Assessing the Impact of Sensitivity/Uncertainty Selection Criteria on Computational Bias Prediction

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Overview

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Motivation

Sensitivity/Uncertainty (S/U)-based selection criteria can be used to form a validation suite of experiments similar to an application to estimate computational bias.

If using a quantitative metric, some threshold must be chosen to delineate similarity.

How is the selection criterion affecting the computational bias prediction?

Scope

- Investigate this question for c_k and E, two integral indices for similarity produced by TSUNAMI-IP
  - c_k is the correlation coefficient between data-induced uncertainties in two systems
  - E is a measure of similarity based solely on shared sensitivities to nuclear data
- Use the Verified Archived Library of Inputs and Data (VALID), a collection of reviewed critical benchmark evaluation models and sensitivity data, to assess effects of S/U criteria cutoff.

c_k and E as Integral Indices Between Two Systems

c_k near -1

There is a large inverse correlation of shared propagated nuclear data uncertainties

$c_k = 0$

The systems do not share sensitivities OR the data with shared sensitivity has no uncertainty

c_k near 1

There is a large positive correlation of shared propagated nuclear data uncertainties

E near -1

There is a large inverse correlation to shared sensitivities

$E = 0$

The systems do not share sensitivities

E near 1

There is a large positive correlation to shared sensitivities

Method

- Develop a tool to calculate the predicted computational bias for a given application as a function of the chosen trending parameter
- Apply this tool to critical experiment benchmarks with known computational biases
  - Computational bias is defined by $\beta = C/E - 1$
- Each application's bias is predicted by averaging the computational biases of similar benchmark experiments
- Then calculate the bias error
  - The difference between the predicted and actual computational bias

Method Application - VALID

- This method was applied to a set of benchmark experiments in VALID, with the following breakdown of benchmark case types
- **Total: 616**

Category	Label	Cases
HEU-COMP-INTER	HCI	1
HEU-MET-FAST	HMF	46
HEU-SOL-INTER	HIS	2
HEU-SOL-THERM	HST	52
IEU-MET-FAST	IMF	10
LEU-COMP-THERM	LCT	140
LEU-SOL-THERM	LST	19
MIX-COMP-FAST	MCF	2
MIX-COMP-THERM	MCT	49
PU-MET-FAST	MST	10
PU-SOL-THERM	PMF	12
U233-COMP-THERM	PST	81
U233-MET-FAST	UCT	5
U233-SOL-INTER	UMF	10
U233-SOL-MIXED	USI	29
U233-SOL-MIXED	USM	8
U233-SOL-THERM	UST	140

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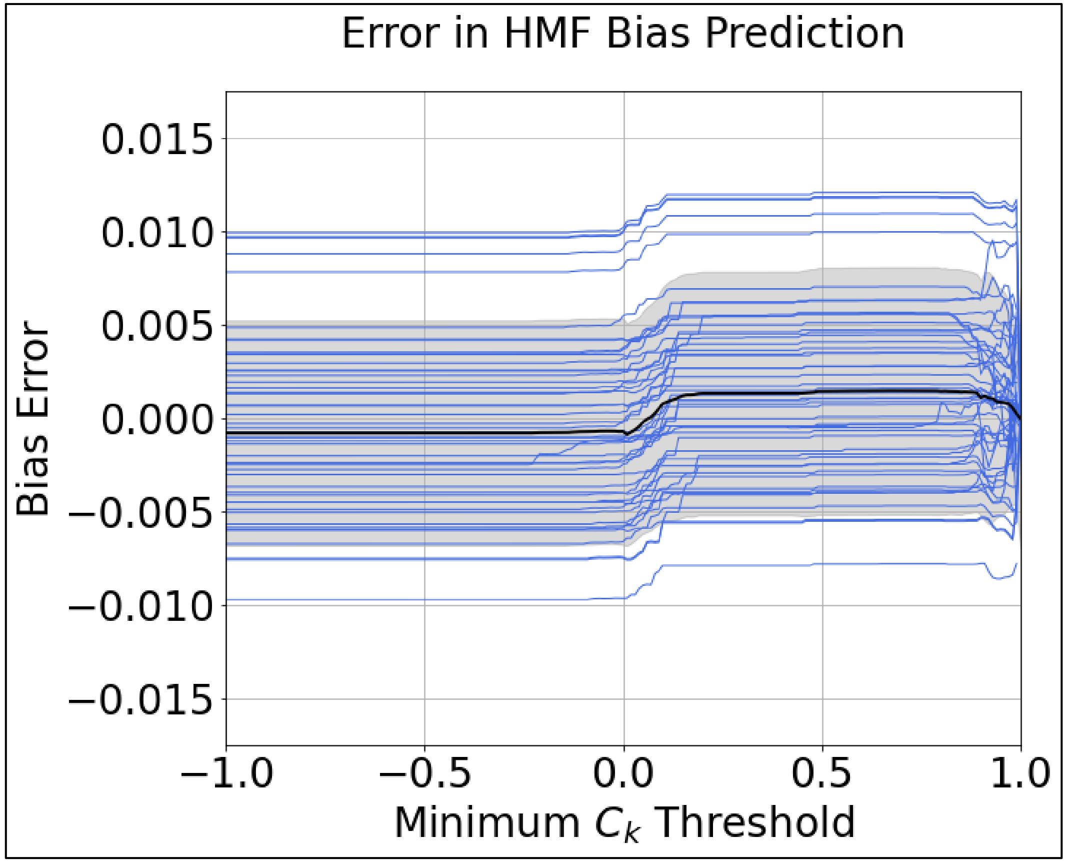
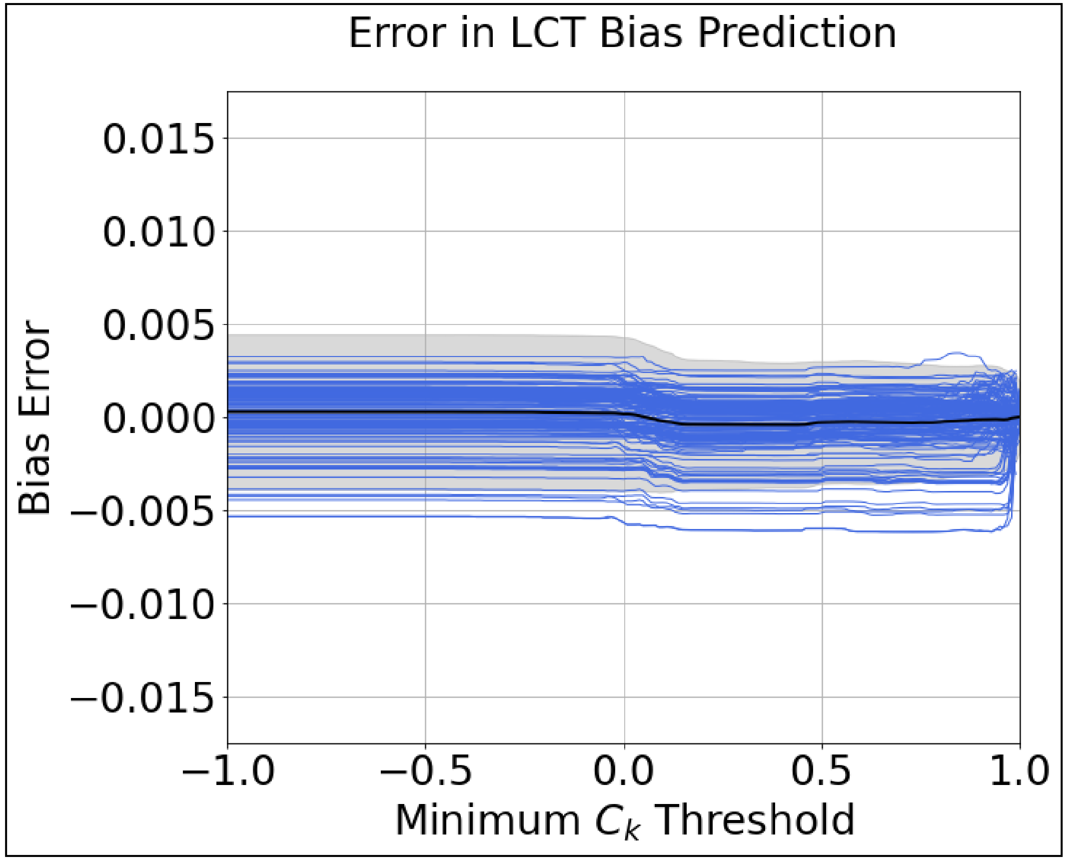
Results: HMF and LCT Bias Prediction Error with c_k



HMF: Average bias error near 0 but large spread



LCT: Average bias error near 0 but small spread

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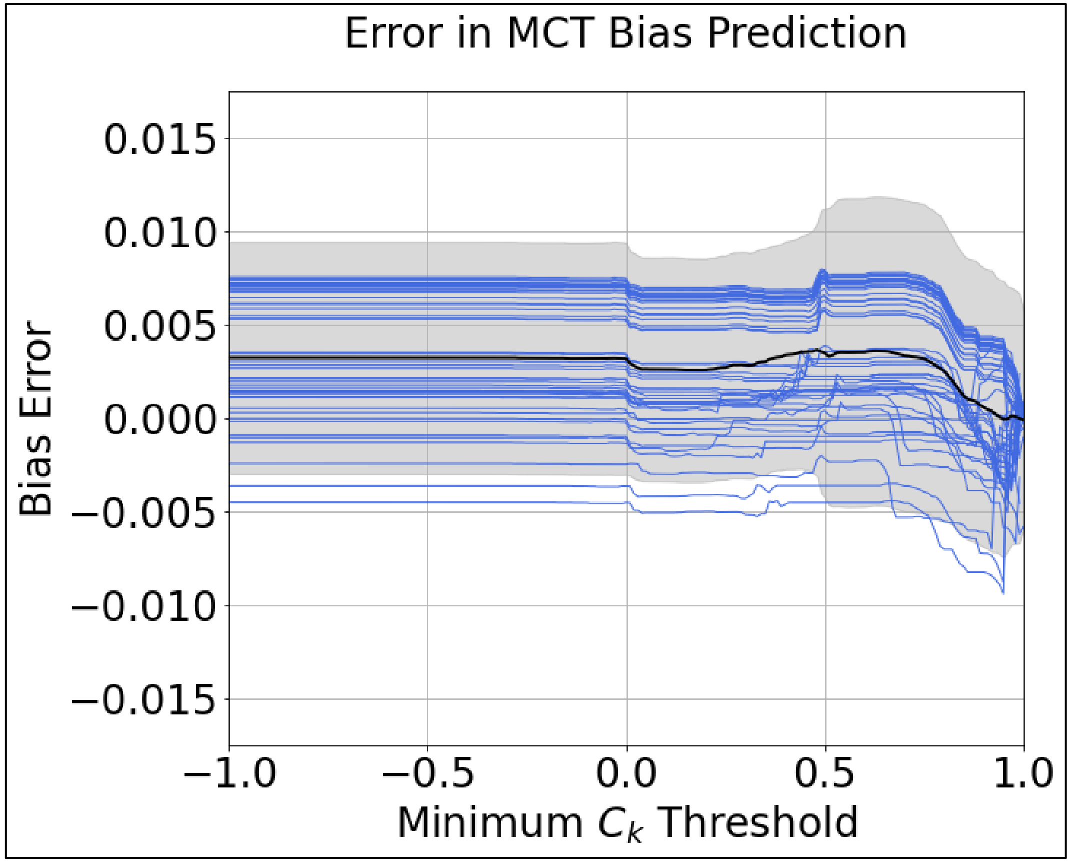
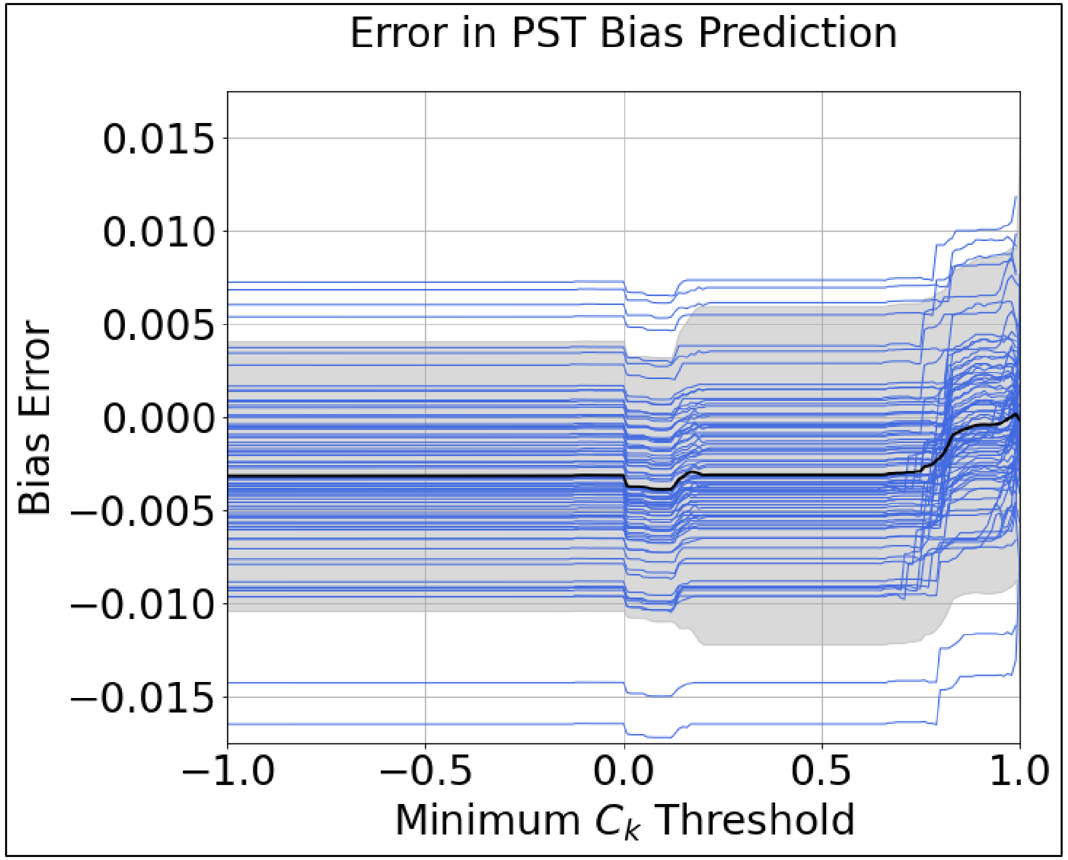
Results: MCT and PST Bias Prediction Error with c_k

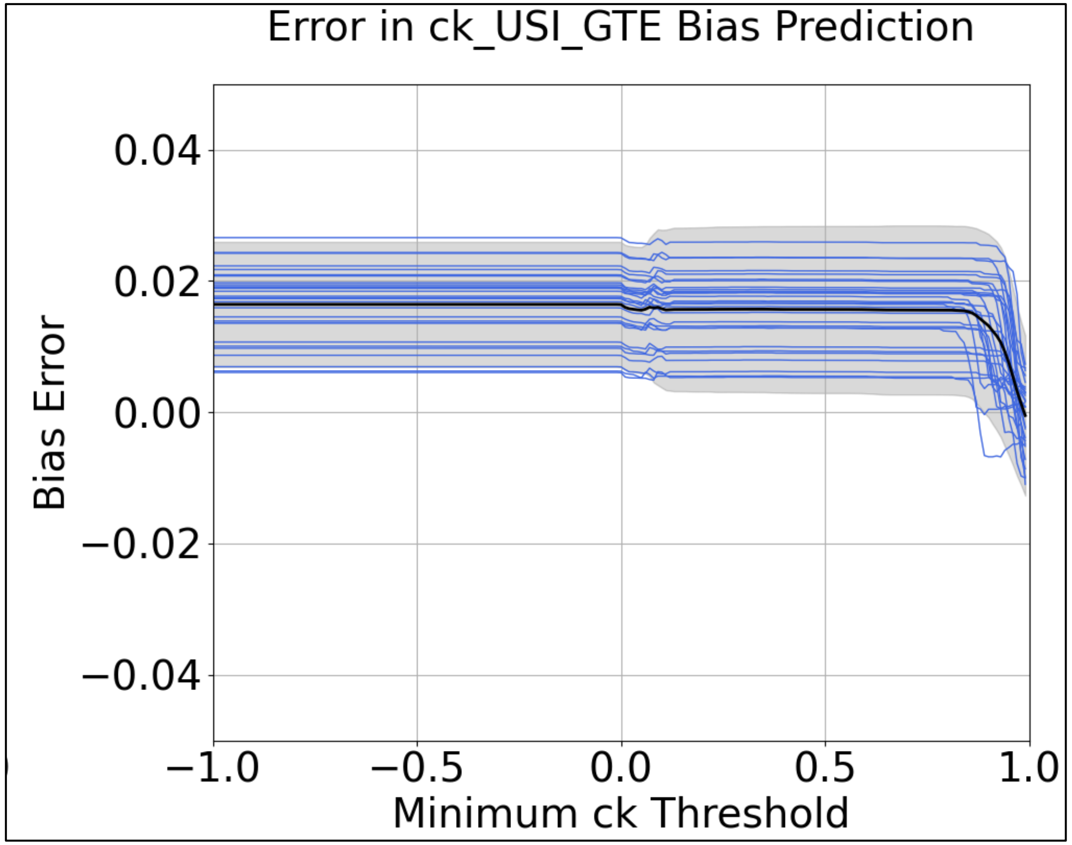


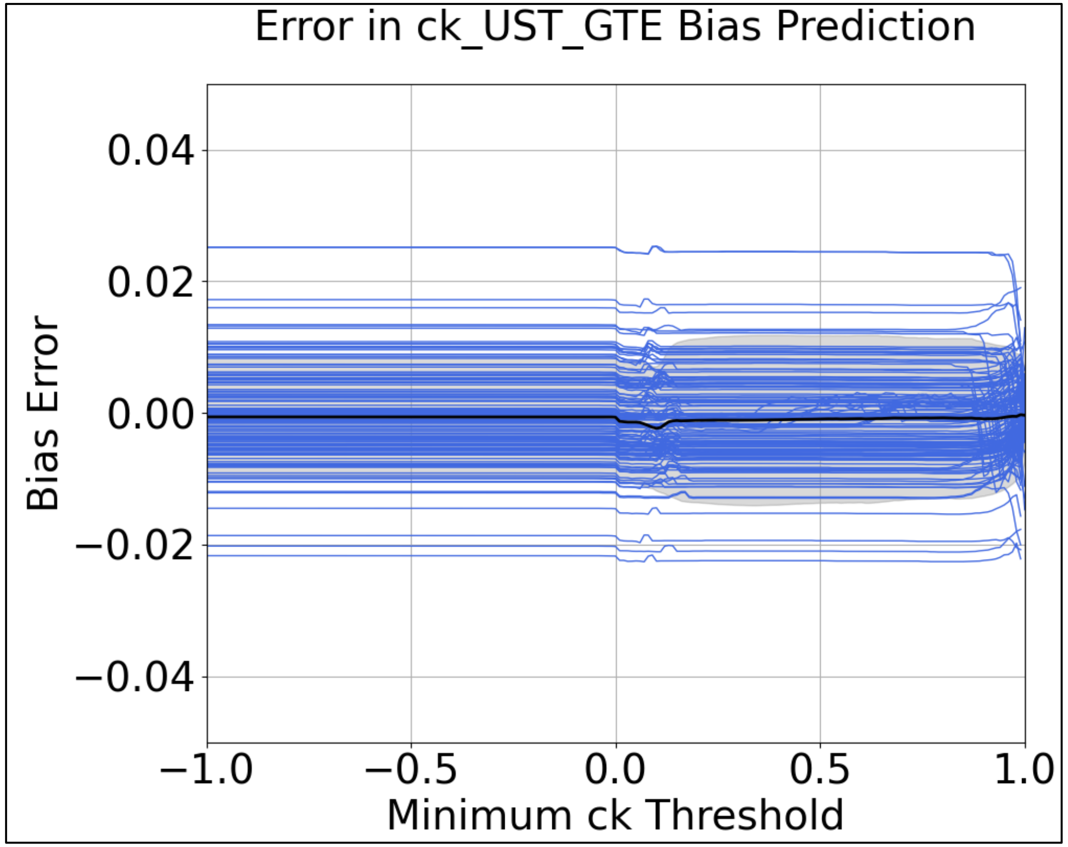


MCT: Bias error averages high but approaches 0 with c_k near 1

PST: Bias error averages low but approaches 0 with c_k near 1

Results: USI and UST Bias Prediction Error with c_k

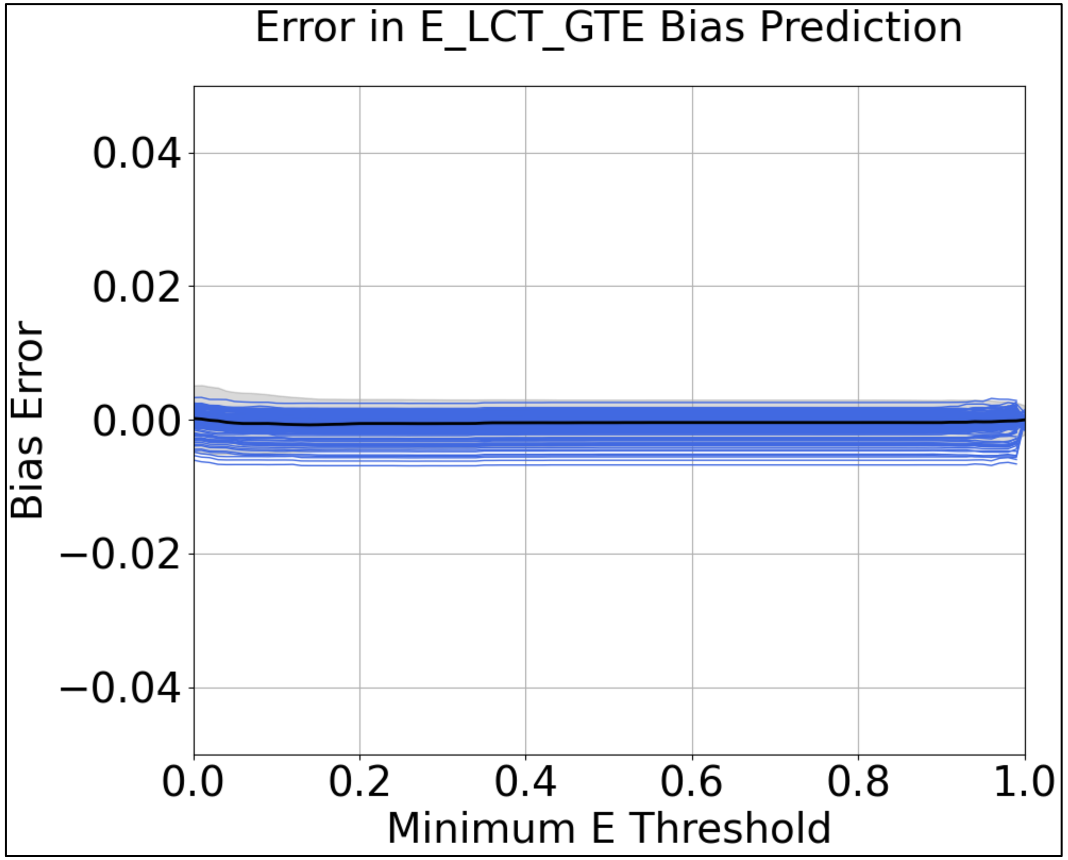


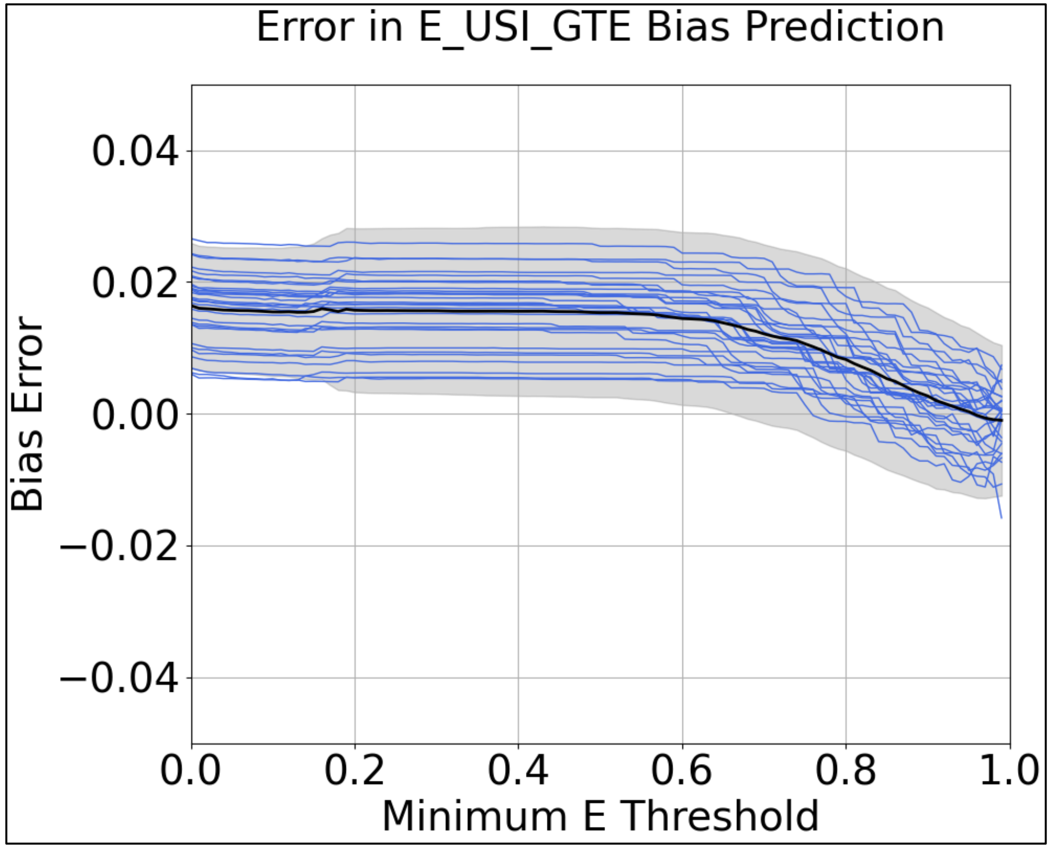


USI: Bias error averages high but approaches 0 *sharply* with c_k near 1

UST: Bias error with large spread relatively unaffected with threshold

Results: LCT and USI Bias Prediction Error with E





LCT: Bias error with low spread and low E dependence for bias error - typical

USI: Bias error with large spread relatively steadily approaches 0 error average near 1

Conclusions and Future Work

- Each system type features unique behavior when assessing bias error as a function of c_k or E
- The examples presented here are just a subset on the effect of selection criteria cutoffs for predicting computational bias
- Typical E threshold dependence was low-none for bias prediction error (with exceptions), but c_k trending effects were typically more prominent
- Further analysis would be needed to support a statement on updated cutoff guidance

More Considerations

- The results of these analyses are dependent on the data available, so results will change as more experiments are incorporated into VALID
- Generalization is still tricky for similar reasons, and the method assumes all experiments are independent of one another

Acknowledgement

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