Carolan, 2017). Additional systemic institutional obstacles include the high transaction costs associated with navigating fragmented regulatory environment and obtaining sustained financing to fund operations (Hall et al., 2006).

Systemic and structural barriers

Systemic barriers are the most enduring and profound: insufficient rural digital connectivity, disjointed and poor-quality agricultural data ecosystems that limit model training and validation, and the structural concentration of AI research and investment in high-income countries with little relevance to tropical smallholder lives (Vinuesa et al., 2020). The issue of an increasing divide between the data-rich, technology-enabled large-scale agricultural systems of high-income countries and the data-poor, under-resourced smallholder systems of LMICs (the so-called AI divide) threatens to exacerbate rather than mitigate agricultural inequalities, unless corrective policy and investment interventions are undertaken (Heitmann et al., 2022).

Hierarchical adoption barrier model for AI in climate-smart agriculture is shown in Table 3.

Table 3: Hierarchical adoption barrier model for AI in climate-smart agriculture

Barrier Level	Key Barriers	Underlying Drivers	Enabling Strategies and References
Individual	Low digital literacy; device affordability;	Limited education access; low incomes; cultural unfamiliarity	Voice-based local language interfaces; peer-to-peer learning; trusted intermediary models (Tsan et al., 2021)

Barrier Level	Key Barriers	Underlying Drivers	Enabling Strategies and References
	distrust in algorithmic advice		
Community / Social	Gender exclusion; tenure insecurity; collective action failure	Patriarchal social norms; insecure land rights; social capital deficits	Gender-responsive co-design; land tenure reform; farmer cooperative AI platforms (Klerkx et al., 2019)
Institutional	Weak extension capacity; IP restrictions; NARS capacity deficits	Chronic underfunding; brain drain; restrictive IP regimes	Extension system reform; open-source AI development mandates; South-South technology transfer (Hall et al., 2006)
Systemic / Structural	Infrastructure deficits; data ecosystem fragility; AI divide	Colonial data extraction legacies; low R&D investment; market failures	Rural broadband investment; national data infrastructure; international AI equity compacts (Vinuesa et al., 2020; Heitmann et al., 2022)

NARS = National Agricultural Research Systems; IP = Intellectual Property.

Source: Created using synthesized data

Future research roadmap

The following time-horizoned roadmap is the authors' own prioritization and sequencing of research needs, which was determined by synthesizing the gaps and unresolved questions identified in the Results and Discussion sections, and ordering them according to the approximate timeframe required to address each priority (short-term field validation and data infrastructure; medium-term institutional and methodological development; longer-term systems-level and governance questions). It is not a set of findings, or a consensus-based timeline of research priorities as reported in the reviewed literature, but instead it is presented as a reasoned agenda for the field to consider and debate, and where applicable, to the evidence gaps that motivate the research priorities. Future research roadmap for AI in climate-smart agriculture is summarized in Table 4.

Short-term priorities (2025–2027)

The most urgent immediate research needs include: (i) rigorous field testing of available AI tools across a variety of smallholder environments in tropical LMICs, beyond demonstrations of proof of concept to randomized controlled trials and longitudinal impact studies with adequate statistical power; (ii) the creation of low-cost, offline-capable, standardized data collection systems and participatory data platforms. These priorities must be sought with the help of multi-actor partnerships which will clearly involve farmer organizations, national governments, CGIAR centres and civil society together with technology developers.

Medium-term priorities (2027–2032)

The medium-term research agenda must concentrate on: (i) establishing and implementing federated learning architectures that would allow AI model improved by distributed, sovereignty-respecting data sources over national and regional agricultural networks (McMahan et al., 2017), (ii) embedding XAI methods as a design principle in all publicly funded farmer-focused AI-based advisory systems; (iii) investing in sustainable interdisciplinary capacity building in AI and data science in national agricultural research systems of LMICs through post-graduate training, visiting scholar initiatives and equitable North-South-South research partnerships; and (iv) creating multi-country AI-for-CSA experimental learning platforms to generate comparative evidence across a range of agro-ecological and socio-economic environments, to enable robust evidence synthesis and adaptive learning (Thornton et al., 2018).

Long-term priorities (2032–2040)

The long-term vision focuses on farmer focused, contextually responsive and climate tolerant agricultural intelligence systems that are wholly incorporated in the national food system governance. The research and development priorities are: (i) agricultural digital twins systems at both landscape and sub-national scales proven and applied to tropical farming settings (Pylianidis et al., 2021); (ii) AI-assisted integrated landscape management systems that can optimally food production, carbon sequestration, biodiversity conservation, and watershed service provisioning at once; and (iii) the anticipatory governance of progressively independent AI-driven agricultural systems, addressing reflective questions of human agency, accountability, liability, and the privileges of farmers in AI-mediated agricultural judgments (Vinuesa et al., 2020).

Table 4: Future research roadmap for AI in climate-smart agriculture

Time Horizon	Priority Research Areas	Key Actors	Success Indicators
Short-term (2025–2027)	Field validation; participatory data platforms; carbon MRV pilots; XAI integration	CGIAR; national NARS; NGOs; mobile network operators	Validated tools in 20+ LMIC contexts; open datasets released; 5 MRV pilots operational
Medium-term (2027–2032)	Federated learning networks; LMIC capacity building; multi-country comparison platforms; XAI standards	Governments; CGIAR; universities; bilateral development agencies	National AI-agriculture strategies in 30+ countries; 500+ trained researchers; federated networks in 3 regions
Long-term (2032–2040)	Digital twins for tropical landscapes; integrated landscape AI; autonomous system governance frameworks	UN bodies; multilateral development banks; private sector; civil society	AI-enabled CSA contributing measurably to NDC targets; equitable AI access achieved globally

Source: Created by author using synthesized data

Suggestions for future improvements

Empower agricultural data ecosystems in tropical systems

Future directions should focus on the co-design and implementation of inexpensive, interoperable, offline-capable data collection infrastructure designed for the specific needs and constraints of tropical smallholder farming systems, such as participatory phenotyping platforms, community-based soil and weather networks, and digital crop diary tools that enable farmers to be active data contributors (Rao et al., 2019). The national agricultural data platforms are to use open standards, to legislate the rights to data ownership by farmers, and to data distribution between research institutions funded by the state. The scale of investment in multi-country agricultural data commons, in the line of the Global Open Data for Agriculture and Nutrition (GODAN) project, must be increased significantly.

Develop contextually appropriate and culturally adapted AI tools

Smallholder CSA AI tools should be tailored to target user communities, with initial designs that support the limitations and abilities of the target groups, using local language voice interfaces, low data and connectivity needs, and offline functionality modes (Brown et al., 2020). Institutionalized, systematic, participatory co-design, with farmers, extension workers, and local knowledge holders as authentic design partners (not passively end-using) should become a non-negotiable condition of all publicly-funded AI-for-agriculture projects. The reported advantages of the indigenous and local knowledge inclusion to the AI model development should be included in the standard model development practice and reporting policies (Rist et al., 2010).

Make an investment in interdisciplinary capacity in LMIC research systems

Sustainable AI-enabled CSA requires, it is necessary to develop a generation of agricultural scientists who will be a combination of agronomic, social science, and computational skills. The long-term endogenization of AI-for-CSA innovation requires prior investment in postgraduate training programs, regional research fellowships, and South-South technology exchange platforms that strengthen this interdisciplinary capacity within national agricultural research systems of LMICs (Hall et al., 2006). Dedicated capacity-building streams of funding in international AI development and bilateral donors should be established to identify the LMIC research systems, with success metrics being based on long-term institutional capacity outcomes, instead of short-term publication outputs.

Match carbon market structures to the realities of smallholder agriculture

The new AI-certified carbon sequestration of soil to earn carbon market income to smallholder farmers must be a purposeful policy and technical challenge. The MRV methodologies need to be rigorously validated in the context of smallholder tropical systems, which are subject to spatial heterogeneity, heterogeneity in management practices, and data constraints. The technical MRV innovation needs to be supplemented by carbon credit aggregation, open benefit-sharing schemes, and specific capacity building to engage farmers in carbon markets (Bryngelsson et al.,

2022; Vermeulen et al., 2012;). FAO and UNFCCC ought to collaborate in designing methodological guidelines of AI-verified agricultural carbon calculation in smallholders.

Create fair AI regulatory (in agriculture) structures

With the increased involvement of AI systems in the decision-making of agricultural activities, there is a growing need to establish strong governance frameworks that promote accountability, transparency, fairness, and protection of the rights of farmers (Vinuesa et al., 2020). Regulatory organizations at the national and international levels are encouraged to come up with AI-specific agriculture-related ethics that will tackle the issue of algorithmic bias, privacy of data, liability in the event of recommendation failure, and the right of the farmer to understanding and challenge AI outputs. The just governance of AI in agriculture has to be acknowledged as a food systems justice concern that is equally important as land rights, trade equity, and seed sovereignty - and should be included as a standing agenda item in the Committee on World Food Security (CFS).

Limitations

This review has several limitations that would be associated with the narrative review method used. First, it is important to note that study selection was relied on the broad eligibility criteria and professional judgment of a single reviewer, which means that the synthesis could be biased as sources that support the concept of the emerging AI-CSA narrative may have been more easily identified and included than those that contradict it. Second, the heterogeneous evidence base (a wide range of peer-reviewed articles, grey literature, and policy documents) has not been formally appraised by applying a quality-appraisal instrument such as PRISMA, GRADE, or a validated critical-appraisal checklist; the checks for indexing status and authority described in the Methodology are informal credibility checks and do not systematically reflect study quality in the synthesis. Third, the review was limited to material in the English language only, which could have resulted in the omission of material that is relevant but exists in other languages, such as national-level policy and practice literature in LMICs that do not use English. Finally, many of the quantitative results presented in this review (such as the 15-30% lower RMSE for yield predictions, the 20-40% water savings in precision irrigation, and the 60-80% decrease in MRV costs) come from individual experiments, often under controlled or semi-controlled conditions, and are not accompanied by confidence intervals or information regarding sample size. These should therefore be taken as examples of potential documented, not as generalizable effects sizes, and should not be used as a reliable representation of likely performance in the wide range of situations of smallholder tropical agriculture. The source as summarized in this review not an independently audited fact and readers relying on specific numerical claims for decision-making should consult the original sources directly.

Conclusions

This literature review has compiled 177 sources published within the years 2015 and 2025 to give a thorough evaluation of the AI applications in the key areas of climate-smart agriculture. It is factual that the AI methods, which include machine learning, deep learning, computer vision, NLP, and reinforcement learning, provide provable success in the accuracy, efficiency, and accessibility of the agricultural information and decision support in the areas of yield prediction,

water management, pest surveillance, soil carbon monitoring, and extension delivery. These advances extend beyond incremental improvements in various areas; AI is now making possible qualitatively new types of agricultural intelligence - landscape-scale, near-real-time, and highly personalized - which are practically unattainable using traditional methodological tools. But the review has also highlighted an on-going and deeply disturbing disconnect between the potential of AI to CSA and its actual implementation at the scale and at the places where most are most in need of transformative action. Most of the world food producers (smallholder farmers in climate-vulnerable tropical regions) have yet to benefit substantially of the AI agricultural revolution, even though they are the most vulnerable to climate change since they bear a disproportionate share of climate-related risks. The hierarchical adoption barrier model proposed in this review places this exclusion not as a technological issue but as a governance, equity, and investment issue: the potential consequence of an innovation system that is heavily skewed in its investment in AI research and development towards large-scale, commercially enticing agricultural settings in high-income nations, as opposed to the complex, data-poor reality of tropical smallholder farming.

This challenge requires a paradigm shift in priorities at the science-policy-practice interface. The science community needs to invest in the co-development of AI tools with the farming communities, sharing high-quality agricultural data underrepresented LMIC situations, and the field testing of AI systems under harsh tropical conditions. The policy community needs to specifically incorporate AI-for-CSA into national climate adaptation plans, establish fair data governance systems that safeguard the rights of smallholder data, and target climate finance mechanisms to AI-enabled agricultural innovation in the poorest countries. The practice community extension services, farmer organizations, agri-input companies, and NGOs have to redesign service delivery architectures to realize the benefits of AI without sacrificing the human relationship and local knowledge networks that cannot be replaced by AI to ensure successful farmer engagement. The bridge between science, policy and practice suggested in the title of this review is not figurative but practical. Even the most technologically advanced AI system does not produce any climate advantage when it cannot be trusted, comprehended, and put into practice by the farmers who are the ones who have to make the management adjustments that it suggests. The creation of this bridge - among disciplinary silos, institutional borders, and the profound global disparities of the agricultural innovation system - is the challenge of the field and the opportunity of the field in the coming decade.

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Data availability statement

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Author Contribution

As the sole author, I am responsible for all aspects of this review, including conceptualization, literature search and screening, data extraction and synthesis, and drafting and revising the manuscript.

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