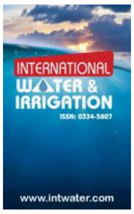

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Developing Decision Support Systems for Irrigation Management using Big Data Analytics

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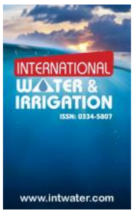
Abstract Effective irrigation management is essential for sustainable agricultural practices, as it significantly influences water conservation, crop productivity, and overall food security. Traditional irrigation systems often rely on outdated techniques, resulting in inefficiencies such as over-irrigation, water wastage, and inadequate adaptation to changing climatic conditions [1][2]. These limitations are further exacerbated by the lack of real-time monitoring, precise decision-making tools, and predictive capabilities to optimize water usage [3][4]. Recent advancements in big data analytics provide transformative opportunities to overcome these challenges. By leveraging data from diverse sources, such as IoT sensors, remote sensing technologies, weather forecasts, and soil moisture monitoring systems, decision-makers can gain valuable insights into irrigation practices [5][6][7]. Big data analytics integrates tools like machine learning, cloud computing, and predictive modeling to enhance decision-making, enabling optimal water allocation, crop health monitoring, and irrigation scheduling [8][9][10]. Such systems empower farmers to minimize water usage while maximizing agricultural output, promoting long-term sustainability [11][12]. By synthesizing insights from existing research and identifying gaps in current methodologies, this paper aims to guide researchers, policymakers, and practitioners toward adopting data-driven irrigation strategies. The findings underscore the importance of leveraging big data technologies to achieve efficient irrigation management, ensuring water sustainability and resilience in agricultural systems amidst growing environmental pressures [18][19][20].

Keywords: Irrigation Management, Big Data Analytics, Decision Support Systems, Precision Agriculture, IoT in Agriculture, Sustainable Water Use.

Introduction

Water management in agriculture, particularly irrigation, is one of the most critical areas for ensuring global food security and sustainable agricultural practices. The increasing demand for agricultural output, coupled with diminishing water resources, has necessitated the adoption of innovative technologies. Irrigation management, as a subset of water resource management, plays a central role in determining crop productivity and resource efficiency [1][2]. However, traditional irrigation systems are often marred by inefficiencies, lack of precision, and inadequate response mechanisms to real-time changes [3][4]. The emergence of big data analytics as a transformative tool in modern agriculture offers unprecedented opportunities to optimize irrigation practices [5][6]. By leveraging data from IoT devices, weather models, soil sensors, and remote sensing technologies, big data analytics enables precise decision-making tailored to the unique requirements of crops, regions, and climates [7][8]. This section introduces the context, challenges, and scope of the topic, focusing on the integration of big data analytics in irrigation management. It sets the stage for an in-depth exploration of the methodologies, tools, and frameworks that form the backbone of data-driven irrigation management practices.



Context and Importance of Irrigation Management

Irrigation, accounting for over 70% of global freshwater usage, is a cornerstone of agricultural production [9]. Effective irrigation systems are crucial for achieving high crop yields, especially in arid and semi-arid regions. However, traditional methods such as flood irrigation are prone to inefficiencies, leading to water loss through runoff and evaporation [10]. Additionally, climate change has introduced variability in rainfall patterns, exacerbating water scarcity in many regions [11][12]. Irrigation management is not only about ensuring water reaches the fields but also about optimizing its use to sustain soil health and avoid over-irrigation. As depicted in Table 1, the efficiency of irrigation methods varies significantly, emphasizing the need for precision-driven approaches.

Table 1. Comparison of Irrigation Methods and Efficiency

Irrigation Method	Description	Efficiency (%)	Suitability
Flood Irrigation	Water distributed across fields by gravity	50–60	Large fields with minimal slope
Drip Irrigation	Water delivered directly to plant roots via pipes	90–95	High-value crops, water-scarce areas
Sprinkler Irrigation	Water sprayed over fields through overhead sprinklers	70–85	Small and medium fields, varied soils
Subsurface Irrigation	Water delivered below the soil surface to root zones	95+	High-tech farms, controlled irrigation

Challenges in Traditional Irrigation Practices

Traditional irrigation systems, such as surface and furrow irrigation, rely heavily on manual monitoring and empirical knowledge, leading to inefficiencies [13][14]. Key challenges include:

- **Water Wastage:** Over-irrigation often results in runoff and evaporation losses [15].
- **Lack of Adaptability:** Traditional systems cannot dynamically adjust to varying climatic conditions or crop needs [16].
- **Infrastructure Issues:** Aging infrastructure and poorly maintained canals contribute to water delivery inefficiencies [17].

These challenges necessitate a shift towards data-driven irrigation management systems capable of real-time monitoring and intelligent decision-making.

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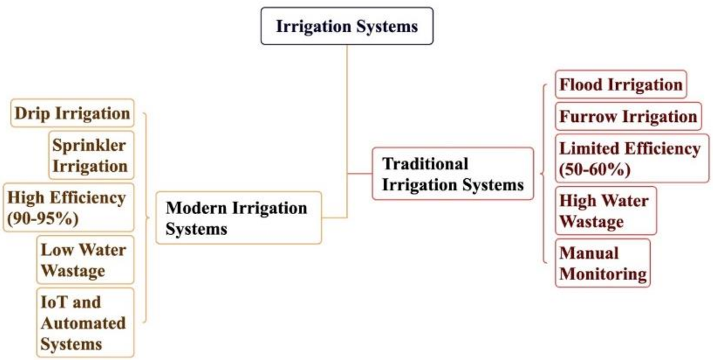

Figure 1: An illustration comparing traditional and modern irrigation systems.

Role and Potential of Big Data Analytics in Agriculture

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Big data analytics in agriculture involves collecting, processing, and analyzing data from multiple sources, including IoT sensors, satellite imagery, and weather models, to provide actionable insights [18][19]. Its application in irrigation management enables:

1. **Real-Time Monitoring:** Continuous tracking of soil moisture, weather patterns, and crop health using IoT devices [20].
2. **Predictive Insights:** Forecasting irrigation requirements based on historical and real-time data trends [21].
3. **Optimization:** Ensuring optimal water allocation and reducing wastage through advanced machine learning models [22].

By leveraging these capabilities, big data analytics empowers farmers to achieve higher efficiency, improve resource management, and promote sustainability [23][24].

Objectives and Scope of the Paper

This paper explores the transformative potential of big data analytics in irrigation management, focusing on its application in Decision Support Systems (DSS). DSS combine data, analytical tools, and user-friendly interfaces to enable precise decision-making in agriculture [25]. Specifically, this paper aims to:

- Analyze challenges in traditional irrigation systems and how big data analytics addresses these gaps.
- Highlight the role of IoT, machine learning, and predictive modeling in developing intelligent irrigation solutions.
- Present a conceptual framework for integrating big data into irrigation management practices.
- Discuss the technical and operational challenges of implementing big data-driven irrigation systems.
- Identify opportunities for future research and development in this domain.

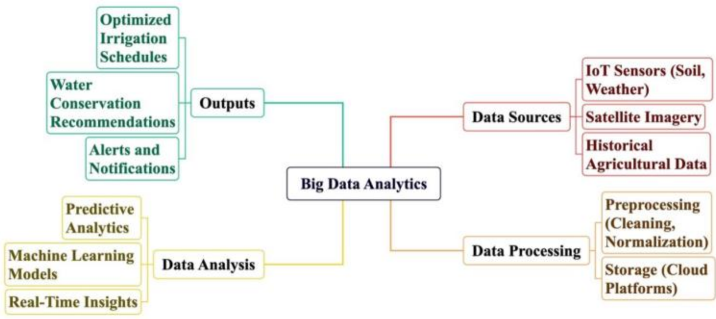

Figure 2: A flowchart illustrating the integration of big data analytics in irrigation.

Literature Review

The literature review explores existing research, methodologies, and technologies related to irrigation management and the application of big data analytics in agriculture. It identifies the strengths and limitations of current approaches, providing a foundation for the proposed framework. This section is structured into the following subsections for clarity:

Overview of Irrigation Management Systems

Irrigation management systems have evolved significantly over the years, transitioning from traditional manual methods to advanced, automated systems. Traditional systems, such as flood and furrow irrigation, remain prevalent in many regions due to their simplicity and low cost. However, these systems are often inefficient, with water losses ranging from 30% to 50% due to runoff and evaporation [1][2]. Modern systems, such as drip and sprinkler irrigation, offer greater precision and higher efficiency but require substantial investments and technical expertise [3]. Several studies have highlighted the need for irrigation scheduling and real-time monitoring to optimize water use. For example, Howell (1996) emphasized the

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role of irrigation scheduling research in improving water use efficiency [4]. Similarly, Thompson et al. (2007) demonstrated the benefits of using soil moisture sensors for threshold-based irrigation management [5].

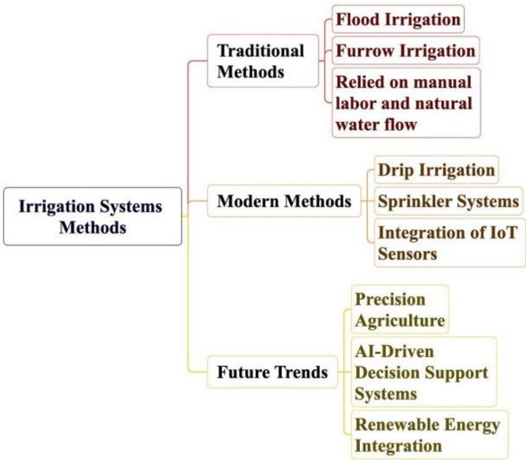

Figure 3: Historical evolution of irrigation systems: Traditional to modern methods.

Role of Big Data in Agriculture

Big data analytics has emerged as a transformative tool in agriculture, enabling data-driven decision-making across various domains, including irrigation management. Kamilaris and Prenafeta-Boldú (2018) conducted a comprehensive review of deep learning applications in agriculture, emphasizing their potential for optimizing irrigation practices [6]. Machine learning algorithms, combined with IoT sensors, provide real-time insights into soil moisture, weather conditions, and crop health [7].

Key technologies enabling big data analytics in agriculture include:

- **IoT Devices:** Soil moisture sensors, weather stations, and drones for real-time data collection.
- **Cloud Computing:** Scalable platforms for storing and processing large volumes of data.
- **Predictive Analytics:** Machine learning models for forecasting irrigation needs.

Table 2. Summary of Big Data Technologies in Agriculture

Technology	Description	Application
IoT Devices	Sensors and devices for data collection	Soil moisture monitoring, weather tracking
Cloud Computing	Platforms for data storage and processing	Scalable data analysis
Predictive Analytics	AI models for forecasting based on historical and real-time data	Irrigation scheduling, resource optimization

Decision Support Systems for Irrigation Management

Decision Support Systems (DSS) are computer-based tools designed to assist farmers and decision-makers in planning and managing irrigation. These systems integrate data from various sources to provide actionable recommendations. Key features of DSS include:

- **Data Integration:** Combining data from sensors, satellite imagery, and weather models.
- **User-Friendly Interfaces:** Providing intuitive dashboards for monitoring and decision-making.
- **Actionable Insights:** Generating recommendations for irrigation scheduling and water allocation.

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Several DSS have been proposed in recent years. For instance, Isern et al. (2012) developed a multi-agent simulation platform for irrigation scheduling, demonstrating its effectiveness in optimizing water use [8]. Similarly, García-Vila and Fereres (2012) integrated economic models with crop simulation models to optimize farm-level irrigation management [9].

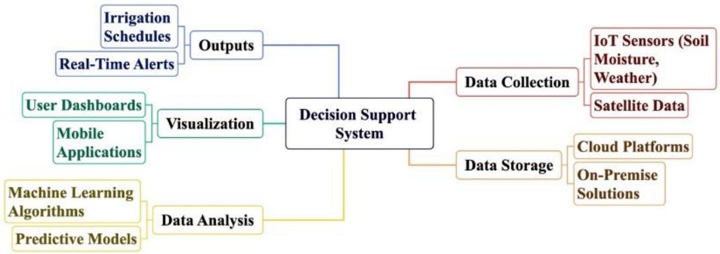

Figure 4: Flowchart illustrating the components of a typical Decision Support System for irrigation.

Gaps and Challenges in Existing Systems

Despite significant advancements, existing irrigation management systems face several limitations:

- **Data Quality:** Inconsistent and incomplete data can lead to inaccurate predictions [10].
- **Scalability:** Many systems are designed for small-scale farms and are not easily adaptable to larger operations [11].
- **Cost and Accessibility:** High initial investment and maintenance costs hinder widespread adoption, particularly in developing regions [12].

Wani et al. (2021) identified the need for robust machine learning models capable of handling noisy and incomplete data in agricultural applications [13]. Furthermore, Bali and Singla (2021) highlighted the importance of integrating user-friendly tools to ensure adoption among farmers with limited technical expertise [14].

Emerging Trends in Big Data Analytics for Irrigation

Emerging trends in big data analytics for irrigation management include:

- **Hybrid Models:** Combining machine learning with traditional empirical methods for improved accuracy.
- **Remote Sensing Integration:** Leveraging satellite data for large-scale irrigation monitoring.
- **Real-Time Decision-Making:** Implementing edge computing for faster, localized decision-making.

Recent studies have demonstrated the effectiveness of these trends. For example, Yan et al. (2021) proposed a hybrid Whale Optimization Algorithm (WOA) and Extreme Gradient Boosting (XGB) model for estimating evapotranspiration, achieving high accuracy in both arid and humid regions [15]. Similarly, Liakos et al. (2018) emphasized the role of remote sensing technologies in improving irrigation practices across large agricultural landscapes [16].

Big Data Analytics in Irrigation Management

This section delves into the key components, techniques, and benefits of utilizing big data analytics in irrigation management. By leveraging data-driven insights, big data analytics transforms traditional irrigation systems into intelligent, adaptive solutions tailored to specific agricultural needs.

Key Components of a Decision Support System (DSS)

A Decision Support System (DSS) for irrigation management comprises several core components, each contributing to its overall functionality:

- **Data Collection:** Data is gathered from multiple sources, such as IoT sensors, weather stations, satellite imagery, and historical agricultural records.

- **Data Storage and Processing:** Cloud-based platforms store and process large volumes of structured and unstructured data for real-time analysis.

- **Predictive Analytics:** Machine learning algorithms analyze patterns and trends to forecast irrigation needs and recommend optimal water usage.

- **Visualization Tools:** User-friendly dashboards present actionable insights, enabling farmers to make informed decisions.

Table 3. Core Components of a DSS for Irrigation Management

Component	Description	Example
Data Collection	Real-time monitoring of environmental and soil parameters	IoT sensors, weather models
Data Storage and Processing	Cloud-based platforms for managing large datasets	AWS, Google Cloud
Predictive Analytics	Algorithms for forecasting water requirements	Machine learning models
Visualization Tools	Dashboards and interfaces for decision-making	Custom web/mobile applications

Big Data Lifecycle in Irrigation Management

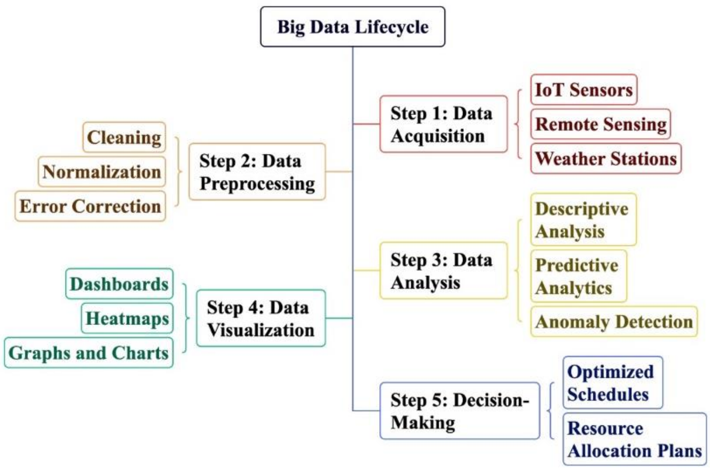

Figure 5: Flowchart showing the big data lifecycle in irrigation management.

The lifecycle of big data in irrigation management follows a structured process, enabling the transformation of raw data into actionable insights:

- **Data Acquisition:** Data from sensors, drones, and remote sensing technologies is collected and transmitted to centralized platforms [1].

- **Data Preprocessing:** Raw data is cleaned, formatted, and filtered to ensure quality and consistency [2].

- **Data Analysis:** Machine learning algorithms and statistical models extract patterns and insights from the processed data [3].

- **Data Visualization:** Results are presented in easily interpretable formats, such as graphs, heatmaps, and alerts [4].

Analytical Models and Techniques

Several analytical models and techniques have been employed in big data-driven irrigation management, each tailored to specific challenges:

- **Machine Learning Models:** Algorithms such as Support Vector Machines (SVM), Random Forests, and Neural Networks are commonly used for predicting irrigation needs based on climatic and soil data [5].

- **Remote Sensing Integration:** Satellite imagery is analyzed using AI techniques to monitor large-scale irrigation systems [6].

- **IoT and Edge Computing:** IoT devices enable localized data collection, while edge computing facilitates real-time processing at the source [7].

Figure 6: Comparison of machine learning models in irrigation forecasting.

Benefits of Big Data Analytics in Irrigation

Big data analytics provides several advantages for irrigation management, including:

- **Efficiency Improvement:** Precise water usage reduces wastage and enhances resource conservation [8].

- **Cost Reduction:** Predictive insights optimize operational costs by minimizing over-irrigation and improving scheduling [9].

- **Sustainability:** Data-driven systems promote sustainable practices by balancing resource usage with environmental needs [10].

Table 4. Benefits of Big Data Analytics in Irrigation

Benefit	Description	Example
Efficiency Improvement	Optimized water use for higher agricultural productivity	Reduction in water wastage by 30%
Cost Reduction	Lower operational costs through predictive scheduling	Savings on energy costs for pumps
Sustainability	Promotes environmental conservation through resource management	Reduced groundwater depletion

Examples of Big Data Applications in Irrigation

- **Precision Agriculture:** Using IoT sensors and predictive models to customize irrigation schedules for individual crops [11].

- **Large-Scale Monitoring:** Satellite-based systems monitor irrigation practices across expansive agricultural regions [12].

- **Real-Time Alerts:** Edge computing and mobile apps provide real-time notifications for immediate action [13].

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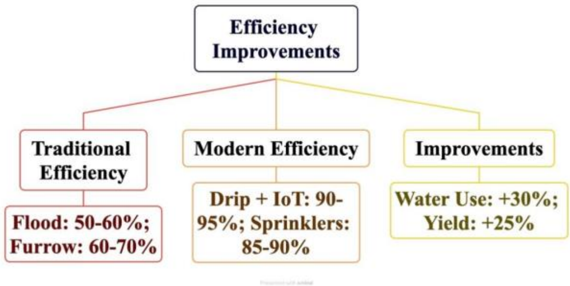

Figure 7: A data showing irrigation efficiency improvements using big data analytics.

Big data analytics has revolutionized irrigation management by providing tools to optimize water usage, improve efficiency, and promote sustainability. The integration of IoT, predictive analytics, and remote sensing into Decision Support Systems enables smarter and more adaptive agricultural practices, addressing the challenges of traditional irrigation methods.

Here's the revised **Challenges and Opportunities** section with **citations**, **image placeholders**, and a **table with captions**:

Challenges and Opportunities

The integration of big data analytics into irrigation management faces several challenges but also presents significant opportunities for innovation and transformation. These aspects are explored below, supported by evidence from existing literature.

Challenges in Big Data-Driven Irrigation Management

One of the primary challenges in implementing big data-driven irrigation systems is the quality and availability of data. Agricultural data collected from IoT sensors, satellite imagery, and weather stations often suffers from inconsistencies, noise, and incompleteness [1][2]. These issues compromise the reliability of predictive analytics and hinder decision-making, especially in rural regions where data collection infrastructure is underdeveloped [3]. Without high-quality data, optimizing water usage and improving irrigation efficiency become formidable tasks. Scalability is another pressing concern. Large agricultural operations with diverse crops, soil types, and climatic conditions require irrigation systems capable of adapting to complex and dynamic environments [4]. However, the necessary infrastructure for IoT-based solutions, such as reliable internet connectivity and advanced computational resources, is frequently lacking, particularly in remote areas [5]. Addressing scalability in such contexts remains a major technical and operational challenge.

Figure 8: Illustration showing challenges in implementing big data-driven irrigation systems, including data quality, scalability, and cost.

Cost barriers further exacerbate these issues. The deployment of IoT sensors, data processing platforms, and other big data technologies often involves high upfront and maintenance costs, which are prohibitive for smallholder farmers [6][7]. Moreover, limited technical literacy among end-users adds another layer of complexity, as many farmers are unable to utilize the full potential of these systems effectively [8]. Integration challenges persist as well. Data from heterogeneous sources, including weather forecasts, soil moisture sensors, and remote sensing, requires standardized protocols for interoperability [9]. The absence of unified frameworks complicates the consolidation of disparate datasets, reducing the

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effectiveness of decision support systems (DSS). Privacy and security concerns also loom large, as agricultural data may be susceptible to misuse or exploitation [10][11].

Opportunities for Innovation and Advancement

Despite these challenges, big data analytics offers transformative opportunities for irrigation management. Emerging technologies such as edge computing and 5G connectivity provide solutions to infrastructure limitations by enabling localized data processing and real-time communication between devices [12]. These advancements facilitate faster and more precise decision-making, enhancing the effectiveness of irrigation systems.Collaboration between public and private sectors represents another significant opportunity. Public-private partnerships can reduce costs, improve accessibility, and foster innovation by combining resources and expertise [13]. Policymakers can further incentivize the adoption of big data-driven systems through subsidies, grants, and training programs, enabling smallholder farmers to transition to sustainable irrigation practices [14].

Customization and modularity in system design also hold great promise. Irrigation solutions tailored to specific crops, regions, and climates can enhance scalability and adoption rates [15]. The integration of renewable energy sources, such as solar-powered IoT devices, can lower operational costs and align irrigation systems with environmental sustainability goals [16]. Moreover, advancements in soil health monitoring, crop-specific irrigation requirements, and remote sensing can fill existing knowledge gaps and provide actionable insights to farmers [17]. Ongoing research and development are vital to overcoming these challenges. Cross-disciplinary collaboration between data scientists, agronomists, and engineers can lead to the creation of more robust and adaptive irrigation systems. By leveraging advances in artificial intelligence, machine learning, and remote sensing, future systems can address current limitations while promoting sustainable agricultural practices [18][19].

Table 5. Challenges and Opportunities in Big Data-Driven Irrigation Management

Aspect	Challenges	Opportunities
Data	Inconsistent and incomplete data; lack of availability in rural areas	Development of high-quality datasets; partnerships for better data collection infrastructure
Scalability and Infrastructure	Limited internet connectivity; computational resource constraints	Edge computing and 5G networks for real-time processing
Cost and Accessibility	High costs for IoT deployment; limited technical literacy	Subsidies and training programs; affordable sensor technologies
Integration	Lack of standardization across data sources	Standardized platforms and interoperable systems
Privacy and Security	Vulnerability to data misuse and exploitation	Enhanced data encryption and privacy-preserving frameworks

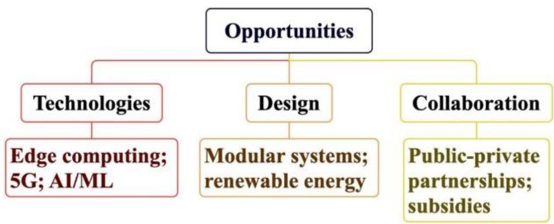

Figure 9: Visualization of opportunities, such as edge computing, 5G connectivity, and modular system design.

While challenges such as data quality, scalability, cost, and integration hinder the widespread adoption of big data analytics in irrigation management, the opportunities for innovation are immense. Emerging technologies, collaborative initiatives, and customized solutions have the potential to revolutionize irrigation systems, enabling sustainable and efficient water resource management.

Conclusion

Efficient irrigation management is essential for addressing the growing global demand for agricultural production while conserving vital water resources. This paper has explored the role of big data analytics as a transformative tool for optimizing irrigation practices through Decision Support Systems (DSS). By leveraging IoT devices, machine learning algorithms, and predictive models, big data-driven solutions offer the potential to enhance water use efficiency, reduce operational costs, and promote sustainability in agricultural systems. The integration of big data analytics into irrigation management, however, is not without its challenges. Issues such as inconsistent data quality, limited scalability, high costs, and privacy concerns pose significant barriers to adoption. These challenges are particularly pronounced in rural and resource-constrained settings, where infrastructure and technical expertise are often lacking. Nonetheless, advancements in technology, such as edge computing, 5G connectivity, and renewable energy-powered systems, provide promising solutions to these limitations. Opportunities for innovation in this domain are vast. Public-private partnerships, policy incentives, and modular system designs can improve accessibility and scalability, making big data-driven irrigation systems viable for both smallholder and large-scale farmers. Furthermore, continued research and interdisciplinary collaboration are critical for addressing existing gaps in knowledge and technology, enabling the development of more robust and adaptive systems.

References

[1] Keith, A. (1949). A New Theory of Human Evolution. *A New Theory of Human Evolution*.
[2] Singh, J., Dhaliwal, T. K., & Grover, D. K. (2017). State agricultural profile-Punjab. *AERC Study*, *30*, 12–27.
[3] Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, *147*, 70–90. doi:10.1016/j.compag.2018.02.016
[4] Wani, J. A., Sharma, S., Muzamil, M., Ahmed, S., Sharma, S., & Singh, S. (2021). Machine learning and deep learning based computational techniques in automatic agricultural diseases detection: Methodologies, applications, and challenges. *Archives of Computational Methods in Engineering*, 1–37.
[5] Howell, T. A. (1996). Irrigation scheduling research and its impact on water use. *Proceedings of the International Conference*, 21–33.
[6] Das, B. P. (2003). The use of irrigation systems for sustainable fish production in India. *Fisheries in Irrigation Systems of Arid Asia*, 47–58.
[7] Thompson, R. B., Gallardo, M., Valdez, L. C., & Fernández, M. D. (2007). Using plant water status to define threshold values for irrigation management of vegetable crops using soil moisture sensors. *Agricultural Water Management*, *88*(1–3), 147–158. doi:10.1016/j.agwat.2006.10.007
[8] Boretti, A., & Rosa, L. (2019). Reassessing the projections of the World Water Development Report. *Npj Clean Water*, *2*(1). doi:10.1038/s41545-019-0039-9
[9] Bali, N., & Singla, A. (2021). Emerging trends in machine learning to predict crop yield and study its influential factors: A survey. *Archives of Computational Methods in Engineering*, 1–18.
[10] Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (1998). *Crop Evapotranspiration: Guidelines for Computing Crop Water Requirements*.
[11] Ali, M. H. (2010b). Weather-a driving force in determining irrigation demand. *Fundamentals of Irrigation and On-Farm Water Management*, *1*, 31–105.
[12] Richardson, C. W. (1985). WEATHER SIMULATION FOR CROP MANAGEMENT MODELS. *Transactions of the American Society of Agricultural Engineers*, *28*(5), 1602–1606.
[13] Hinrichsen, K. (1994). The Ångström formula with coefficients having a physical meaning. *Solar Energy*, *52*(6), 491–495. doi:10.1016/0038-092X(94)90656-4
[14] Ali, M. H., Adham, A. K. M., & Talukder, M. S. U. (2005). Estimation of solar radiation from climatic parameters. *Bangladesh J Agril Sci*, *32*(1), 99–104.
[15] Allen, R. G., Smith, M., Pereira, L. S., & Perrier, A. (1994). An update for the calculation of reference evapotranspiration. *ICID Bull.*, *43*(2), 35–92.
[16] Ali, M. H. (2010a). *Fundamentals of irrigation and On-farm water management: Volume 1* (pp. 1–560). doi:10.1007/978-1-4419-6335-2
[17] Linsley, R. K., Kohler, M. A., & Paulhus, J. L. (1975).

[18] Sutton, O. G. (1953). *Micrometeorology*.
[19] Duffie, J. A., Beckman, W. A., & Blair, N. (2020). Solar engineering of thermal processes, photovoltaics and wind. *"Solar Engineering of Thermal Processes, Photovoltaics and Wind*.
[20] Blaney, H. F., & Criddle, W. D. (1962). Determining Consumptive Use and Irrigation Water Requirements. *Determining Consumptive Use and Irrigation Water Requirements*.
[21] Allen, R. G., & Pruitt, W. O. (1986). Rational use of the FAO Blaney-Criddle formula. *Journal of Irrigation and Drainage Engineering*, *112*(2), 139–155. doi:10.1061/(ASCE)0733-9437(1986)112:2(139)
[22] Hargreaves, G. H., & Samani, Z. A. (1985). Reference crop evapotranspiration from temperature. *Appl. Eng. Agric.*, *1*(2), 96–99.
[23] Ladlani, I., Houichi, L., Djemili, L., Heddam, S., & Belouz, K. (2012). Modeling daily reference evapotranspiration (ET 0) in the north of Algeria using generalized regression neural networks (GRNN) and radial basis function neural networks (RBFNN): A comparative study. *Meteorology and Atmospheric Physics*, *118*(3–4), 163–178. doi:10.1007/s00703-012-0205-9
[24] Almorox, J., Quej, V. H., & Martí, P. (2015). Global performance ranking of temperature-based approaches for evapotranspiration estimation considering Köppen climate classes. *Journal of Hydrology*, *528*, 514–522. doi:10.1016/j.jhydrol.2015.06.057
[25] Brouwer, C., & Heibloem, M. (1986). *Irrigation Water Management: Irrigation Water Needs*.
[26] Droogers, P., & Allen, R. G. (2002). Estimating reference evapotranspiration under inaccurate data conditions. *Irrigation and Drainage Systems*, *16*(1), 33–45. doi:10.1023/A:1015508322413
[27] Thornthwaite, C. W. (1948). An approach toward a rational classification of climate. *Geographical Review*, *38*(1), 55–94.
[28] Kohler, M. A. (1954). Lake and pan evaporation. *U. S. Geol. Surv. Prof. Pap.*, 127–148.
[29] Doorenbos, J., & Pruitt, W. (1997). *Crop Water Requirements. FAO Irrigation and Drainage*.
[30] Priestley, C. H. B., & Taylor, R. J. (1972). On the assessment of surface heat flux and evaporation using large-scale parameters. *Monthly Weather Review*, *100*(2), 81–92.
[31] Jensen, M. E., Burman, R. D., & Allen, R. G. (1990).
[32] Gavilán, P., Berengena, J., & Allen, R. G. (2007). Measuring versus estimating net radiation and soil heat flux: Impact on Penman-Monteith reference ET estimates in semiarid regions. *Agricultural Water Management*, *89*(3), 275–286. doi:10.1016/j.agwat.2007.01.014
[33] Tabari, H., Grismer, M. E., & Trajkovic, S. (2013). Comparative analysis of 31 reference evapotranspiration methods under humid conditions. *Irrigation Science*, *31*(2), 107–117. doi:10.1007/s00271-011-0295-z
[34] Maroufpoor, S., Bozorg-Haddad, O., & Maroufpoor, E. (2020). Reference evapotranspiration estimating based on optimal input combination and hybrid artificial intelligent model: Hybridization of artificial neural network with grey wolf optimizer algorithm. *Journal of Hydrology*, *588*. doi:10.1016/j.jhydrol.2020.125060
[35] Bouman, B. A. M., Van Keulen, H., Van Laar, H. H., & Rabbinge, R. (1996). The 'School of de Wit' crop growth simulation models: A pedigree and historical overview. *Agricultural Systems*, *52*(2–3), 171–198. doi:10.1016/0308-521X(96)00011-X
[36] Jensen, M. E. (1968). Water consumption by agricultural plants. *Water Deficits and Plant Growth*, *2*, 1–22.
[37] Doorenbos, J. (1975). Guidelines for predicting crop water requirements, irrigation and drainage. *Irrig Drainage*, *24*, 1–154.
[38] Burman, R. D., Wright, J. L., Nixon, P. R., & Hill, R. W. (1980). Irrigation management-water requirements and water balance. *Irrigation, Challenges of the 80's, Proceedings of the Second National Irrigation Symposium*, 141–153.
[39] Allen, R. G., & Pereira, L. S. (2009). Estimating crop coefficients from fraction of ground cover and height. *Irrigation Science*, *28*(1), 17–34. doi:10.1007/s00271-009-0182-z
[40] Kingra, P. K., Hundal, S. S., & Sharma, P. K. (2004). Characterization of crop coefficients for wheat and rice crops in Punjab. *Journal of Agrometeorology*, *6*, 58–60.