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REVIEW PAPER **OPEN ACCESS**

The Evolution of Weather-Based Deep Learning in Smart Irrigation: A Systematic Review of Sustainable Approaches and Perspectives

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Abstract

This paper presents a systematic literature review of 191 peer-reviewed studies that link short-term weather information with learning based forecasting and control in irrigation or related applications, focusing on 191 peer-reviewed studies published between January 2020 and early 2025, with four foundational studies published prior to 2020 included via backward citation tracking. The review follows a PRISMA-inspired protocol, with database searches in Scopus, IEEE Xplore, and Web of Science, clear inclusion and exclusion criteria, and structured data extraction on the application domain, sensing and IoT architecture, forecasting models, reinforcement learning algorithms, and reported performance metrics. The results show that deep learning models, especially CNN, LSTM, and their hybrids, are frequently used for short-term environmental prediction and typically outperform classical machine learning baselines. Almost 50 studies employ reinforcement learning or deep reinforcement learning, but only five (≈2.6% of the full corpus) apply these methods directly to irrigation control, while most DRL applications appear in energy and smart-grid management. Around a quarter of the corpus explicitly implements IoT architectures, yet very few systems integrate IoT with reinforcement learning in a closed loop at the edge or fog. Sustainability-related outcomes, such as water use, energy savings, costs, and emissions, are mentioned, but they are not consistently quantified using comparable metrics. The review provides a structured mapping of methods and architectures, clarifies how existing work is fragmented across domains, and highlights open opportunities for developing weather-aware, IoT-enabled, and sustainability-oriented reinforcement-learning frameworks for smart irrigation.

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I. Introduction

Irrigated agriculture sits at the center of the nexus of water, food, energy, and climate. Intensifying climate variability has increased the uncertainty of rainfall timing and magnitude, while heat extremes and shifting evapotranspiration patterns shorten the horizon over which irrigation plans remain valid. Rule-based schedules and static thresholds that worked in average years now tend to over- or under-irrigate, wasting water and energy, stressing plants, and increasing production risk. In parallel, farms and greenhouses increasingly deploy Internet of Things (IoT) sensing and controllable pumps and valves, creating the data and actuation pathways required for closed-loop irrigation across open-field crops, horticulture, protected cultivation, and urban landscapes. What remains missing is a consolidated, evidence-based view of how short-term weather prediction and learning-based control can be combined into robust, scalable, and sustainable smart irrigation systems.

Two technical streams have matured and now converge on this problem. The first is short-term weather forecasting for decision support. Beyond statistical baselines, hybrid deep models that combine convolutional and recurrent components have improved the capture of spatial–temporal structure in meteorological signals. Representative studies using CNN–LSTM-type architectures report accuracy gains at horizons of 0–72 hours that directly affect irrigation timing and volume [1], [2], [3]. These gains matter because errors in near-term rainfall and reference evapotranspiration propagate into over-watering or plant water stress, especially when decisions are automated at sub-daily cadences.

The second stream is reinforcement learning for autonomous irrigation control. Since irrigation is a sequential decision problem with continuous actions and delayed rewards, deep reinforcement learning (DRL) algorithms that handle continuous control, notably Soft Actor–Critic and related actor–critic methods, have emerged as strong candidates for adaptive scheduling under uncertainty. Field-tested prototypes show that DRL controllers can reduce water use while maintaining yields when compared with conventional rules. For example, a DRL-based controller deployed in perennial orchards

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achieved measurable water savings relative to baseline practices [4], and other studies that embed data-driven predictors inside an RL framework report concurrent gains in productivity and reductions in irrigation volume in vegetable systems [5], [6]. Together, these results point to the potential of learning-based control to balance agronomic targets with resource constraints.

Despite this progress, the literature remains fragmented across algorithms, crops, climates, hardware stacks, and performance metrics. Several previous reviews address adjacent parts of the problem space. For instance, Hammouc et al. provide a broad systematic review and meta-analysis of intelligent irrigation systems, but do not focus on the explicit coupling of weather forecasters with closed-loop controllers or deep reinforcement learning. Other surveys focus on machine-learning techniques for smart irrigation [7] or more generally on AI in agriculture, without systematically analysing how short-term weather prediction feeds into sequential decision-making and control. Likewise, reviews of IoT-based smart farming and cyber-security in irrigation [8] primarily discuss connectivity, security, or sensor deployment, rather than the joint design of forecasting and control policies. In short, existing surveys either address smart irrigation without DRL-enabled control or discuss DRL and cyber-physical control without the specific context of irrigation and its weather dependencies.

At the same time, forecasting and control are often treated in isolation. Forecasting studies typically stop at accuracy metrics without tracing impacts on water, energy, or yield. Control studies frequently document relative water savings but omit analysis on forecast quality or clear baseline comparators. Integration patterns vary from loosely coupled designs, where forecasts enter as periodic exogenous inputs, to fully closed-loop architectures that fuse forecasts, real-time sensor feedback, and actuation. Yet latency budgets, failure modes, and edge–cloud deployment choices are rarely described in a comparable way, even though they are critical for real-world reliability. Sustainability is frequently mentioned but not reported with consistent metrics: PV-powered pumping and energy-aware policies are discussed, although energy–water co-metrics, carbon accounting, and techno-economic indicators are not consistently aligned with agronomic outcomes.

Beyond irrigation, closely related cyber-physical domains such as microgrids, smart buildings, and other energy systems have developed mature DRL frameworks for continuous control under uncertainty. These domains share key characteristics with irrigation, sequential decision-making, resource constraints, and strong dependence on weather and demand forecasts, so their methods can inform irrigation control even if the physical outputs differ. Explicitly incorporating such neighbouring domains into the evidence base helps reveal transferable algorithmic patterns, reward designs, and deployment strategies that have not yet been fully exploited in irrigation.

This article addresses these gaps through a systematic literature review conducted under the PRISMA 2020 statement and structured by the PICOC framework. PRISMA is used to ensure transparent reporting of identification, screening, and inclusion decisions, while PICOC provides a decision-oriented structure that links Population, Intervention, Comparison, Outcomes, and Context to the research questions. These protocols were explicitly selected to maximise methodological transparency, reproducibility, and traceability of the mapping of evidence to design recommendations for smart irrigation control.

This review synthesizes 191 primary studies published predominantly between January 2020 and January 2025, with four additional foundational studies included through backward citation tracking to capture key pre-2020 developments in DRL-based irrigation and weather-aware control. Distinct from previous reviews, we explicitly include studies from closely related cyber-physical domains, particularly energy management, smart grids, and building control, because they offer mature DRL and IoT integration patterns for sequential control under uncertainty that are mathematically transferable to the nascent field of smart irrigation control.

The complete list of included studies appears in the References as items [1]–[191]. Our contributions are fourfold.

1. We provide a taxonomy and performance synthesis of weather-prediction methods used in irrigation contexts, with emphasis on hybrid deep architectures such as CNN–LSTM, and we report accuracy in decision-relevant terms at operational horizons [9], [10].
2. We present a structured comparison of DRL controllers for irrigation, focusing on state design, action parameterization, and reward shaping for continuous control, with particular attention to Soft Actor–Critic and related actor–critic variants, and we summarize reported gains and trade-offs relative to rule-based and fuzzy baselines [11], [12].
3. We analyze integration patterns from loosely coupled to real-time closed-loop architectures, including data flow, latency, reliability, and edge–cloud splits, and we document safety fallbacks and actuator constraints that are rarely harmonized across studies.
4. We synthesize sustainability reporting, collating how studies treat energy use, renewable integration, emissions, and cost, and we identify missing elements such as multi-objective optimization across water, energy, emissions, and yield, as well as the lack of standardized reporting.

Guided by these aims, we pose the following research questions.

- RQ1. Which short-term weather-prediction methods are used for irrigation, and how do they compare on decision-relevant metrics?
- RQ2. How are DRL controllers for irrigation formulated in terms of state, action, and reward,

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and what gains and trade-offs are reported versus baselines?

- RQ3. How are forecasts integrated with control from loosely coupled to fully closed-loop designs, and what are the architectural and reliability implications?
- RQ4. To what extent are sustainability dimensions such as water, energy, emissions, and cost quantified and jointly optimized?

The remainder of the article is organized as follows. Section 2 details the review protocol, databases, search strings, screening criteria, and data-extraction framework. Section 3 presents results mapped to the four research questions, including comparative tables and integration schematics. Section 4 discusses cross-cutting insights, threats to validity, and implementation guidance. Section 5 concludes with a forward agenda for real-time, field-validated, and explicitly multi-objective smart irrigation.

II. Materials and Method

This review follows PRISMA 2020 and is structured using the PICOC framework to ensure transparency, reproducibility, and decision relevance. The end-to-end identification and selection of studies is summarised in Figure 1 (PRISMA flow diagram). PRISMA provides a standardised way to document how records are identified, screened, and included, while PICOC anchors the inclusion criteria in irrigation-relevant decision contexts. The complete database queries, search strings, filters, and search dates are described in the Search Strategy subsection, while the schema used to extract variables from each included paper is detailed in the Study Selection and Data Extraction subsection.

A. Protocol and PICOC (PRISMA 2020)

Population: irrigation systems and closely related cyber-physical applications in agriculture, energy, and smart infrastructures that can inform smart irrigation control, including open fields, greenhouses, horticulture, and urban or landscape contexts.

Intervention: short-term weather prediction methods and learning-based irrigation control, with an emphasis on hybrid deep forecasting models, such as CNN–LSTM, and deep reinforcement learning controllers, such as Soft Actor-Critic and DDPG.

Comparison: rule or threshold scheduling, fuzzy logic, and alternative ML or DL baselines.

Outcomes: decision-relevant forecast accuracy for short horizons, water-use efficiency, over- or under-irrigation rates, soil-moisture in-band percentage, yield or proxy agronomic metrics when available, energy and emissions indicators, reliability, and latency.

Context: IoT-capable settings with sensors and actuators, edge or cloud computation, and, when applicable, solar-powered operation.

B. Search Strategy and Data Sources

The primary database search focused on studies published between January 1, 2020, and January 31, 2025. This timeframe was chosen to capture the rapid recent advancements in deep learning (DL), IoT technologies, and DRL-based control relevant to smart irrigation and closely related cyber-physical systems. To ensure the reproducibility of this review, the exact Boolean search strings utilised for each database are detailed in Table 1. The queries combined keywords related to the application domain ("smart irrigation", "precision agriculture", "greenhouse", "agriculture"), the methods ("reinforcement learning", "deep learning", "neural network", "LSTM", "CNN"), and the integration targets ("weather", "forecast", "IoT", "control", "optimisation").

Table 1 Search strings and query logic used for each database

Database	Search Query / String
Scopus	(TITLE-ABS-KEY("smart irrigation" OR "precision agriculture" OR "greenhouse" OR "agriculture") AND TITLE-ABS-KEY("reinforcement learning" OR "deep learning" OR "neural network" OR "LSTM" OR "CNN") AND TITLE-ABS-KEY("weather" OR "forecast" OR "rainfall" OR "evapotranspiration") AND TITLE-ABS-KEY("control" OR "optimization" OR "IoT"))
IEEE Xplore	(("Abstract":"smart irrigation" OR "precision agriculture" OR "greenhouse") AND ("Abstract":"reinforcement learning" OR "deep learning") AND ("Abstract":"weather" OR "forecast") AND ("Abstract":"control"))
Web of Science	TS=("smart irrigation" OR "precision agriculture") AND TS=("reinforcement learning" OR "deep learning") AND TS=("weather" OR "forecast")

C. Backward Citation Tracking and Study Selection

Recognising that strict date filtering might exclude foundational methodologies, we complemented the database search with backward citation tracking. Five key survey or overview papers on smart irrigation, AI in agriculture, and intelligent irrigation control were first identified from the search results. Their reference lists were then manually screened to locate earlier works that (i) combined weather or environmental information with learning-based forecasting and control, and (ii) formulated irrigation or closely related water-management problems as sequential decision-making tasks. This yielded four additional significant studies published prior to 2020. Although outside the primary time window, these studies were included because they introduced fundamental DRL architectures or weather-aware control formulations that serve as baselines for modern research. They are clearly flagged as pre-2020 in our descriptive statistics but are included in the qualitative synthesis.

D. Inclusion and Exclusion Criteria

The identified records were screened based on the PICOC framework. A key element of the screening process was the exclusion of purely agronomic or

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hydrological works without an explicit AI or control component, in order to maintain focus on technological integration.

In this review, an "explicit AI or control component" is defined as a system that uses an algorithm (e.g., machine learning, fuzzy logic, model-based control, or reinforcement learning) to actively make decisions or generate control signals, thereby closing the loop between sensing and actuation. Studies that only monitored environmental parameters using IoT sensors without automated decision-making, or that relied solely on static, open-loop timer schedules, were excluded. This ensures that the corpus focuses on the integration of sensing, prediction, and automated control, while acknowledging that agronomic and hydrological studies still provide valuable background for modelling crop response and soil processes.

After applying these criteria, the final corpus comprised 191 studies: 187 papers from the 2020–2025 database search and four pre-2020 papers from backward citation tracking.

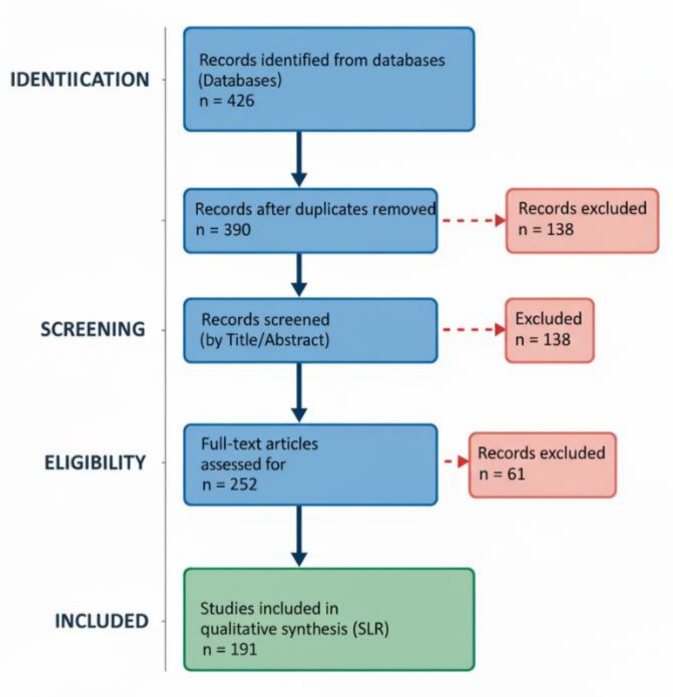

Fig. 1. **PRISMA flow diagram**

E. Screening Flow (PRISMA diagram)

The search identified 426 records from databases and supplementary sources. After deduplication, 390 unique records remained. Title and abstract screening excluded 138, leaving 252 for full-text assessment. Sixty-one full texts were excluded with documented reasons. The final dataset included 191 studies (187 from the 2020–2025 search window and 4 pre-2020 studies from backward citation tracking). Figure 1 summarises the PRISMA counts from identification through eligibility to final inclusion. All included studies are enumerated in the References as [1]–[191].

F. Quality Assessment (rubric and rating)

We used a 10-item rubric tailored to ML-enabled cyber-physical irrigation. Each item was scored 0, 0.5, or 1, for a maximum of 10. Two reviewers assessed all studies independently, resolved disagreements through discussion, and used a third reviewer to break ties. Cohen's kappa was computed on a 20 percent sample. High quality was defined as a total score of at least 8 with no more than two zeros and no failure on baseline or metric adequacy. Low-quality studies were kept for qualitative mapping when they addressed unique contexts but were excluded from any quantitative aggregation. In the synthesis, low-quality studies are used only for qualitative mapping and illustrative case descriptions. They are clearly flagged in our internal coding and are excluded from any quantitative aggregation, such as frequency counts of algorithm families, distributions of forecast accuracy, or any attempted meta-analysis. When insights from low-quality studies are referenced in the narrative, they are treated as hypothesis-generating rather than as definitive evidence.

G. Study Selection and Data Extraction

Study selection followed the PRISMA-inspired flow described above. After removing duplicates and screening titles and abstracts, full texts of potentially relevant papers were assessed against the inclusion criteria. To ensure consistent comparison across studies, we designed a structured data-extraction form that captured the same set of variables for each article. For each study, we recorded bibliographic information (identifier, year, database source, publication type) and coded the application domain and setting (agriculture/irrigation, energy and smart grids, weather and climate, IoT/cyber-physical systems, transport/traffic, and other related control problems such as building HVAC, manufacturing systems, hydropower, and water-resource scheduling). We also noted whether the use case involved open-field irrigation, greenhouses, orchards or horticulture, microgrids, buildings, or other infrastructures, and the geographic region when reported. Data and sensing fields captured sensor types and measured variables (e.g., soil moisture, air temperature, rainfall, solar radiation, power, and load), together with data resolution and duration.

Forecasting-related fields specified the predicted variable, forecast horizon, and model family (deep learning, classical ML, statistical time series, hybrid, or rule-based). Control and decision-making information included the control objective, strategy (rule-based, fuzzy, optimisation, model predictive control, RL/DRL), and, when relevant, the RL/DRL algorithm family (e.g., DDPG, PPO, SAC, DQN) and main state and action variables. IoT and deployment aspects were recorded including whether an explicit IoT/IIoT architecture was described, the main computing layer (cloud, edge, or on-device), and the communication technologies used (e.g., Wi-Fi, LoRa, ZigBee, cellular, wired). Finally, we extracted performance metrics (prediction and control) and any operational or sustainability indicators (water, energy,

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cost, emissions), as well as limitations and explicit suggestions for future work, which were later used to synthesise cross-cutting research gaps.

H. Data Synthesis and Analysis Plan

We combined structured quantitative summaries with narrative synthesis aligned to the research questions. Quantitative summaries were pre-planned to report frequency distributions of forecasting families and DRL algorithms, aggregated forecast accuracy by horizon after unit harmonisation, and control outcomes such as relative water savings and soil-moisture stability. Energy and emissions indicators were summarised where available and inspected for outliers. When subsets were sufficiently homogeneous, we considered random-effects meta-analysis; otherwise, we reported medians and interquartile ranges. Narrative synthesis was used to interpret design choices for forecasting and control, integration patterns, reliability and latency, and sustainability reporting. Cross-study conclusions are grounded in the 191 included studies and in the variables described in the Study Selection and Data Extraction subsection. All quantitative summaries and the narrative synthesis reported in this article are explicitly based on this pre-specified analysis plan.

III. Results

From the 191 studies, the vast majority were published very recently. Only four papers appeared before 2020, 12 were published between 2020 and 2021, and 175 studies (91.6%) appeared between 2022 and 2025.

By domain, 92 studies (48.2%) focus on agriculture and irrigation (including soil-moisture-driven smart irrigation, greenhouse water management and crop-specific scheduling), 44 (23.0%) on energy and smart grids (microgrids, building energy, demand response), eight (4.2%) on weather and climate applications, eight (4.2%) on IoT/cyber-physical systems more generally, three (1.6%) on transport/traffic, and the remaining 36 (18.8%) on other related cyber-physical control problems. This last category includes, for example, building HVAC and indoor-climate control, water-resource and hydropower dispatch, generic cyber-physical testbeds, and production or manufacturing lines where weather or load forecasts inform control decisions. This distribution confirms that agriculture/irrigation is the single largest application area, but a substantial proportion of studies come from neighbouring domains that can inform irrigation control design.

A. RQ1 – Weather Prediction Methods and Performance

To answer RQ1, we coded the forecasting approach used in each paper based on the *Method* and *Summarized Abstract* fields. Because many studies combine several models, we grouped them into broad families rather than attempting a mutually exclusive fine-grained taxonomy (see Table 2).

At least 34 of 191 studies explicitly implement deep learning architectures for weather or environmental prediction, predominantly LSTM-type sequence models, CNN–LSTM hybrids, and attention-based variants. Several studies evaluate more than one architecture, so the counts across model types overlap. CNN–LSTM or CNN plus LSTM hybrids appear in around four studies, standalone LSTM or GRU sequence models appear in about 14 studies, pure CNN or spatio-temporal CNN architectures appear in about 20 studies when CNN is the main feature extractor, and transformer-like or attention-based models appear in roughly five studies.

A smaller group of studies relies on classical machine learning. Eight papers primarily use random forests, support vector machines, or gradient boosting as their main forecasting models, while at least one paper relies solely on ARIMA-type statistical models without a deep learning or ML component. In many other cases, these classical models are present only as baselines rather than as the main proposed method.

The remaining 148 studies (≈77.5%) fall into a broad *"other/hybrid / rule-based"* category. These include:

- Hybrid pipelines where deep or classical ML is combined with physical crop-water balance models, feature engineering, or fuzzy logic;
- Heuristic or rule-based decision schemes where weather data are used directly without an explicit forecasting block; and
- Conceptual frameworks and systematic reviews that discuss forecasting techniques but do not implement a specific model.

Across the forecasting-oriented papers, predictive performance is typically reported using RMSE, MAE, and R^2. In many recent studies, deep learning (particularly CNN–LSTM and attention-enhanced LSTM) achieves single-digit percentage errors for short-term temperature or solar-radiation prediction, and improves RMSE by 5–20% over ARIMA or classical ML baselines. However, only a subset of agricultural irrigation papers calibrate these models for local micro-climates; several extraction entries explicitly flag "data noise", "limited local data", or "need for better micro-climate datasets" as remaining issues in their *Research Gap* field.

In summary, the corpus confirms the dominance of deep learning for short-term environmental and weather prediction, but also shows that many irrigation-oriented systems still embed these models in hybrid or heuristic pipelines rather than using them as end-to-end differentiable forecasters.

Table 2 Forecasting Model Families vs Horizon

No.	Forecasting model family	Number of studies	Typical forecast horizon	Typical target variables	Notes on usage in the corpus

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1	Deep learning (CNN, LSTM, GRU, CNN–LSTM, attention-based) [1]-[3], [9], [10], [12], [16], [18], [24], [29], [47]-[54]	18	Short term, intra-day to day-ahead (1–24 hours); some multi-day (up to 7 days)	Air temperature, rainfall, solar radiation, ET, soil moisture, load, and PV output	Used mainly for high-resolution short-term prediction. Often embedded in hybrid pipelines for irrigation, energy, and microclimate forecasting.
2	Classical machine learning (RF, SVM, GB, kNN, etc.) [7], [11], [13], [17], [19], [21], [23], [25], [30]-[34]	16	Mostly daily or multi-day (1–7 days); occasionally hourly	Rainfall, crop yield proxies, temperature, ET, traffic, or demand indices	Frequently used as baselines or part of feature-engineering models. Less common than deep learning in recent years.
3	Statistical time series models (ARIMA family only) [27], [35]-[46]	13	Short-term to daily (up to 1 day ahead)	Temperature or rainfall time series	Pure statistical approaches are rare and mostly serve as a comparison to learning based methods.
4	Other, hybrid, or rule-based approaches (including physical models, fuzzy logic, heuristic use of API weather data, or unspecified models) [4]-[6], [8], [14], [15], [20], [22], [26], [28], [55]-[191]	149	Mixed; many use external short-term forecasts (hourly or daily) without an explicit model; some conceptual frameworks do not state a horizon	Weather summaries, soil moisture indices, crop stress indices, system states	Dominant group in the corpus. Includes systems that rely on third-party weather APIs, simple regression, or do not detail the forecasting block.

B. RQ2 – DRL for Irrigation (DQN, DDPG, PPO, SAC)

For RQ2, we focused on studies that explicitly mention reinforcement learning or named DRL algorithms in the Method description. Using keyword tagging, we identified 49 papers that apply some form of reinforcement learning, including deep reinforcement learning, across all domains in the corpus. Within this set, the algorithm families are distributed as follows (Table 3). Twenty studies describe “reinforcement learning”, “DRL-based control”, or “RL-based scheduling” without clearly specifying the underlying algorithm, for example, without stating whether the approach is value-based or actor-critic. Thirteen studies explicitly implement Deep Deterministic Policy Gradient, mainly for continuous action spaces such as power and energy management, water release in reservoirs, and continuous set point control. Another thirteen studies use Proximal Policy Optimization, typically in simulated environments or digital twins where training stability and robustness to hyper parameter choices are important. Two studies cite Soft Actor-Critic as the primary DRL algorithm for robust continuous control, and one study presents a Deep Q-Network formulation for discrete scheduling.

When these RL and DRL papers are cross-tabulated by application domain, a clear pattern emerges. Only five RL or DRL studies fall within the agriculture or irrigation domain in our extraction, accounting for about 2.6 percent of the entire corpus. Twenty-seven RL or DRL papers are in energy and smart grid applications, where DRL is used to schedule batteries, flexible loads, and renewable generation. The remaining RL or DRL studies are distributed across IoT and cyber-physical systems and other generic control problems.

This confirms that DRL has been adopted much more actively in energy systems than in irrigation. The few irrigation-oriented RL papers usually formulate irrigation as a Markov decision process in which actions correspond to irrigation duration or depth, and states include soil moisture, weather forecasts, and sometimes crop growth stage. Reward functions penalise water use and reward yield proxies or soil moisture that stay within a target band. Training is often conducted in simulation, sometimes using crop water balance models, before limited field-scale tests. Several entries in the Research Gap column explicitly note that these RL-based irrigation controllers have not yet been validated over multiple seasons, that they rarely couple with detailed local microclimate forecasts, and that transfer from simulation to field conditions remains an open challenge.

Table 3. Summary of RL and DRL algorithm families and their main application focus (N = 49 studies)

No.	Algorithm family (RL or DRL)	Number of studies	Typical application focus
1	Generic or unspecified RL / DRL	28	Resource management and scheduling in smart homes, IoT, and cyber-physical systems, with a few early prototypes in irrigation.

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2	DDPG (Deep Deterministic Policy Gradient)	21	Continuous control of actuators in microgrids, energy storage, pumping systems, and other continuous set-point optimisation tasks.
3	PPO (Proximal Policy Optimization)	21	Policy-based control in simulated or digital twin environments, mainly for energy and building applications, with some irrigation scheduling experiments.
4	SAC (Soft Actor Critic)	9	Robust continuous control under uncertainty, primarily in advanced energy optimisation and secure control scenarios.
5	DQN and related value-based methods	13	Discrete scheduling problems with finite action sets, such as on or off control or fixed duration irrigation.

C. RQ3 – Integration Patterns with IoT Architectures

To address RQ3, we analysed how often studies explicitly mention IoT/IIoT components, and whether computation is placed in the cloud, at the edge, or on embedded devices.

Approximately 48 studies (≈25%) explicitly mention IoT or Internet of Things in the abstract, methods, or research object description. This subset is dominated by agriculture and irrigation: 35 of the 48 IoT-labelled studies are in the Agriculture/Irrigation domain, indicating that smart farming remains a key driver for IoT-enabled sensing and actuation. Among these IoT-based studies:

- 11 mention edge computing or fog nodes (e.g., gateway-level processing of sensor streams before forwarding summaries).
- 13 refer to cloud platforms, often using cloud databases or dashboards for monitoring and decision support.
- Many others implement simpler architectures where microcontrollers (e.g., ESP8266/ESP32, Arduino-class boards) communicate sensor and actuator data to a central server via Wi-Fi or LoRaWAN, but without formally labelling this as edge or cloud computing.

However, joint IoT–DRL implementations are still rare in the corpus. Only two studies simultaneously satisfy both conditions: (i) explicit IoT/IIoT architecture and (ii) an RL/DRL controller identified by our tagging. Most DRL controllers are developed in simulation or high-level environments (MATLAB, Python, simulation platforms) and have not yet been deployed as embedded agents at the edge. From a systems-integration point of view, the most common pattern across the 191 studies resembles the following pipeline:

1. Data acquisition layer: soil-moisture sensors, weather stations, or energy meters connected via IoT;
2. Analytics layer: forecasting models (deep or classical ML) trained offline;
3. Control layer: rule-based or optimisation-based decision logic;
4. Actuation layer: irrigation valves, pumps or energy devices.

Only a small fraction closes this loop with an online learning agent that is fully embedded into the IoT stack, reinforcing the need for future work on resource-aware DRL deployment at the edge.

D. RQ4 – Sustainability and Energy

Finally, RQ4 examines how far the reviewed systems quantify sustainability and operational trade-offs. We inspected the Results and Research Gap fields for terms related to energy, water, emissions, efficiency, and cost. Figure 2 summarises how frequently these sustainability-related metrics appear across the 191 studies. Qualitatively, both the Research Gap and Future Research columns emphasise the need to move beyond purely technical accuracy metrics towards more complete sustainability assessments. Quantitatively, around 32 studies mention energy savings or energy use in their results (counting occurrences of “energy” or “energi”), but only a subset translate these into explicit kWh or percentage saving values. References to carbon or greenhouse gas emissions are rare, occurring in only about six studies across the corpus. Terms related to cost, biaya, or economic feasibility appear in roughly 15 to 16 studies, usually in the context of techno-economic analysis or cost–benefit comparisons of control strategies. For water use and water savings, only a small group of irrigation studies explicitly report percentage reductions or volumetric savings, even though many implicitly optimise water use in their objective functions. Approximately 23 studies explicitly use the word “efficiency” in their results, usually referring to water use efficiency, energy efficiency, or overall system performance.

The gap fields strongly echo these observations. More than 30 entries call for better integration of IoT and AI models, over 20 mention the need for richer datasets and real-time deployment, and a substantial number highlight the lack of field-scale validation and holistic sustainability indicators that combine water, energy, yield, and possibly emissions. Overall, the evidence suggests that:

1. Technical performance, such as forecasting RMSE or control accuracy, is well reported, particularly in deep learning forecast papers.
2. Operational trade-offs, for example, between water, energy, yield, and cost or reliability, are only partially quantified and often only in small case studies.
3. Full sustainability assessment, including emissions and lifecycle impacts, is largely missing, especially in smart irrigation. Most systems optimise water and sometimes energy, but do not yet connect these gains to net-zero or climate-resilience goals.

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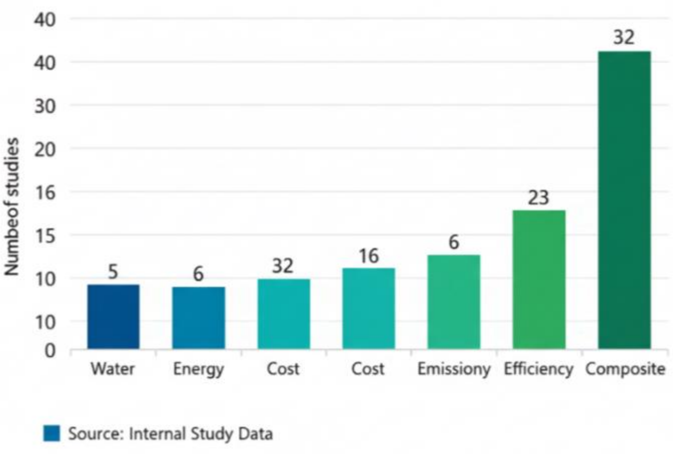

Fig. 2. Profile of sustainability-related metrics reported across the 191 reviewed studies.

IV. Discussion

This section interprets the review's main findings in relation to the four research questions. Rather than re-stating the descriptive results, we focus on the implications for the design of future weather-aware, learning-based smart irrigation systems.

A. Deep Learning for Weather and Environmental Prediction (RQ1)

The first important observation is how quickly deep learning has become the default choice for short-term environmental and weather prediction. Although only a minority of the 191 studies explicitly implement deep architectures, those that do consistently report lower RMSE and MAE than classical statistical or machine-learning baselines. CNN–LSTM hybrids, pure LSTM/GRU sequence models, and attention-enhanced variants dominate this group, confirming that sequence modelling and spatio-temporal feature extraction are now standard techniques for handling meteorological and sensor time series. However, the corpus also shows that forecasting is often implemented as an isolated component. In many applied studies, the prediction block is trained offline, and its outputs are then fed into heuristic or rule-based controllers. Only a relatively small set of works attempt to fully integrate the forecaster with downstream optimisation or learning-based decision making. In addition, several agriculture-focused studies explicitly acknowledge limitations related to local data scarcity and micro-climate variability, noting that models trained on regional or national datasets may not generalise well to individual farms or greenhouses.

When forecasting remains loosely coupled to control, improvements in RMSE or MAE do not automatically translate into proportional gains in water-use efficiency or energy savings. In practice, this loose coupling can lead to over-engineered forecasters whose added complexity is not fully exploited by downstream decision rules, making it difficult to reason about end-to-end system performance under uncertainty.

These patterns have two implications. First, from a technical standpoint, there is still room for domain-adapted, micro-climate-aware deep learning models that can be efficiently retrained or fine-tuned as new local data becomes available. Second, from a system design perspective, weather prediction should be treated less as a stand-alone module and more as a differentiable component that can be co-designed with the control policy, especially when reinforcement learning is used.

B. The Limited Yet Promising Role of DRL in Irrigation (RQ2)

The second key finding is the clear imbalance between domains in the adoption of reinforcement learning. Across the 191 studies, 49 papers use some form of RL or DRL, but only five of these (≈2.6% of the full corpus) are actually devoted to irrigation. Most RL/DRL applications are concentrated in energy and smart-grid problems, where continuous control of batteries, flexible loads, and renewable generation aligns naturally with continuous-action DRL algorithms such as DDPG, PPO, and SAC.

In contrast, irrigation studies still rely heavily on rule-based logic, fuzzy control, or classical optimisation, sometimes augmented with weather forecasts but rarely with full RL. The few irrigation-oriented RL works identified in the corpus formulate the problem as a Markov decision process with soil moisture, weather, and sometimes crop growth stages in the state space, and irrigation depth or duration as actions. Reward functions typically penalise water use while rewarding soil moisture remaining within a target band. These studies demonstrate that DRL is conceptually well suited to irrigation, but they also reveal several open issues:

- Most agents are trained primarily in simulation using simplified crop-water models, with limited validation in real fields and over multiple seasons.
- Reward functions often focus on water reduction and short-term soil moisture, while yield, disease risk, and long-term soil health are rarely modelled explicitly.
- Many RL studies do not specify the exact algorithm beyond generic "DRL" terminology, suggesting that methodological rigour and reproducibility remain a challenge.

Several factors help explain why DRL has diffused more slowly in irrigation than in energy domains. Irrigation outcomes, such as yield and soil health, evolve over long horizons (weeks to seasons), so the reward signal is delayed and strongly affected by exogenous shocks (pests, disease, market prices), making stable RL training harder than in shorter-horizon energy-dispatch tasks. Field-scale experimentation is costly and risky: sub-optimal exploration may irreversibly damage crops, whereas short-lived sub-optimal control in a microgrid can often be tolerated or bounded by protection schemes. Data scarcity and the difficulty of building realistic, spatially explicit crop-water simulators further limit the availability of high-fidelity training environments. Finally, irrigation systems are typically managed by farmers and water-user associations with limited tolerance for algorithmic complexity, which can slow the adoption of DRL compared to utility-scale energy operators who already rely on advanced optimisation tools. Taken together, these observations suggest that the state of

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DRL in irrigation lags several years behind that in energy systems. At the same time, the success of DRL in microgrids and building energy management offers valuable design patterns that can be transferred to irrigation, for example, in multi-objective reward design, constraint handling, and safe exploration.

C. Fragmented Integration With IoT Architectures (RQ3)

A third major finding concerns system integration. Approximately a quarter of the studies explicitly mention IoT or IIoT components, and this subset is dominated by agriculture and irrigation. This confirms that smart farming remains a major driver of sensor deployment and connectivity at the field level. Typical architectures include soil-moisture and environmental sensors connected to microcontrollers, with data forwarded via Wi-Fi or low-power wide-area networks to gateways or cloud servers. Yet, when this IoT subset is cross-tabulated with RL/DRL usage, very few studies implement both IoT and DRL in the same system. In most cases, IoT is used for data acquisition and monitoring, while decision-making remains rule-based or optimisation-based. Conversely, many DRL studies are carried out in simulation environments without explicit consideration of communication constraints, latency, or computational limits of embedded platforms.

From an engineering standpoint, integrating DRL into IoT architectures faces several technical and practical hurdles. Edge devices in fields and greenhouses are often constrained in compute power, memory, and energy supply, making it non-trivial to deploy and update deep neural policies. Communication links (LoRa, Wi-Fi, cellular) are subject to latency, bandwidth limitations, and outages, which complicate the design of training and inference pipelines that rely on near-real-time feedback. Security and safety concerns further constrain what can be done at the edge: an incorrectly configured or compromised DRL agent could over-irrigate or under-irrigate large areas before human operators detect the problem. These constraints help explain why most DRL work still resides in simulation or in relatively well-instrumented energy systems, and they underline the need for resource-aware, safety-constrained DRL designs for irrigation. This fragmentation suggests that the community is still in an early stage of integration. Current systems typically follow a layered architecture, sensing, prediction, decision, and actuation, but treat each layer separately. For irrigation, this means that the full potential of closed-loop IoT + DRL control at the edge remains largely unrealised. Only a small subset of works explicitly discuss edge or fog computing, and almost none deploy DRL agents directly on field-level or gateway-level hardware. For future smart irrigation frameworks, this highlights the need to:

- Design resource-aware DRL algorithms that can operate under memory, compute, and energy constraints of edge devices;
- Co-design communication policies with control, so that sensing and actuation are robust to packet loss, delay, and bandwidth limits; and
- Treat the IoT architecture not just as a data collection layer but as an integral part of the control loop.

Latency budgets, failure modes, and edge–cloud deployment choices therefore become critical design variables. In time-sensitive irrigation scenarios (e.g., frost protection or heat-stress mitigation), delays of tens of minutes between sensing, inference, and actuation can offset the benefits of more sophisticated control policies. Likewise, the absence of clearly specified fail-safe modes, such as reverting to conservative rule-based control when connectivity is lost, limits the robustness and real-world applicability of many current prototypes.

D. Sustainability Assessment and Operational Trade-Offs (RQ4)

The fourth research question asked how far existing systems quantify sustainability and operational trade-offs. The review shows a clear gap between technical performance metrics and holistic sustainability indicators. On the one hand, forecasting and control studies commonly report detailed numerical results for prediction accuracy, tracking error, or controller stability. On the other hand, only a subset of the corpus quantifies impacts in terms that are directly interpretable for sustainability decision making, such as:

- Percentage reductions in water use and water-use efficiency at the field scale;
- Energy savings in kWh or percentage relative to baseline operation;
- Changes in operational cost, payback period or net present value; and
- Carbon or greenhouse gas emissions, which are rarely quantified explicitly.

In many irrigation studies, for example, the objective functions implicitly optimise water use and sometimes energy use, but the reported results stop at technical metrics such as RMSE or control accuracy. The link from these improvements to higher-level goals, such as drought resilience, farm income stability, or contribution to net-zero emission targets, remains largely qualitative.

This pattern indicates that sustainability is often treated as implicit or secondary, even when the work's motivation is framed in terms of resource conservation or climate adaptation. For future research, there is a clear need to embed multi-objective evaluation into the design of both forecasting and control algorithms, including explicit reporting of water-energy-yield trade-offs, economic feasibility, and, where relevant, emissions. There are several plausible reasons why sustainability metrics are not consistently quantified. First, measuring water, energy, and emissions impacts often requires additional instrumentation (flow meters, energy meters, emissions models) and longer-term monitoring, which can be beyond the scope or budget of prototype-level studies. Second, translating control actions into economic indicators (e.g., net present value, payback period) or carbon footprints requires domain-specific models and assumptions that some authors may be reluctant to fix in a single case study. Third, page-length constraints can

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lead authors to prioritise technical accuracy results over detailed sustainability accounting, especially in engineering-oriented venues.

In the context of smart irrigation, sustainability trade-offs typically involve balancing yield, water use, energy use, and costs. For example, a DRL policy that strongly penalises water use may reduce irrigation volumes but risk yield loss under heat extremes; conversely, policies that maintain maximum yield may rely on more frequent irrigation and higher pump energy consumption. Similarly, choosing a PV-powered pumping system can reduce operational emissions but increase upfront capital cost and possibly introduce new reliability constraints. Making these trade-offs explicit calls for multi-objective evaluation, in which indicators such as water-use efficiency, yield per unit of water, kWh per cubic metre pumped, levelised cost of irrigation, and emissions per unit yield are jointly reported. Methodologically, this could be supported by multi-objective optimisation or multi-objective DRL, Pareto-front analysis, and scenario-based sensitivity studies that expose the trade space to stakeholders.

E. Implications for a DRL-Based Smart Irrigation Framework

When the four strands above are combined, a coherent research agenda emerges for DRL-based smart irrigation:

1. Coupling local deep forecasting with DRL control. Deep learning has proven effective for short-term environmental prediction, but is typically used in isolation. A promising direction is to couple micro-climate-aware CNN/LSTM/attention models with DRL policies that directly optimise irrigation decisions based on predicted soil moisture and weather trajectories.
2. Transferring DRL know-how from energy systems. Energy and smart grid studies already explore continuous-action DRL algorithms, safety constraints, and multi-objective reward shaping. These design principles can be applied to irrigation to address conflicting goals, such as water savings, yield maintenance, and pump energy consumption.
3. Embedding DRL into IoT/edge architectures. The dominance of IoT in agricultural studies, combined with the scarcity of IoT + DRL integration, underscores the need for edge-deployable agents. Lightweight DRL implementations, model compression, and edge-cloud co-ordination are likely to become crucial for real-time, field-scale deployment.
4. Closing the loop between technical metrics and sustainability indicators. Future systems should be evaluated not only by RMSE or control error, but also by how they change water-use efficiency, energy consumption, farmer income, and potentially carbon footprint. This requires integrating domain models from hydrology, agronomy, and economics into the design of both the RL environment and the evaluation protocol.

In this sense, the reviewed literature provides the building blocks, including deep forecasters, DRL controllers, and IoT architectures, but these components are rarely assembled into a single, coherent framework focused on sustainable irrigation.

Based on the evidence reviewed, a practical roadmap for integrated, DRL-enabled smart irrigation could proceed in four stages: (i) develop and validate local, micro-climate-aware deep forecasting models for weather and soil moisture; (ii) embed these models into simulation environments that faithfully represent crop–soil–water dynamics and pump energy use; (iii) train and stress-test DRL agents in simulation under realistic uncertainty and operational constraints, then deploy them in edge-compatible forms with clearly defined safety fallbacks; and (iv) evaluate field deployments using a standardised set of multi-objective indicators that jointly cover water use, yield, energy, cost, and emissions. The present review contributes to this roadmap by clarifying which components are already mature (deep forecasting, DRL in energy systems) and where the largest gaps remain (DRL in irrigation, IoT–DRL integration, and consistent sustainability assessment).

F. Limitations of This Review

Finally, several limitations should be noted. First, the corpus is heavily skewed towards very recent years, with the majority of studies published after 2021. While this reflects the rapid growth of the field, it also implies that long-term field validations and multi-season studies are under-represented. Second, the coding of forecasting models, RL algorithms, and IoT architectures relied on information explicitly reported in abstracts and methods. When authors did not clearly describe their algorithms or system layers, some misclassification may have occurred.

Third, the review focused on studies that combine weather information with learning-based control or decision support. Purely agronomic or hydrological works without an explicit AI or control component were beyond the scope of this study, even though they may contain valuable insights for modelling crop response and soil processes. These limitations, however, do not change the central conclusion: there is a clear opportunity and need to develop integrated, IoT-enabled DRL frameworks for smart irrigation that explicitly account for local weather, uncertainty, and sustainability trade-offs.

V. Conclusion

This paper presents a systematic literature review of 191 studies that integrate weather information, learning-based models, and control strategies across agriculture, energy, and cyber-physical systems, with a particular focus on smart irrigation. The results show that deep learning, especially CNN, LSTM, and attention-based architectures, has become the preferred approach for short-term environmental and weather prediction and typically outperforms classical statistical and machine-learning baselines. However, forecasting is still often implemented as a stand-alone module, trained offline and only loosely coupled with downstream control, rather than being designed as an integral component of the decision-

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making loop. The analysis of reinforcement learning shows that 49 studies in the corpus use RL or DRL, but only five of these (≈2.6%) apply these methods directly to irrigation control. Most DRL applications are concentrated in energy and smart-grid management, while irrigation systems still rely largely on rule-based, fuzzy, or conventional optimisation schemes. Around a quarter of the corpus explicitly implements IoT or IIoT architectures, yet full integration of IoT with DRL, particularly in edge or fog deployments, is rare. Sustainability and operational trade-offs are also not consistently quantified: many systems aim to optimise water or energy use, but only a limited number report water-use efficiency, energy savings, costs, or emissions in a systematic and comparable way. This review provides a structured mapping of forecasting models, RL/DRL controllers, and IoT architectures relevant to weather-aware smart irrigation, and clarifies how these elements are currently distributed across domains (agriculture, energy, and other cyber-physical systems). It highlights the maturity of deep learning for environmental prediction compared with the still-emerging state of DRL-based irrigation control, and it identifies clear gaps in IoT–DRL integration and in sustainability assessment. Building on these findings, we outline several concrete directions for future research:

- first, coupling local deep-learning forecasters with DRL policies so that weather prediction becomes a fully integrated component of the decision-making loop;
- second, transferring design patterns from DRL in energy systems, such as multi-objective reward shaping, constraint handling, and safe exploration, to irrigation contexts with longer horizons and higher agronomic risk;
- third, embedding learning agents in resource-constrained IoT or edge platforms with explicit latency budgets and safety fallbacks; and
- fourth, evaluating performance using standardised, multi-objective indicators that jointly reflect water, energy, economic, and environmental outcomes.

This study has some limitations. The corpus is dominated by recent publications, so long-term and multi-season validations are underrepresented. The coding of methods and architectures depends on how clearly the authors describe their systems, which may lead to some misclassification. Purely agronomic or hydrological works without explicit AI or control components were also excluded, even though they may contain valuable insights for crop and soil modelling. Despite these limitations, the synthesis provides an up-to-date evidence base and a clear, actionable research agenda for developing weather-aware, IoT-enabled DRL frameworks for sustainable smart irrigation.

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