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Article

The Role of Artificial Intelligence in Water Harvesting The Mediating Role of the Interfering Wave Strategy

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Abstract: Water resources management systems are facing increasing challenges as a result of climate change, growing demand, and the inefficiency of traditional methods. The study aims to analyze the role of artificial intelligence in improving the efficiency of water harvesting systems, with a focus on the mediating role of the overlapping wave strategy in enhancing the effectiveness of management decisions, and adopted an integrative approach that combines theoretical analysis and practical application, through the development of a smart water sustainability system (W-SMART), and the use of a random forest algorithm to process hydrological and operational data and predict the Total Water Sustainability Index (W-SWSI), the results showed that the level of sustainability in the baseline scenario was average, with gaps in water loss and reuse indicators, while the application of intelligent predictive modeling contributed to a significant improvement in the value of the Water Sustainability Index. The results also proved that the overlapping wave strategy played a role in the water sustainability index.An effective medium in transforming AI outputs into integrated strategic decisions. The study concludes that the integration of artificial intelligence and flexible management frameworks represents a promising entry point to achieve water sustainability and support decision-making systems in complex aquatic environments

Keywords: Random forests, Water harvesting, Nesting wave strategy

1. Introduction

Water resource management is one of the biggest challenges facing the world today, especially with rapid population growth, climate change, and increasing water demand. In arid and semi-arid regions, water is a critical factor for human activity by ensuring the availability of some water needs and enhancing water for supplemental irrigation or recharging groundwater reservoirs through harvesting surface runoff to reduce water losses through leakage, evaporation, or mixing. This is achieved by directing water to nearby natural or industrial lowlands close to receiving and usage areas to provide survival mechanisms in arid and semi-arid areas. Water harvesting increases the efficiency of utilizing available but often unknown potential water resources. Amid these challenges, artificial intelligence becomes a key tool in enhancing efficiency. In the use, distribution and maintenance of water resources, it contributes to water management by integrating environmental and water resources with smart algorithms such as random forest algorithms used to process large and complex data, to achieve higher predictability, to provide proactive solutions to many water resources problems and to other techniques used in water resources management, to analyze mechanical learning techniques, to analyze large data and deep learning that contribute to environmental protection and promotion of sustainability, and that the employment of these technologies is often separate techniques without incorporating them into management and strategic frameworks that can transform intelligent analysis outputs into effective and efficient operational decisions, Al is now capable of producing novel and realistic outputs across various fields, guided by user input, According to (Ramo&Abd D awwod,2022), Smart technologies are becoming more widely used, especially in the field of image generation. This study aims to integrate these tools to develop a sustainable and effective practical model for water harvest management.

so the need to adopt smart strategies illustrating the mechanism in which these transformations emerged The overlapping waves strategy aims to integrate these tools to develop a sustainable and effective practical model for water harvesting management.

Research Problem

Water resources management systems are facing increasing challenges due to water scarcity, irregular rainfall, high rates of water loss, and the impact of climate change. Despite the remarkable development in the applications of artificial intelligence in supporting water resources management, the employment of these technologies is often done in a separate technical way without integrating them into management and strategic frameworks capable of transforming the outputs of intelligence into effective and efficient operational decisions.Many water harvesting systems still rely on traditional methods or partial interventions that lack flexibility and integration, limiting their ability to adapt to the complexity of these water systems and leading to persistent efficiency gaps and poor water sustainability.

Research Gap

Despite the increasing number of studies that have dealt with the use of artificial intelligence technologies in water resources management, especially in the fields of drought monitoring, demand forecasting, and improving irrigation efficiency, most of these studies have focused on technical aspects separately, without integrating them into integrated administrative and strategic frameworks capable of maximizing the benefit of the outputs of smart analysis. A review of the literature indicates that research on the mediating role of flexible management strategies, such as the nesting wave strategy, is limited in linking the use of artificial intelligence to improve the efficiency of water harvesting systems and support decision-making. In addition, it lacks applied models that combine water sustainability indicators and predictive modeling within a unified and viable smart system.Based on this, the study seeks to provide an integrated model that integrates artificial intelligence technologies with interlocking wave strategy, in a way that contributes to improving the efficiency of water harvesting systems, enhancing water sustainability, and supporting administrative decisions.

Research Objectives

1. Analyze the role of AI in improving the efficiency of water harvesting systems and promoting water sustainability

2. Developing an integrated smart system (W-SMART) based on water sustainability indicators to support water performance assessment.

3. Employing a random forest algorithm to predict the Total Water Sustainability Index (W-SWSI) and analyze the importance of the variables influencing.

4. Testing the Mediating Role of the Interfering Wave Strategy in Enhancing the Relationship between Artificial Intelligence Outputs and the Quality of Administrative and Technical Decisions in Water Harvesting Systems.

5. Quantitative impact assessment of the application of intelligent predictive modeling by comparing the baseline scenario and the intelligent optimization scenario.

In the study, an integrated application model is presented that integrates artificial intelligence techniques and interfering wave strategy to support water harvesting systems, distinguishing it from previous studies that focused on technical aspects apart from the administrative and strategic dimension. It also contributes to the development of the Total Water Sustainability Index (W-SWSI) within an intelligent system capable of moving from descriptive evaluation to predictive analysis, to support data-driven decision-making in complex aquatic environments. It provides a practical framework that can be used to design smart and flexible water management systems.

Previous Studies

Recent studies have indicated the growing role of artificial intelligence techniques in improving the efficiency of water resource management, especially in demand forecasting, water quality monitoring, and surface runoff management. A comprehensive review of AI applications in surface water management was presented by (Gacu et al., 2025), highlighting the superiority of machine learning algorithms such as random forests, artificial neural networks, and support vector machines in dealing with uncertainty and non-linearity in hydrological data compared to traditional physical models. The study emphasized the importance of integrating AI with geographic information systems (GIS) and remote sensing to support water decision-making. In the field of water harvesting, a study (Asrade, et al., 2024) focused on identifying areas with high potential for rainwater harvesting using Random Forest and XGBoost algorithms integrated with Geographic Information Systems. The results showed that this integration is an effective tool for improving spatial planning of water harvesting projects and enhancing water resource sustainability, especially in arid and semi-arid regions. Additionally, the study (Al-Safi & Saravi, 2021) indicated that integrating artificial intelligence into rainwater harvesting systems contributed to increasing collection efficiency by over 22% compared to traditional methods and reducing waste caused by human prediction errors. The study by (Alshahri, et al., 2022), the employment of artificial intelligence techniques in predicting overlapping waves of coastal structures proved the superiority of intelligent models in estimating water quantities compared to traditional empirical equations, highlighting their potential to support coastal structure design and reduce flood risks. The study by(Kumar et al., 2024) confirmed that using the overlapping waves strategy as an intermediate mechanism for signal and data processing helped AI understand severe seasonal variations of floods, leading to optimal water harvesting during peak times. Meanwhile, the study by (Wang & Zhang., 2022) demonstrated that the overlapping waves strategy prevents data conflicts and accelerates smart decision-making by 30%, making it an effective intermediary between data collection tools (AI) and the environmental goal (water harvesting). These results are of immediate importance in the context of water harvesting, as they can be utilized within the framework of the inter wave strategy to maximize the efficiency of available water resources. The literature reveals a research gap characterized by the limited studies that addressed the intermediary role of the inter wave strategy in linking artificial intelligence applications and improving the efficiency of water harvesting systems, which necessitates developing flexible integrative models capable of application in different geographical and climatic environments, thereby enhancing water sustainability. In light of previous studies demonstrating an increasing effectiveness of AI applications in water resource management and water harvesting, it is clear that these technologies contribute to improving forecasting accuracy, enhancing resource utilization efficiency, and supporting decision-making. However, most of these studies addressed technical aspects separately, without sufficient focus on the administrative and strategic frameworks that organize the deployment of AI and the integration of its stages. Therefore, there is a need to develop an integrated theoretical framework that clarifies the role of AI in improving the efficiency of water harvesting systems, highlighting the intermediary role of the interwoven wave strategy in enhancing the effectiveness of administrative and technical decisions and achieving water sustainability.

First: 1-1 Artificial Intelligence

One of the branches of computer science that is concerned with the design of computer machines and programs It has the ability to Simulation of human mental abilities depends on analyzing large amounts of data and using it for learning and decision-making (Amin, Khairuddin & Al-Zahra, 2025)(Whisper)(Walke & Winkler, 2025)Mechanism that The ability of systems to interpret and learn from external data and employ learning This To achieve specific goals and tasks through flexible adaptation mechanisms , and confirms(Yu *et al.*, 2024)These systems Its ability perform complex cognitive tasks such as learning,Problem solving, natural language understanding,To expand its applications

1-2 Water Harvesting

One of the main axes in contemporary hydrological studies, for its significant role in mitigating Effects of water scarcity Enhancing the efficiency of rainwater utilization, reducing losses resulting from unregulated runoff, and optimizing the use of rainwater. in Rainy seasons, see (Abdulaziz, 2024) that The process of converting water from an untapped natural resource to a versatile economic resource, varies according to the mechanisms of collection and storage. (Beithou *et al.*, 2024)It is a promising technical solution to address water scarcity globally, by collecting available water using physical technologies.E and directing them to storage and use sites. and morphology applied to the ground to increase the soil's ability to retain water, or to collect runoff water in designated locations such as dams and barriers(Turkish,2023)

1-3 The Role of Artificial Intelligence in Water Harvesting

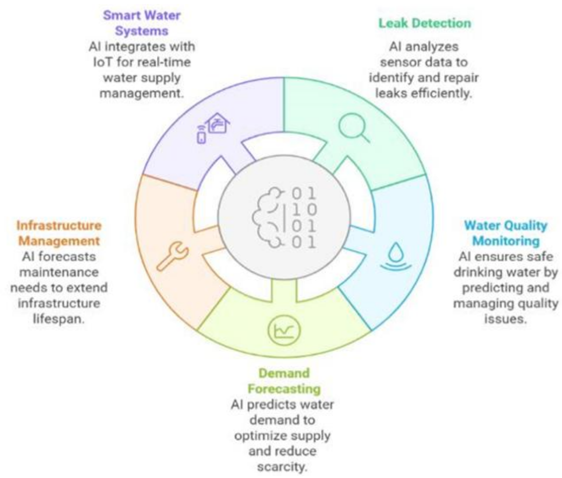
1. Water Demand Forecasting :Basis in strategic planning of water resources and the emergence of artificial neural networks (ANN), as a powerful tool To process Employing technologies contributes to reducing the gap between supply and demand. Help Accuracy of Models Decision Makers on Improving Water Distribution Efficiency and Infrastructure Development (Krishnan,2022).

2. Water Quality Monitoring: Artificial Intelligence Technologies Represent a tool pivotal in the transformation Water Quality Monitoring Systems from Traditional Statistical Assessments to Advanced Predictive Modeling, and Allows prediction of hydro chemical variables with high accuracy, Providing accurate assessments to take proactive action to manage resources and protect them from pollution (El-Ghaghaby..et al,2023)

3. Leak detection in water networks: Like Using an algorithm Random jungle to analyze data from IoT sensors in real-time. These technologies convert raw data into predictive models capable of detecting abnormal patterns with up to 94% accuracy in leak detection, compared to 70–80% in traditional methods, enabling problems to be identified within seconds and reducing disruption (Tahrour& Djeffal,2021) and predict pollution indicators with up to 92% accuracy, providing A proactive decision-making tool

4. Predictive Infrastructure and Maintenance :AI is transforming water plant management from a traditional reactive-based approach to proactive and intelligent, by integrating IoT and machine learning technologies to monitor and control supply networks in real-time and the ability to predict equipment failures Before it happens, And also Early detection of leaks and breaks in pipes, reducing water wastage by up to 40% (Tahrour& Djeffal,2021)

5. Smart Water Systems: depend Integrate AI and deep learning technologies with the IoT framework to design smart mechanisms that include water quality monitoring via advanced sensors, smart irrigation (Krishnan,2022)



Application of AI in water harvesting

Second: The Strategy of the Overlapping Waves

Contemporary organizations, whether private or public, service-oriented or production-oriented, face increasing challenges due to rapid changes in technological, economic, and organizational environments. Amid these shifts, traditional administrative methods are no longer sufficient to achieve goals effectively, which calls for adopting modern methods characterized by flexibility and adaptability to dynamic changes. Among these methods, the Interconnected Waves Strategy emerges as a layered and interwoven administrative framework that coordinates planning, implementation, and evaluation stages, and enhances the ability to turn challenges into growth opportunities. In the field of water harvesting, especially in arid and semi-arid environments, artificial intelligence can improve planning and execution by predicting rainfall, analyzing hydrological properties, identifying optimal sites, and increasing resource utilization efficiency. The overlapping wave strategy plays an intermediary role in coordinating these processes, thereby enhancing water sustainability and reducing environmental risks.

The Strategy of the Overlapping Waves define A managerial and cognitive approach based on the gradual interaction between prior and new knowledge, To improve Quality of Decision Making (Siddhartha Paul Tiwari, 2022) (Saleh, 2023).and from Leadership Focus on Integrating previous experiences with innovative thinking to achieve organizational goals (Chief and Dhattarwal, 2021).and from Educational and Applied Aspects It contributes to stimulating thinking, promoting deep understanding, and integrating knowledge into mental therapists(Mohammed, Adnan Jassim & Ashour, 2024) (Al-Banna, 2023).

Dimensions of the Overlapping Wave Strategy

It consists of four dimensions that integrate to form a coherent knowledge and administrative framework The first dimension is BManaging the Future And he The organization's ability to predict future changes, reduce uncertainty, and make proactive decisions. (Ghelani, 2022) (Daoud, 2020) (Saleh, 2023) (Abdulzahra, 2024) The second dimension is Strategic Direction And he Effective use of information and knowledge to generate added value and ensure the competitiveness of the organization (Khudair, 2023).The third dimension is represented byKnowledge Leadership I mean Promote explicit and implicit knowledge sharing among staff to support decision-making(Hello,

2023) aFor the fourth dimension it is Genius leadership is stimulating creativity and innovative thinking to raise the level of performance and solve problems.(Salem, & Eldaly, 2024)These dimensions are integrated within a dynamic model, genius leadership is the first wave of awareness, guided by strategic direction, while knowledge leadership acts as a continuous feeding wave, and future management represents the inclusive wave, creating a multiplier strategic capacity for the organization to adapt, innovate, and sustain, The strategy acts as an intermediate variable that connects the use of artificial intelligence with improving the efficiency of water harvesting systems, by integrating knowledge, experience, and modern technology.and promote Quality of Administrative Decisions

Third: Random Forest Algorithm

One of the most prominent machine learning models in complex data processing (Al-Sayedzayed, 2025) It was proposed by Breiman (2000) to build a set of independent decision trees and combine, and then a majority vote determines the final outcome, reducing variance and improving accuracy compared to a single decision tree (Salman et al., 2024), (Dabiri et al., 2022). Random forests are characterized by their ability to handle large, nonlinear data, as well as manage missing and outlier values without strict distribution assumptions, making them suitable for water systems information challenges and hydrological analysis ,While they are used in both classification and regression tasks, and have demonstrated their versatility in handling datasets containing thousands of input variables (Oyounalsoud et al., 2024). The steps to implement random forests include:

1. Creating Bootstrap datasets by random sampling with replacement.

2. Selecting random features to calculate information gain at each decision node.

3. Training a specified number of decision trees on these samples.

4. Using the majority voting mechanism to determine the final prediction on test data (Priyatno et al., 2024). And practical applications in water resource management show that the random forest algorithm performs strongly in a number of water management tasks, including improving the prediction of surface runoff in hydrological basins, where its results are compared with other models and demonstrate competitive capabilities in predicting daily water releases ,Random forests have also been used to develop decision support models for water resource management in major water sources catchments, such as estimating potential evaporation in Nigerian basins, enhancing water planning efficiency (Applied Water Science research). Similarly, the random forest algorithm has proven effective in predicting potable water quality, where it was integrated with parameter optimization techniques to provide accurate predictions that outperform traditional models in this field (Zhang et al., 2025). It has also been employed in short-term water demand forecasting in urban areas, demonstrating its ability to process complex time series and accurately capture the influence of affecting variables (MDPI study).

2. Conclusion

Previous studies have shown that integrating artificial intelligence techniques with wave-based strategies can significantly enhance the efficiency of water harvesting systems, this is achieved by improving planning processes, accurate forecasting, and analyzing complex hydrological data (Al-Suhili & Khan, 2023; Zhang & Wang, 2024). The Random Forest algorithm is also considered a highly effective tool for prediction and classification in this field, as it overcomes traditional decision tree limitations and handles large, complex data with high accuracy and flexibility (Tyralis et al., 2019; Maxwell et al., 2021). Combining these strategies and algorithms works to provide an integrated framework that coordinates the stages of data collection, decision making, and implementation in an interconnected and gradual manner, thus supporting water sustainability and enhancing the quality of technical and administrative decisions (Khatri & Sudheer, 2023; Nguyen & Bui, 2025). Accordingly, this study offers a practical model for deploying artificial intelligence to support water harvesting, focusing on the intermediary role of the interwoven wave strategy, and achieving cognitive and technological integration that improves performance efficiency and ensures the sustainability of water resources.

Practical Aspect

It is based on the design and implementation of an Intelligent Water Resources Management System (W-SMART), which relies on the integration of water sustainability indicators with artificial intelligence technologies, especially the random forest algorithm, to analyze the relationships between variables and predict the overall water sustainability index. The practical aspect was implemented through a series of sequential and interconnected stagey within the W-SMART system, to assess the current status of water harvesting systems, and then move on to intelligent predictive analysis and decision support.These stages are designed to reflect a logical sequence starting

with data collection and baseline analysis, then applying artificial intelligence techniques, ending with impact assessment and improving the efficiency of water sustainability, in the first stage, an interactive graphical interface was designed to represent the sustainability board, which is the starting point to assess the current status of the water system and enable the user to enter basic operational data and display water performance indicators instantly and accurately.To assess the current state of the water system before moving to the stages of advanced intelligence, it includes several indicators, namely network units, irrigation, drought, and dashboard in preparation for the application of artificial intelligence technologies later on.

Figure (1) W-SMART System Main Control Panel for Selection of Water Sustainability Assessment Units

This module allows the compilation and analysis of the basic operational indicators of the water system, and provides an initial assessment that reflects the current level of sustainability before any intelligent intervention or advanced predictive techniques are applied

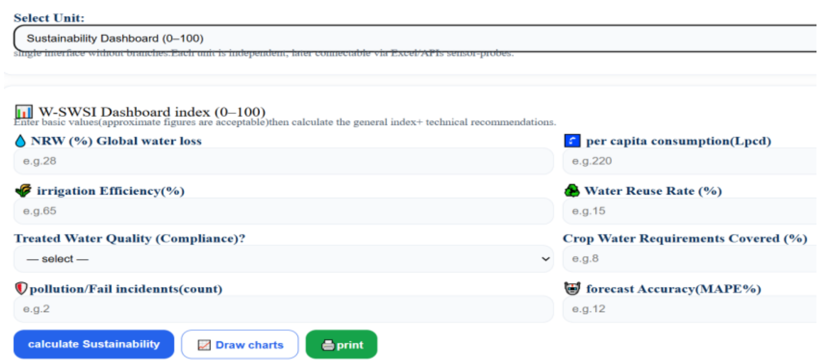


Figure (2) Water Sustainability Indicators Data Entry Interface

Actual operational data are included to enable the system to calculate the Total Water Sustainability Index (W-SWSI) with the aim of identifying a baseline that reflects the efficiency of the current water system, and serves as an analytical reference for evaluating performance before initiating technical interventions or applying intelligent predictive models

Total Water Sustainability Index (W-SWSI): The Total Sustainability Index was calculated based on the integration of a set of sub-sustainability indicators of different relative importance using the following formula:

$$W - SWSI = \sum_{i=1}^{N} wi \times Ii$$

W-SWSI : Represents the overall water sustainability index

II : Represents (i) the value of the sub-index

Wi : Represents the relative weight of the sub-index

N : Number of water sustainability indicators adopted in the study

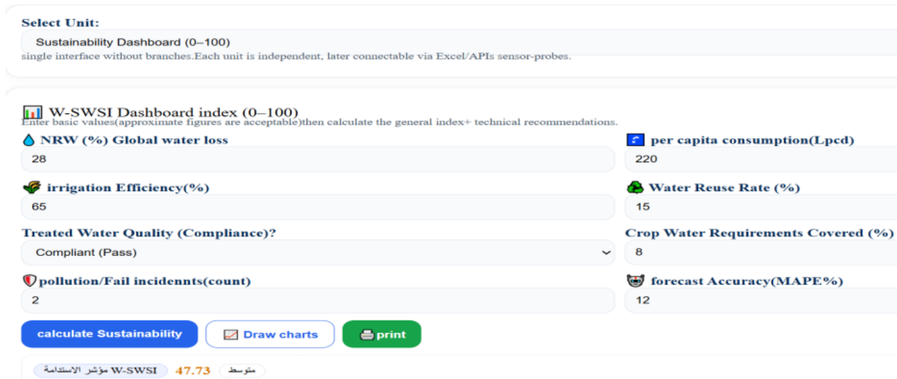


Figure (3) Interface for calculating the Total Water Sustainability Index

Baseline Analysis and Shift to Intelligent Predictive Modeling

The overall Water Sustainability Index achieved a value of 47.73, and the system's sustainability is classified as "medium". While irrigation efficiency and treated water quality recorded acceptable levels, significant gaps in unaccounted water management (NRW) and reuse rates emerged, reflecting the current system's reliance on traditional operating patterns that lack proactive control mechanisms. Accordingly, the W-SMART system has moved from the descriptive evaluation phase to predictive analysis by integrating a random forest algorithm. This intelligent methodology aims to address the nonlinear and complex relationships between operational variables and predict the behavior of the system under various optimization scenarios. The algorithm enables modeling of the impact of proposed interventions on the total value of the indicator prior to actual implementation, supporting data-driven decisions) to raise the efficiency of water resources management

Random Forest Model Preparation and Training Parameters

The random forest model was developed within the system based on key water sustainability indicators, such as water loss rate, irrigation efficiency, reuse, and water demand, after subjecting the data to initial processing and selecting the impacting characteristics. The model is based on the aggregation of the outputs of a large number of decision trees trained on random samples of data and variables, which enhances the accuracy of prediction and generalizability. The analysis of the importance of variables contributed to supporting the implementation of the overlapping wave strategy by identifying indicators with impact In addition to anticipating future scenarios that support data-driven decision-making, the Feature Importance scale was adopted within random forests to identify the indicators that have the most impact on the value of the overall Water Sustainability Index. This scale is based on the average reduction in impurity resulting from each variable across all decision trees, providing a quantitative tool to support the prioritization of the intervention. It contributes to activating the mediating role of the interlocking wave strategy by linking technical outputs to administrative and strategic decisions through the equation

$$FIj = \frac{1}{T}\sum_{t=1}^{T} \Delta Ij,t$$

j represents the importance of the variable in FIj

The amount of decrease in impurity caused by the use of the variable, and T represents the number of decision trees in the random forest.

Comparison between the baseline scenario and the smart optimization scenario: The proposed improvements, such as reducing water loss and increasing water use efficiency, are contributing to moving from a medium sustainability level to a higher level that reflects better efficiency in water resources management. This comparison underscores the effective role of AI in transforming evaluation results from a mere diagnosis of the status quo to a proactive tool for improving performance and making data-driven decisions. To measure the quantitative impact of AI adoption , the amount of improvement in the overall water sustainability index was calculated by the difference between the value of the indicator in the smart optimization scenario and its value in the baseline scenario, allowing a direct assessment of the effectiveness of smart interventions in raising the level of water sustainability.

$$\Delta W - SWSI = W - SWSI_{AI} - W - SWSI_{Baseline}$$

Water Networks

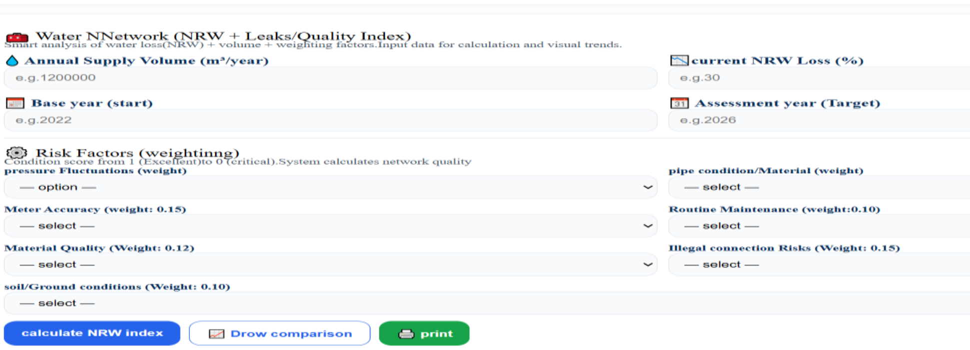


Figure (4) Water network module interface

Used to enter water loss, annual capacity, year of assessment, and a range of weighted risk factors such as pipe life, operational stress, and material quality. Contributes to a quantitative assessment of network efficiency and identification of sources of waste, supporting the proposal of operational improvement actions based on intelligence

W-SMART Drought Assessment Unit

After analyzing the efficiency of water networks and water losses, the system moves to the Drought Assessment Unit, which aims to analyze the severity and frequency of drought

based on a set of climatic and hydrological indicators to support advance planning and reduce the risks associated with water scarcity.

Figure (5) Drought Prediction Unit interface

It is used to introduce a range of climatic and hydrological variables, such as rainfall, deviation from normal temperatures, soil moisture, and storage levels in rivers and reservoirs. It is used to calculate the total drought risk index, allowing the assessment of the current water situation and supporting decision makers in anticipating potential drought levels

W-SMART IRRIGATION PROGRAM

Based on the outputs of the Drought Prediction Unit and the assessment of risk levels associated with water scarcity, the system moves to the smart response phase by activating the Smart Irrigation Management Program.To improve the efficiency of agricultural water use by adapting irrigation quantities and timings to climatic and hydrological changes and reducing water wastage.

The role of the random forest algorithm in the smart irrigation program: It is based on the integration of the outputs of a group of decision trees to improve the accuracy of estimating the water needs of crops and reduce the risk of water stress, its performance is evaluated by comparing the predicted values with the actual values of water consumption and crop needs, based on statistical indicators such as the determination coefficient (R^2), mean square error (MSE), and the square root of the mean error square (RMSE)). The results of the evaluation show the high efficiency of the model in supporting smart irrigation decisions and improving the reliability of water demand management, and it is done according to the following equations:

Determination coefficient (R^2):

$$R^2 = 1 \frac{\sum_{I=1}^{N}(yi - yi)^2}{\sum_{i=1}^{n}(yi - y)^2}$$

Average Error Box (MSE)

$$MSE = \frac{1}{N}\sum_{I=1}^{N}(yi - yi)^2$$

Root Square Error Mean (RMSE)

$$RMSE = \sqrt{MSE}$$

3. The results and discussion

show that the practical application of the W-SMART system demonstrates the effectiveness of integrating artificial intelligence techniques, particularly the Random Forest algorithm, within data-driven irrigation and drought management frameworks. The system enabled an integrated processing of climatic, hydrological, and operational data within a unified analytical framework, which contributed to improving water resource management efficiency in drought-prone and climate-unstable environments. The drought prediction unit's results indicated that the composite risk indicator used in the system is capable of accurately describing variations in drought levels by integrating multiple variables, including rainfall amounts, temperature deviations, and water storage levels. This multi-dimensional approach reflects a higher capacity to represent the complexity of drought phenomena compared to relying on single indicators. It also supports the shift from a reactive response to proactive planning for water resource management. Regarding the smart irrigation program, the results showed that the Random Forest model achieved a significant improvement in the accuracy of estimating crop water needs compared to traditional irrigation scheduling methods. The model enabled the analysis of nonlinear relationships between drought indicators, soil moisture, and water demand, resulting in more flexible and adaptable irrigation recommendations to climate changes. Additionally, the collective nature of the model contributed to reducing prediction fluctuations and enhancing the stability of operational decisions. Performance evaluation results showed that the random forests algorithm has high predictive efficiency, with a decrease in error rates and an improvement in accuracy indicators compared to the non-intelligent scenario. This performance is attributed to the ensemble structure of the algorithm, which limits the impact of outliers and reduces the problem of over fitting, thereby enhancing the model's reliability and its ability to generalize across different drought scenarios. Additionally, the comparison between traditional water resource management and intelligent management based on the W-SMART system revealed a clear improvement in water use efficiency and reduction in water wastage. The integration of the drought prediction unit with the smart irrigation program contributed to better alignment between water supply and actual demand, and reduced arbitrary decisions related to drought management, thereby supporting long-term water sustainability. The study's results confirm that integrating the Random Forest algorithm within a strategic framework based on an interleaved wave strategy enhances the effectiveness of water decision support systems. This framework connects technical analysis with the administrative level and ensures the transformation of predictive model outputs into flexible operational policies adaptable to future changes, thereby supporting informed leadership and strengthening strategic orientation in the water sector. Based on the above, the research findings indicate that transitioning from traditional management models to smart management models based on predictive analysis and multi-source data is a necessary strategic option to address the challenges of climate change and water scarcity. This study also contributes to enriching the scientific literature by presenting a comprehensive applied framework that combines artificial intelligence and strategic water resource management, which can be applied and developed in other regions suffering from similar water condition

4. Conclusion

The results of the practical application of the W-SMART system showed the exceptional effectiveness of artificial intelligence technologies, especially the random forest algorithm in enhancing the efficiency of water resources management in drought-prone areas, and drought prediction proved to be a superior ability to analyze multiple variables (rainfall, temperature, soil moisture) and overcome the complexities of the drought phenomenon compared to traditional indicators and achieved a significant reduction in error rates, and in irrigation management, the integration of the drought prediction unit with the smart irrigation system contributed to improving the accuracy of needs. The results also showed that the inclusion of the random forest algorithm within the framework of the overlapping wave strategy is an integrated application model that combines artificial intelligence and strategic management, which contributes to achieving the goals of sustainable development of water resources in the long term.

References

1. Beithou, N. *et al.* (2024) “Atmospheric Water Harvesting Technology: Review and Future Prospects,” *Journal of Ecological Engineering*, 25(3), pp. 291–302. Available at: https://doi.org/10.12911/22998993/182814.
2. Bhavsar, J., Khara, S. and Dave, J. (2025) “Artificial Intelligence in Nutrition: A Comprehensive Review of Applications and Challenges,” *Proceedings of 2025 International Conference on Emerging Trends in Industry 4.0 Technologies, ICETI4T 2025*, pp. 1–27. Available at: https://doi.org/10.1109/ICETI4T63625.2025.11132215.
3. Chief, E. and Dhattarwal, S.K. (2021) “Counseling with Tooth Brushing Demonstration Method as an Effort to Improve Tooth Brushing Skills and the Status of Dental and Oral Hygiene in Early Childhood at School,” *Medico-Legal Update*, 21(1). Available at: https://doi.org/10.37506/mlu.v21i1.2391.
4. Dabiri, H. *et al.* (2022) “Applications of Decision Tree and Random Forest as Tree-Based Machine Learning Techniques for Analyzing the Ultimate Strain of Spliced and Non-Spliced Reinforcement Bars,” *Applied Sciences (Switzerland)*, 12(10), pp. 1–13. Available at: https://doi.org/10.3390/app12104851.
5. Daoud, A. (2020) “Effectiveness of Using the Overlapping Waves Strategy During the Teaching of Geography in Acquiring the Realistic Thinking Skills and Improving the Attitudes Toward it Among the Sixth Grade Students in Jordan,” *Journal of Educational and Psychological Studies*, 14(2), pp. 250–269. Available at: https://doi.org/10.53543/jeps.vol14iss2pp250-269.
6. Ding, K. *et al.* (2020) “Machine learning improves accounting estimates: evidence from insurance payments,” *Review of Accounting Studies*, 25(3), pp. 1098–1134. Available at: https://doi.org/10.1007/s11142-020-09546-9.
7. Ed-Dehbi, W., Ahlaqqach, M. and Benhra, J. (2025) “Artificial Intelligence for Optimal Water Resource Management: A Literature Review †,” *Engineering Proceedings*, 97(1), pp. 1–10. Available at: https://doi.org/10.3390/engproc2025097052.
8. Ghelani, D. (2022) “Cyber Security, Cyber Threats, Implications and Future Perspectives: A Review,” *American Journal of Science, Engineering and Technology*, 3(6), pp. 12–19. Available at: https://doi.org/10.11648/j.
9. Oyounalsoud, M.S. *et al.* (2024) “Drought prediction using artificial intelligence models based on climate data and soil moisture,” *Scientific Reports*, pp. 1–16. Available at: https://doi.org/10.1038/s41598-024-70406-6.
10. Priyatno, A. M. (Year). Title of the Article. Journal of Economic and Statistical Analysis, Volume(Issue), Pages. https://jesa.aks.or.id
11. Ramo,R.M., & Abd Dawwod, S.(2022). Digital image compression by using intelligence swarm algorithms.comput.sci,17(12), 785-794
12. Saleh, A.M. (2023) “Overlapping Waves Strategy and Its Impact on Entrepreneurial Motivation,” *Journal Port Science Research*, 6(3), pp. 286–309. Available at: https://doi.org/10.36371/port.2023.3.9.
13. Salem, A., Mansour, Y. and Eldaly, H. (2024) “Generative vs. Non-Generative AI: Analyzing the Effects of AI on the Architectural Design Process,” *Engineering Research Journal (Shoubra)*, 53(2), pp. 119–128. Available at: https://doi.org/10.21608/erjsh.2024.255372.1256.
14. Siddhartha Paul Tiwari (2022) “Knowledge Management Strategies and Emerging Technologies - an Overview of the Underpinning Concepts,” *International Journal of Innovative Technologies in Economy* [Preprint], (1(37)). Available at: https://doi.org/10.31435/rsglobal_ijite/30032022/7791.
15. Walke, F., Klopfers, L. and Winkler, T.J. (2025) “Leveraging Generative AI and ChatGPT in SMEs: A Grounded Model,” *Proceedings of the Annual Hawaii International Conference on System Sciences*, 8, pp. 5479–5488. Available at: https://doi.org/10.24251/hicss.2025.658.
16. Wang, L., & Zhang, Y. (2022). The interlocking wave strategy in data fusion for environmental monitoring systems. IEEE Sensors Journal, 22(9), 8934–8945. https://doi.org/10.1109/JSEN.2022.3161204
17. Yu, J. *et al.* (2024) “Artificial intelligence-generated virtual influencer : Examining the effects of emotional display on user engagement,” *Journal of Retailing and Consumer Services*, 76(April 2023), p. 103560. Available at: https://doi.org/10.1016/j.jretconser.2023.103560.
18. Al-Banna, Z.R.A. (2023) "The effectiveness of a program based on the overlapping wave strategy in developing the basic thinking skills for gifted kindergarten children with learning disabilities in the light of a discovery subject."
19. Al-Sayedzayed, M.A.A. (2025) "The Impact of Artificial Intelligence on Sustainable Development."
20. Al-Safi, H. I., & Saravi, S. (2021). Application of artificial intelligence in rainwater harvesting systems optimization. Journal of Water Climate Change, 12(4), 1145–1162. https://doi.org/10.2166/wcc.2021.284

21. Al-Suhili, R., & Khan, A. (2023). "Integration of AI and Hydrological Modeling for Optimized Rainwater Harvesting Systems." Journal of Water Resources Planning and Management, 149(4), 04023005
22. Khairuddin & Zahra, Z.F. (2025) "The Role of Artificial Intelligence in Enhancing Water Use Efficiency in the Agricultural Sector: The Saudi Arabian Experience,'" 2025, pp. 306–326.
23. Turki, A.A. (2023) "Rainwater harvesting and its investment potential in the Wadi Al-Atalia basin in the Iraqi Jazira desert."
24. Tyralis, H., Papacharalampous, G., & Langousis, A. (2019). "A review of applications of random forests in hydrology and water resources." Water, 11(5), 910
25. Khudair, S.M. (2023) *The Role of Strategic Orientation in Achieving Organizational Superiority: An Analytical Study in Areej Al-Warith and Central Construction Investment Companies in Karbala*.
26. Kumar, R., Sharma, A., & Singh, P. (2024). Wavelet-based AI models for hydrological forecasting and water harvesting management. Water Resources Management, 38(3), 1025–1043. https://doi.org/10.1007/s11269-023-03689-w
27. Khatri, S., & Sudheer, K. P. (2023). "Frameworks for Sustainable Water Management Using Integrated AI Platforms." Water Resources Management, 37(8), 3125-3142.
28. Salam, A. (2023) *Artificial Intelligence and Water and Climate Issues*.
29. Abdulzahra, A.H. (2024) "Proactive Leadership, Its Impact and Impact on Achieving Organizational Pride through the Application of Interlocking Wave Strategy: An Analytical Study in the State Company for Marketing Petroleum Products (SOMO)," 20(66), pp. 38–58 .
30. Abdelaziz, A. (2024) "Rainwater harvesting techniques in semi-arid areas of the Kart Basin in northeastern Morocco as a model."
31. Mohammed, Adnan Jassim & Ashour, A.A.Z. (2024) "The Effect of Interfering Wave Strategy with Hyper-Interfering Media on Student Rolling Skills," 30(125) .
32. Maxwell, A. E., Warner, T. A., & Fang, F. (2021). "Implementation of machine learning algorithms and Random Forest in hydro-environmental mapping: A review."IEEE Access,9, 34211-34225.
33. Hadi, D.F.M. (2024) "The Role of Modern Technology in Promoting Sustainable Urban Renewal ," *Journal of Planner and Development*, 29, pp. 179–199
34. Moreno-Rodenas, A., Verbist, K., Mertens, A., Gerritsma, I., Deng, J., Haag, A., Taner, Ü., Nuttall, J. D., Dahm, R., Meshgi, A., Korving, H., Bianchini, S., Tofani, V., Casagli, N., Ray, P., Rahat, S. H., Guan, J., Chen, Y., Zhang, L., Amarnath, G (2025). Title of the publication. UNESCO.
35. Nguyen, T. H., & Bui, D. T. (2025). "Decision Support Systems in Water Harvesting: Merging Machine Learning with Iterative Operational Strategies." Environmental Earth Sciences, 84(1), 42
36. Zhang, L., & Wang, Y. (2024). "Advanced Predictive Analytics in Hydrology: The Role of Wavelet-AI Hybrid Models." Hydrological Sciences Journal, 69(2), 215-230