Embracing Large Language Model (LLM) Technologies in Hydrology Research

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Abstract

The growing complexity of hydrological systems necessitates innovative approaches to data management, knowledge management, and model development. Large Language Models (LLMs) have great potential to revolutionize hydrological research by unifying and advancing these three critical aspects. In this perspective work, we review recent advances and applications of LLMs and exemplify using LLMs in hydrology studies. We demonstrate that LLMs can enhance data accessibility by efficiently extracting and organizing information from diverse sources and formats. Moreover, LLMs facilitate comprehensive knowledge management through knowledge retrieval and synthesis, enabling the integration of various datasets. Furthermore, LLMs, combined with modular development, Chain-of-Thought reasoning, and the intent-based network framework, hold immense promise for transforming physical model development and fostering model unification across scales. We highlight that LLMs are powerful tools for integrating domain hydrological knowledge and advances in machine learning, ultimately serving as an indispensable resource to meet the evolving demands of transdisciplinary hydrological research.

1 The emergence of Large Language Models

Large Language Models (LLMs) provide unified platforms for a wide spectrum of problems and have profoundly accelerated scientific discovery (Zhang et al., 2024a). The release of the web-based chatbot ChatGPT, in 2022 demonstrated their remarkable capabilities, captivating global attention with their understanding, reasoning, memorization, and generalization abilities (Gemini Team et al., 2024; OpenAI et al., 2023; Anthropic PBC, 2024). Since then, the LLM landscape has rapidly evolved, with continuous advancements enhancing their abilities and mitigating potential risks(Dong et al., 2022; Wei et al., 2022; Shinn et al., 2023; Yao et al., 2022; Wei et al., 2021; Lewis et al., 2020; Paranjape et al., 2023; Patil et al., 2023). This growth has fostered a thriving LLM ecosystem (Figure 1)(Foroumandi et al., 2023; Zhu et al., 2023; Halloran et al., 2023), and LLMs are now being leveraged to advance research in diverse scientific domains, including mathematics, physics, biology, chemistry, materials science, etc (Yu et al., 2023; Zhang et al., 2024a; Perkowski et al., 2024; Fang et al., 2023). However, the use of LLM in hydrology remains at an early stage and their potential is largely unexplored. Inspired by recent LLM advancements and their successful applications in other disciplines, we provide a perspective on how to leverage LLMs and their recent advances to better use domain hydrological knowledge in the following three aspects: 1) data management, 2) knowledge management, and 3) physical and machine learning model development (Figure 1).

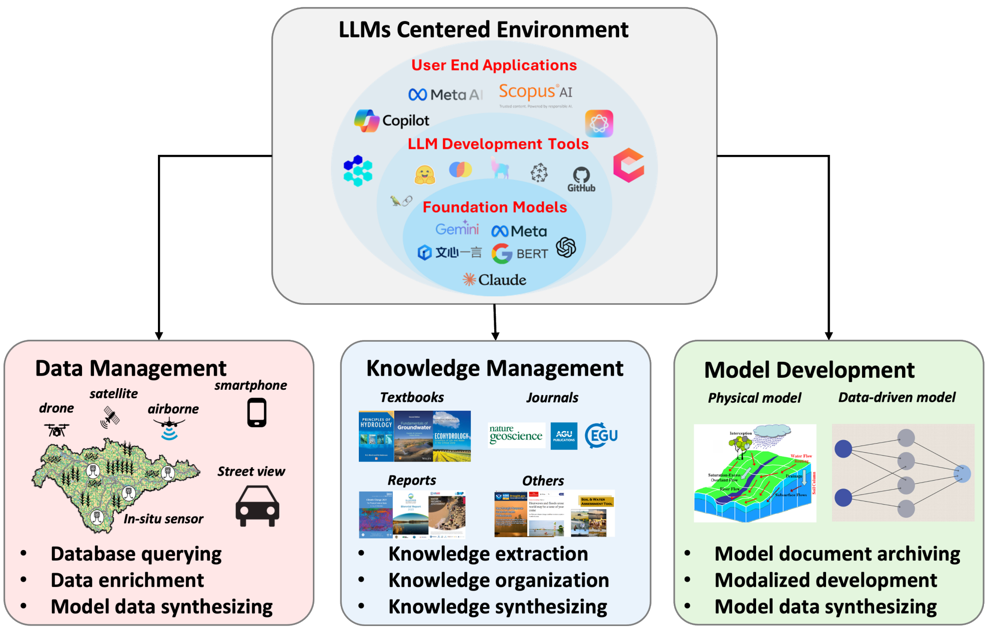

Figure 1: LLMs' application in hydrology data management, knowledge management, and model development. With the development of LLMs, an LLMs-centered environment encompassed by the foundation models, LLM development tools, and applications can be used in hydrology research. In this perspective, we proposed that LLMs could help with hydrology research in three aspects: 1) data management; 2) knowledge management; and 3) model development.

2 The need for LLMs in hydrology

The LLMs-based environment helps to meet the growing demand for hydrology in data management, knowledge management, and model development (Figure 1). With the decadal development, hydrology is now a transdisciplinary science to study the intrinsic relationships between water and humans, nutrients, organisms, and landscape evolution under climate changes across different scales (Wagener et al., 2010; Guo and Lin, 2016; Sivapalan et al., 2014; Brantley et al., 2007; Li et al., 2021; Rangecroft et al., 2021; BlÃűschl and Sivapalan, 1995; Miao et al., 2024; Rodriguez-Iturbe, 2000). This evolution presents significant challenges to traditional labor-intensive approaches in data management, knowledge synthesis, and model development, creating an urgent need for innovative solutions. First, data is central to scientific discovery in hydrology, and data management in hydrology faces several challenges: 1) massive data categories and types (McCabe et al., 2017), 2) spatial and temporal heterogeneity (Zhi et al., 2024), 3) the emergency of unstructured data, especially with the emergence of citizen science (Wang et al., 2018; McCabe et al., 2017). LLMsâĂŹ ability to understand, process, and synthesize information from natural language could revolutionize data management in data querying, synthesizing, and enrichment (Fernandez et al., 2023; Borisov et al., 2022; Tang et al., 2023), which also provides unique opportunities for multi-source, multi-scale, and multi-type data management in hydrology. Further, LLMs provide a unique chance to enable model integration with heterogeneous data (Luo et al., 2023). Second, the interdisciplinary nature of hydrology necessitates efficient knowledge acquisition and management. LLMs, trained on vast text corpora, are promising in text classification, summarization, and knowledge retrieval(Han et al., 2022; Zhang et al., 2024b, 2019; Agrawal et al., 2023). Combined with text embedding and vector databases, LLMs can significantly enhance the efficiency of knowledge searching, synthesis, and sharing, accelerating the pace of scientific discovery (Lewis et al., 2020; Karpukhin et al., 2020; Vaghefi et al., 2023; Lund and Wang, 2023; AI4Science and Quantum, 2023). Third, hydrology models across various spatiotemporal scales are valuable for making predictions, managing water resources, and gaining scientific insights (Addor and Melsen, 2019; BlÃűschl and Sivapalan, 1995). As the expanded hydrology connotation, there is a growing need for new model development, including the development of new physical models and machine learning models, as well as updating existing hydrology models to incorporate new processes and functionalities (i.e., environmental contaminant, greenhouse gas emissions, socioeconomic analysis, etc.) (Vogel et al., 2015; Beven et al., 2015; Li et al., 2021). LLMs could help advance physical model development with embedded hydrological processes and mechanisms and enhance the machine learning modelsâĂŹ prediction power. With newly emergent techniques, especially the autonomous agent framework, LLMs have shown remarkable ability in context understanding and code generation tasks (Wu et al., 2023b; Huang et al., 2023a; Qian et al., 2023; Cognition Labs, 2024), which could assist physical model development by understanding existing knowledge in literature and model technical documents. Besides, the protocols and methods in designing LLMs could inform the development of domain-specific large models with improved machine learning modelsâĂŹ ability, for example, the Pangu-Weather (Schmude et al., 2024; Bi et al., 2023).

3 The use of LLMs in hydrology: data management

Incorporating LLMs into data management will help to harmonize data access, expand data by utilizing unstructured data, and harmonize different data types in hydrology (Fernandez et al., 2023; Vijayan, 2024; Prasad et al., 2024). Firstly, LLMs could revolutionize hydrological data queries. Hydrological data encompasses a diverse range of measurements like streamflow, water levels, precipitation, water quality, groundwater, evapotranspiration, etc., generated by various approaches, for instance, in-situ sensors, samplings, unmanned aerial vehicles (UAV), satellites, personal portable devices, and model reanalysis (McCabe et al., 2017; USGS, 2021; Boryan et al., 2011; Fan et al., 2013; Lin et al., 2019; Sterle et al., 2022; Kratzert et al., 2023; PRISM Climate Group, 2024). Different datasets have distinct structures and are maintained by various groups/organizations, each with unique data accessing and processing protocols. LLMs allow users to query data in natural language for their ability to understand and synthesize both natural languages and programming languages (Fernandez et al., 2023). For instance, LLMs have been used to transfer natural language to SQL queries to access SQL data (Li et al., 2024b, 2023). Besides, LLMs can automatically interpret dataset documentation, including metadata and access protocols (Trummer, 2021). These capabilities enable the automatic code generation and API utilization to retrieve data from different sources based on natural language, eliminating the need for users to navigate disparate systems and formats, as exemplified by using LLMs to access a standard climate dataset PRISM (Case 1 in Box 1). Further, the LLMsâĂŹ ability in language translation facilitates access to data in different languages (Shen et al., 2023b; Zhang et al., 2023), which could reduce bias in research and promote greater inclusivity within the hydrological community.

LLMs are a promising tool for meeting the need for data extraction from unstructured data in hydrology (Castro et al., 2024; Li et al., 2024a). The wide spreading of citizen science in hydrology expands data collection and engages communities in hydrology studies (Silvertown, 2009; Buytaert et al., 2014). New technologies, such as smartphones, mobile applications, street view vehicles, etc, provide rich datasets that largely promote scientific discovery and social management (Wang et al., 2018; Jiang et al., 2024; Yan and Ryu, 2021). Meanwhile, those data are highly unorganized, consisting of free-form text, images, and videos, which poses a significant challenge to data collection and processing. LLMs have demonstrated the ability to extract information via either the âĂIJquestion and answerâĂİ approach or prediction (Vijayan, 2024; Dagdelen et al., 2024; Mai et al., 2024). For instance, LLMs have been used to recognize geographical entities from given texts (Mai et al., 2024) and identify the input variables for a stream water temperature prediction model (Luo et al., 2023). Furthermore, multimodal LLMs can analyze combined data sources, including text, images, and videos, to gain more comprehensive insights (Huang et al., 2023b; Koh et al., 2023; OpenAI, 2024; Wu et al., 2023a). This capability facilitates applications like flood detection from social media images (Twitter/X) and improved land classification using street view imagery (Yan and Ryu, 2021; Wang et al., 2018; de Bruijn et al., 2020; Kadiyala et al., 2024). By harnessing the power of LLMs to extract knowledge from unstructured data, hydrologists can gain a more complete understanding of hydrological processes and improve decision-making in a data-rich world.

4 The use of LLMs in hydrology: knowledge management

LLMs enable efficient knowledge extraction, organization, and synthesizing with the explosion of newly generated knowledge and increasing knowledge requirements for transdisciplinary study. LLMs offer a transformative solution by automating the process of extracting key information from vast amounts of hydrology-related literature and identifying patterns (Cai et al., 2024). Over the decades, the number of hydrological research articles has increased steadily and the growth rate has accelerated since 2018 (Miao et al., 2024), which poses challenges for hydrologists to chase recent advances. Besides, hydrology research extends beyond the mere study of water, which requires hydrologists to expand their knowledge to other disciplines (e.g., geology, soil science, social science, computer science, etc.) (Rangecroft et al., 2021). LLMs enable efficient and comprehensive knowledge extraction. For instance, this is particularly valuable for conducting meta-analyses, which provide comprehensive insights by synthesizing findings across numerous studies (Gurevitch et al., 2018). Traditional expert-based meta-analyses are limited by the manual effort required to review and categorize individual studies. LLMs overcome this bottleneck by automatically extracting relevant metadata from thousands of publications (Gurevitch et al., 2018; Lin et al., 2024; Wang et al., 2022). For example, LLMs have been successfully applied to conduct a large-scale meta-analysis of the geographic patterns and research themes of wildfire research using over 60,000 peer-reviewed papers (Lin et al., 2024). A recent study leveraged LLMs to analyze four decades of hydrological research, revealing the evolution, hot spots, and hot regions in hydrological studies in over 310,000 peer-reviewed papers (Miao et al., 2024). We provided examples of using LLM to extract metadata from published papers (Case 2 in Box1 and Text S2). By automating knowledge extraction and synthesis, LLMs empower hydrologists to efficiently navigate the growing body of research, uncover hidden connections, and accelerate scientific progress.

LLMs are revolutionizing knowledge management by enhancing both the knowledge organization and synthesizing processes in personal databases. Traditional knowledge management systems often require lengthy periods to digest stored knowledge, prompting users to turn to external search engines (O'Leary, 2024; Davenport, 2015). LLMs integrate the knowledge retrieval and synthesis processes to overcome traditional knowledge management shortages (O'Leary, 2024). LLMs can automatically generate structured summaries based on user queries, providing a more flexible and intuitive alternative to rigid keyword-based categorization (Vijayan, 2024; Dagdelen et al., 2024). Specifically, LLMs could leverage the benefits of vector databases in unstructured knowledge storage, providing greater flexibility and allowing for more nuanced understanding and retrieval of information, which overcomes the information loss inherent in structured databases. The Retrieval-Augmented Generation (RAG) framework exemplifies this enhancement (Figure S5) (Lewis et al., 2020). The external knowledge sources are first broken down into smaller, semantically rich snippets which are then indexed and stored within a vector database. Upon receiving a user query, RAG identifies relevant snippets from the database and feeds them to an LLM. The LLM then synthesizes these snippets, generating an informative response grounded in the provided knowledge base. The RAG framework has been used to extract information on climate change based on the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR6)(Vaghefi et al., 2023). We exemplified using RAG in knowledge retrieval and synthesis based on a well-known hydrology book, Groundwater Science (Fitts, 2002) (Case 3 in Box 1). Unlike web-based applications (i.e., ChatGPT), in which the knowledge is implicitly embedded in the parameters, potentially leading to hallucination, lack of domain knowledge, and outdated knowledge (Gao et al., 2023), RAG leverages LLMs' leverages LLMs to process explicit and curated domain-specific knowledge, ensuring the transparency, reliability, and accuracy (Gao et al., 2023). This framework enables highly scalable and personalized knowledge management systems, empowering hydrologists to efficiently access, synthesize, and utilize vast amounts of information.

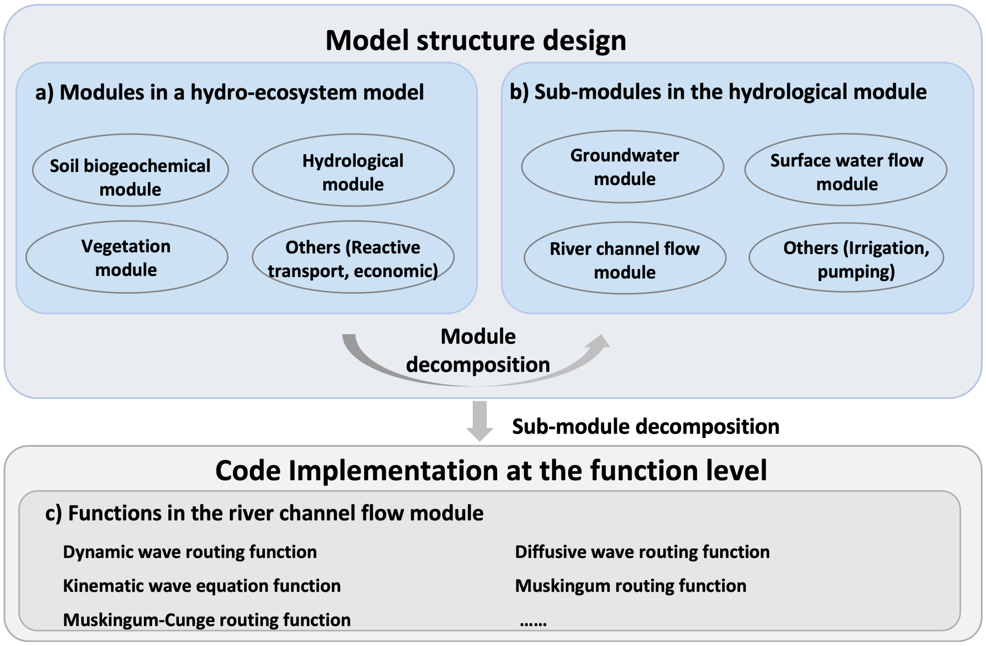

Figure 2: An illustration of modularization development of a hydro-ecosystem model. A complex hydro-ecosystem model could be decomposed into modules that handle different processes. Each module can be further decomposed into sub-modules. The decomposition can be done iteratively until the sub-module is broken down into individual functions, which can be implemented based on existing scientific literature and model documentation.

5 The use of LLMs in hydrology: model development

LLMs can revolutionize the hydro-ecosystem model development to address evolving requirements across various fields. LLMs help to meet the model development needs by empowering hydrologists with comprehensive and accessible knowledge to guide informed model selection and development. As hydrology expands to address pressing environmental challenges, models require new functionalities to capture these complexities. For example, incorporating reactive transport modules is crucial for assessing ecosystem environmental outcomes, and soil biogeochemical modules are essential for understanding greenhouse gas emissions in a changing climate (Li et al., 2021; Li, 2007). However, selecting appropriate modules for new models is often limited by researchers' education and accessibility to models (Addor and Melsen, 2019). By enhancing knowledge management and acquisition, LLMs can expose hydrologists to a broader range of existing models and their underlying theories. This expanded awareness enables more informed decisions regarding model selection, ensuring that new models are built upon the most relevant and robust approaches for addressing specific research questions.

Building complex hydro-ecosystem models, which simulate intricate interactions between the soil, plant, atmosphere, and human activities, is challenging. LLMs, combined with modular design and Chain-of-Thought (CoT) strategy (Wei et al., 2022), offer a possible solution to automatic model implementation. Modular development by breaking down a complex hydro-ecosystem model into smaller sub-modules, each representing a specific module (Voinov et al., 2004; Fenicia et al., 2011), has long been advocated in the hydrology model development (Voinov et al., 2004; Fenicia et al., 2011; Wegner, 1990). Modular development improves code organization, reusability, scalability, and model testing. Similarly, the Chain-of-Thought strategy decomposes complex tasks into simpler and solvable tasks and has been employed in tasks like mathematical reasoning, text-to-video generation, and recommendation systems (Wei et al., 2022; Jimenez et al., 2023; Shen et al., 2023c; He et al., 2023). By combining modular development with CoT reasoning, LLMs can automate the construction of complex hydro-ecosystem models. A complex model can be decomposed into modules representing specific components, such as hydrology, biogeochemistry, vegetation dynamics, reactive transport, etc. (Figure 2). Each module can be further decomposed into sub-modules. The decomposition can be done iteratively until the sub-module is broken down into individual functions, often well-documented in scientific literature and model documentation (Robertson et al., 2019; Lawrence et al., 2019; Seibert and Vis, 2012). Then, LLMs can leverage their code generation and mathematical reasoning abilities (Wu et al., 2023b; Cognition Labs, 2024; Huang et al., 2023a; Romera-Paredes et al., 2024) to automatically generate code for each function. We show the utilization of GPT4 in constructing a simple hydrology model, the Hydrologiska ByrÃěns Vattenbalansavdelning (HBV) model (Case 4 in Box 1). We first used GPT4 to outline the model structure based on the HBV document (Seibert and Vis, 2012) under human supervision. Then, the core modules (i.e., snow module, soil moisture module, groundwater module, and discharge module) were implemented individually, with LLMs generating and refining the pseudocode and Python codes. The LLM-built model was validated with the pre-calibrated parameter and corresponding input. While challenges remain in scaling this approach to more complex hydro-ecosystem models, the combination of LLMs, modular design, and CoT reasoning offers a promising pathway toward automating and democratizing model development in hydrology.

LLMs provide an alternative way to build a versatile modeling framework targeting various hydrological problems across different scales, and accommodating spatiotemporally heterogeneous input data Figure 3. As the best mechanism representation in a hydrology model generally varies with the scales and depends on the targeted questions (BlÃűschl and Sivapalan, 1995), a perfect model across all scales will be not feasible. Using modular combinations from a model collection to address specific questions at specific scales is a possible solution for versatile model development (Leavesley et al., 2002; Branger et al., 2010). This mimics network configuration for specific tasks in computer networks, which involves setting up policies, controls, and flows in a system of interconnected physical and virtual devices (Leivadeas and Falkner, 2023). The intent-based network is a technology for automatically configuring networks based on user objectives. LLMs have been used to help translate user intent into actionable network configurations to fulfill that intent (Ding, 2024; Mekrache et al., 2024). Ideally, in a versatile hydrological modeling framework, LLMs can first understand the âĂIJintentâĂİ of the user request, such as identifying specific hydrological problems and corresponding spatial and temporal scales, described in natural languages. Then, LLMs will choose the appropriate model or subset of models based on the identified problem and scales. Furthermore, LLMs will be used to streamline data flow between different models with their ability in data curation to restructure the structured output from one model to another. Besides, the frequency and the availability of observed hydrological data usually vary across space (Zhi et al., 2024; Luo et al., 2023), which also poses great challenges to building a general model to digest inconsistent data on different periods and locations. LLMs can address this by harmonizing input data, which has been demonstrated in building a global water temperature model that integrates data with varying temporal resolutions (Luo et al., 2023). We acknowledge that achieving such a versatile modeling framework presents significant challenges. For instance, software engineering efforts are required to standardize interfaces for poorly structured models and improve documentation for existing ones. Nevertheless, with the modular model development approach mentioned earlier, we argue that LLMs hold promise for realizing a versatile hydrological modeling framework in the future.

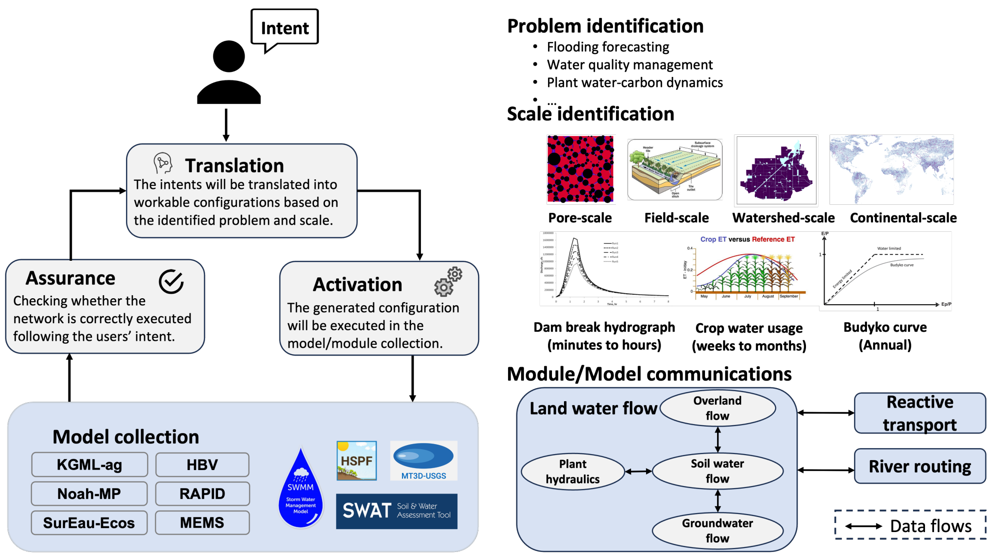

Figure 3: Intent-based network in a general hydrology model framework. The intent is the user-defined hydrology tasks in natural languages, reflecting their expected outcomes from the integrated model systems. Intent translation is the process of translating human intent in natural language into the network configuration. Intent activation is the process of applying the translated network configuration across the network. Intent assurance is the process of checking whether the state/outcome of the network satisfies human intent. In a hydrological intent-based network, the LLMs could help to identify the hydrological problem, identify spatial and temporal scale from the human intent natural language, select a subset of models/modules from a collection of a model collection, and define the communication rules. The models in the model collection can be both machine learning models and physical models targeting various problems/processes.

Leveraging the above-mentioned approaches, LLMs can help lower the barriers of extensive domain knowledge and complex numerical implementation and thus democratize physical model development. Further, LLMs can facilitate the integration of cutting-edge techniques from high-performance computing into hydrological modeling to close the gaps. For example, LLMs can help integrate GPU-based acceleration techniques (e.g., CUDA and differential modeling) into physical models, enabling real-time forecasting (Buttinger-Kreuzhuber et al., 2022; Shen et al., 2023a). Meanwhile, the design and methods in designing LLMs could inform the development of domain-specific large models with improved machine learning modelsâĂŹ ability (Bi et al., 2023). By embracing LLMs, we can envision a new era of hydrological modeling characterized by automation, knowledge accessibility, and the seamless integration of diverse modeling paradigms. This transformation will empower hydrologists to tackle increasingly complex environmental challenges and advance our understanding of Earth's critical water systems. Recently, with the advance of artificial intelligence (AI) techniques, efforts have been made to leverage AI and physical processes understanding in hydrology modeling. For instance, knowledge-guided machine learning (KGML), differential modeling, and explainable artificial intelligence (XAI) are the promising ones with different approaches in combining physics and machine learning (Ribeiro et al., 2016; Tripathy and Mishra, 2024; Shen et al., 2023a). LLMs provide an alternative to integrate machine learning and AI in physical modeling in two ways, explicitly digesting well-documented physical knowledge and using physical knowledge implicitly embedded in both machine learning and physical models.

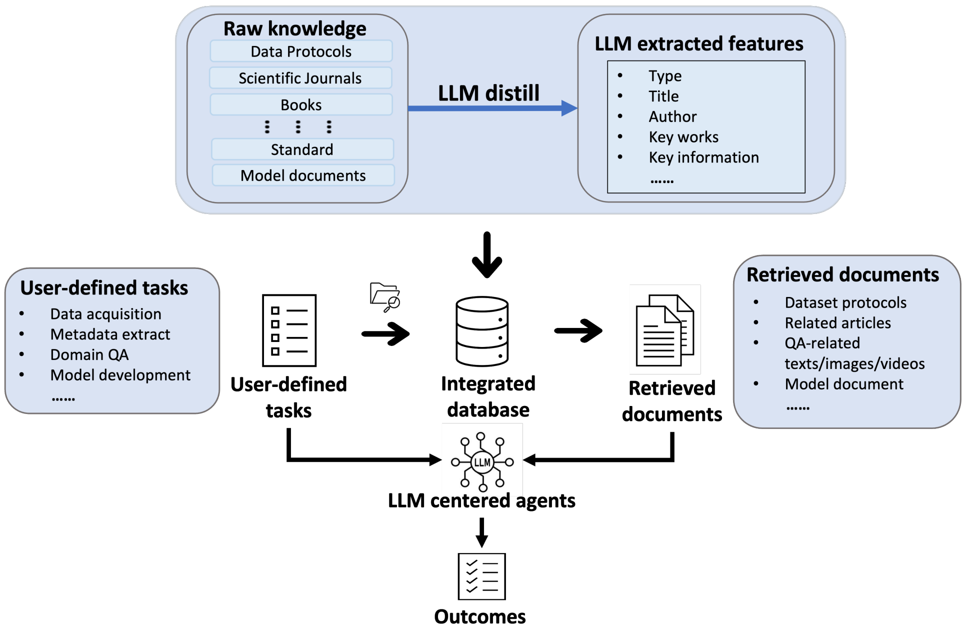

Figure 4: A unified LLM framework for hydrology research. In the unified framework, the LLMs have two tasks, extracting key information from raw knowledge pieces and reacting to user-defined tasks based on task-relevant documents. In this framework, the system takes the tasks from a user. Then, a retriever will retrieve relevant documents from an integrated database. The integrated database consists of multi-source and multi-media raw knowledge pieces, and LLMs are employed to extract key features from each raw knowledge piece to facilitate knowledge management. Last, LLMs-centered agents will finish the task by referring to the retrieved documents.

6 Move forward along with LLMs in hydrology

In this perspective, we argue that LLMs have shown large potential to transform data management, accelerate knowledge synthesis, and automate key aspects of model development. The three areas (i.e., data management, knowledge synthesis, and model development) can be harmonized in an integrated LLM-based framework (Figure 4). In the integrated framework, multi-source and multi-media knowledge pieces are stored and managed in an integrated database. Relevant documents are retrieved based on the user-defined tasks, and the LLMs-centered agents will execute the tasks informed by document retrieval results. With this integrated framework, the LLMs can synthesize knowledge in dataset protocols, research articles, and model documents in data acquisition, and conduct metadata extraction and model development tasks in a logical way. LLMs provide new opportunities to unify AI and domain knowledge and enable using knowledge in various forms to guide new development, such as texts, equations, and even the knowledge embedded in existing machine learning and physical models. Further, using LLMs could potentially change the way hydrologists identify problems and conduct research. For instance, leveraging the intent-based network framework might accelerate the hydrology research transition to a more problem-driven and mission-driven way, freeing productivity in hydrology research. In return, the changed perception will further facilitate the use of LLMs in hydrology research (Griffin et al., 2024; Office of Water Prediction, NOAA, 2021).

However, realizing the full potential of LLMs in this field requires a concerted effort from both the hydrology and computer science communities. Hydrology itself is diverse in different sub-areas and poses different requirements for the LLMsâĂŹ capability (BlÃűschl and Sivapalan, 1995). For instance, the equations in the hydrology model vary from the mass balance centered bucket models to the complex 3D hydrodynamics models with Saint-Venant's equation and RichardsâĂŹ equation, posing different requirements to LLMs (Dwivedi et al., 2021; Seibert and Vis, 2012). Therefore, research and comprehensive testing are essential to fully understand and utilize LLMs' capabilities across these different complexities and scales to meet various demands. Hydrologists are critical in guiding LLM development for successful integration into this domain. Articulating the scientific questions clearly by hydrologists is essential for relevant and impactful LLM-based applications. Hydrologists must actively guide the development and application of LLMs to ensure they align with hydrological principles and best practices, including defining appropriate model structures, evaluation metrics, and ethical considerations. Also, it is critical to develop and share well-documented, domain-specific datasets for training and evaluating LLMs for hydrological applications under the supervision of hydrologists to ensure robust outcomes with accurate hydrological concept understanding (Sun et al., 2024; Ge et al., 2023; Li et al., 2024b). This includes expanding datasets beyond numerical data to incorporate diverse forms of information, such as text, images, and videos, to leverage the full potential of LLMs, which are still missing in hydrology. Openly sharing code, data, and methodologies will accelerate the development and adoption of LLM-based tools within the hydrology community. This includes advocating for using machine-readable formats (e.g., HTML, LaTeX, Markdown) when documenting data, knowledge, and models to facilitate information extraction and knowledge discovery (Li et al., 2024b). For instance, the EGU publish group has provided HTML files with PDFs. With those contributions, we could foresee a growing, high-quality dataset, which would help finetune LLMs or even build new hydrology LLMs, providing a means to mitigate hallucination and increase professionalism.

The discussion in this perspective much lies on LLMsâĂŹ reasoning ability in context understanding and language generation, including programming language. However, their memorizing ability is like a rose among thorns, beautiful but dangerous. No one could read and memorize so much stuff as a LLM model. Meanwhile, the responses based on their implicit knowledge can be misleading (e.g., hallucinations and bias) (Griffin et al., 2024; Sallam, 2023; van Dis et al., 2023). The development of LLMs continues, and each new version consistently impresses and excites us. We hope that as LLMs evolve, these concerns can be mitigated and ultimately diminished (Griffin et al., 2024). LLMs are still in their infancy, and our journey with them in hydrology has just begun.

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