

AI for Resource Security: Leveraging Predictive Analytics for Sustainable Management of Water, Energy, and Food Supplies in Arid Climates

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Abstract

Arid and semi-arid regions face intensifying pressure on limited water, energy, and food (WEF) resources as population growth and climate change amplify cross-sector dependencies. Artificial intelligence (AI), particularly predictive analytics, can support a shift from reactive resource management toward anticipatory forecasting, allocation, and maintenance. This study presents a systematic literature review of peer-reviewed research indexed in Scopus, Web of Science, and IEEE Xplore from January 2016 to March 2024. After deduplication, 842 unique records were screened, 157 full texts were assessed, and 29 empirical studies focused on arid or semi-arid contexts were included. The review maps AI methods, applications, datasets, regional contexts, performance measures, and implementation constraints across the WEF nexus. Long Short-Term Memory (LSTM) and related deep-learning models dominate time-series forecasting, while optimisation and digital-twin approaches support irrigation, water allocation, desalination, network operation, and energy-management decisions. The synthesis identifies a scalability paradox: regions with the greatest potential benefit frequently have the lowest adoption capacity because of sparse data, weak digital infrastructure, institutional fragmentation, cost, skills gaps, and limited trust in opaque models. A multi-level framework is proposed that links open and interoperable data, low-bandwidth and explainable AI, local co-design, capacity development, and cross-sector governance. Technical performance is necessary but insufficient; equitable resource security depends on aligning AI deployment with context-specific data, institutional readiness, and ethical safeguards.

Keywords: Artificial Intelligence, Water-Energy-Food (WEF) Nexus, Resource Security, Arid Climates, Predictive Analytics.

1 Introduction

The stable and sustainable availability of water, energy, and food is directly related to human security and development (Willis et al., 2016). In arid environments, long-term water scarcity intensifies the interdependencies represented by the Water-Energy-Food (WEF) nexus (Liu et al., 2020): water is required for energy production, energy is required for water treatment and distribution, and both are essential to food production (De Laurentiis et al., 2016; Farrokhzadeh et al., 2020; Jägermeyr et al., 2016). These dependencies are especially acute in drylands, where water scarcity increases reliance on energy-intensive desalination, pumping, treatment, and cooling while agricultural demand remains high (Kashifi et al., 2022). The synthesis therefore prioritises arid-region irrigation, water allocation, desalination, energy-water coupling, and food-system resilience. Selected adjacent infrastructure studies on building-energy modelling and circular material

use are cited only to illustrate transferable resource-efficiency and systems-integration principles, not as direct WEF performance evidence (Al-Azazi, 2026b; Alkhatib et al., 2021; Bangalore Ramu et al., 2025; Mohammed et al., 2025). Integrated management must also account for Sustainable Development Goal interactions and systemic uncertainty (D'Amore et al., 2022; Ahmad et al., 2021; Ermolieva et al., 2021).

Conventional resource-management systems frequently operate reactively, with interventions initiated only after scarcity reaches a critical threshold; this approach is poorly suited to the hydrological uncertainty of arid zones (Ajami et al., 2008; Hunter et al., 2015). AI can support a substantive shift toward proactive and anticipatory management (Chang et al., 2023), with predictive analytics enabling early warning, demand forecasting, allocation, and maintenance planning (Núñez-López et al., 2021). Machine-learning (ML) and deep-learning (DL) algorithms can process large, heterogeneous datasets from remote sensing and Internet of Things (IoT) sensors to forecast demand and supply and improve resource allocation across the nexus (Mahardhika & Putriani, 2023). Applications range from daily evapotranspiration prediction (Pino-Vargas et al., 2022) to urban-water-system optimisation (Fu et al., 2023) and water-stress prediction (Gorlapalli et al., 2022).

This review evaluates both the potential and the limits of predictive analytics for WEF security through a systematic, cross-sectoral synthesis. It identifies the scalability paradox: locations with the highest potential gains often have the lowest capacity to generate data, maintain digital infrastructure, coordinate institutions, finance deployment, and build stakeholder trust. Increased digital integration also introduces cybersecurity and data-governance risks (Al-Azazi, Alawag, et al., 2025; Al-Tayar et al., 2025). Evidence from adjacent safety and infrastructure research is used only to interpret transferable implementation risks, rather than as direct WEF performance evidence. The review concludes with a multi-level framework linking technical options to institutional, socio-economic, and ethical conditions.

Existing reviews commonly examine AI in water management, deep learning in hydrology, or the WEF nexus at a broad conceptual level (Hassan et al., 2025; Qasem et al., 2025). They rarely combine three features in one evidence synthesis: restriction to arid and semi-arid settings; comparison of predictive applications across water, energy, and food; and evaluation of deployment conditions alongside reported model performance. Accordingly, this review has three objectives: (1) identify the principal AI and predictive-analytics methods used for WEF management in arid settings; (2) synthesise their applications, performance measures, datasets, baselines, and regional contexts; and (3) explain how data, infrastructure, institutional, cost, and trust constraints shape scalability and equitable adoption. The third objective develops the scalability paradox as the review's conceptual contribution.

2 Research Method

The current study employs a Systematic Literature Review (SLR) to identify, appraise, and synthesise evidence on AI-supported WEF security in arid and semi-arid contexts. A predefined search, screening, quality-appraisal, and data-extraction protocol was used to improve transparency and repeatability.

2.1 Search Strategy

Scopus, Web of Science Core Collection, and IEEE Xplore were searched for peer-reviewed studies published between January 2016 and March 2024. The search combined three concept blocks: WEF/resource terms, AI/predictive-analytics terms, and aridity terms. Database syntax was adapted as follows:

Scopus: TITLE-ABS-KEY(("water-energy-food" OR "WEF nexus" OR "water management" OR "energy system*" OR "food security") AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "predictive analytics") AND (arid OR "semi-arid" OR dryland* OR "water scarcity")).

Web of Science: TS= (("water-energy-food" OR "WEF nexus" OR "water management" OR "energy system*" OR "food security") AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "predictive analytics") AND (arid OR "semi-arid" OR dryland* OR "water scarcity")).

IEEE Xplore: (("All Metadata": "water-energy-food" OR "All Metadata": "WEF nexus" OR "All Metadata": "water management" OR "All Metadata": "energy systems" OR "All Metadata": "food security") AND ("All Metadata": "artificial intelligence" OR "All Metadata": "machine learning" OR "All Metadata": "deep learning" OR "All Metadata": "predictive analytics") AND ("All Metadata": arid OR "All Metadata": "semi-arid" OR "All Metadata": dryland OR "All Metadata": "water scarcity")).

Search results were exported to a shared spreadsheet and deduplicated first by DOI and then, where a DOI was unavailable, by normalised title, first author, and publication year. The 842 records reported in Figure 1 are the unique records retained after deduplication. Searches were not restricted by country name; arid or semi-arid relevance was verified during screening.

2.2 Study Selection and Criteria

Two authors independently screened the titles and abstracts of 842 unique records against the eligibility criteria. The same two authors then assessed 157 full-text articles, recorded reasons for exclusion, and resolved disagreements through discussion and consensus; a third author was consulted when consensus could not be reached.

- i. Inclusion criteria: studies had to (i) apply AI, ML, DL, optimisation, or predictive analytics; (ii) address at least one WEF sector or an explicit nexus interaction; (iii) report empirical data, model validation, a quantitative case study, or a documented operational application; and (iv) concern an arid or semi-arid context or directly address resource management under arid-region conditions.
- ii. Exclusion criteria: conceptual-only papers, non-arid applications without direct transfer relevance, reviews without a new empirical synthesis, non-peer-reviewed items, duplicate records, and studies lacking sufficient methodological or outcome detail were excluded. Following full-text assessment, 29 studies met all criteria and were included in the synthesis.

2.3 Quality Appraisal and Data Extraction

The 29 included studies were appraised using a structured checklist covering clarity of the objective and arid-region context; adequacy of dataset description; appropriateness and validation of the AI method; transparency of the comparator or baseline and performance metrics; and reporting of limitations, transferability, and implementation barriers. Appraisal results informed the interpretive weight given to each finding but did not result in further exclusions. Data extraction captured bibliographic details, region, WEF sector, dataset source and scale, AI model, comparator or baseline, validation design, performance metric, reported benefit, and data, infrastructure, institutional, cost, trust, and adoption constraints. Two authors cross-checked the completed extraction sheet and resolved discrepancies by consensus.

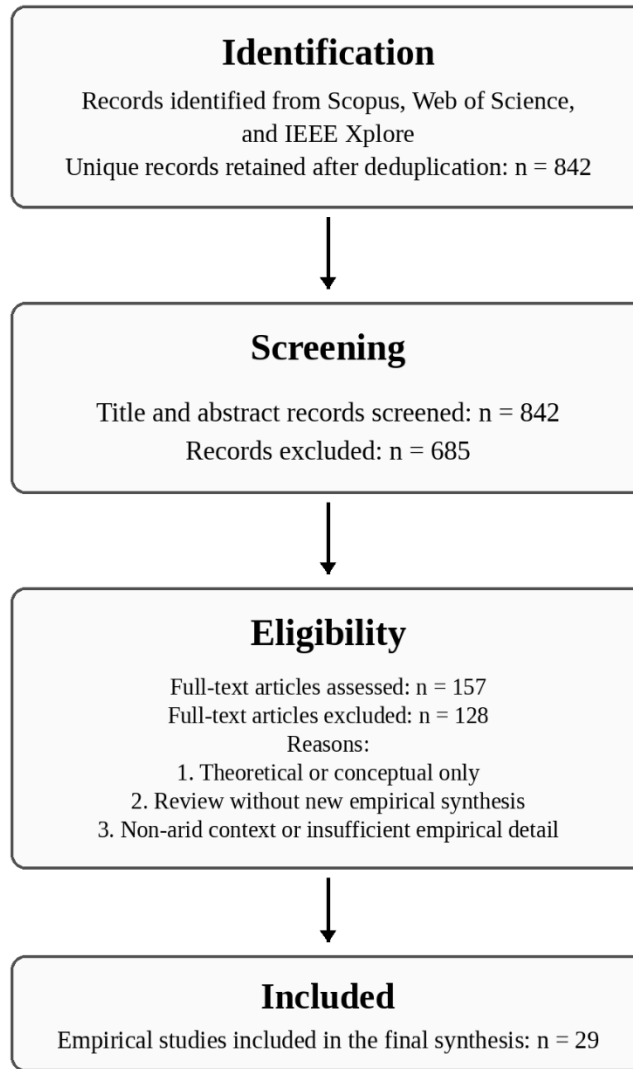


Figure 1. Study-selection flow for the systematic literature review

3 Results and Discussion

3.1 State-of-the-Art AI Applications in WEF Management

The 29-study evidence base shows measurable gains from AI applications across forecasting, optimisation, and decision support. As summarised in Table 1, LSTM and other neural-network models are used primarily for time-series forecasting, including irrigation demand and rainfall, whereas optimisation methods and digital twins support network operation, desalination, and integrated infrastructure decisions. LSTM performance is strong where temporal dependencies and sufficiently consistent local data are available (Mohammed et al., 2023; Tanchangya et al., 2024). However, model choice remains task- and data-dependent; therefore, Table 1 presents application patterns rather than a universal ranking. Computational methods in adjacent infrastructure domains are cited only as transferable examples of optimisation under environmental loads (Alkhatib et al., 2024).

Table 1. Taxonomy of Common AI Models in WEF Nexus Research

Model Category	Specific Model/Technique	Primary Application(s)	Key Source(s)
Neural Networks	Long Short-Term Memory (LSTM)	Time-series forecasting for irrigation needs and rainfall prediction.	Mohammed et al. (2023); Tanchangya et al. (2024)
	Deep Learning (General)	Rainfall prediction and evapotranspiration forecasting.	Tanchangya et al. (2024); Pino-Vargas et al. (2022)
Ensemble Methods	XGBoost	Comparative modelling for irrigation requirements.	Mohammed et al. (2023)
Kernel-Based	Support Vector Regression (SVR)	Comparative modelling for irrigation requirements.	Mohammed et al. (2023)
Optimisation & Simulation	AI-driven Optimisation	Optimising water distribution networks and desalination plant efficiency.	Ramirez et al. (2022); Krishnan et al. (2022)
	Digital Twins	Integrated management of urban water and energy infrastructure.	Fu et al. (2023)

Despite these advances, the reviewed literature identifies structural barriers to large-scale deployment. Data scarcity and bias can reduce model reliability; institutional silos constrain cross-sector coordination; and opaque models can weaken stakeholder trust (Al-Azazi et al., 2026; Al-Tayar et al., 2025; D'Amore et al., 2022; Richards et al., 2023). Evidence from other digital-infrastructure sectors is used here only to interpret transferable adoption and transparency challenges. Figure 2 summarises the reinforcing mechanism: limited data produce poorly calibrated or opaque models, low confidence reduces adoption and data sharing, and the resulting lack of new data perpetuates the initial constraint.

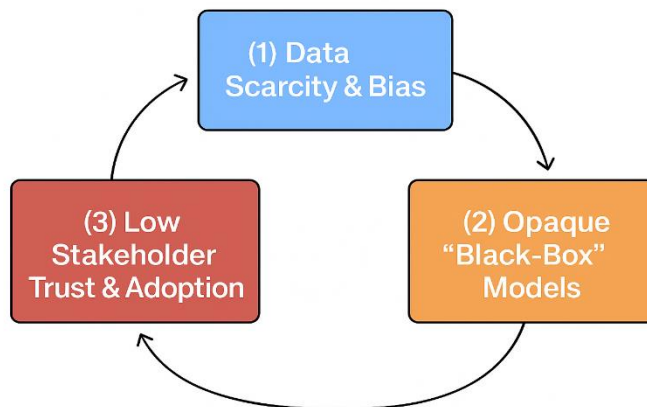


Figure 2. Vicious cycle of AI implementation barriers

Reported benefits are study-specific and should not be interpreted as pooled effects. In the Saudi date-palm experiment by Mohammed et al. (2023), LSTM models were tested using meteorological variables and palm

age across four solar-powered micro-irrigation systems; the reported R-squared values and water-saving ranges are therefore tied to that crop, climate, dataset, and experimental configuration. The urban-network, desalination, groundwater, and rainfall findings summarised in Table 2 likewise reflect their source regions, datasets, and conventional or unoptimised comparators. Table 2 identifies these contexts so that performance claims are interpreted within the scope of, rather than beyond, the original evidence.

Table 2. Key Applications and Performance Metrics of AI in Water Management

Application Area	AI Technique/Model		Context/Region		Key Performance Metric(s)	Source(s)
Smart Irrigation	LSTM Networks	Neural	Saudi Arabia; date palms; sensor-based solar micro-irrigation		R ² =0.90–0.92; 18–30% water savings	Mohammed et al. (2023)
Water Distribution	AI-driven Optimisation		Jordan; national strategy scenarios	WEF	15-30% efficiency enhancement	Ramirez et al. (2022)
Desalination	Predictive Optimisation		Industrial systems; review-based evidence	water	10–20% energy savings; reduced downtime	Krishnan et al. (2022)
Urban Water Networks	Digital Twins, ML		Urban infrastructure; perspective and case evidence	water	20–35% water/energy savings	Fu et al. (2023)
Groundwater Mgmt.	Predictive Modelling		Arid and semi-arid groundwater evidence	case	Improved sustainable extraction planning	Zaresefat & Derakhshani (2023); Pittock, J., et al. (2016)
Rainfall Prediction	Deep Learning		Semi-arid rainfall-forecasting studies		Enhanced drought preparedness	Tanchangya et al. (2024)

Table 3 extends the synthesis to energy and food systems. Energy applications emphasise load forecasting, leak detection, and predictive maintenance, while food applications emphasise crop-yield forecasting, pest and disease detection, and supply-chain loss reduction. Reported values such as up to 50% downtime reduction or 90% predictive accuracy are retained as source-specific findings and are not directly comparable because the studies use different datasets, baselines, and validation designs. Together, Tables 2 and 3 show that the strongest evidence concerns bounded operational tasks rather than fully integrated nexus-scale deployment.

Table 3. AI-driven efficiencies in energy and agricultural systems

Sector	AI Application	Reported Benefit / Metric	Context/Example	Source(s)
Energy	Predictive Maintenance	Reduced downtime by up to 50%	Hydropower (Norway)	Jeroen et al. (2024)
	Load/Usage Prediction	Enhanced grid management	Utility Operations	Alhendi et al. (2022)

	Leak Detection/Optimisation	20-35% savings	energy	Urban Distribution	Water	Fu et al. (2023)
Agriculture	Crop Yield Forecasting	Up to 90% predictive accuracy		Precision Farming		Perumal et al. (2024)
	Supply Chain Mgmt.	Reduced food wastage		Farm-to-Consumer Logistics		Anwar et al. (2023)
	Pest/Disease Detection	Increased productivity, reduced inputs		Smart Platforms	Farming	Gupta et al. (2023)

Model selection must be interpreted within a defined task, dataset, and validation design. Table 4 reproduces the testing-set R-squared values reported by Mohammed et al. (2023) for predicting irrigation-water requirements (IWR1) and electrical-energy requirements (EER1) at optimum water-use efficiency (WUE). The models compared are Long Short-Term Memory (LSTM), extreme gradient boosting (XGBoost), support vector regression (SVR), and linear regression (LR). The irrigation systems are subsurface irrigation (SIS), subsurface drip irrigation (SDIS), drip irrigation (DIS), and bubbler irrigation (BIS). Within this single Saudi date-palm study, LSTM produced the highest R-squared value for every system and outcome, but the ranking should not be generalised beyond the original data and testing design.

Table 4. Comparative performance of ML models for predicting optimum water and electrical-energy requirements (adapted from Mohammed et al., 2023)

Parameter		Irrigation System	Evaluation Metric	LSTM	XGBoost	SVR	LR
Irrigation Water		SIS	R ²	0.9256	0.8899	0.8494	0.8504
(IWR1; WUE)	optimum	SDIS	R ²	0.9245	0.8858	0.7565	0.8475
		DIS	R ²	0.9297	0.8889	0.7151	0.8534
		BIS	R ²	0.9318	0.8981	0.7595	0.8564
Electrical Energy		SIS	R ²	0.9339	0.8950	0.7575	0.8544
(EER1; WUE)	optimum	SDIS	R ²	0.9349	0.8909	0.7252	0.8534
		DIS	R ²	0.9370	0.8971	0.6878	0.8574
		BIS	R ²	0.9339	0.8930	0.7817	0.8524

Note: IWR1 and EER1 denote irrigation-water and electrical-energy requirements, respectively, when the target is optimum WUE. Values are testing-set results from Mohammed et al. (2023), based on limited meteorological inputs and date-palm age; they are not pooled estimates for all arid irrigation settings.

Figure 3 integrates the reviewed applications into a data-to-decision architecture. Sensor, remote-sensing, meteorological, policy, and economic data feed a predictive analytics engine; outputs support water, energy, and food decisions (Hassan et al., 2025; Mohammed et al., 2025; Qasem et al., 2025); and operational monitoring provides feedback for model updating. The figure is conceptual rather than a validated software

architecture, and its value is to show where cross-sector data standards, accountability, and human oversight are required.

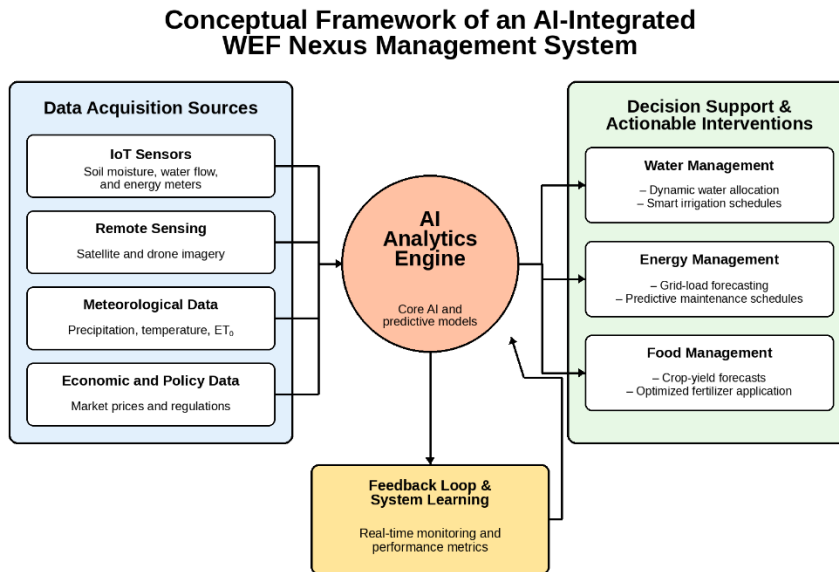


Figure 3. Conceptual framework of an AI-integrated WEF nexus management system

3.2 Discussion: The Scalability Paradox

The reviewed evidence supports the scalability paradox illustrated in Figure 4: the potential benefit of AI tends to increase with resource stress, while the capacity to implement it can decline where data systems and institutions are weakest. Performance-oriented studies commonly rely on local sensors, remote sensing, meteorological histories, or infrastructure records that are unavailable or incomplete in low-capacity settings. WEF governance studies identify sectoral institutional separation, while responsible-AI and technology-adoption studies identify capital cost, digital skills, model opacity, trust, and adoption readiness as additional constraints (D'Amore et al., 2022; Richards et al., 2023; Kasim et al., 2025). The paradox is therefore supported by the convergence of technical, institutional, and socio-economic evidence, rather than by a single model result (Al-Azazi, Alaghbari, et al., 2025).

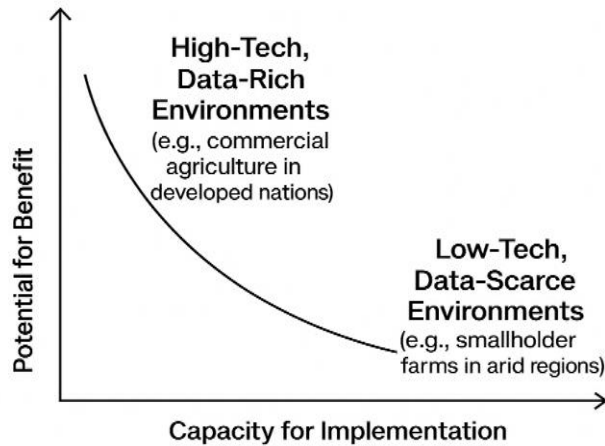


Figure 4. Scalability paradox in AI-enabled resource-security applications

Figure 4 visualises the mismatch between expected benefit and implementation capacity. Table 5 translates the underlying evidence into a multi-level response: open and interoperable repositories address fragmented or missing data; modular low-bandwidth AI-as-a-Service and capacity development address cost and skills constraints; explainable AI and living labs address trust and local validity; and cross-ministerial governance bodies and regulatory sandboxes address institutional silos, privacy, and accountability. These solutions are therefore linked directly to the barriers identified in the reviewed studies rather than presented as generic recommendations.

Table 5. A Multi-Level Framework for Overcoming AI Implementation Barriers

Barrier Category	Specific Challenge	Strategic Solution(s)
Data & Technical	Lack of localised, high-quality data; high cost of technology; skills gap.	Establish national open-access data repositories for hydrological and meteorological data, incentivising private data sharing through water credit schemes. Develop modular, affordable AI-as-a-Service platforms tailored for low-bandwidth environments. Implement 'Living Labs' frameworks where local farmers, engineers, and policymakers co-design and validate context-specific AI tools.
Institutional	Siloed governance structures; regulatory lag.	Establish cross-ministerial nexus governance bodies with budgetary authority to fund integrated projects. Create agile regulatory sandboxes for data privacy, security, and sharing to allow innovation while managing risk.
Socio-Economic	Low adoption rates are due to mistrust and high costs, as well as the digital divide.	Prioritise Explainable AI (XAI) to build trust by making algorithmic decision-making transparent to end-users. Implement policies for equitable access, such as subsidised digital extension services for smallholders. Launch targeted digital literacy programmes in partnership with local agricultural cooperatives and community centres.

3.3 Policy, Ethics, and Future Research

Policymakers should align national AI strategies with Sustainable Development Goals and WEF-governance objectives (D'Amore et al., 2022). Ethical safeguards are necessary because biased training data or poorly specified objectives can distribute water, energy, or agricultural benefits inequitably. Future research should prioritise explainable AI (XAI), privacy-preserving and decentralised approaches, robust models for data-poor settings, and applied validation in fragile contexts (Al-Azazi et al., 2026; Al-Tayar et al., 2025; Díaz et al., 2022; Fu et al., 2023; Richards et al., 2023). Studies should also report datasets, baselines, error measures, transfer tests, and stakeholder-validation procedures consistently so that findings can be compared and replicated. Evidence from Industry 4.0 and blockchain adoption in adjacent infrastructure sectors is retained only as analogous support for governance, security, and transparency considerations, not as direct WEF performance evidence (Alawag et al., 2024b, 2024c).

3.4 Theoretical, Practical, and Policy Implications

Theoretical implication. The scalability paradox extends AI-WEF research by treating adoption capacity as part of system performance. It predicts a negative association between expected resource-security benefit and implementation readiness where data infrastructure, institutional coordination, affordability, skills, and trust are weak.

Practical implication. Resource agencies should begin with bounded, high-value use cases supported by auditable local data, transparent baselines, uncertainty reporting, and human-in-the-loop validation. Modular and low-bandwidth tools, local co-design, and staged monitoring are more appropriate than direct transfer of data-intensive models from temperate, sensor-rich settings (Al-Azazi, 2025; Al-Azazi, 2026a).

Policy implication. The evidence supports interoperable public data repositories, cross-ministerial WEF governance, regulatory sandboxes for data sharing and privacy, targeted digital-skills programmes, and equitable financing for smallholders and low-capacity utilities. These measures correspond directly to the data, institutional, cost, and trust barriers summarised in Table 5.

4 Conclusion

This review synthesised 29 empirical studies on AI-supported WEF management in arid and semi-arid settings. LSTM and related deep-learning models were most frequently applied to time-series forecasting, while optimisation models and digital twins supported irrigation, water allocation, network operation, desalination, and cross-sector decisions. Reported benefits included improved predictive accuracy, water and energy savings, and reduced downtime, but the metrics were heterogeneous and strongly dependent on local datasets, crops, infrastructure, validation procedures, and baselines.

The synthesis supports the scalability paradox: settings with the greatest resource-security need often have the weakest data infrastructure, institutional coordination, technical capacity, affordability, and stakeholder trust. This conceptual contribution links model performance to adoption readiness and explains why successful pilots may not translate into system-wide or equitable implementation.

The evidence therefore supports a combined response based on open and interoperable data systems, low-bandwidth and explainable AI, local co-design and digital-skills development, and cross-sector governance with clear privacy and accountability rules. These measures align directly with the barriers identified in the reviewed studies and provide a practical path for responsible AI deployment in arid regions.

This review is limited by its coverage of three databases, the January 2016-March 2024 publication window, the applied eligibility criteria, and the comparability of the available evidence. Performance metrics were not pooled because studies differed substantially in datasets, spatial and temporal scales, validation procedures, and

baselines. Publication and reporting bias may also favour successful applications. Future reviews should update the evidence base, incorporate additional regional sources where quality can be assessed, and promote harmonised reporting standards.

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Declaration of Conflicting Interests

All authors declare that they have no conflicts of interest.

Author Contribution

Conceptualization: Radhwan Hazza'a Mohammed, Aawag Mohsen Alawag; Methodology: Aawag Mohsen Alawag; Validation: Saleem Ahmed Al-Azazi; Formal Analysis: Radhwan Hazza'a Mohammed; Investigation: Radhwan Hazza'a Mohammed; Resources: Saleem Ahmed Al-Azazi; Data Curation: Radhwan Hazza'a Mohammed; Writing-Original Draft Preparation: Radhwan Hazza'a Mohammed; Writing-Review and Editing: Aawag Mohsen Alawag, Saleem Ahmed Al-Azazi, Abdullateef Ali; Visualization: Radhwan Hazza'a Mohammed; Supervision: Aawag Mohsen Alawag; Project Administration: Aawag Mohsen Alawag.

Declaration of Generative Ai in The Writing Process

During the preparation of this work, the authors used OpenAI ChatGPT to improve readability, language quality, and copy-editing consistency. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Data Availability/Supplementary Materials

No new primary datasets were generated in this study. All information analysed in this systematic literature review is derived from the published sources cited in the article.

Ethics Statement

The authors declare that this research did not involve human participants or animal subjects; therefore, ethics committee approval and informed consent were not required.

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