Impacts of Climate Change on Subannual Hydropower Generation: A Multi-model Assessment of the United States Federal Hydropower Plants

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Abstract. Hydropower is a low-carbon emission renewable energy source that provides competitive and flexible electricity generation and is essential to the evolving power grid in the context of decarbonization. Assessing hydropower availability in a changing climate is technically challenging because there is a lack of consensus in the modeling representation of key dynamics across scales and processes. The SECURE Water Act requires a periodic assessment of the impact of climate change on the United States federal hydropower. The uncertainties associated with the structure of the tools in the previous assessment was limited to an ensemble of climate models. We leverage the second assessment to evaluate the compounded impact of climate and reservoir-hydropower models' structural uncertainties on monthly hydropower projections. While the second assessment relies on a mostly-statistical regression-based hydropower model, we introduce a mostly-conceptual reservoir operations-hydropower model. Using two different types of hydropower model allows us to provide the first hydropower assessment with uncertainty partitioning associated with both climate and hydropower models. We also update the second assessment, performed initially at an annual time scale, to a seasonal time scale. Results suggest that at least 50% of the uncertainties, both at annual and seasonal scales, are attributed to the climate models. The annual predictions are consistent between hydropower models which marginally contribute to the variability in annual projections. However, up to 50% of seasonal variability can be attributed to the choice of the hydropower model in regions over the western US where the reservoir storage is substantial. The analysis identifies regions where multi-model assessments are needed and presents a novel approach to partition uncertainties in hydropower projections. Another outcome includes an updated evaluation of CMIP5-based federal hydropower projection, at the monthly scale and with a larger ensemble, which can provide a baseline for understanding the upcoming 3rd assessment based on CMIP6 projections.

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1. Introduction

Hydropower provides low-carbon electricity with fast and high ramping capabilities, which are essential to integrating variable renewable energy such as wind and solar into the grid, among other contributions like energy storage [Key et al., 2012]. As new generations of climate model projections have become available, regular assessments of the effects of climate change on water availability for hydropower generation have been carried out using a combination of downscaled climate projections, hydrology models, and reservoir operation models (referred to as modeling toolchains hereafter) [e.g., Low et al., 2011, Christensen et al., 2004, Forrest et al., 2018, Hidalgo et al., 2020, Kao et al., 2015, Schaefli et al., 2007]. Evaluating the impacts of climate change on hydropower generation over large areas across disconnected river basins can provide the opportunity to inform long-term planning of electric grids, but so far no single modeling toolchain can be applied across all relevant temporal and spatial scales. The scale challenge requires different techniques that vary according to the overall science questions, such as questions related to general knowledge, interactions with other sectors of activities, specific applications to long-term energy planning, and of course, data availability [Turner and Voisin, 2022].

Leveraging Turner and Voisin [2022]'s review of modeling toolchains for the purpose of large-scale hydroclimate-hydropower assessments, we simplify the typology into three types with (1) Type-1: reservoir-based toolchains that links climate, hydrology, river routing and reservoir management models to simulate hydropower; (2) Type-2: hydrology-based toolchains that link climate and hydrology models to simulate hydropower directly (i.e., Type-1 without river routing, and reservoir management models); and (3) Type-3: statistical or machine learning-based toolchains where hydropower is computed directly from climate model information, or from regulated flow derived statistically from a climate model with or without a generalized reservoir model. An evaluation of Type-1 toolchains was performed by Haddeland et al. [2014], in which seven reservoir-based toolchains were compared using an ensemble of climate projections with an emphasis on agriculture rather than hydropower. Since then, evaluation of multi-model uncertainty has evolved from quantifying the spread of climate projections to partitioning uncertainties [Lehner et al., 2020].

In the United States, the SECURE Water Act of 2009 requires periodic assessment of climate change risks on water availability for federal hydropower marketing and generation. Federal hydropower differs from other public utilities and privately owned entities because the dams were built primarily for other purposes than hydropower, such as water supply and flood control, and the sales of federal power are given preference to public bodies such as electric cooperatives and municipalities (also known as preference customers) at the lowest possible rates. While optimization models are used for short-term hydropower scheduling, long-term hydropower planning is driven by seasonal water operations for all competing uses [Helseth et al., submitted, Low et al., 2011]. The first round of assessment [Sale et al., 2012] comprehensively evaluated all federal hydropower plants located in various geographical regions in the US using a Type-2 hydrology-based toolchain. A strong linear relationship between regional runoff and historical hydropower generation was identified and applied in conjunction with a series of hydroclimate projections to project annual hydropower across federal marketing regions for both near-term and mid-term future periods. In the second round of assessment [Kao et al., 2016], the modeling toolchain was enhanced with a dynamically downscaled ensemble of climate predictions, higher spatial resolution hydrologic projections, and a monthly regression-based hydropower model, but remained as a Type-2 toolchain. Also, while regression-based hydropower models have demonstrated accuracy, they have limited abilities to propagate non-stationarity in flow in hydropower projections [Zhou et al., 2018], and do not allow for coordination with evolving water uses and operations.

In this study, we expand the application of Kao et al. [2016] by adding a Type-1 representation of hydropower where reservoir storage and release operations are explicitly represented, complementing climate, hydrology and river routing models to demonstrate how a Type 1 representation may complement the assessments. Instead of a simple comparison, we propose to facilitate the adoption of a multi-model framework by extending the uncertainty analysis and specifically the partitioning of uncertainties associated with climate projections and hydropower model structures through the analysis of variance (ANOVA). The outcome is an updated multi-model projection of future federal hydropower generation based on downscaled Coupled Model Intercomparison Project Phase 5 (CMIP5) global climate models (GCMs). To the best of our knowledge, this is the first conterminous US (CONUS)-scale climate impact assessment of hydropower that evaluates the annual and seasonal partitioning of hydropower projections relative to the diversity of models included in the toolchain, in this case, climate and hydropower models. The outcome will provide insight into how hydropower model structures contribute to uncertainty in the assessment and consistency of the overall projections. This insight is critical for future large-scale and also watershed-scale assessments where utilities should enhance assessment by including uncertainties in water demands and other water uses. The findings are also intended to inform regional multi-sectoral planning and improve toolchains required to support long-term electricity planning under evolving water and electricity demands as well as water uses for river managements.

2. Methodology

2.1. Study Area and Modeling Strategy

The US federal hydropower plants analyzed in this study include 132 facilities that were built and/or operated by US Army Corps of Engineers (USACE), Bureau of Reclamation (Reclamation), and the International Boundary and Water Commission (IBWC), with a combined 36.6 GW or about 40% of the total US hydropower capacity. The electricity generated by these hydropower plants was marketed through four Power

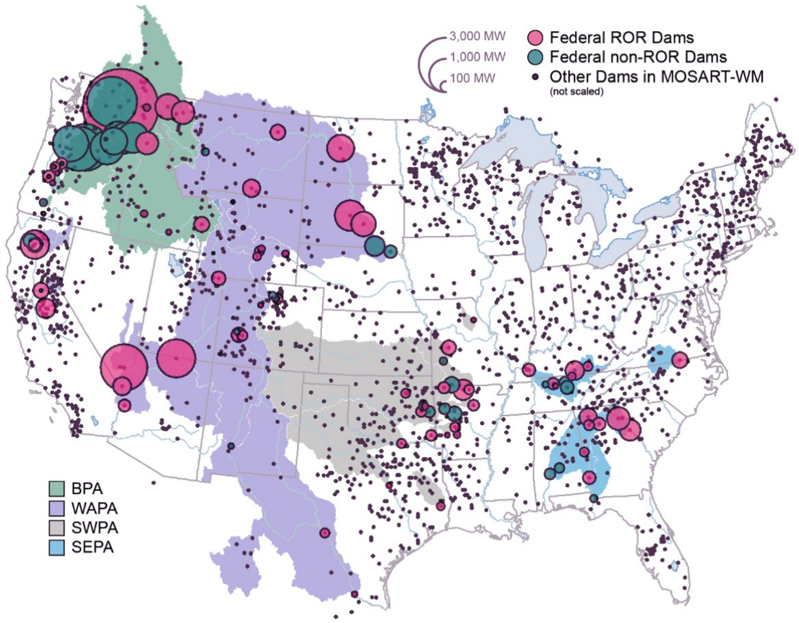

Figure 1. Federal hydropower plants and power marketing regions in the United States

Marketing Administrations (PMAs), including Bonneville Power Administration (BPA), Southeastern Power Administration (SEPA), Southwestern Power Administration (SWPA), and Western Area Power Administration (WAPA) (Figure 1). Given our focus on PMA-marketed hydropower, we do not consider other US federal hydropower plants such as the entire Tennessee Valley Authority (TVA) fleet, Saint Marys Falls and St. Stephen projects managed by USACE, and also some non-federal hydropower plants that are located at federal dams. For a detailed description of the US federal hydropower refer to Kao et al. [2016].

GCM	Spatial resolution (latitude/longitude)	Modeling center
ACCESS1-0	1.24°/1.88°	CSIRO, Australia
BCC-CSM1-1	2.81°/2.81°	BCC, China
CCSM4	0.94°/1.25°	NCAR, USA
CMCC-CM	0.75°/0.75°	CMCC, Italy
GFDL-ESM2M	2°/2.5°	GFDL, USA
MIROC5	1.41°/1.41°	JAMESTEC, U of Tokyo, Japan
MPI-ESM-MR	1.88°/1.88°	MPI, Germany
MRI-CGCM3	1.13°/1.13°	MRI, Japan
NorESM1-M	1.88°/2.5°	NCC, Norway
IPSL-CM5A-LR	1.88°/3.75°	IPSL, France

Table 1. GCMs used for global climate projections.

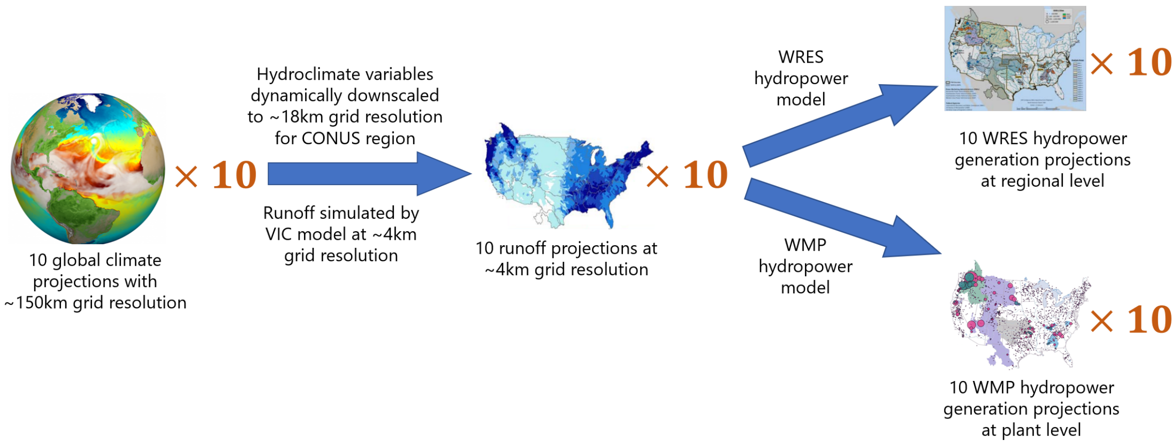

Figure 2. Cascade of system-specific models (10 climate models, 1 hydrology model, 2 hydropower models) and resulting 20-member ensemble of hydropower projections.

A cascading modeling toolchain was designed to project monthly hydropower generation from each US federal hydropower region. The modeling toolchain employed a series of models and approaches with different spatial resolutions to transfer global climate change signals to watershed-scale hydrologic projections to support the predictions for hydropower generation (Figure 2). The modeling framework starts with global climate projections made by 10 CMIP5 GCMs (Table 1). The GCMs were selected based on the availability of sub-daily three-dimensional atmospheric data for the dynamical downscaling in thenext step. The future greenhouse gas (GHG) emission scenario is representative concentration pathway (RCP) 8.5, which reflects the highest level of global warming and the upper bound for hydrological changes, with a radiative forcing reaching 8.5 Wm^{-2} by the end of the 21st century. Each GCM consists of a historical period from 1966 to 2005, and a future period from 2011 to 2050.

Next, the Abdus Salam International Centre for Theoretical Physics Regional Climate Model, version4 (RegCM4) [Pal et al., 2007, Giorgi et al., 2012] was used to dynamically downscale GCM projections from the native spatial resolution (around 150 km) to 18 km resolution over the Continental US. The downscaling resulted in 10 sets of meteorological variables (e.g., precipitation, temperature, and wind), one for each climate model. After bias-correction by historic observations, the widely used semi-distributed Variable Infiltration Capacity (VIC) model [Liang et al., 1994, Nijssen et al., 1997, Cherkauer et al., 2003, Zhou et al., 2016] was used to translate the projected meteorological signals into hydrological responses such as surface runoff and baseflow. To study the large-scale climate change effects on various river systems across the US, in this study the VIC model was implemented for the entire CONUS at a refined 1/24 ° (about 4 km) grid resolution. A computationally intensive calibration for the VIC model was performed to increase the model accuracy. Readers are referred to Oubeidillah et al.

[2014] and Naz et al. [2016] for more technical details about the hydrology model setup, and Ashfaq et al. [2016] for the dynamical downscaling.

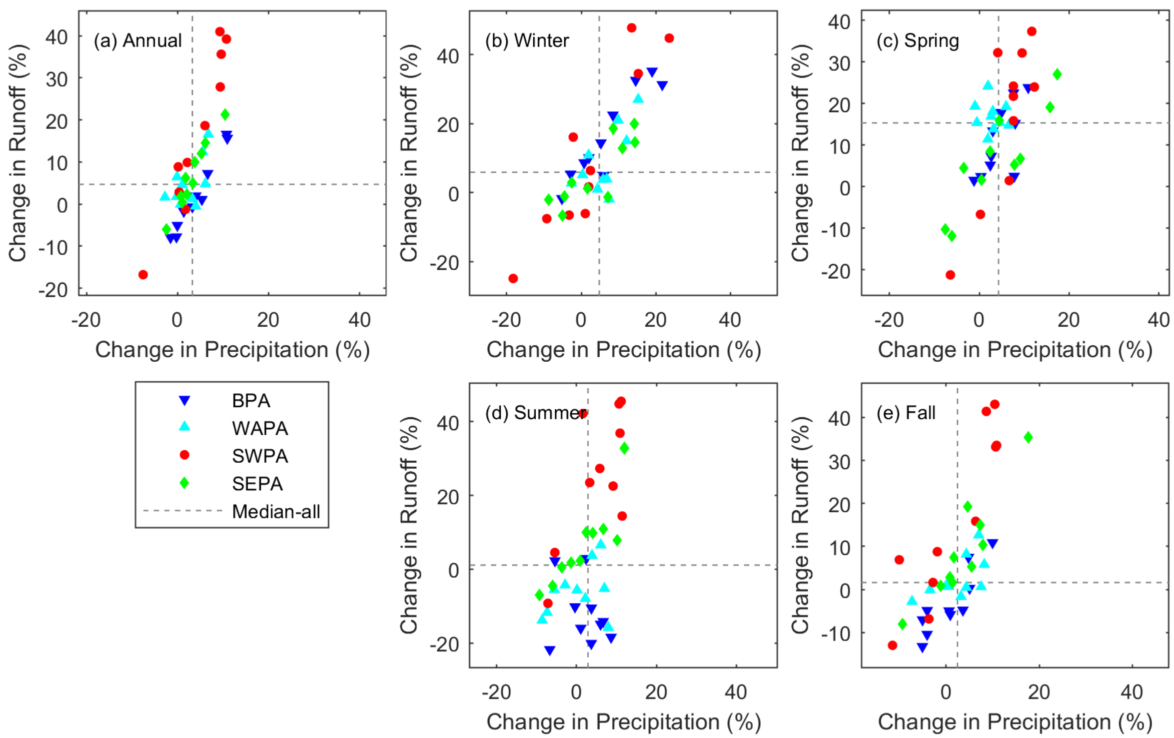

Figure 3. Scatter plots of annual and seasonal precipitation and runoff changes (1966-2005 to 2011-2050) for 10 GCM projections over the four PMAs.

Given that this study focuses on a regional assessment at the PMA level rather than at individual reservoirs or power plants, it enables comprehensive evaluation of climate change impacts across a large number of hydropower plants along distinct river systems. An overview analysis of the GCM projected future precipitation and VIC-simulated runoff changes across the PMAs (Figure 3) suggested that both precipitation and runoff will increase in annual and seasonal time scales when taking all four PMAs into account. However, the PMAs lie in distinct climate and hydrological regions leading to distinct seasonal sensitivity to climate change signals.

2.2. Regional Hydropower Models

The spatially distributed runoff generated by the VIC model informed river routing (and water management) models that have a regional hydropower component for hydropower generation projections. Two reservoir operations and hydropower models with different mechanisms were applied. They included a regression-based Watershed Runoff-Energy Storage (WRES) model and a process-based Water Management Hydropower (WMP) model.

2.2.1. Watershed Runoff-Energy Storage Model

The WRES model was developed by Kao et al. [2016] to examine how seasonal and annual hydropower generation may change under the projected future climate and hydrologic conditions. WRES is a lumped regional hydropower model used to simulate the total hydropower generation from multiple hydropower plants in a region. To account for the diverse hydrologic conditions and operational objectives associated with various types of federal hydropower systems, WRES was designed with minimum site-specific restrictions to maintain an internally consistent modeling approach that isolated the effects of climate change on runoff availability and hydropower generation. Based on the discussion in Section 1, WRES can be considered a Type-2 modeling toolchain component.

There are two main steps in WRES: (1) monthly generation prediction based on regression, and (2) watershed runoff storage calculation. The first step of WRES simulation determines an initial estimate of monthly watershed runoff release and hydropower generation based on hydrologic inflow/outflow conditions (e.g., the amount of precipitation and runoff inputs) and hydropower generation from previous time steps. After testing several combinations of variables and lag times using historical monthly rainfall, runoff, and hydropower generation data from 1980 to 2009, generalized multivariate regression formula are developed for each hydropower region.

The second step of WRES is to ensure that the initial estimates of monthly runoff release and hydropower generation will not yield physically unreasonable conditions. In particular, although the regression formula can provide a good first estimate, it can be unreasonable during extremely wet or dry conditions. Most of the reservoirs follow the established operation curves in which seasonal maximum/minimum pool elevations are specified. During drought conditions, the storage in the system may be close to the minimum so that the water release and generation would be reduced for water conservation. Conversely, during wet conditions, the storage may approach a maximum capacity for flood-risk management. Water release and hydropower generation will increase during wet conditions, and sometimes water may be spilled (i.e., not pass through hydropower turbines) during flood conditions. To account for these constraints, a runoff mass balance calculation procedure was developed to revise the initial estimates of runoff release and hydropower generation based on the maximum and minimum runoff storage capacity of each hydropower region. For each PMA region, the WRES model used the monthly precipitation and natural runoff as inputs, performed a water mass balance calculation for the total monthly storage in all reservoirs and retention facilities in the watershed, and simulated the monthly regulated release and hydropower generation through the system. Details of the WRES model are described by Kao et al. [2016].

2.2.2. Water Management Power Model

The WMP model is a process-based (Type-1) model that was first introduced by Zhou et al. [2018]. It consists of two parts: (1) a river-routing water management model to represent water managements and dam operations, and (2) a process-based hydropower generation module to estimate energy produced through turbines at individual hydropower plants. The first part of WMP includes the large-scale river routing and water management using MOSART-WM, which consists of a grid-based river routing Model for Scale Adaptive River Transport (MOSART) [Li et al., 2013] and a water management component [Voisin et al., 2013] used to simulate water withdrawals and distribution and associated reservoir storage, release, and spatially distributed regulated flow. Based on the discussion in Section 1, WMP can be considered a Type-3 modeling toolchain component for hydropower projects that have substantial storage.

In this study, the VIC-simulated runoff at an original 4 km resolution was aggregated to 1/8th degree (about 12km) resolution (approximately 65,000 grid cells in the CONUS domain). To address the lack of available information about individual reservoir operating rules and the computational tradeoffs associated with the spatially distributed nature of the model, each reservoir uses generic operating rules [Hanasaki et al., 2006, Voisin et al., 2013] based on their main operating purposes (e.g., irrigation, flood control). The daily gridded water demand data is required for MOSART-WM to guide the irrigation and non-irrigation water withdrawals from the streamflow and upstream reservoirs [Voisin et al., 2017]. The data was derived from the integrated Global Change Assessment Model [Hejazi et al., 2015], which considers multiple water demand sectors and several socioeconomic variables, such as population, labor productivity, and technology [Edmonds and Reilly, 1985, Edmonds et al., 1997, Kim et al., 2006]. In this study, the water demands for MOSART-WM were set to be fixed at 2010 level. The MOSART-WM model was run at daily time steps from 1966 to 2050 after a five-year spin-up with the 1966 runoff.

The regulated streamflow time series at each federal hydropower plants simulated by MOSART-WM was then used as input for the hydropower generation module. The hydropower module processes storage-based and Run-of-the-River (RoR) plants differently. For hydropower plants associated with reservoirs, the MOSART-WM-simulated storage time series was also extracted to derive the hydraulic heads. For RoR dams, the hydraulic heads (h, m) were obtained from the National Inventory of Dams (NID) database and were assumed to be fixed. For reservoir-associated dams, the time series of hydraulic heads were estimated based on the simulated monthly reservoir storage in the first step through a simple empirical relationship. Fourteen parameters were introduced into the power model to adjust the streamflow passing through the dam and to constrain the generation of power. The parameters include a bias correction factor accounting for the annual bias at the US hydrologic subregion level (HUC4), 12 monthly spill correction factors for monthly ecological purposes and spinning reserve at the plant level, and a penstock intake adjustment factor to account the actual maximum intake of the penstock relative to the reported penstock capacity at the plant level.

2.3. Model Calibration and Analysis

The WRES and WMP models were calibrated against the observed monthly hydropower generation data provided by the U.S. Energy Information Administration (EIA). The WRES model parameters, including initial, maximum / minimum monthly storage, and maximum hydropower capacity, were estimated for the historical period from 1980-2008. The calibrated parameters were then be used for validation over 2009-2012 period. For WMP, the 14 parameters were estimated through a two-step multiscale calibration process, which applied Shuffled Complex Evolution (SCE-UA) method to minimize the mean absolute error of the annual generation at the regional level (first step) and the Kling-Gupta Efficiency (KGE) of the monthly generation at the plant level (second step). The calibration was performed from 1980-2004. While the initial validation was performed from 2005-2012, the validation is presented here over 2009-2012 to be consistent with WRES.

2.4. Uncertainty Partitioning

We use ANOVA to assess the impacts of climate models and hydropower models on the spread of future annual and seasonal hydropower projections at each PMA region. ANOVA was used to partition the total ensemble variance to contributions from different sources of variation and the interaction between them. In our application, there are two variables (climate model and hydropower model), and each combination provides one unique projection of change. To diminish the effects of unequal numbers of climate (10) and hydropower (2) models in traditional ANOVA, we used a sub-sampling technique proposed by Bosshard et al. [2013] to sample two climate models and their respective hydropower model combinations to evaluate the variance contribution. The unexplained variance is labeled as residual. The results are presented at the PMA level for annual and seasonal scales.

3. Results

3.1. Hydropower Model Performance

(Figure 4) shows the regional monthly hydropower generation simulations and observation. Despite the fundamental differences in modeling approaches, both models were able to reasonably simulate the monthly hydropower generations with correlation coefficients over 0.8 during the validation periods. The models also performed reasonably well in other metrics (e.g., Nash–Sutcliffe efficiency [NSE] and mean annual bias). The metrics during the validation period are comparable to those during the calibration period, and are satisfactory for the purpose of this study (Table 2). Note that the performance of WRES is slightly better than that of WMP, which might be attributed to the different nature of the models and the longer calibration period for the WRES model.

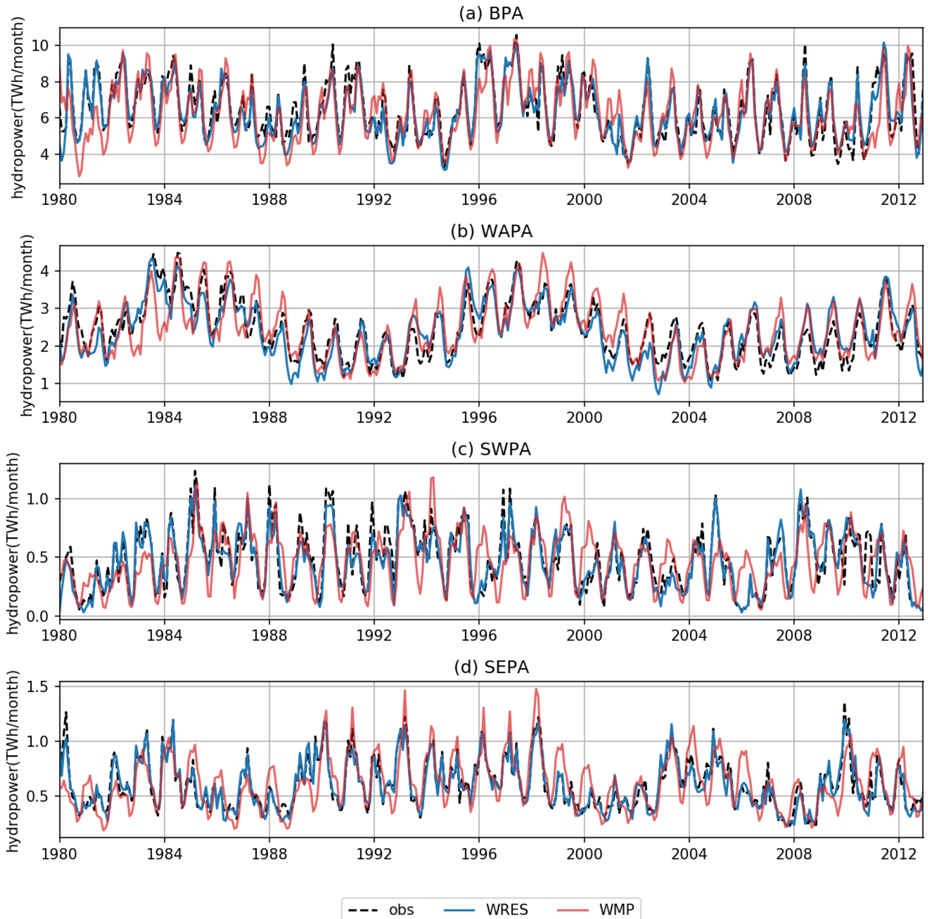

Figure 4. Monthly hydropower generation time series - comparison between simulations and observation

	period	RMSE (TWh/month)	correlation coefficient	NSE	mean annual bias
WMP training	1980-2004	1.31	0.84	0.62	-3.1%
WMP validating	2009-2012	1.41	0.80	0.61	-1.5%
WRES training	1980-2008	0.75	0.95	0.88	-2.5%
WRES validating	2009-2012	1.07	0.89	0.78	3.2%

Table 2. Error statistics for hydropower generation over all PMAs.

3.2. Multi-Model Hydropower Projections

The projected annual and seasonal hydropower generation from all and each PMA region is summarized in Figure 5 for near-term (NT, 2011-2030) and mid-term (MT, 2031-2050) future periods. Each panel of Figure 5 shows the single-model projection from Kao et al. [2016] using WRES and the updated multi-model ensemble projection using WRES and WMP. Each box defines the 25th to 75th percentile and the whiskers define the 5th to 95th percentile of all ensemble members. The historical baseline (thicker black line) are the mean values over 1966-2005.

3.2.1. Annual and Seasonal Projections

By comparing the median projections (the thin line in each box) and the baseline generations over the historical period, we note that for the annual generation by all PMAs as a whole, despite minor differences in the spread of the predictions, the WRES and ensemble project a 1 TWh decrease in the NT median and an increase of about 6 TWh or 4-5% in the MT median. Despite the choice of climate models and the overall modeling framework, the NT projection is consistent with the estimate from previous assessment [Sale et al., 2012] in which the median federal projects is projected to be -2 TWh over the 2000-2039 future period, based on a 1960-1999 historical baseline period. BPA has the largest generation across all PMAs, and the PMA total overall follows BPA's annual trends and seasonal patterns. Note that BPA does experience a 5 TWh decrease in annual projection during the NT and a 2-3 TWh increase in MT. This opposite change direction might be attributed to the changes in hydrological regimes with the projected decrease in average April 1st snow water equivalent (SWE) and the reduction in snow-covered days, as well as the projected increase in winter liquid precipitation in the western US regions, driven by an increase in the projected winter temperature in these regions. These changes in runoff generation mechanisms suggest higher streamflow conditions earlier in the spring and lower streamflow conditions in the summer, which might further reshape the overall hydropower generations in the BPA areas due to limited seasonal storage. For WAPA, the median ensemble projection is close to the baseline in the NT and about 8% higher in the MT. For SWPA, both NT and MT are projected to increase with MT being higher than NT. It is noted that WRES generally has a higher projection and slightly larger uncertainties (longer boxes) across the GCMs, compared to the ensemble projection. Divergence between the WRES and the ensemble is also noticed in SEPA, where the median generation projected by WRES is slightly lower than the ensemble projection in both terms. Given that the hydropower projects in SWPA and SEPA have much less storage capacity than other PMAs, the projections of hydropower generation more closely follow the change in runoff, albeit with higher sensitivity to assumptions in storage management.

Seasonal projections suggest greater variations than annual changes and larger differences between WRES-only and ensemble projections. The overall PMA seasonal MT projections are higher than NT in all seasons for both WRES and ensemble projections. The winter and spring projections tend to be close between the single model and the multi-model ensemble with a slight increase in NT and an increase in MT. Summer is the season when both NT and MT are projected to be lower than the baselines. Note that the ensemble projection is constantly higher than the WRES-only projection in most of the regions except SWPA. In the fall, the differences between the single model and the multi-model ensemble include both the spread of uncertainty and the predictions. Ensemble projections are lower than WRES-only projections with NT lower than and MT close to the baseline. As expected, there

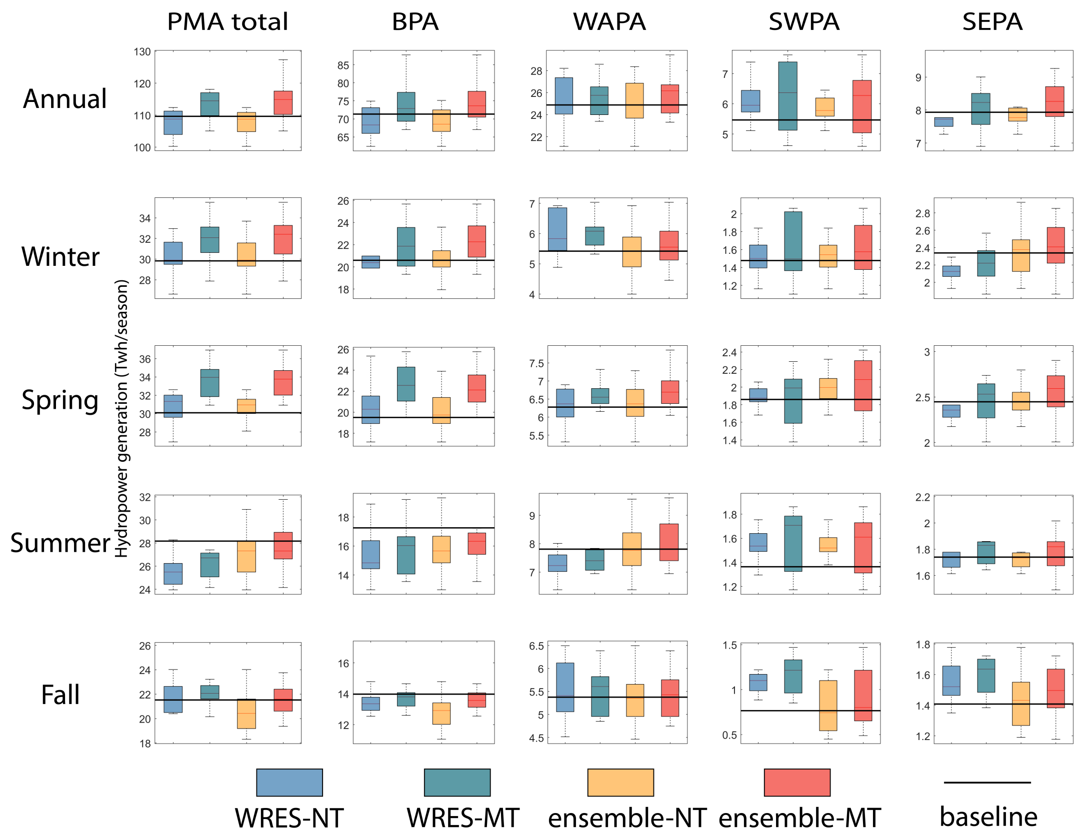

Figure 5. Annual and seasonal hydropower generation compared between near-term (NT, 2011-2030), mid-term (MT, 2031-2050) from WRES model only and multi-model ensemble (WRES and WMP). The baselines (1966-2005) are derived from the ensemble mean.

are more seasonal differencesin the hydropower models across the PMAs. A relative change comparison between WRES and WMP (Figure S1) hightlights a few regions with relatively large differences in terms of trend and the range of uncertainty. For instance, the two models projected different directions of change in MT over BPA in the fall and in NT over WAPA in the spring. In SEPA, the NT-projected fall generation has noticeably greater uncertainty in WRES than in WMP. These differences could lead to systematic uncertainty with different choices of model. To further investigate the seasonal differences between models, we focus next on the projection consistency analyses.

3.2.2. Projection Consistency

Projection consistency between two hydropower models was investigated using the relative projection changes normalized by the baseline projections from each model. To simplify the comparisons, we combined the NT and MT into one single future period and compare the projections across GCMs at annual and seasonal scales (Figure 6).

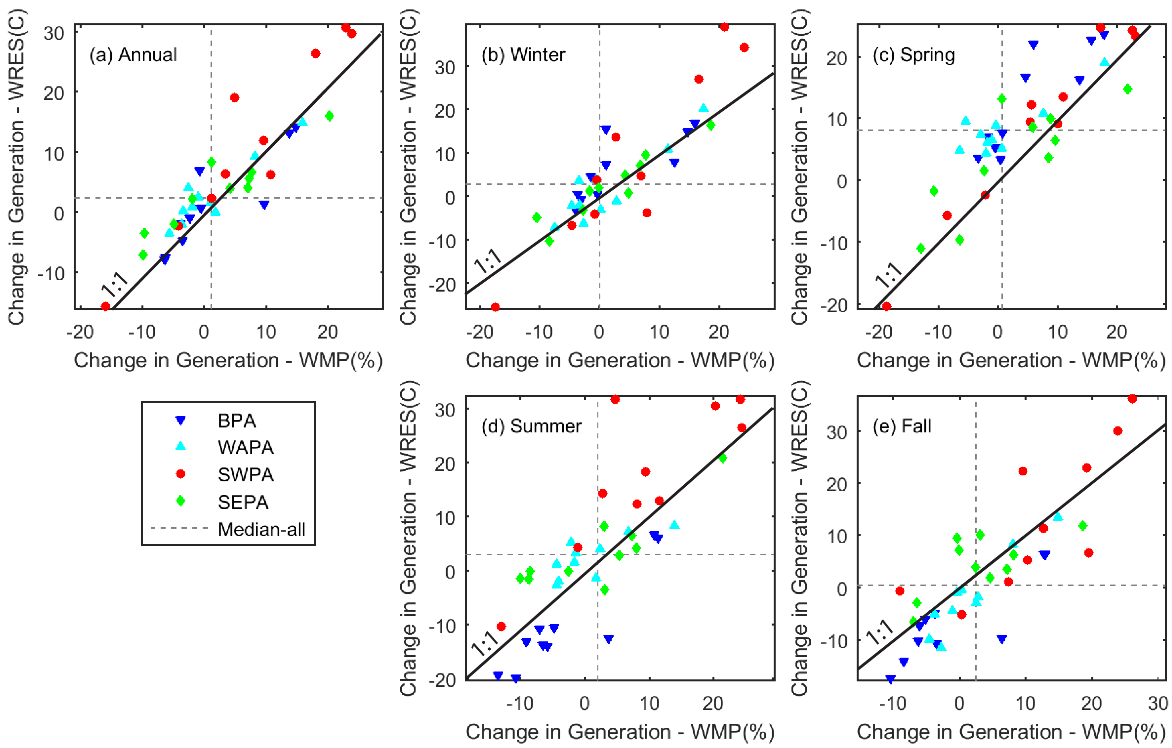

Figure 6. Scatter plots of annual and seasonal generation changes (1966-2005 to 2011-2050) from two hydropower models for 10 GCM projections over the four PMAs.

The results indicate that there is a hydropower model agreement at the annual scale for a +3% in WRES and a +1% in WMP across all PMAs and GCMs. The projections are close to the 1:1 line, reflecting consistent agreement across all PMAs as well and across wet and dry GCMs. At the seasonal scale, the projections from two hydropower models are consistent in terms of the direction of change. However, the difference in changing rate could be as high as about 8% in the spring, due to the large difference in historical predictions.

A comparison of cumulative distribution function (CDF) curves generated from seasonal median projections (Figure 7) provides an overview of the distribution of the projections. Generally speaking, the same hydropower models tend to follow the same distribution shapes with different median values responding to the climate signal in different projection periods. Different hydropower model, on the other hand, may project different distribution shape with close median values (e.g. BPA-summer, SEPA-summer), or different distribution shape with different median values (e.g. WAPA-fall, WAPA-winter, SWAP-fall), or even similar distribution shapes with different median values (e.g., WAPA-summer, SEPA-winter). The different climate-signal-responding-mechanisms of the hydropower models enrich the spectrum of the projections in extreme values but also raise a question about the contribution of the uncertainty from the choice of hydropower model, which is analyzed in the next subsection.

3.3. Uncertainty Contributions

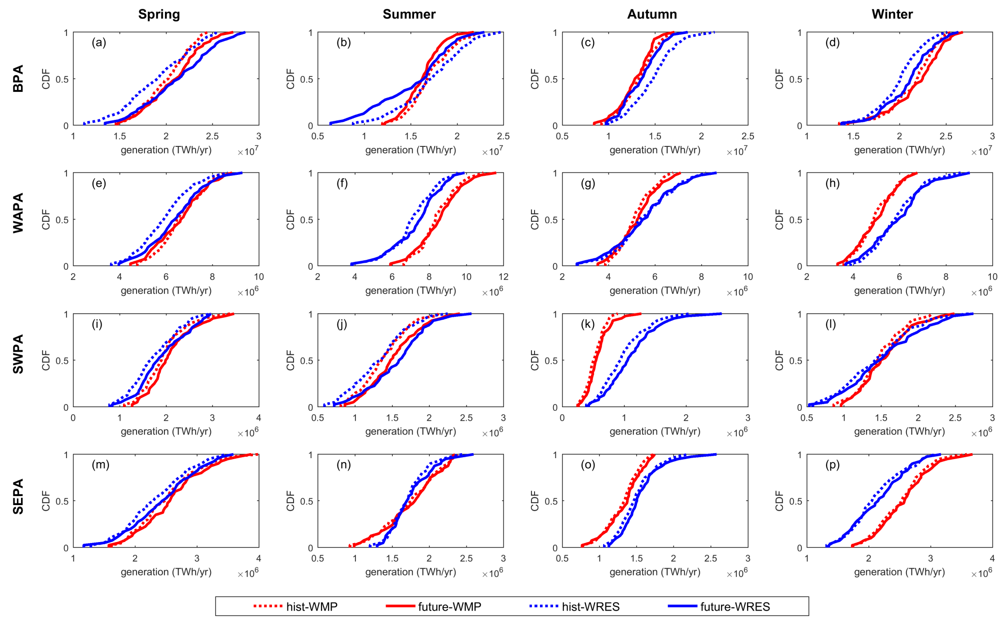

Figure 7. 1966-2005 and 2011-2050 seasonal median generation cumulative distribution function (CDF) compared between WRES and WMP over the four PMAs

The ANOVA technique is employed to understand and quantify the contributions to systematic uncertainty from different modeling structures (i.e., multi-hydropower models versus multi-GCMs) for annual and seasonal hydropower projections (Figure 8). The bars shown on each panel in the figure consist of three components (climate model, hydropower model, and residual), indicating their contributions to the total variance of future hydropower projections. The results reveal that at the annual time scale, the climate model can explain nearly 70% of the variance across the PMAs, while the contribution from hydropower model remains in the range of 11-17% . However, at the seasonal scale, the contribution of hydropower model starts to become more prominent. The contribution of uncertainties can go as high as 48% for BPA in spring and summer, and 50% in WAPA in spring. These results indicate that the choice of hydropower model could have large impacts on the overall modeling results, especially at the seasonal time scale.

4. Discussion

4.1. Additional Insights from Multi-Model Projections

Overall, the annual projections in near-term and mid-term future periods were consistent between two hydropower models, with more nuances occurring by region at the seasonal scale. The addition of WMP in the multi-model ensemble tends to increase the range of the spread in projections, albeit in consistent directions. However, at an annual

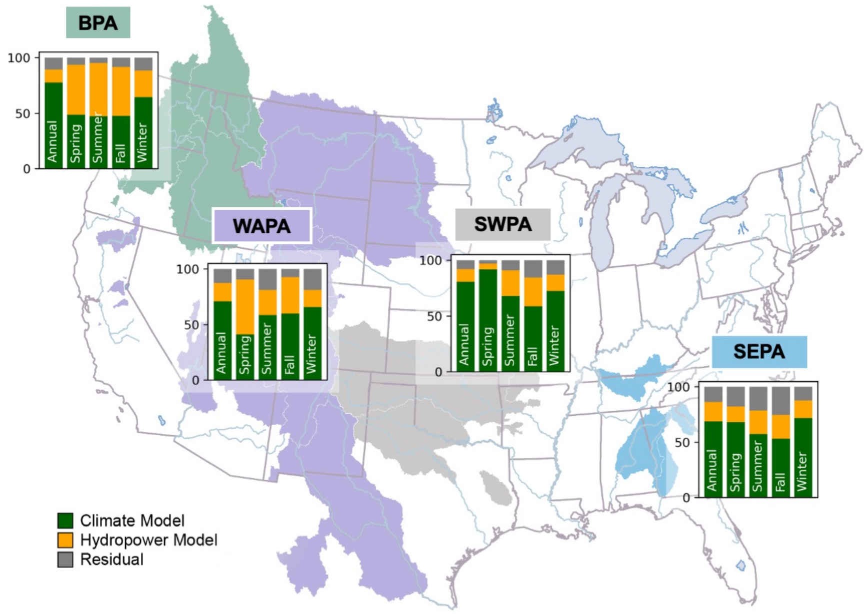

Figure 8. Major contributions to the variance in hydropower generation over the four PMAs

time scale, diversity in GCMs explains most of the variance in the overall hydropower projections.

The seasonal projections are more sensitive to the diversity in hydropower model structure than the annual projections, especially in the Western US where reservoir storage is greater. This result is expected because reservoir operations have an impact on the seasonal timing of the streamflow, while the annual volume remains controlled by water demand and overall runoff. The seasonal time scale complements the previous assessment - which was limited to the annual scale - and supports actionable insight into long-term planning by supporting the evaluation of seasonal coincidences between hydropower and climate-sensitive electricity demand variations [Turner et al., 2019].

4.2. Potential Change in Future Operations

Zhou et al. [2018] demonstrated that updating the reservoir operations to future flow rates would affect the seasonal hydropower projections - specifically the timing of change even though in magnitude the difference was very small due to the regulated nature of the flow. In this study, we focused on developing a multi-hydropower model ensemble with as much consistency as possible. The process-based representation of hydropower can represent non-stationarity and is thus critical for federal hydropower where multiple water objectives take priority over hydropower, including seasonal water supply operations. Other factors could change the operations and seasonal shape of hydropower generation in non-federal facilities such as changes in markets, in electricity demand seasonality, and the evolving generation portfolio.

5. Summary and Conclusions

We extended a previous assessment of the effects of climate change on US federal hydropower generation with a multi-model modeling approach and focused on seasonal assessment with uncertainty partitioning. To the best of our knowledge, this is a first CONUS-scale hydropower assessment that attempts to perform uncertainty partitioning associated with both climate and hydropower models. The modeling toolchain consists of an ensemble of downscaled climate projections, a high-resolution hydrology model, and further informing two hydropower models (regression-based and process-based). The regression-based model displays a lower mean absolute error over the historical period than the process-based approach. While the overall projection range has increased, the directions of projections are consistent. The seasonal analysis reveals the importance of using a multi-hydropower model approach in the Western US regions where storage is substantial, and where the hydropower model structure contributes to the variance in seasonal projections. Overall, total federal hydropower generation is projected to increase, with 8 out of 10 climate models showing an increase with both hydropower models. Among all federal regions, the Northwest (BPA) average hydropower generation is the only one projected to decrease in the near-term, while all regions are projected to increase in the long-term. The value of using a multi-hydropower model approach is demonstrated over the BPA and WAPA regions where up to 50% of seasonal variability can be attributed to the structure of the hydropower model. Those projections remain long-term trends that do not reflect ongoing droughts across the US, and more research is needed to account for multi-year droughts in those long-term assessments.

The emphasis of this work was to demonstrate the impact of hydropower representations on overall hydropower projections. Specifically, the monthly regression-based model currently has lower mean absolute errors, which is desired for informing long-term electricity reliability studies [Voisin et al., 2020]. However, the process-based approach allows to support climate change impact assessment consistently across a range of water-dependent sectors such as agriculture toward understanding tradeoffs and designing co-resilient adaptation strategies [Reed et al., 2022]. Future analysis could also include multiple hydrology models and downscaling approaches. Nevertheless, the current analysis allows for the identification of regions where multi-sectoral assessments will need to address accuracy in representing hydropower representation for actionable insights.

6. Data Availability

The monthly hydropower generation projections for the United States Federal Hydropower plants for the periods of 1966-2005 (historical period) and 2011-2050 (future period) from WRES and WMP are made available at https://doi.org/10.5281/zenodo.6506089. The input runoff datasets of the hydropower models used in this study are prepared by the second 9505 Climate Change Impact Assessments team, and are available upon reasonable request from https://www.ornl.gov/project/effects-climate-hydropower.

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References

T. Key, L. Rogers, D. Brooks, and A. Tuohy. Quantifying the value of hydropower in the electric grid: Final report. Report, USDOE, 2012. URL https://www.osti.gov/biblio/1057586.

P. Low, M. Annamalai, B. Kuepper, E. Nielsen, D. Hua, B. Glabau, T. White, B. Koehler, J. Tran, T. Turner, L. Postlethwait, and J. Barton. Climate and hydrology datasets for use in the rmjoc agencies' longer-term planning studies: Part iii—reservoir operations assessment: Columbia basin flood control and hydropower. *Bureau of Reclamation, Boise, Idaho. Reservoir Management Joint Operating Committee*, 2011. URL https://www.usbr.gov/pn/climate/planning/reports/part3.pdf.

N S Christensen, Andrew W. Wood, and Nathalie Voisin. The effects of climate change on the hydrology and water resources of the colorado river basin. *Climatic change*, pages 337–363, 2004.

Kate Forrest, Brian Tarroja, Felicia Chiang, Amir AghaKouchak, and Scott Samuelsen. Assessing climate change impacts on california hydropower generation and ancillary services provision. *Climatic Change*, 151(3):395–412, 2018. ISSN 1573-1480. doi: 10.1007/s10584-018-2329-5. URL https://doi.org/10.1007/s10584-018-2329-5.

Ieda Geriberto Hidalgo, Javier Paredes-Arquiola, Joaquin Andreu, Nestor Lerma-Elvira, Joao Eduardo Goncalves Lopes, and Francesco Cioffi. Hydropower generation in future climate scenarios. *Energy for Sustainable Development*, 59:180–188, 2020. ISSN 0973-0826. doi: https://doi.org/10.1016/j.esd.2020.10.007. URL https://www.sciencedirect.com/science/article/pii/S0973082620303161.

S.-C. Kao, M. J. Sale, M. Ashfaq, R. Uría Martínez, D. P. Kaiser, Y. Wei, and N. S. Diffenbaugh. Projecting changes in annual hydropower generation using regional runoff data: An assessment of the united states federal hydropower plants. *Energy*, 80:239–250, 2015. ISSN 0360-5442. doi: 10.1016/j.energy.2014.11.066.

B. Schaefli, B. Hingray, and A. Musy. Climate change and hydropower production in the swiss alps: quantification of potential impacts and related modelling uncertainties. *Hydrol. Earth Syst. Sci.*, 11(3):1191–1205, 2007. ISSN 1607-7938. doi: 10.5194/hess-11-1191-2007. URL https://hess.copernicus.org/articles/11/1191/2007/.

Sean W. D. Turner and Nathalie Voisin. Simulation of hydropower at subcontinental to global scales: a state-of-the-art review. *Environmental Research Letters*, 17 (2):023002, 2022. ISSN 1748-9326. doi: 10.1088/1748-9326/ac4e38. URL https://dx.doi.org/10.1088/1748-9326/ac4e38.

Ingjerd Haddeland, Jens Heinke, Hester Biemans, Stephanie Eisner, Martina Flörke, Naota Hanasaki, Markus Konzmann, Fulco Ludwig, Yoshimitsu Masaki, Jacob Schewe, Tobias Stacke, Zachary D. Tessler, Yoshihide Wada, and Dominik Wisser. Global water resources affected by human interventions and climate change. *Proceedings of the National Academy of Sci-*

ences, 111(9):3251–3256, 2014. doi: doi:10.1073/pnas.1222475110. URL `https://www.pnas.org/doi/abs/10.1073/pnas.1222475110`.

F. Lehner, C. Deser, N. Maher, J. Marotzke, E. M. Fischer, L. Brunner, R. Knutti, and E. Hawkins. Partitioning climate projection uncertainty with multiple large ensembles and cmip5/6. *Earth Syst. Dynam.*, 11(2): 491–508, 2020. ISSN 2190-4987. doi: 10.5194/esd-11-491-2020. URL `https://esd.copernicus.org/articles/11/491/2020/`.

A. Helseth, A.C.G. Melo, Q.M. Ploussard, B. Mo, M.E.P. Maceira, A. Botterud, and N. Voisin. Hydropower scheduling toolchains – comparing experiences in brazil, norway and usa and implications for synergistic research. *Journal of Water Resources Management and Planning*, submitted.

M. J. Sale, S.-C. Kao, M. Ashfaq, D. P. Kaiser, R. Uría Martínez, C. Webb, and Y. Wei. *Assessment of the Effects of Climate Change on Federal Hydropower*. Number ORNL/TM-2011/251 in 0. Oak Ridge National Laboratory, Oak Ridge, TN, 2012. doi: 10.2172/1220238.

S.-C. Kao, M. Ashfaq, B. S. Naz, R. Uría Martínez, D. Rastogi, R. Mei, Y. Jager, N. M. Samu, and M. J. Sale. *The Second Assessment of the Effects of Climate Change on Federal Hydropower*. Number ORNL/SR-2015/357 in 0. Oak Ridge National Laboratory, Oak Ridge, TN, 2016. doi: 10.2172/1340431.

Tian Zhou, Nathalie Voisin, and Tao Fu. Non-stationary hydropower generation projections constrained by environmental and electricity grid operations over the western united states. *Environmental Research Letters*, 13:074035, 2018. doi: 10.1088/1748-9326/aad19f. URL `https://doi.org/10.1088/1748-9326/aad19f`.

Jeremy S. Pal, Filippo Giorgi, Xunqiang Bi, Nellie Elguindi, Fabien Solmon, Xuejie Gao, Sara A. Rauscher, Raquel Francisco, Ashraf Zakey, Jonathan Winter, Moetasim Ashfaq, Faisal S. Syed, Jason L. Bell, Noah S. Diffenbaugh, Jagadish Karmacharya, Abourahamane Konaré, Daniel Martinez, Rosmeri P. Da Rocha, Lisa C. Sloan, and Allison L. Steiner. Regional climate modeling for the developing world: The ictp regcm3 and regcnet. *Bulletin of the American Meteorological Society*, 88(9):1395–1410, 2007. ISSN 0003-0007. doi: 10.1175/bams-88-9-1395. URL `https://dx.doi.org/10.1175/bams-88-9-1395`.

F. Giorgi, E. Coppola, F. Solmon, L. Mariotti, M. B. Sylla, X. Bi, N. Elguindi, G. T. Diro, V. Nair, G. Giuliani, U. U. Turuncoglu, S. Cozzini, I. Güttler, T. A. O'Brien, A. B. Tawfik, A. Shalaby, A. S. Zakey, A. L. Steiner, F. Stordal, L. C. Sloan, and C. Brankovic. Regcm4: model description and preliminary tests over multiple cordex domains. *Climate Research*, 52:7–29, 2012. URL `https://www.int-res.com/abstracts/cr/v52/p7-29/`.

Xu Liang, Dennis P. Lettenmaier, Eric F. Wood, and Stephen J. Burges. A simple hydrologically based model of land surface water and energy fluxes for general circulation models. *Journal of Geophysical Research: Atmospheres*, 99(D7):14415–

14428, 1994. ISSN 0148-0227. doi: https://doi.org/10.1029/94JD00483. URL `https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/94JD00483`.

Bart Nijssen, Dennis P. Lettenmaier, Xu Liang, Suzanne W. Wetzel, and Eric F. Wood. Streamflow simulation for continental-scale river basins. *Water Resources Research*, 33(4):711–724, 1997. ISSN 0043-1397. doi: https://doi.org/10.1029/96WR03517. URL `https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/96WR03517`.

Keith A. Cherkauer, Laura C. Bowling, and Dennis P. Lettenmaier. Variable infiltration capacity cold land process model updates. *Global and Planetary Change*, 38(1):151–159, 2003. ISSN 0921-8181. doi: https://doi.org/10.1016/S0921-8181(03)00025-0. URL `https://www.sciencedirect.com/science/article/pii/S0921818103000250`.

Tian Zhou, Bart Nijssen, Huilin Gao, and Dennis P. Lettenmaier. The contribution of reservoirs to global land surface water storage variations. *Journal of Hydrometeorology*, 17:309–325, 2016. ISSN 10.1175/JHM-D-15-0002.1. doi: 10.1175/JHM-D-15-0002.1. URL `https://doi.org/10.1175/JHM-D-15-0002.1`.

A. A. Oubeidillah, S. C. Kao, M. Ashfaq, B. S. Naz, and G. Tootle. A large-scale, high-resolution hydrological model parameter data set for climate change impact assessment for the conterminous us. *Hydrol. Earth Syst. Sci.*, 18(1):67–84, 2014. ISSN 1607-7938. doi: 10.5194/hess-18-67-2014. URL `https://hess.copernicus.org/articles/18/67/2014/`.

Bibi S. Naz, Shih-Chieh Kao, Moetasim Ashfaq, Deeksha Rastogi, Rui Mei, and Laura C. Bowling. Regional hydrologic response to climate change in the conterminous united states using high-resolution hydroclimate simulations. *Global and Planetary Change*, 143:100–117, 2016. ISSN 0921-8181. doi: https://doi.org/10.1016/j.gloplacha.2016.06.003. URL `https://www.sciencedirect.com/science/article/pii/S0921818116300443`.

Moetasim Ashfaq, Deeksha Rastogi, Rui Mei, Shih-Chieh Kao, Sudershan Gangrade, Bibi S. Naz, and Danielle Touma. High-resolution ensemble projections of near-term regional climate over the continental united states. *Journal of Geophysical Research: Atmospheres*, 121(17):9943–9963, 2016. ISSN 2169-897X. doi: https://doi.org/10.1002/2016JD025285. URL `https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/2016JD025285`.

Hong Yi Li, Mark S. Wigmosta, Huan Wu, Maoyi Huang, Yinghai Ke, André M. Coleman, and L. Ruby Leung. A physically based runoff routing model for land surface and earth system models. *Journal of Hydrometeorology*, 14:808–828, 2013. doi: 10.1175/JHM-D-12-015.1.

Nathalie Voisin, Hong Yi Li, D. Ward, Maoyi Huang, M. Wigmosta, and L. Ruby Leung. On an improved sub-regional water resources management representation for integration into earth system models. *Hydrology and Earth System Sciences*, 17: 3605–3622, 2013. doi: 10.5194/hess-17-3605-2013.

Naota Hanasaki, Shinjiro Kanae, and Taikan Oki. A reservoir operation scheme for global river routing models. *Journal of Hydrology*, 327:22–41, 2006. ISSN 0022-1694. doi: 10.1016/j.jhydrol.2005.11.011.

Nathalie Voisin, Mohamad I Hejazi, L. Ruby Leung, Lu Liu, Maoyi Huang, Hong Yi Li, and Teklu K. Tesfa. Effects of spatially distributed sectoral watermanagement on the redistribution of water resources in an integrated water model. *Water Resources Research*, pages 4253–4270, 2017. ISSN 6176273099. doi: 10.1002/ 2016WR019767.

Mohamad I Hejazi, Nathalie Voisin, Lu Liu, Lisa M Bramer, Daniel C Fortin, John E Hathaway, Maoyi Huang, Page Kyle, L. Ruby Leung, Hong Yi Li, Ying Liu, Pralit L Patel, Trenton C Pulsipher, Jennie S Rice, Teklu K Tesfa, Chris R Vernon, and Yuyu Zhou. 21st century united states emissions mitigation could increase water stress more than the climate change it is mitigating. *Proceedings of the National Academy of Sciences of the United States of America*, 112:1421675112–, 2015. ISSN 1091-6490 (Electronic)0̊027-8424 (Linking). doi: 10.1073/pnas.1421675112.

Jae Edmonds and J Reilly. *Global Energy: Assessing the Future.* Oxford University Press, 1985. URL `https://www.osti.gov/biblio/5079369`.

Jae Edmonds, Marshall Wise, Hugh Pitcher, Richard Richels, Tom Wigley, and Chris Maccracken. An integrated assessment of climate change and the accelerated introduction of advanced energy technologies. *Mitigation and Adaptation Strategies for Global Change*, 1(4):311–339, 1997. doi: 10.1007/bf00464886.

Son H. Kim, Jae Edmonds, Josh Lurz, Steven J. Smith, and Marshall Wise. The objects framework for integrated assessment: Hybrid modeling of transportation. *The Energy Journal*, 0(Special I):63–92, 2006.

T. Bosshard, M. Carambia, K. Goergen, S. Kotlarski, P. Krahe, M. Zappa, and C. Schär. Quantifying uncertainty sources in an ensemble of hydrological climate-impact projections. *Water Resources Research*, 49(3):1523–1536, 2013. ISSN 0043-1397. doi: https://doi.org/10.1029/2011WR011533. URL `https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2011WR011533`.

S. W. D. Turner, N. Voisin, J. Fazio, D. Hua, and M. Jourabchi. Compound climate events transform electrical power shortfall risk in the pacific northwest. *Nature Communications*, 10(1):8, 2019. ISSN 2041-1723. doi: 10.1038/s41467-018-07894-4. URL `https://doi.org/10.1038/s41467-018-07894-4`.

Nathalie Voisin, Ana Dyreson, Tao Fu, Matt O'Connell, Sean W. D. Turner, Tian Zhou, and Jordan Macknick. Impact of climate change on water availability and its propagation through the western u.s. power grid. *Applied Energy*, 276, 2020. ISSN 03062619. doi: 10.1016/j.apenergy.2020.115467.

Patrick M. Reed, Antonia Hadjimichael, Richard H. Moss, Christa Brelsford, Casey D. Burleyson, Stuart Cohen, Ana Dyreson, David F. Gold, Rohini S. Gupta, Klaus Keller, Megan Konar, Erwan Monier, Jennifer Morris, Vivek Srikrishnan, Nathalie Voisin, and Jim Yoon. Multisector dynamics: Advancing the science of complex adaptive human-earth systems. *Earth's Future*, 10(3):e2021EF002621, 2022. ISSN 2328-4277. doi: https://doi.org/10.1029/2021EF002621. URL `https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2021EF002621`.