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Transforming Water Management: The Crucial Emergence of Artificial Intelligence for Efficiency and Sustainability

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Abstract:

Water resource management is critical for human development and environmental stability, but it faces increasing challenges due to climate variability, pollution, and resource scarcity. Traditional methods, including statistical models and field data collection, have provided valuable insights but are often inadequate for managing complex, dynamic water systems. Artificial Intelligence (AI) offers a promising complement to these conventional approaches, enhancing predictive modeling, pollution detection, and decision-making processes in water management. This paper explores the integration of AI in water resource management, focusing on its applications in drinking water systems, pollution tracking, water temperature prediction, and decision-making tools. Examples, such as AI-driven leak detection in water distribution networks and the use of generative AI in urban planning, demonstrate the potential of AI to revolutionize water management by providing real-time insights, optimizing resource allocation, and facilitating sustainable solutions. Despite challenges related to data quality and model adaptation, AI represents a transformative tool in enhancing water management strategies and ensuring a resilient water future.

Keywords: Artificial intelligence; Pipe leak detection; Pollution traceability; Water management; Water temperature prediction.

I Introduction

Water is one of the most essential natural resources, supporting human development, environmental stability, and ecological well-being. Managing water sustainably is critical to ensure freshwater is available for a wide range of human needs and the demands of natural ecosystems (Chartzoulakis & Bertaki, 2014; Russo et al., 2014). Achieving this balance requires combining theoretical knowledge, field data, practical skills, and advanced technology to create strategies that address the needs of urban, agricultural, industrial, and environmental sectors. Because of its complexity, water management is inherently interdisciplinary (Cosgrave & Loucks, 2015).

Global water management presents multiple challenges that demand a tailored approach to data collection and decision-making for specific contexts and goals (Selvaraj et al., 2022). In natural systems, important factors include temperature changes, how well terrain retains water, groundwater connections, soil permeability, risks of contamination, ecosystem dynamics within river catchments, and local climate conditions. For human-made systems, additional complexities arise from issues like pollution, infrastructure efficiency, waste management, and varying water demands. These factors interact dynamically, creating intricate networks of cause and effect that make monitoring and management more challenging.

Traditional water management methods use statistical models, experimental research, and field data collected through sampling tools to understand water behavior, availability, and the impacts of decisions (Cosgrave & Loucks, 2015; Russo et al., 2014). While these approaches have contributed significantly to our understanding, growing challenges such as climate variability and resource scarcity call for more advanced tools. Artificial intelligence (AI) has emerged as a powerful complement to traditional methods, enhancing data analysis and prediction capabilities.

This paper examines how AI can be applied in water management, discussing its methodologies, current gaps, and limitations. Examples such as predictive modeling, pollution tracking, leak detection, and resource optimization highlight how AI can enhance traditional practices and drive innovation in managing water resources.

II Concepts of artificial intelligence

The concept of Artificial Intelligence (AI) and the initial research into this field began in the 1980s (Fig. 1) (Grzybowski et al., 2024). In recent years, advances in technology and their increasing applications have propelled AI into widespread discussion—not just within scientific research, but also in everyday life. What was once primarily confined to the domain of Information Technology (IT) has now become widely recognized for its potential across a diverse range of fields. In environmental sciences, particularly in handling large datasets (commonly referred to as "big data"), the adoption of these modern techniques has been growing steadily. To fully grasp its potential in environmental science applications, it is first essential to understand what Artificial Intelligence is.

Intelligence, as defined by the Merriam-Webster Dictionary, is "the ability to learn or understand or to deal with new or trying situations." Traditionally, this definition has been applied to human intelligence. However, Artificial Intelligence extends this concept to computers, enabling them to simulate learning and reasoning in a digital environment (Zohuri & Behgounia, 2023).

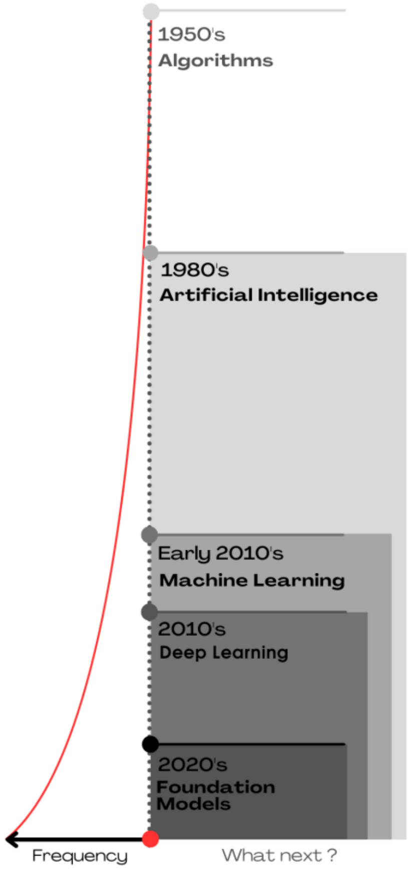

Figure 1: Timeline of AI subset development and use frequency based on IBMTechnology video (88) IBM Technology - YouTube.

AI encompasses six key subsets (Fig. 1), including: Machine Learning (ML), Deep Learning (DL), Expert System (foundational AI subset), Natural Language processing (NLP) and Speech Recognition (subsets of foundation models), Robotics and Machine Vision (Javatpoint.com).

Among these, the most publicly recognized application of AI is **Generative AI (GenAI)**. GenAI refers to computational techniques that, using trained models, can generate new content such as text, audio, images, or videos—examples include tools like ChatGPT. While graphic generation programs and chatbots are popular and widely known, they represent only a fraction of AI's broader capabilities. Many other AI techniques, such as Machine Learning and Deep Learning, have profound implications for scientific research, especially in statistical analysis and predictive modeling (Feuerriegel et al., 2024).

Machine Learning (ML) is an AI technique that uses data and past patterns to build models capable of improving predictive accuracy without requiring reprogramming. Depending on the task, ML can operate under supervised, unsupervised, or other specialized learning methods (McElheran et al., 2024; Nozari et al., 2024). It relies on problem-specific training data to analyze and execute specific tasks effectively.

Deep Learning (DL), a more advanced branch of ML, draws inspiration from the structure of the human brain. It employs multi-layered neural networks—complex systems of interconnected nodes that mimic brain activity—to automatically identify and learn patterns from vast datasets. DL often outperforms traditional ML in applications requiring high-level abstraction, such as image recognition or natural language understanding (Janiesch et al., 2021).

However, the complexity of DL models comes at a cost: they demand significantly more computational power and advanced programming skills compared to ML.

III Application of ai in water sciences

1 Drinking water system

Artificial Intelligence (AI) is transforming many fields, including water management. In Water Distribution Networks (WDNs), which provide most people with their daily water, AI is helping tackle issues like leaks (Fig. 2). Leaks happen due to internal problems like pipe aging and corrosion or external factors like environmental damage and human interference (Chan et al., 2018). These leaks cause significant water loss and financial costs. For instance, about 18.7% of drinking water in France is lost every year due to leaks (Observatoire des services publics d'eau et d'assainissement, 2024).

Traditional methods to detect leaks, such as using sound, vibration, or flow monitors, are divided into "passive" or "active" approaches based on their level of intervention. However, these methods often have limitations, like high resource demands or outdated technology. This has led to the adoption of AI-based methods, which are more accurate and efficient. AI uses tools like neural networks and Support Vector Machines to analyze sensor data and detect leaks. These tools can quickly find patterns, predict issues before they occur, and help reduce water loss in real time (Abdelmageed et al., 2022; Islam et al., 2022).

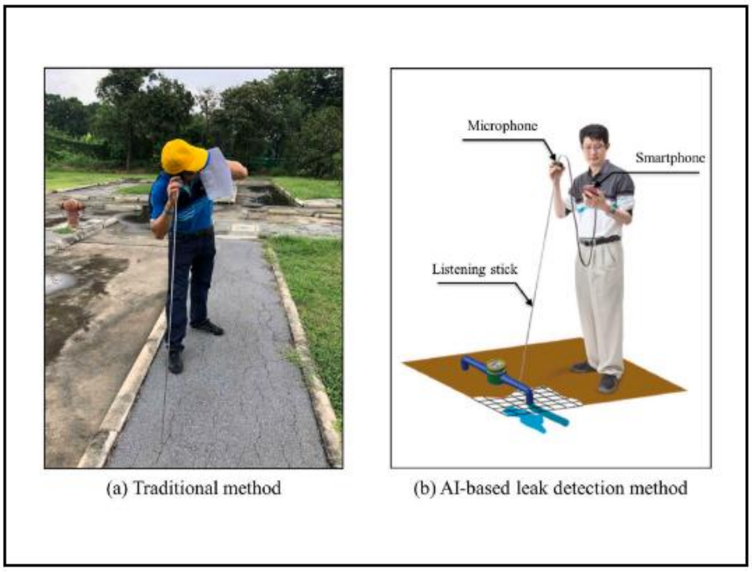

Figure 2: Application of leak detection device in the field (a ; b) and AI based water leakage detection (Vanijjirattikhant et al.,2022)

AI, thus, holds transformative potential in leak detection for WDNs, promising greater sustainability and efficiency. As these technologies evolve, AI's role in water management will continue to expand, offering essential tools to manage leaks more effectively and protect global water resources (Chan et al., 2018). On the other hand, similar methods can be used for defect recognition in drainage and sewer pipes (Fig. 3).

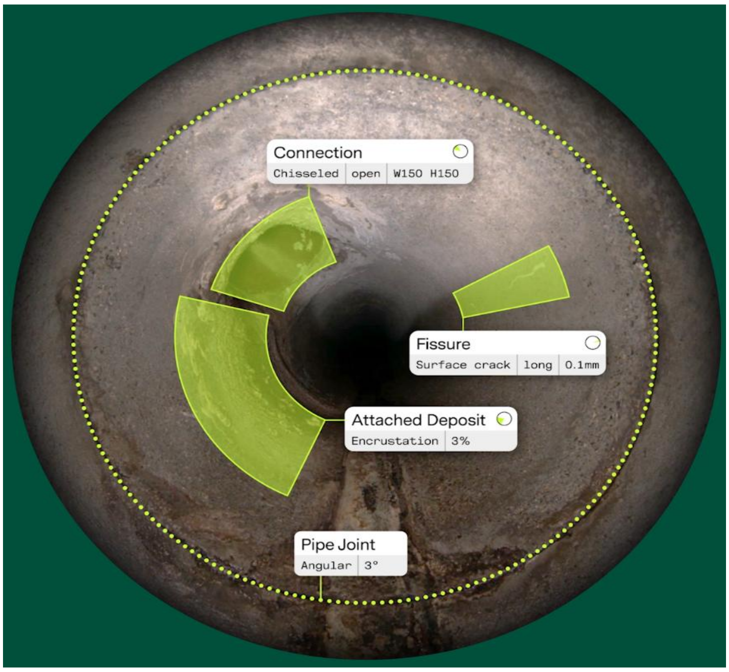

Figure 3: AI tool for defect recognition in drainage and sewer pipes (https://www.pallon.com/)

2 Detection and traceability of pollutants in aquatic environments

Artificial Intelligence (AI) is revolutionizing how water pollution is detected and tracked (Fig. 4), overcoming the limitations of traditional methods like spectroscopy, GIS, and hydro-chemical modeling, which are often slow and less effective for large-scale applications (Jin et al., 2024; Duan et al., 2024). By leveraging AI, the water sector can monitor pollution more quickly and accurately, gaining deeper insights into pollution sources and migration patterns. These capabilities are essential for risk assessment and environmental management. For instance, in Ghana's Pra River Basin, AI-powered models help pinpoint pollution from illegal mining activities, such as heavy metal contamination, and provide timely data to guide interventions that protect water quality and public health. Machine learning (ML) methods are highly effective in detecting microplastics and predicting water quality, while deep learning analyzes pollution movement and enhances water treatment simulations under varying conditions (Maurya et al., 2024). These approaches also improve the calculation of the Water Quality Index (WQI), which is especially beneficial in areas with limited resources (Maurya et al., 2024). However, challenges remain in adapting AI models to specific regional conditions and ensuring the availability of high-quality data to maintain accuracy and reliability. Despite these hurdles, AI represents a significant shift in water quality management, offering faster, more precise, and effective tools that complement traditional methods while opening new opportunities for proactive environmental monitoring and decision-making (Jin et al., 2024; Maurya et al., 2024).

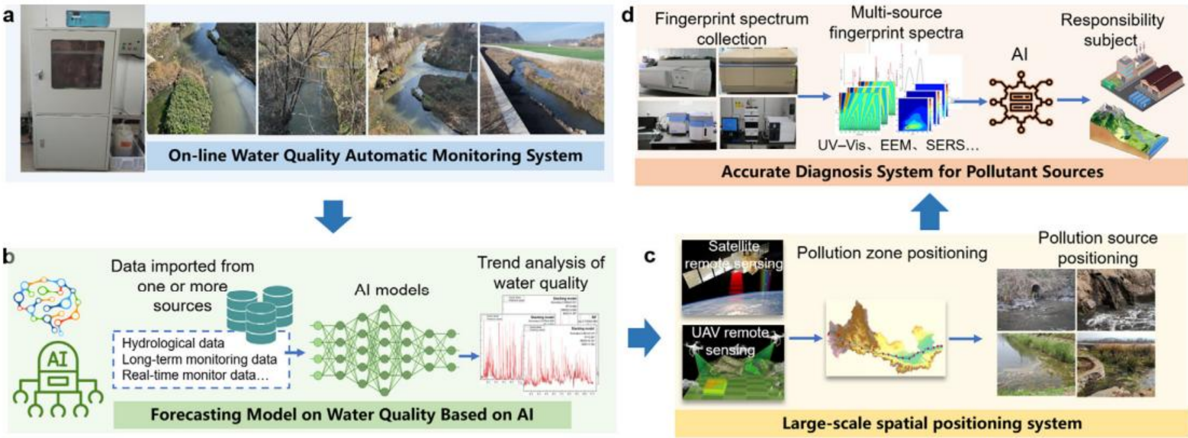

Figure 4: A multi-technology integrated S-WEQM system. (a) Various sensing devices for real-time water quality monitoring; (b) AI models for predicting and warning the water quality change trends; (c) Satellite or UAV remote sensing systems are used for spatial positioning of pollution sources; (d) multi-source fingerprint spectrum data for accurately diagnosing the responsible parties for pollution (Duan and al, 2024)

3 Temperature Prediction

AI has emerged as a powerful tool for forecasting river water temperatures, leveraging two primary modeling approaches. The first approach, process-based models, uses energy exchange analyses requiring numerous physical parameters such as air temperature, sunlight, water depth, and flow rates. These models rely on complex equations to provide interpretable predictions. The second approach involves statistical models, which focus on identifying correlations between environmental variables (e.g., day of the year, air temperature, discharge…) and water temperature (Caissie, 2006; Dugdale et al., 2017). This is where AI, particularly ML and DL, plays a crucial role in enhancing statistical analyses and enabling more robust predictions. While statistical models are generally less complex than process-based models, they can be highly effective when trained on sufficient and appropriate data, allowing them to "learn" from past patterns (Chen and Xue, 2024). However, this learning process can sometimes misinterpret unique local patterns, underscoring the importance of integrating AI with other modeling techniques to achieve more reliable forecasts.

AI methods, particularly ML and DL, have demonstrated significant potential in improving RWT forecasting by uncovering patterns in large datasets. As illustrated in Fig. 5, the predicted data (in red) closely aligns with observed data (in blue). Despite these advancements, traditional statistical models remain competitive in certain contexts, leading to two key strategies for further improvement. First, hybrid models combine AI techniques with traditional methods to boost prediction accuracy and adaptability. Second, there is a growing emphasis on understanding and optimizing AI mechanisms. This includes fine-tuning model parameters for more precise calculations, employing robust validation methods to compare predictions with actual RWT values, and analyzing the influence of explanatory variables on predictions. By leveraging the strengths of both AI and traditional approaches, these strategies aim to deliver precise, flexible, and reliable forecasting solutions (Feigl et al., 2021; Qiu et al., 2020).

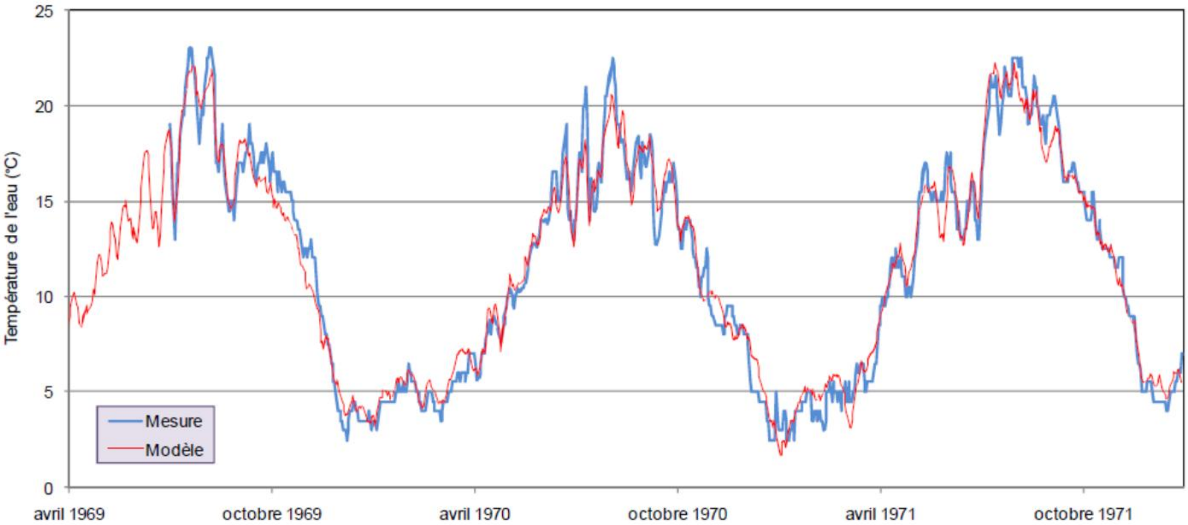

Figure 5: Water temperature (from 0°C to 25°C) modelized (red line) by Neural Network, a DL model compared to observed water temperature (blue line) from April 1969 to October 1971, at Bugey station, Rhône, France. (Poirel et al., 2015).

In the water domain, we can also estimate local water temperature and not the whole river or stream temperature. For example, based on personal internship, fishes need cold areas in rivers and streams to maintain essential physiological processes to survive during migration in hot summer. To preserve those places, we need to predict where the biggest thermal areas are to protect them on large territory by legislative levers. To do that, we calculated the surface of thermal areas (Fig. 6) using AI to extrapolate local temperature measurement.

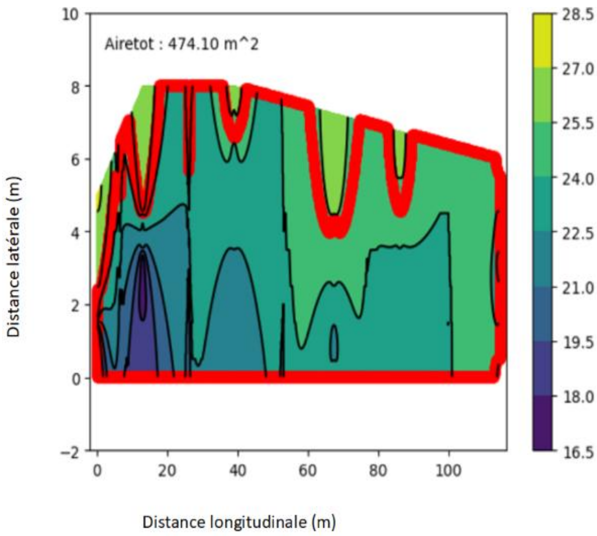

Figure 6: Calculated surface of the thermal area for fishes. The red line is the estimated limit of the thermal area.

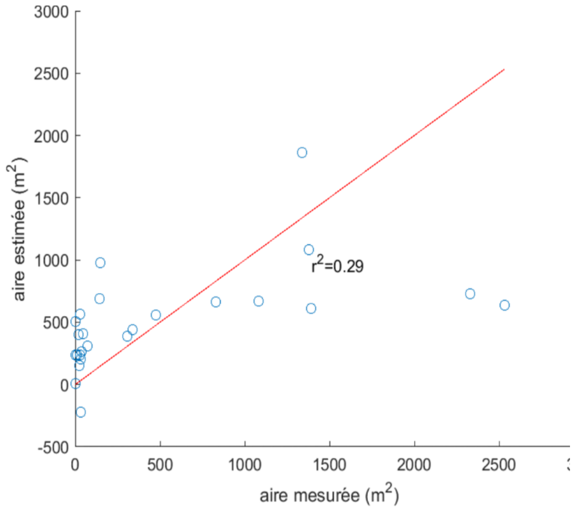

Figure 7: Estimated surface compared to calculated (measured) surface. The red line is the secant line (when the point is on it, the estimate is the same as the calculate).

After grouping the data, we used an AI model to predict those thermal areas. The methodology here was to remove one thermal area and use the others to predict it. Unfortunately, the result is not sufficient to propose that model to the scientific community (Fig. 7, $r^2 = 0{,}29$ meaning that the model can only well predict 29% of the thermal area). So, other studies will be provided to enlarge the data set and improve thermal areas prediction.

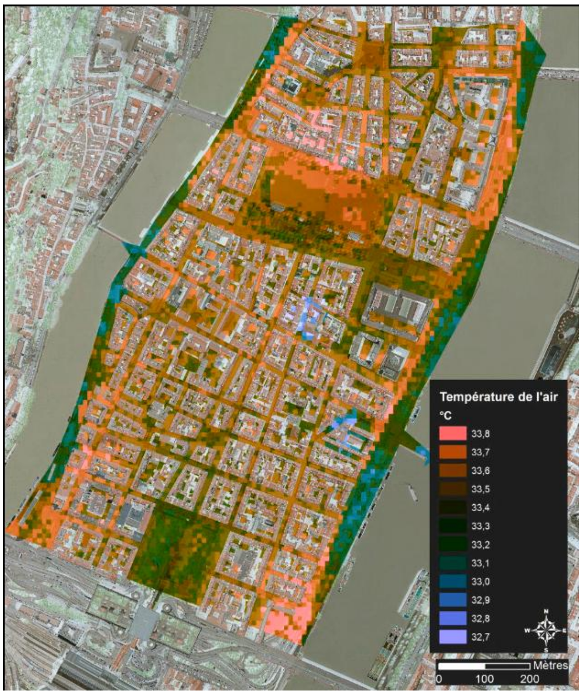

Figure 8: Urban Heat Island (UHI) measured by air temperature modeling in the dense urban center of Lyon on July 19th, 2018 (Alonso et Renard 2020).

To effectively predict temperature, remote sensing, an imagery data collection method that doesn't need direct contact with the studied object (e.g., camera), is commonly used. Relying on sensors to detect energy emissions or reflections from the Earth's surface, remote sensing employs two main types of sensors: passive sensors, which capture naturally emitted or reflected energy, and active sensors, which emit their own energy and measure its reflection from targets (Janga et al., 2023). Thanks to DL and ML, remote sensing data can be more easily used for image fusion, feature extraction and the application of classification algorithms for further analysis. A crucial method in temperature prediction, thermal remote sensing, utilizes thermal cameras and other sensors to measure flux in specific infrared wavelengths, enabling the assessment of an object's temperature, emissivity, and reflectivity. In urban areas like Lyon (Fig. 8), this technique is particularly useful for monitoring Urban Heat Islands (UHI), meaning that an urban surface experiences higher temperatures than surrounding rural areas due to human activities, materials light absorption, impervious surfaces, …. Remote sensing is also usable at larger scales to analyze broader surfaces (Fig. 9) but it's a trade off with a lower resolution.

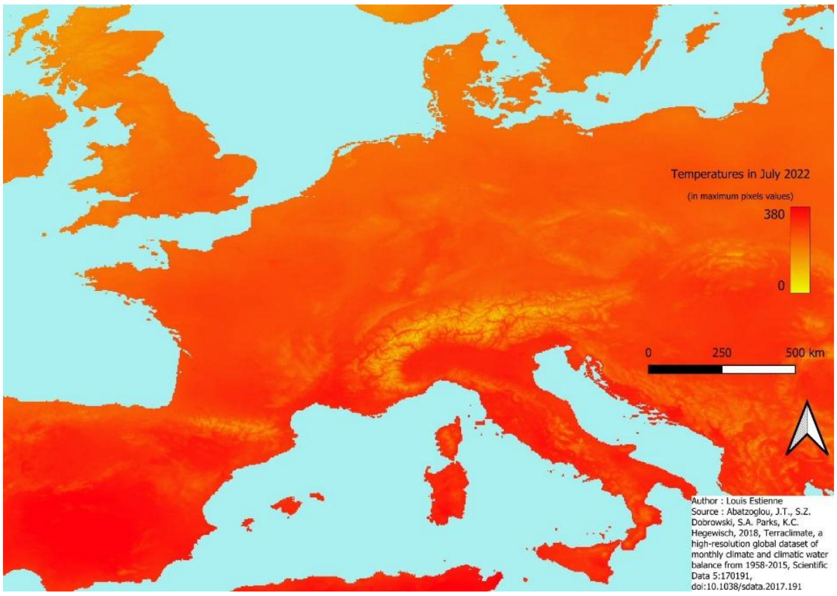

Figure 9: Maximum temperature in Europe for July 2017 (TerraClimate: Monthly Climate and Climatic Water Balance for Global Terrestrial Surfaces, University of Idaho)

4 Decision-making tools: Stakeholders

As a reminder for the first part, Generative AI is computational techniques that, using trained models, can generate new content such as text, audio, images, or videos—examples include tools like ChatGPT. This GenAI is rapidly becoming a game-changer in water resource management, offering new ways to generate complex scenarios, enhance decision-making with real-time insights, and develop innovative solutions for water-related challenges. By integrating historical data, predictive modeling, and real-time monitoring, generative AI can forecast future water demands, climate impacts, and resource conditions, providing stakeholders with a dynamic, forward-looking view of management outcomes. This enables the visualization and simulation of potential effects from policy changes, infrastructure investments, or resource reallocation, offering a flexible, informed approach that can adapt to evolving environmental and human factors (Jiang et al., 2024).

The forward-thinking use of generative AI has the potential to transform water management frameworks, supporting the development of tailored, resilient solutions that align with sustainable development goals. By facilitating scenario testing in diverse, multi-variable contexts, AI models help build a framework of solutions that can adapt to both expected and unforeseen challenges in water governance. One example of generative AI's role in improving water management is a project in Bellecour Square in Lyon, a historic public space (Fig. 10). The initiative aims to use nature-based solutions, methods consisting in a reproduction of nature processes to solve socio-environmental issues, to address urban heat while benefiting both the environment and the community. Generative AI could be used to simulate various design scenarios, evaluating how incorporating green parks and water features might reduce summer temperatures and create more comfortable microclimates. By modeling these scenarios, urban planners could visualize the advantages of integrating features like rain gardens or permeable surfaces, which not only manage stormwater runoff but also act as pollution buffers before the water reaches nearby rivers.

Figure 10: AI generated images of "Place Bellecour" produced with focus AI software to illustrate a decision-making tool.

This approach would not only make Bellecour Square more enjoyable and sustainable, but also align with the city's green policies. By predicting the effects of different strategies, decision-makers can choose the best solutions that balance the needs of the environment with urban development goals. This example demonstrates the potential of generative AI to facilitate innovative solutions in water resource management, ultimately contributing to the resilience and livability of urban spaces (Jiang et al., 2024; Lyon City Hall, 2023).

IV Conclusion

In conclusion, Artificial Intelligence (AI) is proving to be an invaluable asset in modern water resource management. By enabling more accurate predictions, real-time monitoring, and the development of innovative solutions, AI is addressing the complexities of managing water systems in a rapidly changing world. From improving leak detection and pollution traceability to optimizing water temperature forecasting and informing decision-making, AI is enhancing the efficiency and sustainability of water management practices. However, to maximize its potential, it is crucial to overcome challenges such as data quality, model adaptability, and regional specificity. The integration of AI with traditional methods, especially through hybrid models, will continue to shape the future of water management, supporting tailored, resilient solutions that align with both environmental and human needs. As we move forward, AI-driven approaches will play a central role in achieving sustainable water management, fostering resilience in urban spaces, and advancing global water security.

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