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Towards equitable hydrological data in the age of Earth observations and artificial intelligence

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Earth observation and artificial intelligence provide unprecedented opportunities to monitor water systems. However, unequal access to data and underrepresentation of diverse perspectives risk reinforcing existing disparities.

The need for systematic monitoring of freshwater systems worldwide to address water crises has become increasingly apparent[1]. Recent advances in Earth observation (EO), satellite remote sensing, and artificial intelligence (AI) provide unparalleled opportunities to improve hydrological observations. Yet addressing water crises requires more than greater volumes of data. It also demands fair representation as well as equitable access to, sharing of, and capacity to use such water data across regions and stakeholders. Here we argue that, while technological advances offer unprecedented opportunities, they also pose challenges that may hinder the equitable use of hydrological data.

Inequalities and Earth observations

A major challenge with EO is that inequalities can emerge across the entire data chain: from acquisition to application. Despite advances in open data policies, satellite infrastructure and data production remains concentrated in a small number of technologically advanced countries, creating structural asymmetries in data access and governance[2]. Figure 1a illustrates these imbalances by showing the number of organizational partnerships in the satellite sector, aggregated by country. Such partnerships can serve as a proxy for power relations[2], because they reflect both control over satellite operations and the concentration of expertise required for satellite development and deployment.

These disparities are compounded by uneven technical capacity, limited computational infrastructure and gaps in data latency, particularly in the Global South.

As a result, the effective use of EO data[3], even when it is freely available, is constrained, especially in regions where such data could be most beneficial. Lower-resourced countries remain dependent on externally provided data streams and support, leaving them vulnerable to shifting priorities and funding conditions. This dependence reflects deeper structural imbalances in how EO systems are organized and maintained, and what data are collected and by whom. These barriers therefore extend beyond data access to encompass the governance of EO systems[2]. Technical challenges, including limited interoperability and inconsistent adherence to the FAIR principles of data provision (findability, accessibility, interoperability and reusability)[4], further reduce usability and integration across systems, thereby increasing the uneven distribution of EO benefits.

Moreover, inequalities are evident not only in what EO data are collected, but also in what those data represent and how they are interpreted. Biases in datasets and analytical models can lead to uneven representation and misinterpretation of socio-hydrological conditions. These limitations underscore that open access alone is insufficient to achieve equitable access and representation in hydrological data.

Inequalities and AI

AI developments can also exacerbate inequalities in access to computational resources and use of hydrological data. For instance, although

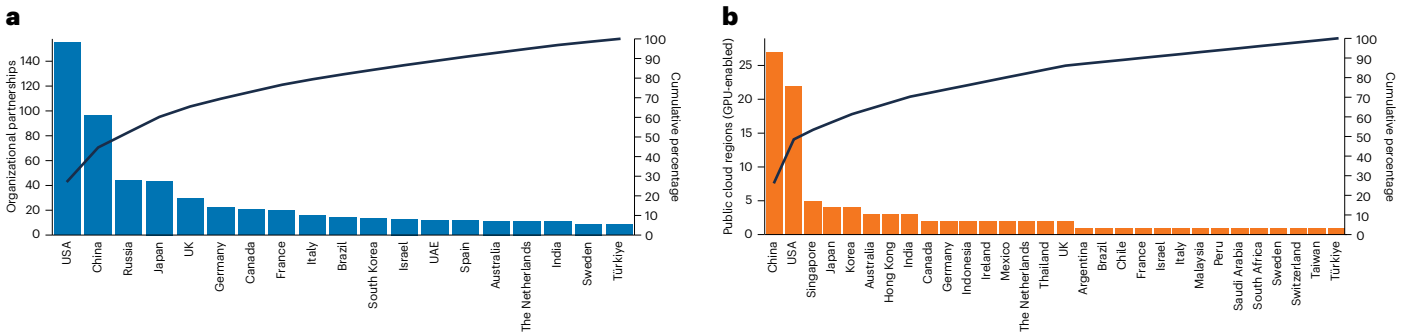

Fig. 1 | Global inequalities in Earth observations and artificial intelligence. **a**, Number of organizational partnerships in the satellite sector, aggregated by country. Data are taken from ref. 2. **b**, Number of public cloud regions that are GPU-enabled, aggregated by country. Data are taken from ref. 5. Cumulative percentages (Pareto curves; black lines) in both panels indicate that a small number of countries account for the majority of both satellite-sector partnerships and cloud-computing capacities worldwide. Although disparities are already pronounced among the countries shown here, they become even more marked when all countries are considered globally. GPU, graphics processing unit; UAE, United Arab Emirates.

AI tools can improve hydro-climatic forecasts, these advances are unequally distributed[5]. Global disparities in public cloud regions and graphics processing units[6] mean that only a few countries have access to better data and the ability to adapt models to local conditions (Fig. 1b).

Large language models (LLMs), in particular, are rapidly changing how hydrological information is processed and analysed. However, because LLMs are trained mainly on English-language, Global-North-centric, and often uncurated datasets, they can inherit stereotypes and misrepresent already-vulnerable and marginalized communities[7]. Research has shown that LLMs have skewed representations of locations with lower socioeconomic conditions[8] and reproduce biases against certain groups[9]. Furthermore, access to state-of-the-art models and the expertise needed to adapt them to local contexts is concentrated in well resourced institutions, reinforcing disparities in data production, also because of the abovementioned asymmetries (Fig. 1).

In addition to these concerns, LLMs are extremely water-demanding. Recent estimates suggest that AI's global water footprint could reach 4.2 to 6.6 billion cubic metres annually by 2027, with many data centres located in water-stressed regions[10]. These challenges can risk concentrating the benefits of emerging AI technologies among already privileged groups or specific sectors, further increasing their influence over water governance and decision-making, including the allocation of freshwater resources.

Water data are not neutral

Furthermore, advances in EO and AI do not address what remains unmeasured, excluded or rendered invisible within these dominant approaches to water monitoring and assessment. Specifically, although these technologies can provide detailed representations of water balances, they are less able to capture how socio-hydrological processes unfold locally and how they are experienced, interpreted and managed by communities on the ground. This limitation becomes problematic if not explicitly recognized and addressed. Processes of datafication often equate relevant knowledge solely with data that is quantifiable and scalable, privileging standardized measurements over community-generated data, context-specific qualitative insights and Indigenous knowledge[11]. As a result, water governance processes continue to be largely informed by quantitative data, while overlooking forms of knowledge that are essential for more just and transformative water futures[12].

Insights from data justice and critical data studies also warn that water data are not neutral. Decisions about what data to collect, how to collect them and what counts as valid evidence are shaped by social and political values. These decisions, in turn, influence how water problems are framed and addressed[13]. In this context, the growing reliance on EO and AI risks reproducing and amplifying existing inequalities through data-driven forms of discrimination and epistemic exclusion.

Equitable access and representation in hydrological data, therefore, cannot be reduced to improving access and sharing alone. We must also confront how knowledge is defined and validated, and create space for experience-based and affective data that goes beyond the current focus on standardized, quantitative and scalable forms of knowledge[12]. Expanding access to, sharing of and the capacity to use hydrological data should not be seen as an endpoint, but as an opportunity to bring community-generated, qualitative and Indigenous forms of knowledge into dialogue with other data and ways of knowing water.

Equitable access and representation

The rapid expansion of hydrological data in the age of EO and AI demands more than technological progress; it requires a redistribution of power in how data are produced, governed and used. Scientists, governments, funders, data providers and technology developers should ensure that the data shaping water knowledge does not reinforce existing inequalities. This means investing not only in technological innovation, but also in the institutions, capacities and participatory processes needed to ensure that diverse forms of water knowledge can shape how and which data are produced, interpreted and used.

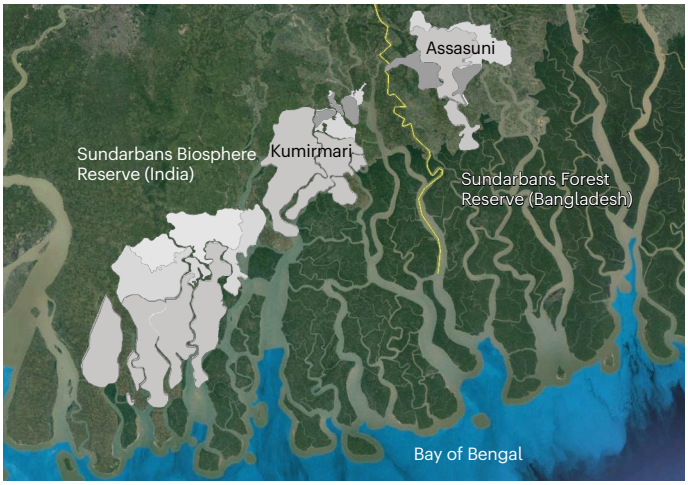

Fig. 2 | Participatory action research initiatives in the Sundarbans. Grey areas indicate the territories affected by cyclone storm surges since 2009 (refs. 14,15). Sampling locations and annotations are by J.M.; basemap source is Google Earth. Publ. Note: Springer Nature is neutral about jurisdictional claims in maps.

To illustrate, we present the case of hydrological data in the Sundarbans, the world's largest mangrove delta, shared between India and Bangladesh (Fig. 2). This vast archipelago of about 10,000 km^2 is one of the most hydrologically dynamic and data-sparse environments on Earth[14]. Satellite observations of land-cover change, coastline retreat and salinity intrusion across the Sundarbans have yielded valuable macro-scale insights. However, they systematically underperform at the granular, temporally fine-grained scales that matter most for local communities[14]. Tidal channels shift quickly, flooding patterns vary over short distances, and soil salinization driven by cyclone storm surges plays out at smaller scales than most satellite products can detect. Importantly, these are not only technical blind spots: they point to a deeper mismatch between what EOs can capture and what communities on the ground are actually living through: multiple disruptive risks[15], such as threats to freshwater access, farming viability and everyday livelihoods.

Participatory action research initiatives in the area demonstrate an alternative approach (for example, see https://engage4sundarbans.org/). By involving local communities in data collection and interpretation, they generate place-based data: measuring salinity in ponds and water bodies, noting when tidal flooding occurs and how far it reaches, and tracking shifts in aquatic resources that formal monitoring stations and big data tend to miss.

Hence, achieving equitable hydrological data requires concrete changes in how data infrastructures are built and governed towards a practice that is inclusive, participatory and transparent. Communities, Indigenous groups, practitioners and decision-makers should be able not only to access data, but also to interrogate, contribute to and shape the knowledge systems that inform water decisions. In practice, this

requires three linked commitments: equitable access to high-quality data; meaningful participation in how datasets are produced, interpreted and shared; and redistributed expertise by redefining what counts as knowledge and who has authority to produce, interpret and mobilize it (as illustrated by the Sundarbans example above).

Concrete mechanisms include enabling funding agencies and universities to establish formal pathways for publishing community-generated and Indigenous hydrological knowledge, rewarding researchers who integrate diverse knowledge and data systems, and revising research evaluation criteria so that epistemic pluralism is recognized in promotion and grant decisions. Without these shifts, the data revolution in hydrology could perpetuate some of the inequities it aims to address. However, with these shifts, EO and AI could instead underpin more just and sustainable water futures.

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Competing interests

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