






Making waves: A conceptual framework exploring how large language model-based multi-agent systems could reshape water engineering

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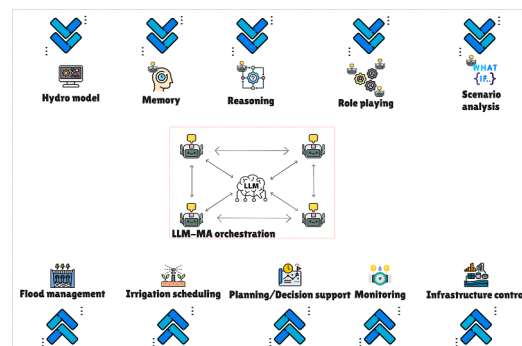
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HIGHLIGHTS

- LLM-MA systems can enhance water engineering by improving data integration, monitoring, and decision-making.
- Specialized agents can support ground-water monitoring, irrigation scheduling, reservoir management, and post-disaster response.
- Key challenges include data access, computational demands, bias, hallucinations, and governance issues.

GRAPHICAL ABSTRACT



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ABSTRACT

Large Language Model-based Multi-Agents (LLM-MAs) are emerging systems that manage complex tasks with specialized and coordinated agents. In this paper, we present new perspectives on the integration of LLM-MA systems into enhancing water engineering practices. Water engineering typically involves data integration, analysis, modeling, decision-making, and cross-disciplinary collaboration, which often present significant

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difficulties. To address these domain-specific complexities, we explore how LLM-MA systems can support advanced operations in water engineering and facilitate them. By pointing out the linguistic capabilities of LLMs and the modular, scalable, and collaborative architecture of LLM-MA systems, we investigate the role of intelligent agents in enabling timely, adaptive, and traceable solutions. Various practical applications were identified, e.g., LLM-MA for pressure drop detection in water distribution networks, flood management, or in their role as potential negotiating agents to find a balanced solution considering differing goals. Our investigation highlights both the capabilities and limitations of LLM-MAs in water engineering and proposes practical recommendations for their effective implementation within the field. This study seeks to develop a foundational framework for understanding how LLM-MAs can shape the future of water engineering processes.

1. Introduction

The concept of *water engineering* serves as an umbrella term for a broad range of long-standing practices, spanning infrastructure design, system management, operational maintenance of water systems, and others, that have supported the development and functioning of societies throughout history (Zolghadr-Asli et al., 2017a). While the field has evolved from early manual systems such as aqueducts and canal maintenance (Deming, 2020) to contemporary automated networks, the basic objective of managing water substantially remains relatively unchanged. Today, however, the nature of practice is being transformed through the automation of routine tasks and the redefinition of decision-making processes. Advancements in artificial intelligence (AI), interpreted as the capacity of machines to simulate human cognitive functions such as learning, reasoning, and adaptation (Du-Haripur et al., 2020), could potentially and significantly facilitate water engineering tasks, such as data acquisition, modeling, and decision-making processes (Kamyab et al., 2023; Zolghadr-Asli et al., 2024).

Whereas traditional engineering is mostly human-dependent for designing, planning, and execution, today's water engineering, with the presence of AI, has the potential to become increasingly AI-assisted. While significant innovations in AI are emerging, their widespread adoption in practical applications remains limited and continues to evolve gradually. Among these innovations are machine learning (ML) techniques that enable systems to identify patterns and make inferences directly from data, reducing reliance on predefined rules. Within this domain, deep learning (DL) models—multilayered neural networks capable of capturing complex relationships (Du-Haripur et al., 2020)—can, for instance, predict floods before they strike (Almikaee et al., 2025), and support “smart” reservoir operations by automatically adjusting releases in real time (Jia et al., 2023), offering promising directions for future practical applications. These techniques have also enabled water engineers to predict leakages in a water distribution network, thus minimizing the need for extensive human inspection and emergency repairs (McMillan, 2023; Beig Zali et al., 2024; Latifi et al., 2024). By processing data gathered from hard-to-reach areas via remote sensing data, AI-powered models can assess water quality and enable experts to monitor environmental conditions remotely and efficiently (Sheffield et al., 2018; Ying et al., 2021; Bekmurzaeva et al., 2024; Hong et al., 2024). As noted above, the influence of AI has been steadily expanding across all sectors in water engineering, with its impact potentially becoming progressively more profound in practice (Hosseini and Moeini, 2025; Kisi et al., 2025; Samani et al., 2025).

Amid the growing dominance of AI, the advent of large language models (LLMs), such as ChatGPT, Gemini, DeepSeek, and Llama, has created opportunities for exploring their potential applications across various domains, including water engineering. In general, LLMs are a kind of DL model trained on a vast dataset to generate human-like text (Hassanin and Moustafa, 2024). To explore their potential, a range of disciplines have already started integrating these models into novel applications. DrHouse, as an AI model for disease diagnosis (Yang et al., 2024), a Python assistant for coding support (Nam et al., 2024), and BloombergGPT for financial analysis and decision-making (Wu et al., 2023) are just a few examples of LLMs being applied across domains.

While LLMs are already beginning to find their way into sectors like healthcare and finance, water engineering is only starting to explore their transformative potential. Unlike conventional models designed for specific tasks, LLMs introduce a new approach as versatile tools capable of learning across domains, integrating varied data sources, and interpreting unstructured information (Lehmann et al., 2024; Shen, 2024; Freire et al., 2025). This adaptability opens new possibilities for supporting integrative decision-making, helping connect physical modeling, environmental policy, and the operational aspects of water management. In this regard, Xu et al. (2025) assessed the performance of eight LLMs in performing water engineering and research tasks. In another effort, WaterGPT—a language model trained on four types of data (i.e., knowledge-based inputs, task-oriented queries, negative samples, and multi-turn dialogues)—was developed by Ren et al. (2024). Hosseini and Pourzangbar (2026) proposed a rubric and assessed the performance of DeepSeek, ChatGPT, and Gemini in answering water science questions. Moreover, HydroLLM-Benchmark was introduced by Kizilkaya et al. (2025) as a benchmark dataset to assess the capabilities of LLMs in responding to hydrological questions. Pursnani et al. (2024) introduced HydroSuite AI, an LLM to answer hydrological and environmental questions; such applications, including automated code generation, represent emerging implementations of LLMs in water engineering. Although, as shown above, a few research-based efforts have introduced LLMs into water engineering, many areas remain underexplored (e.g., how LLMs might interact with numerical models, handle spatiotemporal data, and contribute to complex real-world decision-making processes with sufficient robustness).

The versatility of LLMs as generative-AI, which refers to AI systems capable of creating new and original content by learning from existing data (Pahuja et al., 2025; Taşabat, 2025), that can work with text and integrate with diverse systems, has unlocked opportunities for developing more intelligent and adaptive systems. Notably, LLM-based multi-agent (LLM-MA) systems are an extension of this evolution that facilitates the harmonization of multiple specialized agents to collaboratively solve complex problems across various domains. With the presence of natural language as an interface and interaction of goal-directed agents, LLM-MA systems have emerged that are smarter than their collective parts, a group of expert agents coordinating and delegating tasks to autonomously execute a complex process—e.g., responding to the technical questions in a wastewater treatment plant and water quality enabled by agents' collaboration (Vald et al., 2024; Rothfarb et al., 2025). Through such architectures, agents can communicate and have access to external tools, resources, and services to support their functions (Li et al., 2024). Moreover, as a case in point, Wang et al. (2025) in a water distribution study introduced an LLM-MA system featuring an Orchestrating Agent that coordinates with three specialized agents: a Knowledge Agent for hydraulic reasoning, a Modeling Agent for interaction with external simulation tools, and a Coding Agent for autonomous code generation and execution. Additionally, LLMs and AI agents have recently also been used for flood mitigation, water resources management, water quality assessment, and water distribution networks (Goldstein et al., 2025; Kadiyala et al., 2025; Pursnani et al., 2025; Shrestha et al., 2025).

These scalable intelligence systems appear to have great potential to

make the multi-faceted and challenging processes of water engineering more straightforward. As stated earlier, LLM-MAs are expanding into various disciplines, and since their application in water engineering is only beginning to take shape, much of their potential remains untapped, which opens up rich opportunities for exploration and innovation. It is very likely that in the near future, LLM-powered hydro systems will show an evolution from single-agent intelligence to coordinated distributed cognition to facilitate processes. Therefore, this paper aims to explore the characteristics of these systems as a window into how LLM-MAs could transform routine practices in water engineering, while also examining the potential challenges and concerns that may emerge as they become operational.

2. Understanding the architecture and workflow of LLM-MAs

LLMs are sophisticated DL models developed using large-scale datasets comprising text from diverse sources such as academic publications, books, and online materials, enabling them to interpret and generate language like human communication (Hassanin and Moustafa, 2024). While LLMs possess impressive capabilities for natural language

processing (NLP) and generation, their potential can be significantly amplified when integrated into MA systems, which allow for more dynamic, distributed, and context-aware problem-solving.

In general, an LLM-MA system typically comprises several key components, including *intelligent agents*, a *memory model*, *scheduling and coordination mechanisms*, *communication and interaction protocols*, and *quality assurance processes*. In such systems, complex tasks are broken down into subtasks and distributed among multiple specialized agents, each responsible for generating potential solutions or providing outputs that may serve as inputs for subsequent agents (Chen et al., 2024). In Fig. 1, an overall view of an LLM-MA system and its key features in water engineering is presented. At their core, most implemented LLM-MA systems remain fundamentally anchored in one or more LLMs. With the availability of well-known LLMs, these models exhibit strong *zero-shot* (i.e., generalizing to new tasks without any task-specific training examples) or *few-shot learning* (i.e., generalizing from only a small number of training examples) capabilities (He et al., 2025). A critical feature of LLM-MA systems is their memory component, which plays a significant role in managing long-term conversational contexts and supporting the execution of complex and multi-step tasks (Zou et al.,

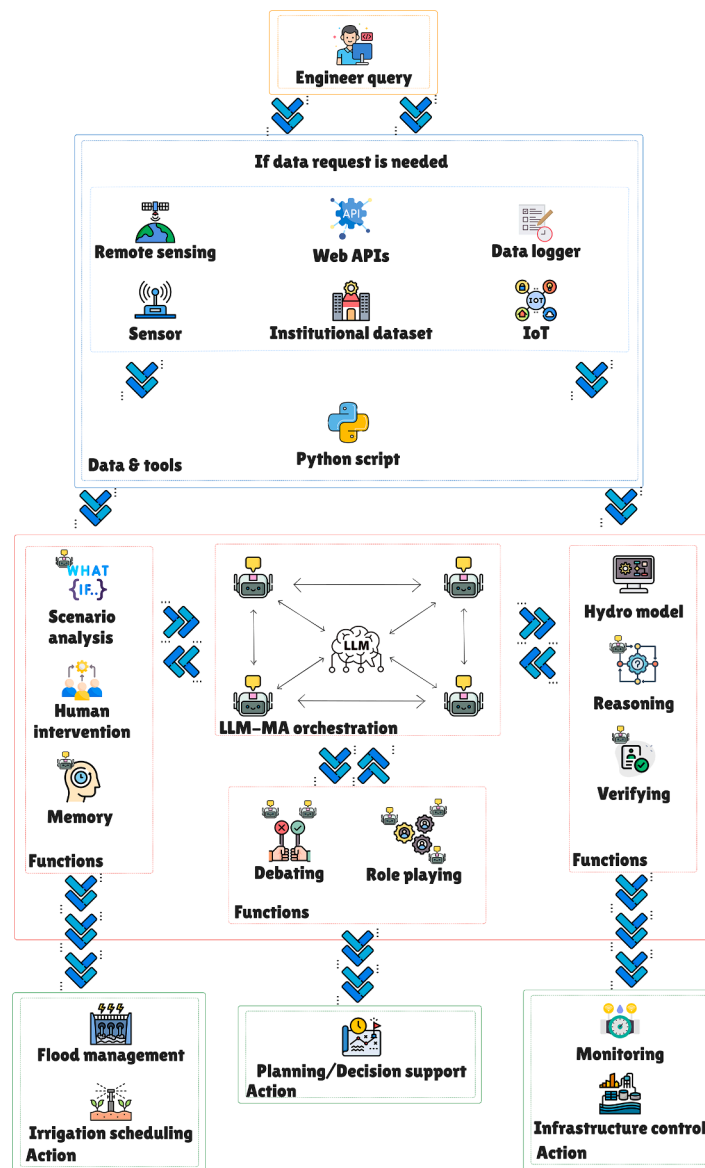


Fig. 1. Conceptual framework of implementing an LLM-MA system in water engineering, showing how diverse data sources and intelligent agent capabilities interact to support monitoring, control, and decision-making across multiple applications.

2024). The memory capability helps the system to retain and recall previous actions along with their corresponding outcomes. Task scheduling is another vital aspect that involves decisions about when and how agents should act to prevent task redundancy or conflict. Efficient scheduling and resource allocation are fundamental to ensuring that agents operate harmoniously, share relevant information, and work toward common objectives (Zou et al., 2024; Sun et al., 2025). Agents within an LLM-MA system can interact not only with one another but also with humans and external tools (Cheng et al., 2024). The architecture of an LLM-MA system controls the level of interaction and the amount of information exchanged between agents, allowing for flexible orchestration depending on the task requirements. To evaluate system performance, metrics such as computational and financial costs (e.g., Application Programming Interfaces (API) usage fees), task completion time, and the number of LLM queries can be monitored (Irugalbandara et al., 2024). These assessments help identify inefficiencies, such as unnecessary agent loops or delays, thereby improving overall system effectiveness. In short, an LLM-MA system can be seen as a coordinated network of intelligent agents, functioning as a team of experts capable of reasoning, delegating tasks, and coordinating actions to achieve shared goals.

LLM-MA systems offer *modularity* by enabling the deployment of specialized agents configured to specific tasks (Chen et al., 2023; Jiang et al., 2024; Zhang et al., 2024). These systems are inherently *scalable*, which allows for effortless expansion through the integration of new agents across various disciplines (Chandrasekaran, 2024; Shamim and Singhal, 2025). The *parallelism* characteristic of agents supports concurrent task execution, which can enhance system responsiveness and reduce time-to-completion (Chen et al., 2023; Guo et al., 2024). To generate more comprehensive solutions and incorporate diverse perspectives, agents within LLM-MA systems can collaborate on function delivery by sharing intermediate results, exchanging contextual knowledge, and dynamically coordinating their actions to collectively address different facets of a problem (Abdelnabi et al., 2024; Barbosa et al., 2025). Their *reusability* further contributes to system efficiency, as agents can be repurposed for different tasks and domains, in some cases, with minimal reconfiguration (Jiang et al., 2024; Zhang et al., 2024). LLM-MA systems are also highly adaptable, which makes them capable of dynamically adjusting their behavior in response to environmental changes and evolving task demands (Zhang et al., 2024; Zou et al., 2024). In an LLM-MA system, *transparency* is promoted through the integration of mechanisms, such as smart contracts and formal logic frameworks, which support clear, auditable, and trustworthy interactions among agents and stakeholders (Calvaresi et al., 2018; Dwarakanath et al., 2024). Moreover, these systems demonstrate high efficiency, enabled by advanced planning strategies, streamlined workflows, and optimized resource allocation (Chandrasekaran, 2024; de Curtó et al., 2025; Zhang et al., 2025). Finally, their *interoperability* enables seamless integration with a wide range of platforms and technologies (Calvaresi et al., 2018; Jin et al., 2024).

While LLM-MA systems offer various benefits and advanced capabilities, it is important to acknowledge that they are also computationally expensive and resource-intensive (Zou et al., 2024). The orchestration of agents (i.e., how they are scheduled, coordinated, and prioritized) plays a significant role in determining the overall system performance and computational efficiency. Moreover, since the foundation of these systems remains the LLM itself, any limitations or vulnerabilities inherent to LLMs could also be present in LLM-MA systems. Consequently, the appropriate selection or fine-tuning of an LLM becomes a critical consideration, especially when adapting the system for project-specific needs. A persistent challenge involves identifying optimal solutions that align with user-defined constraints, such as security requirements, operational limitations, or stakeholder preferences, which differ from project to project (Xing et al., 2024). In addition to previous issues, enhancing agents' role-playing capabilities and improving the reliability of their outputs are essential steps toward

reducing *hallucinations* (i.e., cases where models' outputs are seemingly plausible or sound true yet are erroneous or misleading information) and boosting system robustness (Chandrasekaran, 2024). Another significant issue is *information asymmetry* within LLM-MA systems, wherein each agent typically has access only to the data provided by its associated human user. This limited visibility can hinder collaboration, as agents may lack the broader context needed to effectively coordinate, share insights, or make well-informed collective decisions (Liu et al., 2024). Additionally, the restricted context window of LLMs constrains their ability to manage extended dialogues or execute long-term, multi-step tasks. This limitation often results in difficulty retaining earlier information and maintaining continuity, thereby highlighting the importance of incorporating enhanced memory mechanisms to support more context-aware and coherent interactions over time (Zou et al., 2024).

3. Toward the integration of LLM-MAs in water engineering

Water engineering tasks often demand extensive time commitments, computational, and financial resources (Lach et al., 2005). The nature of these problems is mostly inherently multifaceted and complex (Singh et al., 2017). Decisions made in favor of one stakeholder can inadvertently impact others, which reflects the interdependence of interests within water-related systems. Many projects involve multiple organizations, diverse engineering disciplines, and socio-political dynamics that show the interdisciplinary character of water engineering challenges (Magnuszewski et al., 2018; Gourbesville et al., 2022; Muller et al., 2024). Additionally, certain problems, due to their urgency or criticality, require real-time or near-real-time decision-making, which introduces further complexity and elevates the risks associated with rapid-response scenarios (Romano and Kapelan, 2014; Wang et al., 2020; Giudicianni et al., 2021). Failures in decision-making or proper task execution in such contexts can result in high costs and long-lasting consequences.

In response to these multifaceted challenges, the careful adoption and integration of advanced technological tools are essential to improving efficiency and reliability. Despite their vast capabilities and growing track record in other disciplines, LLM-MAs have yet to be thoroughly explored or widely applied within water engineering and adjacent domains. As with other modeling paradigms, LLMs and, by extension, their MA configurations offer significant advantages, while also presenting thought-provoking challenges in water engineering. Both dimensions deserve careful examination. This section discusses the key opportunities and limitations associated with the application of LLM-MAs in water engineering.

3.1. Key characteristics of LLM-MAs and their benefits for water engineering

Building on the *modular* and *collaborative* architecture of LLM-MA systems pointed out earlier, data analysis in water engineering represents a natural domain for their implementation. As a critical component of modeling in water engineering, data analysis frequently requires the integration and investigation of diverse datasets from multiple water-related disciplines, such as hydrological, meteorological, water quality, geospatial, geopolitical, land use, socio-economic, infrastructural, and climate-related datasets. This process is often time-consuming and typically demands domain-specific expertise. Moreover, water engineering problems rarely occur in isolation. In fact, they are part of complex feedback loops, where one issue can trigger, amplify, or mask another. Therefore, it is crucial to analyze the variability and interactions among these processes to better understand their behavior and inform response strategies. These context-specific dynamics underscore the need for task-aware and distributed data analytical frameworks capable of tracing *cause-and-effect* relationships (Zolghadr-Asli et al., 2021). In this regard, LLM-MA systems, with their

ability to support task-specific specialization, concurrent execution, and adaptive coordination, can offer a promising approach to data analysis and improving data quality. By assigning distinct data analysis roles to individual agents—some powered by LLMs for text-based reasoning, others by multimodal foundation models for processing sensor, image, or data stream—each designed to operate autonomously yet in coordination, these systems enable distributed, role-specific processing (Rasheed et al., 2024). Furthermore, the *adaptability and interoperability* of LLM-MAs allow specialized agents to interface with external sources or non-text data [e.g., sensors, data loggers, CCTVs, internet of things (IoT) devices, websites and social media APIs] via intermediate tools like Python scripts. This enables real-time data retrieval, improved data integrity and consistency, and system-level responsiveness, all features that are crucial for managing the dynamic and evolving data-related demands of water engineering tasks. For instance, an LLM-MA system is able to monitor groundwater withdrawals in real-time and deploy quota-enforcing agents to balance agricultural and urban allocations. Moreover, APIs enable two or more digital applications or services to exchange data and information. As a useful tool, in this regard, ModelScope-Agent was designed to enable straightforward integration with both model APIs and commonly used APIs, offering an efficient and accessible approach to utilizing AI functionality (Li et al., 2023). With the availability of global online datasets such as GLDAS, GRACE, CHIRPS, MODIS, and FAO AQUASTAT/FAOSTAT, it is possible to use established Python packages to connect with each database's API and efficiently download the required data and then use them. In addition to agent-level capabilities, LLMs within an LLM-MA system can be equipped with Retrieval-Augmented Generation (RAG)—a technique that enhances the capabilities of LLMs—to integrate external knowledge sources (James et al., 2025). In this approach, relevant documents or data are first retrieved based on the input query, typically using information retrieval mechanisms, and then used to inform the generation process (Shahade and Deshmukh, 2024; Rajaei et al., 2025; Tian et al., 2025). By reinforcing outputs in retrieved content, RAG enables LLMs to generate more accurate and contextually relevant responses (Rajaei et al., 2025; Shahade and Deshmukh, 2024; Varma et al., 2025).

The design principles underlying LLM-MA systems, particularly their *modularity, adaptability*, closely mirror the structural and operational complexities inherent in water engineering decision-making frameworks. In the context of water engineering, once a problem has been formulated and multiple potential solutions identified, selecting the optimal option becomes especially critical when decisions carry long-term implications and involve diverse stakeholders with competing priorities. For instance, in urban runoff mitigation planning, implementing decision-making methods is necessary to evaluate both technical and economic aspects when choosing low-impact development (LID) strategies (Nazari et al., 2023). In such cases, the integration of systems capable of translating complex technical findings into actionable insights would be highly advantageous, an area where LLM-MAs have demonstrated effectiveness, particularly in dynamic settings that require spatial decision-making, risk management, and sustainable long-term strategies (Chen et al., 2024). Moreover, LLM-MA systems, through embedded *reasoning capabilities* and iterative agent *collaboration mechanisms*, provide a structured approach for addressing decision-making challenges. By allocating decision-support responsibilities to task-specific agents, the system can methodically decompose complex strategic problems into discrete, goal-driven components aligned with clearly defined objectives and constraints (He et al., 2024). A relevant implemented example is the TrainerAgent system (Li et al., 2023), which utilized multiple coordinated agents, each assigned to roles such as task interpretation, data handling, and model deployment, to automate the development of AI models based on user-defined requirements. In the industrial wastewater discharge context, a model agent can simulate pollutant transport to predict downstream water quality impacts, while a policy agent assesses compliance with discharge permits and environmental thresholds. A

communication agent then synthesizes the findings into actionable summaries for plant operators and regulatory authorities, which highlight potential legal risks and recommend mitigation strategies. This illustrates how LLM-MA *modularity* and *collaboration* can translate high-level goals into executable outcomes, a capability directly relevant to decision-support systems in water engineering. Agents within an LLM-MA system can then coordinate evaluation of alternatives and conduct sensitivity analyses. Thanks to its *modularity* and *reusability*, LLM-MA architecture enables decision-making agents to be rapidly adapted across domains, such as transitioning from urban runoff planning to pipe leakage detection (Zhang et al., 2023). In a hydropower system, LLM-MAs can also link reservoir operations with market signals, adjusting generation in response to high loads and price fluctuations. Those agents can support real-time diagnostic assessment and guide operational decisions without a complete system overhaul. For real-time irrigation scheduling practices, a weather-soil agent can be connected to weather prediction models, dynamically adjusting irrigation schedules in response to the upcoming rainfall to prevent overwatering. Besides these capabilities, the integration of expert input (human-in-the-loop) through *feedback loops* supports dynamic refinement of objectives and promotes both *transparency* and *accountability*. In settings where direct stakeholder engagement is limited, LLM-MA systems, through an intermediary, can serve as adaptive survey platforms (e.g., via SMS) to gather and incorporate stakeholder perspectives into the decision-making process. Once established, these systems function as customizable, context-aware decision-support tools that can be reused for structurally similar problems, which, in turn, enhances both *efficiency* and *responsiveness* in water engineering applications.

One of the defining strengths of LLM-MA systems lies in their advanced natural language understanding and generation capabilities, which can empower agents to produce more insightful, semantically grounded, and context-sensitive outputs. These capabilities go well beyond the limitations of traditional alert systems in water engineering, which typically lack the expressive capacity for detailed text-based input and output. As such, instead of a simple alert code, an LLM-MA can deliver informative and semantically rich alert messages such as: “*Increased turbidity at Node X correlates with upstream rainfall event Y and recent construction permit Z.*” Such linguistic flexibility also enhances user interaction. By interpreting free-text prompts with contextual awareness, LLM agents offer a more intuitive and human-centered interface. Therefore, LLM-MAs can be implemented in alarm systems and provide reports (Sun and Liu, 2025). A query like “*The pressure drop near the X Street valve sounds rough. Could it be due to sediment buildup?*” would allow the system to infer that “sounds rough” indicates mechanical stress and link “sediment” to historical corrosion events in similar pipes within the specified water distribution network. These interpretive abilities stem from the *collaborative communication protocols* and *shared memory* frameworks described earlier, which support agents in resolving ambiguity, sharing contextual knowledge, and adapting to user intent.

Beyond diagnostics and alerts, these language capabilities extend to scenario analysis and stakeholder modeling. LLM-MAs can process hypothetical or “what-if” scenarios expressed in natural language, extract the relevant parameters, and, with the help of integrated tool agents, translate these into structured numerical inputs for modeling. Once the analysis is performed, results can be presented in various formats, including text, voice, or video, depending on the system's integration with external tools. Such language processing ability enhances agent-to-agent communication, even in contexts requiring nuanced interpretation and negotiation. During a regional flood event, municipalities, utilities, and emergency services should collaborate to coordinate dam releases, infrastructure shutdowns, and evacuation plans (Persson and Granberg, 2021). In such a situation, agents in an LLM-MA system can be represented as governing and operational bodies, and can identify and reconcile conflicting interpretations, such as when upstream dam releases conflict with downstream evacuation timing. Beyond floods,

LLM-MAs can support post-disaster monitoring, reporting, and response by rapidly analyzing sensor and drone data to guide emergency water supply restoration and infrastructure repair. In multi-stakeholder policy design, agents can be developed to simulate distinct perspectives (e.g., a farmer agent, an environmental Non-Governmental Organization (NGO) agent, or a municipal finance agent), each grounded in relevant training data and customized prompts. This form of agent-based role-playing, enabled by the *modularity* and *reasoning* features, supports the construction of robust, multi-perspective policy simulations that can reflect the complexity of real-world decision-making processes. For instance, AutoGen is a versatile framework designed to support multi-agent conversational systems across diverse applications (Chu et al., 2024; Wu et al., 2024) that has the potential to be applied in water and environmental domains.

Obviously, the scope of water engineering goes well beyond designing dams, developing physical or ML models, or managing pressure within water distribution networks. It also encompasses institutional structures and human expertise, which make organizations that bring together multidisciplinary professionals an integral part of the water engineering processes. In many cases, effective internal communication and cross-organizational collaboration are essential for successful project execution. In this context, LLM-MA systems can be strategically designed to enhance institutional coordination and information exchange. By collecting and integrating inputs from various stakeholders, such systems can streamline access to relevant knowledge and support more efficient analysis and decision-making. Furthermore, at the organizational level, an LLM-MA system could serve as a valuable tool for onboarding new employees and assisting them in aligning with company-specific protocols, standards, and expert practices. Over time, these systems can evolve into adaptive institutional knowledge hubs and reinforce organizational memory while supporting consistent and informed project-level analysis and resolution.

3.2. Concerns and challenges about using LLM-MAs in water engineering

As stated, receiving, analyzing, managing, and transmitting data could be among LLM-MAs' capabilities. While LLM-MAs can handle data-related tasks, their effectiveness depends on access to high-quality and domain-specific datasets, which in water engineering may not always be openly available online, with some critical data still requiring time-consuming manual collection. Apart from availability, the coordination of agents involving raw data exchange can pose serious risks, including the potential exposure of personally identifiable information (PII) or vulnerabilities in critical infrastructure (Alnemari et al., 2019). Furthermore, the storage of aggregated data within a centralized LLM orchestrator introduces the risk of a *single point of failure*. These system vulnerabilities could be exploited through cyberattacks, potentially resulting in severe consequences, such as terrorism-related threats or competitive disadvantages (Zolghadr-Asli et al., 2017b). For instance, unauthorized access to asset details (e.g., location, material, connectivity) or pipe corrosion data could compromise municipal infrastructure security, while leaked farm-level irrigation records could undermine the competitiveness of agricultural stakeholders. LLM-MA systems frequently handle sensitive information across various domains. In another case, leakage of household smart meter data may inadvertently disclose occupancy patterns, travel routines, or other privacy-sensitive behaviors. In addition to these points, LLMs are susceptible to targeted extraction attacks, in which adversarial prompts can elicit memorized training data (Ma et al., 2023), potentially compromising individuals whose personal information was included in the training datasets (Jiao et al., 2025). While these systems can also benefit from agents designed to improve data quality, issues that may arise during intermediate stages must be considered. For example, the performance of an outlier detection agent depends on context-sensitive thresholds, which vary between streamflow and temperature time series. Similarly, a missing data imputation agent may introduce an

artificial trend if poorly designed or not verified by an expert. In an LLM-MA system, the reliability of the outputs depends on the quality of processed data. This highlights the role of data-related agents in preventing error propagation, since the spread of such errors throughout the system can ultimately undermine trustworthiness.

Another critical concern arises from jurisdictional discrepancies in data governance. A large portion of the world's freshwater resources is transboundary in nature, and variations in legal frameworks make their management complex (Deribe et al., 2024). In practice, to overcome management challenges, these regions should shift from fragmented and reactive approaches toward integrated strategies (Prniyazova et al., 2025). LLM-MAs operating across regions must comply with local data protection laws, which can vary significantly. This is particularly relevant in transboundary water basins, where a single watershed may span multiple legal authorities, each with distinct rules, regulations, and policy frameworks, serving as a clear example of data sovereignty issues. As a result, regulatory conflicts are likely to emerge and must be proactively anticipated and managed in the design and deployment of such systems. In such cases, data sharing mechanisms between regions with conflicting interests (Loodin et al., 2023) should be integrated into an LLM-MA framework to facilitate coordinated water governance.

Beyond data governance and infrastructure risks, ethical considerations also require attention. LLMs can exhibit biases, typically stemming from the composition of their training data and the algorithms employed in their development (Jiao et al., 2025). In water engineering, one potential bias regarding the use of LLM is the socioeconomic bias, which refers to the model's tendency to associate different demographic groups with varying levels of wealth, poverty, or social status based on patterns present in training data (Arzaghi et al., 2024). This socioeconomic bias in an LLM-MA system for water engineering could be challenging when agents are tasked with allocating limited water resources among competing sectors such as agriculture, industry, environment, and drinking water supply. If the system, influenced by biased training data or skewed language inputs, consistently favors industrial or urban stakeholders over rural, environmental, or agricultural needs, it may lead to inequitable access, degradation of ecosystems, and marginalization of vulnerable communities. The outcomes of such a biased LLM-MA system not only undermine fairness but also threaten the resilience and sustainability of integrated water resource management.

Implementing LLM-MAs in modeling and optimization is another area that should be meticulously considered, as there remains a gap on this front. Agents capable of executing external modeling tools (e.g., software) require natural language input to define numerical requirements (e.g., objectives and constraints in an optimization formulation of a water engineering problem). However, such numerical requirements may not always be strictly enforced; thus, they become "soft" instead of "hard" physical constraints that are not always fully met (Wang et al., 2025). Furthermore, for some mathematical optimization tasks, agents may exhibit tendencies toward local optima. Although some efforts have been made to integrate LLMs into metaheuristic optimization algorithms (Dat et al., 2025; Forniés-Tabuenca et al., 2025), further research in water engineering is needed to test their usage. LLM-MA systems can benefit from integrating hydrological and hydraulic models within a unified programming environment such as Python. For simulating urban runoff, groundwater flow, hydrology, soil-water-crop interactions, and water allocation, a wide range of Python libraries, including *PySWMM*, *FloPy*, *PyHSPF*, *AquaCrop-OSPy*, and *Pywr*, are available and can be incorporated into LLM-MA systems. However, achieving interoperability between LLM-MAs and graphical user interface (GUI)-based models is not as straightforward as using these Python libraries. Tools such as the Basic Model Interface (BMI) (Peckham et al., 2013) and the Open Modeling Interface (OpenMI) (Harpham et al., 2019) have been specifically developed to facilitate model interoperability and coupling, with BMI focusing on standardizing model interfaces and OpenMI providing a framework for runtime data exchange among coupled models.

Hallucination, as stated earlier, is a known limitation inherent to LLMs, and, in short, it refers to instances where models generate factually inaccurate or misleading content that seems correct. In the context of LLM-MAs, this misinformation issue can propagate across agents, which leads to cascading errors throughout the system. Notably, poorly designed LLM-MA architecture can exacerbate this problem, which allows hallucinated outputs to influence multiple interrelated tasks. It is also important to emphasize that hallucination is especially prevalent in domain-specific applications, where gaps in training data reduce the model's reliability and complicate trust in autonomous decision-making systems (Ji et al., 2023). Although several studies have proposed methods to mitigate hallucination in LLMs (Zhang et al., 2023; Hegselmann et al., 2024), addressing this challenge lies beyond the scope of this paper. Another linguistic challenge in LLM-MA systems involves misinterpreting domain-specific terminology, particularly when a single term carries different meanings across disciplines. This is especially problematic in multidisciplinary projects with overlapping contexts. In drinking water standards, total dissolved solids (TDS) have distinct threshold values compared to agricultural applications. Similarly, total water availability (TWA) may refer to different quantities and temporal scales in hydrology, irrigation management, or infrastructure planning. Besides these issues, generally, LLMs inherently lack embedded physical reasoning capabilities. Their core strength lies in linguistic processing (i. e., generating text based on input prompts) rather than in applying physics-based inference, such as mass balance or flow continuity. As a result, without integration with external models or domain-specific engines, LLMs may produce physically inconsistent outputs. These limitations underscore the importance of *contextual sensitivity* and the need for robust disambiguation mechanisms within LLM-MA systems, particularly when operating in complex and interdisciplinary domains.

Like any engineered system, LLM-MAs are susceptible to performance faults. While these systems are often designed to provide a traceable chain of actions through agent interactions, increasing architectural complexity can significantly hinder fault diagnosis. Multilayered and highly interconnected structures complicate the process of error tracing, especially when faults, such as hallucinations, are masked by compensatory outputs from other agents. For instance, an erroneous inference or analysis by one agent may be unintentionally corrected by another, thus masking the root cause and delaying resolution. Inefficient

scheduling and poor coordination among agents can further exacerbate system performance issues, which can lead to task duplication, delayed responses, or computational overload. Additionally, extended MA dialogue communication sequences introduce processing delays, which are incompatible with time-sensitive operations, such as flood control. Finally, LLM-MAs are computationally demanding (Tang et al., 2025), which requires substantial GPU/CPU resources and memory. In architectures with high complexity or when deployed on hardware-constrained platforms, task execution times can increase substantially. In addition to the notable financial burden of deploying these models locally, this latency, as mentioned before, poses a serious limitation for real-time monitoring and management tasks that demand rapid decision-making/action in water engineering. Table 1 presents a summary of the benefits and challenges associated with different agents' roles across potential fields where LLM-MAs can be applied in water engineering.

4. Recommendations and practical considerations

The flexibility of agents within LLM-MA systems enables the exchange of insights without requiring raw data transfer, thereby supporting data privacy. One effective method for achieving this is *federated learning*, in which agents rendezvous virtually to train a shared model using local data while transmitting only encrypted model updates instead of raw readings or datasets. This decentralized approach preserves data confidentiality while enabling collaborative learning across distributed nodes. Another privacy-preserving technique is the application of differential privacy (DP), which involves injecting statistical noise into aggregated outputs (Arzovs et al., 2025; Li et al., 2025). Applying DP to generated district-level water demand reports allows decision-makers to observe general consumption patterns for planning purposes, while concealing individual factory-level usage data. However, a simpler, rule-based strategy involves constraining agents to operate only on specific subsets of data, masking irrelevant or sensitive information, and deliberately ignoring unrelated datasets. This approach minimizes the risk of *data leakage* while ensuring that agents remain focused on their designated tasks.

Relying solely on agents' outputs within a complex architecture, without visibility into the processes of data acquisition and task

Table 1
Summary of potential applications of LLM-MAs with benefits and challenges of agents.

Application	Agent Roles	Expected Benefits	Challenges
Data analysis and integration	Data retrieval agents, preprocessing agents, sensor/API connectors, RAG-enabled reasoning agents	Real-time data collection from diverse sources (e. g., sensors, APIs, IoT), improved data quality, context-aware analytics	Limited access to high-quality datasets, data privacy risks, potential propagation of input errors or bias
Groundwater and surface water monitoring	Monitoring and verifying agents, quota-enforcing agents	Automated tracking of withdrawals, adaptive allocation between sectors, early anomaly detection	Dependence on reliable sensor networks, data synchronization across scales, cybersecurity vulnerabilities
Urban runoff and flood management	Scenario analysis agents, hydro-model coupling agents, decision-support agents	Dynamic "what-if" simulation, risk assessment, coordination across institutions during floods	Real-time performance under computational load, model interoperability, latency in emergency response, cybersecurity vulnerabilities
Irrigation scheduling and soil-water-crop optimization	Weather-soil agents, predictive reasoning agents, human-in-the-loop agents	Dynamic adjustment of irrigation plans based on rainfall forecasts and soil moisture, improved water-use efficiency	Integration with IoT devices, uncertainty in climate inputs, local infrastructure limitations
Industrial and municipal water quality management	Diagnostic and policy agents, communication agents	Prediction of pollutant transport, compliance checking, generation of actionable reports for operators and regulators	Need for domain-specific calibration
Decision support and policy negotiation	Role-playing and debating agents, stakeholder simulation agents	Multi-perspective evaluation of trade-offs, transparent justification of recommendations, inclusive planning	Socio-economic bias in training data, cross-jurisdictional governance conflicts, explainability requirements
Institutional knowledge management and training	Knowledge-memory agents, onboarding and communication agents	Streamlined internal communication, knowledge transfer, institutional memory building	Resistance of organizations to AI adoption, need for ethical and transparent oversight
Model coupling and optimization	Model-executing agents, reasoning and verifying agents	Integration of hydrological/hydraulic models within one framework	Complex interoperability with GUI-based tools, computational load
Alert and diagnostic systems	Language-interpreting agents, diagnostic agents	Context-rich, semantically meaningful alerts, improved interpretability of system health	Hallucinations or misinterpretation of technical terminology, difficulty in tracing root-cause errors, false alarm

execution within agent loops, may raise concerns regarding the validity and reliability of the results. To address this, cross-validation mechanisms can be embedded into LLM-MA systems through the inclusion of *verifier agents*, which are designed to assess and confirm one another's outputs. This verification layer can help mitigate errors, such as hallucinations or ethical biases, and enhance the overall accuracy of the system. Moreover, incorporating the RAG technique into an LLM-MA system, particularly through enhancements in the retrieval process, can help mitigate hallucinations and produce more accurate and contextually relevant responses (Njeh et al., 2025). Furthermore, incorporating a *debate stage*, in which agents iteratively critique and refine proposed solutions, can lead to more robust and precise outcomes by using diverse reasoning pathways before finalizing decisions. In addition, mitigating ethical concerns within an LLM-MA system requires careful attention to the composition of datasets used for fine-tuning agents. Ensuring that these datasets reflect a balanced representation of all relevant stakeholders is essential to reduce bias and promote equitable outcomes.

The implementation of a *shared language* or ontology is essential for ensuring consistency and interoperability across diverse agents and knowledge domains. Within a given project, this shared framework can be reused, promoting coherence and reducing the need for redefinition across similar tasks or modules. Moreover, ensuring transparency by clearly delineating the task execution process and requiring detailed reporting for high-sensitivity tasks enhances accountability, facilitates auditing, and supports the identification of potential errors or anomalies in LLM-MA systems.

To address the high computational costs and improve adaptability in LLM-MA systems, modular fine-tuning presents a practical and efficient solution. Techniques, such as Low-Rank Adaptation (LoRA), enable parameter-efficient fine-tuning by introducing a small number of trainable parameters into existing models, rather than retraining the entire architecture (Hu et al., 2021). This can reduce resource requirements, while allowing agents to specialize in domain- or task-specific subtasks, such as hydrological forecasting, infrastructure diagnostics, or stakeholder simulation in water engineering.

5. Concluding remarks

LLMs have gained significant attention in recent years, and their application in water engineering has become the subject of growing academic interest. In this paper, LLM-MA systems were examined, with a focus on their potential applications and associated challenges in the context of water engineering. The principal outcomes of the paper are outlined as follows:

- Water engineering has the potential to take advantage of LLM-MA systems as opportunities to enhance core processes, such as data analysis, monitoring, planning, decision-making, and scheduling.
- An LLM-MA system consists of specialized agents, integrated memory, reasoning, adaptive modular architecture, and coordination mechanisms, which make these systems highly flexible and capable of performing various expert-level tasks.
- The advanced language understanding capabilities of LLM-MA systems—derived from LLM characteristics—facilitate effortless and context-aware communication, which enables agents to interpret queries, generate semantically rich outputs, and support tasks such as scenario analysis and multi-stakeholder decision-making in complex water engineering tasks.
- Considering computational demands, as well as issues of transparency, reliability, misinformation, and ethics, the adoption of LLM-MA systems in water engineering requires careful attention and mitigation.

While this paper endeavored to explore the extensive capabilities and real-world potential of adopting LLM-MA systems in water

engineering, it should be emphasized that research on LLM-MA systems within water-related contexts remains in its infancy stages and is actively evolving. Future work should prioritize the development of domain-specific benchmarks, such as event simulation, hydrological/hydraulic model integration, and decision-making practices, to evaluate LLM-MA performance, alongside a focus on actionable solutions to improve model transparency, manage computational limitations, and mitigate ethical concerns such as bias and data privacy. These efforts are essential to fully unlock the potential of LLM-MAs in advancing water engineering, resource management, and decision-support systems.

Ethical approval

The authors declare that all data and materials, as well as software applications or custom codes, are in line with published claims and comply with field standards.

Consent to participate

All authors contributed to the study and agreed to participate in the preparation and submission of this manuscript.

Consent to publish

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Declaration of competing interest

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

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