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COMMENTARY
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Advancing the Representation of Human Actions in Large-Scale Hydrological Models: Challenges and Future Research Directions

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Key Points:

- Human actions are still represented crudely in large-scale hydrological models
- Hyper-resolution modeling, new satellite missions, and machine learning tools offer a fertile environment for challenging this status quo
- Challenges range from creating hyper-resolution data sets to improving the characterization of human actions on water quantity and quality

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Abstract

Characterizing the impact of human actions on terrestrial water fluxes and storages at multi-basin, continental, and global scales has long been on the agenda of scientists engaged in climate science, hydrology, and water resources systems analysis. This need has resulted in a variety of modeling efforts focused on the representation of water infrastructure operations. Yet, the representation of human-water interactions in large-scale hydrological models is still relatively crude, fragmented across models, and often achieved at coarse resolutions (∼10–100 km) that cannot capture local water management decisions. In this commentary, we argue that the concomitance of four drivers and innovations is poised to change the status quo: “hyper-resolution” hydrological models (∼0.1–1 km), multi-sector modeling, satellite missions able to monitor the outcome of human actions, and machine learning are creating a fertile environment for human-water research to flourish. We then outline four challenges that chart future research in hydrological modeling: (a) creating hyper-resolution global data sets of water management practices, (b) improving the characterization of anthropogenic interventions on water quantity, stream temperature, and sediment transport, (c) improving model calibration and diagnostic evaluation, and (d) reducing the computational requirements associated with the successful exploration of these challenges. Overcoming them will require addressing modeling, computational, and data development needs that cut across the hydrology community, thereby requiring a major communal effort.

Plain Language Summary

Humans have been impacting the hydrological cycle in a variety of manners, such as by using groundwater to support agricultural production or altering river discharge to produce hydropower or reduce flood risks. Hydrological models focusing on large regions can capture some of these actions, but with a level of detail that is still rather crude. We argue that the increasing interest in hyper-resolution models (∼0.1–1 km) and the availability of new remotely-sensed observations can help change this status quo. This would require addressing four key challenges, namely (a) creating data sets that describe water management practices with an unprecedented level of detail, (b) improving the accuracy with which anthropogenic impacts on water quality and quantity are represented in hydrological models, and ensuring that models continue to be (c) reliable and (d) computationally efficient.

1. Introduction

In October 2022, and for the first time in over 20 years, the U.S. Geological Survey released a new water cycle diagram featuring humans at its core (Duncombe, 2022). This is a significant step forward, as it reflects how the human domination of the global hydrological cycle has begun to permeate public perception (Abbott et al., 2019). The representation of human *actions* (i.e., observable decisions that affect the water cycle, such as when, where, and how water is withdrawn, released, or allocated) in large-scale hydrological studies (from multi-basin to the global scale) has followed a similar pathway: in the early 1990s, scientists started to compare water availability and use at the continental and global scales (i.e., Falkenmark, 1989, 1997; Shiklomanov, 1997), but it took a few

Table 1
Research Directions Identified in Four Literature Reviews on the Representation of Water Management in Large-Scale Hydrological Models

Research directions	Nazemi and Wheater (2015a)	Nazemi and Wheater (2015b)	Pokhrel et al. (2016)	Wada et al. (2017)
Data collection		∘	∘	∘
Process representation	∘	∘	∘	∘
Model intercomparisons	∘		∘	∘
Computing and calibration algorithms		∘		

Note. The black circle indicates whether a given research direction is included in a given study.

more years before the representation of human actions on terrestrial water fluxes transitioned from the first pioneering modeling effort (Alcamo et al., 1997) to a broader and widely-accepted modeling challenge (Nazemi & Wheater, 2015a; Wada et al., 2017). The growing extent of the human footprint has further emphasized this need (Döll et al., 2009; Haddeland et al., 2014; Vörösmarty et al., 2003); to date, there are three categories of models reflecting the efforts of three, partially overlapping, communities concerned with representing human-water interactions across large spatial domains. These are land surface models, subcontinental-to-global hydrological models, and dynamic vegetation models (Bierkens, 2015). Hereafter, we refer to all of these models as large-scale hydrological models.

As outlined in previous reviews (Nazemi & Wheater, 2015a, 2015b; Pokhrel et al., 2016; Wada et al., 2017), the representation of human actions in large-scale hydrological models has typically focused on surface water withdrawals for irrigative and non-irrigative demand as well as the operations of artificial reservoirs and regulated lakes, with less emphasis placed on streamflow diversions, aquifers, and urban water infrastructures. These reviews identified major research directions (Table 1), including the collection and sharing of data on human water management (e.g., groundwater pumping), improvements in how various water resources management practices are represented in hydrological models (e.g., representation of groundwater withdrawals and artificial recharge), model intercomparisons to help address the lack of standardized frameworks and best practices, and the use of computing and calibration algorithms to improve model accuracy. A common thread connecting these directions is the "rather crude" representation of human actions (Pokhrel et al., 2016), which in turn affects model accuracy and thus utility. This matter is well exemplified by Puy et al. (2022), who showed that the estimates of global irrigation withdrawals may be highly inaccurate, owing to the number of modeling choices made during the model design (e.g., use of a fixed irrigation efficiency value per country or region). The causes of such crude representation are many, from the lack of accurate data to the fact that operational decisions are usually made at the sub-grid scale for models adopting coarse spatial resolutions (∼10–100 km). Another cause is the intrinsic complexity of human actions, which are difficult to represent in a generalized form, and may not always be reasonably represented by rational decision-makers (Simon, 1957; Yoon et al., 2022). There is also a legacy issue to account for: Aside from a few exceptions (e.g., WaterGAP; Alcamo et al., 1997), large-scale hydrological models were originally conceived to reproduce the behavior of natural systems, so updating them to account for human actions is an effort that comes with substantial computational and software development challenges (e.g., Dang, Vu, et al., 2020; Hanasaki et al., 2018; West et al., 2024). Existing models must be run in a computationally-intensive iterative mode to represent a reservoir operator's use of seasonal inflow forecasts to guide water release, for example, (Turner et al., 2020). Moreover, modeling these decision-making processes ideally requires not only inflow data and dam design specifications, but also bespoke information on streamflow forecasts, operating objectives, and administrative constraints (Turner et al., 2020)—all elements that must be integrated within the "original" hydrological model. Importantly, these elements are typically captured by small-scale models used for engineering applications (e.g., Taylor et al., 2024). This leads us to the last point: the field of large-scale hydrology has yet to integrate the advances of other disciplines that develop computational models of human *behavior*—in primis, water resources systems analysis (Brown et al., 2015)—namely models of the underlying decision-making processes or rules that generate observed human actions. As we shall see later, research in this area has yielded models depicting single representative decision-making entities across relatively large domains ($\sim 10^2$-10^4 km^2) (Hejazi et al., 2008; Lin, Alegria, et al., 2024), so there are opportunities for including these advances in large-scale hydrological models.

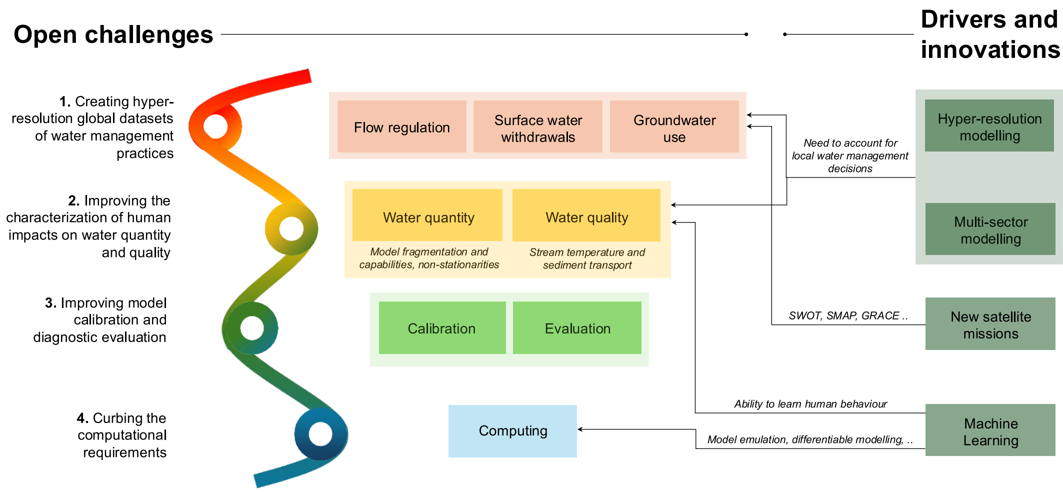

Figure 1. Graphical representation of the four open challenges identified and discussed in this commentary (left). The order with which the challenges are presented follows four sequential steps, namely data collection, model development, model diagnostics, and reduction of the computational requirements. The four boxes on the right represent the drivers and innovations that can support the exploration of the four challenges.

We believe this an opportune moment for taking a fresh look at the challenges—outlined above—that underpin the representation of human actions in large-scale hydrological modeling. During the past few years, we have witnessed the emergence of multiple drivers and innovations that will provide a fertile environment for the successful exploration of these challenges (Figure 1). First, major strides have been made during the past decade to implement hydrological and land surface models at much higher spatial resolution (~1 km globally and ~100 m at continental scales), referred to as the "hyper-resolution" (Wood et al., 2011). These efforts have started to yield the first results (e.g., Hanasaki et al., 2022; Hoch et al., 2023; Vergopolan et al., 2021) and, most importantly, will provide further impetus to account for local water management decisions. Second, large-scale hydrological models serve an increasingly broader spectrum of downstream modeling applications, all requiring an accurate representation of human-water interactions. Examples include national-scale river forecasting (Vegad & Mishra, 2022), ecological impact assessments of water infrastructures (Galelli et al., 2022), or multi-sector studies looking at the interaction and competition between multiple socio-economic sectors (Kanyako et al., 2023). Third, recent advances in remote sensing, like the Surface Water and Ocean Topography (SWOT) mission (Biancamaria et al., 2016), provide new observations at unprecedented spatio-temporal resolutions. What has also changed is our ability to process large data sets and infer human decisions. This leads us to the fourth driver: A variety of new machine learning tools are now available to learn human behaviors from complex data sets (Ho & Griffiths, 2022), improve modeling accuracy (Kraft et al., 2022; C. Shen et al., 2023), and curb computational requirements (Tran et al., 2021). What we now need is a communal effort that improves the data, approaches, and models used to represent human actions in large-scale hydrological models.

Against this backdrop, this commentary focuses on four main challenges that cut across the hydrological sciences (Figure 1):

- Creating hyper-resolution global data sets of water management practices
- Improving the characterization of human impacts on water quantity and quality
- Improving model calibration and diagnostic evaluation
- Curbing the computational requirements of large-scale models

We begin our presentation with two fundamental building blocks, namely data (Section 2) and process representation (Section 3). We then move to model calibration, validation, and sensitivity analysis (Section 4), and finally outline the challenges associated with computational aspects (Section 5). Naturally, the exploration of these challenges should not necessarily be sequential; the order with which the challenges are illustrated and presented partially reflects the implications that research efforts in one area are likely to have on another—for instance, exploring the uncertainty associated with the representation of a given type of human action is likely to increase the computational requirements.

2. Creating Hyper-Resolution Global Data Sets of Water Management Practices

As large-scale hydrological models move toward higher spatio-temporal resolutions, gathering hyper-resolution data that adequately represent the breadth and depth of human interventions on the global water cycle remains an open challenge. Hyper-resolution data are needed for a variety of tasks, such as parameterization, calibration, validation, or model-forcing preparation. Here, we focus on the data characterizing three main domains, namely flow regulation, water withdrawals and consumption, and groundwater use (Pokhrel et al., 2016; Wada et al., 2017).

2.1. Flow Regulation and Diversion

2.1.1. Dams

The chief infrastructure supporting flow regulation is dams, which globally impound at least 8,000 km^3 of water (Grill et al., 2019). To date, we have fairly detailed information on their location, technical specifications, and, at times, operating purposes (e.g., flood control, hydropower production). These specifications are captured in a variety of databases, including the Global Dam Watch (Lehner et al., 2024), the Global Reservoir and Dam Database (GRanD) (Lehner et al., 2011), the World Register of Dams (WRD) (ICOLD, 2024), and the Global Dam Tracker (GDAT) (Zhang & Gu, 2023). Importantly, these databases do not provide data on reservoir inflow, storage, operating rules, and release, which is why large-scale hydrological models typically rely on routing schemes that estimate reservoir operational decisions on the basis of the only information globally available, such as reservoir purposes or storage capacity (e.g., Abeshu et al., 2023; Hanasaki et al., 2006, 2022; Shin et al., 2019; Van Beek et al., 2011). Setting aside for a moment the question of how accurate these generic rules are and their impact on model reliability (which we will discuss in Section 4), what is important to stress here is that the creation of a global database of reservoir operations is becoming increasingly feasible, at least in partial or inferred form: Since the seminal work of H. Gao et al. (2012) and Z. Duan and Bastiaanssen (2013), we have witnessed a steep increase in the number of studies that leverage remotely-sensed data to infer time series of reservoir storage or storage anomalies at either global (e.g., Busker et al., 2019; Biswas et al., 2021; Hou et al., 2022; Y. Li et al., 2023) or regional scale (e.g., Bonnema & Hossain, 2017; Mahto et al., 2024; Shen, Liu, et al., 2022; Vu et al., 2022).

While these studies focus on observed or estimated states (i.e., storage), they offer valuable building blocks for modeling or inferring operational behavior. Yet, several research gaps still need to be addressed. First, remotely-sensed data on reservoir storage differ in terms of temporal coverage, spatio-temporal resolution, accuracy, and monitored phenomena, so we lack a synergistic approach to consolidate the existing data as well as the methods used to generate them. Compounding these limitations is the scarcity of streamflow observations in many regions of the globe (Do et al., 2018), which hampers our ability to estimate reservoir inflows and release variables needed to move from observed storage to a fuller understanding of reservoir operations. Second, we need ways to combine the existing remotely-sensed data on storage with other remotely-sensed or observed data (e.g., release), and synthesize them to model the decisions made by operators. This could be in the form of either rule curves (periodic target storage values followed by the operators; Shen et al., 2024; Vu et al., 2022) or control policies (defining water release as a function of current-period storage; Turner et al., 2020). Being able to integrate data-driven reservoir simulation into large-scale hydrological models could help us understand the advantages and disadvantages of current routing schemes (Y. Shen et al., 2024; Turner et al., 2020), improve streamflow prediction at ungauged cascade reservoir systems (Du et al., 2022), or improve the accuracy of flood and streamflow simulations (Dong et al., 2023). Third, the validation of remotely sensed data is challenged by the lack of in situ data, an issue that could be solved by the development of more databases, including operational records (Steyaert et al., 2022) and water management rules derived from those data (Turner et al., 2021).

2.1.2. In-Basin and Inter-Basin Water Transfers

In-basin and inter-basin water transfers (IBTs) are yet another type of hydraulic infrastructure found in multiple regions—examples include the water transfers of high-altitude Alpine dams and the surface withdrawals supporting urban water supply and irrigation in the United States, India, or China. Sources of water withdrawal for the world's largest cities have been documented (McDonald et al., 2014) and, more recently, regional and global data sets have been released (e.g., Dobbs et al., 2023; Shumilova et al., 2018; Siddik et al., 2023). However, we lack global databases with details of IBTs locations, purposes, diversion capacities, and actual transfers. As a consequence, the representation of IBTs in large-scale hydrological models is often overlooked or carried out simplistically. For example, when considering surface water withdrawals, it is common practice to extract water from the resources (rivers and lakes) that are present within a cell or in the nearby ones (Biemans et al., 2011, 2013). This process, however, may overlook the presence of existing hydraulic infrastructure, which is typically documented for a handful of countries (Hanasaki et al., 2018). In this context, modelers would benefit from data sets providing specific information on diversion canals (Gopalan et al., 2022), such as width, depth, and bed elevation, which is key for models adopting high spatial resolutions (e.g., below 5-min). A potential game changer for improving our understanding and representation of flow regulation and diversion is the Surface Water and Ocean Topography mission (SWOT), launched in late 2022 and expected to be completed in 2025 (Biancamaria et al., 2016). SWOT will provide global observations on changing water levels, stream slopes, and inundation extents in rivers, lakes, and floodplains, thereby representing a major source of information on dam operations and IBTs, albeit with limited information for small streams. A complementary strategy to globally map water infrastructure is to use satellite data and open geographic databases (e.g., OpenStreetMap) together with AI-based methods (H. Li et al., 2021).

2.2. Water Withdrawals and Consumption

Data on actual water use (i.e., withdrawal and consumption), rather than potential water demand, are key to accurately representing how different human activities affect the water cycle. Here, we focus on four main sectors—namely urban, industrial, and livestock (Section 2.2.1) and irrigation (Section 2.2.2)—independent of the source of water.

2.2.1. Urban, Industrial, and Livestock Water Use

Research efforts have focused on the creation of data sets that capture urban, industrial, and livestock water use (Bijl et al., 2016; Huang et al., 2018; Vassolo & Döll, 2005). For all these sectors, the fundamental challenge lies in the fact that observations (typically available in the form of country-level statistics) are reported with coarse spatial and temporal resolutions. To generate the gridded, time-varying inputs needed for large-scale hydrological models, these national values are disaggregated to grid cells using spatial proxies such as population density or economic activity, and temporal development is estimated using models or interpolations (Flörke et al., 2013; Wada et al., 2011; Wada, Wisser, & Bierkens, 2014). For example, one may use information on socio-economic variables (e.g., population, GDP, energy consumption) to calculate time series of industrial water demand starting from statistics representing a single, given, year. Despite these efforts, current data sets remain limited in resolution and often fail to capture spatial and temporal heterogeneity, especially for domestic and manufacturing water use. This presents a major challenge for hyper-resolution modeling, where a typical $0.5°$ grid cell spans an area more than 2,000 times larger than that of a $30''$ grid.

Urban. The representation of urban water demand in large-scale hydrological models typically consists of global gridded data sets containing information on municipal and industrial water use (e.g., Hejazi et al. (2014); Vassolo and Döll (2005); Wada, Wisser, & Bierkens, 2014). The physical processes captured by these data sets may be simpler than those pertaining to flow regulation or irrigation, but still require compelling research efforts. In fact, we foresee three. First, these data sets rely on country-based statistics that can quickly become obsolete in face of the ongoing urbanization rates—a problem that can be easily avoided by keeping them updated with the current statistics. Second, the growing interest in hyper-resolution modeling is likely to require urban water demand data with a spatial resolution higher than the $0.5° \times 0.5°$ grid that is typically adopted. This challenge could be addressed in a variety of ways: Flörke et al. (2018), for instance, combined a data set of urban water sources of ~500 cities with estimates of future water demand to estimate (with the WaterGAP3 modeling framework) urban surface-water deficit in the 2050s. Yan and Jia (2023), instead, mapped global gridded municipal water withdrawal with a $0.1° \times 0.1°$ resolution using an artificial neural network that takes as input multiple predictors accounting for climate, topography, and socio-economic conditions. Third, we need more detailed information on the infrastructures affecting water withdrawals (e.g., desalination; Ai et al. (2022)), as well as water quality parameters, for example, wastewater treatment types or removal efficiencies per pollutant and treatment level (Jones et al., 2021; Van Vliet et al., 2021).

Industrial. Moving to industry, the water use of this sector is either aggregated at the sectoral scale (e.g., Wada, Wisser, & Bierkens, 2014) or disaggregated among different sub-sectors, typically electricity production, mining, and manufacturing (e.g., Bijl et al., 2016; Huang et al., 2018). Among these sub-sectors, electricity generation is the largest user of water (i.e., withdrawal and consumption for cooling of thermoelectric power plants), and has thus received closer scrutiny. Plant-scale time series of water withdrawals and consumption are generally not available, and are thus replaced by estimates based on annual electricity production, water intensity of the power station, or excess heat (Bijl et al., 2016; Larsen & Drews, 2019; Vassolo & Döll, 2005). Here, the main challenges lie in the maintenance and enhancements of these data sets: thermoelectric power fleets are changing across the globe, and so are their operations, which must respond to rapidly varying market conditions (Chandel et al., 2011; Zhang et al., 2018). Another challenge is the need to estimate not only the water use of thermoelectric power plants, but also their signature on the temperature of the receiving water bodies—a point to which we will return in Section 3. As for manufacturing and mining, the temporal and spatial downscaling of water withdrawal data using grid-cell population estimates remains a rather common approach (Huang et al., 2018; Voisin et al., 2013), although more advanced approaches based on additional information—such as nighttime lights or industry value added in inflation and purchasing power—have emerged (Bijl et al., 2016; Panda & Kim, 2024; Vassolo & Döll, 2005). Similarly to the case of electricity generation, the challenge is the maintenance and enhancements of these data sets. In this regard, an opportunity may be represented by water footprinting techniques, whose scalability, however, has yet to match the spatial domains of large-scale hydrological models (Northey et al., 2016).

Livestock. As anticipated above, direct water use (or withdrawals) for livestock shares the same challenge as data depicting urban and industrial water use; data are often available for a few reference years and with coarse resolutions (Mubareka et al., 2013), thus requiring the use of disaggregation algorithms. We also note that some models compute direct water use for livestock by considering the number of livestock animals per grid size (e.g., WaterGAP2; see Telteu et al., 2021); a modeling approach that is also constrained by the spatio-temporal resolution of the available data. For livestock, an interesting, yet long-term, development is represented by digital livestock farming, which is poised to provide animal biometric data with unprecedented resolutions (Neethirajan & Kemp, 2021).

2.2.2. Irrigation Water Requirements

Since the early 20th century, agricultural expansion has vastly altered the global hydrological cycle through land use changes as well as surface and groundwater withdrawals. Data on (a) cropping patterns (crop species and calendar), (b) area actually irrigated (on a seasonal to annual basis), (c) irrigation methods, timing, and amount, and (d) reference and actual evapotranspiration (ET) are needed to characterize agricultural practices and irrigation water requirements (McDermid et al., 2023). Historically, some of these data have been provided by global census-based statistics, such as the Food and Agriculture Organization's (FAO) AQUASTAT, which provides global maps of irrigated areas and other agricultural water management variables. A limitation of these data sets concerns their spatial and temporal resolution, which can only be partially addressed by statistics provided at the country level; finer-scale irrigation water withdrawal data, for example, are only provided by a handful of countries, such as the US or China (Dieter, 2018; Sun et al., 2022). A complementary source of information is thus represented by satellite missions; examples include Landsat, MODerate Resolution Imaging Spectroradiometer (MODIS), and the Soil Moisture Active Passive (SMAP) mission, which have been used to estimate crop growth (F. Gao et al., 2017), ET (Jin et al., 2011; Mu et al., 2007), irrigation demand (Lawston et al., 2017; Zaussinger et al., 2019), irrigated areas, and irrigation volumes and timing (Chen et al., 2018; Dari et al., 2020, 2023).

Despite the increase in the quantity and quality of these data, several key developments are required to ready them for use in hyper-resolution, large-scale hydrological models. First, additional research in remote sensing and data analysis is needed to improve the accuracy of all remotely-sensed data products. Estimates of irrigated area, for instance, typically show good accuracy because of the specific spectral features used to estimate them (as well as the low temporal resolution with which they are required) (McDermid et al., 2023). This is not, however, the case of irrigation water volumes, whose estimates depend on several factors, such as cloud cover, sensitivity to vegetation, or the trade-off between the spatial and temporal resolutions of the adopted satellite data (Massari et al., 2021). Moreover, the applicability of satellite data varies by variable and context: Landsat and MODIS data have shown high reliability in detecting irrigated areas and crop phenology, while products such as MODIS- and SMAP-derived soil moisture anomalies offer promising but more indirect insights into irrigation demand and timing (Lawston et al., 2017). The accuracy of these latter estimates remains contingent on factors such as crop type, landscape heterogeneity, and climatic conditions, and typically improves when multiple data sets are fused or used in conjunction with ground-based or census-derived observations (Massari et al., 2021).

Second, we need to expand the spatial coverage of key data sets: WaPOR, for instance, provides satellite-derived data on water productivity, actual and potential ET, and crop calendar at up to 30 m resolution, but is only available for Africa and the Middle East. The availability of such data sets, coupled with continued efforts of validating remotely-sensed data with in situ observations and census-based statistics, will allow for improved characterization of modeling uncertainty. The case of estimated consumptive use is emblematic: as pointed out by Döll et al. (2016), there are various, equally plausible, algorithms used to calculate reference or potential ET, so the estimates of consumptive use tend to vary across models. Such uncertainty could be limited by cross-validating model estimates satellite-derived and census-based data. Third, we need to better understand any discrepancies between current modeling assumptions and actual agricultural practices. Improving the representation of irrigation is a process that begins with a stronger appreciation of existing limitations, and will require more operational data than is currently available or being collected. In particular, we need data sets that can help us factor deficit irrigation due to water scarcity, constraints, and limitations (Zhou et al., 2020). Promising results have been shown at the country scale (Sorooshian et al., 2012), so we need an effort to upscale them at the global scale. This also requires better data on flow diversion and groundwater withdrawals, on which we elaborate next. Fourth, we must develop data sets describing the loadings of nitrogen and phosphorous, which are necessary to improve the representation of agricultural practices on water quality (Section 3). Fifth, if we can use databases on water productivity or water use efficiency (Mbava et al., 2020; Xue et al., 2015), it is possible to further constrain crop and vegetation evaporation estimates using reported yields and remotely-sensed biomass estimates (Ahmad, Hossain, et al., 2021).

2.3. Groundwater Use

The availability of global data sets has facilitated a number of recent advances in groundwater modeling, such as the representation of lateral groundwater flow (Felfelani et al., 2021) and of the interaction between groundwater availability and river discharge (de Graaf et al., 2019). Examples of these data sets include maps of permeability (Gleeson et al., 2011, 2014), groundwater table (Fan et al., 2013), and depth-to-bedrock (Pelletier et al., 2016). In this modeling context, a game changer has been the Gravity Recovery and Climate Experiment (GRACE) satellite mission (Tapley et al., 2004) and its Follow-On (GRACE-FO), whose observations are often used to infer change in terrestrial water storage, thereby providing a valuable source of information to large-scale modeling efforts (e.g., Döll et al., 2014; Felfelani et al., 2021; Pokhrel et al., 2015; Nie et al., 2018). Whereas Section 2.2 focused on surface water withdrawals across sectors, this section centers on groundwater as a resource, discussing both human use and natural recharge processes. Looking at the specific impact of human actions on groundwater resources, the two chief processes to consider are groundwater withdrawal capacity (and rates) and recharge. As explained below, the quest and development of data describing these processes must be combined with better hydrogeology data.

Groundwater withdrawal is often obtained by first calculating total water demand using socio-economic data (see Section 2.2) and then distributing the demand to groundwater (or surface water) withdrawal. This calculation can be based on a location-specific ratio of groundwater-to-surface water abstraction (based, for instance, on groundwater infrastructure installed; Siebert et al. (2005)). Alternatively, it can be based on the relative availability of surface water (streamflow) and groundwater (groundwater recharge) (De Graaf et al., 2014). Resulting estimates are then evaluated or tuned using global reports of groundwater and surface water withdrawals (e.g., FAO AQUASTAT) or more detailed data, such as those reported by the United States Geological Survey for the High Plain and Central Valley Aquifer (Maupin & Barber, 2005). Sutanudjaja et al. (2018) tried to improve these estimates by capping groundwater withdrawal with the installed withdrawal capacity available from the International Groundwater Resources Assessment Centre (IGRAC) GGIS database. By capping groundwater withdrawal with a pumping capacity installed, one ensures the part of the demand that is not met, making a water gap possible. Otherwise, all non-met demand would result in non-renewable groundwater withdrawal, in turn resulting in an overestimation of groundwater depletion (Wada et al., 2010). Estimating withdrawal capacity installed is, however, rather problematic, for instance because the IGRAC GGIS data underestimate actual withdrawals (e.g., Ruess et al., 2023). Recently, several data sets have become available that provide locations, depths, purpose and—for a small fraction—capacity of groundwater pumping wells for the U.S. (Lin, Miller, et al., 2024; Perrone & Jasechko, 2019) as well as for other parts of the world (Jasechko & Perrone, 2021). These data could be combined with machine learning methods to map groundwater withdrawal capacity using features such as well depth, well purpose, estimates of total water demand, groundwater recharge and permeability of the subsoil (Majumdar et al., 2020; Thomas et al., 2021).

Groundwater recharge is important because it determines the maximum withdrawal rate that is possible without causing groundwater depletion. Here, it is important to include both the diffuse recharge as well as concentrated recharge from streams, where both of these can be impacted by lowering water tables (Bierkens et al., 2024; Cuthbert et al., 2023). Several global hydrological models (Müller Schmied et al., 2021; Sutanudjaja et al., 2018) include both recharge processes, but their estimates should be improved if they are to be used for more detailed local-to-regional scale estimates (Berghuijs et al., 2022, 2024). Improvements can be expected when calibrating global hydrological models to site-specific groundwater recharge estimates (Moeck et al., 2020), or regionalized estimates based on these data (Berghuijs et al., 2022; Jung et al., 2024).

As anticipated above, a major challenge is the correct portrayal of the hydrogeological setup of the subsurface. This is needed to estimate withdrawal capacity first, but it also determines the impact of withdrawal rate on groundwater depth, which in turn determines how long groundwater withdrawal remains economically feasible (Bierkens et al., 2024; Niazi et al., 2024). However, there are no detailed multilayer global hydrogeological models. Apart from surface lithology (Gleeson et al., 2014) and thickness to bedrock not exceeding 50 m (Shangguan et al., 2017), there is the two-layer model of de Graaf et al. (2017) and a model of coastal hydrogeology (Zamrsky et al., 2024). We refer to the perspectives of Gleeson et al. (2021) and Condon et al. (2021) for possible pathways to improve global hydrogeological parameterizations.

Despite the aforementioned developments in data describing withdrawal capacity (and rates), recharge, and hydrogeology, the availability of in situ data (with high spatio-temporal resolution) is likely to remain a challenge in the years to come—particularly in developing regions—offering opportunities for data collection and model parameterization. One opportunity consists in the use of observations provided by satellite missions. Felfelani et al. (2018), for instance, used soil moisture estimates from SMAP satellite to better parameterize the representation of irrigation in the Community Land Model. Similarly, data from the GRACE mission have been used to constrain groundwater simulations (Nie et al., 2018, 2019). The second opportunity concerns the "transfer" of parameterizations from data-rich to data-scarce regions; Kabir et al. (2023), for example, demonstrated the applicability of the Community land Model over the Mekong River basin by using parameterizations developed over the CONUS domain.

3. Improving the Characterization of Human Impacts on Water Quantity and Quality

Improving the characterization of human impacts on water availability must be carried out in concert with an enhanced representation of physical processes. As pointed out by Pokhrel et al. (2016), realistically simulating the effects of groundwater pumping, for instance, requires an adequate representation of both the water table dynamics and the allocation of water withdrawals. Here, we focus on the improvement of human impact representation, since the representation of physical processes in large-scale hydrological models is covered in previous works (e.g., Bierkens, 2015; Wood et al., 2011). We identify four specific arenas of further research.

3.1. Addressing the Fragmentation Across Models

A look at the latest inter-model comparisons for large-scale models (e.g., Telteu et al., 2021) shows macroscopic differences in how human actions are conceptualized and implemented, a problem that challenges our ability to draw robust insights across different modeling exercises. It is worth stressing that our community is not alone in facing this challenge, as major differences have emerged among and within scientific communities working on the representation of human systems in computational models (Yoon et al., 2022), such as integrated assessment modeling (Wilson et al., 2021) or water resources systems analysis (Brown et al., 2015). The observation here is that solutions appealing to these communities may also have potential application to ours. Specifically, we argue that the macroscopic differences across large-scale hydrological models could be addressed by developing or adopting shared frameworks for synthesizing human systems modeling across models.

An excellent example of such framework is the typology introduced by Yoon et al. (2022), which consists of two main components. The first component is a categorization of human *actors* organized across sectors (e.g., agriculture, power supply) and three categories of actors, namely (a) governing, (b) provisioning, and (c) utilizing,

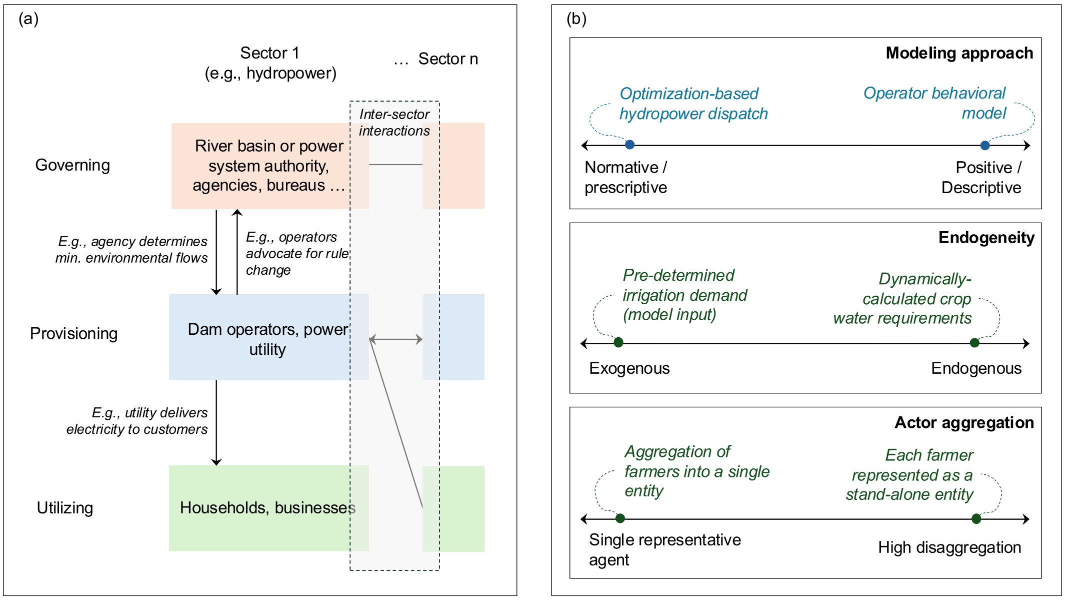

Figure 2. Conceptualization of human actors, adapted from Yoon et al. (2022). Panel (a) illustrates three types of actors, namely governing, provisioning, and utilizing. Arrows represent actions. Inter-sectoral interactions depict situations in which information, goods, or services are exchanged between sectors. Panel (b) illustrates three spectra of human system representation in models. These are the modeling approach (from prescriptive to descriptive), endogeneity, and spatial aggregation.

which represent (groups of) individuals that define the institutional environment for a sector, are involved in the actual provisioning of a sectoral product or service, and receive the product or service, respectively (Figure 2a). To further illustrate this categorization, consider, for instance, the case of hydropower generation within a given basin: the actors defining the institutional environment (governing actors) could be represented by the river basin authority or the power system authority, while the actors providing the service (provisioning actors) could be represented by dam operators or energy utility. The utilizing actors could entail a broad spectrum of individuals or organization involved in utilizing water and energy. The categorization of actors based on specific roles helps map out all human elements that affect—through different actions—the hydrological processes in a given spatial domain. In turn, this assists with the identification of the key human actors, or actions, that should be modeled.

The second component of the typology is a multidimensional spectrum that helps identify how human actors are operationalized in a hydrological model. Key dimensions of interest are modeling approach, endogeneity (i.e., whether a given actor is represented in the model but is imposed by the modeler externally or takes an action in dynamic response to the modeled state of the system), and actor spatial aggregation (Figure 2b). Using the same example of a hydropower dam, we note a variety of modeling approaches historically used to represent dam operators, ranging from normative, goal-driven assumptions to empirically driven representations of observed behavior. At one end, we find prescriptive models (based on the assumption that operators behave as fully rational individuals optimizing an objective) (e.g., Cáceres et al., 2022; Hoang et al., 2019); at the other, models that infer operator behavior directly from historical data (e.g., Turner et al., 2021). This framing echoes the range of approaches introduced in Section 2.1, from predefined rule curves to data-driven control policies. A similar observation applies to endogeneity, which reveals whether an action is treated exogenously or endogenously. Irrigative demand, for instance, can be provided as external input to a large-scale hydrological model but can also be directly (and dynamically) calculated at the grid scale by simulating optimal crop growth (Nazemi & Wheater, 2015a). Spatial aggregation can also vary widely; irrigation activities, for instance, can be represented by aggregating water demand across a given spatial domain but can also be represented by adopting a dedicated model for specific groups of farmers (Yoon et al., 2024).

Overall, it is worth stressing that the execution of inter-model comparisons and adoption of shared frameworks should not be aimed at standardizing models, but rather at creating a common ground to enable consistent comparisons and examine uncertainties. Moreover, such common ground would help us identify which actors, and actions, are missing, thereby informing model development. This leads us to the next arena of research.

3.2. Advancing Our Modeling Capabilities

Looking backwards, a major missed opportunity we identify is the lack of interaction between large-scale hydrology and water resources systems analysis. The explanation arguably lies in their overarching goals and the corresponding spatial domains of study they adopt. The former aims to understand the hydrological cycle as well as the human impact on hydro-climatic variability (Bierkens, 2015), thereby stemming from the observation that our impact on hydrological processes goes beyond the catchment scale (Eagleson, 1986). Since its inception (Maass et al., 1962), the latter has typically focused on optimal planning of multi-objective water infrastructure and collaborative water management, with the ultimate goal of supporting decision-making (Loucks & Van Beek, 2017; Soncini-Sessa et al., 2007). Because of that, water resources systems analysis generally builds on location-specific models. The tide, however, may change, as both disciplines are faced with important challenges. Going hyper-resolution will force large-scale hydrological models to work at the resolution that has long been adopted by water systems analysts. Meanwhile, water resources systems analysis is confronted with the challenge of expanding its domain of action, since cross-sectoral interactions emerge—and are best captured—at larger scales (Reed et al., 2022).

One major field of research that would benefit from an interaction between the two communities is the detailed characterization and simulation of water resources state variables at the global scale; a point that was first stressed by Brown et al. (2015). Building on observational data sets of human decisions (e.g., dam release decisions), models depicting a single representative decision-making entity across relatively large domains ($\sim 10^2$–10^4 km^2) have already been developed; examples include dam operators (Hejazi et al., 2008; Turner et al., 2021) and farmers (Giuliani et al., 2016; Lin, Alegria, et al., 2024; Lin et al., 2022). The next big step is to expand the scope of these studies to larger domains, an effort that would require more data (Section 2) and, perhaps, more powerful machine learning tools (Ekblad & Herman, 2021). Broadly put, there is a wealth of simulation tools developed by the water resources systems community that await scaling for and integration into large-scale hydrological models. Specific domains that would benefit from these modeling tools are agricultural water management (e.g., representation of field-level management practices leading to irrigation decisions, integration of irrigation models with crop models), reservoirs operations (i.e., moving from generic to site-specific operating rules), and groundwater management (e.g., inclusion of economic constraints and local water governance). Overall, we believe the goal is not to entirely replace the approaches currently adopted, but rather to expand the options available to large-scale hydrological modelers. Ultimately, we envision an adaptive and modular approach to human system representation, meaning that one could choose which model (describing human decisions) to integrate into a hydrological model depending on specific modeling conditions, such as data sets at hand, spatial domain and resolution, and, naturally, the specific research question(s) driving the research.

However, the process of choosing among different representations of human action would inevitably require to reason about uncertainty, a task that can be carried out with exploratory modeling (Bankes, 1993). This approach uses computational experiments to explore epistemic uncertainties in how a given system is represented, like those that emerge when modeling human actions (Yoon et al., 2022). Exploratory modeling could therefore help us answer questions such as: How should the representation of human actions in large-scale hydrological models depend on the specific research questions at hand? Where (and how) is increased model complexity warranted? How does the representation of human actions relate to an enhanced simulation of physical processes? Given the large number of simulations typically adopted (e.g., Giuliani et al., 2022; Lamontagne et al., 2018), we note that the application of exploratory modeling tools to large-scale hydrology would entail major computational requirements (see Section 5).

3.3. Accounting for Past Non-Stationarities in Infrastructure Development and Operations

So far, our discussion has been mostly centered on how the operation of water infrastructures is represented in large-scale hydrological models attempting to simulate how climate forcings, human actions, and other drivers affect hydrological processes. In these models, the presence of water infrastructures is generally represented by one scenario depicting the presence of the infrastructures of interest. Their deployment over time is then either held constant over the simulation horizon (i.e., a static scenario) or represented explicitly—some global

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hydrological models (e.g., PCR-GLOBWB, WaterGAP, H08), for instance, place dams on the drainage network and expand irrigated areas over time. Yet, we still lack detailed data regarding human actions (Section 2), which have evolved over time scales that are often shorter than the scenarios themselves. Examples are many. In the High Plains Aquifer (US), for instance, groundwater use has evolved substantially over time and there have been major changes in the way water is used (Steward & Allen, 2016). In the Amazon, deforestation is resurging after a decline during the early 21st century (Baudena et al., 2021) and the recent rise in dam construction has been altering the hydrology in unprecedented ways (Chaudhari & Pokhrel, 2022). How to best deal with these past non-stationarities is still an open question. The representation of land use and land-cover change is, perhaps, one of the most advanced study areas: while the static representation of land use remains the standard approach, researchers have long experimented with the *delta* approach (i.e., the comparison of simulation runs with two different land use maps; e.g., Miller et al. (2002), Li et al. (2009)) and, more recently, with dynamic representation of land use change (Chu et al., 2010; Wagner & Waske, 2016). The increased availability of satellite images (Section 2) and land use models (e.g., CLUE; Verburg & Overmars, 2009) will provide tools to address this gap. The same modeling capability is often unavailable when accounting for other human actions, such as groundwater pumping, irrigation scheduling, or dam release decisions, whose representation does not encapsulate the response of water agencies to environmental and socio-economic conditions. For dams, for example, we need models that tell us not only how release decisions are made, but also when management policies were modified to account for new federal guidelines or sedimentation conditions, as illustrated by Patterson and Doyle (2019). Another example can be drawn from irrigation activities: farmers often do not follow "agronomically" ideal ways (McDermid et al., 2023), but also follow socio-economic factors that introduce non-stationary—and poorly predicted—patterns (Jain et al., 2015).

We finally note that the study of future infrastructural developments can be executed and supported by large-scale hydrological models; example include the estimation of seawater desalination needs (Hanasaki et al., 2016) and the adaptation to future climatic conditions (Biemans et al., 2013; Gopalan et al., 2022; Padiyedath Gopalan et al., 2021; Wada, Gleeson, & Esnault, 2014). These modelling efforts, however, are often carried out by first processing the information provided by other studies or models (e.g., adaptation pathway to a given climate scenario), a research element that goes beyond the scope of our discussion.

3.4. Accounting for Human Impacts on Water Quality

Large-scale hydrological models typically prioritize water quantity aspects, thus overlooking (or adopting simplified approaches to represent) the impact of human actions on water quality. There are, therefore, many opportunities for expanding the capabilities of the models that are currently used, especially in light of potential climate impacts on water quality (Van Vliet et al., 2023). Here, we present research opportunities for the representation of stream temperature and sediment transport, which are within the reach of the large-scale hydrological modeling community. As shown below, these water quality aspects are mapped to the anthropogenic interventions introduced in Section 2. Naturally, the spectrum of water quality processes affected by human interventions goes beyond the ones covered here, encompassing, for instance, dissolved oxygen (DO), total nitrogen (TN), total phosphorous (TP), salinity, and organic pollution. The representation of these processes, however, also involves a broader spectrum of models than the one covered here. For this specific topic, we refer the reader to recent reviews on the representation of complex terrestrial systems (Davies-Barnard et al., 2020; Fisher & Koven, 2020).

Beginning with flow regulation and diversion, one fundamental variable to consider is water temperature, a key control of riverine ecosystems (Barbarossa et al., 2021). There are, in particular, two types of infrastructure affecting water temperature, namely reservoirs and thermoelectric stations. The problem associated with dams stands in the fact that water stored in dams is often stratified in warmer seasons, since solar heating attenuates with depth. This means that accurate prediction of water temperature in the reservoir release requires not only an adequate simulation of reservoir hydrothermal behavior, but also knowledge of water intake level, portion of outflows to turbine and spill (which may be drawn from different depths), and presence of selective withdrawal infrastructure at the dam. These dam characteristics are presently unrepresented in regional and global data sets. Overall, the problem of reservoirs in stream temperature modeling is a well-known problem that has long found its way into the agendas of institutional actors (e.g., U.S. Department of Interior, 1993), ultimately leading to the development of location-specific models that predict water temperature anomalies or support water release decisions (Castelletti et al., 2014; Rheinheimer et al., 2015). A similar observation applies to thermoelectric stations

—especially those utilizing open-loop cooling—whose water use can largely affect downstream water bodies (Logan et al., 2021). Accounting for these processes is a pressing need, since (a) the number of dams and thermoelectric stations is increasing and, with them, the associated thermal impacts (Bonnema et al., 2020; Wang et al., 2019), (b) future increases in air and water temperature (Bosmans et al., 2022) will likely put emphasis on the role played by dams and thermoelectric stations, and (c) the progressive development of hyper-resolution models will force us to account for processes that may appear less relevant at larger spatial scales (Xiong et al., 2020). And yet, water temperature dynamics are raraely considered in large-scale hydrological models (see Li et al., 2015; Liu et al., 2020; Tokuda et al., 2019; van Vliet et al., 2013), with even fewer models considering thermal stratification in lakes and reservoirs (Wanders et al., 2019; Yigzaw et al., 2019). There is thus a need for the following three research directions. First, we need models that help us account for the impact of thermoelectric stations on water temperature across large domains, as recently estimated by Raptis et al. (2016), Van Vliet et al. (2021). This research direction currently banks on data sets that describe, at the plant level, cooling systems and thermal emissions (Raptis et al., 2016), and would thus benefit of new observational data sets providing information on withdrawn water volumes, water discharge temperatures, and the determinants of these variables (Sjöstedt et al., 2025). Second, we need to develop different approaches to thermal stratification modeling in lakes and reservoirs, especially for data-scarce regions. Leveraging the information provided by satellite data could be a viable option (Ahmad, Hossain, et al., 2021). Third, we should carry out comparative assessments, especially in regions that are endowed with reliable observational data sets (Segura et al., 2015).

Flow regulation and diversion infrastructures also have a major impact on sediment transport, nutrients, and DO on downstream water bodies (Winton et al., 2023). Similarly to the case of water temperature, the development of location-specific models is a rather established approach (e.g., Lindenschmidt et al., 2019); what we are missing is the representation of these processes in large-scale hydrological models. Taking the case of sediment transport as an example, it is worth noticing that modeling efforts spanning across large spatial domains have been primarily relying on a static modeling approach (e.g., Schmitt et al., 2019; Wild & Loucks, 2014). Recently, though, we have started to witness the emergence of dynamic sediment connectivity models that quantify spatio-temporal sediment (dis)connectivity in river networks (Tangi et al., 2022). Should we be able to deploy these models over large domains and couple them with macro-scale hydrological models, we would then have a pathway for deepening our understanding of how water infrastructures affect sediment transport across the globe. This is yet another area that will benefit from recent advances in remote sensing, which has produced observations of large-scale patterns of sediment transport. Two examples relevant to studies focusing on sediment transport and dams are RivSed, a database of satellite-based estimates of Suspended Sediment Concentration (SSC) across 460 large US rivers (Gardner et al., 2023), and the data set of SSC and flux for 414 major rivers across the globe produced by Dethier et al. (2022). Beyond dams, other relevant examples of data sets include the satellite-derived observations of riverine sediment response to mining (Dethier et al., 2023) and deforestation (Narayanan et al., 2024).

4. Improving Model Calibration and Diagnostic Evaluation

The calibration and evaluation of large-scale hydrological models is a challenging exercise, owing to the number of free parameters involved, the lack of adequate data at the regional and global scales, and the computational requirements that arise when trying to apply the sophisticated methods for parameter estimation (e.g., Duan et al., 1992; Tang et al., 2006; Vrugt et al., 2003) and uncertainty and sensitivity analysis (e.g., Beven & Binley, 1992; Song et al., 2015) traditionally used in catchment-scale modeling. All these issues are only made more complex in regions where hydrological processes are heavily affected by human interventions.

4.1. Calibration

While global hydrological models have historically been mostly uncalibrated, the increasing availability of large-sample hydrology data sets, and particularly river discharge data, has stimulated several calibration attempts in recent years (e.g., Beck et al., 2020, Yoshida et al., 2022). Sensitivity analysis can be used to guide the calibration by showing how parameter importance varies in space and between metrics and thus identifying the subsets of parameters that should be prioritized for calibration in different regions and for different modeling applications (Kupzig et al., 2023).

When strong human influences are present, a potential pitfall of model calibration is represented by parameter interactions and equifinality (Beven, 1993): for example, parameters in one part of the model may be assigned

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unrealistic values to compensate for a poor representation of water infrastructures, leading us to the "right" results for the wrong reasons (Clark et al., 2021; Kirchner, 2006). This is exemplified by Dang, Chowdhury, and Galelli (2020), who set up two instances of the Variable Infiltration Capacity model (Liang et al., 2014) for the Upper Mekong River basin. One instance was coupled with the Lohmann's routing scheme (conceived for pristine catchments; Lohmann et al. (1996, 1998)), while the other adopted a variant of the routing scheme to explicitly represent reservoir operations. The calibration exercise showed that both models can achieve the same accuracy in reproducing river discharge at the catchment outlet, but the model without reservoirs does so through "optimal" soil parameters that are unrealistic and are only selected to compensate for the structural error of neglecting dams, ultimately biasing the representation of surface runoff, infiltration, and baseflow.

While including explicit representation of human actions may help reducing parameter estimation biases by removing structural errors, it will also add further complexity to the calibration exercise. There are various gaps that future research should address. A first, fundamental one is that, to date, we have a very limited understanding of how different approaches to human systems modeling, and associated parameter uncertainties, influence the simulation of terrestrial water fluxes and storages across space and time. There is therefore a need for sensitivity analysis studies that help us discover, and target, a variety of matters, such as parameter estimation biases and equifinality. We speculate that such explorations are particularly challenging in the presence of strong non-stationarities in the development and operations of infrastructures (see Section 3), or when dealing with models requiring several free parameters to characterize human actions. An associated challenge is the computational requirements required by such explorations, a matter to which we shall return later.

The second gap regards the development of model calibration routines that curb our reliance on discharge data, thereby reducing the degrees of freedom during a calibration exercise. Recent research has shown a variety of promising directions to tackle this issue for hydrological models of natural (unimpacted) catchments, such as regionalisation techniques (Beck et al., 2016; Samaniego et al., 2017), expert knowledge (Gharari et al., 2014), calibration based on the Budyko framework (Greve et al., 2020), or the use of multiple data sources (López López et al., 2017; Zink et al., 2018). How to use these techniques while explicitly accounting for human interventions on the hydrological cycle remains a largely unexplored area (see the recent study by Hosseini-Moghari et al. (2020)).

4.2. Evaluation

Another element of the modeling process arguably requiring additional research efforts is model evaluation, that is, how we establish that the calibrated model is acceptable for a given purpose. A standard approach to this end, often referred to as model "validation," is to quantitatively evaluate the model predictions against new observations not used in calibration (Refsgaard & Henriksen, 2004). We should focus, in particular, on what variables are involved in the validation process, how time series are handled, and, finally, which performance metrics are used. First, in light of the discussion outlined above, we stress the importance of carrying out validation exercises that are not solely focused on river discharge and that include other hydrological processes, such as terrestrial water storage or evapotranspiration. Furthermore, the ultimate purpose, or downstream application, of a large-scale model should be explicitly considered in the validation. Hydrological models used to inform studies on hydropower production (e.g., Cáceres et al., 2022; Turner et al., 2017; Van Vliet et al., 2016), for instance, should ideally be evaluated against observations of reservoir storage, release, or hydropower production—a matter intertwined with the challenge of expanding the observational records at our disposal (Section 2). Second, studies relying on quantitative validation exercises should not neglect the potential pitfalls that lie in data splitting methods that define a single calibration and validation period—a simplified variation of the split-sample test (Klemeš, 1986) commonly used in deterministic modeling frameworks (e.g., Rakovec et al., 2019; Schlef et al., 2021). These pitfalls have recently come under closer scrutiny: as shown by Shen, Tolson, and Mai (2022), calibrating on older data and then validating on more recent periods tends to lead to inferior model performance. This is particularly relevant in the presence of anthropogenic disturbances, whose non-stationarity may limit the parameter transferability across calibration and validation periods, ultimately deteriorating model performance. The research opportunities for addressing this matter are many, from exploring alternative split-sample tests (Shen, Liu, et al., 2022) to accounting for uncertainty in performance metrics. Modeling practice shows that large-scale hydrology and water systems analysis are not immune to the abuse of performance metrics, meaning that commonly-used metrics (e.g., Nash-Sutcliffe Efficiency, Kling Gupta Efficiency; Gupta et al., 2009; Nash & Sutcliffe, 1970) are adopted in a deterministic fashion that neglects the sampling uncertainty (Clark et al., 2021). It is, therefore, necessary to quantify the uncertainty in the performance metric estimators, work with a broad spectrum of metrics, and carry out model benchmarking exercises that are tailored to the application at hand.

A complimentary approach to these data-based evaluation strategies is the so called response-based evaluation (Wagener et al., 2022), whereby models are evaluated based on the consistency of their input-output response with our understanding of the system functioning (e.g., Kupzig et al., 2023) or comparing functional relationships emerging from different global hydrological models (Gnann et al., 2023).

5. Curbing the Computational Requirements

When looking at the computational requirements associated with the research directions we identified, we should highlight two important points. First, hyper-resolution modeling is a driver for advancing the representation of human actions in large-scale hydrological models, but also a source of major computational complexity (Bierkens, 2015; Wood et al., 2011). Second, the successful exploration of the research questions we pointed to would further exacerbate the computational requirements. So, how do we resolve this deadlock? One obvious answer stands in the solutions that have been identified for hyper-resolution modeling, such as massively parallel, high-performance computing and advanced numeric algorithms (e.g., de Jong et al., 2022; Keune et al., 2016; Maxwell et al., 2015). Research in Earth system modeling has, in the meanwhile, started to create more solutions that may appeal to the aforementioned deadlock. We refer, in particular, to the use of machine learning tools to replace, complement, or improve (the performance of) large-scale hydrological models. The process of replacing a model means building on emulation modeling (Castelletti et al., 2012; Razavi et al., 2012), namely the identification of low-order, computationally efficient representations that could be used to address computationally demanding tasks, such as exploratory modeling (Section 3) or sensitivity analysis (Section 4) (Cheng et al., 2023). Learning data-driven models through the lens of process-based hydrological models is not only a practical solution; it is also a way to preserve domain knowledge and endow data-driven models with comprehensive learning data sets and interpretable predictions. The availability of deep-learning surrogate (or emulation) frameworks may provide practical tools to explore this research direction (Sun et al., 2023), although it is still unclear whether deep learning models can accurately emulate all variables represented in global hydrological models, especially those with restricted spatial relevance such as human water use.

Naturally, not all applications require us to completely replace process-based hydrological models. In this regard, a promising research avenue is the idea of leveraging observational data—and short simulations from only high-resolution model components—to identify simpler models, or parameterizations, that are then incorporated into the original model. This hybrid approach has started to surface in Earth system models (e.g., Gentine et al., 2018) and has recently been applied to a global hydrological model using a differentiable, physics-informed neural network framework (Kraft et al., 2022). Exploiting this approach could help us address a variety of issues, such as the exploration of uncertainties in human system representations. A closely related and increasingly influential research direction is differentiable modeling (Shen et al., 2023), in which physical knowledge is embedded into trainable neural architectures, enabling discovery of unknown or poorly constrained relationships. Differentiable modeling has so far been primarily applied to pristine catchments; this said, one might expect that the modeling flexibility of neural networks—or other machine learning algorithms—could be exploited to represent human decisions. Finally, machine learning tools could be used to post-process the outputs of large-scale hydrological models, with the ultimate goal of improving their accuracy (Yang et al., 2019). This may be particularly appealing in regions where the lack of data undermines our ability to capture human impacts on the water cycle.

6. Concluding Remarks

During the past three decades, the field of large-scale hydrology has taken major steps to improve the data and models used to represent human actions. In this commentary, we argue that the concomitant availability of new data sources and modeling tools, coupled with ongoing research efforts on hyper-resolution and multi-sector modeling, makes this is an opportune moment for "putting anthropogenic interventions at the core of the water cycle diagram." Doing this will require addressing four challenges, namely creating hyper-resolution global data sets of water management practices, improving the characterization of human impacts on water quantity and quality, developing a deeper model diagnostic process, and curbing the computational requirements of large-scale hydrological models. At the same time, it is essential to recognize that hyper-resolution modeling can also give rise to what Beven et al. (2015) call "hyperresolution ignorance": The illusion of precision in the absence of adequate process understanding or data quality. Addressing this risk will require pairing technical advances with a continued focus on model realism, diagnostic evaluation, and uncertainty quantification.

Looking forward, we thus envision a future in which we could rely on data sets of human actions with unprecedented granularity. In turn, such data could be used to identify models of human behavior (the decision-making processes underlying those actions) with different underlying philosophies (e.g., prescriptive vs. descriptive), complexity (e.g., exogenous vs. endogenous), and spatial aggregation. This "modular" approach—where behavioral components can vary in structure and complexity—would be underpinned by a deeper model diagnostic process as well as data analytics that help tackle the increase in computational requirements. Importantly, the availability of such a modular approach to human system representation would help explore model uncertainty and ensure that both data and models are appropriate for their purpose. In other words, being able to explore the uncertainty associated to (hyper-resolution) data and models could help us ensure that the representation of human actions in large-scale hydrological models is properly tailored to the specific data and research questions at hand. In turn, a deeper understanding of the relation between the quality of the available input data, the available modeling approaches, and the purpose of large-scale modeling will further solidify the key role that these models serve in broader, multi-sectoral applications, such as studies on terrestrial ecosystems (Fisher & Koven, 2020) or global change assessments (Niazi et al., 2024).

To conclude, we believe that addressing the research gaps outlined here is a major challenge for hydrologists because of the modeling, computational, and data development needs that it entails. Even more important is the convergence of multiple communities: large-scale hydrology, catchment hydrology, water resources systems analysis, and socio-hydrology would all substantially benefit of mutual interactions that put human-water interactions at the center of the conversation. Ideally, such convergence should be underpinned by the international hydrological community.

Data Availability Statement

This work did not use and generate data and software to support its conclusions.

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