Development of an Uncertainty Envelope for the 2055 Climate Change Scenario

Modeling Workgroup Quarterly Review
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Motivation

Discuss **potential short-term approaches** to characterize uncertainty surrounding 2055 climate change scenario **that**:

- provide a realistic balance between practical uncertainty assessment and time/resources availability

- best leverage outcomes of existing parallel work (e.g. CHAMP project)

Why focus on 2055 scenario?

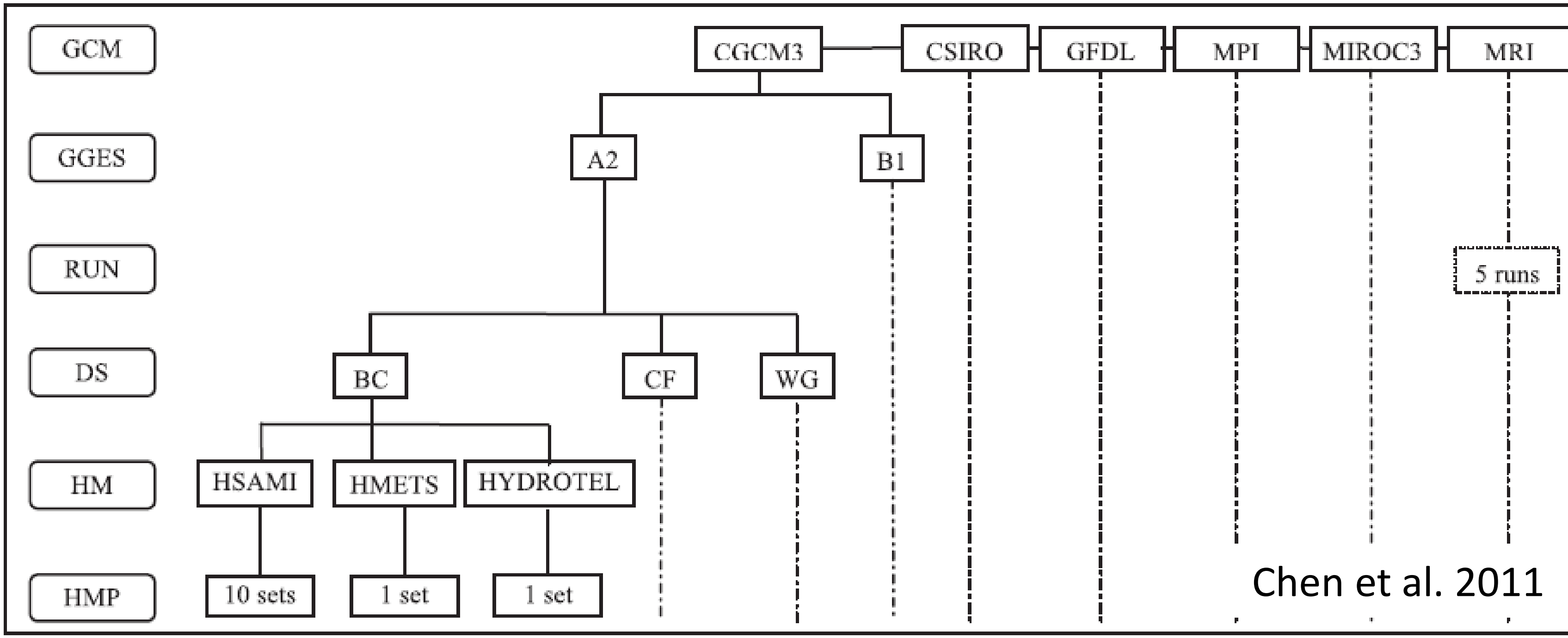
No formal and approved/broadly accepted uncertainty quantification framework is available at this point

It was decided to maintain consistency with past "decisional" model outputs when providing **2025** results

The team recognizes the need to move in the direction of incorporating uncertainty into decisions

It seems reasonable to start discussing uncertainty approaches using **2055** scenario (non-decisional at this point) as a test bed

Climate change impact analyses entail several sources of uncertainty



Chen et al. 2011

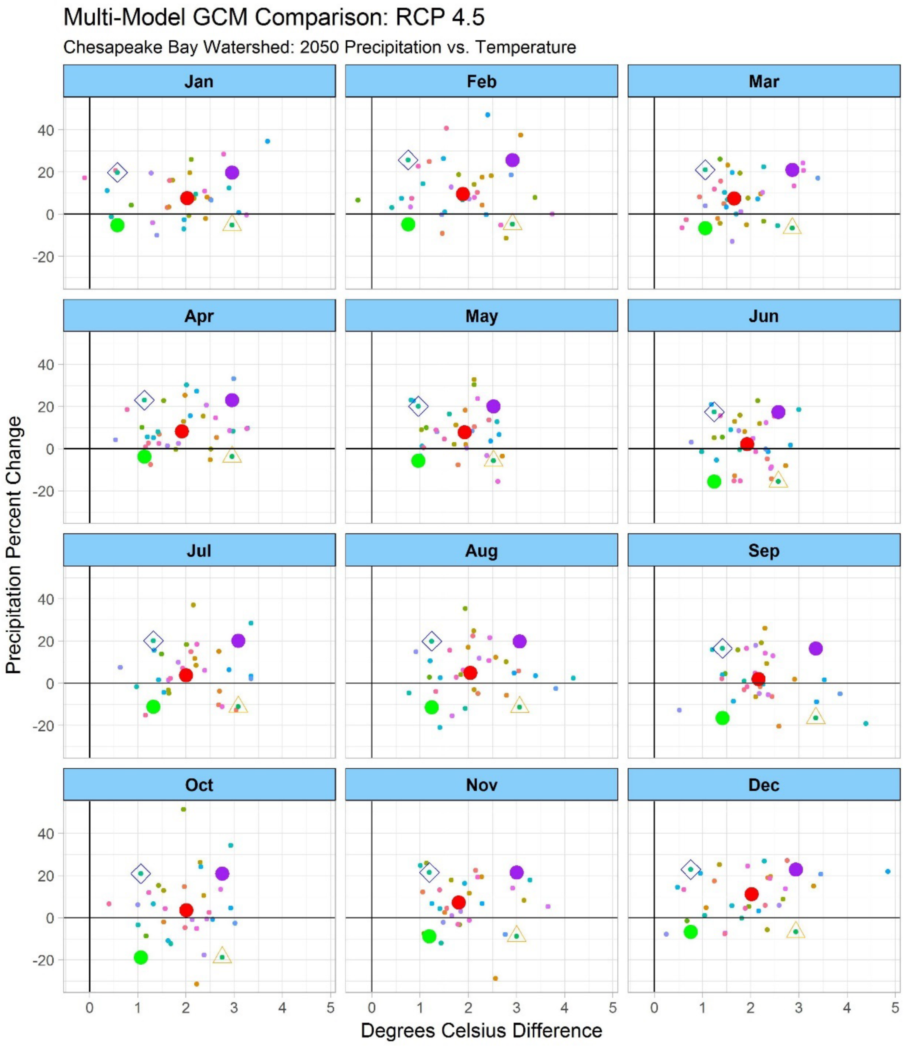
Quantifying all sources of uncertainty is not feasible in the near term

Previous studies (see Ross & Najjar, 2019) and preliminary results from CHAMP indicate that GCM structural uncertainty is often one of the major sources of uncertainty

-> Uncertainty due to different GCMs is a reasonable place to start

Current approach: approximate range of model projections

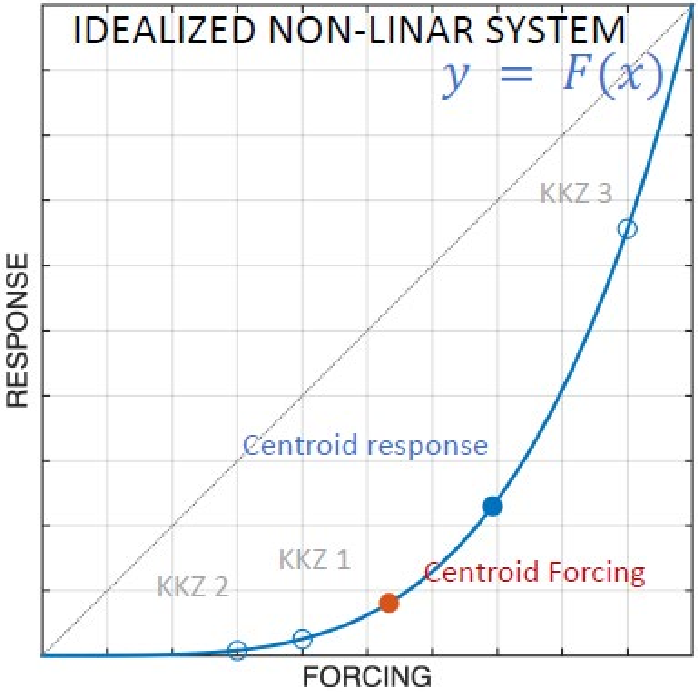
Run 10th and 90th percentiles of 31-member GCM ensemble through watershed and estuarine model to approximate a range of expected responses for 2055



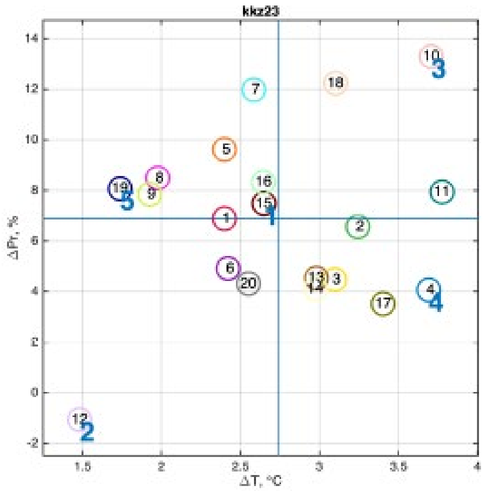
2019 Climate Change Documentation

Suggestions from CHAMP project

MOTIVATION FOR KKZ ranking: RETAIN THE RANGE OF FUTURE CLIMATES , RATHER THAN USING THE MEAN



$$\overline{F(x)} \neq F(\overline{x})$$



"Select models that have the largest possible spread from each other, that is, to cover a widest range of model uncertainty that can be achieved with a small subset of GCMs"

Herrmann & Najjar, CHAMP MTAG 2019

Approximate probability distribution of model projections?

1. Select a limited sub-sample of GCMs (e.g., 5) through appropriate method (see Ross & Najjar, 2019)

2. Run 5 GCMs through watershed and estuarine model

3. Use ensemble averaging method (e.g., Bayesian Model Averaging; Raftery et al., 2005; Duan et al., 2007) to assign a probability distribution to future projections

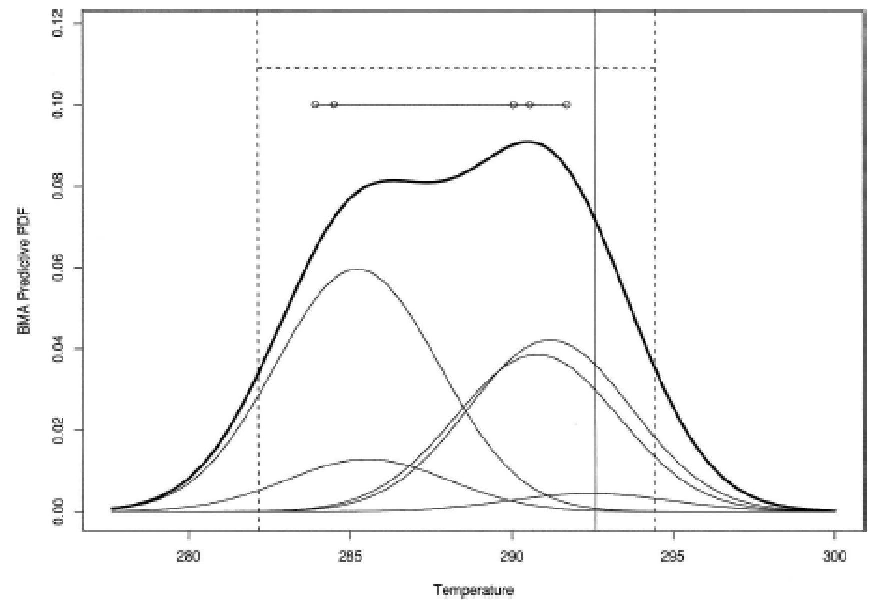


FIG. 3. BMA predictive PDF (thick curve) and its five components (thin curves) for the 48-h surface temperature forecast at Packwood, WA, initialized at 0000 UTC on 12 Jun 2000. Also shown are the ensemble member forecasts and range (solid horizontal line and bullets), the BMA 90% prediction interval (dotted lines), and the verifying observation (solid vertical line).

Raftery et al. 2005

Note: central tendency of probability distribution might differ from current projection based on median of GCMs

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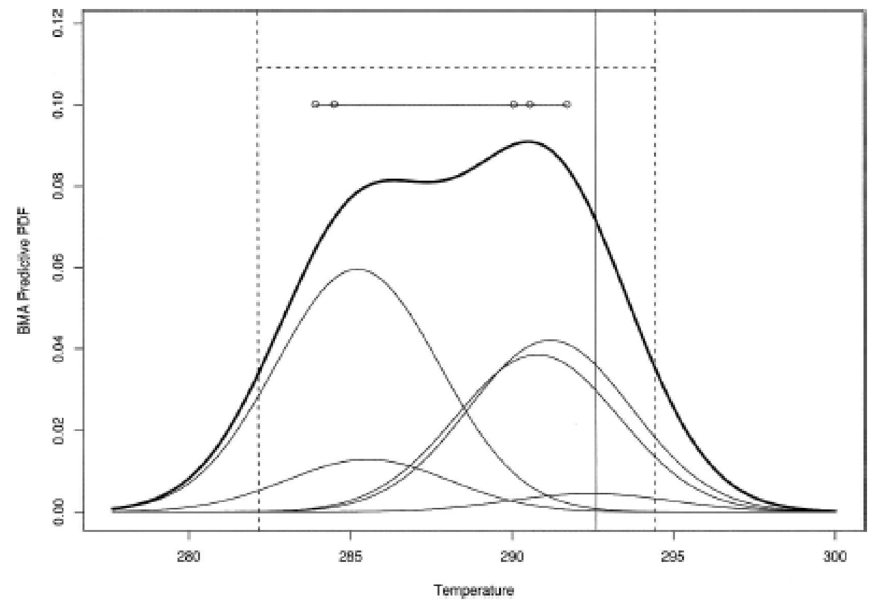

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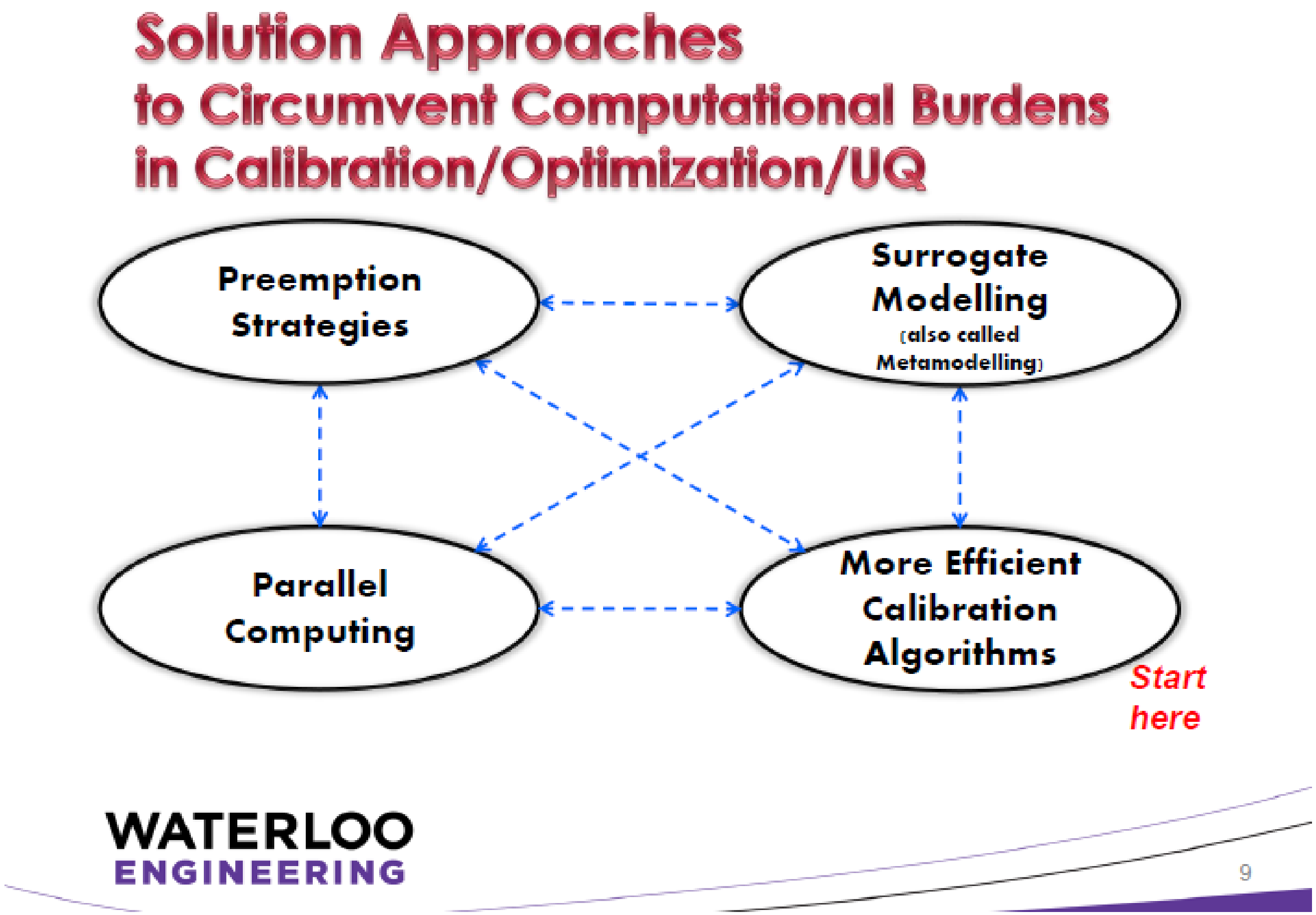
Raftery et al. 2005

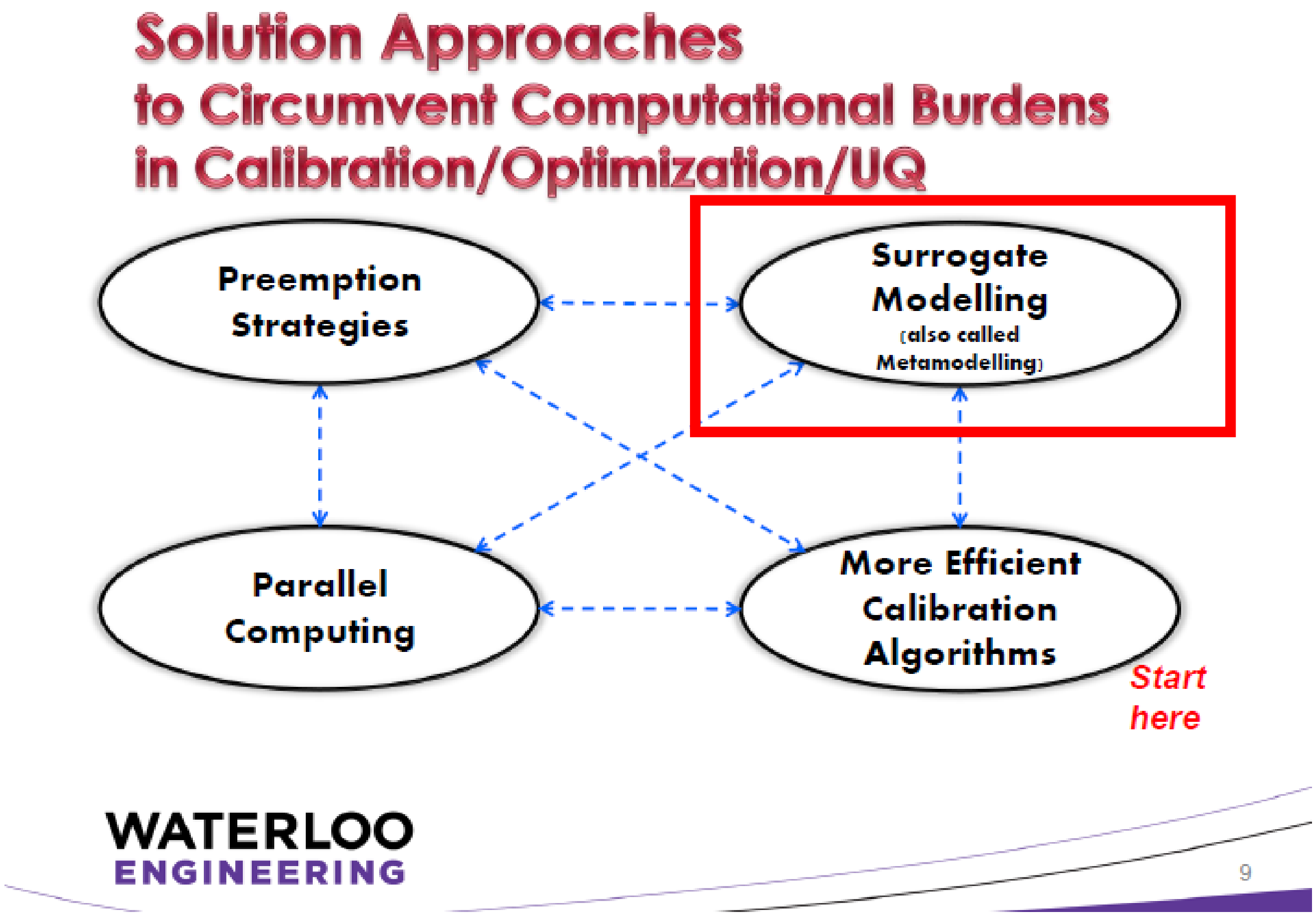
Main bottleneck: time/resources needed to run estuarine model

Approximate probability distribution of model projections?



Tolson, 2016 - *STAC Workshop: Assessing Uncertainty in the Chesapeake Bay Program Modeling System*

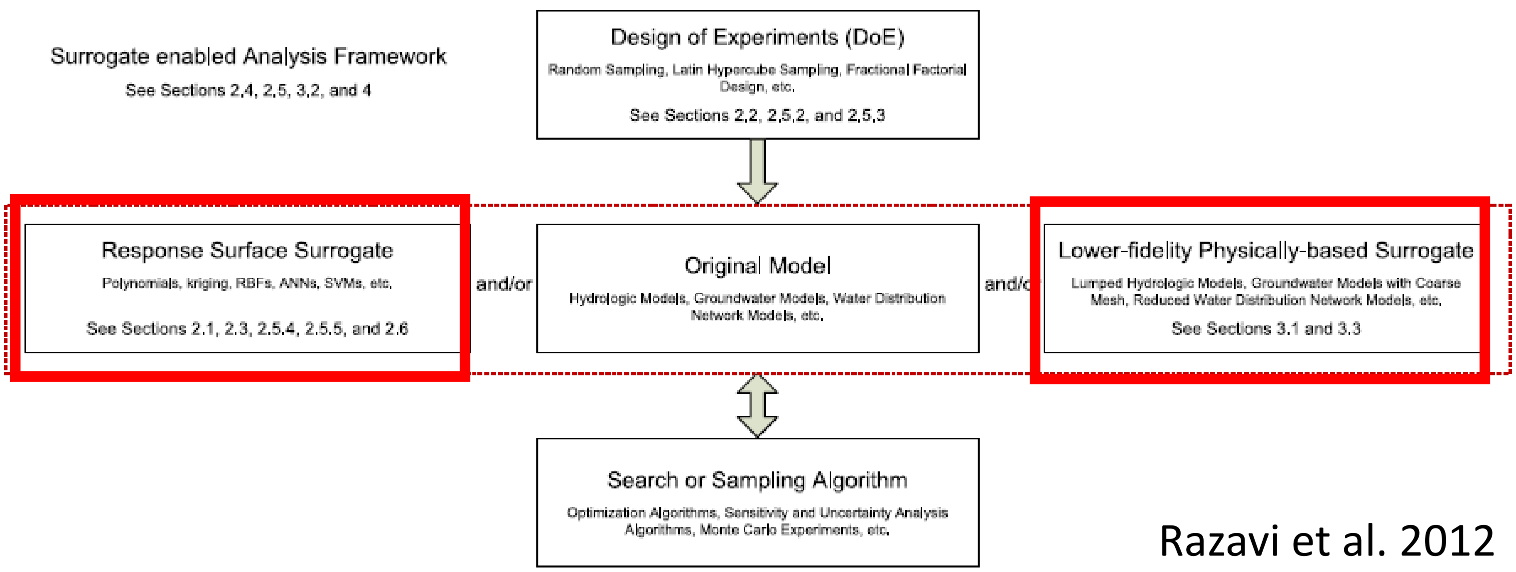
Approximate probability distribution of model projections?



Tolson, 2016 - *STAC Workshop: Assessing Uncertainty in the Chesapeake Bay Program Modeling System*

Approximate uncertainty in estuarine model response through surrogate modeling

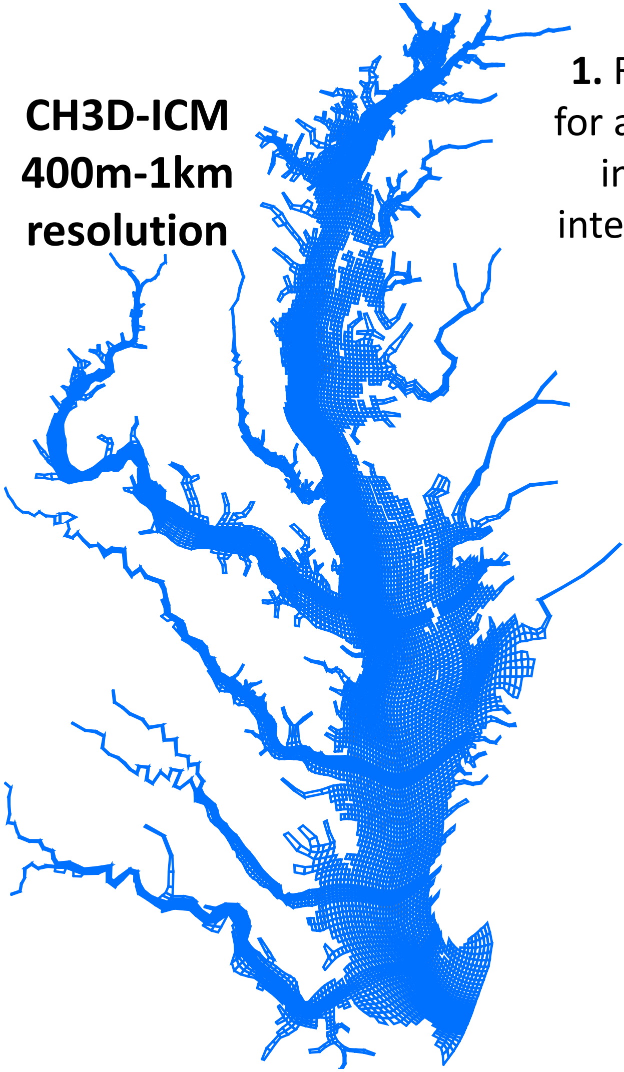
Develop a computationally efficient surrogate of a numerically complex high-fidelity model to approximate the complex model`s response for various values of input variables of interest



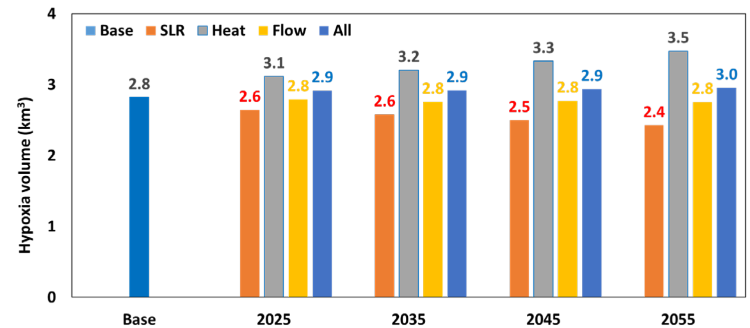
Razavi et al. 2012

Surrogate modeling: statistical emulator

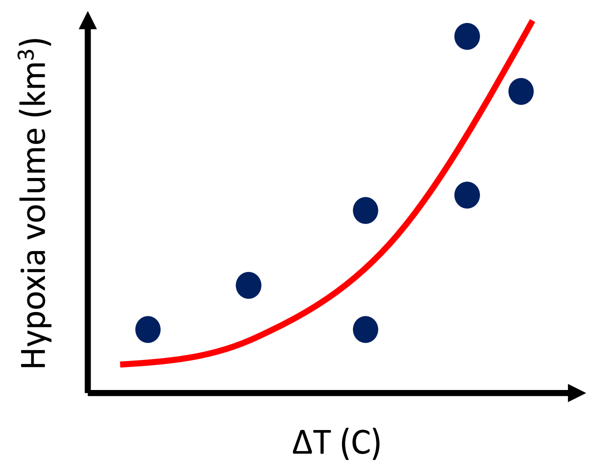
CH3D-ICM 400m-1km resolution



1. Run complex model for a set of values of the input variable(s) of interest ("Design Sites")



2. Fit statistical model to design sites to approximate the response of the original model to changes in the input variable(s) of interest

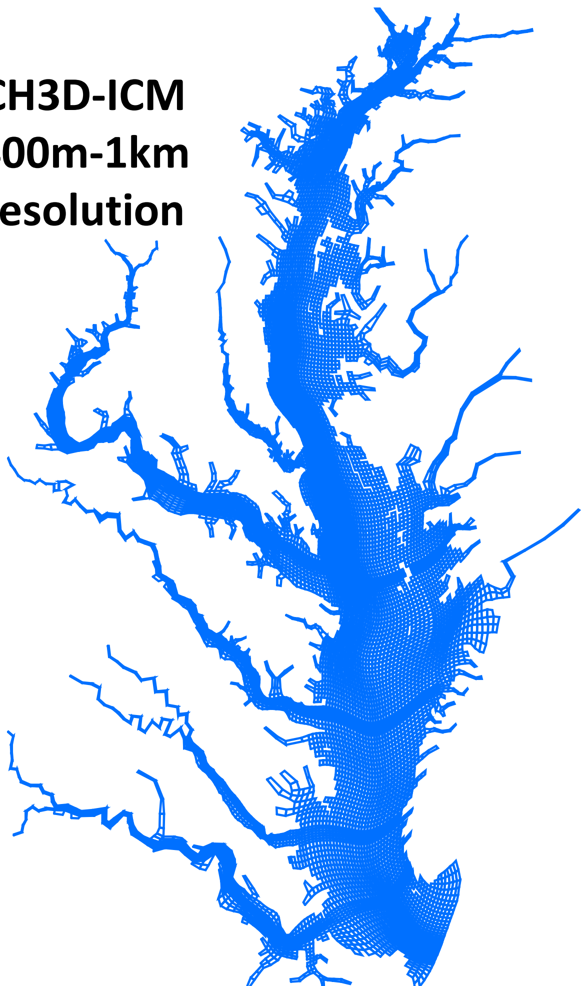


3. Use surrogate statistical model to perform uncertainty runs

Surrogate modeling: lower-fidelity, physically-based surrogate

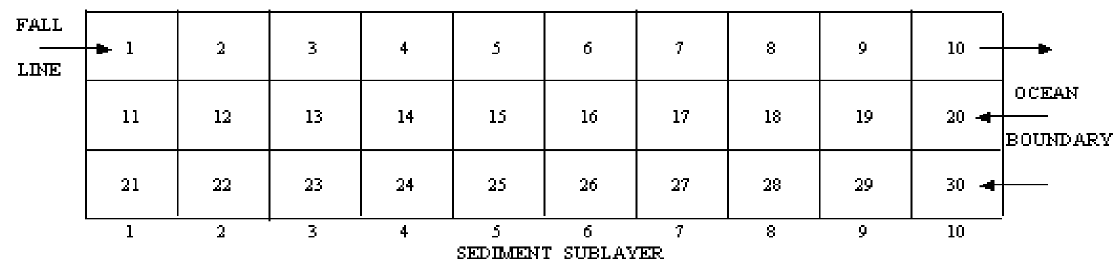
“High-fidelity” (**HF**) model

CH3D-ICM
400m-1km
resolution



“Low-fidelity” (**LF**) model

30-box model



Simplified version of the original high-fidelity model with coarser spatial/temporal grid size or where some physics modeled by the high-fidelity model is ignored or approximated

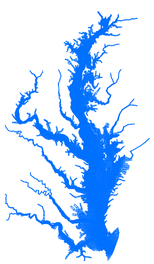
Surrogate modeling: lower-fidelity, physically-based surrogate

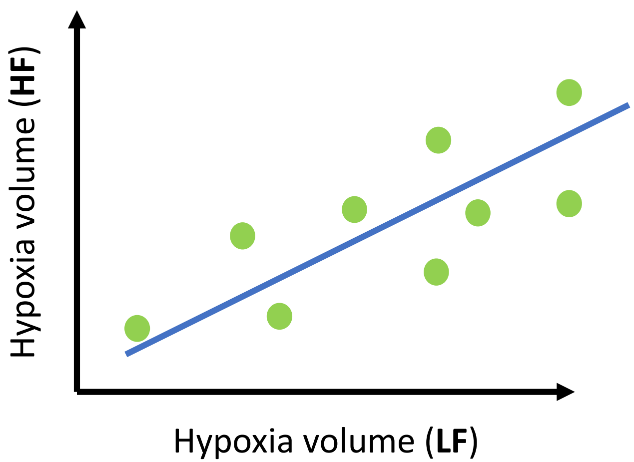
Assumptions:

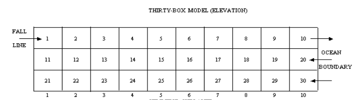
HF: accurate, but computationally expensive

LF: less accurate, but computationally cheap

There is some correlation between the response of HF and LF to input variable(s) of interest







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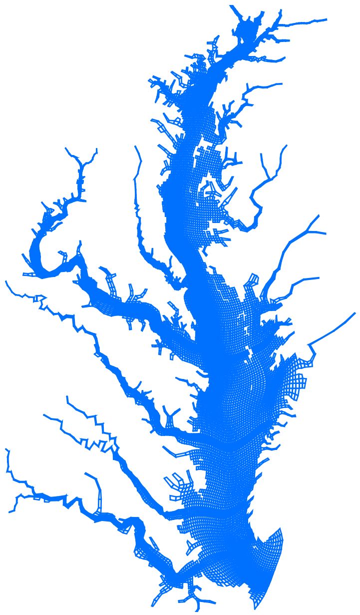
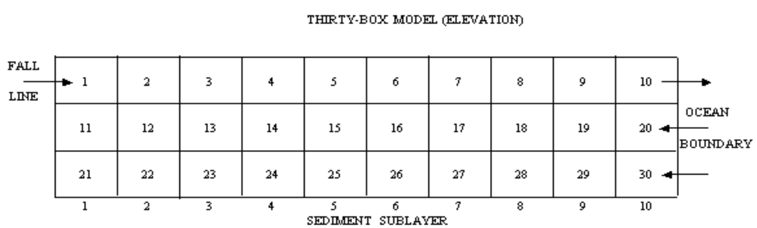
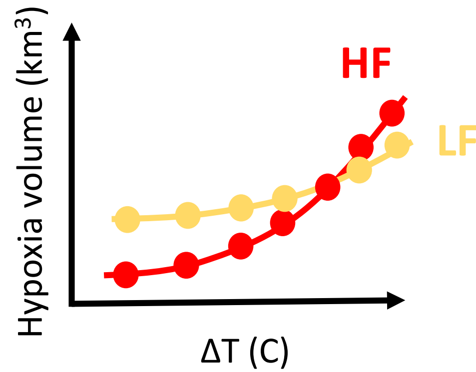
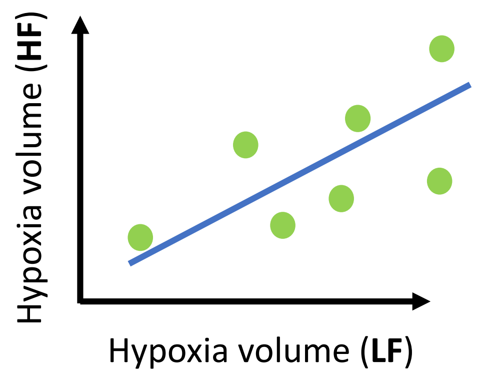




1. Run HF and LF for a set of values of the input variable(s) of interest



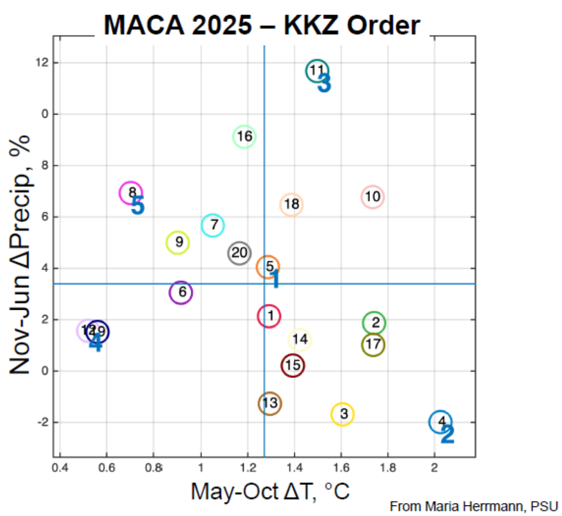
2. Develop "correction function" to account for discrepancies between HF and LF response

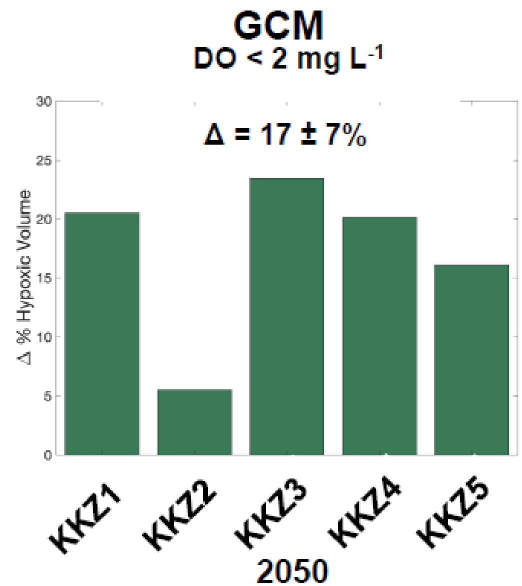


3. Use surrogate LF model + correction function to perform uncertainty runs

A different twist on surrogate modeling: can we leverage CHAMP results?

Kyle has done a lot of work **and model runs** to assess GCM and DS uncertainty as part of CHAMP (guided by Maria and Raj for GCM selection) and might do more in the near future?





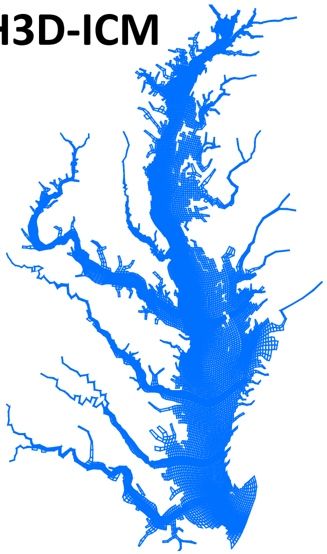
Hinson et al., CHAMP MTAG 2019

Can we develop a more formal framework to incorporate CHAMP results in the CBP climate change assessment?

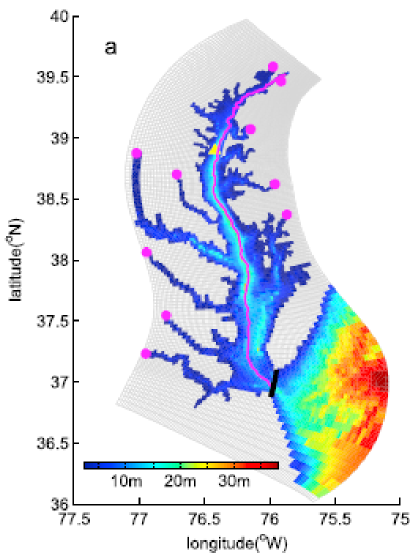
Can we use VIMS model runs as a “surrogate” for the CBP estuarine model?

A different twist on surrogate modeling: can we leverage CHAMP results?

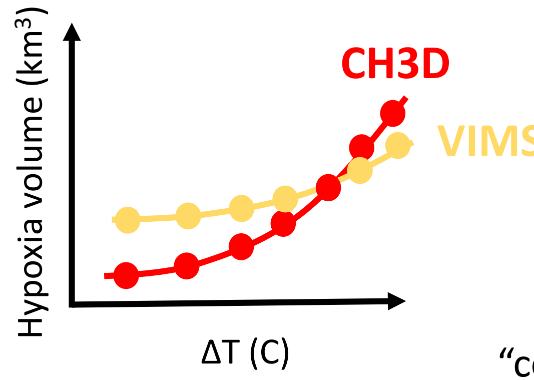
CH3D-ICM



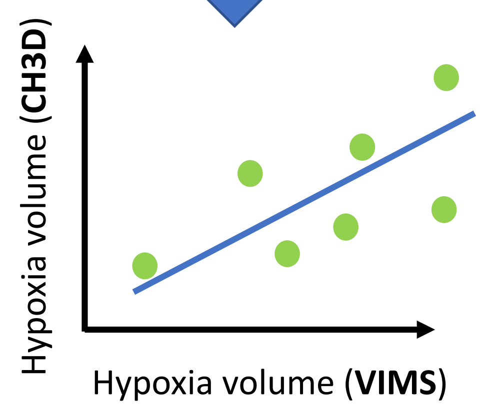
VIMS



1. Run CH3D-ICM and VIMS for a set of values of the input variable(s) of interest (we may already have enough previous runs?)



2. Develop "correction function" to account for discrepancies between CH3D and VIMS response



3. Use CHAMP VIMS model runs + correction function to approximate CH3D uncertainty for 2055

Summary of potential short-term approaches so far (more ideas welcome)

- P10 and P90 range
- Select a minimum feasible number of GCMs (e.g. through KKZ) followed by BMA to estimate probability distribution
- Develop statistical surrogate model of CBP estuarine model response to range of climate forcings and use that to assess uncertainty
- Explore using results of CHAMP (VIMS model) as surrogate for CBP estuarine uncertainty (explore expanding sources of uncertainty, e.g. **<u>different RCPs</u>**?).