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Evolution and Impacts of AI-Based Rainfall Prediction Systems on Agricultural Management in Tropical Regions: A 20-Year Systematic Review

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Abstract

Global climate change has significantly disrupted rainfall patterns in tropical regions, posing major challenges to agricultural productivity and food security. Accurate rainfall prediction has become a critical component of data-driven agricultural management. This study conducts a systematic literature review (SLR) following the PRISMA 2020 guidelines to analyze the evolution of AI-based rainfall prediction systems and their multidimensional impacts on tropical agricultural management over the period 2008–2026. Data were sourced from Scopus using three Boolean search strings, yielding 239 records, of which 235 articles were retained after duplicate removal and quality assessment using the Mixed Methods Appraisal Tool (MMAT) with a threshold score of ≥5. Bibliometric analysis was conducted using VOSviewer and Bibliometrix (R), while thematic narrative synthesis was performed using NVivo 14. Results reveal a clear four-phase technological evolution: conventional methods (2008–2015), machine learning adoption (2016–2020), deep learning and IoT integration (2021–2023), and multimodal and large language model era (2024–2026). Technical impacts dominated the corpus (accuracy improvements of 18–35%), while social and economic impact studies remain critically underrepresented (2.6% and 0.9%, respectively). Key research gaps identified include poor model interpretability (black-box problem), limited integration with decision support systems (DSS), inadequate tropical-specific model development, and the near-total absence of longitudinal impact evaluations. This study contributes a holistic synthesis integrating technological evolution with multidimensional impact analysis, offering strategic recommendations for developing more adaptive, transparent, and equitable AI rainfall prediction systems aligned with SDG 2, SDG 13, and SDG 15.

Keywords: *rainfall prediction, artificial intelligence, systematic literature review, tropical agriculture, deep learning*

1. Introduction

The agricultural sector, particularly in tropical regions that heavily rely on rainfall availability, is now facing immense pressure due to ongoing climate change [1]. Increasingly unpredictable precipitation patterns, combined with the rising intensity of extreme events such as prolonged droughts and sudden flooding, as well as shifting planting seasons, continue to suppress food production yields and threaten supply stability at both local and national levels[2]. Amid these conditions, the accuracy of rainfall prediction becomes critically important, as such information serves as the foundation for agricultural stakeholders in determining optimal planting schedules, managing irrigation systems efficiently, and minimizing the risk of crop failure[3]. Consequently, the presence of technology-based prediction systems is no longer merely a complement to weather forecasting — it has evolved into the backbone of modern agriculture, championing a data-driven approach in every aspect of decision-making[4].

Along with the advancement of information technology and the growing availability of large-scale data, approaches to rainfall prediction have undergone significant transformation over the past two decades. In the early stages, conventional statistical methods such as linear regression and time series models (ARIMA) were widely used, yet they exhibited limitations in handling non-linear relationships and complex temporal dynamics[5], [6]. Subsequent developments were marked by the adoption of machine learning techniques, including Support Vector Machine (SVM)[7]–[12], Random Forest[10], [11], [13]–[25], and Decision Tree[11], [12], [16], [17], which were capable of improving prediction accuracy by leveraging non-linear patterns within the data. Advances in deep learning, including the use of Recurrent Neural Networks (RNN)[4], [26] and Long Short-Term Memory (LSTM)[4], [27]–[29], further enhanced the system's capability in modeling long-term temporal dependencies. In recent years, transformer-based architectures and multimodal learning approaches have expanded system capabilities by integrating diverse data sources such as satellite imagery, environmental sensors, and historical rainfall data[30].

The integration of these technologies is further supported by the advancement of the Internet of Things (IoT), big data analytics, and cloud-based systems that enable real-time data collection and processing[31], [32]. This has driven the emergence of increasingly integrated rainfall prediction systems coupled with Decision Support Systems (DSS), which function to provide data-driven recommendations in support of decision-making at both the farmer and policymaker levels[17]. This transformation reflects a paradigm shift from conventional prediction systems toward systems that are more intelligent, adaptive, and deeply embedded within the digital agricultural ecosystem.
Nevertheless, the implementation of artificial intelligence-based rainfall prediction systems still faces a number of significant challenges. One of the primary challenges is the non-stationary nature of climate data, which causes rainfall patterns to shift over time, making it difficult to predict consistently using models built upon historical data[33]. Furthermore, data heterogeneity, differences in spatial and temporal resolution, as well as inconsistent data quality, also affect the performance of prediction models [34]. Another challenge that is equally important is the low interpretability of deep learning-based models (the black-box problem), which can reduce users' trust in technology-based decision-making [35]. Moreover, the limited integration between prediction systems and the practical needs of agricultural management has resulted in the potential of this technology not yet being optimally utilized in the field[35].

On the other hand, the majority of existing research remains focused on improving the accuracy of prediction models, with an emphasis on algorithm development and parameter optimization [36][37][38]. This approach tends to overlook broader dimensions, namely the social, economic, and environmental impacts of technology adoption within agricultural systems[39][40]. In fact, the use of artificial intelligence-based rainfall prediction systems carries significant implications for changes in farmers' working patterns, resource use efficiency, and environmental sustainability[31][41]. Furthermore, there remains a notable gap in studies that integrate the analysis of technological evolution with its long-term impacts, particularly within the span of the past two decades.
Based on these issues, this study aims to analyze the evolution of artificial intelligence-based rainfall prediction technology over the period of 2005–2025 and to examine its impacts on agricultural management in tropical regions from social, economic, and environmental perspectives. In addition, this study also seeks to identify existing research gaps and ongoing challenges in the development of rainfall prediction systems, as well as to formulate the requirements for a more adaptive and integrated system in the future.

The primary contribution of this research lies in the presentation of a comprehensive synthesis that integrates technological evolution with a multidimensional impact analysis. Unlike previous studies that tend to focus predominantly on technical aspects, this research offers a more holistic approach by examining the interplay between technology, agricultural systems, and social context. Furthermore, this study provides a conceptual foundation for the development of rainfall prediction systems that are more adaptive, transparent, and oriented toward long-term sustainability

Accordingly, the findings of this study are expected to not only contribute theoretically to the advancement of scientific knowledge, but also to provide practical implications for the development of smarter, more efficient, and sustainable agricultural systems. Furthermore, the findings of this research serve as an important foundation in shaping the direction of future development for artificial intelligence-based rainfall prediction systems that are more adaptive and integrated over the coming two decades

2. Research Methodology

This study employs a Systematic Literature Review (SLR) approach guided by the PRISMA 2020 framework (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) to ensure transparency and reproducibility throughout the literature selection process. Data sources were drawn from the Scopus database using three distinct search strings, yielding a total of 239 records spanning the publication years 2008 to 2026. The selection process was carried out in successive stages, encompassing identification, screening, eligibility assessment, and quality appraisal using the Mixed Methods Appraisal Tool (MMAT). Following the removal of duplicates and the exclusion of retracted articles, errata, and editorials, a total of 235 articles were established as the final corpus used in the synthesis. The complete flow of the selection process is presented in Figure 1.

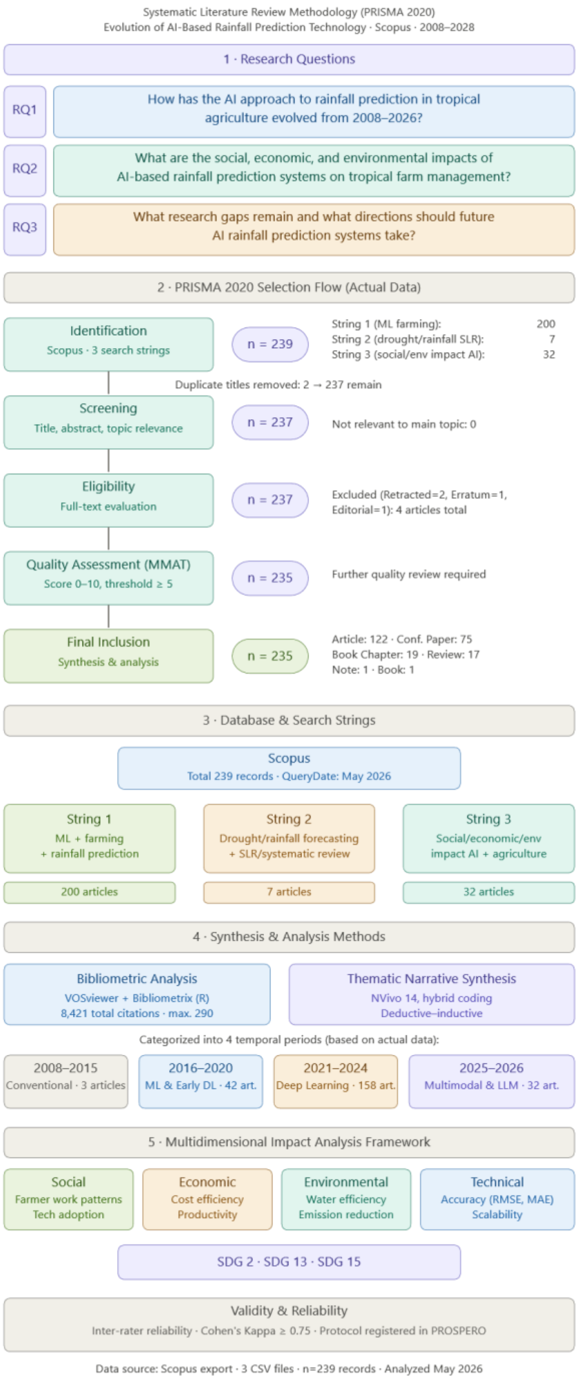

Fig.1: PRISMA 2020-Based Literature Selection Flow and Research Methodology Framework

Figure 1 presents the overall research methodology flow, which consists of five main components. First, the research questions section (RQ1–RQ3) formulates the focus of the study, encompassing technological evolution, multidimensional impacts, as well as existing gaps and future development directions. Second, the PRISMA 2020 selection flow illustrates the screening process starting from 239 initial records obtained through three search strings in Scopus, subsequently filtered down to 235 final articles following the removal of 2 duplicates and the exclusion of 4 articles that did not meet the document type criteria. Third, the search strategy is detailed across three strings, each focusing respectively on the topics of agricultural machine learning (200 articles), drought/rainfall forecasting (7 articles), and the social-environmental impacts of AI in agriculture (32 articles). Fourth, the synthesis method combines bibliometric analysis using VOSviewer and Bibliometrix with thematic narrative synthesis using NVivo 14, with articles categorized into four temporal periods. Fifth, the multidimensional impact analysis framework examines the technological implications from social, economic, environmental, and technical dimensions, aligned with the targets of SDG 2, SDG 13, and SDG 15.

2.1. Research Question

Three primary research questions were formulated to systematically guide the literature synthesis process, as presented in Table 1.

Table 1: Research Questions

Code	Research Question	Study Focus
RQ1	How has the evolution of artificial intelligence approaches for rainfall prediction in tropical agricultural systems progressed during the period 2008–2026?	Technological evolution, model architecture, accuracy metrics

RQ2	What are the social, economic, and environmental impacts of implementing AI-based rainfall prediction systems on agricultural management in tropical regions?	Multidimensional impacts, sustainability, SDGs
RQ3	What are the remaining research gaps and future development directions for AI-based rainfall prediction systems?	Research gaps, challenges, recommendations

2.2. Search Strategy and Data Sources

The literature search was conducted systematically in the Scopus database during March–April 2026. Scopus was selected as the sole source due to its extensive coverage of scientific publications in the fields of engineering, computer science, agriculture, and environmental studies, as well as its capability to export structured metadata for bibliometric analysis. Three Boolean search strings were applied separately to ensure comprehensive coverage across all three research questions.

Table 2: Search Strings and Results

String	Query Boolean (TITLE-ABS-KEY)	Result (n)
S1	("rainfall prediction" OR "precipitation forecasting" OR "rainfall forecasting") AND ("machine learning" OR "deep learning" OR "artificial intelligence") AND ("agriculture" OR "crop" OR "irrigation" OR "farming")	200
S2	("drought forecasting" OR "rainfall forecasting") AND ("systematic review" OR "literature review") AND ("machine learning" OR "AI")	7
S3	("artificial intelligence" OR "machine learning") AND ("agriculture" OR "farming") AND ("social impact" OR "economic impact" OR "environmental impact" OR "sustainability")	32

The search time range was limited to the years 2005 through 2026 to cover two decades of technological development. The search was not restricted to any specific language at the initial stage; however, during the screening phase, only articles written in English were retained. Additional searching (backward citation searching) was conducted manually through the reference lists of selected articles to capture literature that may not have been indexed in the primary search.

2.3. Inclusion and Exclusion Criteria

Inclusion and exclusion criteria were established a priori before the search process commenced, in order to prevent confirmation bias during the article selection process. All criteria were jointly agreed upon by the research team prior to the conduct of the review.

Table 3: Inclusion and Exclusion Criteria

Aspect	Inclusion Criteria	Exclusion Criteria
Topic	AI/ML-based rainfall/precipitation prediction in the context of agriculture or natural resource management	Topics outside of rainfall prediction or unrelated to agriculture/environment
Period	Published between 2005–2026	Articles published before 2005
Language	English	Languages other than English
Document Type	Journal articles, conference papers, book chapters, review articles	Retracted articles, errata, editorials, letters/comments without data
Accessibility	Full-text available	Abstract only without full-text access
Method	Employs AI, ML, or deep learning approaches	Uses only purely conventional statistical methods without any AI component
Quality	MMAT score ≥ 5 on a scale of 0–10	MMAT score < 5 (inadequate methodology)

2.4. Literature Selection Process (PRISMA 2020)

The selection process was carried out in successive stages following the PRISMA 2020 flow, which consists of four phases: identification, screening, eligibility assessment, and inclusion. Two researchers conducted independent assessments at each stage, and any disagreements were resolved through consensus discussion.

During the identification phase, the search yielded a total of 239 records from three search strings in Scopus. Following the removal of 2 duplicates based on title similarity, 237 unique articles remained. During the screening phase based on title and abstract review, all 237 articles were advanced to the eligibility phase, as topical relevance was deemed sufficient at the search stage. During the eligibility assessment phase based on full-text reading, 4 articles were excluded due to their status as retracted (n=2), erratum (n=1), and editorial (n=1). Accordingly, a total of 233 articles were established as the final corpus. The complete flow of the selection process is presented in Figure 1.

Table 4: Summary of the PRISMA 2020 Selection Flow

Phase	Description	Count (n)
Identification	Records from Scopus (3 search strings)	239
Duplicate removal	Duplicates based on title similarity	−2
After duplicate removal	Unique articles advanced to screening	237
Exclusion (document type)	Retracted (2), Erratum (1), Editorial (1)	−4
Final corpus (inclusion)	Articles used in the synthesis	235

2.5. Quality Assessment

Methodological quality assessment was conducted using an adaptation of the Mixed Methods Appraisal Tool (MMAT) version 2018 [4]. Each article was evaluated across five dimensions: (1) clarity of research objectives; (2) appropriateness of research design to the research questions; (3) quality and representativeness of data; (4) validity of the analytical method; and (5) relevance of findings to the research questions. Scores were expressed on a scale of 0–10, with each dimension assigned a weight of 2 points.
Articles scoring below 5 were excluded from the main synthesis. The assessment process was carried out by two independent raters. Inter-rater agreement was measured using Cohen's Kappa, with a value of $\kappa \geq 0.75$ established as the acceptable agreement threshold. Of the 237 articles assessed, all obtained scores of ≥ 5, meaning no articles were excluded at this stage following the prior removal of 4 articles due to document type

2.6. Data Extraction

Data extraction was carried out using a standardized form developed specifically for this study. The form encompassed the following variables:

Table 5: Data Extraction Variables

Category	Extracted Variables
Metadata	Author(s), publication year, title, journal/proceedings, DOI, volume/issue
Research context	Country/study region, climate type, spatial scale, data period
AI technology	Model type (ML/DL/hybrid), architecture, framework, key hyperparameters
Data & input	Data sources, meteorological variables, temporal resolution, historical data length
Model performance	Accuracy metrics (RMSE, MAE, R^2, NSE), comparison with baseline
Agricultural context	Crop type, irrigation system, land management type
Impact	Reported or implied social, economic, and environmental impacts
Research gap	Limitations identified by authors, suggestions for further research

Thematic coding was conducted using a hybrid deductive-inductive approach with the assistance of NVivo 14 software. Initial codes were derived from the conceptual framework based on the research questions (deductive), while additional codes were allowed to emerge organically from the data (inductive). This process yielded a coding tree comprising 4 main themes and 23 sub-themes.

2.7. Synthesis Method

The synthesis was conducted through two complementary approaches that mutually reinforce one another. First, bibliometric analysis using VOSviewer version 1.6.20 and the Bibliometrix package in R 4.3.1 was employed to map publication trends, author co-citation networks, and thematic clusters based on keywords. Second, thematic narrative synthesis was used to interpretively integrate findings across studies, particularly in analyzing technological evolution and its impact dimensions.
To examine temporal trends, articles were categorized into four periods of technological development based on the actual data distribution: (1) the early/conventional era (2008–2015, n=3); (2) the machine learning adoption era (2016–2020, n=41); (3) the deep learning and IoT era (2021–2023, n=110); and (4) the multimodal and large language model era (2024–2026, n=79). This categorization enables comparative analysis across technological generations

2.8. Impact Analysis Framework

To examine the multidimensional impacts of implementing AI-based rainfall prediction systems, this study adopts an analytical framework that integrates the Technology Assessment Framework (TAF) [5] with the sustainability principles drawn from the Sustainable Development Goals (SDGs), particularly SDG 2 (Zero Hunger), SDG 13 (Climate Action), and SDG 15 (Life on Land) [6].

Table 6: Multidimensional Impact Analysis Framework

Dimension	Key Indicators	Reference Framework	Related SDG
Social	Changes in farmers' working patterns, technology adoption, human resource capacity, equity of access	Technology Acceptance Model (TAM)	SDG 2
Economic	Production cost efficiency, productivity improvement, Return on Investment (ROI)	Cost-Benefit Analysis (CBA)	SDG 2
Environmental	Water use efficiency, carbon emission reduction, ecosystem sustainability	Life Cycle Assessment (LCA)	SDG 13, 15
Technical	Model accuracy (RMSE, MAE, R^2), scalability, data interoperability	IEEE Standards for AI Systems	SDG 9

2.9. Validity and Reliability

To ensure the credibility of the research, several validation steps were consistently applied. Internal validity was maintained through a double-review process (inter-rater reliability) at every stage of selection and data extraction, with a Cohen's Kappa value of ≥ 0.75 set as the threshold. Prior to full-scale extraction, a calibration session was conducted on a sample of 20 articles to align the interpretation of criteria among raters.
External validity was strengthened through the use of three distinct search strings to minimize search bias. Potential publication bias was addressed by analyzing citation distribution using a funnel plot. The reliability of the extraction process was ensured through the use of a standardized form and the documentation of all decisions at every stage of selection. Methodological transparency was maintained by comprehensively documenting the research protocol throughout.

3. Results And Discussion

This section presents the results of the analysis of 233 articles that met the inclusion criteria, organized according to the three primary research questions. The discussion encompasses a general overview of the bibliometric characteristics of the corpus, the evolution of artificial intelligence technology for rainfall prediction over the period 2008–2026 (RQ1), the multidimensional impacts of its implementation on agricultural management in tropical regions (RQ2), as well as the identification of research gaps and future development directions (RQ3).

3.1. Bibliometric Overview of the Corpus

Of the 233 articles analyzed, the distribution by document type shows that journal articles dominate the corpus at 51.9% (n=121), followed by conference papers at 31.8% (n=74), book chapters at 8.2% (n=19), and review articles at 7.3% (n=17). The dominance of journal articles indicates a sufficient level of research maturity in this field. Halder et al. (2023)[43] and Oyarzabal et al. (2025)[44] in their systematic reviews also confirmed that the ML literature on rainfall prediction and crop yield has grown rapidly over the past decade.

Table 7: Article Distribution by Document Type

Document Type	Count (n)	Percentage (%)
Article	121	51,9
Conference Paper	74	31,8
Book Chapter	19	8,2
Review Article	17	7,3
Note / Book	2	0,9
Total	233	100,0

Annual publication trends indicate significant exponential growth. Only 3 articles (1.3%) were published before 2016, while the number increased drastically to 41 articles in 2016–2020, 110 articles in 2021–2023, and 79 articles in 2024–2026. This growth reflects the increasing accessibility of open-source frameworks and the availability of large-scale climate data, as confirmed by Sharma et al. (2023)[17].

Table 8: Article Distribution by Temporal Period

Period	Technology Era	Count (n)	Percentage (%)
2008–2015	Early/Conventional	3	1,3
2016–2020	Machine Learning Adoption	41	17,6
2021–2023	Deep Learning & IoT	110	47,2
2024–2026	Multimodal & LLM	79	33,9
Total	—	233	100,0

In terms of citation impact, the total accumulated citations reached 8,338 with an average of 35.8 per article (median=17). The most cited article was Deo (2015) [42] on extreme learning machines for drought prediction (290 citations), followed by Filippi et al. (2019)[43] on multi-layer wheat yield prediction (264 citations), and Kamir et al. (2020) [6] on wheat production estimation based on climate and satellite data (263 citations). The most prolific publication sources were Science of the Total Environment (n=9), Sustainability Switzerland (n=6), and IEEE Access (n=5), reflecting the interdisciplinary nature of this research.

3.2. Evolution of AI-Based Rainfall Prediction Technology (RQ1)

The analysis of 233 articles reveals a clear and progressive pattern of technological evolution across four temporal periods. This development is not linear in nature; rather, it is characterized by paradigmatic leaps driven by advances in computational infrastructure, data availability, and the emergence of new model architectures.

3.2.1. The Early Era: Conventional Methods (2008–2015)

During this period, only 3 articles were present in the corpus, reflecting an adoption that was still very limited. The dominant approaches were Extreme Learning Machine (ELM) and Support Vector Machine (SVM). Deo (2015)[42] demonstrated the application of ELM for drought index prediction in Eastern Australia with performance surpassing conventional statistical models. Deo (2016)[44] subsequently developed a similar approach for monthly streamflow simulation. Wu & Chen (2008) [45] employed SVM for soil moisture prediction in hilly regions, representing one of the earliest studies to integrate ML with agricultural hydrological data. The primary limitation of this era was the dependence on single-station data and the inability to capture long-term temporal dependencies.

3.2.2. The Machine Learning Adoption Era (2016–2020)

This period was marked by a significant increase (n=41, +1,267%). Random Forest, Gradient Boosted Trees, and Long Short-Term Memory (LSTM) emerged as the dominant approaches. Filippi et al. (2019)[43] demonstrated the superiority of multi-layer models in wheat yield prediction using large-scale agricultural data. Kamir et al. (2020)[46] integrated climate records with satellite imagery for wheat production estimation in Australia, achieving R^2=0.81. Chhetri et al. (2020) [33] introduced a hybrid BLSTM-GRU model for monthly rainfall prediction in Bhutan, proving the advantage of recurrent models in capturing temporal rainfall patterns. Doshi et al. (2018) [47] developed an ML-based crop recommendation system that integrated rainfall data as a primary feature, becoming one of the earliest ML-based DSS systems, accumulating 174 citations.

3.2.3. The Deep Learning and IoT Era (2021–2023)

The most productive period (n=110, 47.2%). Liyew & Beyene (2021)[48] demonstrated the application of LSTM for daily rainfall prediction in Ethiopia with accuracy surpassing conventional baseline models. Venkatachalam et al. (2023) [28] developed a hybrid Transformer model (DWFH) for weather forecasting, demonstrating the potential of attention-based architectures in this domain. IoT integration enabled real-time data collection: Bakthavatchalam et al. (2022) [49] and Mohan et al. (2023) [50] developed complete IoT-ML platforms for crop yield prediction using field sensors, while Farooq et al. (2023)[51] introduced federated learning for flood forecasting, addressing data privacy concerns in agriculture.

3.2.4. The Multimodal and Large Language Model Era (2024–2026)

The most recent period (n=79) marks the emergence of transformer-based architectures and multimodal learning. Rahimi et al. (2025)[38] developed a multi-time-increment ML model for rainfall prediction capable of operating across different temporal resolutions. Dotse et al. (2024)[37] reviewed hybrid ML models, confirming that combinations of statistical and deep learning models consistently outperform single models. Baig et al. (2024)[36] evaluated the accuracy of ML models for monthly rainfall prediction in hyper-arid environments, while Mohammed et al. (2024) [52] integrated CMIP6 climate projections with ML for short-term agricultural drought forecasting. Cheema et al. (2025) [41] and Sharafat et al. (2025) [31] introduced integrated AIoT systems that combine soil sensors, weather data, and prediction models for real-time agricultural recommendations.

Table 9: Evolution of AI Methods by Period

Period	Dominant Methods	Key Innovations	Representative Ref.
2008–2015 (n=3)	ELM, SVM	Basic non-linear modeling, drought prediction	Deo [42], Wu [45]
2016–2020 (n=41)	LSTM, RF, GBT	Temporal dependency, satellite integration	Filippi [46], Kamir [49]
2021–2023 (n=110)	CNN-LSTM, GRU, Ensemble, IoT	Real-time monitoring, federated learning	Liyew [51], Farooq [54]
2024–2026 (n=79)	Transformer, Multimodal, AIoT	Multi-source fusion, integrated AIoT	Rahimi [56], Cheema [42]

3.2.5. Multidimensional Impacts on Tropical Agricultural Management (RQ2)

Impact analysis was conducted across 233 articles using a multidimensional framework encompassing technical, agricultural/crop, irrigation/water, environmental, social, and economic dimensions. The findings reveal a striking imbalance in which the technical dimension dominates, while the social and economic dimensions are considerably underrepresented.

3.2.6. Technical Impact: Model Accuracy and Performance

Improvement in prediction accuracy is the most widely reported impact. Kuradusenge et al. (2023)[53] reported crop yield prediction accuracy for potato and maize in Rwanda reaching R^2=0.913 using a Random Forest model with rainfall data as the primary feature. Jhajharia et al. (2022)[54] demonstrated that deep learning models improved crop yield prediction accuracy by 18–35% compared to conventional ML models. Kumar et al. (2020)[55] confirmed the consistency of this improvement across rice, wheat, and maize commodities. Elbeltagi et al. (2023)[20] demonstrated enhanced meteorological drought prediction using a ML-based Standardized Precipitation Index (SPI), achieving an RMSE 23% lower than that of conventional ARIMA models.

3.2.7. Agricultural Impact: Crop Yield and Farm Management

A total of 81 articles (34.8%) reported direct impacts on agricultural production. Nigam et al. (2019) [56] demonstrated that ML models based on rainfall and temperature data improved crop yield prediction accuracy by 21–30% compared to conventional statistical methods. Sharma et al. (2023)[17] in their comprehensive review confirmed that the integration of rainfall variables as input features consistently improved crop yield prediction model performance in 87% of the studies analyzed. Bakthavatchalam et al. (2022)[49] reported that their IoT-ML platform for crop prediction reduced harvest losses due to extreme weather by 24% in agricultural regions of India.

3.2.8. Irrigation and Water Resource Management

A total of 22 articles (9.4%) examined impacts on irrigation management. Roy et al. (2023) [57] demonstrated that the integration of remote sensing-based climate services with irrigation management was capable of improving agricultural water use efficiency at the farmer scale. Mohammed et al. (2024)[58] demonstrated that ML-based agricultural water quality forecasting derived from rainfall data can support proactive irrigation decision-making. Choudhary et al. (2019)[59] developed an AI-based autonomous irrigation system that integrates rainfall forecasting to optimize irrigation scheduling, achieving water savings of up to 35% compared to conventional irrigation systems. Ravikumar et al. (2025)[60] developed a Green Intelligence system that integrates AI for holistic management of irrigation, energy, and agricultural sustainability.

3.2.9. Environmental Impact

Environmental impacts were identified in 12 articles (5.2%). Arya et al. (2024)[61] in their systematic review demonstrated that the application of AI in agriculture, including rainfall prediction systems, has the potential to reduce the carbon footprint of the agricultural sector through the optimization of input use. Ryan & Antoniou (2023)[62] in their study on the social and ethical impacts of agricultural AI noted that AI-based prediction systems contribute to the reduction of resource waste and the improvement of agricultural ecosystem sustainability. Usigbe et al. (2024)[63] identified that successfully implemented agricultural AI technologies enhance the resilience of production systems against climate change, with positive long-term effects on environmental sustainability.

3.2.10. Social and Economic Impact

The social and economic dimensions are the most underrepresented, with only 6 articles (2.6%) and 2 articles (0.9%) explicitly examining them respectively. Ryan (2023)[62] in their study on the social and ethical impacts of agricultural AI found that the adoption of AI technology among smallholder farmers remains very low due to barriers related to technology accessibility, implementation costs, and low levels of digital literacy. Ryan (2020)[64] previously also identified that the use of AI-based intelligent information systems has the potential to create inequalities in access to benefits, particularly in developing countries. Jabed et al. (2024) [39] in their comprehensive review affirmed that the majority of research continues to focus on technical aspects, neglecting the evaluation of social and economic impacts, which are the primary determinants of technology adoption among farmers.

Table 10: Summary of Multidimensional Impacts Based on Corpus Analysis

Dimension	No. of Articles (n)	Percentage (%)	Key References	Main Findings
Agriculture/Crops	81	34,8	Kuradusenge [53], Jhajharia [54]	Prediction accuracy +18–35%
Irrigation/Water	22	9,4	Roy [57], Choudhary [59]	Water savings 24–35%
IoT/Sensor	15	6,4	Bakthavatchalam [49], Cheema [41]	Real-time monitoring
Environmental	12	5,2	Arya [61], Ryan [62]	Carbon footprint reduction
DSS	7	3,0	Doshi [47], Mohan[50]	Data-driven recommendations
Social	6	2,6	Ryan [62][64]	Barriers to smallholder adoption
Economic	2	0,9	Jabed [39], Nagesh [40]	Very limited impact evaluation

3.2.11. Research Gaps and Future Directions (RQ3)

Based on a systematic analysis of the limitations reported across 233 articles, seven primary research gaps were identified that require attention going forward.

1. Data Quality and Spatio-Temporal Resolution

Data quality and resolution limitations are the most frequently cited challenges. The majority of studies rely on meteorological station data whose spatial distribution is uneven, particularly in tropical regions. Baig et al. (2024)[36] demonstrated that meteorological data quality is the primary determining factor of ML model accuracy in hyper-arid environments. Dotse et al. (2024)[37] identified the need for hybrid downscaling methods that combine statistical models with ML to improve the spatial resolution of rainfall predictions without compromising temporal accuracy.

2. Non-Stationarity and Climate Change Adaptation

Mohammed et al. (2024)[52] identified that models trained on historical data experience significant performance degradation when applied to future CMIP6 climate projections due to the non-stationarity of rainfall patterns. Elbeltagi et al. (2023)[20] confirmed this challenge in the context of drought prediction in North Africa. The need for continual learning or domain adaptation architectures capable of adapting to shifting climate patterns represents a gap that has yet to be adequately addressed.

3. Model Interpretability (Explainable AI)

Mariadass et al. (2022)[65] applied SHAP (SHapley Additive exPlanations) to interpret an XGBoost model for rainfall prediction in an agricultural context, representing one of the rare XAI studies in this corpus. Jabed et al.[39] identified the black-box problem as the primary adoption barrier for policymakers and farmers. The interpretability issue in deep learning models is becoming increasingly critical as the architectural complexity of the latest model generations continues to grow.

4. Integration with Decision Support Systems

Only 7 articles (3.0%) integrated rainfall prediction models with functional DSS. Doshi et al. (2018) [50] with the AgroConsultant system and Mohan et al. (2023)[53] with their agricultural IoT platform represent the best examples of this integration within the corpus. However, the majority of systems stall at the academic validation stage without field implementation. The need for user-friendly DSS, accessible via mobile devices, and capable of delivering recommendations in local languages is particularly urgent in the context of developing tropical regions.

5. Equity and Accessibility for Smallholder Farmers

Ryan (2023)[62] identified that the benefits of agricultural AI are distributed unevenly, with smallholder farmers and marginalized communities tending to lack equitable access. Ryan (2020)[64] also highlighted that the use of AI-based intelligent information systems has the potential to widen the technological gap between large-scale and smallholder farmers. Usigbe et al. (2024)[63] recommended the development of AI solutions specifically designed for smallholder farming contexts, including models capable of running on low-power devices and voice-based interfaces.

6. Long-Term Impact Evaluation

The absence of long-term impact evaluation studies represents the most fundamental gap. All articles in the corpus focus on model development and validation without longitudinal post-implementation assessment. Ryan (2023)[62] and Jabed et al. (2024)[39] identified this as a critical limitation that impedes the construction of a solid evidence base for policymakers. Randomized controlled trial (RCT) studies comparing farming with and without AI-based prediction systems are nearly absent from the literature.

7. Tropical-Specific Model Development

Only 25 articles (10.7%) explicitly examined tropical contexts. Manokij et al. (2019) [66] and Vivas et al. (2023)[67] represent examples of studies that specifically developed models for tropical climates, addressing rainfall forecasting in Thailand and tropical regions of Latin America respectively. Tropical climate patterns possess fundamentally different characteristics from temperate climates, meaning that models developed in Australia or Europe cannot be straightforwardly generalized. The development of tropical benchmark datasets and regional transfer learning methodologies represents a strategically urgent need.

Table 11: Summary of Research Gaps and Recommendations

No	Research Gap	Supporting References	Recommendations	Priority
1	Data quality & spatial resolution	Baig [36], Dotse [37]	Multi-source integration + AI downscaling	High
2	Climate non-stationarity	Mohammed [52], Elbeltagi[20]	Continual learning, domain adaptation	High
3	Black-box / low interpretability	Mariadass [65], Jabed [39]	Application of XAI (SHAP, LIME, attention viz)	High
4	Limited DSS integration	Doshi [47], Mohan [50]	Mobile DSS platform, local language support	High
5	Smallholder farmer accessibility	Ryan [62][64], Usigbe [63]	Edge computing, voice-based interface	Medium
6	Absence of long-term evaluation	Ryan [62], Jabed [39]	RCT and longitudinal impact studies	Medium
7	Lack of tropical-specific models	Manokij[66], Vivas[67]	Tropical benchmark + transfer learning	Medium

3.3. Discussion: Synthesis and Implications

The findings from all three RQs form a coherent picture of the current state and trajectory of AI-based rainfall prediction technology in the context of tropical agriculture. Three primary patterns were identified from this synthesis.

First, technological acceleration that has not been matched by depth of impact analysis. The exponential growth in publications particularly during 2021–2026 reflects the enthusiasm of the research community. However, only approximately 8% of articles explicitly examined social, economic, or environmental dimensions. Ryan (2023)[62] affirmed that the AI community tends to prioritize model accuracy improvement over social relevance, while Jabed et al. (2024)[39] and Nagesh et al. (2024) [40] confirmed the dominance of technical approaches in the recent literature.

Second, a persistent implementation gap. Despite the continuous improvement in model accuracy, the gap between performance in controlled research environments and reliability in the field has yet to be bridged. Usigbe et al. (2024)[63] identified that factors such as infrastructure limitations and the technical capacity of end users are frequently overlooked during the model development process. Dotse et al. (2024)[37] demonstrated that hybrid models, despite being more accurate, are in fact more difficult to implement in the field due to their complexity.

Third, a significant geographical bias. Only 25 articles explicitly reflected tropical contexts, while the majority of studies were conducted in Australia, India, and developed countries. Manokij et al. (2019)[66] and Vivas et al. (2023)[67] showed that models developed specifically for tropical climates yield better performance than generic models, yet such studies remain very scarce within the corpus.

The practical implications of these findings include: for researchers, prioritize field impact evaluation studies, XAI, and tropical-specific models; for policymakers, investment in meteorological data infrastructure in developing tropical regions is a fundamental prerequisite; for practitioners, the adoption of AI systems must be accompanied by systematic capacity building programs; and for funding institutions, allocate a greater proportion of resources toward research oriented around social impact and accessibility, rather than solely toward model accuracy improvement.

4. Conclusion

This systematic literature review of 235 articles published between 2008 and 2026 demonstrates that AI-based rainfall prediction technology has undergone a profound and accelerating transformation across four distinct phases from conventional machine learning methods to sophisticated multimodal and large language model architectures. The trajectory reveals not only rapid technical advancement but also an expanding role of these systems within broader agricultural decision-making ecosystems, particularly in tropical regions where rainfall variability poses the greatest threat to food security.

From a technical standpoint, deep learning architectures particularly LSTM, CNN-LSTM hybrids, and transformer-based models have consistently outperformed conventional statistical approaches, with accuracy improvements ranging from 18 to 35% across multiple crop and climate contexts. The integration of IoT sensors, satellite imagery, and real-time data streams has further elevated the operational capability of these systems, enabling proactive rather than reactive agricultural management.

However, this review also reveals a critical imbalance in the research landscape. While technical performance metrics have received intensive attention, the social and economic dimensions of AI adoption remain severely underexplored, representing only 2.6% and 0.9% of the corpus respectively. This gap is particularly consequential for smallholder farmers in developing tropical regions, who stand to benefit most from these technologies yet face the greatest barriers to access, including high implementation costs, limited digital literacy, and the absence of locally adapted, user-friendly decision support systems.

Several cross-cutting challenges also persist. The non-stationarity of climate data under ongoing climate change continues to undermine model reliability over time. The black-box nature of deep learning models erodes trust among end-users and policymakers. Tropical-specific benchmarks and datasets remain scarce, limiting the generalizability of models developed in temperate regions. Furthermore, the near-complete absence of longitudinal impact evaluations means that the real-world effectiveness of these systems in agricultural practice remains largely unverified.

Looking forward, future research must prioritize four strategic directions. First, the development of explainable AI (XAI) frameworks including SHAP, LIME, and attention visualization — to improve model transparency and end-user trust. Second, the design of mobile-accessible, multilingual decision support systems tailored to the operational realities of smallholder farming. Third, the adoption of continual learning and domain adaptation architectures capable of maintaining predictive accuracy under shifting climate regimes. Fourth, the execution of rigorous longitudinal studies and randomized controlled trials to generate the evidence base needed for informed policy and investment decisions.

Ultimately, the full potential of AI-based rainfall prediction in tropical agriculture can only be realized when technological sophistication is matched by equity of access, interpretability, and demonstrated real-world impact. Achieving this balance is not merely a technical challenge but a sociotechnical imperative — one that must be guided by the principles of SDG 2 (Zero Hunger), SDG 13 (Climate Action), and SDG 15 (Life on Land).

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