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A Review on Trends and Effectiveness of Rainfall Prediction Models for Smart Irrigation: Toward Future Development

Olivia Wardhani[1,*], *Rayfal Mayvandra Aurora Akbar*[2], *Yasabuana Athallahaufa Natawijaya*[3]

[1,2,3]*Universitas Tidar, Magelang,* Indonesia

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Correspondence

E-mail: olivia@untidar.ac.id*,

A B S T R A K

Prediksi curah hujan merupakan komponen penting dalam mendukung irigasi presisi, terutama di wilayah pertanian tropis yang rentan terhadap variabilitas iklim. Kajian ini secara sistematis menelaah 15 artikel ilmiah terbitan tahun 2019 hingga 2024 dengan menggunakan kerangka PRISMA, untuk mengevaluasi kinerja dan relevansi model prediksi curah hujan dalam konteks pertanian presisi. Model yang dianalisis mencakup pendekatan statistik (misalnya ARIMA), kecerdasan buatan (seperti ANN, LSTM, ELM), serta model hibrida (seperti Neural Prophet–LSTM dan ANFIS). Sintesis kuantitatif berdasarkan indikator RMSE, MAE, MAPE, dan R^2 menunjukkan bahwa model hibrida umumnya memberikan akurasi prediksi tertinggi (misalnya RMSE = 0,0633; R^2 = 0,98), sementara model AI efektif untuk data harian yang kompleks namun membutuhkan sumber daya komputasi dan keahlian teknis yang tinggi. Di sisi lain, ARIMA tetap menjadi pilihan paling praktis untuk peramalan bulanan di wilayah dengan keterbatasan data dan infrastruktur, karena mampu menyeimbangkan akurasi dan kemudahan operasional (misalnya RMSE = 69,506; MAPE = 31,41%). Faktor kontekstual seperti ketersediaan data, kesiapan infrastruktur digital, dan kapasitas pengguna sangat memengaruhi kesesuaian model. Kajian ini juga mengidentifikasi tantangan implementasi nyata, termasuk keterbatasan sensor dan rendahnya literasi teknologi. Secara keseluruhan, ulasan ini memberikan panduan komparatif dalam memilih model berdasarkan performa statistik dan kesiapan penerapan, serta mendukung upaya ketahanan pangan nasional melalui pemodelan prediksi yang kontekstual dan adaptif terhadap iklim.

Abstract

Rainfall prediction is critical for enabling precision irrigation, particularly in tropical agricultural regions vulnerable to climate variability. This review systematically examines 15 peer-reviewed articles published between 2019 and 2024, using the PRISMA framework to evaluate the performance and applicability of rainfall prediction models for precision agriculture. The models are categorized into statistical (e.g., ARIMA), artificial intelligence (e.g., ANN, LSTM, ELM), and hybrid approaches (e.g., Neural Prophet–LSTM, ANFIS). Quantitative synthesis based on RMSE, MAE, MAPE, and R^2 reveals that hybrid models generally yield the highest predictive accuracy (e.g., RMSE = 0.0633; R^2 = 0.98), while AI models perform well on daily, nonlinear datasets but require extensive computational resources and expertise. In contrast, ARIMA remains the most practical and reliable option for monthly forecasting in data-scarce environments, offering a balance between accuracy and operational feasibility (e.g., RMSE = 69.506; MAPE = 31.41%). Contextual factors such as data availability, digital infrastructure, and user capacity significantly influence model suitability. The review also highlights real-world implementations and practical challenges—such as sensor limitations and technical skill gaps—associated with deploying advanced models. Ultimately, this review provides a comparative perspective to guide model selection based on statistical performance and implementation readiness. It further supports national food security goals by aligning predictive modeling with the operational needs of climate-resilient agriculture in supporting climate-resilient agriculture in tropical regions.

1. Introduction

Indonesia is a country heavily reliant on the agricultural sector, both as a primary source of livelihood for its population and as a cornerstone of national food security. According to data from the Central Statistics Agency (Badan Pusat Statistik), more than 28 million Indonesians are employed in agriculture, making it the largest employment sector in the country. Furthermore, its contribution to the national Gross Domestic Product (GDP) remains significant, accounting for over 12% in 2023 [1]. Therefore, ensuring the sustainability and productivity of agriculture through digital transformation and climate adaptation has become a national strategic agenda, as outlined in the National Medium-Term Development Plan (RPJMN) 2025–2029 [2], [3].

In practice, the agricultural sector is highly sensitive to climatic factors, especially rainfall. Rainfall information is crucial not only for determining planting schedules and crop selection, but also for effective irrigation water management. When rainfall patterns deviate from expectations, the risks of crop failure, drought, and inefficient water usage increase significantly [4], [5]. This condition is exacerbated by the impact of climate change, which renders rainfall patterns increasingly erratic and difficult to predict.

As a response to these challenges, agricultural water management has been shifting towards data-driven approaches, particularly through the implementation of precision irrigation [6] [7]. This concept aims to optimize water use by incorporating real-time and predictive environmental data [8]. Precision irrigation enables more efficient water distribution by aligning irrigation with crop-specific needs and rainfall forecasts [9]. However, the implementation of such systems in Indonesia remains limited due to insufficient access to accurate rainfall data and predictive technologies that could support farmers in making timely decisions [10]. To support these systems, accurate rainfall forecasting is essential to ensure timely and efficient irrigation scheduling [11].

However, selecting the most appropriate method for rainfall prediction is not straightforward. A wide range of methods from classical statistical to modern machine learning models have been proposed in the literature, each with varying degrees of success and complexity. Meanwhile, agricultural practitioners and irrigation planners often face difficulties in identifying the most suitable prediction model for their specific contexts.

Several studies have examined different approaches to rainfall forecasting. Simamora et al. (2019) employed the Extreme Learning Machine (ELM) method in Poncokusumo and reported promising accuracy levels [4]. Musfiroh et al. (2023) combined Principal Component Analysis (PCA) and Long Short-Term Memory (LSTM) for daily rainfall prediction in Luwu Utara [12]. Tee & Mansor (2024) applied a hybrid time series model in Selangor, emphasizing the importance of model stability for short-term forecasting [13]. Meanwhile, Ardi et al. (2021) compared Mamdani and Sugeno fuzzy models within a rule-based inference system [14]. These varied findings suggest that no single approach is universally superior across all contexts.

Despite this progress, existing review studies often remain fragmented in scope. For instance, Lakhiar et al. (2024) primarily focuses on irrigation hardware, control systems, and water conservation strategies, with minimal attention to rainfall forecasting models [8]. Paparrizos et al. (2023) reviewed local rainfall forecast knowledge for agriculture across global contexts, yet lacks a structured taxonomy of modeling approaches and does not assess the applicability of advanced predictive models in tropical regions [15]. Saggi and Jain (2022) examined decision support systems for smart irrigation, but their scope is limited to DSS architectures, with less emphasis on the comparative performance of rainfall prediction models [16]. Similarly, Sham et al. (2025) provided a comprehensive overview of AI-based rainfall forecasting methods, but did not establish direct links between predictive accuracy and field-level irrigation planning [17].

These gaps underline the need for a more targeted review that not only classifies rainfall prediction models systematically, but also evaluates their relevance and applicability to precision irrigation systems—especially in tropical, agriculture-dependent regions like Indonesia.

This review aims to contribute by providing a systematic categorization of rainfall prediction models based on methodological trends, forecast outputs (daily, monthly, seasonal), and evaluation metrics. In doing so, it seeks to bridge the gap between academic research and practical applications in the field, particularly in supporting efficient and climate-adaptive precision irrigation systems.

Building on this background, the present literature review is designed to provide a comprehensive overview of the trends and effectiveness of rainfall prediction models applied in various studies. It not only maps the existing models, but also evaluates their strengths and limitations, and assesses their potential to inform decision-making in modern agricultural systems. The findings are expected to serve as an initial reference for researchers, practitioners, and policymakers in selecting contextually appropriate and efficient rainfall prediction methods—especially in tropical regions like Indonesia.

2. Research Methodology

This study adopts a Systematic Literature Review (SLR) approach to explore, classify, and evaluate scholarly articles on rainfall prediction models and their relevance to precision irrigation systems. The methodology was designed to ensure transparency, replicability, and thematic rigor in synthesizing diverse research findings. The review process was guided by the PRISMA framework to transparently document the flow of literature selection and inclusion. The methodology consisted of five main stages: source selection and search strategy, inclusion and exclusion criteria, screening and eligibility assessment, data extraction and thematic categorization, and synthesis of findings [18].

2.1. Source Selection and Search Strategy

Scientific articles were retrieved from reputable databases, including Scopus, ScienceDirect, IEEE Xplore, and Google Scholar, covering a publication period from 2019 to 2024. This five-year window was selected to capture recent methodological developments and ensure relevance to current agricultural and climate adaptation challenges. The keywords used in the search included: "rainfall prediction", "rainfall forecasting", "precision irrigation", "climate-based agriculture", and "smart farming".

2.2. Inclusion and Exclusion Criteria

To ensure relevance and methodological soundness, the following inclusion criteria were applied:

a. The study utilized historical rainfall data as a primary variable;
b. The model employed was based on statistical, artificial intelligence (AI), or hybrid methods
c. The study was contextually relevant to tropical agriculture or precision irrigation;
d. The article was published between 2019 and 2024.

Additionally, literature focusing on water-use efficiency, irrigation scheduling, and food security enhancement was included to provide broader contextual insights. Articles were excluded if they met any of the following criteria:

a. The study was not directly related to rainfall prediction or its agricultural applications;
b. The study focused solely on irrigation hardware without integrating rainfall forecasting;
c. The study used synthetic or simulated data as its primary basis;

The study emphasized other climate variables (e.g., temperature, humidity) without positioning rainfall as a central variable.

2.3. Screening and Eligibility Assessment

To ensure methodological rigor and thematic relevance, the literature screening process followed a structured and multi-stage evaluation procedure. This stage aimed to progressively filter the identified articles to retain only those that meet the inclusion criteria and align closely with the research objectives.

An initial search resulted in 114 articles. After removing duplicates (n = 11), a total of 103 articles were screened by examining their titles and abstracts for relevance. Seventy articles were retained for full-text assessment. Upon applying the inclusion and exclusion criteria, 49 articles were deemed eligible, and from these, 15 articles were selected for detailed analysis based on their methodological quality and contextual relevance. The article selection process is illustrated in Figure 1, which follows a PRISMA-inspired flow diagram.

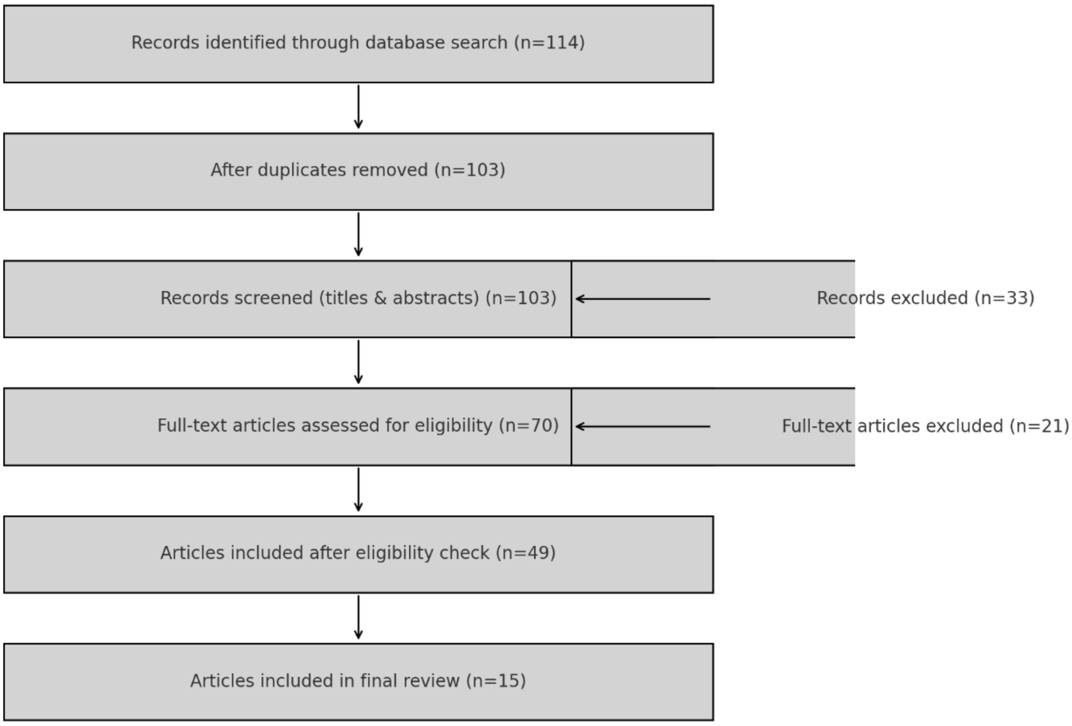

Figure 1. Article selection process based on PRISMA-inspired flow diagram

2.4. Data Extraction and Thematic Categorization

The 15 selected articles were subjected to in-depth thematic analysis. The following information was extracted from each study:

a. Type of predictive model employed (e.g., ARIMA, LSTM, ELM);
b. Geographical location of the study;
c. Evaluation metrics used (e.g., RMSE, MAE, MAPE, R^2);
d. Practical implementation context (e.g., irrigation scheduling, crop planning, water management).

Based on this information, the articles were classified into three major model categories:

1. Statistical models (e.g., ARIMA and its variants);
2. Artificial Intelligence models (e.g., ANN, LSTM, ELM);
3. Hybrid models that combine statistical and AI approaches (e.g., ANFIS, NeuralProphet + LSTM).

These categories also encompass modeling techniques such as time series analysis, fuzzy inference systems, and modern machine learning approaches.

2.5. Synthesis and Comparative Analysis

To synthesize the findings from the selected studies, a thematic synthesis approach was adopted within the framework of a Systematic Literature Review (SLR). This method enabled the structured identification and comparison of key themes, methodological patterns, and performance indicators across diverse studies. The synthesis focused on the following dimensions:

- Dominant trends in predictive modeling approaches;
- Comparative performance based on standardized statistical metrics (e.g., RMSE, MAE, MAPE, R^2);
- Practical applicability and relevance of each model type to precision irrigation systems, especially in tropical agricultural contexts.

Given the heterogeneity of research designs, model architectures, and reporting practices, a meta-analysis was not feasible. Instead, the thematic synthesis followed an inductive process, mapping recurring elements such as model categories, implementation contexts, and evaluation strategies. Where applicable, quantitative metrics were summarized in comparative tables to support visual and descriptive assessments. This thematic integration ensures analytical rigor and aligns with the systematic nature of the review.

3. Result and Discussion

3.1. Classification of Rainfall Prediction Models

Rainfall prediction models reviewed in the selected literature can be classified into three main categories: statistical models, artificial intelligence (AI)-based models, and hybrid models that combine two or more approaches. Each category has distinct methodological characteristics, data requirements, and implementation complexity, which influence the level of prediction accuracy and its applicability to support precision irrigation systems.

Statistical approaches—particularly the Autoregressive Integrated Moving Average (ARIMA) model and its variants—are among the most frequently used in the analyzed studies. ARIMA has been applied in research by Ahmar & Mokhtar (2024), Bora & Hazarika (2023), and Tee & Mansor (2024), primarily due to its efficiency and simplicity in modeling seasonal and short-term data [13], [19], [20]. Additionally, Alam & Majumder (2024) and Aborass et al. (2022) compared ARIMA with other statistical methods such as Exponential Smoothing (ETS) and other smoothing techniques to evaluate predictive accuracy under specific local and semi-arid climate contexts [5], [21].

The artificial intelligence (AI) category includes models such as Artificial Neural Networks (ANN), Extreme Learning Machine (ELM), Long Short-Term Memory (LSTM), and basic neural networks. Simamora et al. (2019) demonstrated that ELM and simple neural networks can be effectively used for rainfall prediction across various regions in Indonesia [4]. Musfiroh et al. (2023) showed that a combination of PCA and LSTM is effective for daily forecasting [12], while reviews by Thakur et al. (2021) and Zou et al. (2019) illustrated the significant growth of ANN applications in rainfall prediction research [22], [23]. AI-based models, especially recurrent neural networks like LSTM, are well-suited to capture nonlinear and temporal dependencies in meteorological data, which are often missed by traditional linear models.

Hybrid models have emerged to leverage the advantages of both statistical and AI-based methods. Prasad et al. (2023) employed a combination of Neural Prophet and LSTM to enhance daily prediction accuracy, yielding excellent results [24]. Pham et al. (2024) developed an Adaptive Neuro-Fuzzy Inference System (ANFIS) optimized with metaheuristic algorithms (Artificial Bee Colony and Genetic Algorithm), which demonstrated strong correlations in daily prediction scenarios [25]. Furthermore, Barrera-Animas et al. provided a comparative analysis of modern machine learning models within tropical agricultural settings, enriching the understanding of hybrid model potential

[26]. Fuzzy inference systems like Mamdani and Sugeno, as explored by Ardi et al. (2021), have been applied in agricultural contexts to embed expert knowledge into decision-making frameworks, such as estimating water demand based on linguistic variables [14].

These model categories show an evolutionary logic: while statistical models dominate in simplicity and interpretability, they often underperform in highly variable or nonlinear datasets. AI models, particularly deep learning variants, excel in such conditions due to their ability to learn from complex data structures. Hybrid models arise as a natural progression, combining the interpretability of statistical models with the predictive power of AI, offering an optimal solution for complex real-world scenarios like tropical rainfall prediction for irrigation.

Overall, the classification results show that statistical models such as ARIMA continue to dominate in tropical agricultural contexts due to their stability, ease of implementation, and effectiveness in modeling seasonal data. Meanwhile, AI-based and hybrid approaches are rapidly advancing to meet the increasing accuracy demands of complex data environments and the digital transformation of agriculture. The selection of the most appropriate model depends heavily on the specific use case, the quality of available data, and the readiness of systems and users to adopt the model sustainably.

A summary of the predictive models used in the 15 selected articles is presented in Table 1, which includes model types, study locations, evaluation indicators, and the implementation context of each study.

Table 1. Summary of rainfall prediction models

Author (year)	Model used	Location	Evaluation indicator	Implementation context
Musfiroh et al. (2023)[12]	PCA + LSTM	Luwu Utara (Indonesia)	MAPE	Decision support for irrigation
Simamora (2019)[4]	Extreme Learning Machine (ELM)	Poncokusumo (Indonesia)	MSE, MAPE	Planting schedule and irrigation
Tee & Mansor (2024)[13]	Combined ARIMA	Selangor (Malaysia)	RMSE	Flood anticipation and irrigation planning
Ahmar & Mokhtar (2024)[19]	ARIMA	Polewali Mandar (Indonesia)	MAPE, RMSE	Short-term forecasting for water management
Alam & Majumder (2024)[21]	ARIMA vs Other Statistic	Kolkata (India)	MAPE, R^2	Model comparison in statistical forecasting
Prasad et al. (2023)[24]	NeuralProphet + LSTM	India	RMSE, MAE	Precision forecasting using deep learning
Thakur et al. (2021)[22]	Artificial Neural Network (ANN)	Multi-country (review)	-	ANN techniques for rainfall forecasting
Bora & Hazarika (2023)[20]	ARIMA	India	RMSE, MAE	Short-term rainfall prediction
Zou et al. (2019)[23]	Artificial Neural Network (ANN)	Multi-location (survey)	-	ANN survey for rainfall forecasting
Ardi, Effendi & Nababan (2021)[14]	Fuzzy Mamdani vs Sugeno	Indonesia	Accuracy	Fuzzy model comparison for agriculture
Aborass et al. (2022)[5]	ARIMA vs ETS	Palestina	MAPE	Forecasting for semi-arid regions
Pham et al. (2024)[25]	ANFIS + Metaheuristics	Vietnam	Visual, R	Hybrid ANFIS model for daily rainfall
Barrera-Animas et al. (2022)[26]	Machine Learning	Tropical	Descriptive	Comparative analysis of modern ML models

Author (year)	Model used	Location	Evaluation indicator	Implementation context
	(Comparative Study)			
Andre et al. (2022)[27]	Neural Network	South America	RMSE	Extreme rainfall prediction
Pathan et al. (2022)[28]	ML Model Comparison	India	R^2	Rainfall-based water level prediction

This information forms the foundation for subsequent analysis aimed at assessing the effectiveness of each predictive model in the following sections.

3.2. Evaluation of Model Performance Based on Statistical Indicators

Assessing the effectiveness of rainfall prediction models necessitates the use of reliable metrics that accurately reflect both precision and consistency. Consequently, the majority of reviewed studies employ statistical indicators such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). Lower values of RMSE, MAE, and MAPE, alongside R^2 values approaching 1, generally indicate superior model performance.

The ARIMA model demonstrates stable and consistent performance across several studies, particularly for seasonal and short-term data. For instance, the study by [19] reported that ARIMA achieved an RMSE of 69.506 mm, MAE of 48.100 mm, and MAPE of 31.41% for monthly rainfall data in Polewali Mandar. In another instance, study by [13] utilized a combined ARIMA model to forecast monthly rainfall in Selangor, achieving an RMSE of 27.91 mm, MAE of 18.14 mm, MAPE of 19.65%, and R^2 of 0.8145. This RMSE value is considered relatively low for monthly rainfall prediction in tropical climates, suggesting that the model was effective in capturing seasonal rainfall variability. Similarly, study [21] compared ARIMA with other statistical models in Kolkata, reporting an RMSE of 15.68 mm, MAE of 11.47 mm, MAPE of 13.81%, and R^2 of 0.82.

Although AI-based and hybrid models demonstrate higher accuracy in controlled experimental settings, ARIMA remains highly relevant, especially in developing regions with limited computational infrastructure and incomplete datasets. Its transparent modeling process, relatively low resource requirements, and robust performance for monthly or seasonal data make it a practical choice for integration in existing meteorological and agricultural systems. Moreover, ARIMA is easier to interpret and implement in policy-level decision-making contexts, particularly where explainability and consistency are prioritized over experimental performance gains.

Artificial Intelligence (AI)-based models such as Extreme Learning Machine (ELM), Artificial Neural Network (ANN), and Long Short-Term Memory (LSTM) also yielded competitive results, particularly for daily predictions involving nonlinear patterns. Simamora (2019) [4] demonstrated that ELM achieved a MAPE of 3.6852%, outperforming traditional statistical approaches, although other statistical metrics were not explicitly stated. Likewise, Musfiroh et al. (2023) [12] reported high accuracy from the PCA-LSTM combination for daily rainfall forecasts in Luwu Utara, with RMSE of 9.693, MAE of 6.452, MAPE of 12.135%, and R^2 of 0.964. Reviews by [22] and [23] supported the potential of ANN in handling complex rainfall data, though their performance is highly dependent on the quality of historical data and model configuration.

Hybrid models exhibited even stronger predictive performance. Study [24] reported that a Neural Prophet-LSTM combination yielded an RMSE of 0.0633 and an MAE of 0.0452 for daily data, with a MAPE of 3.94% and R^2 of 0.98, indicating exceptionally high accuracy. Similarly, Pham's study [25], which developed an Adaptive Neuro-Fuzzy Inference System (ANFIS) optimized with metaheuristic algorithms, demonstrated a strong predictive correlation (R approaching 0.9), though explicit RMSE and MAPE values were not provided.

These findings highlight the importance of aligning model selection with contextual priorities such as data availability, system complexity, and policy needs. While advanced AI and hybrid models offer impressive accuracy, traditional models like ARIMA remain indispensable in regions where interpretability, operational feasibility, and resource limitations are critical considerations. Therefore, model effectiveness should not be assessed solely by numerical performance but also by its adaptability and integration potential within the broader environmental and institutional ecosystem.

To present a more comprehensive view of the relative effectiveness of these approaches, Table 2 summarizes the quantitative evaluation results from studies that explicitly report statistical metrics. In contrast, Table 3 compiles studies that assess model performance only through visual inspection or descriptive analysis, without reporting exact metric values. This absence of standardized indicators in several studies—often due to exploratory research goals, limited data structure, or emphasis on qualitative interpretation—can limit the comparability and generalizability of their findings. While these studies may offer valuable insights into model behavior or conceptual frameworks, the lack of statistical benchmarks constrains their utility for performance-based selection or replication in operational forecasting systems.

Table 2. Summary of Statistical Evaluation of Rainfall Prediction Models

Author (year)	Model	Location	RMSE	MAE	MAPE	R^2
Ahmar & Mokhtar (2024) [19]	ARIMA	Polewali Mandar	69.506	48.100	31.41%	-
Tee & Mansor (2024) [13]	Combined ARIMA	Selangor	27.91	18.14	19.65%	0.8145
Alam & Majumder (2024) [21]	ARIMA vs Other Statistics	Kolkata	15.68	11.47	13.81%	0.82
Simamora (2019) [4]	ELM	Poncokusumo	-	-	3.6852 %	-
Musfiroh et al. (2023) [12]	PCA + LSTM	Luwu Utara	9.693	6.452	12.135 %	0.964
Prasad et al. (2023) [24]	Neural Prophet + LSTM	India	0.0633	0.0452	3.94%	0.98

Table 3. Studies Without Explicit Statistical Evaluation Metrics

Author (Year)	Model	Location	Evaluation type	Notes
Thakur et al. (2021) [22]	ANN (review)	Multi-country	Descriptive	Review of ANN performance across various studies
Zou et al. (2019) [23]	ANN (survey)	Multi-country	Descriptive	Survey of ANN use in rainfall forecasting
Ardi, Effendi & Nababan (2021) [14]	Fuzzy Mamdani vs Sugeno	Indonesia	Visual	Visual comparison of fuzzy inference model accuracy
Pham et al. (2024) [25]	ANFIS + Metaheuristics	Vietnam	Visual + R	High predictive correlation (R ~ 0.9) without explicit metrics
Barrera-Animas et al. (2022) [26]	ML Comparative Study	Tropical	Descriptive	Comparative analysis of ML models in tropical contexts
Andre et al. (2022)[27]	Neural Network	Amerika Selatan	Visual	Extreme rainfall forecasting without explicit metrics
Pathan et al. (2022) [28]	ML Model Comparison	India	R^2	Water level prediction based on daily rainfall data

3.3. Relevance of Predictive Models in the Context of Precision Irrigation

Accurate rainfall prediction plays a critical role in supporting precision irrigation, particularly in determining the optimal timing and volume of water application for various crops. Accurate forecasts enable more efficient and adaptive water management aligned with weather conditions—an increasingly important factor amidst climate change and erratic rainfall patterns.

Several studies reviewed in this work explicitly link rainfall prediction models with practical applications in irrigation systems. For instance, the PCA–LSTM model has been practically applied for daily rainfall forecasting to support sensor-based irrigation scheduling in Luwu Utara, Indonesia, demonstrating its reliability in a tropical agricultural environment [12]. In East Java, the ELM model was implemented to guide planting and irrigation schedules in Poncokusumo, where digital infrastructure is limited [4]. In Polewali Mandar, the ARIMA model helped support monthly irrigation planning based on rainfall forecasts, demonstrating effectiveness even under data and resource constraints [19]**.**

ARIMA remains a widely used model due to its simplicity, stability, and low computational requirements. The study by Ahmar and Mokhtar [19] applied ARIMA to monthly rainfall data in Polewali Mandar and reported an RMSE of 69.506 mm and a MAPE of 31.41%, which—despite being moderate—illustrate its usability in regions with minimal data infrastructure. Similarly, Tee and Mansor [13] achieved an RMSE of 27.91 mm and applied the model to inform regional water management in Selangor, Malaysia. Other studies [20], [21] emphasize ARIMA’s consistent performance and limited data requirements, making it suitable for tropical regions with low technological capacity.

Conversely, hybrid models such as those proposed in [24], [25] offer high accuracy and adaptability to complex data structures. The Neural Prophet–LSTM model, for instance, achieved an RMSE of 0.0633, making it highly suitable for real-time irrigation control in data-rich environments. However, practical implementation of these models presents several challenges. These include the availability and reliability of field sensors, inconsistencies in historical rainfall data, and limited technical capacity among farmers or local system operators. In many rural areas, issues such as sensor calibration errors, internet connectivity gaps, or a lack of training hinder the adoption of advanced AI systems**.**

In summary, selecting an appropriate rainfall prediction model to support precision irrigation requires considering not only statistical accuracy but also the practical implementation context—including data availability, infrastructure readiness, and end-user capacity. In tropical agricultural settings, models that are simple, robust, and not overly reliant on advanced technology hold significant practical value, while high-performance hybrid models are best leveraged in digitally mature environments equipped with automated control systems and trained personnel.

3.4. Discussion and Implications for Model Selection

The findings of this review underscore that no single rainfall prediction model universally outperforms others across all contexts. The effectiveness of a model depends heavily on factors such as data quality and structure, prediction objectives (e.g., daily vs. seasonal), available infrastructure, and human resource capacity. Evaluation metrics such as RMSE, MAE, or MAPE must also be interpreted in relation to the model's intended use, geographic context, and temporal resolution.

Statistical models such as ARIMA continue to demonstrate strong performance, especially in short-term and seasonal forecasting. Beyond their competitive accuracy, ARIMA’s primary advantages lie in its structural simplicity, ease of implementation, and low dependence on external variables or complex preprocessing techniques. Studies [13], [19], [20], [21] reinforce this, showing that

ARIMA can provide accurate and stable forecasts using monthly data across various tropical regions. These traits make ARIMA particularly suitable for irrigation planning in areas with limited computational resources or incomplete datasets, as shown in Polewali Mandar and Selangor.

Artificial intelligence models such as ANN, LSTM, and ELM excel in handling nonlinear and complex data patterns. The study by Simamora [4] highlighted ELM's adaptability to local datasets, achieving MAPE values below 10%. The combination of PCA and LSTM in [12] also delivered high accuracy in daily predictions. However, AI model implementation often requires computational resources, large training datasets, and technical skills for parameter tuning—elements that may be lacking in conventional farming regions. These challenges were evident in real-world contexts such as Luwu Utara, where digital infrastructure limits scalability.

Hybrid models, as developed in [24], [25], demonstrate that integrating statistical and AI techniques can significantly improve forecast accuracy. Prasad's combination of Neural Prophet and LSTM achieved an RMSE of 0.0633 and MAE of 0.0452, along with a MAPE of 3.94% and R^2 of 0.98, indicating exceptionally high accuracy in daily rainfall prediction. Similarly, Pham et al. reported that their ANFIS model, optimized using metaheuristic algorithms, delivered strong daily predictive correlations. Nevertheless, the implementation complexity and reliance on digital systems make these approaches more suitable for modern agriculture or advanced research environments.

Overall, this discussion illustrates that rainfall prediction model selection should be informed by more than statistical precision. Local contextual factors—such as data accessibility, user technical capacity, and digital infrastructure readiness—are critical to successful model adoption. In precision irrigation applications within tropical developing regions, models such as ARIMA remain highly relevant due to their balance of simplicity, reliability, and field-level feasibility. This aligns with broader food security goals outlined by FAO (2021), which emphasize that climate-informed irrigation planning is critical to achieving resilient agricultural systems in vulnerable regions facing erratic rainfall and water scarcity [29].

4. Conclusion

This review quantitatively compared statistical, AI-based, and hybrid models for rainfall prediction using metrics such as RMSE, MAE, MAPE, and R^2. Among the studies analyzed, the hybrid Neural Prophet–LSTM model demonstrated the lowest RMSE (0.0633) and highest R^2 (0.98), indicating exceptional accuracy in daily forecasts. Meanwhile, the PCA–LSTM model yielded strong performance (RMSE: 9.693; MAPE: 12.14%) with effective application in real-time sensor-based irrigation. However, both models require high-quality data, technical expertise, and supporting digital infrastructure.

Conversely, ARIMA models, though statistically less accurate (e.g., RMSE: 69.506; MAPE: 31.41% in Polewali Mandar), offer critical advantages in operational settings—particularly in tropical agricultural regions with limited data and infrastructure. Their simplicity, low computational cost, and ease of interpretation make them suitable for monthly or seasonal irrigation planning at the policy or farmer-cooperative level

Thus, model selection should be context-sensitive. For data-limited and infrastructure-constrained regions, ARIMA remains the most deployable and scalable option. AI and hybrid models, while highly accurate, are more applicable in digitally mature environments where IoT systems and real-time analytics are in place.

Practically, integrating rainfall prediction into irrigation scheduling systems—whether through Excel-based planning tools for ARIMA or through automated irrigation platforms for hybrid models—can significantly optimize water use and crop outcomes. Policymakers and agricultural planners should match model complexity with user capacity, ensuring that predictive tools are both usable and actionable.

Future studies should focus on validating models in operational farm settings, evaluating cost-effectiveness, and developing simplified user interfaces for smallholder applications. Additionally, regional-scale trials can inform guidelines for model deployment aligned with national food and water security frameworks, including those promoted by FAO.

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