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Digital technologies for water use and management in agriculture: Recent applications and future outlook

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ABSTRACT

This article provides a comprehensive overview of digital technologies for water use and management in agriculture, examining recent applications and future prospects. It examines key water-related challenges - scarcity, pollution, inefficient use and climate change - and shows how various digital technologies such as Remote Sensing, Artificial Intelligence, the Internet of Things, Big Data, Robotics, Smart Sensors and Blockchain can help address them. The review finds that these technologies offer significant potential for improving water management practices, with Remote Sensing and Artificial Intelligence emerging as the most versatile and widely adopted. Efficient irrigation strategies appear to be the most common application across technologies. Digital solutions significantly reduce water wastage, help identify pollution hotspots, and improve overall water resource management. For example, remote sensing-based approaches (e.g. UAV-mounted multispectral cameras) can accurately monitor soil moisture to optimise irrigation scheduling, while AI-driven models (e.g. random forest or neural networks) can predict groundwater recharge or forecast rainfall events. However, several barriers to widespread adoption are identified, including high implementation costs, lack of technical expertise, data management challenges, and infrastructure and connectivity constraints. The study concludes by suggesting priorities for future research and development, highlighting the need for integrated technological solutions, improved accessibility and affordability, improved efficiency and sustainability, improved water quality, enhanced data management capabilities, and strategies to address emerging concerns such as cybersecurity and the environmental impact of digital technologies themselves. This review aims to inform future research, policy and practice in agricultural water management and support the development of more productive, resilient and sustainable agricultural systems.

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1. Introduction

Water is a finite resource that plays an irreplaceable role in sustaining life and supporting agricultural production. Water scarcity is a critical challenge affecting regions around the world, particularly in arid and semi-arid areas, with profound implications for global food security and the economic and environmental sustainability of human activities. In fact, water scarcity affects about two-thirds of the world's population, with about four billion people facing severe water shortages for at least one month each year, particularly in India and China, and half a billion people facing severe water scarcity throughout the year (Mekonnen and Hoekstra, 2016). This situation is exacerbated by increased demand for water due to climate change and population growth (Gosling and Arnell, 2016), with the global population projected to reach nearly 10 billion by 2050, up from 8 billion in 2022 (United Nations, 2022). It is predicted that more than 2 billion urban dwellers could face water scarcity by 2050, with India facing the most severe water-scarce urban population growth (He et al., 2021).

Agriculture is a major consumer of freshwater, accounting for approximately 70 % of global freshwater withdrawals (Ridoutt et al., 2021). Population demand for water-intensive crops continues to grow, increasing pressure on limited water resources (Hachimi et al., 2023; Sarker et al., 2019a). Water scarcity, coupled with climate change, poses a significant threat to food production, with increasing competition for water between agriculture and other sectors (Mancosu et al., 2015). Inefficient water use, particularly in agriculture, contributes to water scarcity. Significant amounts of water are lost through poor irrigation practices, highlighting the need for improved water management (Fereres and Soriano, 2007). This is a global problem that affects both developed and underdeveloped countries. In countries such as Pakistan, for example, inefficient irrigation systems exacerbate water losses, further threatening food security (Zhang et al., 2021). Implementing advanced technologies and improving water use efficiency are critical to mitigating water scarcity (Tzanakakis et al., 2020).

Water quality issues, such as pollution and salinity, exacerbate water scarcity problems. Polluted return flows from excessive water withdrawals are degrading water quality, particularly in densely populated regions such as eastern China and India (van Vliet et al., 2021). In addition, over-extraction of groundwater for irrigation is lowering water tables and increasing soil salinity, reducing crop yields and affecting rural livelihoods (Sun et al., 2015). Addressing water quality challenges is critical to ensuring sustainable water supplies and maintaining ecosystem health (Liu et al., 2016). Sustainable water management strategies are needed to address these challenges and secure future food supplies (Kannan and Anandhi, 2020).

Agriculture 4.0, or digital agriculture, is a transformative approach that integrates digital technology into agricultural practices. This ongoing revolution in agriculture leverages Remote Sensing, the Internet of Things, Big Data, Artificial Intelligence and Robotics, among other technologies, to improve the efficiency, productivity and sustainability of agriculture and agri-food businesses (Hassoun et al., 2023; Latino et al., 2022; Parra-López et al., 2024b). Within the Agriculture 4.0 paradigm - characterised by data-driven, connected and automated processes - digital technologies have emerged as key enablers of 'smart' water management. These technologies align with Agriculture 4.0 principles through the use of real-time data flows, predictive analytics, and automation (Parra-López et al., 2024b; Wolfert et al., 2017). As an extension, the emerging concept of Agriculture 5.0 encourages the integration of these digital solutions with human-centred design, sustainability, and advanced robotics to further optimise efficiency while protecting the environment (Balaska et al., 2023).

Digital technologies are playing an increasingly central role in the management and use of water in agriculture, which is crucial given the sector's significant water consumption. The use of digital solutions facilitates more precise agricultural practices, optimising inputs and striking a balance between minimising environmental impacts and maximising agricultural output (Wolfert et al., 2017). By using real-time data from sensors and satellite imagery, farmers can make informed decisions that lead to more efficient resource use and improved crop management (Liakos et al., 2018). For example, Remote Sensing technologies and drones provide detailed data on crop health and water requirements, facilitating targeted interventions to prevent both under- and over-irrigation (Marques et al., 2024; Messina and Modica, 2022; Sishodia et al., 2020). These technological advances are making a significant contribution to addressing the challenges of water scarcity and ensuring the sustainable use of water resources in agriculture.

Despite a considerable body of research on digital technologies for agricultural water use and management, there are notable gaps in the existing literature that warrant further investigation. Much of the current research tends to focus on specific technologies such as remote sensing (e.g. Karthikeyan et al., 2020) or machine learning (e.g. Haggerty et al., 2023), within specific local or regional contexts, limiting the broader applicability of the findings. Furthermore, while some review studies have examined a range of digital technologies, they often focus on specific agricultural practices, such as irrigation (Bounajra et al., 2024), or specific challenges, such as inefficient water use and targeted strategies to address them (Preite et al., 2023). These limitations highlight the need for more comprehensive, holistic and up-to-date research approaches that include a wide range of digital technologies and their recent applications in different agricultural practices. Such studies should address the multiple challenges related to water use and management from a global perspective, considering different strategies. Furthermore, it is crucial to explore both the opportunities and barriers to the adoption of these technologies in order to advance the discourse and research in this area.

In this context, the paper has four main objectives: 1) provide a comprehensive analysis of current key water-related challenges and strategies for water use and management; 2) examine recent applications of digital technologies related to agricultural water use and management in different contexts; 3) examine potential barriers and challenges to the widespread adoption of these technologies; 4) propose future research directions and actions to support the further integration of digital technologies in agriculture. By addressing these objectives, this study aims to contribute to a more nuanced and holistic understanding of the role of digital technologies in agricultural water use and management, thereby informing future research, policy and practice in this critical area. It aims to contribute to harnessing the potential of digital technologies to improve agricultural practices, increase water use efficiency and address global challenges related to water scarcity and management in the context of climate change.

2. Key challenges and strategies for water use and management in agriculture

This section provides an overview, based on the literature, of the main strategies for improving water use and management in agriculture, focusing on their benefits and applicability to the different water-related challenges under consideration. A summary of the identified strategies, their associated techniques and practices, and their main benefits is presented in Table 1.

2.1. Water scarcity

Water scarcity is a major and growing concern, resulting from an imbalance between freshwater demand and availability in specific regions and at specific times (Huang et al., 2021; Khondoker et al., 2023; Scanlon et al., 2023). In agriculture, this scarcity poses a critical risk to food security, driven by population growth and competition for water with non-agricultural users (Ingrao et al., 2023). Water scarcity in agriculture can be attributed to both physical and economic factors (He and Rosa, 2023): 1) Physical water scarcity: This includes a) green water scarcity, which occurs when there is insufficient rainfall and soil

Table 1
Strategies, practices and benefits for improving water use and management in agriculture.

Key challenges	Strategies	Techniques and practices associated	Key benefits	References
Water scarcity	Deficit irrigation	Application of recommended and prescribed rates through deficit irrigation management strategies (e.g. soil moisture monitoring)	Reduces risk of food insecurity, efficient use of water	Rosa et al., (2020a); (Dingre and Gorantiwar, 2021); Chen et al., (2023); Berríos et al., (2024)
	Soil water retention	Conservation agriculture practices such as no-till, cover crops, crop rotations, mulching and crop residue retention	Increases soil moisture, conserves green water	Ricciardi et al., (2020); He and Rosa, (2023); Hashimi et al., (2023); Berríos et al., (2024); Al-Shammary et al., (2024); He and Rosa, (2023); Rodríguez et al., (2024)
	Improvement of infrastructure and water storage systems	Water harvesting, collection and storage of run-off using tanks, ponds and natural systems (e.g. managed aquifer recharge); water infrastructure inspections and improvements	Effective options for reducing water deficits	Rockström and Falkenmark, (2015); Jägermeyr et al., 2016; Ricciardi et al., (2020); Rosa et al., (2020a)
	Sustainable water resources management	Using advanced techniques and technologies to identify potential groundwater, predict water levels and recharging patterns	A decision support tool to optimise water resources management	Banerjee et al., (2024); Rajasekhar et al., (2022); Roy et al., (2024); Shahbazi et al., (2024); Siddi Raju et al., (2019)
	Utilisation of non-conventional water resources	Irrigation with treated wastewater and desalinated seawater	Addresses water scarcity and provides alternatives and renewable water sources	Garcia and Pargament, (2015); Singh, (2021); Ofori et al., (2021); Martínez-Alvarez et al., (2016); Martínez-Álvarez et al., (2023); Ben Abdallah et al., (2023)
	Water governance	Stakeholder collaboration and participation in sustainable water use and management	Improves water use and management, reduces conflicts	Argente García et al., (2024), (2024); Cao et al., (2024); Nouri et al., (2023)
Water pollution and quality degradation	Monitoring and forecasting water quality	Improvement of water quality monitoring programmes through intelligent decision support systems and tools, joint monitoring of surface water and groundwater, use of better water sampling approaches for quality monitoring, use of advanced wireless technologies and smart techniques, use of water quality indices, etc.	Improve water quality, provide accurate and efficient assessment of water resources, prevent pollution	Behmel et al., (2016); Liu et al., (2021); Lothrop et al., (2018); Chow et al., (2020); Mohammed et al., (2024); Rahaman et al., (2024); Essamlali et al., (2024); Johnston et al., (2024)
	Improved management of agricultural inputs (fertilisers, pesticides)	Precision management of agricultural inputs, reducing the use of synthetic fertilisers and pesticides	Reduce contaminants, improve soil and water health	Bongiovanni and Lowenberg-Deboer, (2004); Iho and Laukkanen, (2012); Ding et al., (2024); Luna Juncal et al., (2023); Saha et al., (2023)
	Strategies to reduce pollutant run-off	Biogeochemical, conservation farming practices, vegetation of drainage ditches, wetlands, buffers, drip irrigation, etc.	Minimise the discharge of pollutants, protect water bodies	Kröger et al., (2012); Luna Juncal et al., (2023); Mitchell et al., (2022)
	Strategies for livestock and manure management	Improved manure storage and application aspects (timing and techniques), sustainable wastewater management	Manage waste, improve water quality, reduce emissions and discharges to water	Saha et al., (2023); Silva-Gálvez et al., (2024); Xu et al., (2023)
	Circularity	Sustainable wastewater recovery and recycling (treatment and reuse), drainage water recycling, hydroponic crops, etc.	Improve nutrient recovery, minimise pollutant losses, reuse water, reduce resource depletion, provide supplemental irrigation	Crovella et al., (2024); Koseoglu-Imer et al., (2023); Silva-Gálvez et al., (2024); Magwaza et al., (2020); Moursi et al., (2023)
Inefficient water use	Efficient irrigation strategies	Smart irrigation, sustainable and regulated deficit irrigation, decision support tools, irrigation control and monitoring	Improve water productivity, reduce water wastage	Benzaouia et al., (2023); Bwambale et al., (2022); Nouri et al., (2023)
	Land use management	Choice of crops (e.g. C4 or C3 crops) and cropping systems (e.g. monocropping or double cropping) according to water availability, multiple use of water through mixed/integrated farming systems (e.g. mixed crops and livestock and fisheries), adoption of intercropping systems, etc.	Adapting to local conditions, improving water availability and productivity	Franco et al., (2018); Riaz et al., (2020); Yadav et al., (2024)
	Soil moisture management	Precise management of soil moisture (i.e. accurate measurements through smart technologies), use of mulching through plastic or biological resources (e.g. straw or residues)	Controlling and optimising soil moisture, increasing water use efficiency and productivity	Mane et al., (2024); Susha Lekshmi et al., (2014); Yadav et al., (2024);
	Field, plant and foliar monitoring and measurements	Measurements and analyses of soil, plant and leaves to improve input management (e.g. use of potassium fertiliser to increase water use efficiency in certain climatic and soil conditions), measurements of photosynthesis and transpiration by measuring gas exchange in leaves to determine and control water use efficiency	Improve decision making and water efficiency	Medrano et al., (2015); Yang et al., (2023)
Climate change	Crop improvement	Adoption of resilient and less water-intensive crops and varieties	Adapting to climate change, drought resilience	Turral et al., (2011); Pixley et al., (2023); Towolawi et al., (2024)
	Water saving	Irrigation scheduling and monitoring techniques and technologies; hydroponics; drip irrigation	Reduce water consumption, increase efficiency	Benzaouia et al., (2023); Mi et al., (2021); Saitta et al., (2021); Pomoni et al., (2023)
	Forecasting and prediction	Early warning systems for droughts, extreme weather events and water-related diseases	Prepare for extreme events, timely response	Cai et al., (2024); Masupha et al., (2021); Girotto et al., (2024)

(*continued on next page*)

Table 1 (*continued*)

Key challenges	Strategies	Techniques and practices associated	Key benefits	References
	Water harvesting	Rooftop rainwater harvesting systems; micro-catchment, macro-catchment and in-situ water harvesting, etc.	Increasing water availability, supporting crops	Boers and Ben-Asher, (1982); Carpio-Vallejo et al., (2024); Lin et al., (2019); Nouri et al., (2023)
	Soil conservation practices	Direct seeding, cover crops, crop rotation, mulching and crop residue retention	Improve soil health, retain water	Hashimi et al., (2023); Liu et al., (2024); Verma et al., (2024)
	Use of renewable energy for irrigation	Geothermal heat pumps, solar energy for water pumping (solar PV) and wind energy for desalination systems, etc.	Sustainable irrigation, reducing carbon footprint	Ben Abdallah et al., (2023); Khattak et al., (2024); Majeed et al., (2023)

moisture to meet the water needs of crops (Liu et al., 2022; Rosa et al., 2020b; Schyns et al., 2019) and is of particular concern in rainfed agricultural systems where crops depend solely on rainfall; and b) blue water scarcity, which refers to the insufficient availability of renewable water in surface and groundwater sources to sustainably meet irrigation needs (J. Liu et al., 2017; Rosa et al., 2020a; Vanham et al., 2018). Unsustainable irrigation practices in many regions are exacerbating blue water scarcity, leading to over-extraction and depletion of water resources (He and Rosa, 2023; Jägermeyr et al., 2017; Rosa et al., 2018); and 2) Economic water scarcity: It results from economic and institutional barriers that prevent the effective mobilisation of available renewable blue water resources for irrigation, thereby exacerbating the effects of green water scarcity (Ingrao et al., 2023; Rosa et al., 2020a). This is often due to inadequate infrastructure, underinvestment in water management and poor governance. According to Rosa et al. (2020a), 76 % and 25 % of the world's cropland faces green water scarcity (at least one month per year) and economic water scarcity, respectively, while 16 % of cropland is unsustainably irrigated.

In this context, different strategies can be adopted to address water scarcity in agriculture, focusing on different agricultural practices and components. These include estimated and recommended deficit irrigation rates (Berríos et al., 2024; Chen et al., 2023; Dingre and Gorantiwar, 2021; Rosa et al., 2020a), together with the development of appropriate infrastructure and storage facilities (Jagermeyr et al., 2021; Ricciardi et al., 2020; Rockström and Falkenmark, 2015; Rosa et al., 2020a), sustainable water resources management (e.g. identification of groundwater potential, prediction of water levels and recharge patterns) through advanced techniques and technologies (Banerjee et al., 2024; Rajasekhar et al., 2022; Roy et al., 2024; Shahbazi et al., 2024; Siddi Raju et al., 2019), soil water retention practices (Al-Shammary et al., 2024; Berríos et al., 2024; Hashimi et al., 2023; He and Rosa, 2023; Ricciardi et al., 2020; Rodríguez et al., 2024), and water governance for sustainable water use and management (Argente García et al., 2024, 2024; Cao et al., 2024; Nouri et al., 2023), can significantly reduce the risk of food insecurity in water-stressed agricultural regions. For rainfed crops that rely on rainfall (green water) and where irrigation is not feasible, practices that increase soil moisture and retain green water while minimising evaporation are particularly recommended (Al-Shammary et al., 2024; He and Rosa, 2023; Rodríguez et al., 2024). In addition, irrigation with non-conventional water resources such as treated wastewater (Garcia and Pargament, 2015; Ofori et al., 2021; Singh, 2021) and desalinated seawater (Ben Abdallah et al., 2023; Martínez-Álvarez et al., 2023; Martínez-Alvarez et al., 2016) can alleviate water scarcity in many regions, considering the need to further improve some environmental aspects (energy and pollution) associated with their production and use.

2.2. Water pollution and quality degradation

The water crisis is exacerbated by water quality degradation, to which poor management of agricultural drainage and wastewater is a major contributor in many parts of the world (Mateo-Sagasta et al., 2018). The expansion of agricultural land, coupled with irrigation and the use of chemical fertilisers and pesticides, has increased crop production globally, while transferring pollutants to water bodies (Mateo-Sagasta et al., 2017). Otherwise, the increasing intensification of the livestock sector has significant impacts on water quality due to manure management issues and veterinary drug residues (Mateo-Sagasta et al., 2017; Xu et al., 2023; Zhou et al., 2022).

Agricultural water pollution results from the discharge of various pollutants such as nutrients from mineral and organic fertilisers (nitrogen and phosphorus), animal waste, pesticides, organic matter, sediments, metals, salts and others (pathogens, residues, etc.) (Mateo-Sagasta et al., 2017). Agricultural water pollution poses significant risks to human health, aquatic ecosystems (e.g. eutrophication) and biodiversity (Chaudhary et al., 2024; Luna Juncal et al., 2023; Mateo-Sagasta et al., 2018). Deteriorating water quality poses a serious threat to agricultural productivity and long-term water and food supply, as evidenced by the effects of irrigation with saline or brackish water, among others (Mateo-Sagasta and Burke, 2010).

Various options have emerged to address agricultural water pollution and water quality degradation (Luna Juncal et al., 2023; Mateo-Sagasta et al., 2018). These include water quality monitoring and forecasting (Behmel et al., 2016; Chow et al., 2020; Essamlali et al., 2024; Johnston et al., 2024; Liu et al., 2021; Lothrop et al., 2018; Mohammed et al., 2024; Rahaman et al., 2024), better management of agricultural inputs and components (water, soil, fertilisers and pesticides) (Bongiovanni and Lowenberg-Deboer, 2004; Ding et al., 2024; Iho and Laukkanen, 2012; Luna Juncal et al., 2023; Saha et al., 2023; Xue et al., 2023; Young et al., 2022), pollutant runoff reduction strategies and drainage improvements (Kröger et al., 2012; Luna Juncal et al., 2023; Mitchell et al., 2022; Wang et al., 2024; Young et al., 2022), livestock and manure management strategies (Saha et al., 2023; Silva-Gálvez et al., 2024; Xu et al., 2023; Zhou et al., 2022) and circularity (Crovella et al., 2024; Koseoglu-Imer et al., 2023; Magwaza et al., 2020; Moursi et al., 2023; Silva-Gálvez et al., 2024), among others.

2.3. Inefficient water use

Inefficient water use contributes to the depletion of water resources and leads to water scarcity, as observed in many regions of the world (Aboelkhair et al., 2019; Jiang, 2009; Nouri et al., 2023; Yadav et al., 2024). This inefficiency is reflected in lower water productivity when considering yield or agricultural output (e.g. carbon sequestered) per unit of water used, i.e. producing the same yield or agricultural output with more water (Callejas Moncaleano et al., 2021; Nouri et al., 2023; Yadav et al., 2024). Several authors (Kumar et al., 2023; Nouri et al., 2023; Yadav et al., 2024) attribute low water use efficiency to the low adoption of efficient and sustainable water management practices and technologies in many parts of the world.

Improved water use efficiency can be achieved through practices (irrigation, fertilisation and soil management) that increase consumptive evapotranspiration (Nouri et al., 2023; Yadav et al., 2024), strategies that increase and/or adapt to water availability (land use management through crop and cropping system selection, water harvesting, soil evaporation control) (Franco et al., 2018; Nouri et al., 2023; Riaz et al., 2020; van Opstal et al., 2021; Yadav et al., 2024), efficient irrigation strategies (deficit irrigation, precision irrigation) (Benzaouia et al., 2023; Bwambale et al., 2022; Nouri et al., 2023), use of soil moisture management techniques (accurate measurements, mulching, etc.) (Mane et al., 2024; Susha Lekshmi et al., 2014; Yadav et al., 2024), and field, plant and foliar monitoring and measurements for rational use of inputs and control of water use efficiency (Medrano et al., 2015; Yang et al., 2023).

2.4. Climate change

Addressing the above challenges in the context of climate change is particularly challenging, especially in regions already facing water scarcity (Iglesias and Garrote, 2015; Nouri et al., 2023; Rosenzweig et al., 2004). Changes in precipitation patterns and the occurrence of extreme weather events are two particularly critical variables for agriculture, with different profiles in different regions (Iglesias and Garrote, 2015; Ingrao et al., 2023; WMO, 2023). For example, a decreasing trend in precipitation and an increase in droughts have been observed in climate projections for the Mediterranean (Hrour et al., 2023; Iglesias and Garrote, 2015), Iran (Nouri et al., 2023) and West African basins (Mbaye et al., 2020), while increases in precipitation, flood risk and runoff are projected for Korean basins (Noh et al., 2024), and general changes in precipitation patterns and temperature increases are expected in other regions such as Europe (Iglesias and Garrote, 2015).

The World Meteorological Organization (WMO, 2023) shows changing precipitation patterns, the devastating effects of extreme events, increased greenhouse gas (GHG) emissions and a warming climate in many parts of the world over the last decade (2011–2020). Such events threaten both the quantity and quality of water and the ability of ecosystems to provide sufficient water, especially for agriculture (Borsato et al., 2018; Ingrao et al., 2023; Jabal et al., 2022). Agriculture also contributes to climate change through GHG emissions, mainly from animal husbandry and soil management (Kebreab et al., 2006), deforestation and land use change (Barbier, 2004; Pendrill et al., 2022), soil carbon losses (NATH and LAL, 2017; Willekens et al., 2014; Zhang et al., 2018) and energy use (Harding and Peduzzi, 2012; Woods et al., 2010).

Agriculture needs to adapt to and mitigate the effects of climate change. Accordingly, ensuring adaptation and mitigation is the aim of agricultural strategies to this end. These include crop improvement (use of resilient and less water-intensive varieties) (Pixley et al., 2023; Towolawi et al., 2024; Turral et al., 2011), improved water use and management (water-saving technologies, smart irrigation, etc.) (Benzaouia et al., 2023; Mi et al., 2021; Saitta et al., 2021; Sengupta et al., 2023; Pomoni et al., 2023), forecasting and prediction (Cai et al., 2024; Girotto et al., 2024; Masupha et al., 2021), water harvesting (Boers and Ben-Asher, 1982; Carpio-Vallejo et al., 2024; Lin et al., 2019; Nouri et al., 2023), practices that increase water availability and soil moisture such as soil conservation practices (e.g. soil conservation practices, organic fertilisers) (Hashimi et al., 2023; Liu et al., 2024; Verma et al., 2024) and other strategies (e.g. non-conventional water resources, use of renewable energy for irrigation) (Ben Abdallah et al., 2023; Khattak et al., 2024; Majeed et al., 2023).

3. Applications of digital technologies for water use and management in agriculture

This section provides an up-to-date overview of recent digital technology applications for agricultural water management, and how they relate to the challenges and strategies discussed above. The literature review was carried out to identify recent studies and advances for a wide range of recognised digital technologies in the agri-food sector (Hassoun, 2024). First, the Web of Science and Scopus databases were searched using targeted queries for each digital technology (Fig. 1). The most relevant technologies were then selected according to the number of references for each technology. Although Virtual/Augmented Reality (VR/AR) and Digital Twin technologies have potential in agriculture, our database search revealed a limited number of peer-reviewed studies specifically focused on water use or water management in agriculture. Therefore, although they may merit future research attention, these technologies are not included in this review. The references for each selected technology were then manually screened for relevance to the topic of digital technologies in agriculture for water use and management, attempting to focus on the most recent. In a very few cases where the number of studies identified was limited, the search was extended to reputable non-academic sources (government/FAO reports, sector articles, etc.) to obtain complementary evidence.

There has been a remarkable increase in research on the selected digital technologies for water use and management in agriculture since

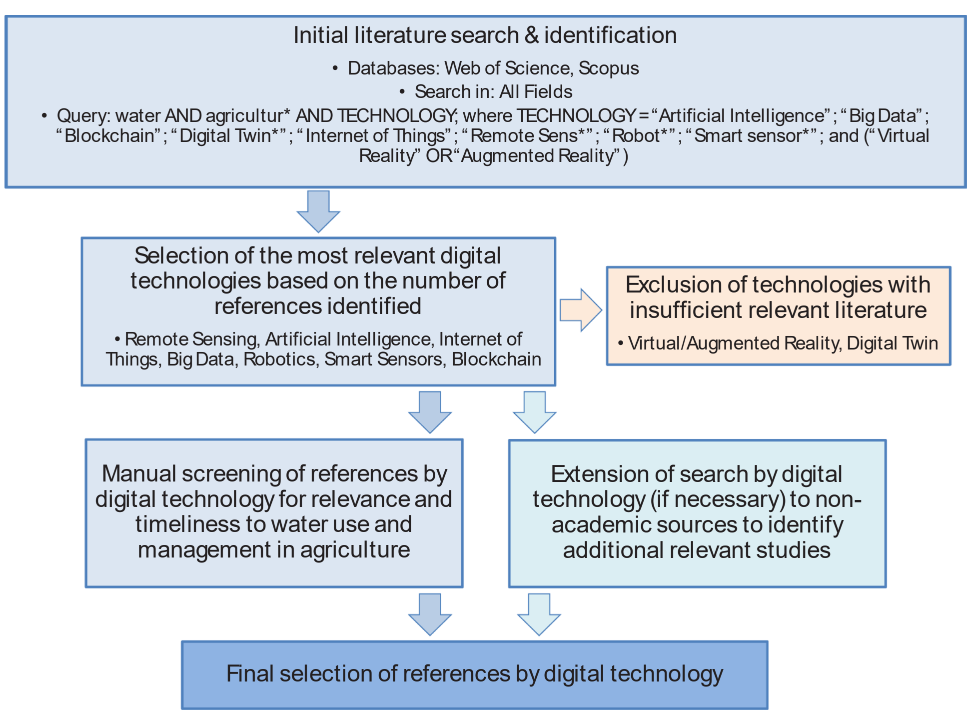

Fig. 1. Schematic of the literature review process to identify relevant digital technologies.

1991 (Fig. 2). The field of Remote Sensing leads with the highest number of publications, indicating its crucial role in resource monitoring. Notably, the field of Artificial Intelligence has experienced a surge in growth, particularly since 2019. This reflects the growing importance of Artificial Intelligence in decision-making processes. In addition, the Internet of Things and Big Data are also gaining momentum, in line with the trend towards data-driven agricultural practices. Although the number of publications on Robotics, Smart Sensors and Blockchain is relatively low, their consistent growth indicates their emerging role in agriculture.

Table 2 provides an overview of the results of the review carried out, indicating the digital technologies analysed, their main applications and contributions, and the relevant references. It also identifies for each application the main water-related challenges addressed and the strategies adopted to improve water use and management, which is directly related to the content of Section 2. These results are presented in detail below.

3.1. Digital technologies and their applications

3.1.1. Remote sensing

Remote Sensing (RS) in agriculture refers to the use of satellite, airborne or ground-based sensor technologies to collect and interpret data about agricultural fields without direct contact. This technology captures information about the surface of agricultural land, including soil conditions, crop health, moisture levels and others, at various spectral, spatial and temporal resolutions. RS data are used to effectively monitor and manage agricultural resources, optimise crop production and improve overall farm management practices (Peng et al., 2021; Sishodia et al., 2020; Tarate et al., 2024).

In agricultural water management, RS technology has become an invaluable asset, providing a variety of applications to improve water use efficiency, monitor crop health and optimise irrigation practices. These advances have led to the emergence of precision irrigation, a specialised approach that stems from the broader field of precision agriculture (Ju et al., 2022; Kumar Singh and Sobti, 2022; Kutyauripo et al., 2023).

One of the main applications of RS in agriculture is to optimise irrigation scheduling and soil moisture monitoring. RS technologies, such as satellite imagery and aerial drones, can provide real-time data on soil moisture and crop water status. By analysing this data, farmers can determine the optimal times to irrigate, ensuring that crops receive the right amount of water at the right time. This not only improves crop yields, but also conserves water resources by preventing over-irrigation and water waste (Awais et al., 2022; Massari et al., 2021; Singh et al., 2023; Toureiro et al., 2017; Zappa et al., 2024). Available references show that high-resolution soil moisture maps are essential for the identification and monitoring of irrigated areas, providing detailed information that is crucial for improving water management practices at both local and regional levels. By providing accurate data on soil moisture conditions, these maps enable more efficient allocation of water resources, support the optimisation of irrigation schedules and help to identify areas of water stress. This leads to improved agricultural productivity and sustainable water use, benefiting both farmers and regional water management authorities (Fan et al., 2015; Peng et al., 2021).

Different RS techniques (i.e. thermal, optical and microwave) and their combinations can be used to provide information on irrigation. For example, a study carried out in the north-east of the Iberian Peninsula in Spain used the DISPATCH (DISaggregation based on Physical And Theoretical scale CHange) method, which allows microwave data to be combined with optical data. The results showed that using these high-resolution RS data to assess soil moisture levels allows accurate estimation of irrigation water requirements, improving water use efficiency and optimising agricultural productivity (Dari et al., 2020). Similar results were later obtained in other studies, confirming that RS can be beneficial in various applications such as irrigation scheduling and farm-scale water management (Dari et al., 2021; Zheng et al., 2021).

Unmanned Aerial Vehicles (UAVs) equipped with RS technology are revolutionising smart irrigation by enabling precise monitoring of soil moisture and crop water content. For example, UAV-based multispectral and thermal infrared imagery was successfully used to accurately map soil moisture at different depths for a kiwifruit orchard using machine learning (Zhu et al., 2023) and ensemble learning algorithms, a subset of machine learning techniques (Zhu et al., 2024).

Regarding crop water content, UAV imagery based on the visible-NIR spectrum was used to plan irrigation for different types of crops in all seasons in the Mutale River catchment in southern Africa (Mndela et al., 2023). The study used linear regression analysis to investigate the relationships between four spectral vegetation indices and crop water content. Significant correlation coefficient values were obtained, indicating that the developed method is effective in optimising irrigation water use while maintaining maximum crop yield. In a similar study, the water status of vineyards was estimated using multispectral images captured by UAV platforms combined with machine learning algorithms to manage irrigation scheduling (Romero et al., 2018). High accuracy was achieved using Artificial Neural Network models developed at the pixel and plant level, suggesting significant potential to support

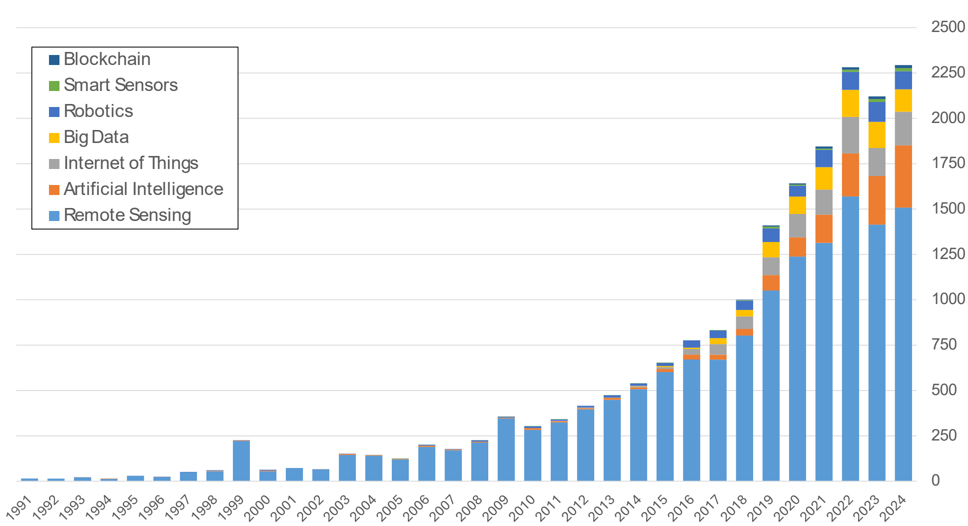

Fig. 2. Annual publication trends (1991-present) for selected digital technologies in agricultural water management. *Source: Based on data from Web of Science.*

Table 2
Digital technology applications and contributions to water use and management in agriculture and key challenges and strategies.

Digital technology	Application	Main contributions	References about applications and their contributions	Key challenges addressed*	Strategies implemented*
Remote Sensing (RS)	Optimisation of irrigation scheduling and soil moisture monitoring	Provides real-time data on soil moisture and crop water status; improves crop yields; conserves water resources; reduces water consumption	Awais et al., (2022); Massari et al., (2021); Singh et al., (2023); Toureiro et al., (2017); Zappa et al., (2024)	Inefficient water use / water scarcity / climate change	Efficient irrigation strategies; soil moisture management / deficit irrigation / water saving
	High resolution soil moisture maps	Enables efficient allocation of water resources; identifies areas of water stress; supports optimisation of irrigation schedules	Fan et al., (2015); Peng et al., (2021)	Water scarcity / inefficient water use / climate change	Deficit irrigation; soil water retention / efficient irrigation strategies / water saving
	Integration of thermal, optical and microwave RS techniques for irrigation	Accurately estimates of irrigation water requirements; improves water use efficiency; optimises agricultural productivity	Dari et al., (2021), (2020); Zheng et al., (2021)	Inefficient water use / climate change	Efficient irrigation strategies / water saving
	UAV-based soil moisture monitoring	Precise monitoring of soil moisture content; supports smart irrigation	Zhu et al., (2024), (2023).	Inefficient water use / water scarcity	Efficient irrigation strategies; soil moisture management / deficit irrigation
	UAV-based crop water content monitoring	Optimises irrigation water use; maintains maximum crop yield	Mndela et al., (2023); Romero et al., (2018))	Inefficient water use	Efficient irrigation strategies; field, plant and foliar monitoring and measurements
	UAV-based drought assessment and management	Predicts drought onset, intensity and duration; implements drought mitigation strategies	Cheng et al., (2023)	Climate change	Forecasting and prediction
Artificial Intelligence (AI)	Identification of groundwater prospect zones	Enables sustainable groundwater management	Roy et al., (2024)	Water scarcity	Sustainable water resources management
	Prediction of groundwater levels in aquifers	Provides data for sustainable use and management of groundwater resources	Shahbazi et al., (2024)	Water scarcity	Sustainable water resources management
	Prediction of groundwater recharge patterns	Helps in planning and adapting to future water availability	Banerjee et al., (2024)	Water scarcity	Sustainable water resources management
	Monitoring snow water equivalent using AI and RS	Assists in understanding water availability from snowmelt	Schilling et al., (2024)	Climate change	Forecasting and prediction
	Rainfall prediction models and decision support systems	Improves irrigation management by anticipating significant rainfall; corrects systemic biases in climate predictions	Goel et al., (2024); Liang et al., (2024)	Inefficient water use / climate change	Efficient irrigation strategies / forecasting and prediction
	Optimisation of water quality monitoring	Ensures safe use of water in agriculture	Mendivil-García et al., (2023)	Water pollution and quality degradation	Monitoring and forecasting water quality
	Estimation of heavy metal content in soils	Addresses soil and water contamination	Taşan et al., (2024)	Water pollution and quality degradation	Monitoring and forecasting water quality; improved management of agricultural inputs
	Prediction of groundwater quality	Provides reliable data for safe agricultural practices	Abbas et al., (2024); Hardas and Tomar, (2024)	Water pollution and quality degradation	Monitoring and forecasting water quality
	Real-time water quality information	Informs water treatment and crop selection for sustainability	Kapoor et al., (2024)	Water pollution and quality degradation	Monitoring and forecasting water quality
	Smart irrigation and scheduling	Reduces water use and improves crop yield; optimises crop yield and quality	Al Mashhadany et al., (2024); Dolaptsis et al., (2024); Durmuş et al, (2024); Patil et al., (2024)	Water scarcity / inefficient water use / climate change	Deficit irrigation / efficient irrigation strategies / water saving
	Anomaly detection in irrigation systems	Ensures reliable data for informed decisions	Benameur et al., (2024)	Inefficient water use	Efficient irrigation strategies
	Evaluation of irrigation systems	Enhances performance and efficiency of irrigation practices	Dehghanisanij et al., (2024)	Inefficient water use	Efficient irrigation strategies
	Advanced integrated systems combining crop forecasting, fertiliser recommendations and automated irrigation	Improves precision crop management; optimises water and nutrient use; improves crop yield and quality	Sharma and Kumar, 2024	Inefficient water use	Field, plant and foliar monitoring and measurements; efficient irrigation strategies
	Smart hydroponics	Optimises nutrient solution, water and light delivery for climate resilience	Rajendran et al., (2024)	Inefficient water use / climate change / water pollution and quality degradation	Efficient irrigation strategies / water saving / circularity
	Classification of crop response to drought using image analysis	Improves irrigation planning under drought conditions	Munaganuri and Rao, (2024))	Climate change	Forecasting and prediction
	Proximal hyperspectral imaging for plant water dynamics	Improves precision in crop water management	Malounas et al., (2024)	Inefficient water use	Field, plant and foliar monitoring and measurements; efficient irrigation strategies
	Overcoming the discontinuity in optical satellite imagery	Enables real-time planning of agronomic activities	Farbo et al., (2024)	Climate change / inefficient water use	Forecasting and prediction / efficient irrigation strategies; field, plant and foliar monitoring and measurements

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Table 2 (*continued*)

Digital technology	Application	Main contributions	References about applications and their contributions	Key challenges addressed*	Strategies implemented*
	Estimation of evaporation	Useful for irrigation planning and water resource management; alternative to traditional estimation methods for irrigation planning	Karahan et al., (2024); Sarıgöl and Katipoğlu, (2024)	Climate change / inefficient water use	Forecasting and prediction / efficient irrigation strategies
	Tiny machine learning for UAV-based smart farming	Guides optimal crop water use	Hayajneh et al., (2024)	Inefficient water use	Efficient irrigation strategies
	Identification of sustainable livestock with low water footprint	Reduces water use and pollution in livestock production	Silveira et al., (2023)	Water pollution and quality degradation	Strategies for livestock and manure management
	Groundwater quality around livestock burial sites	Monitors and ensures safe groundwater use in agriculture	Oh et al., (2023)	Water pollution and quality degradation	Monitoring and forecasting water quality
Internet of Things (IoT)	Real-time water quality monitoring	Enables continuous monitoring and timely detection of pollution; ensures water safety	Bhardwaj et al., (2022); Jan et al., (2021); Mezni et al., (2022)	Water pollution and quality degradation	Monitoring and forecasting water quality
	IoT-based water reuse framework	Facilitates water reuse within greenhouses; reduces pollution risks; optimises resource use	O'Grady et al., (2019); Zia, (2022)	Water scarcity / water pollution and quality degradation	Utilisation of non-conventional water resources / circularity; strategies to reduce pollutant run-off
	Water pipeline monitoring for early leak detection	Prevents water waste and infrastructure damage; ensures pipeline integrity	Mohd Yussof and Ho, (2022))	Water scarcity	Improvement of infrastructure and water storage systems
	IoT-based precision irrigation systems	Optimises water use; automates irrigation processes; maximises crop yields; improves accessibility and usability of irrigation systems	Monteleone et al., (2020)	Inefficient water use	Efficient irrigation strategies
	Smart livestock water monitoring systems	Provides insight into animal health and drinking water quality; enables proactive intervention	Schillings et al., (2021)	Water pollution and quality degradation	Strategies for livestock and manure management
Big Data (BD)	Gathering data from sensors, agricultural machinery, drones and satellites	Provides comprehensive insight into crop water dynamics and irrigation practices	Kamble et al., (2020); Kamyab et al., (2023); Sarker et al., (2019b)	Inefficient water use	Efficient irrigation strategies; soil moisture management; field, plant and foliar monitoring and measurements
	Big Data Analytics (BDA) to transform raw data into actionable information	Optimises water use; enables precise irrigation strategies; reduces water waste	Giray and Catal, (2021); Kamilaris et al., (2017); Rejeb et al., (2021)	Inefficient water use	Efficient irrigation strategies
	Precision irrigation using BD and BDA	Delivers the right amount of water at the right time and place; minimises water run-off; reduces environmental impact	Jaber et al., (2022); Rabhi et al., (2021)	Inefficient water use / water pollution and quality degradation	Efficient irrigation strategies / strategies to reduce pollutant run-off
	Predicting water availability and demand patterns	Improves accuracy of water demand forecasting; supports sustainable water management	Mekruksavanich and Cheosuwan, (2018)	Climate change	Forecasting and prediction
Robotics	Crop and soil monitoring and automated irrigation using weather forecasts	Monitors soil temperature and humidity; automates irrigation decisions; incorporates additional parameters such as stem water potential and leaf density	Baltazar et al., (2021); Dechemi et al., (2023); Wu et al., (2020)	Inefficient water use / climate change	Field, plant and foliar monitoring and measurements; efficient irrigation strategies; soil moisture management / forecasting and prediction
	Robotic irrigation systems with moving bridge manipulator and sensor-based platform	Monitors soil water content and automates irrigation processes	Gravalos et al., (2019)	Inefficient water use	Field, plant and foliar monitoring and measurements; efficient irrigation strategies
	Ground robots with thermal infrared radiometry	Assesses water status in crops such as vineyards	Fernández-Novales et al., (2021)	Inefficient water use	Field, plant and foliar monitoring and measurements; efficient irrigation strategies
	Water quality monitoring robots	Monitors water quality parameters (pH, turbidity, temperature) to determine suitability for irrigation	Gupta et al., (2021)	Water pollution and quality degradation	Monitoring and forecasting water quality
	Robots with visible light and thermal camera for leak detection	Detects water leaks in drip irrigation systems, preventing water waste	Türkler et al., (2023)	Inefficient water use / water scarcity	Efficient irrigation strategies; improvement of infrastructure and water storage systems
	Drones with visible light and thermal cameras for leak detection	Covers larger areas quickly to detect water leaks	Chen et al., (2024)	Inefficient water use / water scarcity	Efficient irrigation strategies / improvement of infrastructure and water storage systems
	Accelerometers for water leak detection	Identifies critical points in irrigation systems that are prone to leaks	Moni et al., (2019))	Inefficient water use / water scarcity	Efficient irrigation strategies / improvement of infrastructure and water storage systems
	Integration of pesticide, fertiliser sprayers and seed planters into multi-purpose robots	Extends the multi-functional capabilities of agricultural robots for efficient farm management	Abhiram and Megalingam, (2022); Chand et al., (2021); Fadhaeel et al., (2022); Munnaf	Inefficient water use / water pollution and quality degradation	Field, plant and foliar monitoring and measurements / improved management of agricultural inputs

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Table 2 (*continued*)

Digital technology	Application	Main contributions	References about applications and their contributions	Key challenges addressed*	Strategies implemented*
			et al., (2024); Prajith et al., (2020)		
Smart Sensors (SS)	Smart irrigation monitoring and control for improved water use efficiency in precision agriculture	Improves water use efficiency; provides real-time data for precise irrigation; reduces water waste	Bwambale et al., (2022)	Inefficient water use	Efficient irrigation strategies
	Multi-sensor water management	Predicts irrigation needs and recommends schedules	Khoa et al., (2019)	Inefficient water use / water scarcity	Efficient irrigation strategies; soil moisture management; field, plant and foliar monitoring and measurements / deficit irrigation
	Open source platform for agricultural water management	Integrates SSs for soil and atmospheric monitoring; alerts farmers of critical thresholds of soil moisture or pest risk	Tzerakis et al., (2023)	Inefficient water use / water scarcity	Efficient irrigation strategies; soil moisture management / deficit irrigation
	Integration with embedded devices and cloud computing for efficient and safe water management	Monitors water levels and responds to weather conditions; compares sensor data transmission between networks	(Bhardwaj et al., 2022)	Inefficient water use / water scarcity	Efficient irrigation strategies / improvement of infrastructure and water storage systems
	Smart irrigation framework using DT and IoT-based SSs	Collects and analyses data to predict soil moisture levels; optimises irrigation practices	Manocha et al., (2024)	Inefficient water use	Efficient irrigation strategies; soil moisture management
Blockchain	Improving water governance, water infrastructure and water management efficiency	Improves data security and stakeholder confidence; improves water governance and infrastructure	Satilmisoglu et al., (2024)	Water scarcity	Water governance / improvement of infrastructure and water storage systems
	Agricultural water rights trading	Reduces transaction confirmation time; minimises transaction costs; improves system efficiency	Liu and Shang, (2022)	Water scarcity / inefficient water use	Water governance / efficient irrigation strategies
	Automated community irrigation management	Increases trust among community members; facilitates resource sharing	Bordel et al., (2019)	Water scarcity / inefficient water use	Water governance / efficient irrigation strategies
	Facilitating collaboration between government, service providers and farmers	Improves collaboration to save water; builds trust between stakeholders	Cao et al., (2024)	Water scarcity	Water governance
	Integration with IoT for water metering and smart contracts	Measures water consumption; securely stores and shares data; distributes incentives among farmers	Pincheira et al., (2021)	Inefficient water use / water scarcity	Efficient irrigation strategies / water governance
	Smart water management system integrating IoT and blockchain	Coordinates use of water resources among communities; improves trust and security of data storage	Zeng et al. (2023)	Water scarcity / inefficient water use	Water governance / efficient irrigation strategies

* The 'Key challenges addressed' and 'Strategies implemented' in this Table correspond to the 'Key challenges' and 'Strategies' in Table 1.

irrigation and vineyard management.

Another application of RS is drought assessment and management. Drought is a major challenge for agriculture, affecting crop yields and water availability. By monitoring vegetation health, soil moisture and meteorological data, RS can help predict the onset, intensity and duration of drought. This information is critical for implementing drought mitigation strategies and ensuring sustainable use of water resources. For example, UAV-mounted multispectral and thermal sensors were used in combination with air temperature to provide three UAV-based drought indices, namely normalised relative canopy temperature (NRCT), temperature vegetation drought index (TVDI) and three-dimensional drought index (TDDI), to monitor crop water status in a maize field in Xinxiang, China (Cheng et al., 2023). Overall, UAV-based observations, especially with the TDDI, offered a promising approach to accurately monitor crop water status and improve remotely sensed drought indices.

An important thermal-based approach is the Crop Water Stress Index (CWSI), which uses canopy temperature relative to air temperature to provide real-time estimates of plant water stress (Jones et al., 2002). Advances in technology have enabled drone-mounted thermal imaging systems to refine CWSI calculations by integrating high-resolution spatial data with machine learning-based calibrations, improving real-time monitoring of crop water stress (Zia et al., 2013). Incorporating CWSI into thermal imaging workflows allows for more precise irrigation scheduling by identifying specific areas of water deficit within a field, thereby optimising water use efficiency and promoting sustainable agricultural practices.

3.1.2. *Artificial Intelligence*

Artificial Intelligence (AI) is being used to address threats to water resources. Groundwater is one of the most reliable sources of freshwater for agricultural use. Machine learning has been used to identify groundwater prospect zones to enable sustainable groundwater management (Roy et al., 2024), and groundwater levels in aquifers (Shahbazi et al., 2024). Various AI models have also been used to predict groundwater recharge patterns under different climate change scenarios (Banerjee et al., 2024).

Rain and snow are critical to global water cycles, and changes to the usual patterns have potentially serious implications for agriculture. AI, particularly random forest and neural network approaches, combined with RS is increasingly being used to monitor snow water equivalent (Schilling et al., 2024). Predictive machine learning models used in advance of a significant rainfall event can provide information for improved irrigation management (Goel et al., 2024). An integrated predictive decision support system is testing machine learning to correct systemic biases due to inevitably incomplete representations of climate physics (Liang et al., 2024).

Otherwise, the ability to predict water quality is critical for safe use. AI has been used to optimise water quality monitoring in an intensive agricultural basin (Mendivil-García et al., 2023). Contamination of agricultural soils with trace metals is a threat to water resources. AI models were found to be reliable and successful in estimating the heavy metal content of soils under intensive rice cultivation (Taşan et al., 2024). Groundwater quality prediction based on AI has been used to address the shortcomings of traditional approaches (Abbas et al., 2024; Hardas and Tomar, 2024). Real-time water quality information supported by AI can inform water treatment and suggest suitable crops for more sustainable agriculture (Kapoor et al., 2024).

In addition, smart irrigation is being implemented to reduce water use for crops (Durmuş et al, 2024), especially in areas of water scarcity. AI combined with the IoT can improve irrigation by monitoring crop and field characteristics (Al Mashhadany et al., 2024), in addition to controlling devices such as water pumps (Al Mashhadany et al., 2024) and spraying systems (Patil et al., 2024). AI-based irrigation scheduling can optimise crop yield and quality (Dolaptsis et al., 2024). AI can be used to analyse anomalies and problems in irrigation systems to ensure reliable and high-quality data for informed decisions (Benameur et al., 2024). AI has also been used to evaluate the performance of different irrigation systems (Dehghanisanij et al., 2024). Advanced integrated systems combine crop forecasts, fertiliser recommendations and automatic irrigation (Sharma and Kumar, 2024). Indeed, irrigation of crops can be a very inefficient use of water resources. Hydroponics is an alternative climate-resilient system for agricultural production. Smart hydroponics, based on AI, can inform the delivery of nutrient solution, water and light (Rajendran et al., 2024).

Otherwise, estimating crop water requirements using traditional methods is imprecise and limited in its adaptability to diverse crops and dynamic environmental conditions. AI is being used in conjunction with image analysis to classify the response of horticultural crops to conditions such as drought (Munaganuri and Rao, 2024). In particular, proximal hyperspectral imaging and automated machine learning have shown significant potential in tasks related to the classification of plant water dynamics (Malounas et al., 2024). AI incorporating normalised difference vegetation index and other variables has been used to address the discontinuity of optical satellite imagery due to cloud cover and the associated processing time for real-time applications to enable planning of agronomic activities such as irrigation (Farbo et al., 2024). To estimate monthly evaporation in the Southeast Anatolia project area, hybrid machine learning models were used to determine their accuracy, which would be useful for irrigation planning, water resource management and hydrological modelling studies in the region (Sarıgöl and Katipoğlu, 2024). Similarly, AI-based estimation of actual daily evapotranspiration is a promising alternative to direct estimation techniques and indirect methods that rely on RS (Karahan et al., 2024). For UAV-based smart farming applications, a tiny machine learning-based framework has been proposed to guide optimal crop water use (Hayajneh et al., 2024).

Although crop management is the main focus of AI applications, studies on livestock, particularly cattle and sheep, are common (Thakur et al., 2024). Machine learning approaches have been used to identify sustainable animals, including those with a low water footprint, using phenotypic biomarkers (Silveira et al., 2023). A supervised machine learning model was applied to groundwater quality around on-farm livestock burial sites (Oh et al., 2023).

To summarise the AI algorithms used in this area, in addition to the random forest and neural network methods described above, ensemble learning, such as Gradient Boosting and XGBoost, and hybrid models are increasingly being used to improve the accuracy of groundwater recharge and evapotranspiration estimates (Banerjee et al., 2024; Karahan et al., 2024). Automated Machine Learning (AutoML) frameworks, such as PyCaret, help to optimise hyperparameters and modelling pipelines with minimal human intervention, especially in tasks such as hyperspectral-based drought detection (Malounas et al., 2024). Tiny Machine Learning (TinyML) enables on-device AI for real-time water management in resource-limited environments (Hayajneh et al., 2024). Meanwhile, Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) show promise for classifying irrigation anomalies, water stress levels, and groundwater prospect zones (Munaganuri and Rao, 2024; Roy et al., 2024).

3.1.3. Internet of things

The Internet of Things (IoT) is emerging as the ideal solution for implementing smart water management applications and precision agriculture to avoid under- and over-irrigation. However, the seamless integration of the different technologies required for its practical use is still a work in progress (Jagtap et al., 2021). The rise of the IoT is attributed to several converging factors, including affordable devices, low-power wireless technologies, the presence of cloud data centres for storage and processing, management frameworks for handling unstructured data from social networks, high-performance computing resources on standard platforms, and computational intelligence algorithms tailored to process vast amounts of data (Ahmed et al., 2023). In recent years, the application of IoT technologies has emerged as a transformative force in agriculture, providing innovative solutions to improve efficiency, sustainability and productivity in various aspects of agriculture, with a focus on irrigation, water reuse, water pollution monitoring and livestock management.

One of the key challenges in agriculture is efficient water management and water quality monitoring. IoT technologies have revolutionised this aspect by enabling real-time monitoring and decision making (Jagtap et al., 2022). For example, studies such as Mezni et al. (2022) and Bhardwaj et al., (2022) present IoT-based frameworks that integrate water quality sensors with cloud platforms for continuous monitoring of water bodies such as rivers or irrigation reservoirs. These systems use sensor nodes such as Waspmote and Raspberry Pi, coupled with cloud computing, to analyse water parameters and detect pollution events in a timely manner (Jan et al., 2021). The use of wireless sensor networks (WSNs) and cloud-based analytics enables timely intervention, ensuring water safety and minimising pollution risks. In addition, the integration of IoT in water reuse provides a sustainable approach to agriculture (Zia, 2022). By leveraging edge computing and cloud platforms such as FIWARE, IoT systems facilitate the recirculation of water within greenhouses, reducing pollution risks and optimising resource use (O'Grady et al., 2019). This smart approach not only saves water, but also increases crop yields through precise irrigation control based on real-time data analysis.

Otherwise, IoT-enabled water pipeline monitoring focuses on early leak detection and pipeline integrity (Mohd Yussof and Ho, 2022). Innovative sensor technologies, such as force sensitive resistors and flow meters integrated with Arduino or Raspberry Pi boards, enable real-time data collection and transmission to central servers. The use of predictive analytics and machine learning algorithms helps identify anomalies, preventing potential water waste and infrastructure damage.

IoT-based irrigation systems also represent a paradigm shift towards precision agriculture (Monteleone et al., 2020). These systems use WSNs and cloud platforms to optimise water use based on real-time environmental data such as soil moisture, temperature and humidity. By automating irrigation processes and integrating actuators controlled by microcontrollers, farmers can achieve significant water savings while maximising crop yields. The development of mobile applications for remote monitoring and control further enhances the accessibility and usability of these systems.

In the livestock sector, IoT plays a key role in ensuring animal health and well-being (Schillings et al., 2021). Smart livestock water monitoring systems, equipped with wearables and contamination sensors, provide farmers with critical insights into animal health and drinking water quality. Real-time data analysis enables proactive interventions to address potential problems in a timely manner, safeguarding animal health and optimising production outcomes.

3.1.4. Big data

Among digital technologies, Big Data (BD) and its analytics offer new opportunities for water use and management (Delgado et al., 2019). BD refers to the huge amount of structured and unstructured data generated from different resources such as sensors, agricultural machinery, drones and satellites used for agriculture (Sarker et al., 2019b). In the case of the agricultural sector, BD includes the information related to weather patterns, crop health, soil moisture levels and data related to irrigation practices (Kamyab et al., 2023). By using this data, stakeholders as well as farmers can gain valuable insights into crop water dynamics and make informed decisions related to the agriculture sector (Kamble et al., 2020). Big Data Analytics (BDA) plays an important role in transforming raw data into actionable information for agricultural water management (Giray and Catal, 2021). The use of advanced analytical techniques, such as machine learning, predictive modelling and spatial analysis, helps to provide unprecedented opportunities to optimise water use (Kamilaris et al., 2017). By using historical data and real-time information, farmers can implement precise irrigation strategies, reducing water waste and increasing crop yields (Rejeb et al., 2021).

Another aspect is precision irrigation, which represents a new shift in water management enabled by BD and BDA. This approach involves delivering the right amount of water to crops at the right time and place based on precise data insights (Jaber et al., 2022). By integrating sensors, weather forecasts and water requirements for specific crops, stakeholders and farmers can optimise irrigation schedules and minimise water run-off. This also helps to reduce environmental impacts (Rabhi et al., 2021). In addition, BDA can help stakeholders predict water availability and demand patterns with greater accuracy. Furthermore, BD and BDA promote sustainable agricultural practices that prioritise resource efficiency and environmental stewardship (Mekruksavanich and Cheosuwan, 2018).

3.1.5. Robotics

Robots can be used in agriculture to save a lot of human labour by performing repetitive physical tasks. Although people have traditionally used agricultural machinery to work faster and with less physical effort (for example, tractors, harvesters, planters and sprayers), these machines have relied on human manoeuvring. The main advantage of using robots on farms is that they can monitor and decide what tasks need to be carried out and then carry them out.

In particular, the main applications of robotics for water management in agriculture are in the areas of crop and soil monitoring, and watering/irrigation. An example of these two applications is the work of Wu et al., (2020), who developed a robot that can monitor soil temperature and humidity and automatically water crops when needed. Their system also used weather forecasts through Long Short-Term Memory, a type of artificial neural network architecture, to make more accurate irrigation decisions. Other parameters are also useful in deciding when to water crops and can be incorporated into robotic irrigation systems, such as stem water potential (Dechemi et al., 2023) and leaf density (Baltazar et al., 2021).

There are a number of other robotic systems that support water use and management in agriculture. For example, Gravalos et al. (2019) developed a robotic irrigation system consisting of a moving bridge manipulator and a sensor-based platform to monitor soil water content. Fernández-Novales et al. (2021) used a ground robot equipped with thermal infrared radiometry to assess water status in vineyards. Robots can also be used to monitor water quality parameters such as pH, turbidity and temperature, and to determine whether a water source should be used for a particular soil (Gupta et al., 2021).

A particularly interesting application of robots in agricultural water management is the detection of water leaks. Türkler et al. (2023) integrated visible light and thermal camera sensors into a robot, enabling the system to detect water leaks in drip irrigation systems. Chen et al. (2024) used similar cameras but integrated them into drones to cover larger areas more quickly. Moni et al. (2019) used accelerometers to detect water leaks in crop irrigation systems. These accelerometers could be placed at critical points in the irrigation system that the robots had previously identified.

In addition, pesticide sprayers can be integrated into irrigation robots to allow simultaneous application of water and pesticides (Chand et al., 2021). There is also potential to integrate fertiliser sprayers (Abhiram and Megalingam, 2022; Munnaf et al., 2024) and seed planters (Fadhaeel et al., 2022; Prajith et al., 2020) into a multi-purpose robot.

3.1.6. Smart Sensors

A Smart Sensor (SS) is a device that can measure physical conditions or other environmental stimuli, convert those measurements into readable signals, and output the data for further analysis and decision making. In agricultural water management, SSs promote water use efficiency and enable precision irrigation. These advanced sensors provide up-to-date information on key environmental parameters such as soil moisture, temperature, humidity and rainfall. They provide real-time data for informed irrigation scheduling and water application decisions. While IoT typically encompasses large networks of sensors and actuators, we explicitly highlight SSs as a separate technology in this review to emphasise that they can function as standalone solutions with embedded processing capabilities. However, these smart sensors are often integrated into broader IoT architectures to enable data sharing and remote control.

Over the years, many researchers have focused on the application of SSs for agricultural water management (Bwambale et al., 2022; Kumar Kasera et al., 2024). Khoa et al. (2019) used IoT multisensors for water management. The system design includes three main components: sensors for data collection, a Long Range Radio Third-generation Technology transmission module for IoT connectivity over large areas, and a single-chip microprocessor for data processing. The system uses real-time data from sensors installed in farm tunnels and other locations to predict watering needs and recommend watering schedules. However, it relies on specific applications, such as Blynk, and has challenges with reliability and internet connectivity. To address this, an alternative solution is to develop a SS combined with other advanced open source technologies such as cloud computing, machine learning and data analytics tools. In this context, Tzerakis et al. (2023) developed an open source IoT platform for water management in agriculture, focusing mainly on optimal irrigation and pest control in olive orchards. The experiment involved the integration of soil and atmospheric monitoring SSs with microcontrollers. These sensors transmit data to a cloud-based IoT platform using the Message Queuing Telemetry Transport protocol. The system immediately alerts farmers when soil moisture falls below critical thresholds or pest risks increase. The platform also calculates the amount of water required for irrigation based on crop needs, helping farmers use water efficiently.

Otherwise, Bhardwaj et al., (2022) conducted a study to develop a SS to improve efficient and safe water management. The system combined SSs with cutting-edge technologies such as embedded devices and cloud computing. The study showed how well the system performed in comparing sensor data transmission between networks, monitoring water levels and responding to weather conditions and rainfall. This demonstrates the importance of integrating SSs with automated control systems for sustainable water management in agriculture. Furthermore, Manocha et al. (2024) implemented a smart irrigation framework using digital twins and IoT-based SSs to collect essential data on soil moisture, temperature and humidity in agricultural fields, which were analysed using machine learning. The results showed that the system could accurately predict soil moisture levels for the coming days, leading to optimised irrigation practices and improved crop growth.

3.1.7. Blockchain

Blockchain is a technology that allows a database to be securely shared with all members of a network, providing them with up-to-date information and recording transactions in a distributed ledger (McKinsey and Company, 2024). Therefore, the main benefit of using blockchain is the ability to share data more securely and efficiently. In the agricultural sector, blockchain can support better water use and management. Satilmisoglu et al. (2024) reviewed applications of blockchain for water management and found promising opportunities to enhance water governance by improving data security and building stakeholder trust. However, they also found that many of these opportunities have yet to be realised and that large-scale implementation of this technology is still to come.

Successful examples of the use of blockchain in water management include its use for agricultural water rights. Blockchain can be integrated into a trading platform to reduce transaction confirmation time, minimise the cost of water rights transactions, and improve the efficiency of the system (Liu and Shang, 2022). In a similar example, Bordel et al. (2019) used a blockchain network to automatically manage water irrigation in communities that compete for the use of this water. The system increases the trust of community members in each other and in the system, making it easier to share this resource. This has also been demonstrated by other authors, such as Cao et al. (2024), who used blockchain to facilitate collaboration between the government, water conservation service providers and farmers, with the ultimate goal of saving water in agriculture.

The benefits of blockchain technology are maximised when

Fig. 3. Relationships between digital technologies, water-related challenges and management strategies in agriculture.

combined with other digital technologies. For example, IoT can be used to collect and share data on different operations and parameters, while blockchain stores this data and shares it securely with other partners. In this sense, Pincheira et al. (2021) developed a system architecture with IoT devices to measure water consumption, a public blockchain infrastructure, and smart contracts that take into account the interests of different water management stakeholders and include a scheme to distribute incentives among farmers. In addition, Zeng et al. (2023) integrated IoT and blockchain into a smart water management system that enables the coordination of water resource use among communities. In both cases, the combined use of IoT and blockchain improves the trust and security of data storage and sharing, which in turn facilitates the use of water in agricultural processes by different farmers and maximises the efficiency of water use.

3.2. Digital technologies across challenges and strategies

Building on the previous findings on the application of digital technologies for water use and management in agriculture (summarised in Table 2), the main patterns of digital technology use across different challenges and strategies were identified and summarised in Fig. 3 and discussed below.

Digital technologies collectively address all four of the major water-related challenges identified: water scarcity, water pollution and quality degradation, inefficient water use, and climate change. This comprehensive coverage highlights the potential of digital technologies to provide holistic solutions to complex agricultural water management problems. In addition, most digital technologies contribute to multiple strategies for improving water use and management, highlighting their versatility in agricultural applications. Indeed, this is consistent with the findings of Liakos et al. (2018), who highlight that digital technologies can effectively address various challenges in agricultural water management, including water scarcity and inefficient use.

In terms of technologies, RS and AI are emerging as the most versatile and widely used digital technologies, contributing significantly to jointly addressing the major challenges related to water use and management in agriculture: water scarcity, water pollution and quality degradation, inefficient water use, and climate change. These technologies show significant adaptability to different agricultural strategies. This observation is supported by Sishodia et al. (2020), who highlight the important role of these technologies in addressing major challenges in water use and management.

IoT also shows broad integration, particularly in addressing the challenge of water pollution and quality degradation. Robotics and BD, while used across multiple strategies, are less frequently used compared to RS, AI and IoT. In addition, Blockchain technology appears to be the least integrated, focusing primarily on the challenge of water scarcity. These patterns suggest potential areas for expanded application of these lesser-used technologies in agricultural water use and management.

In terms of strategies, efficient irrigation emerges as the most widely adopted strategy across all digital technologies, highlighting its critical role in addressing water management challenges. Soil moisture management and field, plant and foliar monitoring and measurement are also widely adopted strategies, particularly using RS, BD, Robotics and SS technologies. On the other hand, water governance strategies are the least common and are uniquely addressed by Blockchain technology, indicating a potential area for growth and further integration with other digital technologies. In addition, most strategies related to climate change are not addressed by digital technologies.

These findings illustrate the complex and interconnected nature of digital technologies in addressing agricultural water challenges, which are also interrelated. It highlights the need for an integrated approach that leverages the strengths of different technologies to implement a wide range of strategies to address different water challenges in agriculture. This comprehensive view supports the development of more resilient, efficient and sustainable agricultural water management systems, capable of meeting current challenges and adapting to future needs.

4. Future outlook

4.1. Barriers and challenges to implementation

Despite the significant potential of digital technologies in agricultural water use and management, several barriers prevent their widespread adoption and implementation. For example, RS data, especially satellite or drone imagery, can be expensive to acquire and process, and its effective use requires technical expertise that may not be widely available. Integrating RS data with other sources of agricultural information and analysing large volumes of data also requires advanced data analytics and modelling techniques. Furthermore, the temporal and spatial resolution of RS data, as well as infrastructure and connectivity issues, can limit its effectiveness, especially in rural and developing areas. Indeed, the high spatial and temporal resolution required for precision agriculture applications often exceeds the capabilities of traditional satellite-based remote sensing (Khanal et al., 2020; Segarra et al., 2020; Sishodia et al., 2020).

For AI, common challenges include the need for large datasets for training, potential biases in algorithms, and the complexity of integrating AI into existing agricultural systems (Ayoub Shaikh et al., 2022). Predictive analysis using AI faces challenges in data acquisition and processing, accuracy of predictions, and understanding the complexity of agricultural ecosystems (Ashraf and Akanbi, 2023; Fu et al., 2021). In hydroponic applications, as sensor technology develops, the volume of data poses a challenge to AI (Rajendran et al., 2024). This requires solutions based on dimensionality reduction (Trollman, 2024). Similarly, models based on the evapotranspiration coefficient are not global in nature (Bounajra et al., 2024). Therefore, the best input parameters and the best AI model to use need to be developed for each region.

AI is expected to drive the revitalisation of agriculture through the retrofitting, installation and integration of automated devices and instruments (Mana et al., 2024). However, there will be associated costs, both in terms of technology and skilled labour, which may hinder widespread adoption. These challenges are exacerbated in regions such as sub-Saharan Africa, where limited infrastructure, access to technology and technical expertise are significant barriers (Wanyama et al., 2024). Keeping humans in the loop, as highlighted by Industry 5.0, can be a challenge in this context (Conde et al., 2024). Although low-cost systems have been proposed, smallholder farmers are particularly reluctant to adopt technological solutions due to their inherent complexity and the potential for sensors or other components to malfunction, leading to inappropriate decisions (Benameur et al., 2024).

With regard to IoT technology, there are several challenges and issues that need to be addressed. In terms of privacy and security concerns, as IoT becomes more integrated into our daily lives, ensuring privacy and security throughout the data lifecycle - from generation to transmission and analysis - is paramount. Sending data over the internet exposes it to potential unauthorised access and cyber threats. Common IoT security risks include data hacking, remote hijacking and Distributed Denial of Service (DDoS) attacks (Salim et al., 2020). In terms of interoperability, IoT systems often involve the convergence of different technologies, including sensor devices, wireless communication protocols, virtualisation, cloud and edge computing, embedded systems and IoT-specific hardware design. Achieving seamless interoperability between these components is a major challenge (Ali et al., 2022). Otherwise, while IoT has immense potential to advance the political, social and economic landscape of developing countries, realising this potential requires addressing unique development challenges. Factors such as infrastructure limitations, skills gaps, regulatory frameworks and resource constraints must be carefully navigated to fully leverage IoT for economic growth (Damilola Oluwaseun Ogundipe, 2024).

Otherwise, while BD and BDA offer new opportunities for water use and management in agriculture, there are also several challenges that need to be addressed (Dash and Priyashantha, 2024). Key challenges include privacy and security concerns, interoperability issues between different platforms, and the digital divide between farmers and stakeholders (Basso and Antle, 2020). In the case of Robotics, applications are beginning to emerge that will enable more efficient management and use of water on farms and reduce human labour. Such machines will become increasingly common among farmers who can afford the significant up-front costs associated with purchasing such equipment. However, the adoption of robotic systems in agriculture faces challenges beyond cost, including the need for robust and reliable systems that can operate in diverse and unpredictable agricultural environments (Floreano and Wood, 2015). Similarly, the use of SSs for water management in agriculture has been limited to date. In order to increase agricultural productivity and sustainability in the future by more effectively managing water resources through the use of SSs, it will be necessary not only to implement cutting-edge technologies, but also to involve end-users to obtain feedback on the usability of the system and to expand its scope. This is in line with the findings of Gago et al. (2015), who highlighted the importance of user-friendly systems for the successful adoption of precision agriculture technologies. Ultimately, this approach could benefit farmers by increasing crop yields and promoting environmentally sustainable water management practices. Furthermore, the integration of multiple sensing technologies, such as combining UAV-based RS with ground-based SS, shows promise in overcoming some of the limitations of individual technologies (Sankaran et al., 2015).

4.2. Priorities for future research and policy

Based mainly on the findings presented in the previous sections, as well as broader considerations in the field of digital agriculture, several priorities for future research and policy in digital technologies for water use and management in agriculture emerge:

- Integrating multiple digital technologies: Future research should focus on integrated systems that combine multiple digital technologies, following the principles of Agriculture 5.0 to build a more sustainable and efficient agriculture (Balaska et al., 2023). For example, IoT sensors combined with blockchain-based smart contracts can enable real-time water governance, ensuring secure data sharing and automated irrigation scheduling at the community or watershed level (Bordel et al., 2019; Pincheira et al., 2021). Similarly, IoT-driven metering systems can track actual water use among farmers, with the blockchain ledger transparently recording transactions or water credits (Liu and Shang, 2022; Zeng et al., 2023). These frameworks can be augmented with AI-driven analytics to forecast demand, detect anomalies, and refine water distribution in real time. Taken together, these convergent models illustrate pragmatic ways to achieve more resilient, efficient, and transparent water management, while addressing issues of trust, stakeholder collaboration, and equitable resource allocation. In addition, other studies have shown that combining multiple RS techniques, such as thermal, optical and microwave data, can provide more accurate estimates of irrigation water requirements and improve water use efficiency (Dari et al., 2021). This holistic approach could lead to significant improvements in water use efficiency and overall farm productivity (Liakos et al., 2018; Wolfert et al., 2017).
- Improving accessibility and affordability: A key priority is to make digital technologies more accessible and affordable, especially for smallholder farmers in developing regions. This could include the development of low-cost sensors, user-friendly interfaces, and training and support for farmers. Research should focus on adapting technologies to local contexts and needs, ensuring their relevance and usability in different agricultural settings. For example, developing simplified versions of advanced algorithms that can run on low-cost, readily available hardware could democratise access to precision farming techniques. Simplifying complex data analysis and developing user-friendly applications can make advanced agricultural technologies more accessible to farmers (Sishodia et al., 2020). In addition, potential solutions to the identified barriers of high costs and lack of expertise could include the establishment of shared service models where smallholders pool resources to collectively purchase and maintain precision technologies (Klerkx and Rose, 2020). Public-private partnerships can further subsidise the cost of equipment and training programmes, accelerating adoption (Pauschinger and Klauser, 2021). In addition, incorporating extension services that provide customised data analysis and AI-based advice can reduce the need for on-farm expertise in interpreting complex models.
- Improving water use efficiency and sustainability: Future research should prioritise the development of digital solutions that not only increase water use efficiency, but also promote the overall sustainability of agriculture. This includes technologies that can help farmers adapt to the impacts of climate change, such as drought-resistant crop varieties and precision irrigation systems. For example, advanced RS techniques combined with machine learning algorithms could provide more accurate predictions of crop water requirements, enabling more precise and efficient irrigation (Dari et al., 2020). In addition, integrating these technologies with weather forecasting models could help farmers anticipate and prepare for extreme weather events, thereby increasing the resilience of agricultural systems (Jiao et al., 2021).
- Addressing water quality and pollution: While much of the focus has been on water quantity, future research should also prioritise technologies to monitor and improve water quality in agricultural systems (Y. Liu et al., 2017; Mateo-Sagasta and Burke, 2010). This could include the development of more sophisticated sensors to detect pollutants and advanced AI algorithms to predict and mitigate pollution risks. For example, real-time monitoring systems could be developed to detect and alert farmers to the presence of harmful contaminants in irrigation water. In addition, AI-based decision support systems could help farmers optimise their use of fertilisers and pesticides (Parra-López et al., 2024c) to reduce the risk of water pollution while maintaining crop yields (Huang et al., 2023).
- Improving data management and analysis: As the volume of data generated by digital technologies increases, there is a need for more advanced data management and analysis capabilities. Future research should focus on developing robust data infrastructures, improving the integration of data from different sources, and improving analytical tools to extract meaningful insights from complex data sets. This could include the development of advanced machine learning algorithms capable of processing and analysing heterogeneous data from different sources such as satellite imagery, ground-based sensors and weather stations. For example, several studies have demonstrated the potential of machine learning techniques to integrate multi-source remote sensing data to map crop types and estimate agricultural yields (Cai et al., 2018; Johnson, 2014). In addition, research should focus on developing standardised data formats and protocols to facilitate data sharing and interoperability between different systems and platforms. This is particularly important as the integration of different data sources, such as satellite imagery, UAV data and in-situ measurements, is becoming increasingly common in precision agriculture applications (Maimaitijiang et al., 2017).
- Addressing the high energy and water consumption and environmental footprint of digital technologies: The high water and energy consumption of some digital technologies is a growing concern. Sensor devices, circuit boards and IoT components with short life cycles can contribute to e-waste (He et al., 2024). In addition, AI-driven applications, especially when they rely on continuous cloud-based computation, can require significant energy, resulting in

a larger carbon footprint (Belkhir and Elmeligi, 2018). Future research should prioritise the development of more energy-efficient algorithms and hardware, and explore the use of renewable energy sources to power digital agricultural systems. For example, AI models can be optimised for low-power devices, and edge computing can reduce energy-intensive data transmission. The integration of solar or wind power systems could also promote more sustainable digital agriculture (Majeed et al., 2023). Addressing the environmental footprint of digital technologies in the long term will require comprehensive life cycle assessments (LCA) of agricultural systems (Acosta-Alba et al., 2019).

– Improving cybersecurity and privacy: As agricultural systems become increasingly digital, ensuring the security and privacy of data is paramount. Future research should focus on developing robust cybersecurity measures and privacy protocols specifically tailored to agricultural applications. This could include developing blockchain-based systems for secure data sharing, creating advanced encryption methods for IoT devices, and developing AI-based threat detection systems (Demestichas et al., 2020). In addition, research should focus on creating frameworks for ethical data use in agriculture to ensure that farmers retain control over their data while benefiting from data-driven insights (Wolfert et al., 2017).
– Improving contribution to climate change adaptation and mitigation: Digital technologies have significant potential to support climate change adaptation and mitigation in agriculture (Parra-López et al., 2024a). At present, however, they are hardly used to address this climate change challenge. Future research should focus on developing more accurate climate prediction models, climate risk assessment tools and technologies that can help reduce greenhouse gas emissions from agricultural activities. This could include the development of AI-based climate models that can provide localised, long-term weather forecasts to help farmers make informed decisions about crop selection and water management. In addition, research into precision farming techniques that optimise the use of resources could significantly reduce the carbon footprint of agriculture. For example, precision irrigation systems guided by RS data have shown potential to reduce water use and associated energy consumption in agriculture (Bellvert et al., 2014).
– Improving human-technology interaction: In line with the principles of Agriculture 5.0 (Hassoun et al., 2024), future research should explore ways to optimise human-technology interaction in agricultural water management. This includes the development of intuitive interfaces, decision support systems and training programmes that enable farmers to effectively use and benefit from digital technologies. Research could focus on the creation of AI-based virtual assistants that can guide farmers through complex decision-making processes, or the development of augmented reality systems that can overlay digital information onto real-world views of crops and fields. In addition, research into the social and psychological factors that influence technology adoption in agriculture could lead to more effective strategies for introducing new technologies to farming communities (Bissadu et al., 2024; Fraser and Campbell, 2019).
– Analysing policy implications and regulatory frameworks: Future research should focus on the policy implications of the widespread adoption of digital technologies in agricultural water management. This should include exploring the need for new legal frameworks to regulate data ownership, privacy and sharing in digital agriculture (Parra-López et al., 2021). Research should also explore how policies can incentivise the adoption of water-efficient technologies while ensuring equitable access across different farm sizes and socio-economic groups. In addition, studies on the potential impact of these technologies on rural employment and the agricultural economy could inform policy decisions. Such research is essential to create an enabling environment that supports sustainable digital transformation in agriculture while addressing potential socio-economic challenges (Wolfert et al., 2017).

5. Conclusions

Digital technologies offer significant potential to address the major water-related challenges facing agriculture, including water scarcity, pollution, inefficient use and climate change impacts. Remote Sensing, Artificial Intelligence, the Internet of Things, Big Data, Robotics, Smart Sensors and Blockchain all contribute to more efficient and sustainable water management practices. Remote Sensing and Artificial Intelligence are emerging as the most versatile and widely adopted technologies, addressing all major water-related challenges in agriculture. Their ability to provide real-time data and support decision-making processes makes them particularly valuable for precision agriculture and irrigation management.

The integration of multiple digital technologies holds great promise for developing more comprehensive and effective water management solutions. For example, combining Remote Sensing with Internet of Things sensors and Artificial Intelligence could enable more accurate and timely irrigation decisions. Efficient irrigation strategies emerge as the most commonly adopted approach across all digital technologies, highlighting the critical importance of optimising water use in agriculture.

Despite the potential benefits, there are several barriers to the widespread adoption of digital technologies in agricultural water management. These include high implementation costs, lack of technical expertise, data management challenges, and infrastructure and connectivity issues, particularly in rural and developing areas. There is a clear need for more accessible and affordable digital solutions, especially for smallholder farmers in developing regions. Future research and development efforts should focus on developing user-friendly, low-cost technologies that can be easily integrated into existing farming practices. The environmental impact of digital technologies themselves, particularly in terms of energy consumption, is an emerging concern that requires further attention and mitigation strategies.

Although infrastructure constraints and lack of technical expertise are often highlighted in underdeveloped regions, developed countries also face technology-related challenges. For example, advanced digital platforms can be prohibitively expensive on a large scale, making the long-term return on investment at farm level uncertain. In addition, many developed regions have a heterogeneous range of farm sizes, from small family farms to large corporate operations, resulting in different capacities to adopt high-cost solutions. Furthermore, despite better connectivity and extension services, there may be gaps in specialised skills (e.g. data analysis, systems integration), which can hinder the widespread adoption of complex digital tools. As a result, technology adoption is not only a matter of economic development, but also of infrastructure, policy incentives and local capacity to manage and sustain these innovations.

Policy and regulatory frameworks play a critical role in facilitating the adoption of digital technologies for agricultural water management. There is a need for supportive policies that encourage innovation while addressing issues such as data ownership, privacy and equitable access to technology. Capacity building and knowledge transfer are essential to ensure that farmers and agricultural stakeholders can effectively use digital technologies. This includes not only technical training, but also education on sustainable water management practices.

While digital technologies are powerful tools for improving water use efficiency, they should be seen as part of a holistic approach to sustainable agriculture. This approach should consider broader environmental, social and economic factors to ensure the long-term sustainability of agricultural water resources. Digital technologies have the potential to revolutionise water use and management in agriculture and make a significant contribution to creating more sustainable, resilient and productive agricultural systems that can meet the growing global demand for food while conserving water resources. However, realising this potential will require a concerted effort by farmers, industry stakeholders, researchers and policy makers.

CRediT authorship contribution statement

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Declaration of Competing Interest

We, the authors, declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

No data was used for the research described in the article.

References

Abbas, F., Cai, Z., Shoaib, M., Iqbal, J., Ismail, M., Arifullah, Alrefaei, A.F., Albeshr, M.F., 2024. Machine learning models for water quality prediction: a comprehensive analysis and uncertainty assessment in Mirpurkhas, Sindh, Pakistan. Water 16. https://doi.org/10.3390/w16070941.

Abhiram, R., Megalingam, R.K., 2022. Autonomous fertilizer spraying mobile robot. INDICON 2022 - 2022 IEEE 19th India Counc. Int. Conf. https://doi.org/10.1109/INDICON56171.2022.10039828.

Aboelkhair, H., Morsy, M., El Afandi, G., 2019. Assessment of agroclimatology NASA POWER reanalysis datasets for temperature types and relative humidity at 2 m against ground observations over Egypt. Adv. Space Res. 64, 129–142. https://doi.org/10.1016/j.asr.2019.03.032.

Acosta-Alba, I., Chia, E., Andrieu, N., 2019. The LCA4CSA framework: using life cycle assessment to strengthen environmental sustainability analysis of climate smart agriculture options at farm and crop system levels. Agric. Syst. 171, 155–170. https://doi.org/10.1016/j.agsy.2019.02.001.

Ahmed, S.F., Alam, Md.S.Bin, Hoque, M., Lameesa, A., Afrin, S., Farah, T., Kabir, M., Shafiullah, G.M., Muyeen, S.M., 2023. Industrial internet of things enabled technologies, challenges, and future directions. Comput. Electr. Eng. 110, 108847. https://doi.org/10.1016/j.compeleceng.2023.108847.

Al Mashhadany, Y., Alsanad, H.R., Al-Askari, M.A., Algburi, S., Taha, B.A., 2024. Irrigation intelligence—enabling a cloud-based Internet of things approach for enhanced water management in agriculture. Environ. Monit. Assess. 196, 438. https://doi.org/10.1007/s10661-024-12606-1.

Ali, O., Ishak, M.K., Bhatti, M.K.L., Khan, I., Kim, K.-I., 2022. A comprehensive review of internet of things: technology stack, middlewares, and fog/edge computing interface. Sensors 22. https://doi.org/10.3390/s22030995.

Al-Shammary, A.A.G., Al-Shihmani, L.S.S., Fernández-Gálvez, J., Caballero-Calvo, A., 2024. Optimizing sustainable agriculture: a comprehensive review of agronomic practices and their impacts on soil attributes. J. Environ. Manag. 364, 121487. https://doi.org/10.1016/j.jenvman.2024.121487.

Argente García, J.E., Yazici, B., Richa, A., Touil, S., Richart Díaz, V.J., Ramallo-González, A.P., Skarmeta Gómez, A.F., 2024. Digitalising governance processes and water resources management to foster sustainability strategies in the Mediterranean agriculture. Environ. Sci. Policy 158, 103805. https://doi.org/10.1016/j.envsci.2024.103805.

Ashraf, H., Akanbi, M.T., 2023. Sustainable agriculture in the digital age: crop management and yield forecasting with IoT, Cloud, and AI. Tensor J. Sustain. Technol. Infrastruct. Dev. Ctries. 6, 64–71.

Awais, M., Li, W., Cheema, M.J.M., Zaman, Q.U., Shaheen, A., Aslam, B., Zhu, W., Ajmal, M., Faheem, M., Hussain, S., Nadeem, A.A., Afzal, M.M., Liu, C., 2022. UAV-based remote sensing in plant stress imagine using high-resolution thermal sensor for digital agriculture practices: a meta-review, 20 Int. J. Environ. Sci. Technol. 2021 20 (1), 1135–1152. https://doi.org/10.1007/S13762-021-03801-5.

Ayoub Shaikh, T., Rasool, T., Rasheed Lone, F., 2022. Towards leveraging the role of machine learning and artificial intelligence in precision agriculture and smart farming. Comput. Electron Agric. 198, 107119. https://doi.org/10.1016/j.compag.2022.107119.

Balaska, V., Adamidou, Z., Vryzas, Z., Gasteratos, A., 2023. Sustainable crop protection via robotics and artificial intelligence solutions. Machines 11. https://doi.org/10.3390/machines11080774.

Baltazar, A.R., Dos Santos, F.N., Moreira, A.P., Valente, A., Cunha, J.B., 2021. Smarter robotic sprayer system for precision agriculture, 2061 10, 2061 Electronics 2021 10. https://doi.org/10.3390/ELECTRONICS10172061.

Banerjee, D., Ganguly, S., Kushwaha, S., 2024. Forecasting future groundwater recharge from rainfall under different climate change scenarios using comparative analysis of deep learning and ensemble learning techniques. Water Resour. Manag. https://doi.org/10.1007/s11269-024-03850-8.

Barbier, E.B., 2004. Explaining agricultural land expansion and deforestation in developing countries. Am. J. Agric. Econ. 86, 1347–1353. https://doi.org/10.1111/j.0002-9092.2004.00688.x.

Basso, B., Antle, J., 2020. Digital agriculture to design sustainable agricultural systems. Nat. Sustain 3, 254–256. https://doi.org/10.1038/s41893-020-0510-0.

Behmel, S., Damour, M., Ludwig, R., Rodriguez, M.J., 2016. Water quality monitoring strategies — A review and future perspectives. Sci. Total Environ. 571, 1312–1329. https://doi.org/10.1016/j.scitotenv.2016.06.235.

Belkhir, L., Elmeligi, A., 2018. Assessing ICT global emissions footprint: trends to 2040 & recommendations. J. Clean. Prod. 177, 448–463. https://doi.org/10.1016/j.jclepro.2017.12.239.

Bellvert, J., Zarco-Tejada, P.J., Girona, J., Fereres, E., 2014. Mapping crop water stress index in a "Pinot-noir" vineyard: comparing ground measurements with thermal remote sensing imagery from an unmanned aerial vehicle. Precis Agric. 15, 361–376. https://doi.org/10.1007/s11119-013-9334-5.

Ben Abdallah, S., Gallego-Elvira, B., Imbernón-Mulero, A., Martínez-Alvarez, V., Maestre-Valero, J., 2023. Environmental footprint of organic and conventional grapefruit production irrigated with desalinated seawater in Spain. Sustain Prod. Consum 39, 326–335. https://doi.org/10.1016/j.spc.2023.05.023.

Benameur, R., Dahane, A., Kechar, B., Benyamina, A.E.H., 2024. An innovative smart and sustainable low-cost irrigation system for anomaly detection using deep learning. Sensors 24. https://doi.org/10.3390/s24041162.

Benzaouia, M., Hajji, B., Mellit, A., Rabhi, A., 2023. Fuzzy-IoT smart irrigation system for precision scheduling and monitoring. Comput. Electron Agric. 215. https://doi.org/10.1016/j.compag.2023.108407.

Berríos, P., Temnani, A., Zapata-García, S., Sánchez-Navarro, V., Zornoza, R., Pérez-Pastor, A., 2024. Effect of deficit irrigation and mulching on the agronomic and physiological response of mandarin trees as strategies to cope with water scarcity in a semi-arid climate. Sci. Hortic. 324, 112572. https://doi.org/10.1016/j.scienta.2023.112572.

Bhardwaj, A., Kumar, M., Alshehri, M., Keshta, I., Abugabah, A., Sharma, S.K., 2022. Smart water management framework for irrigation in agriculture. Environ. Technol. 45 (12), 2320–2334. https://doi.org/10.1080/09593330.2022.2039783.

Bissadu, K.D., Sonko, S., Hossain, G., 2024. Society 5.0 enabled agriculture: Drivers, enabling technologies, architectures, opportunities, and challenges. Inf. Process. Agric. https://doi.org/10.1016/j.inpa.2024.04.003.

Boers, Th.M., Ben-Asher, J., 1982. A review of rainwater harvesting. Agric. Water Manag 5, 145–158. https://doi.org/10.1016/0378-3774(82)90003-8.

Bongiovanni, R., Lowenberg-Deboer, J., 2004. Precision agriculture and sustainability. Precis Agric. 5, 359–387. https://doi.org/10.1023/B:PRAG.0000040806.39604.aa.

Bordel, B., Martin, Di, Alcarria, R., Robles, T., 2019. A blockchain-based water control system for the automatic management of irrigation communities. 2019 IEEE Int. Conf. Consum. Electron. https://doi.org/10.1109/ICCE.2019.8661940.

Borsato, E., Tarolli, P., Marinello, F., 2018. Sustainable patterns of main agricultural products combining different footprint parameters. J. Clean. Prod. https://doi.org/10.1016/j.jclepro.2018.01.044.

Bounajra, A., Guemmat, K., El, Mansouri, K., Akef, F., 2024. Towards efficient irrigation management at field scale using new technologies: a systematic literature review. Agric. Water Manag 295, 108758. https://doi.org/10.1016/j.agwat.2024.108758.

Bwambale, E., Abagale, F.K., Anornu, G.K., 2022. Smart irrigation monitoring and control strategies for improving water use efficiency in precision agriculture: a review. Agric. Water Manag 260, 107324. https://doi.org/10.1016/j.agwat.2021.107324.

Cai, J., Wang, X., Cai, Y., Wei, C., Liao, Z., Li, C., Liu, Q., 2024. An integrated framework consisting of spatiotemporal evolution and driving force analyses for early warning management of water quality. J. Clean. Prod. 462, 142628. https://doi.org/10.1016/j.jclepro.2024.142628.

Cai, Y., Guan, K., Peng, J., Wang, S., Seifert, C., Wardlow, B., Li, Z., 2018. A high-performance and in-season classification system of field-level crop types using time-series Landsat data and a machine learning approach. Remote Sens Environ. 210, 35–47. https://doi.org/10.1016/j.rse.2018.02.045.

Callejas Moncaleano, D.C., Pande, S., Rietveld, L., 2021. Water use efficiency: a review of contextual and behavioral factors. Front. Water. https://doi.org/10.3389/frwa.2021.685650.

Cao, Y., Li, H., Su, L., 2024. Blockchain-driven incentive mechanism for agricultural water-saving: A tripartite game model. J. Clean. Prod. 434, 140197. https://doi.org/10.1016/J.JCLEPRO.2023.140197.

Carpio-Vallejo, E., Düker, U., Waldowski, J., Nogueira, R., 2024. Contribution of rooftop rainwater harvesting to climate adaptation in the city of Hannover: Water quality and health issues of rainwater storage in cisterns and ponds. Int J. Hyg. Environ. Health 256. https://doi.org/10.1016/j.ijheh.2024.114320.

Chand, A.A., Prasad, K.A., Mar, E., Dakai, S., Mamun, K.A., Islam, F.R., Mehta, U., Kumar, N.M., 2021. Design and analysis of photovoltaic powered battery-operated computer vision-based multi-purpose smart farming robot, 530 11 Agronomy 2021 11, 530. https://doi.org/10.3390/AGRONOMY11030530.

Chaudhary, V., Kumar, M., Chauhan, C., Sirohi, U., Srivastav, A.L., Rani, L., 2024. Strategies for mitigation of pesticides from the environment through alternative approaches: a review of recent developments and future prospects. J. Environ. Manag. https://doi.org/10.1016/j.jenvman.2024.120326.

Chen, J., Pádua, L., Marques, P., Dinis, L.-T., Moutinho-Pereira, J., Sousa, J.J., Morais, R., Peres, E., 2024. Detection of leak areas in vineyard irrigation systems using uav-based data, 187 8, 187 Drones 2024 8. https://doi.org/10.3390/DRONES8050187.

Chen, Y., Zhang, J.-H., Chen, M.-X., Zhu, F.-Y., Song, T., 2023. Optimizing water conservation and utilization with a regulated deficit irrigation strategy in woody crops: A review. Agric. Water Manag 289, 108523. https://doi.org/10.1016/j.agwat.2023.108523.

Cheng, M., Sun, C., Nie, C., Liu, S., Yu, X., Bai, Y., Liu, Yadong, Meng, L., Jia, X., Liu, Yuan, Zhou, L., Nan, F., Cui, T., Jin, X., 2023. Evaluation of UAV-based drought indices for crop water conditions monitoring: a case study of summer maize. Agric. Water Manag 287, 108442. https://doi.org/10.1016/J.AGWAT.2023.108442.

Chow, R., Scheidegger, R., Doppler, T., Dietzel, A., Fenicia, F., Stamm, C., 2020. A review of long-term pesticide monitoring studies to assess surface water quality trends. Water Res X 9, 100064. https://doi.org/10.1016/j.wroa.2020.100064.

Conde, G., Guzmán, S.M., Athelly, A., 2024. Adaptive and predictive decision support system for irrigation scheduling: an approach integrating humans in the control loop. Comput. Electron Agric. 217, 108640. https://doi.org/10.1016/j.compag.2024.108640.

Crovella, T., Paiano, A., Falciglia, P.P., Lagioia, G., Ingrao, C., 2024. Wastewater recovery for sustainable agricultural systems in the circular economy – a systematic literature review of Life Cycle Assessments. Sci. Total Environ. https://doi.org/10.1016/j.scitotenv.2023.169310.

Damilola Oluwaseun Ogundipe, 2024. Conceptualizing cloud computing in financial services: Opportunities and challenges in Africa-US contexts. Comput. Sci. amp; IT Res. J. 5, 757–767. https://doi.org/10.51594/csitrj.v5i4.1020.

Dari, J., Brocca, L., Quintana-Seguí, P., Escorihuela, M.J., Stefan, V., Morbidelli, R., 2020. Exploiting high-resolution remote sensing soil moisture to estimate irrigation water amounts over a mediterranean region. Remote Sens. 12, 2593. https://doi.org/10.3390/RS12162593.

Dari, J., Quintana-Seguí, P., Escorihuela, M.J., Stefan, V., Brocca, L., Morbidelli, R., 2021. Detecting and mapping irrigated areas in a Mediterranean environment by using remote sensing soil moisture and a land surface model. J. Hydrol. (Amst.) 596. https://doi.org/10.1016/j.jhydrol.2021.126129.

Dash, S.P., Priyashantha, K.G., 2024. For Sustainable Farming in India. in: Digital Agricultural Ecosystem. John Wiley & Sons, Ltd, pp. 307–318. https://doi.org/10.1002/9781394242962.ch17.

Dechemi, A., Chatziparaschis, D., Chen, J., Campbell, M., Shamshirgaran, A., Mucchiani, C., Roy-Chowdhury, A., Carpin, S., Karydis, K., 2023. Robotic assessment of a crop's need for watering: automating a time-consuming task to support sustainable agriculture. IEEE Robot Autom. Mag. 30, 52–67. https://doi.org/10.1109/MRA.2023.3321391.

Dehghanisanij, H., Emami, S., Emami, H., Elbeltagi, A., 2024. Evaluating performance indicators of irrigation systems using swarm intelligence methods in Lake Urmia basin, Iran. Environ. Dev. Sustain 26, 4175–4195. https://doi.org/10.1007/s10668-022-02878-3.

Delgado, J.A., Short, N.M., Roberts, D.P., Vandenberg, B., 2019. Big data analysis for sustainable agriculture on a geospatial cloud framework. Front Sustain Food Syst. 3. https://doi.org/10.3389/fsufs.2019.00054.

Demestichas, K., Peppes, N., Alexakis, T., 2020. Survey on security threats in agricultural iot and smart farming. Sensors 20. https://doi.org/10.3390/s20226458.

Ding, D., Yang, Z., Wu, L., Zhao, Y., Zhang, X., Chen, X., Feng, H., Zhang, C., Wendroth, O., 2024. Optimizing nitrogen-fertilizer management by using RZWQM2 with consideration of precipitation can enhance nitrogen utilization on the Loess Plateau. Agric. Water Manag 299. https://doi.org/10.1016/j.agwat.2024.108890.

Dingre, S.K., Gorantiwar, S.D., 2021. Soil moisture based deficit irrigation management for sugarcane (Saccharum officinarum L.) in semiarid environment. Agric. Water Manag. 245, 106549. https://doi.org/10.1016/j.agwat.2020.106549.

Dolaptsis, K., Pantazi, X.E., Paraskevas, C., Arslan, S., Tekin, Y., Bantchina, B.B., Ulusoy, Y., Gündoğdu, K.S., Qaswar, M., Bustan, D., Mouazen, A.M., 2024. A hybrid lstm approach for irrigation scheduling in maize crop. Agriculture 14. https://doi.org/10.3390/agriculture14020210.

Durmuş, Yunus, Arslansoy, Gazal, Kızıldeniz Gürbüz, Tefide, 2024. Impact of smart irrigation systems and water management on climate change. BIO Web Conf. 85, 1057. https://doi.org/10.1051/bioconf/20248501057.

Essamlali, I., Nhaila, H., El Khaili, M., 2024. Advances in machine learning and IoT for water quality monitoring: a comprehensive review. Heliyon 10. https://doi.org/10.1016/j.heliyon.2024.e27920.

Fadhaeel, T., Patel, H.C., Al Ahdal, A., Rakhra, M., Singh, D., 2022. Design and development an Agriculture robot for Seed sowing, Water spray and Fertigation. Proceedings of International Conference on Computational Intelligence and Sustainable Engineering Solution, CISES 2022 148–153. https://doi.org/10.1109/CISES54857.2022.9844341.

Fan, L., Xiao, Q., Wen, J., Liu, Q., Jin, R., You, D., Li, X., 2015. Mapping high-resolution soil moisture over heterogeneous cropland using multi-resource remote sensing and ground observations. Remote Sens. 7, 13273–13297. https://doi.org/10.3390/RS71013273.

Farbo, A., Sarvia, F., De Petris, S., Basile, V., Borgogno-Mondino, E., 2024. Forecasting corn NDVI through AI-based approaches using sentinel 2 image time series. ISPRS J. Photogramm. Remote Sens. 211, 244–261. https://doi.org/10.1016/j.isprsjprs.2024.04.011.

Fereres, E., Soriano, M.A., 2007. Deficit irrigation for reducing agricultural water use. J. Exp. Bot. 58, 147–159. https://doi.org/10.1093/jxb/erl165.

Fernández-Novales, J., Saiz-Rubio, V., Barrio, I., Rovira-Más, F., Cuenca-Cuenca, A., Santos Alves, F., Valente, J., Tardáguila, J., Diago, M.P., 2021. Monitoring and mapping vineyard water status using non-invasive technologies by a ground robot. Remote Sens (Basel) 13, 2830. https://doi.org/10.3390/RS13142830/S1.

Floreano, D., Wood, R.J., 2015. Science, technology and the future of small autonomous drones. Nature 521, 460–466. https://doi.org/10.1038/nature14542.

Franco, J.G., King, S.R., Volder, A., 2018. Component crop physiology and water use efficiency in response to intercropping. Eur. J. Agron. 93, 27–39. https://doi.org/10.1016/j.eja.2017.11.005.

Fraser, E.D.G., Campbell, M., 2019. Agriculture 5.0: reconciling production with planetary health. One Earth 1, 278–280. https://doi.org/10.1016/j.oneear.2019.10.022.

Fu, C., Xu, C., Xue, M., Liu, W., Yang, S., 2021. Data-driven decision making based on evidential reasoning approach and machine learning algorithms. Appl. Soft Comput. 110, 107622. https://doi.org/10.1016/j.asoc.2021.107622.

Gago, J., Douthe, C., Coopman, R.E., Gallego, P.P., Ribas-Carbo, M., Flexas, J., Escalona, J., Medrano, H., 2015. UAVs challenge to assess water stress for sustainable agriculture. Agric. Water Manag 153, 9–19. https://doi.org/10.1016/j.agwat.2015.01.020.

Garcia, X., Pargament, D., 2015. Reusing wastewater to cope with water scarcity: Economic, social and environmental considerations for decision-making. Resour. Conserv Recycl 101, 154–166. https://doi.org/10.1016/j.resconrec.2015.05.015.

Giray, G., Catal, C., 2021. Design of a data management reference architecture for sustainable agriculture. Sustainability 13. https://doi.org/10.3390/su13137309.

Girotto, C.D., Piadeh, F., Bkhtiari, V., Behzadian, K., Chen, A.S., Campos, L.C., Zolgharni, M., 2024. A critical review of digital technology innovations for early warning of water-related disease outbreaks associated with climatic hazards. Int. J. Disaster Risk Reduct. 100, 104151. https://doi.org/10.1016/j.ijdrr.2023.104151.

Goel, P., Wasson, V., Singh, I., Kaur, A., Pupneja, A., Nipahde, A., 2024. Machine learning based water requirement prediction for agriculture before a rainfall, in: 2024. Int. Conf. Emerg. Smart Comput. Inform. (ESCI) 1–7. https://doi.org/10.1109/ESCI59607.2024.10497332.

Gosling, S.N., Arnell, N.W., 2016. A global assessment of the impact of climate change on water scarcity. Clim. Change 134, 371–385. https://doi.org/10.1007/s10584-013-0853-x.

Gravalos, I., Avgousti, A., Gialamas, T., Alfieris, N., Paschalidis, G., 2019. A robotic irrigation system for urban gardening and agriculture. J. Agric. Eng. 50, 198–207. https://doi.org/10.4081/JAE.2019.966.

Gupta, S., Kohli, M., Kumar, R., Bandral, S., 2021. IoT based underwater robot for water quality monitoring. IOP Conf. Ser. Mater. Sci. Eng. 1033, 012013. https://doi.org/10.1088/1757-899X/1033/1/012013.

Hachimi, C., El, Belaqziz, S., Khabba, S., Sebbar, B., Dhiba, D., Chehbouni, A., 2023. Smart weather data management based on artificial intelligence and big data analytics for precision agriculture. Agriculture 13. https://doi.org/10.3390/agriculture13010095.

Haggerty, R., Sun, J., Yu, H., Li, Y., 2023. Application of machine learning in groundwater quality modeling-a comprehensive review. Water Res 233. https://doi.org/10.1016/j.watres.2023.119745.

Hardas, B.M., Tomar, K., 2024. Impact of groundwater quality on agricultural productivity: a comprehensive ai-driven analysis. : 2024 2nd Int. Conf. Comput., Commun. Control (IC4) 1–5. https://doi.org/10.1109/IC457434.2024.10486542.

Harding, Peduzzi, 2012. The end to cheap oil: a threat to food security and an incentive to reduce fossil fuels in agriculture. Environ. Dev. 3, 157–165. https://doi.org/10.1016/j.envdev.2012.05.008.

Hashimi, R., Huang, Q., Dewi, R.K., Nishiwaki, J., Komatsuzaki, M., 2023. No-tillage and rye cover crop systems improve soil water retention by increasing soil organic carbon in Andosols under humid subtropical climate. Soil Tillage Res 234. https://doi.org/10.1016/j.still.2023.105861.

Hassoun, A., 2024. Food Industry 4.0. Elsevier. https://doi.org/10.1016/C2022-0-01211-3.

Hassoun, A., Kamiloglu, S., Garcia-Garcia, G., Parra-López, C., Trollman, H., Jagtap, S., Aadil, R.M., Esatbeyoglu, T., 2023. Implementation of relevant fourth industrial revolution innovations across the supply chain of fruits and vegetables: a short update on Traceability 4.0. Food Chem. 409, 135303. https://doi.org/10.1016/j.foodchem.2022.135303.

Hassoun, A., Jagtap, S., Trollman, H., Garcia-Garcia, G., Duong, L.N.K., Saxena, P., Bouzembrak, Y., Treiblmaier, H., Parra-López, C., Carmona-Torres, C., Dev, K., Mhlanga, D., Aït-Kaddour, A., 2024. From Food Industry 4.0 to Food Industry 5.0: identifying technological enablers and potential future applications in the food sector. Compr. Rev. Food Sci. Food Saf. 23, e370040. https://doi.org/10.1111/1541-4337.70040.

Hayajneh, A.M., Aldalahmeh, S.A., Alasali, F., Al-Obiedollah, H., Zaidi, S.A., McLernon, D., 2024. Tiny machine learning on the edge: a framework for transfer learning empowered unmanned aerial vehicle assisted smart farming. IET Smart Cities 6, 10–26. https://doi.org/10.1049/smc2.12072.

He, C., Liu, Z., Wu, J., Pan, X., Fang, Z., Li, J., Bryan, B.A., 2021. Future global urban water scarcity and potential solutions. Nat. Commun. 12, 4667. https://doi.org/10.1038/s41467-021-25026-3.

He, L., Rosa, L., 2023. Solutions to agricultural green water scarcity under climate change. PNAS Nexus 2. https://doi.org/10.1093/pnasnexus/pgad117.

He, Y., Kiehbadroudinezhad, M., Hosseinzadeh-Bandbafha, H., Gupta, V.K., Peng, W., Lam, S.S., Tabatabaei, M., Aghbashlo, M., 2024. Driving sustainable circular economy in electronics: a comprehensive review on environmental life cycle assessment of e-waste recycling. Environ. Pollut. 342, 123081. https://doi.org/10.1016/j.envpol.2023.123081.

Hrour, Y., Fovet, O., Lacombe, G., Rousseau-Gueutin, P., Sebari, K., Pichelin, P., Thomas, Z., 2023. A framework to assess future water-resource under climate change in northern Morocco using hydro-climatic modelling and water-withdrawal scenarios. J. Hydrol. Reg. Stud. 48. https://doi.org/10.1016/j.ejrh.2023.101465.
Huang, Y., Wang, C., Wang, Y., Lyu, G., Lin, S., Liu, W., Niu, H., Hu, Q., 2023. Application of machine learning models in groundwater quality assessment and prediction: progress and challenges. Front Environ. Sci. Eng. 18, 29. https://doi.org/10.1007/s11783-024-1789-2.
Huang, Z., Yuan, X., Liu, X., 2021. The key drivers for the changes in global water scarcity: Water withdrawal versus water availability. J. Hydrol. 601, 126658. https://doi.org/10.1016/j.jhydrol.2021.126658.
Iglesias, A., Garrote, L., 2015. Adaptation strategies for agricultural water management under climate change in Europe. Agric. Water Manag 155, 113–124. https://doi.org/10.1016/j.agwat.2015.03.014.
Iho, A., Laukkanen, M., 2012. Precision phosphorus management and agricultural phosphorus loading. Ecol. Econ. 77, 91–102. https://doi.org/10.1016/j.ecolecon.2012.02.010.
Ingrao, C., Strippoli, R., Lagioia, G., Huisingh, D., 2023. Water scarcity in agriculture: an overview of causes, impacts and approaches for reducing the risks. Heliyon. https://doi.org/10.1016/j.heliyon.2023.e18507.
Jabal, Z.K., Khayyun, T.S., Alwan, I.A., 2022. Impact of climate change on crops productivity using MODIS-NDVI Time Series. Civ. Eng. J. 8, 1136–1156. https://doi.org/10.28991/CEJ-2022-08-06-04.
Jaber, M., Ali, M., Abd, S., Jassim, M., Alkhayyat, A., Aziz, H., Alkhuwaylidee, A., 2022. Predicting climate factors based on big data analytics based agricultural disaster management. Phys. Chem. Earth, Parts A/B/C. 128, 103243. https://doi.org/10.1016/j.pce.2022.103243.
Jagermeyr, J., Mueller, C., Ruane, A.C., Elliott, J., Balkovic, J., Castillo, O., Faye, B., Foster, I., Folberth, C., Franke, J.A., Fuchs, K., Guarin, J.R., Heinke, J., Hoogenboom, G., Iizumi, T., Jain, A.K., Kelly, D., Khabarov, N., Lange, S., Lin, T.-S., Liu, W., Mialyk, O., Minoli, S., Moyer, E.J., Okada, Masashi, Phillips, M., Porter, C., Rabin, S.S., Scheer, C., Schneider, J.M., Schyns, J.F., Skalsky, R., Smerald, A., Stella, T., Stephens, Haynes, Webber, H., Zabel, F., Rosenzweig, C., 2021. Climate impacts on global agriculture emerge earlier in new generation of climate and crop models, 875+ Nat. Food 2. https://doi.org/10.1038/s43016-021-00400-y.
Jägermeyr, J., Pastor, A., Biemans, H., Gerten, D., 2017. Reconciling irrigated food production with environmental flows for sustainable development goals implementation. Nat. Commun. 8. https://doi.org/10.1038/ncomms15900.
Jagtap, S., Skouteris, G., Choudhari, V., Rahimifard, S., Duong, L.N.K., 2021. An internet of things approach for water efficiency: a case study of the beverage factory. Sustainability 13. https://doi.org/10.3390/su13063343.
Jagtap, S., Skouteris, G., Choudhari, V., Rahimifard, S., 2022. Improving Water Efficiency in the Beverage Industry With the Internet of Things. In: Bhatt, C., Kumar, N., Bashir, A.K., Alazab, M. (Eds.), Implementing Data Analytics and Architectures for Next Generation Wireless Communications. IGI Global, Hershey, PA, USA, pp. 18–26. https://doi.org/10.4018/978-1-7998-6988-7.ch002.
Jan, F., Min-Allah, N., Düştegör, D., 2021. IoT based smart water quality monitoring: recent techniques, trends and challenges for domestic applications. Water 13. https://doi.org/10.3390/w13131729.
Jiang, Y., 2009. China's water scarcity. J. Environ. Manag. https://doi.org/10.1016/j.jenvman.2009.04.016.
Jiao, W., Wang, L., McCabe, M.F., 2021. Multi-sensor remote sensing for drought characterization: current status, opportunities and a roadmap for the future. Remote Sens Environ. 256. https://doi.org/10.1016/j.rse.2021.112313.
Johnson, D.M., 2014. An assessment of pre- and within-season remotely sensed variables for forecasting corn and soybean yields in the United States. Remote Sens Environ. 141, 116–128. https://doi.org/10.1016/j.rse.2013.10.027.
Johnston, N., Rolfe, J., Flint, N., 2024. A systematic review of agricultural use water quality indices. Environ. Sustain. Indic. 23, 100417. https://doi.org/10.1016/j.indic.2024.100417.
Jones, H.G., Stoll, M., Santos, T., Sousa, C., de, Chaves, M.M., Grant, O.M., 2002. Use of infrared thermography for monitoring stomatal closure in the field: application to grapevine. J. Exp. Bot. 53, 2249–2260. https://doi.org/10.1093/jxb/erf083.
Ju, C., Kim, J., Seol, J., Son, H., Il, 2022. A review on multirobot systems in agriculture. Comput. Electron Agric. 202, 107336. https://doi.org/10.1016/j.compag.2022.107336.
Kamble, S.S., Gunasekaran, A., Gawankar, S.A., 2020. Achieving sustainable performance in a data-driven agriculture supply chain: a review for research and applications. Int J. Prod. Econ. 219, 179–194. https://doi.org/10.1016/j.ijpe.2019.05.022.
Kamilaris, A., Kartakoullis, A., Prenafeta-Boldú, F.X., 2017. A review on the practice of big data analysis in agriculture. Comput. Electron Agric. 143, 23–37. https://doi.org/10.1016/j.compag.2017.09.037.
Kamyab, H., Khademi, T., Chelliapan, S., Saberikamarposhti, M., Rezania, S., Yusuf, M., Farajnezhad, M., Jeon, B.-H., Ahn, Y., 2023. The latest innovative avenues for the utilization of artificial Intelligence and big data analytics in water resource management. Results Eng., 101566 https://doi.org/10.1016/j.rineng.2023.101566.
Kannan, N., Anandhi, A., 2020. Water management for sustainable food production. Water 12. https://doi.org/10.3390/w12030778.
Kapoor, A., Bhatia, D., Kumar, A., Gupta, S., 2024. Water treatment and crop recommendation model using artificial intelligence, in: 2024. IEEE Int. Conf. Comput., Power Commun. Technol. (IC2PCT 164–169. https://doi.org/10.1109/IC2PCT60090.2024.10486333.
Karahan, H., Cetin, M., Can, M.E., Alsenjar, O., 2024. Developing a new ANN model to estimate daily actual evapotranspiration using limited climatic data and remote sensing techniques for sustainable water management. Sustainability 16. https://doi.org/10.3390/su16062481.
Karthikeyan, L., Chawla, I., Mishra, A.K., 2020. A review of remote sensing applications in agriculture for food security: crop growth and yield, irrigation, and crop losses. J. Hydrol. (Amst.) 586. https://doi.org/10.1016/j.jhydrol.2020.124905.
Kebreab, E., Clark, K., Wagner-Riddle, C., France, J., 2006. Methane and nitrous oxide emissions from Canadian animal agriculture: a review. Can. J. Anim. Sci. 86, 135–157. https://doi.org/10.4141/A05-010.
Khanal, S., KC, K., Fulton, J.P., Shearer, S., Ozkan, E., 2020. Remote sensing in agriculture—accomplishments, limitations, and opportunities. Remote Sens. 12. https://doi.org/10.3390/rs12223783.
Khattak, S., Yousif, M., Hassan, S.U., Hassan, M., Alghamdi, T.A.H., 2024. Techno-economic and environmental analysis of renewable energy integration in irrigation systems: a comparative study of standalone and grid-connected PV/diesel generator systems in Khyber Pakhtunkhwa. Heliyon 10. https://doi.org/10.1016/j.heliyon.2024.e31025.
Khoa, T.A., Man, M.M., Nguyen, T.-Y., Nguyen, V., Nam, N.H., 2019. IoT multi-sensors: a novel watering management system. J. Sens. Actuator Netw. 8, 45. https://doi.org/10.3390/jsan8030045.
Khondoker, M., Mandal, S., Gurav, R., Hwang, S., 2023. Freshwater shortage, salinity increase, and global food production: a need for sustainable irrigation water desalination—a scoping review. Earth 4, 223–240. https://doi.org/10.3390/earth4020012.
Klerkx, L., Rose, D., 2020. Dealing with the game-changing technologies of Agriculture 4.0: How do we manage diversity and responsibility in food system transition pathways? Glob. Food Sec 24, 100347. https://doi.org/10.1016/j.gfs.2019.100347.
Koseoglu-Imer, D.Y., Oral, H.V., Coutinho Calheiros, C.S., Krzeminski, P., Güçlü, S., Pereira, S.A., Surmacz-Górska, J., Plaza, E., Samaras, P., Binder, P.M., van Hullebusch, E.D., Devolli, A., 2023. Current challenges and future perspectives for the full circular economy of water in European countries. J. Environ. Manag. https://doi.org/10.1016/j.jenvman.2023.118627.
Kröger, R., Pierce, S.C., Littlejohn, K.A., Moore, M.T., Farris, J.L., 2012. Decreasing nitrate-N loads to coastal ecosystems with innovative drainage management strategies in agricultural landscapes: an experimental approach. Agric. Water Manag 103, 162–166. https://doi.org/10.1016/j.agwat.2011.11.009.
Kumar, A., Saini, K.S., Dasila, H., Kumar, R., Devi, K., Bisht, Y.S., Yadav, M., Kothiyal, S., Chilwal, A., Maithani, D., Kaushik, P., 2023. Sustainable intensification of cropping systems under conservation agriculture practices: impact on yield, productivity and profitability of wheat. Sustainability 15. https://doi.org/10.3390/su15097468.
Kumar Kasera, R., Gour, S., Acharjee, T., 2024. A comprehensive survey on IoT and AI based applications in different pre-harvest, during-harvest and post-harvest activities of smart agriculture. Comput. Electron Agric. 216. https://doi.org/10.1016/J.COMPAG.2023.108522.
Kumar Singh, D., Sobti, R., 2022. Long-range real-time monitoring strategy for Precision Irrigation in urban and rural farming in society 5.0. Comput. Ind. Eng. 167, 107997. https://doi.org/10.1016/j.cie.2022.107997.
Kutyauripo, I., Rushambwa, M., Chiwazi, L., 2023. Artificial intelligence applications in the agrifood sectors. J. Agric. Food Res 11, 100502. https://doi.org/10.1016/J.JAFR.2023.100502.
Latino, M.E., Menegoli, M., Corallo, A., 2022. Agriculture digitalization: a global examination based on bibliometric analysis. IEEE Trans. Eng. Manag. https://doi.org/10.1109/TEM.2022.3154841.
Liakos, K.G., Busato, P., Moshou, D., Pearson, S., Bochtis, D., 2018. Machine learning in agriculture: a review. Sensors 18. https://doi.org/10.3390/s18082674.
Liang, X.-Z., Gower, D., Kennedy, J.A., Kenney, M., Maddox, M.C., Gerst, M., Balboa, G., Becker, T., Cai, X., Elmore, R., Gao, W., He, Y., Liang, K., Lotton, S., Malayil, L., Matthews, M.L., Meadow, A.M., Neale, C.M.U., Newman, G., Sapkota, A.R., Shin, S., Straube, J., Sun, C., Wu, Y., Yang, Y., Zhang, X., 2024. DAWN: dashboard for agricultural water use and nutrient management—a predictive decision support system to improve crop production in a changing climate. Bull. Am. Meteor. Soc. 105, E432–E441. https://doi.org/10.1175/BAMS-D-22-0221.1.
Lin, C.C., Liou, K.Y., Lee, M., Chiueh, P.Te, 2019. Impacts of urban water consumption under climate change: an adaptation measure of rainwater harvesting system. J. Hydrol. (Amst.) 572, 160–168. https://doi.org/10.1016/j.jhydrol.2019.02.032.
Liu, J., Liu, Q., Yang, H., 2016. Assessing water scarcity by simultaneously considering environmental flow requirements, water quantity, and water quality. Ecol. Indic. 60, 434–441. https://doi.org/10.1016/j.ecolind.2015.07.019.
Liu, W., Liu, X., Yang, H., Ciais, P., Wada, Y., 2022. Global water scarcity assessment incorporating green water in crop production. Water Resour. Res 58. https://doi.org/10.1029/2020WR028570.
Liu, X., Zang, J., Fu, Y., Pan, X., Meng, D., Zhu, Y., Sun, T., 2024. Influences of conservation tillage on soil macrofaunal biodiversity and trophic structure in the Mollisol region of Northeast China. Catena 236. https://doi.org/10.1016/j.catena.2023.107750.
Liu, Y., Shang, C., 2022. Application of blockchain technology in agricultural water rights trade management, 7017 14, 7017 Sustainability 2022 14. https://doi.org/10.3390/SU14127017.
Liu, Y., Engel, B.A., Flanagan, D.C., Gitau, M.W., McMillan, S.K., Chaubey, I., 2017. A review on effectiveness of best management practices in improving hydrology and water quality: needs and opportunities. Sci. Total Environ. 601–602 580–593. https://doi.org/10.1016/j.scitotenv.2017.05.212.
Liu, Y., Wang, P., Gojenko, B., Yu, J., Wei, L., Luo, D., Xiao, T., 2021. A review of water pollution arising from agriculture and mining activities in Central Asia: facts, causes and effects. Environ. Pollut. https://doi.org/10.1016/j.envpol.2021.118209.
Lothrop, N., Bright, K.R., Sexton, J., Pearce-Walker, J., Reynolds, K.A., Verhougstraete, M.P., 2018. Optimal strategies for monitoring irrigation water

quality. Agric. Water Manag 199, 86–92. https://doi.org/10.1016/j.agwat.2017.12.018.
Luna Juncal, M.J., Masino, P., Bertone, E., Stewart, R.A., 2023. Towards nutrient neutrality: a review of agricultural runoff mitigation strategies and the development of a decision-making framework. Sci. Total Environ. https://doi.org/10.1016/j.scitotenv.2023.162408.
Magwaza, S.T., Magwaza, L.S., Odindo, A.O., Mditshwa, A., 2020. Hydroponic technology as decentralised system for domestic wastewater treatment and vegetable production in urban agriculture: a review. Sci. Total Environ. 698, 134154. https://doi.org/10.1016/j.scitotenv.2019.134154.
Maimaitijiang, M., Ghulam, A., Sidike, P., Hartling, S., Maimaitiyiming, M., Peterson, K., Shavers, E., Fishman, J., Peterson, J., Kadam, S., Burken, J., Fritschi, F., 2017. Unmanned Aerial System (UAS)-based phenotyping of soybean using multi-sensor data fusion and extreme learning machine. ISPRS J. Photogrammetry Remote Sens. 134, 43–58. https://doi.org/10.1016/j.isprsjprs.2017.10.011.
Majeed, Y., Khan, M.U., Waseem, M., Zahid, U., Mahmood, F., Majeed, F., Sultan, M., Raza, A., 2023. Renewable energy as an alternative source for energy management in agriculture. Energy Rep. 10, 344–359. https://doi.org/10.1016/j.egyr.2023.06.032.
Malounas, I., Paliouras, G., Nikolopoulos, D., Liakopoulos, G., Bresta, P., Londra, P., Katsileros, A., Fountas, S., 2024. Early detection of broccoli drought acclimation/stress in agricultural environments utilizing proximal hyperspectral imaging and AutoML. Smart Agric. Technol. 8, 100463. https://doi.org/10.1016/j.atech.2024.100463.
Mana, A.A., Allouhi, A., Hamrani, A., Rehman, S., el Jamaoui, I., Jayachandran, K., 2024. Sustainable AI-based production agriculture: exploring AI applications and implications in agricultural practices. Smart Agric. Technol. 7, 100416. https://doi.org/10.1016/j.atech.2024.100416.
Mancosu, N., Snyder, R.L., Kyriakakis, G., Spano, D., 2015. Water scarcity and future challenges for food production. Water 7, 975–992. https://doi.org/10.3390/w7030975.
Mane, S., Das, N., Singh, G., Cosh, M., Dong, Y., 2024. Advancements in dielectric soil moisture sensor calibration: a comprehensive review of methods and techniques. Comput. Electron Agric. 218, 108686. https://doi.org/10.1016/j.compag.2024.108686.
Manocha, A., Sood, S.K., Bhatia, M., 2024. IoT-digital twin-inspired smart irrigation approach for optimal water utilization. Sustain. Comput.: Inform. Syst. 41, 100947. https://doi.org/10.1016/j.suscom.2023.100947.
Marques, P., Pádua, L., Sousa, J.J., Fernandes-Silva, A., 2024. Advancements in remote sensing imagery applications for precision management in olive growing: a systematic review. Remote Sens 16. https://doi.org/10.3390/rs16081324.
Martínez-Alvarez, V., Martin-Gorriz, B., Soto-García, M., 2016. Seawater desalination for crop irrigation — a review of current experiences and revealed key issues. Desalination 381, 58–70. https://doi.org/10.1016/j.desal.2015.11.032.
Martínez-Álvarez, V., Imbernón-Mulero, A., Maestre-Valero, J.F., Ben Abdallah, S., Gallego-Elvira, B., 2023. Agronomic Analysis of the Replacement of Conventional Agricultural Water Supply by Desalinated Seawater as an Adaptive Strategy to Water Scarcity in South-Eastern Spain. Agronomy 13. https://doi.org/10.3390/agronomy13122878.
Massari, C., Modanesi, S., Dari, J., Gruber, A., De Lannoy, G.J.M., Girotto, M., Quintana-Seguí, P., Le Page, M., Jarlan, L., Zribi, M., Ouaadi, N., Vreugdenhil, M., Zappa, L., Dorigo, W., Wagner, W., Brombacher, J., Pelgrum, H., Jaquot, P., Freeman, V., Volden, E., Prieto, D.F., Tarpanelli, A., Barbetta, S., Brocca, L., 2021. A review of irrigation information retrievals from space and their utility for users. Remote Sens (Basel) 13, 4112. https://doi.org/10.3390/RS13204112/S1.
Masupha, T.E., Moeletsi, M.E., Tsubo, M., 2021. Prospects of an agricultural drought early warning system in South Africa. Int. J. Disaster Risk Reduct. 66, 102615. https://doi.org/10.1016/j.ijdrr.2021.102615.
Mateo-Sagasta, J., Burke, J., 2010. Agriculture and water quality interactions: a global overview.
Mateo-Sagasta, J., Zadeh, S.M., Turral, H., 2017. Water pollution from Agriculture: a global review. Executive summary.
Mateo-Sagasta, J., Zadeh, S.M., Turral, H., 2018. More People, More Food, Worse Water?: A Global Review Of Water Pollution From Agriculture. FAO.
Mbaye, M.L., Sy, K., Faty, B., Sall, S.M., 2020. Impact of 1.5 and 2.0 °C global warming on the hydrology of the Faleme river basin. J. Hydrol. Reg. Stud. 31. https://doi.org/10.1016/j.ejrh.2020.100719.
McKinsey & Company, 2024. What is blockchain? [WWW Document]. URL ⟨https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-is-blockchain⟩ (accessed 6.17.24).
Medrano, H., Tomás, M., Martorell, S., Flexas, J., Hernández, E., Rosselló, J., Pou, A., Escalona, J.-M., Bota, J., 2015. From leaf to whole-plant water use efficiency (WUE) in complex canopies: limitations of leaf WUE as a selection target. Crop J. 3, 220–228. https://doi.org/10.1016/j.cj.2015.04.002.
Mekonnen, M.M., Hoekstra, A.Y., 2016. Four billion people facing severe water scarcity. Sci. Adv. 2, e1500323. https://doi.org/10.1126/sciadv.1500323.
Mekruksavanich, S., Cheosuwan, T., 2018. Visual Big Data Analytics for Sustainable Agricultural Development, in: 2018. Int. Jt. Symp. . Artif. Intell. Nat. Lang. Process. (ISAI-NLP) 1–5. https://doi.org/10.1109/iSAI-NLP.2018.8692910.
Mendivil-García, K., Medina, J.L., Rodríguez-Rangel, H., Roé-Sosa, A., Amábilis-Sosa, L. E., 2023. Optimization of the water quality monitoring network in a basin with intensive agriculture using artificial intelligence algorithms. Water Supply 24, 204–222. https://doi.org/10.2166/ws.2023.336.
Messina, G., Modica, G., 2022. Twenty Years of Remote Sensing Applications Targeting Landscape Analysis and Environmental Issues in Olive Growing: A Review. Remote Sens (Basel) 14. https://doi.org/10.3390/rs14215430.
Mezni, H., Driss, M., Boulila, W., Ben Atitallah, S., Sellami, M., Alharbi, N., 2022. Smartwater: a service-oriented and sensor cloud-based framework for smart monitoring of water environments. Remote Sens. 14. https://doi.org/10.3390/rs14040922.
Mi, Q., Li, Xiandong, Li, Xianmei, Yu, G., Gao, J., 2021. Cotton farmers' adaptation to arid climates: Waiting times to adopt water-saving technology. Agric. Water Manag 244. https://doi.org/10.1016/j.agwat.2020.106596.
Mitchell, M.E., Newcomer-Johnson, T., Christensen, J., Crumpton, W., Richmond, S., Dyson, B., Canfield, T.J., Helmers, M., Lemke, D., Lechtenberg, M., Green, D., Forshay, K.J., 2022. Potential of water quality wetlands to mitigate habitat losses from agricultural drainage modernization. Sci. Total Environ. 838. https://doi.org/10.1016/j.scitotenv.2022.156358.
Mndela, Y., Ndou, N., Nyamugama, A., 2023. Irrigation scheduling for small-scale crops based on crop water content patterns derived from uav multispectral imagery. Sustainability 15, 12034. https://doi.org/10.3390/SU151512034.
Mohammed, S., Arshad, S., Bashir, B., Vad, A., Alsalman, A., Harsányi, E., 2024. Machine learning driven forecasts of agricultural water quality from rainfall ionic characteristics in Central Europe. Agric. Water Manag 293. https://doi.org/10.1016/j.agwat.2024.108690.
Mohd Yussof, N.A., Ho, H.W., 2022. Review of water leak detection methods in smart building applications. Buildings 12. https://doi.org/10.3390/buildings12101535.
Moni, N.A., Sigweni, B., Mangwala, M., Kolobe, L., 2019. Water Leak Detection from Irrigation Pipelines in Botswana using Vibration Interpretation Technique. IEEE AFRICON Conf. 2019-Sept. https://doi.org/10.1109/AFRICON46755.2019.9133829.
Monteleone, S., Moraes, E.A. de, de Faria, B., Aquino Junior, P.T., Maia, R.F., Neto, A.T., Toscano, A., 2020. Exploring the adoption of precision agriculture for irrigation in the context of agriculture 4.0: the key role of internet of things. Sensors 20. https://doi.org/10.3390/s20247091.
Moursi, H., Youssef, M.A., Poole, C.A., Castro-Bolinaga, C.F., Chescheir, G.M., Richardson, R.J., 2023. Drainage water recycling reduced nitrogen, phosphorus, and sediment losses from a drained agricultural field in eastern North Carolina, U.S.A. Agric. Water Manag 279, 108179. https://doi.org/10.1016/j.agwat.2023.108179.
Munaganuri, R.K., Rao, Y.N., 2024. PAMICRM: improving precision agriculture through multimodal image analysis for crop water requirement estimation using multidomain remote sensing data samples. IEEE Access 12, 52815–52836. https://doi.org/10.1109/ACCESS.2024.3386552.
Munnaf, M.A., Wang, Y., Mouazen, A.M., 2024. Robot driven combined site-specific maize seeding and N fertilization: an agro-economic investigation. Comput. Electron Agric. 219, 108761. https://doi.org/10.1016/J.COMPAG.2024.108761.
Nath, A.J., Lal, R., 2017. Effects of tillage practices and land use management on soil aggregates and soil organic carbon in the North Appalachian Region, USA. Pedosphere. https://doi.org/10.1016/S1002-0160(17)60301-1.
Noh, S.J., Lee, G., Kim, B., Lee, S., Jo, J., Woo, D.K., 2024. Climate change impact assessment on water resources management using a combined multi-model approach in South Korea. J. Hydrol. Reg. Stud. 53. https://doi.org/10.1016/j.ejrh.2024.101842.
Nouri, M., Homaee, M., Pereira, L.S., Bybordi, M., 2023. Water management dilemma in the agricultural sector of Iran: a review focusing on water governance. Agric. Water Manag. https://doi.org/10.1016/j.agwat.2023.108480.
O'Grady, M.J., Langton, D., O'Hare, G.M.P., 2019. Edge computing: a tractable model for smart agriculture? Artif. Intell. Agric. 3, 42–51. https://doi.org/10.1016/j.aiia.2019.12.001.
Ofori, S., Puškáčová, A., Růžičková, I., Wanner, J., 2021. Treated wastewater reuse for irrigation: pros and cons. Sci. Total Environ. 760, 144026. https://doi.org/10.1016/j.scitotenv.2020.144026.
Oh, J., Kim, H.-R., Yu, S., Kim, K.-H., Lee, J.-H., Park, S., Kim, H., Yun, S.-T., 2023. A supervised machine learning approach to discriminate the effect of carcass leachate on shallow groundwater quality around on-farm livestock mortality burial sites. J. Hazard Mater. 457, 131712. https://doi.org/10.1016/j.jhazmat.2023.131712.
van Opstal, J., Droogers, P., Kaune, A., Steduto, P., Perry, C.J., 2021. Guid. Realiz. Real. Water Sav. Crop Water Product. Interv. https://doi.org/10.4060/cb3844en.
Parra-López, C., Reina-Usuga, L., Carmona-Torres, C., Sayadi, S., Klerkx, L., 2021. Digital transformation of the agrifood system: quantifying the conditioning factors to inform policy planning in the olive sector. Land Use Policy 108, 105537. https://doi.org/10.1016/j.landusepol.2021.105537.
Parra-López, C., Reina-Usuga, L., Garcia-Garcia, G., Carmona-Torres, C., 2024b. Functional analysis of technological innovation systems enabling digital transformation: a semi-quantitative multicriteria framework applied in the olive sector. Agric. Syst. 214, 103848. https://doi.org/10.1016/J.AGSY.2023.103848.
Parra-López, C., Reina-Usuga, L., Garcia-Garcia, G., Carmona-Torres, C., 2024c. Designing policies to promote the adoption of digital phytosanitation towards sustainability: the case of the olive sector in Andalusia. Agric. Syst. 221, 104147. https://doi.org/10.1016/j.agsy.2024.104147.
Parra-López, C., Ben Abdallah, S., Garcia-Garcia, G., Hassoun, A., Sánchez-Zamora, P., Trollman, H., Jagtap, S., Carmona-Torres, C., 2024a. Integrating digital technologies in agriculture for climate change adaptation and mitigation: state of the art and future perspectives. Comput. Electron Agric. 226, 109412. https://doi.org/10.1016/j.compag.2024.109412.
Patil, S.S., Patil, Y.M., Patil, S.B., 2024. Development of an automatic variable rate spraying system based on canopy characterization using artificial intelligence. Agric. Eng. Int.: CIGR J. 26.
Pauschinger, D., Klauser, F.R., 2021. The introduction of digital technologies into agriculture: space, materiality and the public–private interacting forms of authority and expertise. J. Rural Stud. https://doi.org/10.1016/j.jrurstud.2021.06.015.

Pendrill, F., Gardner, T.A., Meyfroidt, P., Persson, U.M., Adams, J., Azevedo, T., Lima, M.G.B., Baumann, M., Curtis, P.G., De Sy, V., Garrett, R., Godar, J., Goldman, E.D., Hansen, M.C., Heilmayr, R., Herold, M., Kuemmerle, T., Lathuillière, M.J., Ribeiro, V., Tyukavina, A., Weisse, M.J., West, C., 2022. Disentangling the numbers behind agriculture-driven tropical deforestation. Science 1979. https://doi.org/10.1126/science.abm9267.

Peng, J., Albergel, C., Balenzano, A., Brocca, L., Cartus, O., Cosh, M.H., Crow, W.T., Dabrowska-Zielinska, K., Dadson, S., Davidson, M.W.J., de Rosnay, P., Dorigo, W., Gruber, A., Hagemann, S., Hirschi, M., Kerr, Y.H., Lovergine, F., Mahecha, M.D., Marzahn, P., Mattia, F., Musial, J.P., Preuschmann, S., Reichle, R.H., Satalino, G., Silgram, M., van Bodegom, P.M., Verhoest, N.E.C., Wagner, W., Walker, J.P., Wegmüller, U., Loew, A., 2021. A roadmap for high-resolution satellite soil moisture applications – confronting product characteristics with user requirements. Remote Sens Environ. 252, 112162. https://doi.org/10.1016/J.RSE.2020.112162.

Pincheira, M., Vecchio, M., Giaffreda, R., Kanhere, S.S., 2021. Cost-effective IoT devices as trustworthy data sources for a blockchain-based water management system in precision agriculture. Comput. Electron Agric. 180, 105889. https://doi.org/10.1016/J.COMPAG.2020.105889.

Pixley, K.V., Cairns, J.E., Lopez-Ridaura, S., Ojiewo, C.O., Dawud, M.A., Drabo, I., Mindaye, T., Nebie, B., Asea, G., Das, B., Daudi, H., Desmae, H., Batieno, B.J., Boukar, O., Mukankusi, C.T.M., Nkalubo, S.T., Hearne, S.J., Dhugga, K.S., Gandhi, H., Snapp, S., Zepeda-Villarreal, E.A., 2023. Redesigning crop varieties to win the race between climate change and food security. Mol. Plant 16, 1590–1611. https://doi.org/10.1016/j.molp.2023.09.003.

Pomoni, D.I., Koukou, M.K., Vrachopoulos, M.G., Vasiliadis, L., 2023. A review of hydroponics and conventional agriculture based on energy and water consumption, environmental impact, and land use. Energies 16 (4), 1690. https://doi.org/10.3390/en16041690.

Prajith, A.S., Nowfiya, B.S., Noushad, N., Muhammed Ashik, S., Subi, S., Dhinu Lal, M., 2020. Automatic agricultural robot-agrobot. Proc. B-HTC 2020 - 1st IEEE Bangalore Humanit. Technol. Conf. https://doi.org/10.1109/B-HTC50970.2020.9297922.

Preite, L., Solari, F., Vignali, G., 2023. Technologies to optimize the water consumption in agriculture: a systematic review. Sustainability 15. https://doi.org/10.3390/su15075975.

Rabhi, L., Noureddine, F., Afraites, L., Belaid, B., 2021. Digital agriculture based on big data analytics: a focus on predictive irrigation for smart farming in Morocco. Indones. J. Electr. Eng. Comput. Sci. 24, 581. https://doi.org/10.11591/ijeecs.v24.i1.pp581-589.

Rahaman, M.H., Sajjad, H., Hussain, S., Roshani, Masroor, M., Sharma, A., 2024. Surface water quality prediction in the lower Thoubal river watershed, India: a hyper-tuned machine learning approach and DNN-based sensitivity analysis. J. Environ. Chem. Eng. 12. https://doi.org/10.1016/j.jece.2024.112915.

Rajasekhar, M., Upendra, B., Raju, G.S., Anand, 2022. Identification of groundwater potential zones in southern India using geospatial and decision-making approaches. Appl. Water Sci. 12, 68. https://doi.org/10.1007/s13201-022-01603-9.

Rajendran, S., Domalachenpa, T., Arora, H., Li, P., Sharma, A., Rajauria, G., 2024. Hydroponics: Exploring innovative sustainable technologies and applications across crop production, with emphasis on potato mini-tuber cultivation. Heliyon 10. https://doi.org/10.1016/j.heliyon.2024.e26823.

Rejeb, A., Rejeb, K., Zailani, S., 2021. Big data for sustainable agri-food supply chains: a review and future research perspectives. J. Data, Inf. Manag. 3, 167–182. https://doi.org/10.1007/s42488-021-00045-3.

Riaz, F., Riaz, M., Arif, M.S., Yasmeen, T., Ashraf, M.A., Adil, M., Ali, S., Mahmood, R., Rizwan, M., Hussain, Q., Zia, A., 2020. Alternative and non-conventional soil and crop management strategies for increasing water use efficiency. Environ. climate plant vegeta. growth 323–338. https://doi.org/10.1007/978-3-030-49732-3_13.

Ricciardi, V., Wane, A., Sidhu, B.S., Godde, C., Solomon, D., McCullough, E., Diekmann, F., Porciello, J., Jain, M., Randall, N., Mehrabi, Z., 2020. A scoping review of research funding for small-scale farmers in water scarce regions. Nat. Sustain 3, 836–844. https://doi.org/10.1038/s41893-020-00623-0.

Ridoutt, B.G., Baird, D., Anastasiou, K., Hendrie, G.A., 2021. An assessment of the water use associated with Australian diets using a planetary boundary framework. Public Health Nutr. 24, 1570–1575. https://doi.org/10.1017/S1368980021000483.

Rockström, J., Falkenmark, M., 2015. Agriculture: increase water harvesting in Africa. Nature 519, 283–285. https://doi.org/10.1038/519283a.

Rodríguez, P.O., Holzman, M.E., Aldaya, M.M., Rivas, R.E., 2024. Water footprint in rainfed summer and winter crops: the role of soil moisture. Agric. Water Manag 296. https://doi.org/10.1016/j.agwat.2024.108787.

Romero, M., Luo, Y., Su, B., Fuentes, S., 2018. Vineyard water status estimation using multispectral imagery from an UAV platform and machine learning algorithms for irrigation scheduling management. Comput. Electron Agric. 147, 109–117. https://doi.org/10.1016/j.compag.2018.02.013.

Rosa, L., Rulli, M.C., Davis, K.F., Chiarelli, D.D., Passera, C., D'Odorico, P., 2018. Closing the yield gap while ensuring water sustainability. Environ. Res. Lett. 13. https://doi.org/10.1088/1748-9326/aadeef.

Rosa, L., Chiarelli, D.D., Sangiorgio, M., Beltran-Peña, A.A., Rulli, M.C., D'Odorico, P., Fung, I., 2020b. Potential for sustainable irrigation expansion in a 3 °C warmer climate. Proc. Natl. Acad. Sci. 117, 29526–29534. https://doi.org/10.1073/pnas.2017796117.

Rosa, L., Chiarelli, D.D., Rulli, M.C., Dell'Angelo, J., D'Odorico, P., 2020a. Global agricultural economic water scarcity. Sci. Adv. 6, eaaz6031. https://doi.org/10.1126/sciadv.aaz6031.

Rosenzweig, C., Strzepek, K.M., Major, D.C., Iglesias, A., Yates, D.N., McCluskey, A., Hillel, D., 2004. Water resources for agriculture in a changing climate: international case studies. Glob. Environ. Change 14, 345–360. https://doi.org/10.1016/j.gloenvcha.2004.09.003.

Roy, Sujit Kumar, Hasan, Md.M., Mondal, I., Akhter, J., Roy, Sonzet Kumar, Talukder, S., Islam, A.K.M.S., Rahman, A., Karuppannan, S., 2024. Empowered machine learning algorithm to identify sustainable groundwater potential zone map in Jashore District, Bangladesh. Ground Sustain Dev. 25, 101168. https://doi.org/10.1016/j.gsd.2024.101168.

Saha, A., Cibin, R., Veith, T.L., White, C.M., Drohan, P.J., 2023. Water quality benefits of weather-based manure application timing and manure placement strategies. J. Environ. Manag. 333. https://doi.org/10.1016/j.jenvman.2023.117386.

Saitta, D., Consoli, S., Ferlito, F., Torrisi, B., Allegra, M., Longo-Minnolo, G., Ramírez-Cuesta, J.M., Vanella, D., 2021. Adaptation of citrus orchards to deficit irrigation strategies. Agric. Water Manag 247. https://doi.org/10.1016/j.agwat.2020.106734.

Salim, M.M., Rathore, S., Park, J.H., 2020. Distributed denial of service attacks and its defenses in IoT: a survey. J. Supercomput 76, 5320–5363. https://doi.org/10.1007/s11227-019-02945-z.

Sankaran, S., Khot, L.R., Espinoza, C.Z., Jarolmasjed, S., Sathuvalli, V.R., Vandemark, G. J., Miklas, P.N., Carter, A.H., Pumphrey, M.O., Knowles, N.R., Payek, M.J., 2015. Low-altitude, high-resolution aerial imaging systems for row and field crop phenotyping: a review. Eur. J. Agron. 70, 112–123. https://doi.org/10.1016/j.eja.2015.07.004.

Sarıgöl, M., Katipoğlu, O.M., 2024. Estimation of monthly evaporation values using gradient boosting machines and mode decomposition techniques in the Southeast Anatolia Project (GAP) area in Turkey. Acta Geophys. 72, 999–1016. https://doi.org/10.1007/s11600-023-01067-8.

Sarker, M.N.I., Islam, Shahidul, Ali, A., Islam, Saiful, Salam, A., Mahmud, S.M.H., 2019a. Promoting digital agriculture through big data for sustainable farm management. Int J. Innov. Appl. Stud. 25, 1235–1240.

Sarker, M.N.I., Wu, M., Chanthamith, B., Yusufzada, S., Li, D., Zhang, J., 2019b. Big data driven smart agriculture: pathway for sustainable development. 2nd Int. Conf. Artif. Intell. Big Data (ICAIBD) 2019, 60–65.

Satilmisoglu, T.K., Sermet, Y., Kurt, M., Demir, I., 2024. Blockchain opportunities for water resources management: a comprehensive review. Sustainability 16. https://doi.org/10.3390/su16062403.

Scanlon, B.R., Fakhreddine, S., Rateb, A., de Graaf, I., Famiglietti, J., Gleeson, T., Grafton, R.Q., Jobbagy, E., Kebede, S., Kolusu, S.R., Konikow, L.F., Long, D., Mekonnen, M., Schmied, H.M., Mukherjee, A., MacDonald, A., Reedy, R.C., Shamsudduha, M., Simmons, C.T., Sun, A., Taylor, R.G., Villholth, K.G., Vörösmarty, C.J., Zheng, C., 2023. Global water resources and the role of groundwater in a resilient water future. Nat. Rev. Earth Environ. 4, 87–101. https://doi.org/10.1038/s43017-022-00378-6.

Schilling, S., Dietz, A., Kuenzer, C., 2024. Snow water equivalent monitoring—a review of large-scale remote sensing applications. Remote Sens. 16. https://doi.org/10.3390/rs16061085.

Schillings, J., Bennett, R., Rose, D.C., 2021. Exploring the potential of precision livestock farming technologies to help address farm animal welfare. Front. Anim. Sci. 2. https://doi.org/10.3389/fanim.2021.639678.

Schyns, J.F., Hoekstra, A.Y., Booij, M.J., Hogeboom, R.J., Mekonnen, M.M., 2019. Limits to the world's green water resources for food, feed, fiber, timber, and bioenergy. Proc. Natl. Acad. Sci. USA 116, 4893–4898. https://doi.org/10.1073/pnas.1817380116.

Segarra, J., Buchaillot, M.L., Araus, J.L., Kefauver, S.C., 2020. Remote sensing for precision agriculture: sentinel-2 improved features and applications. Agronomy 10. https://doi.org/10.3390/agronomy10050641.

Sengupta, S., Patra, S.K., Laha, A., Poddar, R., Bhattacharyya, K., Dey, P., Mandal, J., 2023. Replacing conventional surface irrigation with micro-irrigation in vegetables can alleviate arsenic toxicity and improve water productivity. Ground Sustain Dev. 23. https://doi.org/10.1016/j.gsd.2023.101012.

Shahbazi, M., Zarei, H., Solgi, A., 2024. A new approach in using the GRACE satellite data and artificial intelligence models for modeling and predicting the groundwater level (case study: aspas aquifer in Southern Iran). Environ. Earth Sci. 83, 240. https://doi.org/10.1007/s12665-024-11538-w.

Sharma, K., Kumar, D., 2024. ML- and IoT-Based Crop Prediction System. In: Shaw, R.N., Siano, P., Makhilef, S., Ghosh, A., Shimi, S.L. (Eds.), Innovations in Electrical and Electronic Engineering, Lecture Notes in Electrical Engineering, 1109. Springer, Singapore. https://doi.org/10.1007/978-981-99-8289-9_44. ICEEE 2023.

Siddi Raju, R., Sudarsana Raju, G., Rajasekhar, M., 2019. Identification of groundwater potential zones in Mandavi River basin, Andhra Pradesh, India using remote sensing, GIS and MIF techniques. HydroResearch 2, 1–11. https://doi.org/10.1016/j.hydres.2019.09.001.

Silva-Gálvez, A.L., López-Sánchez, A., Camargo-Valero, M.A., Prosenc, F., González-López, M.E., Gradilla-Hernández, M.S., 2024. Strategies for livestock wastewater treatment and optimised nutrient recovery using microalgal-based technologies. J. Environ. Manag. https://doi.org/10.1016/j.jenvman.2024.120258.

Silveira, R.M.F., Façanha, D.A.E., McManus, C.M., Ferreira, J., da, Silva, I.J.O., 2023. Machine intelligence applied to sustainability: a systematic methodological proposal to identify sustainable animals. J. Clean. Prod. 420, 138292. https://doi.org/10.1016/j.jclepro.2023.138292.

Singh, A., 2021. A review of wastewater irrigation: environmental implications. Resour. Conserv Recycl 168, 105454. https://doi.org/10.1016/j.resconrec.2021.105454.

Singh, M., Karada, M.S., Rai, R.K., Pratap, D., Agnihotri, D., Singh, A.K., Singh, B.K., 2023. A review on remote sensing as a tool for irrigation monitoring and management. Int. J. Environ. Clim. Change 13, 203–211. https://doi.org/10.9734/ijecc/2023/v13i61817.

Sishodia, R.P., Ray, R.L., Singh, S.K., 2020. Applications of remote sensing in precision agriculture: a review. Remote Sens. 12, 3136. https://doi.org/10.3390/RS12193136.

Sun, H., Zhang, X., Wang, E., Chen, S., Shao, L., 2015. Quantifying the impact of irrigation on groundwater reserve and crop production – a case study in the North China Plain. Eur. J. Agron. 70, 48–56. https://doi.org/10.1016/j.eja.2015.07.001.
Susha Lekshmi, S.U., Singh, D.N., Shojaei Baghini, M., 2014. A critical review of soil moisture measurement. Measurement 54, 92–105. https://doi.org/10.1016/j.measurement.2014.04.007.
Tarate, S.B., Patel, N.R., Danodia, A., Pokhariyal, S., Parida, B.R., 2024. Geospatial technology for sustainable agricultural water management in India—a systematic review. Geomatics 4, 91–123. https://doi.org/10.3390/GEOMATICS4020006.
Taşan, M., Demir, Y., Taşan, S., Öztürk, E., 2024. Comparative analysis of different machine learning algorithms for predicting trace metal concentrations in soils under intensive paddy cultivation. Comput. Electron Agric. 219, 108772. https://doi.org/10.1016/j.compag.2024.108772.
Thakur, R., Bhanarkar, P., Thakur, U.P., 2024. Unsupervised/Supervised Algorithms for Multimedia Data in Smart Agriculture. in: Supervised and Unsupervised Data Engineering for Multimedia Data. John Wiley & Sons, Ltd, pp. 111–132. https://doi.org/10.1002/9781119786443.ch5.
Toureiro, C., Serralheiro, R., Shahidian, S., Sousa, A., 2017. Irrigation management with remote sensing: evaluating irrigation requirement for maize under Mediterranean climate condition. Agric. Water Manag 184, 211–220. https://doi.org/10.1016/j.agwat.2016.02.010.
Towolawi, A.T., Oguntoke, O., Bada, B.S., Adejuwon, J.O., 2024. Water management and crop-resistant varieties adaptation due to climate change by farmers. Theor. Appl. Clim. 155, 3405–3422. https://doi.org/10.1007/s00704-024-04825-w.
Trollman, H., 2024. Feature extraction for artificial intelligence enabled food supply chain failure mode prediction. Discov. Food 4, 22. https://doi.org/10.1007/s44187-024-00090-y.
Türkler, L., Akkan, T., Akkan, L.Ö., 2023. Detection of water leakage in drip irrigation systems using infrared technique in smart agricultural robots, 9244 23, 9244 Sensors 2023 23. https://doi.org/10.3390/S23229244.
Turral, H., Burke, J., Faurès, J.-M., 2011. Climate change, water and food security.
Tzanakakis, V.A., Paranychianakis, N.V., Angelakis, A.N., 2020. Water supply and water scarcity. Water 12. https://doi.org/10.3390/w12092347.
Tzerakis, K., Psarras, G., Kourgialas, N.N., 2023. Developing an open-source iot platform for optimal irrigation scheduling and decision-making: implementation at olive grove parcels, 1739 15, 1739 Water 2023 15. https://doi.org/10.3390/W15091739.
United Nations, 2022. World Population Prospects 2022: Summary of Results. UN Department of Economic and Social Affairs. UN DESA/POP/2022/TR/NO. 3.
Vanham, D., Hoekstra, A.Y., Wada, Y., Bouraoui, F., de Roo, A., Mekonnen, M.M., van de Bund, W.J., Batelaan, O., Pavelic, P., Bastiaanssen, W.G.M., Kummu, M., Rockström, J., Liu, J., Bisselink, B., Ronco, P., Pistocchi, A., Bidoglio, G., 2018. Physical water scarcity metrics for monitoring progress towards SDG target 6.4: An evaluation of indicator 6.4.2 "Level of water stress. Sci. Total Environ. https://doi.org/10.1016/j.scitotenv.2017.09.056.
Verma, G., Dhaka, A.K., Singh, B., Kumar, Adarsh, Choudhary, A.K., Kumar, Amit, Kamboj, N.K., Hasanain, M., Singh, S., Bhupenchandra, I., Shabnam, Sanwal, P., Kumar, S., 2024. Productivity, soil health, and carbon management index of soybean-wheat cropping system under double zero-tillage and natural-farming based organic nutrient management in north-Indian plains. Sci. Total Environ. 917. https://doi.org/10.1016/j.scitotenv.2024.170418.
van Vliet, M.T.H., Jones, E.R., Flörke, M., Franssen, W.H.P., Hanasaki, N., Wada, Y., Yearsley, J.R., 2021. Global water scarcity including surface water quality and expansions of clean water technologies. Environ. Res. Lett. 16, 024020. https://doi.org/10.1088/1748-9326/abbfc3.
Wang, C., Miao, Q., Wei, Z., Guo, Y., Li, J., Fan, Z., Hu, Y., Zhang, H., Sun, J., Cui, Z., 2024. Nutrient runoff and leaching under various fertilizer treatments and pedogeographic conditions: a case study in tobacco (Nicotiana tabacum L.) fields of the Erhai Lake basin, China. Eur. J. Agron. 156. https://doi.org/10.1016/j.eja.2024.127170.
Wanyama, J., Bwambale, E., Kiraga, S., Katimbo, A., Nakawuka, P., Kabenge, I., Oluk, I., 2024. A systematic review of fourth industrial revolution technologies in smart irrigation: constraints, opportunities, and future prospects for sub-Saharan Africa. Smart Agric. Technol. 7, 100412. https://doi.org/10.1016/j.atech.2024.100412.
Willekens, K., Vandecasteele, B., Buchan, D., De Neve, S., 2014. Soil quality is positively affected by reduced tillage and compost in an intensive vegetable cropping system. Appl. Soil Ecol. 82, 61–71. https://doi.org/10.1016/j.apsoil.2014.05.009.
WMO, 2023. The Global Climate 2011-2020. A decade of accelerating climate change. World Meteorological Organization.
Wolfert, S., Ge, L., Verdouw, C., Bogaardt, M.-J., 2017. Big data in smart farming – a review. Agric. Syst. 153, 69–80. https://doi.org/10.1016/j.agsy.2017.01.023.
Woods, J., Williams, A., Hughes, J.K., Black, M., Murphy, R., 2010. Energy and the food system. Philos. Trans. R. Soc. B: Biol. Sci. https://doi.org/10.1098/rstb.2010.0172.
Wu, C.H., Lu, C.Y., Zhan, J.W., Wu, H., Te, 2020. Using long short-term memory for building outdoor agricultural machinery. Front Neurorobot 14, 538852. https://doi.org/10.3389/FNBOT.2020.00027/BIBTEX.
Xu, Y., Ma, T., Yuan, Z., Tian, J., Zhao, N., 2023. Spatial patterns in pollution discharges from livestock and poultry farm and the linkage between manure nutrients load and the carrying capacity of croplands in China. Sci. Total Environ. 901. https://doi.org/10.1016/j.scitotenv.2023.166006.
Xue, J., Na, Q., Zhang, X., Grieneisen, M.L., Lai, Q., Zhang, M., 2023. CalBMP, a web-based modeling tool for evaluating pesticide offsite movement and best management practice scenarios in California agricultural land. Agric. Water Manag 277. https://doi.org/10.1016/j.agwat.2023.108139.
Yadav, M., Vashisht, B., Jalota, S., Jyolsna, T., Singh, S., Kumar, Arun, Kumar, Amit, Singh, G., 2024. Improving Water efficiencies in rural agriculture for sustainability of water resources: a review. Water Resour. Manag. https://doi.org/10.1007/s11269-024-03836-6.
Yang, C., Zhang, W., Gu, H., Liu, A., Guo, Q., Chen, Y., Lu, J., Ren, T., Cong, R., Lu, Z., Zhang, Y., Liao, S., Li, X., 2023. Field, plant, to leaf: A meta-analysis on crop water use efficiency response to potassium fertilization. J. Hydrol. 621, 129578. https://doi.org/10.1016/j.jhydrol.2023.129578.
Young, K.M., Thomson, A., Coronel, E., 2022. Environmental outcomes from on-farm agricultural production in the United States. Crops Soils 55, 37–43. https://doi.org/10.1002/crso.20229.
Zappa, L., Dari, J., Modanesi, S., Quast, R., Brocca, L., De Lannoy, G., Massari, C., Quintana-Seguí, P., Barella-Ortiz, A., Dorigo, W., 2024. Benefits and pitfalls of irrigation timing and water amounts derived from satellite soil moisture. Agric. Water Manag 295, 108773. https://doi.org/10.1016/j.agwat.2024.108773.
Zeng, H., Dhiman, G., Sharma, Ashutosh, Sharma, Amit, Tselykh, A., 2023. An IoT and Blockchain-based approach for the smart water management system in agriculture. Expert Syst. 40, e12892. https://doi.org/10.1111/EXSY.12892.
Zhang, D., Sial, M.S., Ahmad, N., Filipe, A.J., Thu, P.A., Zia-Ud-Din, M., Caleiro, A.B., 2021. Water scarcity and sustainability in an emerging economy: a management perspective for future. Sustainability 13. https://doi.org/10.3390/su13010144.
Zhang, M., Li, X., Wang, H., Huang, Q., 2018. Comprehensive analysis of grazing intensity impacts soil organic carbon: a case study in typical steppe of Inner Mongolia, China. Appl. Soil Ecol. 129, 1–12. https://doi.org/10.1016/j.apsoil.2018.03.008.
Zheng, J., Lü, H., Crow, W.T., Zhao, T., Merlin, O., Rodriguez-Fernandez, N., Shi, J., Zhu, Y., Su, J., Kang, C.S., Wang, X., Gou, Q., 2021. Soil moisture downscaling using multiple modes of the DISPATCH algorithm in a semi-humid/humid region. Int. J. Appl. Earth Obs. Geoinf. 104, 102530. https://doi.org/10.1016/J.JAG.2021.102530.
Zhou, L., Li, S., Li, F., 2022. Damage and elimination of soil and water antibiotic and heavy metal pollution caused by livestock husbandry. Environ. Res. https://doi.org/10.1016/j.envres.2022.114188.
Zhu, S., Cui, N., Zhou, J., Xue, J., Wang, Z., Wu, Z., Wang, M., Deng, Q., 2023. Digital mapping of root-zone soil moisture using uav-based multispectral data in a kiwifruit orchard of northwest China. Remote Sens (Basel) 15, 646. https://doi.org/10.3390/RS15030646.
Zhu, S., Cui, N., Jin, H., Jin, X., Guo, L., Jiang, S., Wu, Z., Lv, M., Chen, F., Liu, Q., Wang, M., 2024. Optimization of multi-dimensional indices for kiwifruit orchard soil moisture content estimation using UAV and ground multi-sensors. Agric. Water Manag 294, 108705. https://doi.org/10.1016/J.AGWAT.2024.108705.
Zia, H., 2022. Water Sustainability through Drainage Reuse in Agriculture – A Case for Collaborative Wireless Sensor Networks. In: Sultan, M., Ahmad, F. (Eds.), Irrigation and Drainage. IntechOpen, Rijeka. https://doi.org/10.5772/intechopen.106486.
Zia, H., Harris, N.R., Merrett, G.V., Rivers, M., Coles, N., 2013. The impact of agricultural activities on water quality: a case for collaborative catchment-scale management using integrated wireless sensor networks. Comput. Electron Agric. 96, 126–138. https://doi.org/10.1016/j.compag.2013.05.001.

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