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Original article

A Systematic Literature Review on LSTM–MPC–GP Integration for Climate-Adaptive Decision Support Systems and Evaluation in Precision Agriculture

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Abstract
Climate change poses a risk to sustainable agriculture through interference with irrigation timing, crop production, and resource management. Combining Artificial Intelligence with MPC and IoT can offer a basis for building climate-resilient decision support systems for precision agriculture. This study presents a Systematic Literature Review (SLR) of research published between 2019 and 2025 that investigates the synergistic use of Long Short-Term Memory LSTM neural networks, MPC, and IoT architectures for adaptive agricultural management. Following PRISMA and Kitchenham guidelines, 147 studies were screened, and 28 were analyzed using a ten-criterion Quality Assessment Checklist (QAC) with Weighted Quality Score (WQS) evaluation. Findings indicate that LSTM-based climate prediction models achieve average $R^2 > 0.9$, while MPC enhances irrigation efficiency by up to 30% under uncertain conditions. IoT infrastructures enable real-time communication and feedback across distributed farm networks, reducing latency and operational costs. The synthesis highlights an emerging shift toward closed-loop predictive–adaptive architectures. Despite significant progress, real-time field deployment remains limited due to computational and interoperability challenges. This SLR proposes a conceptual framework uniting LSTM forecasting, MPC optimization, and IoT-based monitoring for sustainable climate-resilient precision agriculture.
Keywords. LSTM, Model Predictive Control, IoT Precision Agriculture, Climate Adaptation.

Introduction

The agricultural sector utilizes around 70% of the total world's water use, and hence it is quite vulnerable to climate change, including variable rainfall and temperatures [1]. The traditional irrigation systems have been operated using set schedules that fail to adapt to varying environmental factors.

This results in inefficient resource use, reduced yield, and increased vulnerability to climatic stress. In response, precision agriculture has evolved to leverage AI and control-based approaches for climate adaptation. In the field of predictive models, the Long Short-Term Memory (LSTM) artificial neural network model is commonly used to learn the nonlinear time dependencies in the environmental time series data, providing the ability to forecast soil moisture, temperature, and evapotranspiration [2]. At the same time, Model Predictive Control (MPC) provides an approach to decision-making, which optimally regulates irrigation scheduling and resource allocation using predictions [3]. The use of IoT infrastructure allows combining these systems to implement the closed-loop operation.

Despite these technological advances, a research gap persists in the integrated design of predictive–adaptive control frameworks capable of managing uncertainty while ensuring energy and water efficiency. This SLR systematically reviews recent work on LSTM–MPC–IoT integration to evaluate their combined potential for climate-adaptive precision agriculture. Given these developments, recent research has increasingly focused on bridging this gap by integrating LSTM-based predictive modeling, GP–MPC adaptive control, and CPS–WSN system coordination into a unified architecture [3] [4]. Such an integration not only facilitates accurate soil moisture prediction but also aids in intelligent decision-making for irrigation scheduling and actuation. Various works that have utilized hybrid and hierarchical control have proved to be highly successful; however, there is very little work done which involves the evaluation of all three fields of AI control and communication together [5],[6]. Hence, there is a need for a Systematic Literature Review (SLR).

The paper is based on PRISMA methodology and utilizes the PICOC model (Population, Intervention, Comparison, Outcome, and Context) for organization of the literature review.

This research will be focused on peer-reviewed studies from 2019 to 2024 on experimental, simulation, and empirical work on AI-driven irrigation and control systems. A total of 25 articles were analyzed using a Quality Assessment Checklist (QAC) with ten criteria leading to a Weighted Quality Score (WQS) evaluation to assess methodological rigor and relevance. Among AI models, the Long Short-Term Memory LSTM neural network has emerged as one of the most effective deep learning methods for time-series prediction in environmental and agricultural systems. Studies by [4],[7],[8] demonstrated that LSTM can predict soil moisture levels with over 90% accuracy using parameters such as temperature and humidity. The aim os the study is to examine how LSTM models can accurately predict soil moisture from environmental and sensor data within WSN-based frameworks.

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Methodology

This review follows the PRISMA approach and systematic review process as per [9]. The study covers literature between January 2019 and June 2025 with emphasis on peer-reviewed papers using LSTM and MPC with IoT in the application of precision agriculture.

The research followed the PICOC framework:

1- Population: Agricultural systems influenced by climate variability.
2- Intervention: Integration of LSTM for climate forecasting, MPC for adaptive control and IoT for real-time monitoring.
3- Comparison: Traditional irrigation or static decision support systems.
4- Outcome: Improvements in prediction accuracy, irrigation efficiency and resilience.
5- Context: Precision agriculture under varying climatic and geographic conditions.

A total of 147 papers were retrieved from Scopus, IEEE Xplore and ScienceDirect. After applying inclusion–exclusion criteria and QAC evaluation, 28 studies were retained for final synthesis and Weighted Quality Scores (WQS) were computed to assess methodological rigor, innovation, and integration level across studies.

Research Framework

The methodological workflow consists of five major stages:

1. Planning the Review, which defines the research objectives and formulates specific research questions RQ1 and RQ3
2. Identifying Relevant Studies through systematic database searches.
3. Study Selection using inclusion and which ones to leave out.
4. Quality Assessment through a structured checklist and
5. Data Extraction and Synthesis for comparative and thematic analysis.

This structured approach ensures both methodological rigor and reproducibility of the findings [9]. Figure 1 (PRISMA diagram) illustrates the overall flow of the review process from initial identification to final inclusion.

Research Question Development (PICOC Framework)

Formulation of the research question was guided using the PICOC model (Population, Intervention, Comparison, Outcome, and Context), which is commonly employed in evidence-based reviews [10]. PICOC offers a robust logical basis for formulating the parameters of the review.

PICOC Framework Structure

PICOC Element	Definition in This Study
Population (P)	Agricultural soil systems monitored using WSN or CPS infrastructure
Intervention (I)	Integration of LSTM for soil moisture prediction and GP–MPC for adaptive irrigation control
Comparison (C)	Traditional irrigation methods or non-integrated AI/control systems
Outcome (O)	Improved prediction accuracy water and energy efficiency and control robustness
Context (C)	Advancements in smart farming and precision irrigation in either real or artificial environments

From the above context, the following research questions have been formulated:

- **RQ1:** Can soil moisture be predicted using LSTM from environmental variables in Wireless Sensor Network-based monitoring systems?
- **RQ2:** How can GP–MPC integrate the uncertainty of LSTM predictions to produce adaptive and robust irrigation control?
- **RQ3:** To what extent can the integration of LSTM + GP–MPC + CPS–WSN enhance water and energy efficiency while maintaining optimal soil moisture levels?

These questions serve as the conceptual anchor of the review, linking predictive modeling, adaptive control and cyber-physical integration within intelligent irrigation systems.

Search Strategy

A comprehensive search strategy was implemented across multiple scientific databases, Scopus, IEEE Xplore, and ScienceDirect, covering the publication period from January 2019 to March 2024. The search employed Boolean logic with keywords derived from the PICOC elements. The final search string was constructed as follows:

Soil Moisture OR Soil Water Content and Prediction OR Forecasting OR Modeling and LSTM OR Long Short-Term Memory OR Deep Learning and GP-MPC OR Gaussian Process OR Model Predictive Control and CPS OR Cyber Physical System OR IoT and WSN OR Wireless Sensor Network.

In order to increase the synonym coverage, terms like precision agriculture, smart irrigation, and adaptive control were also used. The duplicate references were omitted, and then all the other citations were filtered based on the title and abstract.

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In order to ensure that the increase in the synonyms pool would take place, some additional terms such as precision farming, smart irrigation, and adaptive control were introduced into the pool of search terms. Duplicate references were excluded, and the other references were screened according to the title and abstract.

Inclusion and Exclusion Criteria
Clear inclusion and exclusion criteria were defined to ensure the selection of high-quality and relevant studies [9].

Inclusion Criteria:
1. All the studies should be published between the years 2019 and 2024 in peer-reviewed journals or conference proceedings.
2. Research explicitly focusing on soil moisture prediction, irrigation control, CPS WSN, or AI-based smart farming systems.
3. Studies employing LSTM, GP–MPC or integrated hybrid control frameworks.
4. Papers providing quantitative evaluation metrics (e.g. RMSE, R^2, water/energy efficiency).

Exclusion Criteria:
1. Non-English papers or inaccessible full texts.
2. Review papers without original empirical findings.
3. Studies lacking methodological detail or quantitative results.
4. Research outside the domain of precision irrigation or unrelated control systems.

Such a systematic screening procedure helped ensure that the chosen papers were methodologically sound and relevant to the SLR aims.

Quality Assessment (QAC and WQS)
To assess the methodological quality of the selected studies a Quality Assessment Checklist (QAC) consisting of ten criteria (Q1–Q10) was applied.

Each criterion was scored on a 0–2 scale (0 = No 1 = Partial 2 = Yes) covering aspects such as:
- clarity of research objectives (Q1)
- methodological transparency (Q2)
- data validity and size (Q3)

The resulting scores were normalized into a Weighted Quality Score (WQS) to rank the studies according to overall quality. The WQS results indicated that papers on LSTM (mean WQS = 1.95) and GP–MPC (mean WQS = 1.93) achieved the highest quality, followed by CPS (1.79) and WSN (1.45), reflecting a general trend toward integrated, high-quality research in recent years [11],[12].

Data Extraction and Synthesis
A structured Data Extraction Form (DEF) was used to systematically collect and compare key information from each study, including year, title, methods, dataset performance metrics, main findings, and identified research gaps. The data extraction followed the guidelines by [9].[10].
Each study was coded according to its primary contribution domain (e.g., LSTM GP, MPC, CPS, WSN) to facilitate thematic synthesis.
An evidence synthesis process was conducted through quantitative WQS synthesis as well as qualitative content analysis, which produced two synthesized outputs, including:
(a) Evidence Synthesis Summary Table (ESS) that emphasizes key findings as well as the significance of every study and (b) Study Quality Synthesis Chart depicting quality trends within different research fields.

Validity and Limitations
Several measures were undertaken to enhance the validity and reliability of this SLR. Data triangulation was ensured by cross-checking multiple databases, Scopus, IEEE Xplore, and ScienceDirect, covering studies from 2019 to 2025 across the domains of LSTM GP–MPC CPS and WSN. Quality bias was minimized through dual independent screening and consensus-based inclusion using the Quality Assessment Checklist (QAC) framework [9]. The Weighted Quality Score (WQS) evaluation further strengthened methodological transparency by quantifying the rigor of each study across ten assessment criteria as applied in similar AI-based control reviews [5],[13].
Nevertheless, there are certain shortcomings of this review. Firstly, there is a possibility of publication bias, as only peer-reviewed journal articles were used, thus omitting potentially valuable information from conference proceedings and preprints [14]. Secondly, language bias is evident in this review, as only English-language studies were analyzed, and, therefore, potentially useful findings from local or regional literature were not included [15],[16].

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Finally, although a comprehensive search was performed, certain recent studies on CPS-WSN systems and adaptive GP-MPC controllers could be omitted due to different terminologies used by databases [3],[17]. Nevertheless, the methodological rigor, including structured data extraction, independent scoring, and cross-validation between reviewers, ensures that the synthesized findings maintain a high level of reliability, transparency, and reproducibility consistent with contemporary SLR practices in AI-driven control and agricultural automation research [8],[10].

Overview of Selected Studies

The reviewed studies (2019–2025) span multiple agricultural applications including climate prediction, smart irrigation, and environmental monitoring. Approximately 61% used simulation-based validation (MATLAB, Python) while 39% conducted field implementations via IoT sensor networks. Publication trends indicate a steady growth in integrated LSTM–MPC–GP-IoT research with a strong focus on adaptive irrigation and weather forecasting systems since 2022.

Table 1. Publication Trends and Research Focus (2019 to 2025)

Year	Primary Focus	Representative Studies	Key Contribution
2019–2020	IoT-based sensing	[16]	Wireless sensor deployment and climate monitoring
2021–2022	LSTM prediction models	[2], [8].	Accurate forecasting of soil moisture and climate variables
2023–2025	LSTM–MPC hybrid systems	[3], [19]	Closed-loop predictive–adaptive control

Domain-Wise Comparative Analysis

Each core technology LSTM MPC and IoT contributes uniquely to climate-adaptive agricultural decision support LSTM enhances predictive intelligence MPC provides optimal control IoT ensures real time implementation. Table 2 summarizes their comparative strengths and limitations.

Table 2. Comparative Analysis of LSTM, MPC, and IoT Domains

Domain	Key Function	Main Strengths	Identified Gaps
LSTM	Climate and soil variable forecasting	High accuracy ($R^2 > 0.9$), effective for time-series data	Limited uncertainty quantification; computationally intensive
MPC	Optimization-based irrigation control	Adaptive to dynamic weather, 25–30% efficiency gains	Requires predictive input and high computation cost
IoT	Real-time sensing and feedback	Low latency (<5s) scalable network design	Security and interoperability challenges limited standardization

Cross-Domain Integration Insights

LSTM and MPC together with IoT facilitate closed-loop systems where real-time data leads to adaptive decisions. Cross-domain synthesis reveals that a combination of predictive models with control optimization greatly improves resilience and sustainability. The synergy between the three domains is listed in Table 3 below.

Table 3. Cross-Domain Synergistic Insights (LSTM–MPC–IoT)

Integration Layer	Combined Function	Impact Achieved	Example Study
LSTM + MPC	Predictive–adaptive irrigation control	30% water savings under uncertain climate	[3].
LSTM + IoT	Forecast-based data fusion	Improved accuracy with real-time environmental feedback	[2].
MPC + IoT	Optimization of actuation at the edge	Low latency and 20% energy saving	[19].

Emerging Trends and Research Gaps

Recent advances suggest a shift toward intelligent, distributed and uncertainty-aware systems.

Key trends include:

• Federated and edge learning for scalable LSTM training.
• Reinforcement learning-enhanced MPC for adaptive optimization.
• Digital twins for real-time simulation and control verification.
• IoT–cloud hybrid frameworks for cross-platform data integration.

Persistent gaps include limited field validation, high energy costs of deep models and the lack of unified communication

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protocols between predictive and control modules. Addressing these will be critical for advancing climate-adaptive precision agriculture.

Weighted Quality Score (WQS) Analysis

A Weighted Quality Score (WQS) was computed for each study to evaluate methodological quality.

Table 2 summarizes the WQS distribution per research domain. Results reveal that LSTM and GP–MPC domains achieved benchmark-level quality (WQS ≥1.9) followed by CPS (1.79) and WSN (1.45). LSTM studies displayed high consistency in data preprocessing, hyperparameter tuning, and accuracy validation (R^2 > 0.9). Conversely, WSN studies showed solid technical efficiency but lacked integration with control layers

Table 4. Weighted Quality Score (WQS) Summary by Domain

Domain	Average WQS (0–2)	Quality Level	Key Strengths	Common Weaknesses / Gaps
LSTM	1.95	High–Benchmark	High prediction accuracy, robust validation	No uncertainty modeling; limited field deployment
GP–MPC	1.93	High–Benchmark	Adaptive control robustness under noise	Computationally heavy hardware limitations
CPS	1.79	High	Reliable communication, low latency	Weak AI integration, few real deployments
WSN	1.45	Medium–High	Energy-efficient routing scalability	Lacks bidirectional feedback; static topology

Domain-Wise Evidence Synthesis

To provide a structured understanding of research developments, evidence was categorized by domain. Table 3 summarizes representative studies' methodologies, datasets, performance metrics, and identified research gaps across each domain.

Table 5. Domain-Wise Summary of Key Studies (2019 to 2024)

Domain	Representative Studies	Methods / Models Used	Dataset / Environment	Performance Metrics	Main Results	Research Gaps Identified
LSTM – Prediction Layer	[4]. [7], [8], [14],[20].	LSTM, RNN–LSTM hybrid CNN–LSTM	IoT environmental & soil data	RMSE, MAE, R^2 NSE	>90% prediction accuracy; NSE up to 0.92 high virtual sensor reliability	No uncertainty quantification; limited field validation and real-time deployment
GP–MPC – Control Layer	[3], [13], [21], [22], [23]	GP regression + MPC hybrid multi-agent MPC	Synthetic & real irrigation datasets	RMSE, MAPE, Water/Energy Efficiency	30% water saving 20% energy reduction robust adaptive control under uncertainty	High computational cost limited embedded and real-time implementations
CPS – System Integration Layer	[5], [6], [15], [16], [17].	IoT–CPS framework edge–cloud synchronization; federated learning	Real-time CPS field systems	Latency, ScalabilityAccuracy	<5s latency reliable automation; scalable networked architecture	Limited predictive integration with AI models low adaptability in dynamic environments
WSN – Physical Infrastructure Layer	[24], [25], [26], [27], [28]	LEACH PSO-based clustering SMO optimization, hybrid IoT routing	Simulated and field-deployed WSNs	Energy Use Network Lifetime, Packet Delivery	20–50% extended network lifetime improved energy balance	No AI-driven feedback loop lacks adaptive response to control signals

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LSTM Findings

LSTM models consistently outperformed traditional statistical methods (ARIMA, ANN) in predicting soil moisture. For instance, [4] achieved RMSE < 0.05 and R^2 > 0.9 using environmental sensor inputs. [7] developed a hybrid RNN–LSTM architecture that reached NSE = 0.92 for soybean field moisture prediction. [20] demonstrated that virtual sensing with LSTM–MLP models can effectively replace faulty physical sensors. However, most studies lacked uncertainty quantification and field-scale deployment.

GP–MPC Findings

GP–MPC frameworks integrated probabilistic modeling (GP) with optimization (MPC) to manage environmental uncertainty. [13] found a 30% reduction in water consumption through the application of LSTM-based prediction in MPC control. In the same manner, [3] were able to attain a 20% increase in energy efficiency. However, robust and adaptive GP-MPC algorithms are computationally intensive.

CPS Findings

CPS research focused on connecting sensors, controllers and actuators through IoT and cloud platforms. [15] designed a CPS-based irrigation system achieving <5s response latency, while [5] demonstrated a cloud–edge CPS with improved reliability. Nonetheless, AI integration remains limited, with most CPS frameworks lacking predictive decision-making.

WSN Findings

LEACH and its derivatives improved WSN energy efficiency and scalability [24],[26]. However, WSN protocols still operate in open-loop data transmission mode and lack bidirectional command flow necessary for AI–control integration [25]. Overall, these findings emphasize the complementary strengths of each domain—prediction (LSTM), control (GP–MPC), communication (WSN) and orchestration (CPS).

Cross-Domain Comparative Analysis

To understand interdependencies between domains, Table 4 synthesizes cross-domain insights and illustrates how LSTM and GP–MPC and CPS and WSN collectively form a closed-loop intelligent irrigation architecture.

Table 6. Cross-Domain Comparative Insights (LSTM–GP–MPC–CPS–WSN)

Aspect	LSTM	GP–MPC	CPS	WSN	Integrative Insight
Primary Function	Soil moisture forecasting	Adaptive irrigation control	System orchestration	Data sensing & routing	Combined to form predictive–adaptive closed loop
Input Data	Environmental variables (temp and humidity and rain)	LSTM forecast + uncertainty	Sensor & actuator data	Node data packets	Data pipeline: sensors → prediction → control → actuation
Output / Decision	Moisture prediction	Control signals (valve/pump)	Coordination & feedback	Packet transmission	Integrated irrigation scheduling
Energy Efficiency Impact	Indirect via precise control	High (20% saving)	Moderate	High (cluster routing)	Combined effect yields 30% water & 20% energy gain
Research Stage (2024)	Mature	Advanced	Evolving	Stable	Integration readiness proven by hybrid studies
Aspect	LSTM	GP–MPC	CPS	WSN	Integrative Insight
Primary Function	Soil moisture forecasting	Adaptive irrigation control	System orchestration	Data sensing & routing	Combined to form predictive–adaptive closed loop
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Aspect	LSTM	GP–MPC	CPS	WSN	Integrative Insight
Research Stage (2024)	Mature	Advanced	Evolving	Stable	Integration readiness proven by hybrid studies

This comparative synthesis confirms that AI-driven predictive and adaptive control (LSTM–GP–MPC) supported by CPS–WSN communication layers represent the most advanced direction in current smart irrigation research.

Emerging Trends and Research Challenges

Based on Tables 2–4 and WQS analysis, five key research trends emerge:

1. From Sensing to Intelligence: Transition from passive monitoring (WSN) to predictive–adaptive intelligence (LSTM–GP–MPC).
2. Hybrid Architectures: Increasing focus on multi-layer frameworks that integrate sensing, prediction, and control.
3. Real-Time Feedback Loops: Movement toward CPS-driven closed-loop control replacing static scheduling.
4. Uncertainty Awareness: Adoption of GP models reflects a growing need to quantify prediction confidence.
5. Energy–Water Co-Optimization: Joint improvement of resource efficiency up to 30% water and 20% energy saving.

Notwithstanding the above advancements, some significant areas that require further exploration include:

- . Insufficient application in real-life scenarios outside test environments [7].
- . Lack of standardized communication protocols for bidirectional AI–control interaction [27].
- . High computational complexity for embedded GP–MPC systems [22].
- . Absence of a unified framework integrating prediction, control, and communication layers holistically.

Conceptual Integration Framework

Synthesizing all reviewed evidence, this SLR proposes a conceptual integration framework that unifies LSTM, GP–MPC, CPS, and WSN components. The framework consists of three functional layers:

1. Prediction Layer (LSTM)

Takes input data from WSN node data (temperature and humidity and rainfall and soil) and predicts the moisture content in the soil using LSTM-based virtual sensors.

2. Control Layer (GP–MPC)

Processes LSTM outputs (mean + uncertainty) to compute optimal irrigation set points dynamically, adapting to soil and weather variations.

3. System Layer (CPS–WSN)

Implements real-time communication between sensor cluster controllers and actuators through CPS–WSN integration, ensuring feedback and synchronization.

This architecture enables closed-loop intelligence — data continuously flows from the

This framework allows for closed-loop intelligence where data is continuously transferred from the physical layer (WSN) to the cyber layer (LSTM-GP-MPC) and control commands go back to actuators through CPS for actuation.

In summary, the SLR findings affirm that integrating LSTM for prediction, GP–MPC for control, and CPS–WSN for coordination offers a coherent path toward intelligent irrigation systems that are accurate, energy-efficient, and adaptive to uncertainty. The combination will change existing conventional irrigation into Predictive adaptive management, where the system learns and optimizes resource use all the time. Although substantial steps have been made, the next step is to move from simulations to CPS-integrated solutions in the field.

Conclusion

This SLR consolidates state-of-the-art research on LSTM–MPC–IoT integration for climate-adaptive precision agriculture. Empirical evidence demonstrates that predictive–adaptive architectures can achieve substantial efficiency gains in water and energy management while enhancing system resilience to environmental uncertainty. However, scalability and real-time control remain key limitations. Future work should prioritize lightweight AI–control model standardization of IoT communication protocol standardization, and field-scale deployments to validate the real-world potential of these integrated systems.

Conflict of interest. Nil

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