EGU2020-12440

EGU2020: Sharing Geoscience Online
HS5.1.1: Water resources policy and management - forecast and control methods
6 May 2020

Benefits and limits of seasonal forecasts for hydropower production: a global analysis

D. Lee[1], J.Y. Ng[2], S. Galelli[2], P. Block[1]

[1] Department of Civil and Environmental Engineering, University of Wisconsin-Madison
[2] Pillar of Engineering Systems and Design, Singapore University of Technology and Design

Motivation

- Synoptic assessment of the value of seasonal forecasts for global hydropower production is lacking

  - Potential of seasonal forecasts only demonstrated for specific river basins

- Limited knowledge on how forecast skill and reservoir characteristics translate into forecast value

Our approach

- Global analysis on 1,593 hydropower reservoirs
  - Develop seasonal inflow forecasts for each reservoir leveraging teleconnections between large-scale climate drivers and local hydrology
  - Simulate hydropower production under 3 operating schemes (perfect forecasts, realistic forecasts, no forecast)
  - Explain how reservoir design properties and forecast skill affect value of seasonal forecasts
    - Made possible due to the wide range of climatic conditions and dam characteristics available in our database
  - Identify key geographical regions that would benefit the most from forecasts

Data

Hydropower data

- 1,593 hydropower reservoirs—about 40% of global hydropower capacity
  - General properties: location, purpose
  - Physical properties: storage, surface area, dam height
  - Hydropower properties: installed capacity, hydraulic head, maximum release through turbines
- Compiled by *Ng et al.* (2017) with original data retrieved mainly from
  - Global Reservoir and Dam (GRanD) database, and
  - International Commission on Large Dams (ICOLD) database

Ng, J. Y., S. W. Turner, and S. Galelli (2017), Influence of El Niño Southern Oscillation on global hydropower production, *Environmental Research Letters*, *12*(3), 034,010.

Data

Hydro-climatological data

- 4 large-scale climate drivers

    - ENSO (El Niño Southern Oscillation)
    - PDO (Pacific Decadal Oscillation)
    - NAO (North Atlantic Oscillation)
    - AMO (Atlantic Multidecadal Oscillation)

- 2 local variables

    - Monthly soil moisture (ERA-40 reanalysis product)
    - Lagged inflow (WaterGAP model using WATCH 20th century forcing data)

Methods

Operating schemes

Reservoir model[1]

- Storage dynamics represented by mass-balance equations
- Environmental flow requirements included

Benchmark: control rule → **H_{ctrl}**

- Release decisions based on observed storage, season, inflow

Perfect forecast-informed operations → **H_{PF}**

- Release decisions based on 3-month streamflow forecast

Realistic forecast-informed operations → **H_{DF}**

Dam inflow prediction model[2]

- Monthly prediction model based on climate and local drivers
- Principal component linear regression model

Hydropower production from 1958-2000

[1]Turner, S.W., and S. Galelli (2016), Water supply sensitivity to climate change: an R package for implementing reservoir storage analysis in global and regional impact studies, *Environmental Modelling & Software*, *76*, 13–19.

[2]Lee, D., P. Ward, and P. Block (2018), Attribution of large-scale climate patterns to seasonal peak-flow and prospects for prediction globally, *Water Resources Research*, *54*(2), 916–938, doi:10.1002/2017WR021205.

Methods

Performance evaluation

Expected improvement from perfect forecast-informed operations:

$$I_{PF} = \frac{H_{PF} - H_{ctrl}}{H_{PF}} \times 100\%$$

Expected improvement from realistic forecast-informed operations:

$$I_{DF} = \frac{H_{DF} - H_{ctrl}}{H_{PF}} \times 100\%$$

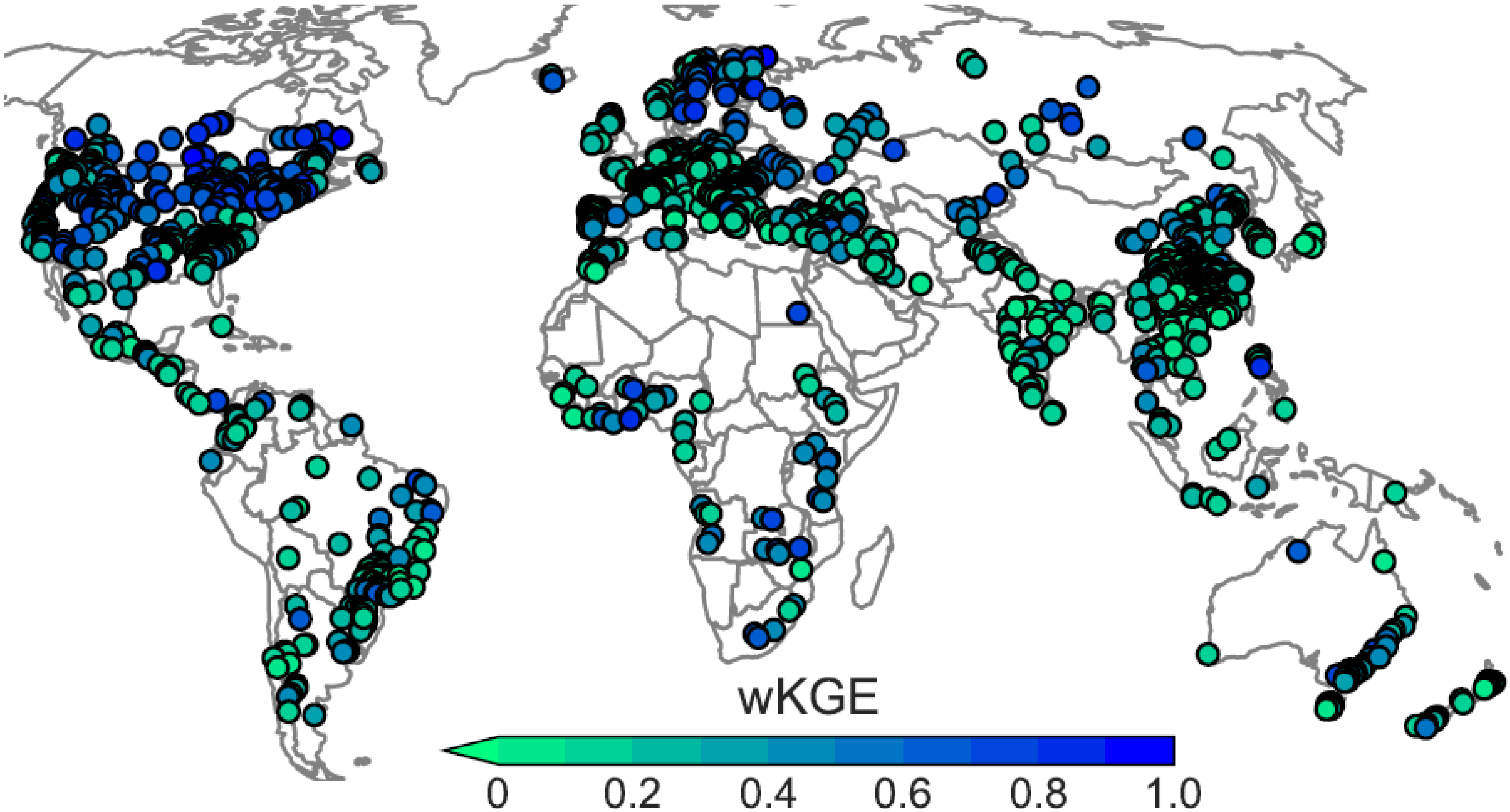
Potential improvement between realistic and perfect forecast-informed operations:

$$I = \frac{H_{DF} - H_{ctrl}}{H_{PF} - H_{ctrl}} = \frac{I_{DF}}{I_{PF}}$$

- Explained likelihood of attaining high I_{PF} and high I using logistics regression with forecast accuracy and reservoir characteristics as predictors

Accuracy of dam inflow prediction model

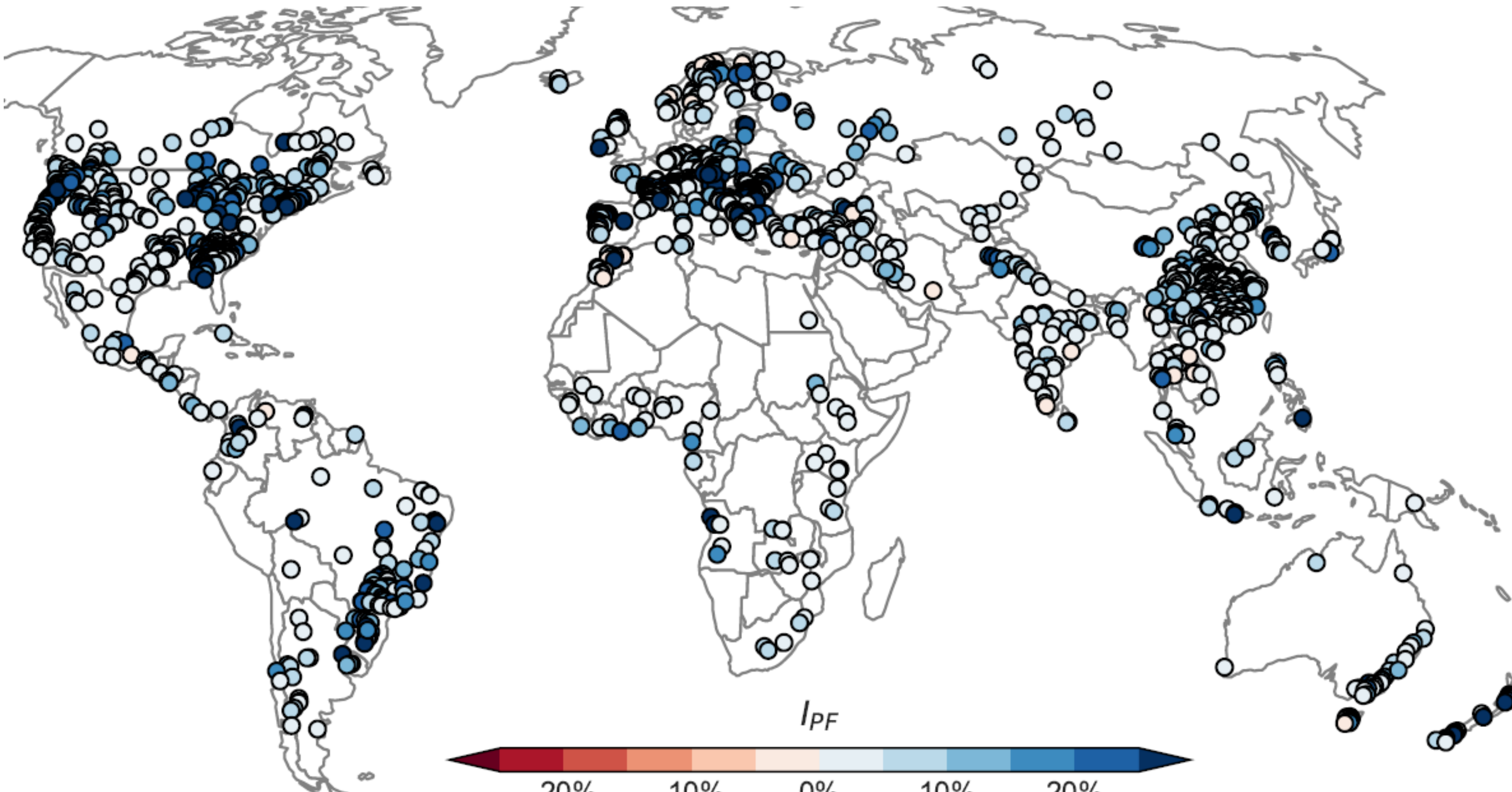
Prediction accuracy for 1-month ahead inflow



- Average weighted KGE is 0.31 for 1-month ahead predicted inflow
- Prediction accuracy decreases with lead time (0.22 and 0.17 for 2-month and 3-month ahead predicted inflow)

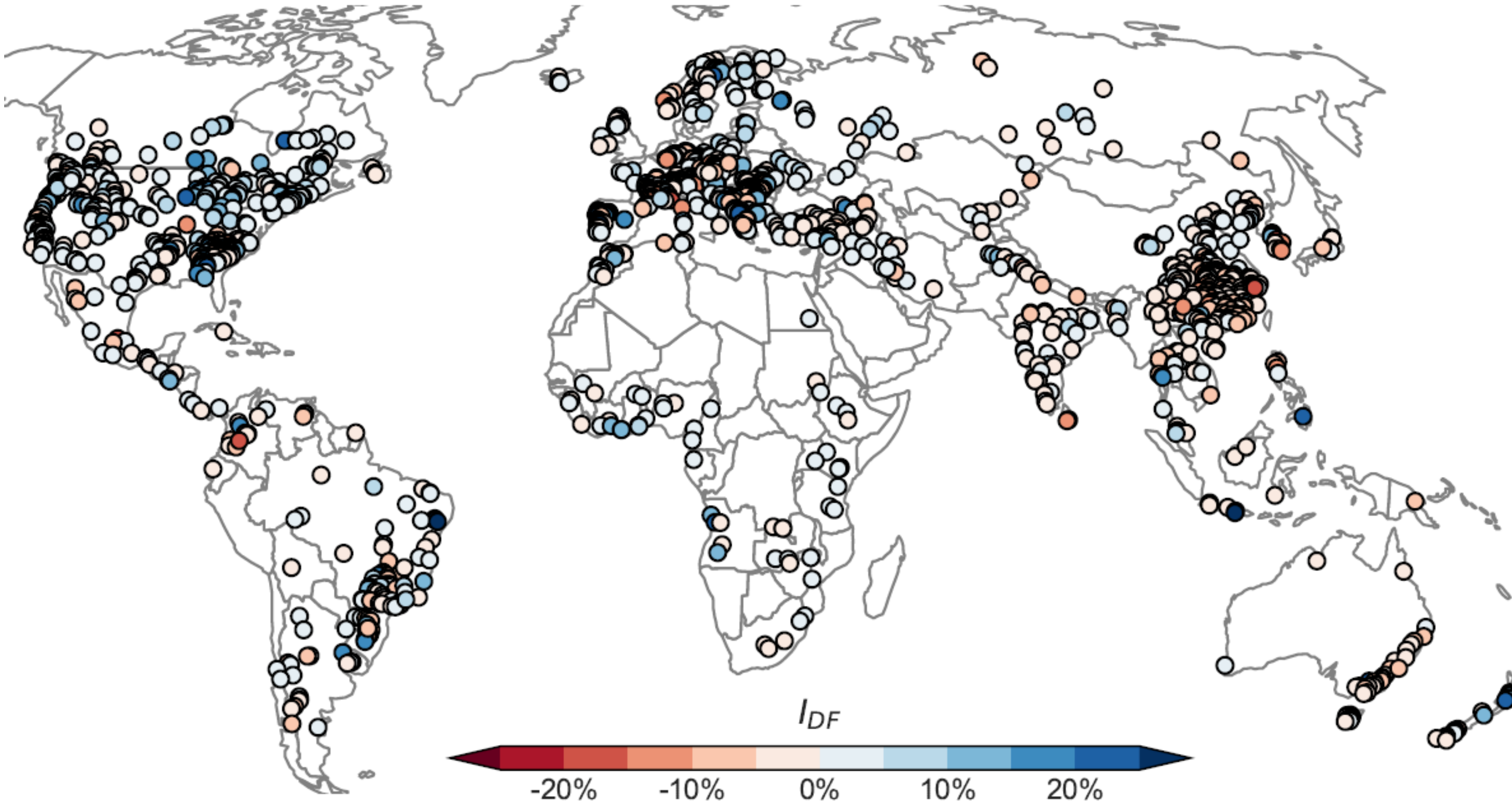
Performance of forecast-informed operations

Performance of perfect forecast-informed operations



- 96% of reservoirs have greater hydropower production, collectively contributing to an additional 219 TWh per year of hydroelectricity

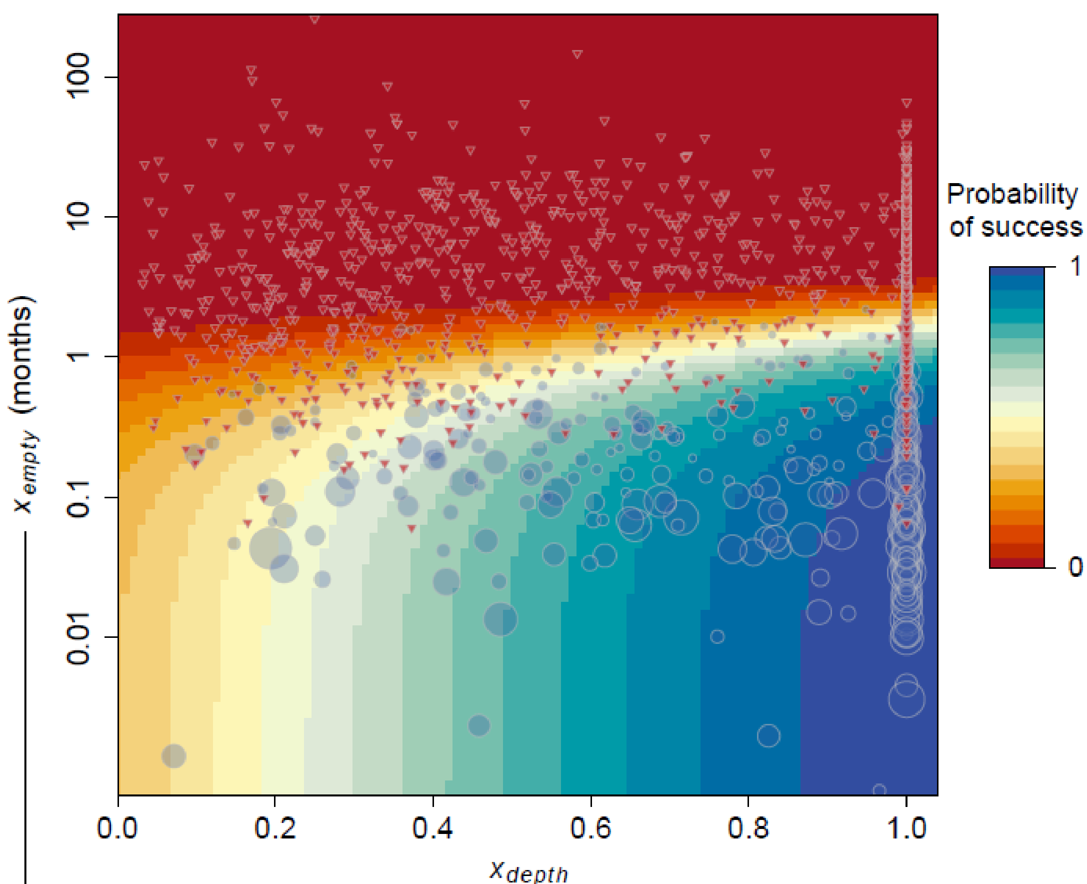
Performance of realistic forecast-informed operations



- 51% of reservoirs have greater hydropower production, collectively contributing to an additional 69 TWh per year of hydroelectricity

Evaluation of prediction accuracy and reservoir characteristics

Explaining potential of perfect forecasts using reservoir characteristics



- Large dams are unlikely to benefit from forecasts as large storage capacity acts as a buffer against inflow uncertainty
- Dams whose hydraulic head is highly dependent on reservoir depth are more likely to benefit from forecasts

Ratio of maximum reservoir depth to maximum hydraulic head

Ratio of reservoir storage capacity to the maximum turbine release rate

Explaining potential of realistic forecasts using reservoir characteristics and forecast accuracy

- Dams with high forecast accuracy are likely to benefit from realistic forecast

- Dams with hydraulic head dependent on reservoir depth can benefit from realistic forecast only when forecast accuracy is high

- Dams that fill quickly and have large fraction of time in which inflow exceeds the maximum turbine release are likely to benefit from realistic forecasts—even when forecasts are not very accurate

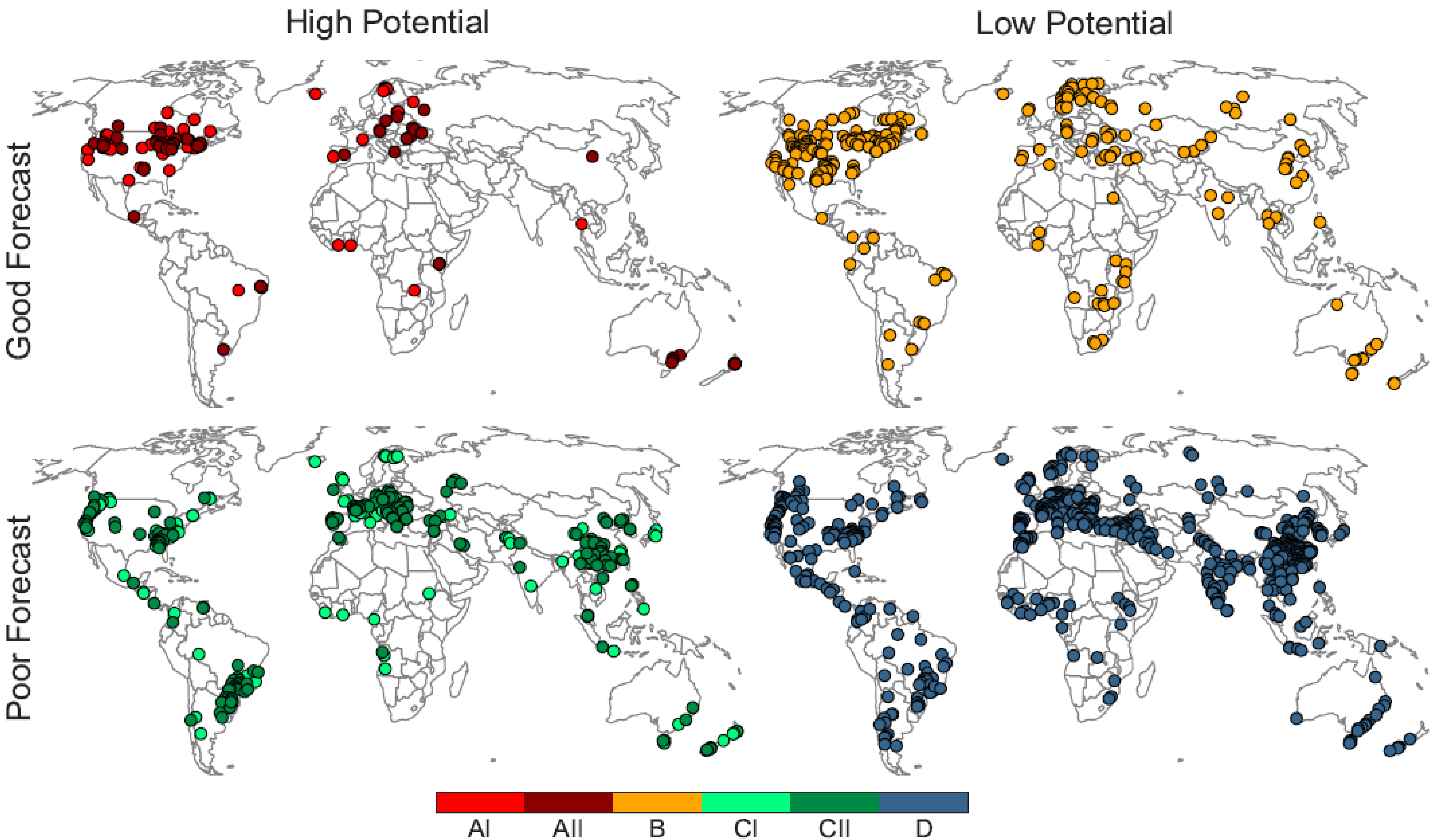
Classification of hydropower dams

Classification of hydropower dams

Based on potential to benefit, forecast accuracy, and design specifications

Group	High potential to benefit from perfect forecasts	High forecast accuracy	Design specifications complement forecast
AI	Y	Y	Y
AII	Y	Y	N
B	N	Y	
CI	Y	N	Y
CII	Y	N	N
D	N	N	

Geographical distribution of dams



- Group AI can reap immediate benefits by switching from control rules to forecast-informed operations
- Group CI can achieve increased hydropower production if investments are made to improve forecasts

Conclusions

- 51% of the hydropower dams evaluated worldwide may benefit from seasonal forecasts conditioned on hydroclimatic predictors

- Potential benefits are predominantly modulated by forecast skill and reservoir characteristics

    - Planned dams with appropriate characteristics (e.g. run-of-the-river hydropower dams in the Amazon and Mekong basin) should consider adopting forecast-informed operations

- Dams in North America, Southeastern South America, Europe, and East Asia can increase hydropower production if more accurate forecasts are developed

Acknowledgements

- This project is supported by Singapore's Ministry of Education (MoE) through the Tier 2 project 'Linking water availability to hydropower supply—an engineering systems approach' (Award No. MOE2017-T2-1-143)

Thanks!

Resilient Water Systems Group
http://people.sutd.edu.sg/~stefano_galelli/

Water Systems & Society Research Group
https://wss.cee.wisc.edu/

References

- Ng, J.Y., S.W. Turner, and S. Galelli (2017), Influence of El Niño Southern Oscillation on global hydropower production, *Environmental Research Letters*, *12*(3), 034,010.

- Turner, S.W., and S. Galelli (2016), Water supply sensitivity to climate change: an R package for implementing reservoir storage analysis in global and regional impact studies, *Environmental Modelling & Software*, *76*, 13–19.

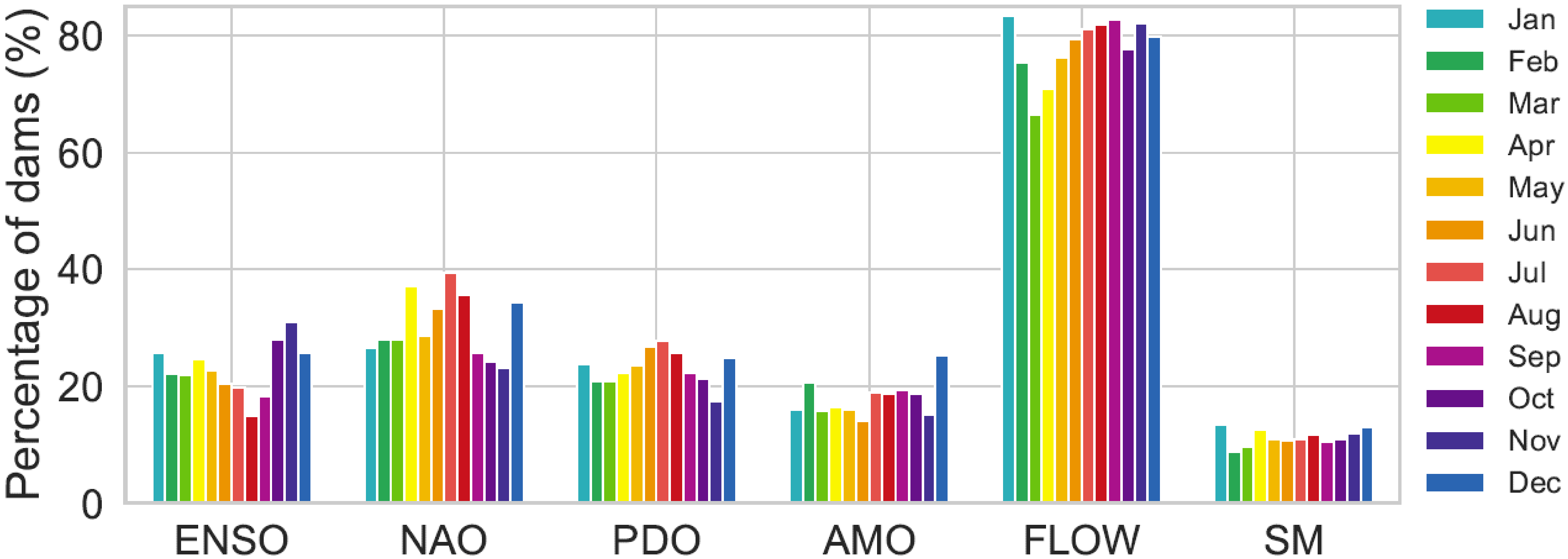
- Lee, D., P. Ward, and P. Block (2018), Attribution of large-scale climate patterns to seasonal peak-flow and prospects for prediction globally, *Water Resources Research*, *54(2*), 916–938, doi:10.1002/2017WR021205.

- Lee, D., J.Y. Ng, S. Galelli, P. Block. Unfolding the relationship between seasonal forecasts skill and value in hydropower production: A global analysis. *Water Resources Research*, under review.

- Lee, D., J.Y. Ng, S. Galelli, P. Block (2020). Global Hydropower Simulation - Forecast, HydroShare, https://doi.org/10.4211/hs.2b38eceeb5ba40c1a88a242e8c18fafe

Appendix

Percentage of dams correlated with climate and local drivers



- 23%, 30%, 23%, and 18% of dams have inflow significantly correlated with ENSO, NAO, PDO, and AMO, respectively
- 78% of dams exhibit significant 1-month lead inflow autocorrelation

Performance of forecast-informed operations for each group