Simulation of hydropower at subcontinental to global scales: a state-of-the-art review

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Abstract
Hydroelectric power is playing a new and often expanded role in the world’s major power grids, offering low carbon generating capacity in industrializing, dam-building economies while providing reserve and flexibility to co-manage fledgling wind and solar resources in high income countries. Driven by river flows, conventional hydropower is exposed to the vagaries of weather and climate, motivating drought and climate change hydropower impact studies at large spatial scales. Here we review methods of climate-driven hydropower simulation at large spatial scales, specifically multi-basin regions to global. We identify four types of approach based on complexity of tools and richness of data applied to the problem. Since the earliest attempts to model climate-driven hydropower at continental scale almost two decades ago, the field has transitioned from one of scientific curiosity to practical application, with studies increasingly motivated by the need to inform power grid expansion planning and operation. As the hydrological and water management models used in large-scale hydropower studies become more sophisticated, new opportunities will emerge to study the impacts of changing hydropower on power system reliability and performance at large power grid scale. To grasp these opportunities, the water resources community must continue to enhance data and models for representing river flows and anthropogenic water use and management at subcontinental to global scales.

1. Introduction

Hydroelectric power is set to play a prominent role in many of the world’s major electrical power grids in the 21st century. Currently, hydropower contributes almost a fifth of the world’s electricity generation and more than half of global renewable electricity generation. The total global hydropower generation output of 4306 TWh in 2019 constituted the single largest annual contribution from a renewable energy technology in history (IHA 2021). Fifty countries added hydropower capacity in the same year, among them the major industrializing economies of Brazil, China, and India, as well as hydropower development hotspots of South East Asia and various parts of Africa. While emerging economies build new dams, high income countries are reviewing the role of existing hydropower assets in the modern power grid. The drive to decarbonize electricity production with expansion of variable wind and solar technologies has underscored the need for the low-carbon generating capacity and short-term balancing capabilities that hydropower can provide (Yang et al 2018).

Power grids that depend on hydropower also depend on the climate to deliver water to reservoirs. Hydropower plants generate electricity by releasing stored water into penstocks to drive turbines. Their reservoirs are filled naturally from river flows, replenished by rainfall and snowmelt or, in the case of pumped storage systems, artificially through pumping previously released water back into storage when energy prices are low. Although water (and thus energy) can be stored for later use, many hydropower reservoirs lack the storage capacity to distribute energy over periods of more than a few days or weeks (run-of-river hydropower plants, which are dominant in some regions, lack any significant storage and must generate power in sync with river flows at daily and sometimes sub-daily timescales). Large reservoirs with over-year capacity can store water to generate...
electricity in later dry periods, but their operators are often motivated to generate promptly to meet other objectives (e.g. maintain a flood buffer) or avoid loss of efficiency as head levels in reservoirs drop and spillage or evaporative water losses accumulate. For these reasons, total annual hydropower generated in a large region is often tightly correlated with same-year or even same-year plus previous year precipitation averaged over the same space (see example of Western U.S. in figure 1). Power grids that rely on hydropower are thus exposed in the short term to the threat of prolonged drought and in the long term to possible drying trends that may erode generating capability over decades.

The threats of climate change and drought have motivated a growing field of research into hydropower generation and potential at large scales, from multi-basin power grids, to continental and global studies (Yalew et al 2020). Such assessments of climate impacts on hydropower have advanced our understanding of the interdependencies between water and energy systems and can inform power grid operations and resource expansion models essential to reliability analysis, investment planning, and energy policy. This review article documents and describes the key methodologies employed in large-scale, climate-driven hydropower analyses. Our aim is to assist the next cohort of scientists engaged in this field by categorizing approaches available and illustrating advantages and limitations for a range of applications, including examination of the world’s hydropower potential, development of sub-continental, sub-annual hydropower scenarios to explore the nexus of water and energy, and creation of data to drive power system models. Prior reviews of large-scale hydropower literature have focused on key findings rather than methods and models applied. These include reviews focusing on specific regions, such as Stanton et al (2016), focusing on electricity generation in Europe, and Falchetta et al (2019) covering sub-Saharan Africa. Craig et al (2018) review studies covering climate impacts on electricity generally, identifying a need for considering impacts jointly across generating technologies (e.g. combined impacts on hydro and thermal power). Yalew et al (2020) offers the most comprehensive review to date, covering results of 220 studies of climate impacts on energy systems across all spatial scales. Of those 220 studies, almost half cover hydropower, indicating significant research funding committed toward understanding the impacts of climate on hydropower across the world. Yalew et al (2020) observe that data, methods, and models employed in the study of climate impacts on electricity supply at large scale vary substantially. Here we address some of the factors influencing an analyst’s decisions on which models to apply, depending on spatial scale, spatiotemporal resolution, and end application.

2. Scope of review and literature search

The scope of our review is large spatial scale, climate driven modeling studies that simulate energy from
hydroelectric dams. We include studies of both potential hydropower and actual hydropower. Potential hydropower is the theoretical amount energy available from water throughout a basin or region subject to a range of possible limiting factors, such as exclusion of land protected for environmental purposes (the various version of hydropower potential are described in section 3.2.2). Actual hydropower is the energy generated at existing or planned plants.

Large spatial scale includes global, continental, and multi-basin power grid (e.g. Brazil, Western United States).

To ensure that our review captured all relevant research, we searched across a very wide sample of literature. We queried the Web of Science database on 9th March 2021 for studies that mention both ‘hydropower’ (or variants, including combinations of ‘water’ and ‘energy’) and either ‘global’, ‘continental’, or the name of a continent or large region in the title field:

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T1=\text{(hydropower OR hydroelectric) OR “hydro power” OR “hydro electric” OR “power grid” OR “power system” OR “water-energy” OR “energy-water” OR (water AND energy)) AND T2=(global OR continent OR region) OR CONUS OR America OR Africa OR United States OR “U.S.” OR US OR Europe OR Asia OR China OR India OR Brazil OR Russia OR Canada OR Australia.}
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The asterisks applied to some of these search terms allows for any extension to the preceding string (e.g. hydroelectric∗ will allow for hydroelectricity and hydroelectrical; region∗ will allow for regions, regional, etc) We added to this the relevant works from a selection of 19 prominent authors, leading to an initial reference list of 1625 unique articles. This list was filtered for journals with impact factor (IF) greater than four and eigen-factor score (ES) greater than 0.003. We removed articles published before 2005, since we find this to be the year of publication of the first continental-scale hydropower simulation study informed by a large-scale hydrological model (LHM). We also removed articles published in journals focusing on geology, transport, space, safety, and so on (full list of removed title strings in a GitHub repository supporting this article—see Data Availability), as well as journals featuring fewer than three articles across the whole list of articles (except for high-impact journals or new journals, such as Nature Energy). From this substantially reduced list, we manually checked titles, abstracts, and article content to identify and remove out of scope articles. Most articles were removed on the basis of either inappropriate scale, subject, or approach (e.g. large-scale hydropower study that does not include a modeling component). We reached a final set of 45 modeling studies of climate-driven hydropower at sub-continental (multi-basin) to global scale.

3. Methods applied in large-scale hydropower analysis

3.1. Hydropower computation at large scale: the basics

Large-scale hydropower modeling conducted by a scientist differs from hydropower modeling conducted by a dam operator or power producer. The main difference is fidelity. Conventional hydropower plants generate electricity by releasing reservoir water into penstocks and through turbines. While those mechanics are well established and easily modeled, the associated hydrological parameters and water management decisions are often complex and site specific. An accurate model of hydropower generation with sub-daily temporal resolution must represent reservoir bathometry, multi-purpose reservoir operations, and local regulatory constraints, including forebay and tailwater elevations, and fish spill requirements, among other features. Input data must also be accurate. The model may be forced with observed inflow records or simulated inflows derived from high-resolution hydrological models built specifically for the watershed of interest. Operators adopt high-fidelity modeling schemes because they seek timely and accurate information on their plants’ near-term capabilities to optimize the bidding of generation and reserve into power markets (Oikonomou et al 2022). Although the large-scale hydropower modeler could benefit from these high fidelity models, the data required to simulate hydropower in such detail is rarely available for a large fleet of hydropower plants spanning a subcontinent.

In lieu of detailed site specific hydropower models across a large spatial scale, the geophysics scientist conducting a subcontinental to global scale hydropower study adopts a large-scale hydrological modeling approach. Hydropower can be computed at various junctures of the large-scale hydrological modeling apparatus, as illustrated in figure 2. All large scale hydropower studies reviewed in this article rely on distributed climate data. These data come from two main sources: reanalysis climate products or global climate model simulations. Linking climate to hydropower generation directly can be an effective strategy for annual energy computation in some cases, as we shall see. Few studies are this simple. Typically climate data will drive a land surface model (LSM) to yield spatially distributed surface runoff, or an LHM and water resource, which routes runoff to streamflow in rivers and may include water management representation, including anthropogenic water consumption. Reservoir operations may also be represented in these models, allowing the user to use reservoir outflow simulations to compute energy at individual plants. Alternatively, simulated streamflow can drive isolated, generalized reservoir models deemed more appropriate for hydropower...
3.2.1 and 3.2.2 total energy generated (J) over the period varies with storage. In many other studies, estimate of hydropower generation from water. Nonetheless, we refer to this as a physics-based constant) should vary as a function of flow and transition, because the efficiency of a turbine (assumed large scale was conducted by Lehner et al. This study pioneered two types of large-scale hydropower modeling applied to the European continent: hydropower from runoff (the focus of this section, here labeled 'Type 1'), and hydropower from routed streamflow (the focus of the next section 3.2.2). Alternatively, an assumed constant \( h \) allows one to model hydropower according to a simple linear relation with no intercept: \( E_p = \alpha \times Q_p \) in which \( \alpha \) can be calibrated to fit observed energy. A slightly different version may assume a mandatory constant volume of spill \( s \) over the period, leading to a linear relation with a non-zero intercept \( E_p = \alpha \times (Q_p - s) = \alpha Q_p - \alpha s = \alpha Q_p + \beta \) (where \( \beta \) is the model intercept). Determining a new relation for different seasons or months of the year provides further flexibility that may account for varying nonpowered release or change in typical head levels by season. Models that are seemingly statistical in nature are thus often interpretable in physical terms.

### 3.2. Four types of large-scale hydropower

Large-scale hydropower studies may be categorized into one of four types, as illustrated in figure 3 and elaborated in the following sections with reference to studies applying each approach (table 1).

#### 3.2.1. Type 1: surface water to hydropower—pioneering studies

The earliest study of climate-driven hydropower at large scale was conducted by Lehner et al (2005). This study pioneered two types of large-scale hydropower modeling applied to the European continent: hydropower from runoff (the focus of this section, here labeled 'Type 1'), and hydropower from routed streamflow (the focus of the next section 3.2.2). These two approaches are labeled method A and

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**Figure 2.** A myriad of pathways for computing hydropower at large scale from spatially distributed climate data. Water availability variables are given in red font.
Figure 3. Four types of large-scale hydropower study.

Type 1: Surface water to hydro

- Climate (spatial grid) → Runoff (spatial grid) → Energy computation → Hydropower

Type 2: Natural river flow to hydro

- Climate (spatial grid) → Runoff (spatial grid) → River routing model → Streamflow (river channels) → Energy computation → Hydropower

Type 3: Reservoir storage and release

- Climate (spatial grid) → Runoff (spatial grid) → River routing model → Streamflow (river channels) → Generalized reservoir model → Storage, release (hydroelectric dams) → Energy computation → Hydropower

Type 4: Statistical / machine learning

- Climate (spatial grid) → Statistical / machine learning approach → Streamflow (river channels) → Generalized reservoir model → Storage, release (hydroelectric dams) → Energy computation → Hydropower

method B in Lehner et al (2005), respectively, and both methods have since been adopted in multiple other settings. 'Method A' introduced the idea of computing 'gross hydropower potential' (GHP) from spatially-distributed runoff simulations. When computed from runoff distributed throughout a watershed, GHP is a measure of the total potential energy available from surface water generated on a land mass. River flow routing is unnecessary, because all energy is harnessed from point of landfall to sea level, and the problem of siting dams is sidestepped. Although useful in scientific settings, GHP has limited practical value, since this theoretical upper bound of hydropower would never be approached in reality. In addition, even though GHP is determined across all individual grid cells of a watershed, the computed data indicate only the origin of hydropower potential and not progression of available energy harnessed along a river system. This GHP determined from runoff is therefore useful only when examining the aggregated potential hydropower at the scale of river basins, as was done for Europe in Lehner et al (2005) and later at global scale in Pokhrel et al (2008). Studies that adopt GHP may explore how gross potential varies across space and time. For example, Zhou et al (2015) performed a
global analysis of GHP to identify countries where vast hydropower resources remain untapped. Zhou et al (2015) also used GHP to show differences between gross potential and more nuanced metrics that bridge the gap between the theoretical upper bound and the actual upper bound after accounting for various physical and economic constraints on harnessing potential energy (such as feasibility of dam construction).

One can also infer possible climate-driven, long-term trends in a region’s hydropower generation directly from trends in GHP. Liu et al (2016) performed such an analysis for China, highlighting nontrivial trends in GHP and recommending closer analysis of actual hydropower generation. Worman et al (2020) determined GHP relating to individual dams by delineating each dam’s upstream area and computing gross potential at each grid cell assuming elevation drop from grid cell to dam site elevation. This is commensurate with accumulating all runoff upstream of the dam site and then forcing it through a turbine of unlimited power generating capacity. With plant-level gross potential assessed, Worman et al (2020) developed an ‘energy-domain specific drought’ to evaluate the candidacy of a hypothetical continental power grid that benefits from diversity of hydropower production from independent weather systems, echoing the earlier the work of Voisin et al (2016) (which introduced a ‘Water Scarcity Grid Impact Factor’) and Voisin et al (2020) (which demonstrated power grid reliability benefits offered by hydrological diversity across Western United States) described in section 3.2.3.

In addition to evaluating potential hydropower generation through GHP, distributed runoff can also be used to estimate actual generation. Since reservoirs allow hydropower operators to store water and shift the timing of generation to some degree, run-off driven computation of hydropower is effective at coarse temporal scales only. This approach has been applied to aggregated clusters of plants (e.g. within a country or river basin) rather than individual plants—owing primarily to data availability. Annual, country-scale hydropower generation data are available from the U.S. Energy Information Administration, for example, and are a popular choice for predicting country-level hydropower from runoff. Successful applications of large-scale, runoff-driven hydropower computation include the earliest study of global climate change impacts on hydropower generation (Hamududu and Killingtveit 2012). In this study, hydropower availability was simulated as a function of change in runoff under alternative climate trajectories. In a more targeted study, Kao et al (2015) examined change in hydropower generation across a major hydropower producing watersheds of the United States, adopting a linear model that predicts annual hydropower total generation in a major power marketing regions as a function of the total annual runoff generated in those regions upstream of major dams.

3.2.2. Type 2: Natural river flow to hydro
In addition to introducing GHP computation from runoff, Lehner et al (2005) considered a more realistic computation of GHP based on streamflow. Rather than computing the potential energy of each unit of surface water as a function of its total head (i.e. elevation relative to sea level), the streamflow-based approach routes the runoff through the river channel network. Hydropower is harnessed along the stream network as a function of the elevation difference between upstream and downstream grid cells. We label this category of approaches ‘natural river flow to hydro,’ emphasizing that this model computes hydropower directly from river flows without considering the role of man-made reservoirs in capturing energy for later use.

GHP is one of many metrics of hydropower potential that may be determined using ‘natural river flow to hydro,’ and has remained a popular choice for a range of studies and applications. Van Vliet et al (2013) computed GHP from streamflow to estimate long-term change of hydropower potential for individual countries of Europe. These results informed a study of cost-optimal power production with international import and export of power. Zhou et al (2015) and later Hoes et al (2017) applied the GHP from streamflow approach at global scale, highlighting a large discrepancy between how much hydropower is actually generated and how much is potentially available. More recently, Zhang et al (2018) computed GHP from simulated streamflow to infer trends in hydropower availability with climate change globally. Another example is Van Vliet et al (2016b)—a global study that explored uncertainty in GHP under alternative emissions scenarios, climate models, and global hydrological models. Lastly, Paltan et al (2021) explored GHP in a global study with a multi-model ensemble to determine climate risk to hydropower in a warmer world.

More nuanced, realistic metrics of hydropower potential can be determined when hydropower is computed along the river network at specific locations where it is harnessed. One may assume a quantile of streamflow above which generation is unavailable, leading to a metric known as ‘Technical Hydropower Potential,’ intended to represent limits of turbines for generating peak flows. One can also filter out the grid cells of a watershed where generation might be infeasible, such as locations with unfavorable land relief and lack of power transmission infrastructure (‘Economic Hydropower Potential’), or lands developed for human activity (agriculture, urban) or protected for environmental preservation (‘Exploitable Hydropower Potential’) (figure 4). This suite of hydropower potential metrics was explored at global scale in Masaki et al (2014), Zhou et al (2015),
Figure 4. Hydropower potential from runoff or streamflow, based on Zhou et al. (2015). The use of streamflow rather than gridded runoff allows one to compute a range of alternative metrics of hydropower potential, including technical potential (streamflow is capped at certain quantile to account for likely turbine design capacity constraints), economic potential (locations filtered for most cost-effective dam sites), and exploitable potential (locations filtered for...).

and later using much higher resolution river network and streamflow data in Gernaat et al. (2017). Hydropower potential is also likely to be correlated strongly with actual generation at annual timescales, and may therefore serve as an indicator of annual generation or trends in average generation under given climate forcing. A climate-driven trend in potential hydropower may be superimposed on average of historical annual hydropower generation to develop hydropower generation scenarios at various spatial aggregations (e.g. plant, basin, country). Trends in expected hydropower generation were analyzed in this fashion for the European continent in Tobin et al. (2018). If based on GCM data, trajectories of available hydropower out to mid or late 21st century may inform capacity expansion modeling under climate change. This approach was taken in a multi energy model study of Brazil in Lucena et al. (2018) and globally to derive input for an integrated assessment model in Zhou et al. (2018a). Following a different tack, Byers et al. (2018) analyzed hydrological indicators (e.g. drought intensity, interannual variability) derived from global hydrological model output with weighting across grid cells determined by total plant capacity.

If existing or planned hydropower dam locations and plant specifications are known, the natural river flow approach can be used to simulate actual generation (as opposed to potential generation) across a large regions. Since reservoir storage dynamics are not captured, this approach is generally best suited to hydropower computation at coarse temporal resolution (annual) with diminishing accuracy as one moves to sub-annual and finer temporal scales (as with runoff-based computation of hydropower). The first study to simulate annual actual hydro from annual unregulated streamflow at dam locations with assumed static head levels was Bartos and Chester (2015). By focusing on the Western United States, the study was able to leverage the available generation observations for individual plants and thus develop linear models to predict annual hydro from streamflow simulated under historical climate forcing. This study was also the first hydropower study to develop a statistical relationship to compute plant level hydro from flow at a large scale.

3.2.3. Type 3a: Regulated river flows
State-of-the art in modeling of hydropower at large scale involves models of reservoirs and computation of hydropower generation using regulated water releases and sometimes dynamic head levels. We distinguish two categories of reservoir operations applied to the study of hydropower at large scale. The first (Type 3a, this section) is the logical extension and improvement on ‘natural river flow to hydro’, wherein reservoirs are implemented in the river routing scheme to regulate releases. An alternative approach, elaborated in the following section (Type 3b), applies a reservoir operations model in post-processing of streamflow simulations.
In a landmark study that was the first to quantify impacts of climate change on global actual hydropower generation, Van Vliet et al (2016c) simulated annual generation across 24 515 power plants using a global hydrological model that includes regulation of water by reservoirs using the generalized method of Haddeland et al (2006). Lacking plant-level generation data to link flow to generation statistically, this study used average (static) head for individual plants based on dam height to determine hydropower energy from first principles. Country-level, annual hydropower generation data were used to scale up total simulated, total hydropower generation for each country to account for any unstimulated capacity. Following the same approach, Van Vliet et al (2016a) quantified the impacts of drought years on global and regional-scale hydropower generation. Wan et al (2021) performed a similar global-scale drought analysis using a more recent hydropower plant database and monthly flows from a large-scale hydrological driving hydropower computation. This study included monthly-varying hydraulic head for plants associated with a reservoir in the hydrological simulation.

A similar approach was adopted in Voisin et al (2016), although here the hydrological analysis was performed at fine spatial resolution (0.125°) and at the regional scale of the interconnected power grid of the Western United States for purpose of coupling with a power grid model. In Voisin et al (2016), the conversion of flow to energy followed a unique approach: water releases from reservoirs were aggregated to annual totals and then computed as an anomaly relative to a base year. This anomaly was then used to linearly scale the monthly hydropower generation pattern observed in the base year. The underlying assumption with this approach is that total annual flow determines total annual hydropower generation, but with repeating seasonality across years to represent hydropower operations driven by water availability and power grid needs. This approach was adopted in a number of subsequent studies focusing on the Western and Southeastern United States, wherein monthly hydropower is used to drive power grid simulations to explore impacts of climate and drought on power system performance and energy expansion decisions (Voisin et al 2018, 2020, O’Connell et al 2019, Fonseca et al 2021).

Another unique case was introduced by Zhou et al (2018b), also applied in Western United States. Here head levels of large storage reservoirs were tracked dynamically in the simulation using a generalized bathymetry model (Fekete et al 2010) to convert storage to lake elevation. Computation of hydropower was performed using parameters to provide flow bias correction, seasonal spill (representing environmental flows or other nonpowered constraints on reservoirs), and penstock intake limits. These parameters were optimized to match observed, monthly hydropower generation. Focusing on the same region, Cohen et al (2020) applied a more parsimonious model, using linear regression to convert monthly regulated flow at dam locations (predictor variable) to monthly power produced (target variable). Monthly varying parameters in this model implicitly capture seasonal variation in typical head levels (captured by the slope parameter) and spill requirements (captured by the intercept) without the need for a numerical solution for parameters (linear regression is solved analytically). A caveat of these studies is that generalized reservoir schemes in LHMs tend to cover only the largest reservoirs on the river network, such as those described in the Global Reservoir and Dams Database (Lehner et al 2011). This means hydropower computed for smaller reservoirs is essentially ‘natural river flows to hydro’ with river flows regulated by upstream dams though not the reservoir at each plant location. In many of these cases this is a legitimate strategy, because often the low storage reservoirs are indeed run-of-river plants that require no storage component for accurate simulation at monthly or even weekly temporal resolution.

In perhaps the most high-fidelity simulation of climate-driven hydropower at a large scale to date, Chowdhury et al (2021) simulated large-scale hydrology with detailed reservoir models that account for bathymetry (including tracking of lake surface area), evaporation from the reservoir surface (varying with surface area), and rule curves designed to replicate typical hydropower operations in the target region (South East Asia) using the methods detailed in Dang et al (2020). While Chowdhury et al (2021) used this model to inform a power systems operations model, the work of Siala et al (2021) applied a similar framework in the same region to inform a power system capacity expansion study, highlighting the scope of applications for large-scale hydropower research in power systems analysis, discussed further in section 4.

3.2.4. Type 3b: Offline reservoir operations
One can also model reservoirs offline to simulate hydropower generation at large scale. This can be the best choice if the reservoir operations embedded in an LHM misrepresent hydropower dam operations (e.g. if the LHM applies generic flood control or water supply rules unsuited to hydropower operations), or if the LHM lacks reservoir regulation altogether. In such cases the analyst extracts the time series of streamflow for each dam location and then uses these data to drive individual reservoir and hydropower models. These models may be determined using either descriptive methods (attempt to reflect actual operations by developing release rules representing reality) or normative methods (develop a set of operating rules that are optimal for meeting some objective function) (see section 4.2).
Stochastic dynamic programming (SDP) models can provide such optimal rules and have been adopted widely in large-scale hydropower analysis. Ng et al (2017) took an existing streamflow simulation, extracted monthly streamflow time series for ∼1600 grid cells (representing the world’s largest hydropower plants), and applied the SDP formulation developed by Turner and Galelli (2016) to define optimal operating policies for each dam. These policies specify release as a function of storage, inflow, and season. The optimal rules targeted maximum hydropower generation subject to uncertain flow conditions, and including effects of reservoir bathymetry, dynamic head and water surface area, and lake evaporation. The same approach was used in Turner et al (2017a) to project impacts of climate change on global hydropower generation, offering a new take on a problem tackled earlier by Van Vliet et al (2016c). Turner et al (2017b) developed the analysis for a larger of GCM ensemble, using the energy outputs to create country-scale hydropower trajectories to force a global integrated assessment model and, later, in regional energy models for Colombia (Arango-aramburo et al 2019). Also adopting the reservoir optimization tool of Turner and Galelli (2016), Caceres et al (2021) executed a deterministic simulated optimal hydropower for 134 plants across Brazil, Colombia, and Peru.

Another approach is to drive existing water supply system models (rather than single-reservoir models) with flows generated from LHMs. For instance, Boehlert et al (2016) calibrated individual water allocation models for 2119 sub-basins of the conterminous United States to simulate hydropower under a range of climate scenarios. This approach allowed for consideration of water supply to competing uses under demand scenarios based on the same climate assumptions driving water availability. Similarly, Kao et al (2016) used unregulated runoff as an input to lumped Watershed Runoff-Energy Storage models for individual Power Marketing Administration of the United States, providing seasonal resolution impacts of climate on actual generation at a zonal (multi-plant) resolution. Lastly, De Queiroz et al (2019) used hydrological model flows as input to a hydro-thermal optimization model for Brazil, illustrating how climate change could affect risk-based planning metrics (‘Assured Energy’) evaluated in the hydro-thermal simulation.

### 3.2.5. Type 4: Climate to hydro using statistical or machine learning models

Having discussed increasingly complex methods of large-scale hydropower computation, we now turn to the category that avoids hydrological modeling altogether: statistical models that relate precipitation and hydropower directly. Simple versions of this approach neglect the non-linearity of catchment processes, but have been found to be effective at coarse resolution, such as annual hydropower generation at the scale of regions, rather than individual plants. This was approach taken in Wang et al (2014), covering nine major hydropower producing provinces in China. If lacking historical generation records, one may still infer vulnerability of hydro to climate change by analyzing the share of a large region’s hydro capacity lying within different precipitation regimes. This approach was taken in Conway et al (2017), in which spatially-correlated rainfall regions across sub-Saharan Africa were first identified. Hydropower vulnerability was inferred by overlaying those regions with watershed delineations upstream of hydropower dams and the associated capacity they support. Also an inference rather than modeling study, Ruffato-ferreira et al (2017) analyzed projected climate using a metric of long-term precipitation minus evaporation under historical and future climate projections to explore possible impacts on hydropower generation across Brazil’s major river basins.

A lack of actual generating data across a wide sample of hydropower plants in a large fleet limits the scope for Type 4 methods that predict hydropower from climate directly; statistical and machine learning methods must be trained to predict a target variable. Type 4 studies have thus been peripheral to this field so far, but could emerge in the form of emulators or surrogate models designed to substitute computationally-demanding hydrological simulations (meaning the target variable is not observed hydropower, but hydropower simulated from a Type 3 modeling arrangement). Instead of relating climate to hydro directly, one can also target reservoir inflows with the statistical or machine learning approach. For instance, De Lucena et al (2009)—and also in De Lucena et al (2010)—simulated reservoir inflows from climate data using a statistical model while performing reservoir operations and energy computation with higher fidelity offline. Changes to the mean and variance of precipitation under a climate projection were used to adjust the parameters of a stochastic process model describing the inflows to hydropower reservoirs across Brazil. The stochastic model then allowed exploration of a range of plausible flow scenarios associated with climate change. Although not yet applied in hydropower research, surrogate models for LHMs have begun to emerge in the scientific literature (Gu et al 2020, Tran et al 2021). These models could be applied in future hydropower analyses to focus on reservoir inflows to drive detailed reservoir operations models. This general approach has been demonstrated at small scale by Ahmad and Hossain (2019), in which a machine learning model replaced the large-scale hydrological model to allow for computation of daily inflows at individual plant locations. Such developments promise significantly
### Table 1. Summary of methods, specific data and model needs, applicable research, and appropriate minimum resolution of hydropower output.

| Method | Specific data and model needs | Common research applications | Appropriate spatial and temporal aggregation |
|--------|-------------------------------|-----------------------------|---------------------------------------------|
| Type 1—Surface water to hydro | Spatially-distributed (gridded) climate time series. Land surface model. | Estimation of Gross Hydropower Potential (GHP). Estimation of annual aggregated generation. | Country or basin-scale, annual. |
| Type 2—Natural river flows to hydro | … + river routing model, plant locations and dam/reservoir specifications. | Estimation of economic, technical, or exploitable hydropower potential. Study of climate impacts on plant-level, annual hydropower generation. Development of national-scale hydropower trends to constrain global integrated assessment models. | Plant-scale, annual. |
| Type 3—Reservoir storage and release | … + water management model with reservoir operations. Data to inform realistic reservoir behavior is desired for sub-annual hydropower. | Study of drought impacts on hydropower generation. Development of hydropower data to drive electrical power system models. Development of plant-level trends for capacity expansion models. | Plant-scale, sub-annual. |
| Type 4—Statistical/machine learning models | Reservoir operations models needed if inflow is the target variable. Observed hydropower required to predict hydro from climate directly. | Inference of a country’s hydropower fleet’s vulnerability to climate change. Possible future application: emulator of a Type 3 hydropower simulation. | Dependent on spatial and temporal resolution of data used to train models, and whether reservoir operations are simulated with a physics-based approach. |

3.3. Summary of methods for subcontinental to global hydropower simulation

The four methods of large-scale hydropower simulation detailed above are summarized in table 1. Further detail on specific models used in each of the 45 featured modeling studies are given in table A1 in the appendix.

4. Bridging the gap between large-scale hydropower simulation and power systems research

4.1. Evolution of large-scale hydropower research

Large-scale hydropower research is changing in concert with the advances in large-scale hydrological modeling, creating new opportunities for power systems research. Studies aimed at computing actual generation rather than potential reflect an increased focus on using large-scale hydropower models to feed power system build-out and operational models. Studies that include models of reservoir operations (Type 3a and 3b) have come to dominate the field (figure 5), while studies that shortcut detailed hydrological models (i.e. Type 4) have yet to proliferate. This transition to increased detail in hydrological and water management modeling is both driven by and beneficial for simulation of sub-annual (monthly, weekly) generation during extreme conditions, including drought. However, realizing accurate sub-annual reservoir simulation in large scale hydrological modeling imposes a number of challenges to be addressed in both hydrological and human behavior modeling. In this closing section of our review we explore the emerging opportunity for both academic and industry-led power systems research, and then summarize the key challenges to be addressed to best serve those communities.
4.2. Opportunities

To explore how power systems research can benefit from the developments in large-scale hydrology, we first must describe how the power systems community uses hydropower data to drive its models. Following Oikonomou et al. (2022), we consider three categories of model: capacity expansion models (CEMs), operational power system models (OPMs) and power flow models (PFMs). CEMs simulate the evolution of the build-out of energy supply, transmission infrastructure, and demand controls to meet long-term projected changes in power supply, demand and policy. Changes to power supply may include planned retirements or change in generating capability at plants, such as reduced hydropower due to climate change impacts on available water. OPMs, in contrast, assume fixed infrastructure. These models simulate at high temporal resolution (typically five-minute to hourly) the unit commitment and economic dispatch of electricity across the fleet of interconnected generating units, including hydropower as well as thermoelectric generators and intermittent renewable resources, namely wind and solar. OPMs identify periods of unserved energy and are a key tool for evaluating operational and economic performances of the system. OPMs are also used to evaluate the sensitivity of operations to hydrometeorological uncertainties, the reliability of new buildouts under global change conditions, and technology innovations. PFMs are used to study network reliability. These models simulate short-duration events ranging from a couple seconds to a handful of days. Thus, CEMs can provide future build-out scenarios, OPMs can simulate the reliability and performance of those grid configurations, and PFMs simulate the network stability of the buildout and operations.

The scale and objective functions in PFMs lead to representations of hydropower relying on snapshots of system states and a representation of hydropower more linked to equipment capabilities and environment regulation rather than water availability. The other two categories of power systems model can benefit from different resolution and fidelity of data from large-scale hydropower studies. CEMs often require hydropower trajectories at coarse temporal resolution and, as such, Type 1, 2, or 4 hydropower simulations can suffice. OPMs, in contrast, require sub-annual resolution hydropower information, requiring Type 3 simulation with reservoir operations. Identify four representations of hydropower availability and operations in OPMs: fixed schedule (price taking), offline water model optimization driven by energy prices (price following) and local energy demand (load following), online co-optimization of water and energy objectives (minimum system cost versus maximum power plant revenues), and hydropower monthly targets, where

![Figure 5. An expanding and evolving field. Climate-driven hydropower studies at large scale are becoming more detailed (requiring streamflow and reservoir models), covering a greater number of regions. Each point denotes a paper published, with color indicating focus continent. Vertical positioning of points within each category is randomized to avoid overlap.](image-url)
the PCM unit commitment aims to minimize the system production cost. At present, the last of these four representations (monthly targets) is most easily amenable to ingesting information from a large-scale hydropower study. Fixed schedule means either observed hourly or simulated daily hydropower at individual plants, typically for run-of-the-river plants that cannot change their day-to-day schedule. Large-scale hydropower simulations lack the fidelity and temporal resolution to provide a reasonable fixed schedule for OPMs. An offline water management model driven by energy prices is most often found in watershed-scale studies and local hydropower plant operations rather than power grid scale studies—also due to the needed accuracy on both inflow and operating rules at high temporal and spatial resolution. Typical applications include evaluating the value of flow forecasts or alternate operations to maintain the value of hydropower while addressing new watershed objectives (e.g. Ibáñez et al 2014, Tarroja et al 2019, Wild et al 2019, Cassagnole et al 2021).

Co-optimization of water and energy implies two-way coupling of the power system optimization and river operations optimization (e.g. Tilmant and Kelman 2007, Helseth et al 2016, Seguin et al 2017)—a significant practical and computational challenge that has limited uptake in large-scale OPM studies. With the energy targets approach monthly hydropower estimates may be derived from the large-scale hydropower study and then input to the OPM, which in turn typically disaggregates to a weekly target following load, and then simulates the hourly hydropower schedule following prices (Dennis et al 2011). The underlying assumption in the OPM is that water management would be able to meet this simulated hourly schedule. Unless the hydropower fleet is dominated by run-of-river facilities, Type 3 large-scale hydropower simulation is desirable for creating the monthly targets at each plant; only by representing seasonal storage and release behavior at individual reservoirs can the generating capabilities of large plants be represented accurately at sub-annual scales. In general, the monthly targets approach is practical for large scale studies where hydropower and water management data are scarce or inconsistent, and computational resources are reserved for power grid oriented science questions rather than water specifically (e.g. Voisin et al 2016, 2018, 2020, O’Connell et al 2019, Fonseca et al 2021).

Grid-scale OPM studies informed by large-scale hydropower can also improve regional OPM grid studies that rely on watershed hydrology and hydropower representations by providing boundary conditions (regional market prices, regional import/export). For example, utilities or operators may be interested in studying the performance of their assets during a drought year using a highly detailed local river and cascade hydropower dam operations model. Large-scale hydropower simulations are of little use in a direct sense. However, the local model requires information on electricity prices, which depend on the operations of the entire interconnected grid that could also be affected by drought. A grid-scale OPM informed by large-scale hydropower simulations can provide those electricity price signals to inform the local model (e.g. Garcia et al 2020).

4.3. Challenges and future work
To grasp the opportunities outlined above, large-scale hydropower models must continue to advance the representation of reservoir operations. A key challenge is that operating policies and data describing operator decision making are often unavailable. Approaches for representing human decisions in this context have been categorized as being either descriptive or normative (Giuliani and Herman 2018, Giudici et al 2021). A descriptive approach aims to model decisions as a function of external factors, such as the storage level of the reservoir and time of year. At the watershed scale, one could execute this approach by first collecting reservoir rule curves specifying target storage levels to guide water release. At a continental or global scale, collecting these rules can be impractical. Alternatively, a normative approach assumes that operators are rational agents whose decisions are aimed at maximizing the benefits of the system according to an objective that is described mathematically and targeted in an optimization of reservoir operations. Lacking a global inventory describing the actual objectives of different reservoirs, this approach is also difficult to justify as a means for representing real-world decision making at individual reservoirs across a large spatial scale. Although reservoir purpose (water supply, flood control, hydropower, etc) is reported for each reservoir in the Global Reservoir and Dams Database (Lehner et al 2011), information on the relative importance, seasonality, and other pertinent details of those objectives (e.g. flood pool level, spill constraints, etc) are unreported.

The challenge extends beyond simply defining the right rule curve or the right operating objective for each individual plant. There are also model structure and computational challenges to overcome to correctly represent reservoirs in LHMs. Reservoirs are often operated in coordination and, although this issue has been identified in literature (Rouge et al 2021), a practical solution to represent coordination within an earth-human systems modeling framework has yet to be demonstrated. Reservoir operations are also often guided by forecasts, yet forecast-informed reservoir operations within an LHM requires an iterative simulation to generate the flow forecast within the model, imposing a computation burden. Lastly, no matter how accurate the reservoir model is, an accurate model will perform poorly if forced with biased inflows common to large-scale hydrological models (Turner et al 2020). As a result of these
challenges, reservoir operations in LHMs have followed generic approaches (e.g. Haddeland et al 2006, Hanasaki et al 2006). While successfully representing general regulating effects of dams, these methods are unlikely to capture realistic water storage and release behavior at sub-annual resolutions sufficient for computing sub-annual hydropower generation to force OPMs. Thus, when reservoir releases from such models are used to simulate hydropower (as described in 3.2.3), the equations developed to connect water release to energy are liable to being overfitted to accommodate inaccuracies in the reservoir releases and elevations. This problem is more pervasive as one moves from annual to monthly and sub-monthly temporal resolution, since no LHM captures the short-term behaviors of hydropower operators releasing water to meet local environmental constraints or power system load or prices. Some of these challenges are already being addressed. Observations of reservoir storage, inflow, and release—if collected for a large enough sample of dams—can be used to infer operating rules to markedly improve on reservoir simulation, as exemplified for the United States in Turner et al (2021). These data could inform realistic hydropower generation estimates at a finer temporal resolution (sub-monthly) to better capture response to hydrological extremes. Such advances stand to greatly enhance the value of Type 3 hydropower computation as reservoir storage and releases more accurately reflect actual decisions across individual dams. Observational records will be unavailable for many world regions where hydropower is important. Remote sensing may therefore have to play a greater role, and here too there has been substantial progress in using satellite images of lake surfaces to estimate volume of water storage across large samples of reservoirs (Van Bemmelen et al 2016, Avisse et al 2017, Zhao and Gao 2019, Cooley et al 2021). These techniques can be combined with process models to further enhance our ability to simulate analyze reservoir behavior, such as lake surface evaporation losses (Zhao et al 2021). If moving to finer temporal scales, such as weekly or daily generation, reservoir operations models must be guided not only by typical weekly storage and release behaviors but should also be responsive to variables relating to environmental regulation, such as ramping rates and dissolved oxygen requirements—maintenance practices, such as unit loading strategies and coordination with other projects, and the power system, such as wholesale electricity prices and local loads. Such operational detail has yet to be applied in large-scale hydropower research, although new national-scale datasets that include key operational characteristics of plants, such as the Existing Hydropower Assets dataset (Johnson et al 2021), may serve as a starting point. Finally, many power systems studies are simulated with perfect foresight of next month and next year hydropower capabilities, for which large-scale hydropower studies may also play a role. This application would demand hydrological and water reservoir system operations modeling under forecast uncertainties pertaining to both natural water availability and human withdrawal and consumption. Since accurate reservoir models will perform adequately only if driven with accurate inflow, the community must also continue to improve the resolution and accuracy of LHMs processes, including runoff generation, groundwater-surface water interaction, evaporation, and snow processes. Anthropogenic influences on water resources are also critical, and include land use change, human withdrawal and consumption of water, and regulation of flows from upstream powered and non-powered dams. The 0.5° grid scale common to global study is for many reservoirs too coarse to represent inflow accurately, due to inadequate basin shape (particularly for small basins) and incorrect drainage network representation (particularly complex headwater regions) among other issues (Wood et al 2011, Bierkens et al 2015, Sutanudjaja et al 2018). Lately, high-resolution (1 km), coupled, processed-based hydrology models conceived for watershed simulation been developed for continental scale research (Maxwell and Condon 2016, Tijerina et al 2021). Although not yet representing human water management at the same detail of coarse-resolution models, such models may be the frontier for large-scale hydropower analysis and coupled-human systems modeling.

Data availability statement

As part of the Integrated Multi-sector, Multi-scale Modeling (IM3) project (funded by the U.S. Department of Energy’s Office of Science; see ‘Acknowledgements’), we are committed to delivering all research products as open-source to benefit those who may have an interest in reproducing or building off of our work. As such, our R script used to screen and filter Web of Science references is available via GitHub repository at https://github.com/IMMM-SFA/Turner_and_Voisin_2022_ERL. The data that support the findings of this study are openly available at the following URL/DOI: https://github.com/IMMM-SFA/Turner_and_Voisin_2022_ERL.

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### Appendix. Models adopted in large scale hydropower studies

#### Table A1. Models adopted in large scale hydropower studies.

| Study Scale Hydrology | River | Reservoir |
|------------------------|-------|-----------|
| **Type 1—Surface water to hydropower** |
| Lehner et al (2005)   | Europe | WaterGAP | — | — |
| Pokhrel et al (2008)  | Global | GSWP2 | — | — |
| Hamududu and Killingtveit (2012) | Global | Not reported | Not reported | — |
| Zhou et al (2015)     | Global | GWAM | — | — |
| Kao et al (2015)      | CONUS | VIC | — | — |
| Liu et al (2016)      | China 8 ISIMIP | — | — |
| Worman et al (2020)   | Europe E-HYPE | — | — |
| **Type 2—Natural river flows to hydro** |
| Lehner et al (2005)   | Europe | WaterGAP DDM30 | — | — |
| Van Vliet et al (2013)| Europe | VIC RBM | — | — |
| Masaki et al (2014)   | Global | H08 | — | — |
| Bartos and Chester (2015) | W. U.S. | VIC-2L | — | — |
| Zhou et al (2015)     | Global | GWAM RTM | — | — |
| Liu et al (2016)      | China 8 ISIMIP | — | — |
| Van Vliet et al (2016b)| Global | PCR | — | — |
| Hoes et al (2017)     | Global | CRF * HOES-17 | — | — |
| Gernaat et al (2017)  | Global | LPJmL | — | — |
| Byers et al (2018)    | Global | H08 | — | — |
| Lucena et al (2018)   | Brazil | GWAM RTM | — | — |
| Kahil et al (2018)    | Africa | ? | — | — |
| Tobin et al (2018)    | Europe | VIC | — | — |
| Zhang et al (2018)    | Global | CRF * DRT/LR | — | — |
| Zhou et al (2018a)    | Global | H08 | — | — |
| Paltan et al (2021)   | Global | HAPPI AGCMS KWR | — | — |
| **Type 3a—Regulated flows** |
| Van Vliet et al (2016c) | Global | VIC DDM30 Had-06 | — | — |
| Van Vliet et al (2016a) | Global | VIC DDM30 Had-06 | — | — |
| Voisin et al (2016)   | W. U.S. | VIC MOSART WM | — | — |
| Voisin et al (2018)   | W. U.S. | VIC MOSART WM | — | — |
| Zhou et al (2018b)    | W. U.S. | VIC MOSART WM | — | — |
| O’Connell et al (2019)| W. U.S. | VIC MOSART WM | — | — |
| Voisin et al (2020)   | W. U.S. | VIC MOSART WM | — | — |
| Cohen et al (2020)    | W. U.S. | VIC MOSART WM | — | — |
| Fonseca et al (2021)  | S.E. U.S. | VIC MOSART WM | — | — |
| Chowdhury et al (2021)| S.E. Asia | VIC-Res | — | — |
| Siala et al (2021)    | S.E. Asia | VIC-Res | — | — |
| WAN et al (2021)      | Global | WaterGAP | — | — |
| **Type 3b—Reservoir operations in post-processing** |
| Kao et al (2016)      | CONUS | VIC DDM30 | — | WRES |
| Boehlert et al (2016) | CONUS | CLIRUN—II WEAP | — | — |
| Ng et al (2017)       | Global | WaterGAP DDM30 ‘reservoir’ | — | — |
| Turner et al (2017a)  | Global | WaterGAP DDM30 ‘reservoir’ | — | — |
| Turner et al (2017b)  | Global | WaterGAP DDM30 ‘reservoir’ | — | — |
| De Queiroz et al (2019)| Brazil | MGB AAR | — | — |
| Caceres et al (2021)  | S. America | Cac-21 ‘reservoir’ | — | — |
| **Type 4—Shortcuts: large-scale hydropower without distributed hydrological models** |
| De Lucena et al (2009)| Brazil | — | SUISHI-O | — |
| De Lucena et al (2010)| Brazil | — | SUISHI-O | — |
| Wang et al (2014)     | China | — | — | — |
| Conway et al (2017)   | Sub-Sa. Africa | — | — | — |
| Ruffato-ferreira et al (2017)| Brazil | — | — | — |
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