

OVERCOMING THE CASCADING ISSUES OF DATA SCARCITY AND UNCERTAINTY FOR SEASONAL HYDROPOWER PLANNING IN EAST AFRICA

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MOTIVATION

- Stochastic programming with recourse assumes that the first stage is **deterministic** [Yeh, 1985].
- Assumption fails if
 - planning horizon is **seasonal**.
 - **reliable inflow observations** are unavailable for post-processing ensemble streamflow forecasts.
- Remote sensing offers **spatially and temporally continuous** measurements of precipitation [Lettenmaier et al., 2015].
- Precipitation datasets exhibit **large variability** [Kidd and Huffman, 2011]
- **Data scarcity** (lack of inflow observations) leads to **data uncertainty** (variability in precipitation observations)

RESEARCH QUESTIONS

Addressing Inflow Data Scarcity

- **Approach:** Post-process ensemble precipitation forecasts instead of streamflow forecasts using RS datasets
- **RQ1:** What is the impact of postprocessing precipitation forecasts on inflow estimates and hence on hydropower production?

Addressing Precipitation Data Uncertainty

- **Approach:** Reformulate stochastic programming with recourse to consider first stage as stochastic
- **RQ2:** How does the stochastic programming with first stage stochastic affect hydropower optimization compared to the classical formulation?

STUDY AREA

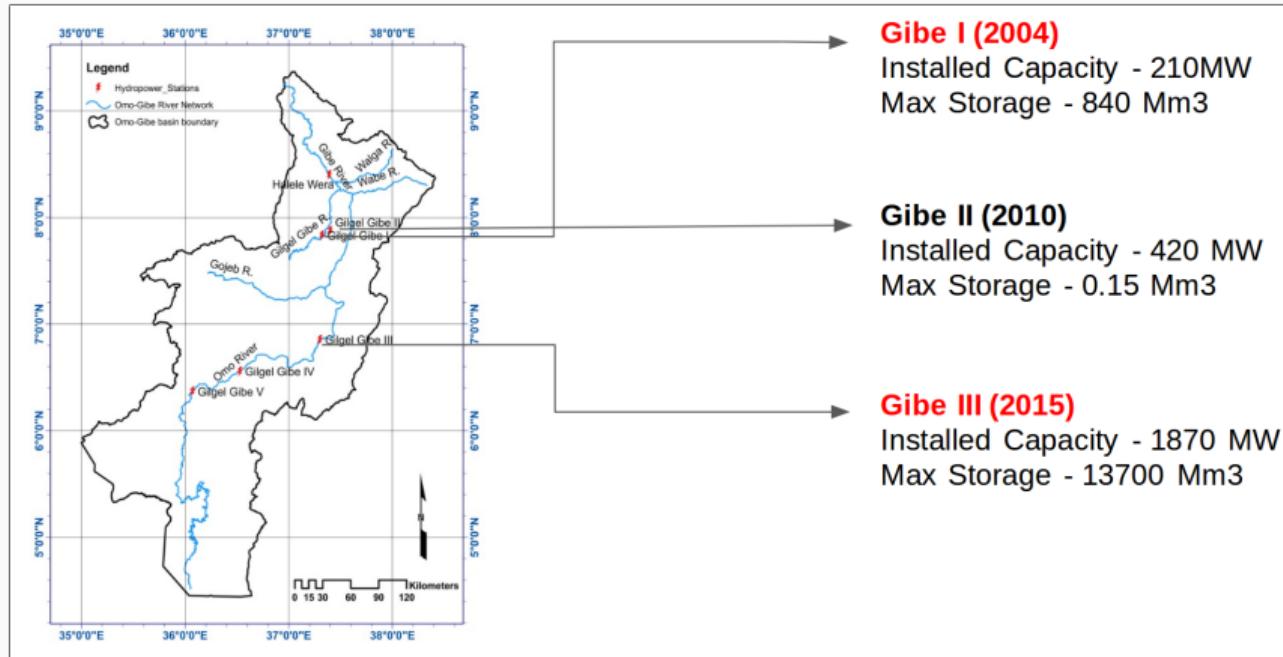


Figure: Omo-Gibe basin in Ethiopia showing the location of hydropower dams

DATA AND MODELS

Meteorological Datasets

- Seasonal Forecasts: CanCM3, CanCM4 and GEOS-5 from **NMME** [Kirtman et al., 2014] - 30 members, 9 months forecast horizon
- Remote Sensing Datasets: **TRMM** [Huffman et al., 2007], **CMORPH** [Joyce et al., 2004], **PERSIANN** [Ashouri et al., 2015]

Hydrologic Model

- **Noah-MP LSM**[Niu et al., 2011] driven through NASA's Land Information System [Kumar et al., 2006]
- Time period: **Jan 2005 to May 2006**, Spatial Resolution: **5km x 5km**

Optimization Algorithm

- **HIDROTERM** non-linear optimization software [Zambon et al., 2012]
- Objective - **Maximize hydropower production**

METHODOLOGY

We compare three different stochastic programming formulations:

I) Deterministic

- Deterministic forecast for the nine stages using Bayesian Model Averaging (BMA) of NMME forecasts
- TRMM used as "ground truth"

II) Classical Stochastic Programming with Recourse

- Deterministic forecast for only the first stage
- Stages 2 to 9 are stochastic.

III) Modified Stochastic Programming with Recourse

- Stochastic forecast for all nine stages

RESULTS

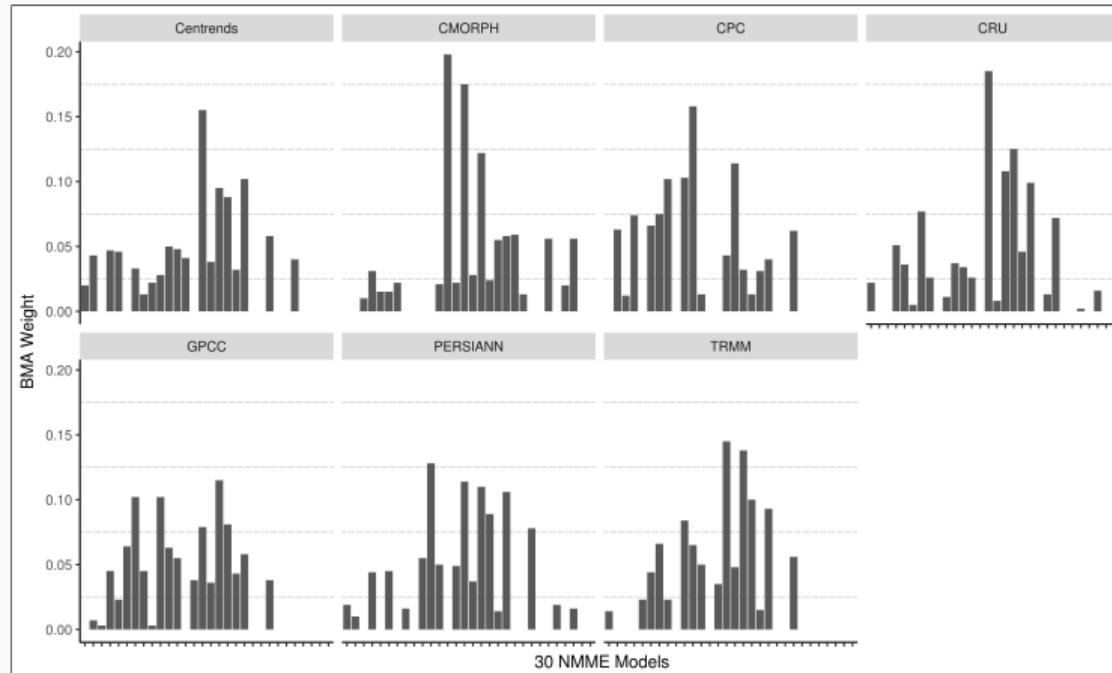
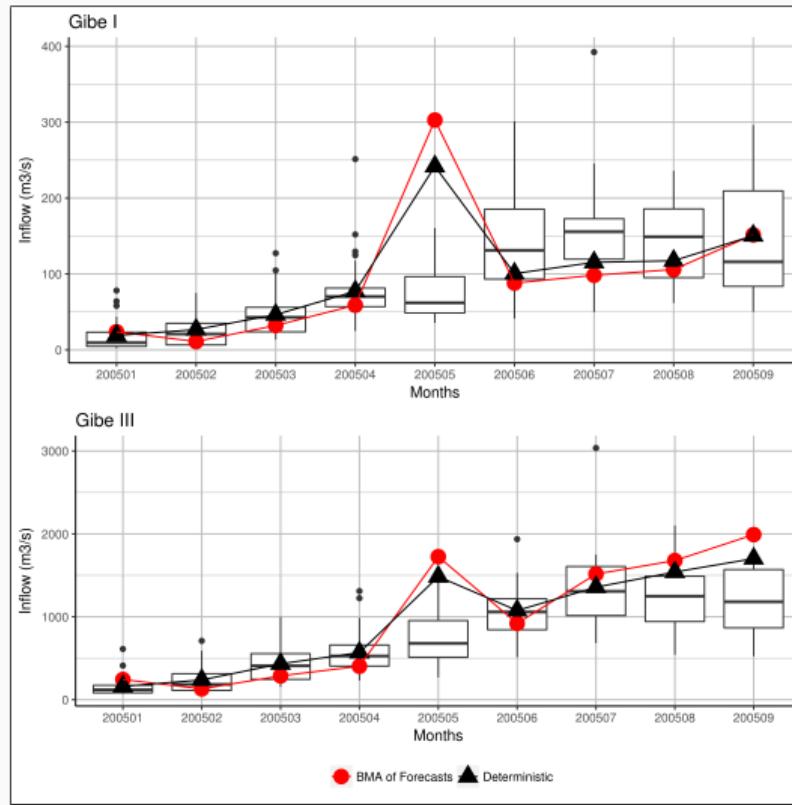
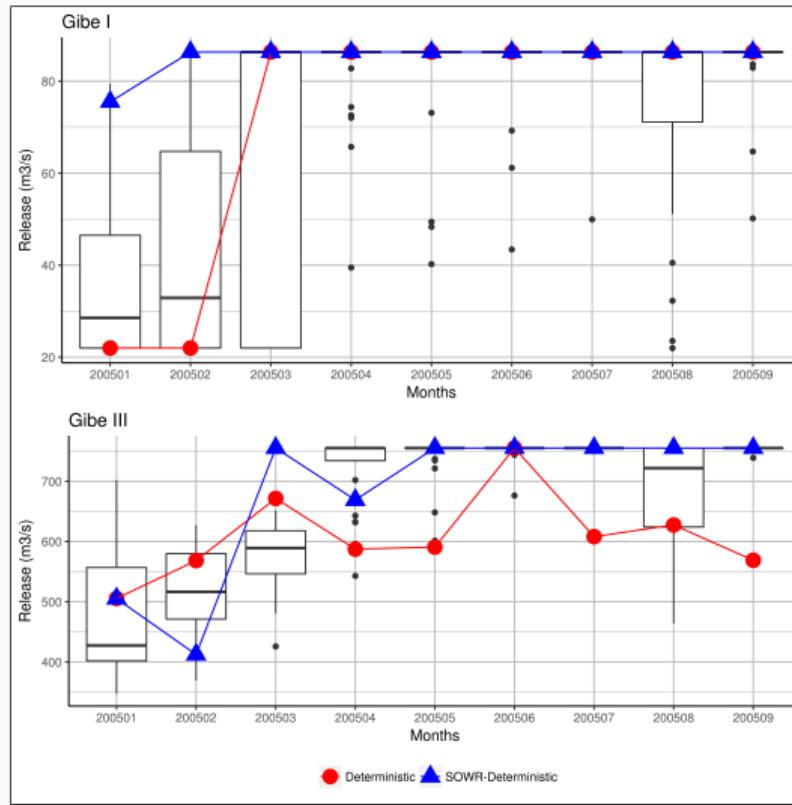


Figure: BMA weights of 30 NMME model using different precipitation datasets

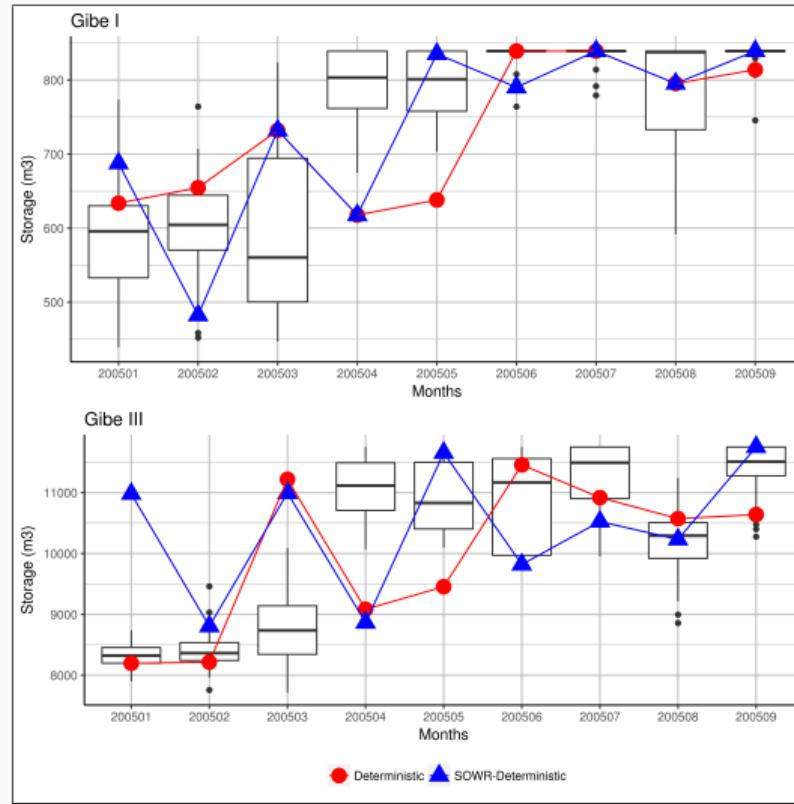
RESULTS



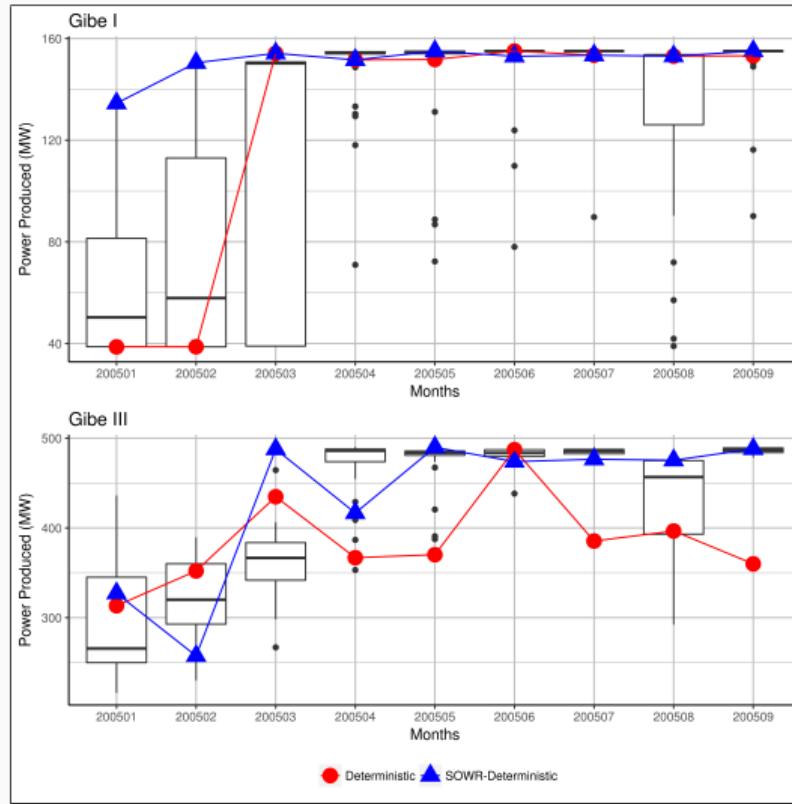
RESULTS



RESULTS



RESULTS



RESULTS

CONCLUSIONS AND FUTURE WORK

ACKNOWLEDGEMENTS

THANK YOU

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