Hydrological Perspectives on Integrated, Coordinated, Open, Networked (ICON) Science

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Key Points:

- ICON framework can strengthen inclusive, equitable, and accessible science in the hydrological community.
- Hydrology-oriented community science bridges the gap between the public and scientists in understanding hydrological data.
- ICON enables integrating big data and machine learning for improved predictivity of multiscale hydrological modeling.

Abstract

This article comprises three independent commentaries about the state of ICON principles in hydrology and discusses the opportunities and challenges of adopting them. Each commentary focuses on a different perspective as follows: (i) field, experimental, remote sensing, and real-time data research and application (**Section 1**); (ii) Inclusive, equitable, and accessible science: Involvement, challenges, and support of early career, marginalized racial groups, women, LGBTQ+, and/or disabled researchers (**Section 2**); and (iii) an ICON perspective on machine learning for multiscale hydrological modeling (**Section 3**). Hydrologists depend on data monitoring, analyses, and simulations from these diverse scientific disciplines to ensure safe, sufficient, and equal water distribution. These hydrologic data come from but are not limited to primary (in-situ: lab, plots, and field experiments) and secondary sources (ex-situ: remote sensing, UAVs, hydrologic models) that are typically openly available and discoverable. Hydrology-oriented organizations have pushed our community to increase coordination of the protocols for generating data and sharing model platforms. In addition, networking at all levels has emerged with an invigorated effort to activate community science efforts that complement conventional data collection methods. With increasing amounts of data, it has become difficult to decipher various complex hydrologic processes. However, machine learning, a branch of artificial intelligence, provides accurate and faster alternatives to understand different biogeochemical and hydrological processes better. Diversity, equity, and inclusivity are essential in terms of outreach and integration of peoples with historically marginalized identities into this professional discipline and respecting and supporting the local environmental knowledge of water users.

Keywords: Hydrology, machine learning, community science, ICON principles, diversity, stakeholders

Index terms: Estimation and forecasting, Geographic Information Systems (GIS), Modeling, Monitoring networks, Time series analysis

Plain Language Summary:

The ICON principles support scientists, researchers, and community leaders in understanding and solving local and global challenges. Such a perspective helps integrate remote sensing, numerical modeling and encourages digital concepts, including machine learning for multiscale modeling and monitoring. Such integration is vital to understanding simple to complex hydrological processes at different temporal and spatial scales. Hydrology with community science and coordination with stakeholders help establish a network where research, education, and collaboration become easy and accessible. As a result, the availability of open data for sustainable water management is increasing. The ICON framework promotes innovation, equality, diversity, inclusion, and open access research in the discipline of hydrology that involves and supports early career, marginalized racial groups, women, LGBTQ+, and/or disabled researchers. Here, we discuss the ICON perspective in the discipline of hydrology.

1. Introduction

Integrated, Coordinated, Open, Networked (ICON) science aims to improve synthesis, availability, applicability, reliability and create open transferable knowledge. This article belongs to a collection of commentaries spanning geoscience on the state and future of ICON science (Goldman et al., 2021).

1. Field, experimental, remote sensing, and real-time data research and application

The elements of ICON have become seamlessly interwoven within data collection and sharing practices in hydrology. Studying different hydrological processes requires knowledge of multiple fields such as atmospheric process, cryosphere science, ecohydrology, biogeochemistry, geomorphology, and land-based interactions. Establishing a depth of community knowledge requires purposeful interactions across different disciplines. Environmental observatory platforms such as the National Ecological Observatory Network (NEON), Long Term Ecological or Agricultural Research (LTER, LTAR) programs, Critical Zone Research Cluster Network (CZCN), Science Focus Areas (SFAs), and their international counterparts (iLTER, OZCAR, TERENO) in places such as Europe and China offer a coordinated effort to measure most of the components of the water cycle and their response to changes in climate and the carbon cycles over time (Weintraub et al., 2019) at the watershed scale. Individually these sites offer local understanding, but together their power increases understanding of the hydrologic response to variability (Wlostowski et al., 2021) at regional and continental scales and, thus, aid our process-based understanding representing hydrology in models (Baatz et al., 2018).

The data collected by these observatories include primary quantitative analysis from laboratory experiments, plot-scale, and field-sites monitoring, or secondary simulated outputs from watershed modeling. Once generated, these data are openly shared as a result of funding agencies, publishers, and the public pushing for discoverable data where results can be reproduced. CUASHI's HydroShare is one example of an integrative platform where hydrology data, models, and code are shared.

Data sharing is critical (e.g., Li et al., 2021) and requires coordinated networked efforts to produce field and lab-based measurements that can help parameterize models and then numerical simulation effort that can help direct field and lab-based monitoring and experiments. One such example is the evolution of mobile or field-based labs (e.g., River Lab; Floury et al., 2017); no longer confined to university infrastructure, laboratory data can now be generated in the field using instruments that employ colorimetry, chromatography, and spectroscopy techniques to provide high temporal resolution measurements of ion and nutrient concentrations allowing for rapid assessment of hydrological processes. Similarly, the development of sensors that can monitor biogeochemical conditions (e.g., nitrate, oxygen, carbon dioxide concentrations) has increased our power to understand real-time hydrologic data from plot and watershed scales. The recent increase in Unmanned Aerial Systems (UASs), also called drones, has shown that UASs are an effective tool to monitor hydrological processes at a much finer scale and resolution and facilitate water resources planning and management. UASs are a rapid and cost-effective technique to characterize better, monitor, and model hydrological processes than satellite-based remote sensing and in-situ measurements. The combination of sensor, lab, and remotely sensed data provide the platform by which watershed models can be derived and provide secondary hydrologic data. However, uncertainty and bias must be accounted for in modeling outputs. The simulated values provide less expensive, timely, and over the vast landscape and for hundreds of years together.

Besides primary and secondary data sources in hydrology, community science can complement traditional scientific data collection methods. Actively engaging communities with scientists not only empowers communities and their voice but establishes a network where research, education, and collaboration result in continuous developments in technology, data processing, and communication (Allen and Berghuijs, 2018). Networking communities with experts are crucial, and open data is necessary, especially when sustainable water management and resources require effective and efficient hydrological monitoring (Buytaert et al., 2014; Njue et al., 2019) and input from stakeholders, leaders, and scientists.

. Community science bridges the gap between the public and scientists, facilitating data flow and knowledge, yet there are barriers to realizing ICON principles. Though combining mobile applications and inexpensive equipment, communities are equipped to document and collect data (Buytaert et al., 2014; Njue et al., 2019; Allen and Berghuijs, 2018). These tools face funding and policy barriers. Promising examples of hydrology-oriented community science initiatives include American Geophysical Union (AGU) Thriving Earth Exchange and Crowd Hydrology. These examples are coordinated using similar structure models, where projects are developed and driven by communities. Through AGU Thriving Earth Exchange, communities are integrated with scientists to form a network to develop and complete a research project designed by the community. Crowd Hydrology is community-led and driven, where they choose to monitor a particular water system and report data through the Crowd Hydrology website, resulting in a network of valid open data.

With public solicitation of water quality data to be incorporated in these reports, communities have the advantage of monitoring their local water system. The limitation is the requirement to follow standards or universal methods (Buytaert et al., 2014; Njue et al., 2019). Other limitations include lack of communication between scientists, political leaders, and communities (; Njue et al., 2019; Allen and Berghuijs, 2018), given that community science emerges at the center of political activism and volunteering. There are also differences in motivation, with community involvement driven by hobbies, environmental concerns, curiosity, and/or livelihoods (Buytaert et al., 2014; Njue et al., 2019). However, increasing opportunities for communities to be active participants in water studies acts as motivation, builds trust between scientists and policymakers, and expands data available to hydrologists to incorporate in other research projects (Buytaert et al., 2014; Njue et al., 2019).

In conclusion, either primary or secondary, hydrologic data is required to unveil the hydrologic processes and promote water resources management. Indeed, their availability is increasing due to open, FAIR, and shared science principles (Cudennec et al., 2020). This has proven to be a boom for data-scarce regions like Kenya, Ghana, Uganda, and others. With increased interdisciplinary research programs and worldwide collaborative networks, different organizations across the globe are working together to collect, evaluate, and share the data via open-source cloud networking. Such actions will help study the impact of natural and anthropogenic factors, including climate change, floods, droughts, sea-level rise, and saltwater intrusion. The gained data are essential to put in mitigation measures or help pre-preparedness to counteract any extreme climatic events and their impact on the community.

1. An ICON perspective on machine learning for multi-scale hydrological modeling

Machine learning (ML) is a branch of artificial intelligence that identifies patterns and generates predictions without explicitly programming (Yao and Liu, 2014). Within the field of hydrology, ML models have been used in rainfall-runoff modeling (Adnan et al., 2021; Chang and Chen, 2018), streamflow forecasting (; Boucher et al., 2020), water quality assessment (Bui et al., 2020), flood forecasting (Mosavi et al., 2018), and soil moisture estimations (Ahmad et al., 2010; Senanayake et al., 2021). Below, we highlighted the characteristics of ML models that make them well suited for incorporating the ICON principles.

ML typically requires large input datasets to train the model accurately (i.e., determine a predictive model from input data). Many ML models leverage data from large, existing, open-access datasets such as the United States Geological Survey, National Water Information System (NWIS), the International Soil Moisture Network (ISMN), the Catchment Attributes and Meteorological dataset (CAMELS), and the National Ecological Observatory Network (NEON). The ability to incorporate data from multiple sources, i.e., "networking of networks", can significantly improve the accuracy and generality of ML models. These datasets are integrated, incorporating multiple types of data (e.g., rainfall, soil moisture, stream discharge) and facilitating physics-informed ML (PIML) models, which are process-based and typically more accurate than an ML approach that does not rely on training data (i.e., unsupervised learning). Despite the rapid advancement of ML modeling in hydrology, the following challenges persist. Firstly, the open-accessed dataset and observations in hydrology tend to be regionally and temporally imbalanced, which hinders multiscale integration in hydrological research (Shen et al., 2018). For instance, while river discharge observations are relatively dense in the United States and Europe, such data are sparse in many other parts of the world, especially in Africa and Latin America (*e.g.*, Global Runoff Data Centre, GDRC). Secondly, as hydrologic ML models represent different processes at different scales, they require the design of protocols for data and model sharing networks to provide universal accessibility without violating intellectual property regulations.

Regardless of the limitations, the ML community is open to addressing these challenges using ICON principles. The PIML approach is increasingly getting more attention to integrate process-based hydrological models with ML techniques. Recent studies have shown that adding physical constraints to ML models improves their simulation performance (Yang et al., 2019; Kratzert et al., 2019a, b; Fan et al., 2020). Besides the hydrological observation data, other observation systems, such as FLUXNet (Jung et al., 2019; Nearing et al., 2018) and earth observation data generated by NASA (Kwon et al., 2019), provide integrated, coordinated, open, and networkable observations that can also be useful in hydrologic machine learning models, albeit with reduced spatial and temporal resolution (Nearing et al., 2021).

Furthermore, along with ML capability enhancement, hardware innovations such as edge computing can be used to generate large datasets at remote sites for live ML applications (Vesselinov et al., 2019; Mudunuru et al., 2021). The recent proliferation of cloud-based storage and computing services (Ahmad & Khan, 2015; Diaby & Rad, 2017; Haris & Khan, 2018) has substantially lowered entry barriers to processing large datasets from laptops. Now, researchers no longer require access to an on-site high-performance supercomputer as cloud-based technologies are more flexible and reasonably economical. Moreover, they significantly enhance collaboration within research teams and share data and code resources publicly.

To further strengthen the incorporation of ICON principles in ML, a potential action would be to coordinate (**C**) an earth digital twin consortium with the ultimate mission of developing an integrated (I) virtual representation of the earth system through interconnected models and data data-model communication protocols. Such a consortium could be established within the AGU network (N) and managed similarly to an existing digital twin consortium for aerospace and natural resources (www.digitaltwinconsortium.org).

1. Inclusive, equitable, and accessible science: Involvement, challenges, and support of early career, marginalized racial groups, women, LGBTQ+, and/or disabled researchers

This section briefly discusses challenges and opportunities within the ICON framework to advance hydrology justice, equity, diversity, and inclusion principles. The perspectives shared here are gleaned from our experiences and interactions with marginalized communities and do not intend to be comprehensive and may not suit every community and their unique needs.

Water is critical to the ecological and social well-being of communities outside of “hydrologists”, and by lacking diversity, we cannot serve equity or inclusively. We must foster inclusion and justice in terms of outreach and integration of peoples with historically marginalized identities into this professional discipline and also respect and support the local environmental knowledge of water users.

A lack of diversity within hydrologic sciences and engineering has 1) led to serving communities inequitably and ignoring historical injustices. For example, environmental justice in pollution (Hajat et al., 2015; Robison et al., 2018), disproportionate climate change/severe weather impacts to low-income minority communities (Parvin et al., 2016; Adeola and Picou, 2017), sexism in water resource management (CDC; UNICEF) and global south weather forecasts are underserved due to models being focused on Europe/United States, as well as a lack of ground data (Vaughan et al., 2019; World Bank). Moreover, 2) leads to less innovation in science (Phillips, 2014; “Science benefits from diversity”, 2018).

We believe that increasing inclusiveness, equitability, and accessible science in hydrology will improve both scenarios. While increasing innovation in science is essential, impacting underserved communities is imperative and will radically change human health and well-being across the globe.

Over the past several years, the development of committees and reading lists in our field has become a typical "first step" to address inclusiveness, equitability, and accessible science (Byrnes et al., 2020; Garousi-Nejd and Byrnes, 2020). This step, while meaningful, is not enough: actionable steps must be taken, and culture must change throughout our hydrological community before policy changes can be effective. We share some emerging inclusiveness, equitability, and accessible science practices in hydrology and ideas that we hope can foster an equity lens throughout water-related practices using the ICON framework.

4.1 Community-led science and environmental justice practices

It is important to build equitable social **networks (N)** and meaningfully engage marginalized communities (including but not limited to interrelated dimensions of race, ethnicity, gender, gender expression, disability, sexuality, nationality, and class) along with government agencies, industry, academia, and citizens (Kirkness and Barnhardt, 2001). These groups need to **coordinate (C)** and build mutual trust to develop innovative approaches to responding to the ICON framework's hydrological issues.

Open (O) data policy must, along with supporting data infrastructures, more comprehensively and consistently address the gaps in JEDI regarding how information and knowledge are distributed and acknowledged. For example, programs and strategies to decolonize science such as the Global Water Futures Program and indigenous community water research bring together researchers across all levels to enhance coordination and broaden impacts with the intent to accelerate a positive paradigm culture shift (GWF, 2018). Indigenous peoples must be responsibly engaged in the scientific processes at all stages, which includes ownership of data and knowledge and having a say in how/when it gets shared (Gardiner, 2011; Lovett et al., 2019; Woodbury et al., 2019; Wong et al., 2020; Cohen and Livingstone, 2021; Goucher et al., 2021). Policies such as Ownership, Control, Access, and Possession, Collective Benefit, Authority to Control, Responsibility, and Ethics and Findability, Accessibility, Interoperability, and Reuse principles can help hydrologists ethically develop protocols relating to the collection, use, and sharing of community data (Wilkinson et al., 2016; Mecredy et al., 2018; Carroll et al., 2020).

4.2 Inclusive workplaces

In addition to hydrologists developing more just practices when engaging with community scientists and non-scientists, we must thoroughly self-evaluate our daily practices and structures to attain inclusiveness, equitability, and accessible science and ICON goals more effectively. Here we share ideas for transferrable best practices through several stages of hydrologist training.

Broad outreach in primary and secondary education 1) must be done to spur interest from diverse future hydrologists and 2) must emphasize at the *beginning* of interaction that these are professional careers with a strong component of service and societal relevance.

We must prioritize how water and the study of water relates to and **integrates (I)** with other disciplines and connects with society and living with the land. Hydrologists can learn from and work collaboratively with folks from other disciplines and walks of life to understand water and hydrologic systems more holistically. We must create a workplace culture with ingrained inclusiveness, equitability, and accessible science values. Identity (*e.g.*, race, gender, sexual orientation), work distribution (Liu et al., 2019; Domingo et al., 2020), and field safety must be critically viewed to accommodate needs and combat stereotypes (Viglione, 2020; Demery and Pipkin, 2021). Hydrologists should institute iterative action plans and policies based on more generalized recommendations (Chaudhary and Berhe, 2020; Ali et al., 2021). Leadership training and opportunities for career growth must be equitably distributed, considering historical biases that have permeated the disciplines (Leverage, 2017). We should aim for diverse and equitable representation at all levels to achieve the goal of justly serving our water-using communities.

Networked (N) science must have justice, service, inclusiveness, equitability, accessible science, and social context is woven clearly and continuously into hydrologic studies. Hydrologists must ask the following four questions in every step of the scientific process and contextualize these with follow-up questions to ensure that they are answered with transparent and actionable inclusiveness, equitability, and accessible science processes.

1. "Who is doing the hydrology?"

How will marginalized communities be involved? Will they have the same "power and privileges" as non-marginalized communities? Who will own the scholarly outputs (*e.g.*, data, grant proposals)?

1. "Who uses the water?"

If marginalized communities are main water users, will they (or their communities) sustain or use the hydrology knowledge research/work effectively (*e.g.*, beyond the end of a project)?

1. "Who benefits from this activity?"

Will marginalized communities get appropriate and meaningful attribution for their contribution? Will resources and infrastructure be available/sustained to marginalized communities after a project ends?

1. "Why?"

What is the purpose of this work, and how will marginalized communities benefit and be supported?

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