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

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Key Points:

- ICON framework helps build more maneuverable and accountable hydrology simulations.
- Open and networking Hydrology-oriented community science bridges the gap between the public and scientists in understanding hydrological data.
- ICON principles can strengthen inclusive, equitable, and accessible science in the hydrological community.

Abstract

Hydrologic sciences depend on data monitoring, analyses, and simulations of hydrologic processes to ensure safe, sufficient, and equal water distribution. These hydrologic data come from but are not limited to primary (lab, plot, and field experiments) and secondary sources (remote sensing, UAVs, hydrologic models) that typically follow FAIR Principles (FAIR Principles - GO FAIR (go-fair.org)). Easy availability of FAIR data has become possible because the hydrology-oriented organizations have pushed the 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. However, it has become difficult to decipher various complex hydrologic processes with increasing data. Machine learning, a branch of artificial intelligence, provide more accurate and faster alternatives to better understand different hydrological processes. The Integrated, Coordinated, Open, Networked (ICONs) framework provides a pathway for water users to include and respect diversity, equity, and inclusivity. In addition, ICONs support the integration of peoples with historically marginalized identities into this professional discipline of water sciences. This article comprises three independent commentaries about the state of ICON principles in hydrology and discusses the opportunities and challenges of adopting them.

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

Index terms: Integrated science, community-driven data sourcing, diversity, and inclusiveness, water for all

Plain Language Summary:

The ICON perspective in the discipline of hydrological sciences helps integrate remote sensing, numerical modeling, data science, and different digital concepts, including machine learning to understand simple to complex hydrological processes at diverse temporal and spatial scales. Other benefits of incorporating the ICON framework include but are not limited to open, shareable, and easy to interpret, accurate, and timely generated monitored/observed or/and simulated water sciences information. Moreover, participation of the community and stakeholders help establish a network where research, education, and collaboration become easy and accessible. Besides, 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.

1. Introduction

This article discusses the ICON principles in hydrology with respect to: field, experimental, remote sensing, and real-time data research and application (Section 1.1); Machine learning for multiscale hydrological modeling (Section 1.2); and Inclusive, equitable, and accessible science: Involvement, challenges, and support of early career, marginalized racial groups, women, LGBTQ+, and/or disabled researchers (Section 1.3); The choice of the three sections is based on a collection of commentaries spanning geoscience on the state and future of ICON science (Goldman et al., 2021a, b).

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

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 **(C)** 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 when integrated **(I),** 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 that is represented in hydrologic 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 shared openly **(O)** due to funding agencies, publishers, and the public pushing for discoverable data. 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 integrated **(I)**, coordinated **(C),** open **(O),** and networked **(N)** efforts. With ICON-driven hydrology studies, the field and lab-based measurements can be generated in real-time and help robustly parameterize models. 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 and thus 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 agrochemicals such as cations, anions, heavy metals, and nutrient concentrations allowing for rapid assessment of hydrological processes. Other examples include developing and applying sensors that can monitor biogeochemical conditions (e.g., nitrate, phosphate, carbon dioxide concentrations), which has increased our power to understand real-time hydrologic data from plots and watershed scales. The recent progress in Unmanned Aerial Systems (UASs), also called drones, has shown that UASs are an effective tool to monitor real-time hydrological processes at a much bigger scale and finer resolution and facilitate water resources planning and management. UASs are a rapid and cost-effective technique to characterize, monitor, and model hydrological processes better than satellite-based remote sensing and in-situ measurements. The combination of sensor, lab, and remotely sensed data provide the coordinated platform for the watershed models simulations and generated secondary hydrologic data. However, uncertainty and bias must be accounted for in modeling outputs.

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 (Maheshwari et al., 2014; Allen and Berghuijs, 2018; Chew et al., 2019). 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 fills the gap between scientists and the public, facilitating data flow and knowledge, yet there are barriers to realizing ICON principles. By 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; Chew et al., 2019). These tools face funding and policy barriers. 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 communities develop and drive projects. Through AGU Thriving Earth Exchange, communities are integrated with scientists to form a network to build 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 limited 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; Maheshwari 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 availability 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 (Oyebande et al., 2009). 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, saltwater intrusion, and dam construction and decommissioning. 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 explicit programming (Yao and Liu, 2014). In 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). Here, we highlight the characteristics of ML models that make them well-suited for incorporating ICON principles.

ML typically requires large input datasets to train a model accurately (i.e., derive a surrogate model from input data). Many ML models leverage data from large, existing, open-access datasets such as the United States Geological Survey (USGS), 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., "network of networks," can significantly improve the accuracy of ML models, allowing them to be applicable across a broader range of applications. Despite the rapid advancement of ML modeling in hydrology, some challenges persist. Firstly, open-source datasets and observations in hydrology are often regionally and temporally imbalanced, hindering multiscale integration in hydrological research (Shen et al., 2018). For instance, while river discharge observations are relatively dense in most of 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 - BfG - The GRDC (bafg.de)). 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 rights and regulations.

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, cloud-based technologies have enhanced ML capabilities, with an easier way to share large datasets at remote sites for live ML applications (Vesselinov et al., 2019; Mudunuru et al., 2021). The advantage is easy access to cloud-based storage and computing services (Ahmad & Khan, 2015; Diaby & Rad, 2017; Haris & Khan, 2018) for the public sharing of data and code resources and improves science in a coordinated and networked manner.

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 open **(O)** 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 communities' ecological and social well-being outside of "hydrologists." We cannot serve equity or inclusivity without diversity. We must foster inclusion and justice in terms of outreach and integrating peoples with historically marginalized identities into this professional discipline and respect and support water users' local environmental knowledge.

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) it leads to less innovation in science (Phillips, 2014; "Science benefits from diversity," 2018). 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.

1. **Community-led science and environmental justice practices**

It is essential 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 justice, equity, diversity, and inclusion principles 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 (Maheshwari et al., 2014; Wilkinson et al., 2016; Mecredy et al., 2018; Carroll et al., 2020).

1. **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. Herein, 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 vital 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. Hydrologists can learn from and work collaboratively with people from different 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) hydrologic science must have justice, service, inclusiveness, equitability, accessible science, and social context, woven clearly and continuously throughout. 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)?

2. "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)?

3. "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?

4. "Why?"

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

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