Human-Centric Intelligent Systems
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REVIEW ARTICLE

Irrigation with Artificial Intelligence: Problems, Premises, Promises

Hanyu Wei[1] · Wen Xu[1] · Byeong Kang[1] · Rowan Eisner[2] · Albert Muleke[2] · Daniel Rodriguez[3] · Peter deVoil[3] · Victor Sadras[4] · Marta Monjardino[5] · Matthew Tom Harrison[2]

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Abstract

Protagonists allege that artificial intelligence (AI) is revolutionising contemporaneous mindscapes. Here, we authoritatively review the *status quo* of AI and machine learning application in irrigated agriculture, evaluating the potential of, and challenges associated with, a wide range of existential AI approaches. We contend that aspiring developers of AI irrigation systems may benefit from human-centred AI, a nascent algorithm that captures diverse end-user views, behaviours and actions, potentially facilitating refinement of proposed systems through iterative stakeholder feedback. AI-guided human–machine collaboration can streamline integration of user needs, allowing customisation towards situational farm management adaptation. Presentation of big data in intuitive, legible and actionable forms for specialists and laypeople also urgently requires attention: here, AI-explainable interpretability may help harness human expertise, enabling end-users to contribute their experience within an AI pipeline for bespoke outputs. Transfer learning holds promise in contextualising place-based AI to agroecological regions, production systems or enterprise mixes, even with limited data inputs. We find that the rate of AI scientific and software development in recent times has outpaced the evolution of adequate legal and institutional regulations, and often social, moral and ethical license to operate, revealing consumer issues associated with data ownership, legitimacy and trust. We opine that AI has great potential to elicit sustainable outcomes in food security, social innovation and environmental stewardship, albeit such potential is more likely to be realised through concurrent development of appropriate ethical, moral and legal dimensions.

Keywords Irrigation management · Industry 5.0 human centric · Smart irrigation · AI · Machine Learning

Abbreviation

AI	Artificial Intelligence
DSS	Decision Support System
SVM	Support Vector Machine
IoT	Internet of Things
ANN	Artificial neural networks

✉ Matthew Tom Harrison
matthew.harrison@utas.edu.au

1 School of ICT, University of Tasmania, Hobart, TAS 7005, Australia

2 Tasmanian Institute of Agriculture, University of Tasmania, Launceston, TAS 7248, Australia

3 Gatton Campus, The University of Queensland, Gatton, QLD 4343, Australia

4 South Australian Research and Development Institute, The University of Adelaide, Adelaide, South Australia 5001, Australia

5 Waite Campus, CSIRO Agriculture and Food, Urrbrae, SA 5064, Australia

1 Introduction

Effective irrigation management facilitates increased crop and pasture yields, reduced water use, production efficiencies, and improved environmental stewardship [1–3]. The complementarity or use of artificial intelligence (AI) in irrigation management has garnered significant interest due to the potential of AI to streamline irrigation procedures within and across fields [4–6]. AI systems may help expedite and refine agricultural decision-making, particularly in response to climate change, for example in predicting shifts in crop phenology associated with global warming [7, 8]. Scenario analysis for irrigation management can employ decision support systems (DSS) to assist farmers and researchers in making informed irrigation decisions [9] and system models to support research [10–12]. In recent times however, much agricultural research has shifted towards the development of technologies and algorithms, with use-cases including climate crisis, greenhouse gas emissions, precision agriculture, decision trees, remote sensing, and predictive analytics [13–15].

Farm-level processes associated with irrigation rate and timing are influenced by several factors, including the type of crop, the volume of water available and required, water resource management, crop or pasture yield, water cost, environmental impact, water allocation, farmer income, labour availability, infrastructure, nitrogen use, implications for soil organic matter, carbon and greenhouse gas emissions, markets and many other factors [1, 16–21]. Owing to their capability to analyse enormous amounts of data, various machine learning techniques, such as support vector machines (SVM) and decision trees, have been employed in irrigation management applications, including prognostics for weather conditions [22], soil moisture, crop water requirements, and irrigation scheduling. As a result, industry and academia are increasingly adopting AI-based tools and methods. To promote sustainability, effective irrigation management must consider not only plausible factors for scenario analysis, but also end-user needs and skills [3, 23]. In addition to developer limitations, the human and social challenges of end-users, including a lack of knowledge or technical competency, difficulties investing in and leveraging Internet-of-things (IoT) or mobile-based applications, and data privacy and ownership concerns, have long impeded implementation of AI systems on small- scale farms [1]. Furthermore, the hype in, and reliability and trustworthiness of, AI systems will together impact future developments. These factors suggest that in many cases, the pace of technology evolution is outpacing not just legal regulations, but also social, moral and ethical license to operate.

To address these shortcomings, technology constructs such as industry 5.0, human-in-the-loop AI, and explainable artificial intelligence have been employed to enhance the accuracy, credibility, legitimacy, salience, transparency and interpretability of machine learning model simulations [24, 25] (Table 1).

These relatively nascent AI frameworks aim to provide credible, legitimate, and salient decision support. Based on intuitive processes and sensible feedback, end-users develop confidence in the decision recommendations and gain trust in utilising such technologies. Indeed, in some cases, end-user confidence in and understanding of decision-support system outputs can reach such an extent that successful adoption is measured by the point with which end-users jettison the DSS [1]. End-users are less likely to have confidence in DSS that are perceived as ‘black boxes’, have irrational outputs, or exceed the bounds of human rationality [10], hence the allure of explainable AI algorithms [27]. Technology developers who aspire to capitalise on AI can better understand the limitations of existing models and refine the interpretation of decision processes employed by AI systems in real-world situations through end-user input and feedback, thereby iteratively improving prototype designs. Complementing traditional participatory action research and people-centric designs paves the way forward in a new direction for AI applications to help dissect complex irrigation decision-making across complex, sometimes competing, sustainability indicators [13, 28]. The successful implementation of the information and communication technology-based 5.0 industrial revolution in agriculture and its future benefits largely depends on the extent to which agricultural technology solves a genuine problem and is adopted by users [27].

This paper aims to review the premises, problems and promises associated with AI in irrigation management, including an assessment of the prospects of future AI approaches, and the limitations of existing systems. The paper canvasses AI applications in irrigation management, from soil moisture monitoring to crop water requirement predictions, and contemplates solutions to problems associated with implementing AI in irrigation management, including those based on foundational premises. The primary goal of this research is to articulate an authoritative view for how AI in irrigation management may been used to improve sustainability for public good. As part of this, we provide a multidimensional analysis of AI applications in irrigation management and examine the impact and potential of human and social aspects on AI development, contrasting

Table 1 Types of AI and exemplar applications in industry

Concept	Description	Example Application	Reference
Industry 5.0	Integration of human and machine collaboration in the production process, focusing on customisation and personalisation of products, and promoting sustainable and socially responsible practices	Customised manufacturing, waste reduction in production lines	[25]
Human-in-the- Loop AI	Human users actively participate in AI decision-making process, refining, validating, and revising AI outputs, in the hope of leading to more reliable and accurate results	Medical diagnosis, content moderation	[24]
Explainable AI	AI models that are transparent and understandable, allowing humans to interpret their decision-making process, fostering trust and facilitating collaboration between humans and AI	Financial risk assessment, autonomous vehicles	[26]

with previous studies [29, 30] that solely focus on technical analysis and performance comparisons. Specifically, we:

- Synthesise *status quo* AI adoption in irrigation management, highlighting various technologies, premises and methods employed
- Evaluate the promise of future AI approaches, and explore challenges and limitations that may be faced associated with developing such AI
- Elicit human, psychological and social aspects, such as end-user knowledge, capacity to learn, training, requirements, technology demand and adoption that have historically shaped the development and implementation of AI systems in irrigation management.
- Present a novel multidimensional framing for AI applications in irrigation management, which contrasts with previous studies that focused primarily on uni-disciplinary technical analysis and performance comparisons, and
- Promulgate conceivable solutions to overcome challenges associated with employing AI in irrigation management, paving the way forward for sustainable, resilient and inclusive agricultural development.

Section 2 explores premises of AI irrigation management technologies, from both domain and data science perspectives, including a discussion of the objectives of using AI in irrigation management. Section 3 articulates evaluation metrics for assessing AI-empowered irrigation management systems, Section 3.2 outlines technical, human and social barriers to progression associated with implementing AI in irrigation management, Section 3.3 canvasses emerging trends in AI-empowered irrigation management, such as human-in-the-loop AI and explainable AI, while Section 3.4 summarises key findings and highlights opportunities and challenges in employing AI for irrigation management, including prospects for research, development, extension and adoption.

2 Premises underpinning AI Adoption in Irrigation Management

2.1 Disciplinary Perspectives

2.1.1 Objectives of Using AI in Irrigation Management

For contemporary irrigation practitioners, several challenges persist, including inefficient water application and crop/pasture use, labor-intensive monitoring, limited real-time data availability, suboptimal resource allocation, and high volatility in market prices. Additionally, the lack of advanced predictive capabilities and the complexity of decision-making further complicate efficient irrigation practices. These issues underscore the need for innovative solutions to enhance irrigation management, with a particular focus on leveraging AI and machine learning technologies to optimise resource utilisation, improve decision-making processes, and address environmental concerns in agriculture.

Applications pertaining to AI in irrigation management have been evolving rapidly (Fig. 1). AI has already engendered digital transformation in the agricultural sector by providing insights and synthesis of real-time data ana- lytic to make informed decisions. With AI-based predictions, applications have been developed that purport to monitor crop health, detect disease prolifera- tion [31], and optimise resource utilisation [7]. Such data-driven approaches allow users to make more timely decisions on when to plant crops, and how to irrigate, fertilise, or apply pesticides, with the objectives of improving crop productivity and cost efficiency and reducing environmental impact [30, 32]. AI applications are particularly suited to big data applications and thus ideally complement real-time data capture devices, such as sensing or optical capture technologies.

Farm manager objectives of using AI in irrigation management may pertain to optimising water usage, irrigation scheduling, detecting malfunction or leaks, and precision

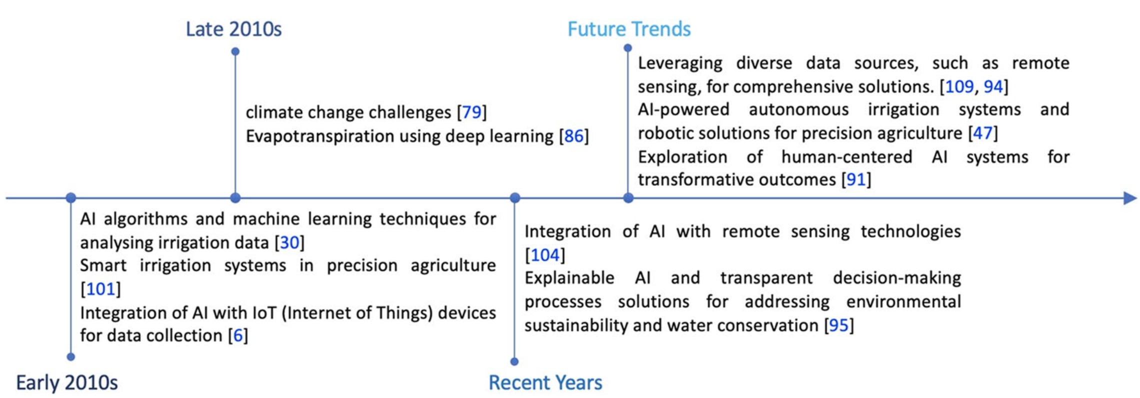


Fig. 1 Evolution of AI algorithms and use cases in agriculture over time

agricultural applications for increasing crop yields and reducing labour costs [1, 33]. For scientists, objectives often comprise developing algorithms, testing technologies, conducting data analysis such as meta-analysis and systematic literature reviews. For example, Talaviya et al. [34] suggest that AI has been used in removing weeds, chemical and fungicide applications, improving fertility and improving product quality. They further opine that AI has and will complement autonomous application devices, including robots and drones.

AI can be used to improve water use efficiency. Drip irrigation systems save water and allow optimal control of soil water content and plant growth [35], while AI systems that enumerate real time development of the crop canopy help assess water usage and more timely drip irrigation [36]. Irrigation analytics computed with artificial neural networks (ANN) can create moisture availability maps that enable variable supply and optimise spatial and daily use of water [37]. Jayaraman et al. [38] summarised machine learning algorithms for improving water quality, while Kumar et al. [39] predict temporal soil moisture availability and usage to plan irrigation. Parra et al. [40] used AI to predict the productive efficiency of an orchard based on irrigation. Using AI modelling, transpiration based on meteorological factors, crop growth status and soil parameters can be predicted, potentially improving water usage [41]. Biswas et al. [42] predicted required water using IoT-collected data such as soil moisture, temperature, humidity, and sunlight, which are processed through an Arduino microcontroller. This data was subsequently transferred to a centralised server, where it was utilised by a machine learning model to make informed predictions on future irrigation needs, thus streamlining and enhancing water management practices. A crucial aspect of agricultural planning involves accurately predicting evapotranspiration [43], as this impacts the scheduling of irrigation water to promote efficient water use. Other authors have presented an intelligent IoT precision irrigation method to improve the efficiency of water use in irrigation systems [44]. This method automatically irrigates the field by detecting soil moisture levels and responding to water needs accordingly.

Optimising irrigation scheduling and reducing labour costs are other purported benefits of using AI. Spatial moisture maps generated using machine learning can reduce the cost of irrigation control systems [37]. This study presents a cost-effective irrigation system leveraging an artificial neural network and low-cost radio frequency moisture sensors for real-time soil moisture estimation. By enabling tailored irrigation control in response to varying conditions, this system curtails unnecessary irrigation, reducing daily water and energy consumption by up to 38%, and therefore lowering the overall operational costs. Similarly, reducing labour required in the greenhouse sector by automating the control greenhouse microclimate may help increase profits [45].

In India, use of AI-based information and communication technology solutions has decreased farmer reliance on farm labourers and has allowed them to maintain consistent levels of income and crop yield [46]. Tyagi et al. [47]. used AI to develop energy-efficient intelligent resource allocation for IoT-embedded agriculture systems. By avoiding dependence solely on field experiments, Shen et al. [48]. proposed a method that enables execution of optimised irrigation schedules and real-time adjustment of irrigation plans in arid and semi-arid regions. Compared with conventional systems, the proposed model combines a long short-term memory network and a dynamic irrigation lower limit to represents the adapting irrigation predictions in real-time. This model significantly improves on crop yield by 10.3% and 4.4% and net profit by 19.1% and 7.4% respectively during the winter wheat growth cycle over a three-year period [48]. AI predictions may help users optimise crop selection based on situational uniqueness, helping optimise planting or harvest times, or making other necessary actions. Industries, including wholesalers, processors and retailers, are also using AI to forecast demand for crop products. In this way, market-based industries are able to modify production from the demand side – allowing farmers to reduce or increase inputs accordingly, reducing wastage and environmental impacts and improving profits [30]. Babaee et al. [49]. used a hybrid approach that combined ANNs with genetic programming to estimate rice yield, which indicates irrigation is the most impacted factor. Widianto et al. [50]. reviewed current trends in AI for smart farming to enhance crop yields and found several key factors contributed, including weather, soil, irrigation, unmanned aerial vehicle technology, pest control, weed control, and disease control. A word cloud of literature in this paper is shown in Fig. 2.

2.1.2 End-User Needs

Industry 4.0 has revolutionised the agricultural sector through the integration of IoT devices and machine learning algorithms [51]. Industry 4.0 can be defined as the current trend of automation and data exchange in manufacturing technologies, involving cyber-physical systems, the Internet of Things, cloud computing, and cognitive computing. This has facilitated greater autonomy, machine processing and jettisoning of manual human labour. In many instances, performance gains achieved by machine learning algorithms with IoT surpasses that of humans, for example, considering the task of monitoring and detecting anomalies in a manufacturing process. Without IoT, human operators may rely on manual inspections or periodic sampling, which can be time-consuming and prone to human error. In contrast, with IoT-enabled sensors collecting real-time data from various points in the production line, machine learning algorithms can analyse the data continuously and detect anomalies

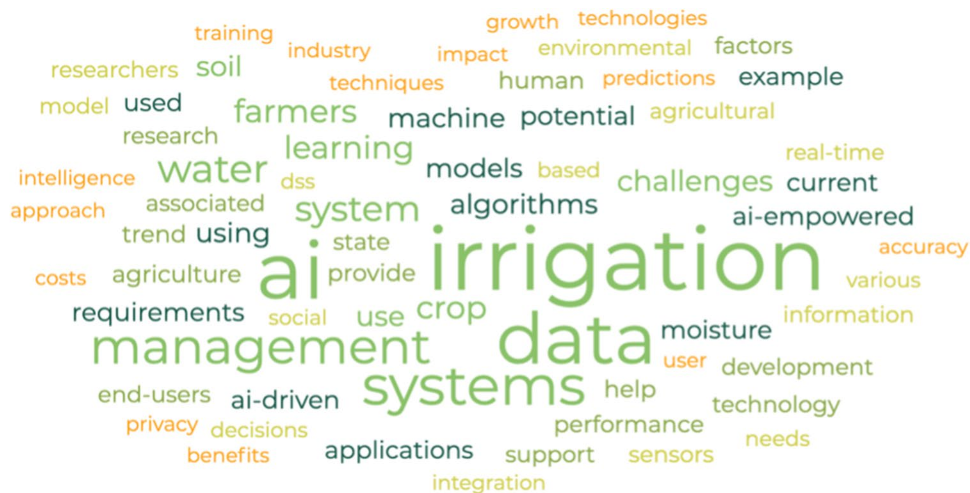


Fig. 2 Word cloud of literature presented in the present paper ('Irrigation with Artificial Intelligence: Problems, Premises and Promises')

with higher accuracy and speed. The algorithms can identify subtle patterns and deviations that may go unnoticed by human operators, enabling early detection of faults or abnormalities. This results in improved operational efficiency, reduced downtime, and enhanced product quality compared to traditional human-centric monitoring methods. Despite these advancements, ethical and moral concerns regarding replacement of humanitarian labour with machines abound. By way of example, Bhatnagar, Poonia, and Sunda conducted a case study on Indian farmers to explore the gap between academic research and the actual needs of farmers [52]. They found that there is a significant lack of awareness and adoption of modern technology in agriculture. Farmers expressed the desire for subsidies, reduced bureaucracy, and access to technology, indicating a need for educational initiatives to bridge the gap and ensure that even older farmers can benefit from the latest systems.

Industry 5.0 builds upon the foundations of Industry 4.0 by emphasising the importance of human perception, sensing, collaboration and decision-making in conjunction with AI-driven systems. In the context of smart irrigation systems, Industry 5.0 enables recognising and catering to the unique requirements of diverse end-users, including farmers, scientists, institutions and policymakers [53]. Aspiring developers of smart irrigation systems may benefit from human-centred design, this heuristic capturing diversified viewpoints and needs of diverse stakeholders, potentially facilitating refinement of proposed systems in line with stakeholder feedback. By fostering human-machine collaboration, empathising with unique user needs, and allowing customisation and adaptability, a more personalised, situational and context-aware approach to irrigation management can be achieved. Streamlined improvement through feedback loops enables more efficient refinement and enhancement of the system over time. An example of AI-guided human-machine growth in the water sector is the development and implementation of smart water management systems [54]. These systems utilise AI algorithms to analyse data from various sources, such as weather forecasts and sensor networks, enabling optimised water usage and improved system efficiency. Real-time insights and recommendations provided by AI algorithms empower human operators to make informed decisions and take proactive measures. This collaborative approach enhances water management practices, ensuring reliability, sustainability, and minimal wastage. Assuming they were to be realised at some point in future, quantum computers - computers with hardware utilising quantum mechanical phenomena - would enable a step-change in computing efficiency beyond that ever seen historically. Quantum computers hold potential in all aspects of agriculture, from production to consumption to regulation and innovation. We suggest that - with appropriate development - quantum computing may help resolve many of the wicked problems facing humanity, including poverty, hunger, climate and biodiversity crises, conflict, lack of access to clean water, sanitation and education, unsustainable resource use, inequality and more.

2.1.3 Farmers

Farmers often predominate the end-user typology of AI-driven irrigation systems. Farmers – including managers, owners, employees and adjuncts - have unique needs and preferences that must be accounted for in the design and implementation of such systems. Their requirements can be categorised into usability, customisation, affordability, training and support, data privacy, ownership, security and ethical use.

- **Usability** A user-friendly interface is essential rapid adoption by practitioners, particularly those who lack a technology background. A system with a well-designed interface can help farmers save time and effort in learning how to use the technology and in managing irrigation [55]. Intuitive graphical user interfaces are essential for farmers, as they often have limited time and resources to learn complex systems, which can lead to ineffective use of the technology, and thus lack of confidence when outputs are nonsense (*ie*. the "garbage in, garbage out" maxim).

- **Customisation** AI-driven irrigation systems should offer customisation to suit specific needs of individuals. Customisation is particularly necessary as farms vary widely, for example due to factors such as crop types, local climate, soil properties, and water availability [56]. Contextualisation in this way better allows AI-driven irrigation systems to optimise resource use (e.g. water, fertilisers) and increase resource-use efficiency [17, 20, 57].
- **Affordability** Affordability and cost-effectiveness are vital for farmers, especially small-scale farmers and those in developing countries. High investment costs and ongoing maintenance expenses can be prohibitive, disincentivising uptake and limiting subsequent benefits [58]. AI-driven irrigation systems should be designed with economic considerations in mind including duration of design process, as this can influence final product cost.
- **Training and Support** To help farmers effectively use and maintain smart irrigation systems, training materials and real-time support should be made available. These sentiments apply to all end-users. Providing on-demand assistance – for software, use and technical questions – helps ensure that users can address issues as they arise.
- **Data Privacy, Security and Ownership** Robust data privacy and security measures should be implemented to protect information and ensure trust in the technology. Users have rightly become increasingly concerned about misuse of their data, part of which pertains to loss of competitive advantage. Such concerns have heightened in recent times with hacking and data theft from large corporate institutions demonstrating increasing efforts needed for cyber defence [59]. Ensuring secure data storage, encryption, and adherence to relevant data protection regulations may help alleviate these concerns [60]. Even so, concerns over ethical and moral use of such data persist and perpetuate, including ownership, commercialisation and use of personal information. We suggest that AI has a very important role to play in ensuring public good in data privacy, security and ownership.

2.1.4 Scientists

Scientists, including domain experts and academics, have differing requirements for AI-driven irrigation systems, such as advanced analytical tools, integration with other research tools, extensibility, and interoperability.

- **Advanced Analytical Tools** Scientists may need access to advanced analytics and data visualisation tools to study water usage and monitor system performance. These tools are crucial for scientists because they enable a deeper understanding of the underlying factors affecting irrigation efficiency and help identify potential areas for improvement. By providing comprehensive insights into various aspects of AI-driven irrigation systems, these tools facilitate data-driven decision-making. Indeed, we premise that a great advantage of AI compared with traditional analyses is the ability to harness and synthesise big datasets. In contrast, AI can break down when datasets are small, suggesting that other methods may be appropriate in such cases.
- **Integration and Extensibility** Scientists may require AI-driven irrigation systems to integrate seamlessly with other research tools, platforms, or databases. Integration allows for streamlined data sharing and collaboration between foreign devices and operating systems, enhancing the research process and enabling scientists to leverage multiple sources of information. By connecting with other research tools, scientists can more effectively study the impacts and benefits of AI-driven irrigation systems in various contexts. Scientists may need open and extensible systems that can accommodate new algorithms, models, or sensors as technology evolves or research needs change. This flexibility ensures that AI-driven irrigation systems can adapt to advancements in the field and remain relevant for ongoing research efforts. Openness and extensibility are crucial for scientists, because they enable continuous improvement and adaptation of technology to the changing needs of the agricultural sector.

2.1.5 Policymakers

Policymakers, such as those in governments or non-governmental organisations, have requirements when considering AI-driven irrigation systems. These include compliance with regulations and standards, scalability and interoperability, and environmental and social considerations, such as the potential for social innovation.

- **Compliance with Regulations and Standards** Systems should be designed to comply with relevant regulations, standards, or policies, including those related to water usage, environmental impact, cost and data privacy. Compliance ensures that AI-driven irrigation systems meet fiduciary standards and follow industry best practices. This requirement is essential for policymakers to ensure that nascent technology adheres to the necessary guidelines.
- **Environmental and Social Considerations for Public Good** Policy-makers may prioritise systems that promote water conservation, energy efficiency, and minimise neg-

ative impacts on local communities and ecosystems. This requirement arises from the need to balance the benefits of AI-driven irrigation systems with potential environmental and social consequences. By considering these factors, policymakers can ensure that AI-driven irrigation systems contribute to sustainable agriculture and responsible resource management.

- **Scalability and Interoperability** Policymakers may require systems that enable scaling to accommodate larger or more complex agricultural operations or that can interoperate with other agricultural systems, such as precision farming or supply chain management platforms. Scalability and interoperability enable technology to be contextualised but also contribute to the broader goals of sustainable agriculture and efficient resource management.

The following table compares the requirements of farmers, scientists, and policymakers in relation to AI-driven irrigation systems.

As shown in Table 2, there are both common and distinct requirements among end-users. Each end-user cohort has unique requirements. By understanding and addressing these requirements, it is possible to design and implement more effective solutions that save time, money, and resources for farmers while contributing to the broader goals of sustainable agriculture, responsible resource management and public good. By analysing and addressing the unique requirements of each user group via Industry 5.0, human- centric AI-driven irrigation systems may better cater for the diverse needs of stakeholders [61].

2.2 Data Science Perspectives

2.2.1 Data Requirements for AI in Irrigation Management

Enabling optimisation of irrigation using AI is becoming increasingly popular. Like all disciplines, various factors influence model performance and effectiveness.

A key factor to success is the type and source of data required for AI models to function in line with that intended when first developed. Data ingested collected should be relevant, accurate and of sufficient quantity and quality to train the model effectively. Data commonly used in irrigation management includes local weather and long-term climate, soil moisture, soil salinity, temperature and crop variables (biomass, phenology, reflectance, leaf area), all of which are empirical data that often are highly variable [62]. Such data is often collected using within-field sensors, satellite imagery [63, 64], aerial photography, scientific experiments under controlled or field conditions [16, 65], web crawler techniques [66], simulator software [48], and integrated methods [23]. Table 3 shows examples of data required for AI-driven irrigation systems.

In general, data harnessing technologies that improve the quality of data required for AI algorithms typically are also conductive to improvement in modelled outputs. The frequency of data collection should be sufficient to ensure that the model receives data on a regular basis, particularly when trends differ from those historically, for example, increasingly frequent extreme events against a background of gradual climate change [18, 67, 68]. Continuous data collection allows real-time AI parameterisation that conceivably refine predictions of future conditions. The adoption of methods related to IoT using sensors for real-time monitoring has become commonplace [69]. For example, Culman et al. [70] used a data fusion approach, an inference method for handlying ambiguous data of agrometeorological information with varying degrees of specificity collected from different sensor. Similarly, to estimate daily evapotranspiration in the arid region of Northwest China, where input data is limited, a new hybrid particle swarm optimisation -extreme learning machine model has been proposed [71]. The study found

Table 3 Sample type and source of data required for AI-driven irrigation systems

Data Type	Data collected Sources	Reference
Soil water	Remote sensing	[64]
Meteorological data	Government database	[48]
Water in plant	Wireless implanted sensor	[62]
Evapotranspiration	Remote sensing	[63]
Irrigation relevant information	Web crawler	[66]

Table 2 User requirements for AI-driven irrigation systems

Requirement	Farmers	Scientists	Policymakers
Ease of use and access to on demand support	Yes	Yes	Yes
Affordability	Yes		
Visualisation	Yes	Yes	Yes
Customisation & Scalability	Yes		Yes
Data Privacy & Security	Yes	Yes	Yes
Integration & Interoperability	Yes	Yes	
Considerations of multiple sustainability indicators		Yes	Yes

that the model performed acceptable accuracy better than t he empirical control approach when given only three input temperature data. Besides, Mahmoudi et al. [72] developed a neuro-fuzzy inference system by using the firefly algorithm to estimate spatial soil moisture using easily accessible inputs, even in the absence of knowledge about soil physical parameters. This model demonstrated exceptional accuracy and minimal estimation error when prediction soil moisture content in both humid and arid weather conditions.

In addition to data collection, sufficient pre-processing and analysis of massive data are required to ensure the effectiveness of AI models. Pre-processing converts raw data into a format suitable for AI. For example, Cloud-based AI services such as IBM Watson Visual Recognition are often used for agricultural analytics due to their ease of pre-processing, minimal training data requirements and ability to outsource computation [73]. This process can include normalisation, scaling, and converting numeric data into categorical data. The analysis phase involves the use of different techniques to identify patterns, relationships, and correlations in the data, helping to build accurate models that provide reliable water demand forecasts or crop yield predictions. In addition to AI applications to domain-based problems, AI applications could be usefully developed in data screening and processing (for subsequent use in other AI algorithms).

2.2.2 AI Algorithms: Status, Application and Efficacy

In the realm of modern agriculture, the integration of advanced technologies has revolutionised traditional farming practices. One such transformative force is the application of artificial intelligence (AI) and machine learning methods in precision agriculture. Here we briefly review the status, application and efficacy of several forms of AI in irrigation management. We highlight benefits and drawbacks associated with each technique.

2.2.3 Machine Learning Methods

Machine learning has been a dominant driver of precision agriculture, facilitating data collected by IoT-enabled sensors, including weather conditions, soil moisture levels and crop growth rates, to make predictions about when to plant, fertilise, irrigation, spray and harvest crops. These predictions are intended to improve crop growth and yield, reduce waste, and minimise the use of synthetic and natural capital resources [74]. Machine learning algorithms can be used for weather and rainfall predictions based on data from sensors, climatic records, and satellite images [75]. Shanrma et al. [76] discussed how machine learning can be used in sustainable agriculture supply chain (ASC) performance. They presented a framework that combines machine learning and ASC to help researchers and practitioners understand the importance of digital technologies in agriculture. Table 4 demonstrates five machine learning techniques' advantages and disadvantages discussed in the following sections.

AI modelling can help overcome challenges associated with conventional methods which has been proved in irrigation water quality evaluation [77]. AI models address this issue by leveraging predictive and analytical capabilities to assess irrigation water quality more efficiently and economically. Machine learning algorithms such as adaptive boosting, random forest, artificial neural network, and support vector regression, can help decision-makers in developing countries to manage irrigation water strategies more effectively, promising low-cost real-time forecasting of groundwater quality [77].

Seyedzadeh et al. [78] used five AI models included artificial neural networks, neuro-fuzzy sub-clustering, neuro-fuzzy c-Means clustering, and least square support vector machine to estimate discharge from drip irrigation based on temperature and pressure. The Global performance

Table 4 Advantages and disadvantages associated with common machine learning algorithms

Machine learning Technique	Description	Advantages	Disadvantages
Transfer Learning	Leveraging knowledge from one task to improve another related task	Reduces data requirement, accelerates deployment	Limited transferability in some cases
Federated Learning	Decentralised training on multiple devices without centralizing data	Preserves data privacy, benefits from diverse data	Communication overhead, potential for slow convergence
Deep Learning	Uses neural networks with hidden layers for complex data relationships	Handles highdimensional data (e.g., images, sensor data)	Requires significant data and computational resources
Reinforcement Learning	Agent learns through interactions to optimise rewards	Adaptive strategies, maximises desired outcomes	Complex to implement, high computation
Natural Language Processing	Understanding and generating human language to analyse textual data	Providing valuable insights from textual data	Requires significant computational resources and human validation

indicator was adopted to examines the five models whereas least square support vector machine model performed better than the other models, followed by ANN, while all five models showed acceptable results. However, different statistical indices may not provide a reliable assessment of the model's performance as each index assesses the model's performance at a distinct level.

Sensor-based irrigation uses sensors to collect data on soil moisture, temperature, and other factors that can affect crop growth, which are then analysed by AI algorithms to determine the optimal amount of water needed for irrigation. Al-Qammaz et al. [22] measured soil moisture and pipeline pressure by wind driven optimisation using least square support vector machine algorithm. They found that the proposed algorithm driven smart irrigation system provides a network architecture using the long-distance and low power communication protocol that extremely helpful in remote and large open farms.

Additionally, a moisture map of an orchard has been estimated by training the data coming from 15 moisture sensors located in an area using the ANN method in a solar powered irrigation system [37]. Through the prevention of unnecessary irrigation, both immediate water demand and cost of freshwater were reduced by 38% of daily water and energy consumption.

Transfer Learning leverages knowledge from one task to improve the performance of another, related task. In the context of smart irrigation systems, transfer learning can be used to apply models trained on data from one region or crop type to another, reducing the amount of training data required for the new context and accelerating the deployment of AI algorithms in new settings. This approach can help overcome challenges related to data scarcity and improve the generalisability of AI models for irrigation management [79].

Federated Learning is a distributed machine learning approach that enables AI models to be trained on data from multiple devices or sensors without the need to centralise the data [80]. In smart irrigation systems, federated learning can be used to protect the privacy of farmer data while still benefiting from the collective intelligence of multiple sources. This approach can lead to more accurate and robust AI models for irrigation management while maintaining data privacy and security.

Deep learning invokes ANN with hidden layers to model complex data relationships [81]. Deep learning techniques, such as convolutional neural networks and recurrent neural networks, have been employed in smart irrigation systems to process high-dimensional data, such as satellite images and sensor data. These algorithms can be used for tasks like crop health monitoring, disease detection, and yield prediction, leading to better-informed irrigation management decisions considering complex relationships in the data.

Reinforcement learning is where an agent learns to make decisions by interacting with its environment and receiving feedback in the form of rewards or penalties, similar to agent-based modelling [23]. Reinforcement learning can be applied to develop adaptive irrigation strategies that maximise crop yield and minimise water usage, for example determination of optimal timing and amount of water to apply, taking into account factors such as soil moisture levels, weather forecasts, and crop growth stages.

Natural language processing focuses on understanding and generating human language. Natural language processing can be employed to analyse textual data, such as farmer feedback, expert reports and research articles, to extract valuable insights about irrigation management practices [82, 83]. These insights can be used to enhance decision-making, identify trends and provide personalised recommendations to decision-makers.

2.2.4 Expert Systems

Expert systems are aimed at mimicking decision-making of human experts in a specific domain. Expert systems can provide recommendations on irrigation management practices based on the data collected from sensors and other sources. For example, a fuzzy expert system can provide recommendations on the revolving speed of the central pivot to address uncertainties of the irrigation system, deceasing rotating speed to 50% of the original control [84]. Yaseen et al. [85] suggested an intelligent expert system based on a new hybrid algorithm, itself the integral of hybrid bat and particle swarm optimisation algorithms wherein weaker parts of each algorithm where substituted with better stronger components from other algorithms to elicit intricate solutions for reservoir systems with multiple purposes, thereby enhancing operation guidelines for similar reservoir systems across the globe.

2.2.5 Image Processing and Remote Sensing

Remote sensing often draws upon satellite or drone imagery [86] to enumerate crop health, canopy green or leaf area, ground cover, soil moisture, and other environmental factors, which can then be analysed by AI [87–89]. It is proposed to gauge crop nitrogen status using multi-spectral imaging obtained from aerial robots aircraft, and satellites to determine current nitrogen status and potential fertilisation needs [24, 86]. From other perspectives, centre pivot irrigation systems can be mapped by using optical remote sensed imagery and automated deep learning approaches and convolutional neural networks for mapping centre pivot irrigation systems [35, 90, 91].

In addition, use of remote sensing is less expensive and requires less manual labour than ground-based surveys, and thus is more suitable for large scale experimentation at the farm, region or continental levels [92]. By employing machine learning algorithms to ingest and synthesis remotely sensed data, a real-time farm-specific management system can be developed to enhance decision-making in a timely fashion [93]. For example, Image processing techniques was used to monitor crops in a real-time manner, which facilitated the prompt identification of plant diseases and pests, leading to timely and efficient actions to reduce their harm to crop yields [94]. Furthermore, it supported the effective handling of water resources, fertiliser application, and addressing plant health concerns, ultimately aiding in optimising agricultural practices in areas grappling with environmental issues such as water scarcity and erratic rainfall.

Another study adopted a message queuing telemetry transport protocol, enabling hundreds of irrigation intelligent IoT devices to report crop charac- teristics and water requirements to a master agent, which then sent cumulative water demand signals to various pump stations. This system creates maps of irrigation underpinned by georeferenced data and water resource partitioning among agents once data supplied [95].

2.2.6 Hybrid Approaches

Hybrid approaches combine AI techniques to tackle complex irrigation management problems. By integrating techniques, such as machine learning, expert systems, and remote sensing, these approaches can exploit the strengths of each method and – ideally - achieve better results than using a single tech- nique per se. For instance, a hybrid approach that combines fuzzy logic and genetic algorithms has been proposed as new data-intelligence models for optimising soil moisture content prediction, demonstrating improved performance over standalone methods in better accuracy and lower estimation error in two tested climates [72].

2.2.7 Decision Support Systems

A DSS for irrigation management can incorporate various data sources, such as weather forecasts, soil moisture sensors and satellite imagery, to provide real-time information on crop water requirements and soil moisture levels. This information can be used to optimise irrigation scheduling and reduce water waste. As the name suggests, DSS are designed for supporting rather than making decisions. Thus, ideally designed DSS output a range of scenarios, and allow the user to compare and potentially action the range of outcomes. As heuristics from DSS can often be learnt from intuition and repetition, the jettisoning of DSS by end-users can signal successful adoption and impact, as the DSS *per se* is no longer required [1, 11, 93]. DSS may also incorporate biophysical models that simulate movement of water through soils and thus the evolution of water stress or superfluity, as well as the implications of such stress on crop development on growth and yield [17, 96, 97]. Process-based models are often tools for scientists rather than farmers, but outputs from such models can be encapsulated into DSS to simplify interrogation of results. For example, the climate-smart decision-support system is designed to model water requirements of rice irrigation interventions, accounting for the changing climate [98]. A nitrogen fertigation management system is proposed as an autonomous software decision support system in order to create a binary action recommendation and accompanying prescription for an impending fertiliser application via a centre pivot irrigation system [86]. By guiding decisions on water allocation, DSS can help better prioritise use of scarce water reserves while maintaining environmental flow requirements [99]. In a study on comparison between DSS and human decisions, two models (as part of a proposed DSS) were used to simulate irrigation to compare with outcomes of humans, with the model showing lower volumes and higher irrigation frequency to optimise water use [100]. This is often because human intelligence is bounded by rationality, which restricts comparison of scenarios in making a decision. In contrast, the capacity of computing infrastructure is more extensive to the extent that more scenarios can been evaluated (see also quantum computing information discussed in section 2.1.2 above). However, computers are often limited by factors not provided as part of the optimisation, such as feasibility, practicality, or skills and barriers to implementation [101].

2.2.8 Crowdsourcing Multi-Agent System

Crowdsourcing – soliciting data or ideas from a diverse and dispersed group by multi-agent systems can be enabled via several autonomous agents that communicate with each other and with a central server. These agents are responsible for gathering data from sensors, analysis, and making decisions about water allocation to each section of the field. For example, a multi-agent system integrates plant disease and pest recognition and provides the crop to be treated using the irrigation pivot [94].

Crowdsourcing can be incorporated into this system by allowing farmers to input data about their crops and soil conditions. This data can be used to supplement the sensor data and provide a more accurate picture of the field's needs. Farmers can also provide feedback on the system's performance, which can be used to improve its accuracy and efficiency over time. Literature provides some case study on this issue. For example, Jimenez et al. [102] proposed the design of an irrigation scheduling system based on rational agents, interacting with the agricultural environment by collecting data on soil moisture, soil temperature, luminosity, air temperature, and rain. By employing membership functions and a Mamdani inference methodology, the agents make irrigation scheduling decisions, utilising data on luminosity and ambient temperature to identify periods with high evapotranspiration rates and soil moisture sensors to assess volumetric water content. This multi-agent approach enables more informative solutions than a single data input by considering various environmental factors and optimising soil moisture to maintain it at levels conducive to crop growth. In addition, Villarrubia et al. [103] presented the methodology that involves creating virtual organizations of agents that communicate with each other to monitor crops efficiently. A low-cost sensor system is employed to enable farmers to optimise resource allocation for crop growth. This system collects diverse data from sensors measuring factors like temperature, solar radiation, humidity, pH, moisture, and wind. The key advantage of this approach is its ability to merge various sensor data types and generate context-specific responses, enabling more precise and adaptive crop management.

Figure 3 summary of technologies discussed in the present paper. Interconnections between these technologies enable data-driven decision-making and automation in irrigation management. For example, IoT devices can be equipped with sensors for remote sensing applications, collecting imagery and data, which can be processed using image processing techniques. Machine learning algorithms then analyse processed data to derive insights and detect patterns (pattern recognition).

3 Evaluation Metrics of AI-Empowered Irrigation Management

3.1 Performance

The performance of an AI system may be quantified using accuracy, speed, and scalability. The accuracy of an AI-based irrigation system can be measured by comparing its predictions to actual outcomes. This can be done by calculating metrics such as precision, recall, F1 score, and accuracy. These metrics evaluate systemic ability to reliably classify types of soil moisture and predict irrigation requirements. For example, common evaluation metrics include normalised root mean square error, mean absolute error, scatter index and correlation coefficient [104–107].

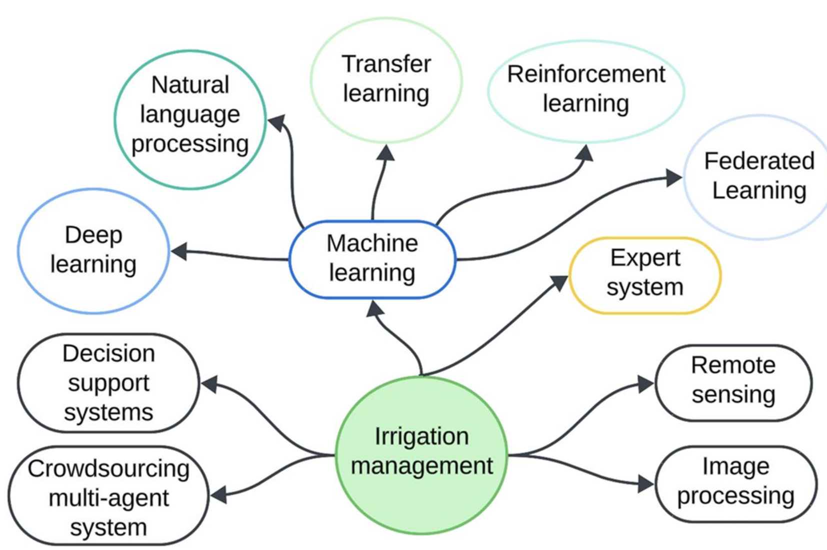
The speed of an AI-based irrigation system can be measured by the time it takes for the system to process and analyse data, make decisions, and control irrigation systems. This can be measured in terms of response time, latency, and throughput. It is important for the system to be fast enough to provide timely and accurate recommendations to end-users.

The scalability of an AI-based irrigation system can be measured by its ability to handle increasing amounts of data or complexity. This can be measured by evaluating performance under different workloads, such as increasing data volumes or more complex soil types. The system should be able to cope with larger data quanta and complexity without sacrificing accuracy or speed. Saggi et al. [43] introduced a framework for training, validating, testing and enhancing classification performance through machine learning. For example, Deep Convolutional Neural Networks have demonstrated a remarkable 98.5% accuracy in predicting experimental results, with Mean Squared Error of 99.25% [39].

3.2 Reliability

Reliability refers to the ability of the AI system to perform consistently and accurately over time. It considers factors such as robustness, stability and error rate, quantifying systemic ability to operate effectively across contexts.

Fig. 3 Associations between techniques applicable to irrigation management



In evaluating the reliability of AI models for irrigation systems, it is essential to examine various aspects that contribute to consistent and accurate performance over time. Robustness is a crucial factor, as models must effectively handle diverse data sources, formats, resolutions, and temporal scales, as well as cope with missing, inconsistent, or noisy data. Ensuring the stability of AI models is equally important, as they should maintain their performance and accuracy while adapting to new data and changing conditions. Assessing error rates, such as false positives and negatives, can provide insights into a model's accuracy and potential weaknesses.

The adaptability of AI models to various farm sizes, irrigation systems, and regional conditions is another critical consideration. Rigorous validation and testing, using varying datasets and realistic scenarios, can gauge the reliability of AI models and identify potential areas for improvement. Cross- validation, holdout testing, or other evaluation techniques can be employed to measure their performance. Scalability of a proposed AI model is vital, ensuring capacity to handle increasing data volume and accommodate growth in the irrigation system or farm expansion.

3.3 Interpretability

Interpretability involves understanding the decision-making processes and the internal workings of the AI system. Factors such as transparency, explainability of decisions, and potential for bias or error must be taken into account. While many existing machine learning techniques have demonstrated good performance in irrigation management systems, their limited interpretability could hinder their adoption and usability by end users.

To assess the interpretability of AI models currently used in irrigation systems, it is vital to examine how well they represent patterns and knowledge in an anthropogenic conceptualisation. For instance, use of fuzzy expert systems and evolutionary algorithms can be evaluated to determine how effectively they interpret acquired knowledge and provide explanations that are accessible to non-experts. Such assessment can help identify potential gaps between the performance and interpretability of AI models, informing the development of more user-friendly and valuable models for stakeholders involved in irrigation management.

3.4 Ethical and Moral Considerations

Considerations of ethical and moral implications of using AI for irrigation include evaluating the downside risks and benefits of using AI in irrigation management, considering who is a stakeholder and then potential stakeholder impact. First, AI-based irrigation systems rely on data collected from various sources such as sensors, weather forecasts, and satellite imagery [35, 86, 90, 91]. This data can include personal information about farmers, such as their location, crop types, and water usage. It is essential to ensure that the data collected is used only for its intended purpose and is not shared or sold to third parties without the consent of the farmers. Second, AI algorithms can be biased based on the data they are trained on. If the data used to train the irrigation system contains biases or is not representative of the entire population of farmers, the system may not be fair to all users. Ensuring that the system is designed and trained in a way that does not discriminate against any particular group of users is essential. As well, the use of AI in irrigation may reduce the autonomy and decision-making power of end-users (see commentary above relating to DSS). It is essential to ensure that the system is designed in a way that empowers farmers and provides them with the information they need to make informed decisions about agricultural systems.

Inclusivity and fairness, too, are considerations that when would correctly implemented ensure that AI-empowered irrigation management are distributed fairly across intersectionalities (age, gender, race, religion and location) and that the system does not discriminate against certain individuals or communities. One potential concern is that AI-empowered irrigation management systems could disproportionately benefit wealthy farmers or large agricultural corporations or developed countries, while leaving small-scale farmers or marginalised communities or developing countries behind. Although multispectral imagery is commercially available, few methods transform data into actionable recommendations and prescriptions [86]. To address this, developers should consider how systems can be made equitable via accessibility to a wide range of users, including those who may have limited access to technology or resources. Accountability considerations include ensuring that proposed system designs are transparent, with stakeholders being informed about how the system works and how decisions are made, and that there is a clear process for resolving disputes or addressing complaints. Additionally, it is important to consider the potential unintended consequences of using AI in irrigation management, such as the impact on biodiversity or the unintended consequences of decisions made by the system.

3.5 Social and Societal Impact

Social and societal impact assessments quantify potentially positive and negative effects of AI applications on society, the economy, and the environment. These also quantify impacts on jobs, income distribution, consumer behaviour, privacy, security and environmental sustainability. By considering these factors, social impact assessment aims to identify and mitigate any unintended negative consequences of AI while maximising its potential benefits. AI can automate many tasks that are currently performed by humans, leading to job displacement in some industries. However, AI can also create new jobs and opportunities for workers to develop new skills. Social impact assessment evaluates the net effect of AI on employment and income distribution and identifies potential strategies to support affected workers. AI can change the structure of markets by introducing new products and services or changing the way existing markets are produced and delivered. AI can help reduce the carbon footprint of some industries, such as energy and transportation, by optimising processes, improving carbon in soils and reducing waste [26, 108]. For instance, Coronavirus disease 2019 (COVID-19) made farms temporarily less accessible, increasing autonomous and remote-control requirements [45, 109].

3.6 Cost-Effectiveness

Cost-effectiveness evaluates economic feasibility of using AI, including potential costs and benefits of implementation. Cost-effectiveness considers factors such as the cost of development and deployment, the potential return on investment, and the overall sustainability of the system [110]. The goal is to determine financial implications for stakeholders, particularly farmers, and to ensure that the benefits derived from AI-driven irrigation management systems outweigh the associated costs. Firstly, evaluating the initial investment costs for implementing AI-based irrigation systems is crucial. This includes the expenses for acquiring necessary hardware, such as sensors, controllers, and communication devices, as well as software development and licensing fees. Analysing the cost of integrating AI technologies with existing irrigation infrastructure and practices can provide valuable insights into the economic feasibility of adopting these systems [37]. For instance, designing a low-cost data collection for the smart irrigation system was dedicated [111]. An irrigation system that employs the ATtiny microcontroller was designed with a highly efficient and cost-effective component [58]. To further enhance affordability and accessibility, the system incorporates a mobile app as the monitoring interface, eliminating need for additional external hardware displays, which can be expensive and complex to install and maintain. A multi-step process based on AI was provided that approach maximises the value of a low-cost soil moisture sensor to allow common farmer to increase the adoption of precision agriculture, especially in emerging geographies, by making technology-driven intelligent solutions more affordable [112, 113].

Assessment of the ongoing operational and maintenance costs is essential. These include expenses related to data storage and processing, system updates, and periodic maintenance of hardware and software components. A thorough evaluation should also consider the costs associated with training farmers and agricultural professionals on the proper use and maintenance of AI-driven irrigation systems, as well as the provision of technical support. The potential financial benefits of AI-based irrigation systems should also be taken into account. This includes improvements in water use efficiency, leading to reduced water consumption and costs and potential for reduced labour costs due to automation of certain irrigation management tasks. Evaluating these benefits in relation to the associated costs can provide a clearer understanding of the overall economic value of AI-driven irrigation systems. Cost challenges are a key aspect of inclusivity across various socioeconomic backgrounds.

4 Problems Associated with AI in Agriculture

4.1 Data Perspective

Data quality and availability are crucial for AI to enable reliable prognostics [50]. AI algorithms, especially data driven approaches, such as machine learning and deep learning, require large volumes of data for model training. An increase in data volume can enhance the accuracy of crop yield and water usage predictions. For example, assuming data is of sufficient quality and adequately screened prior to model training. However, inadequate data pre-processing can limit reliable model applicability, particularly in cases outside the calibration space. In many regions, data can be insufficient, hindering AI ability to generate accurate models and recommendations. The integration of diverse data sources, such as remote sensing, sensor data, and user inputs, can be challenging, particularly when addressing different data formats, resolutions and temporal scales.

4.2 User Perspective

End-users also face challenges in AI application. For example, farmers may lack the necessary technical expertise to effectively use and maintain such systems, highlighting the importance of accessible training and continuing support programs. Many farmers, especially those in developing countries, may not have access to advanced irrigation technologies or the capital to invest in them. Furthermore, user trusted and perceived legitimacy and credibility of company or institution may be hindered by factors such as unfamiliarity or technical complexity. Affordability and accessibility are also concerns the cost of implementing AI-driven irrigation technologies may be prohibitive for small-scale farmers or those in developing countries, leading to lack of inclusivity and/or equity. Privacy, ownership and security concerns may also arise from the collection and storage of sensitive agricultural data [114].

4.3 Integration

Integration with existing systems can present challenges, especially in regions where farmers are resistant to adopting new technologies, have limited resources, or do not have the capacity to update software. Insufficient integration necessitates context-specific solutions. Lastly, AI-based irrigation systems might not fully account for complex environmental phenomena, such as microclimatic inversions, which can influence the efficacy of chemical and herbicide spray applications.

5 Future Directions: Promises for AI Applications in Agriculture

Addressing complex challenges in AI-driven irrigation systems necessitates greater focus on data collection, integration, quality and pre-processing, and augmentation and synthesis. Leveraging diverse data sources, such as remote sensing, soil sensors, and weather stations, promises to provide a more comprehensive solution for tasks like irrigation scheduling, farm management, variable rate nitrogen application or sequential improvement in chemical and herbicide applications with weed kill in subsequent seasons. Additionally, the implementation of data fusion techniques holds the promise of integrating diverse data streams while accommodating various formats, resolutions and temporal scales. Such advances in data utilisation and integration could be expected to enhance the effectiveness and efficiency of AI-driven irrigation systems, ultimately contributing to improved food security and sustainability.

Further investigation of the potential of human-centred AI systems for end-users may result in transformative outcomes. According to Table 5, differences between traditional AI system and human-in-the-loop AI systems are compared from four aspects. Human-centred AI offers the capacity for real-time computation, comprehensibility, development of intuitive information for non-experts, and predictability of robot behaviour [1, 115], all of which hold significant promise for improving user experiences and outcomes. More fundamentally, systems that learn from the effectiveness of their previous learning cycles hold substantial promise for continual improvement and adaptation. The next steps in this domain should focus on applications, as the fundamental science and mathematics of such AI is reasonably well established [116, 117], thereby paving the way for realising the promises of human-centred AI in various fields.

Presentation of big data in intuitive, legible, and meaningful forms for both specialists and the laypeople requires more work. As AI becomes more prevalent in agriculture, forestry, climate, and health, the demand for legible, simple, bespoke AI-explainable AI encompassing interpretability increases. Harnessing human expertise can enhance such AI capability, enabling farmers to contribute their experience, interests, and conceptual understanding into an AI pipeline, enabling bespoke information outputs in line with their interests. Human-centred artificial intelligence combines "artificial intelligence" with "natural intelligence" to augment human performance rather than replace it. Current "explainability" research focuses primarily on providing explanations to experts and system developers rather than end-users. To address these limitations, future research should prioritise developing AI models that can consider and balance different user requirements, which could be captured by multiagent systems. Enabling next- and end-users to share input data and information, leveraging satellite imagery for farm and field boundary identification, and integrating real-time growth, water prices, and seasonal climate forecasts may add value to AI applications. For example, AI techniques could help auto-populate inputs based on previous and contextual data, such as regional and crop-specific information.

Transfer learning and domain adaptation, crowdsourcing and data sharing, and encryption techniques also have roles to play in addressing human data challenges in AI-driven

Table 5 Differences between traditional AI systems and human-in-the-loop AI systems

Aspect	Traditional AI systems	Human-in-the-loop AI systems
Decision-Making Process	Automated based on predefined rules and historical data	Integrates human expertise and judgment
Adaptability	Limited adaptability to changing conditions or unforeseen circumstances	Enhanced adaptability and flexibility
Incorporation of Human Knowledge	Limited capacity to incorporate subjective human knowledge or preferences	Incorporates subjective human knowledge, preferences, and contextual understanding
Presentation of Big Data	May not be intuitive, legible, or meaningful for end-users	Prioritises intuitive, legible, and meaningful presentation of big data for both specialists and laypeople

irrigation systems. Transfer learning in concert with domain adaptation will enable AI application to specific regions, production systems or enterprise mixes, even with limited data. Encouraging data sharing and collaboration among farmers, researchers and organizations can generate comprehensive, high-quality datasets while leveraging crowdsourcing can provide valuable insights and expertise. Implementing privacy-encryption techniques, such as federated learning or differential privacy, may help allow data sharing and collaboration while protecting sensitive information.

Future research should prioritise intelligent information fusion, robotics, and embodied intelligence, together with enhancement, interpretation [118] and verification of trusted decision support for practical application of human-machine intelligence in agriculture and forestry.

6 Concluding Remarks

Our premise is that AI holds great potential for revolutionising the planning, monitoring and management of agricultural systems. We opine that human- centred AI – a paradigm that learns from user inputs and experience over time – together with transfer learning and AI-explainable interpretability hold great promise. We further suggest that research and development may be better placed if it were to focus on the application of such science to transdisciplinary problems, including irrigated agriculture, for optimal outcomes in such domains requires balancing of economic, environmental, social and institutional considerations. The development and commercialisation of sensing devices to harness big data – such as satellite imagery, within-field and machine-mounted sensors – has provided impetus for rapid development of AI in an array of disciplinary applications to harness enormous data streams. However, effective synthesis of such data into meaningful, legible and actionable forms deserves more attention, including with how spatio-temporal variability can be best illustrated. While contemporaneous inertia underpinning technical development of AI as a science has been breathtaking, appropriate legal and regulatory policies have been somewhat outpaced. As such, end-users have become increasingly concerned with encryption, data ownership and privacy of their information, giving rise to issues associated with trust, moral license to operate, legitimacy and credibility of AI and software developers. Public good associated with AI may only be realised if such issues are addressed sooner rather than later.

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Declarations

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