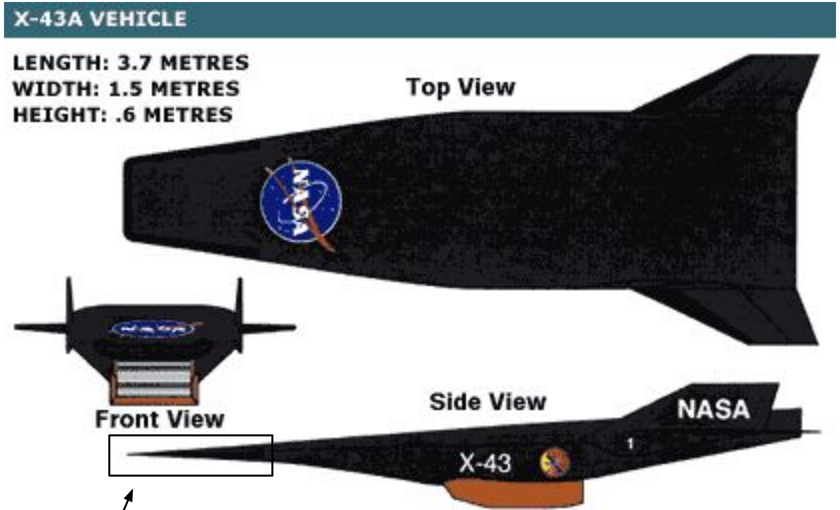
Heat Shielding for Hypersonic Vehicles

Nick Reeder • Ben Kim

W&M • UVA

Overview



Our heat shield

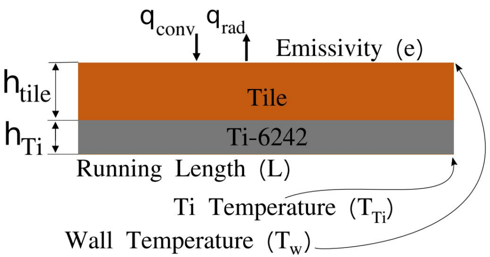


Diagram
for shield

Long term goal:

Perform uncertainty quantification

Challenges

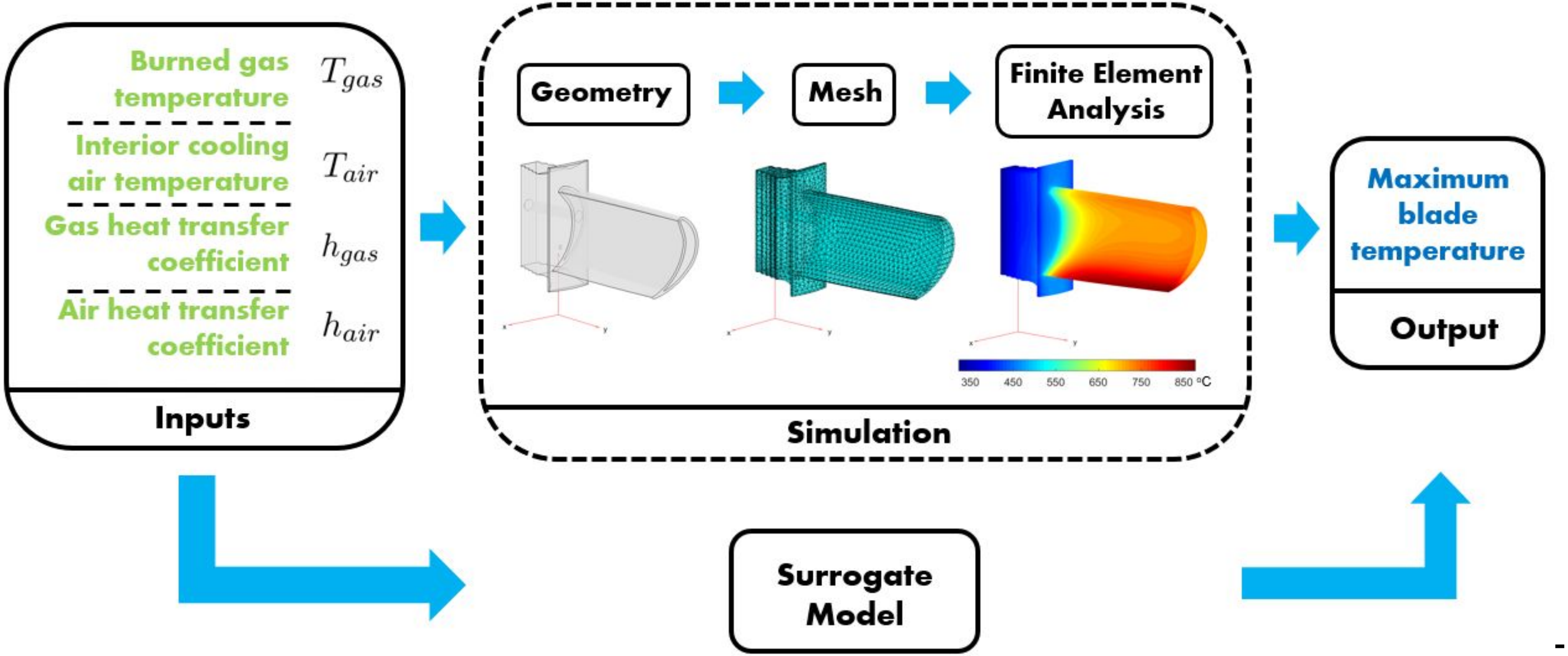
- This requires a lot of data, simulation time, and wind tunnel testing
- Simulations are computationally and financially expensive

Primary goal:

Develop an effective surrogate model to estimate, for instance, temperature of a tile under certain conditions

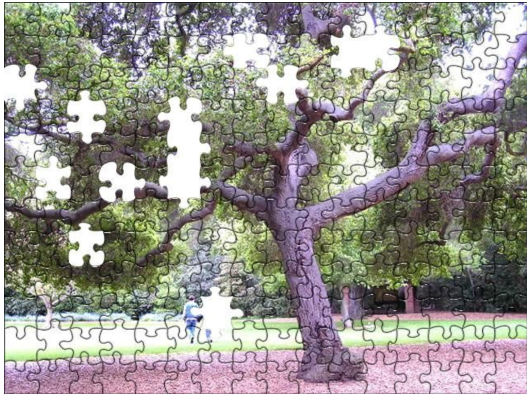
Video of Mach 10 Flight

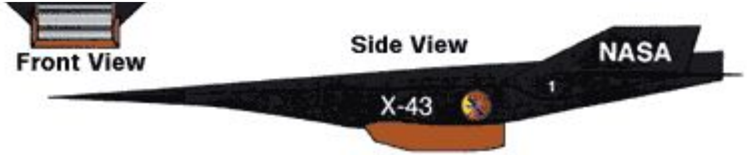
Surrogate Modeling



Our Application

- *Modeling temperature of a thermal protection system*





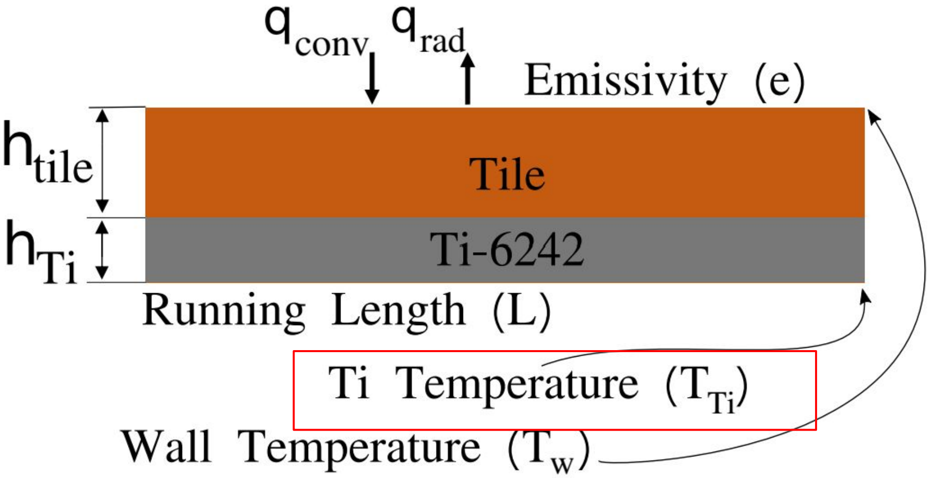
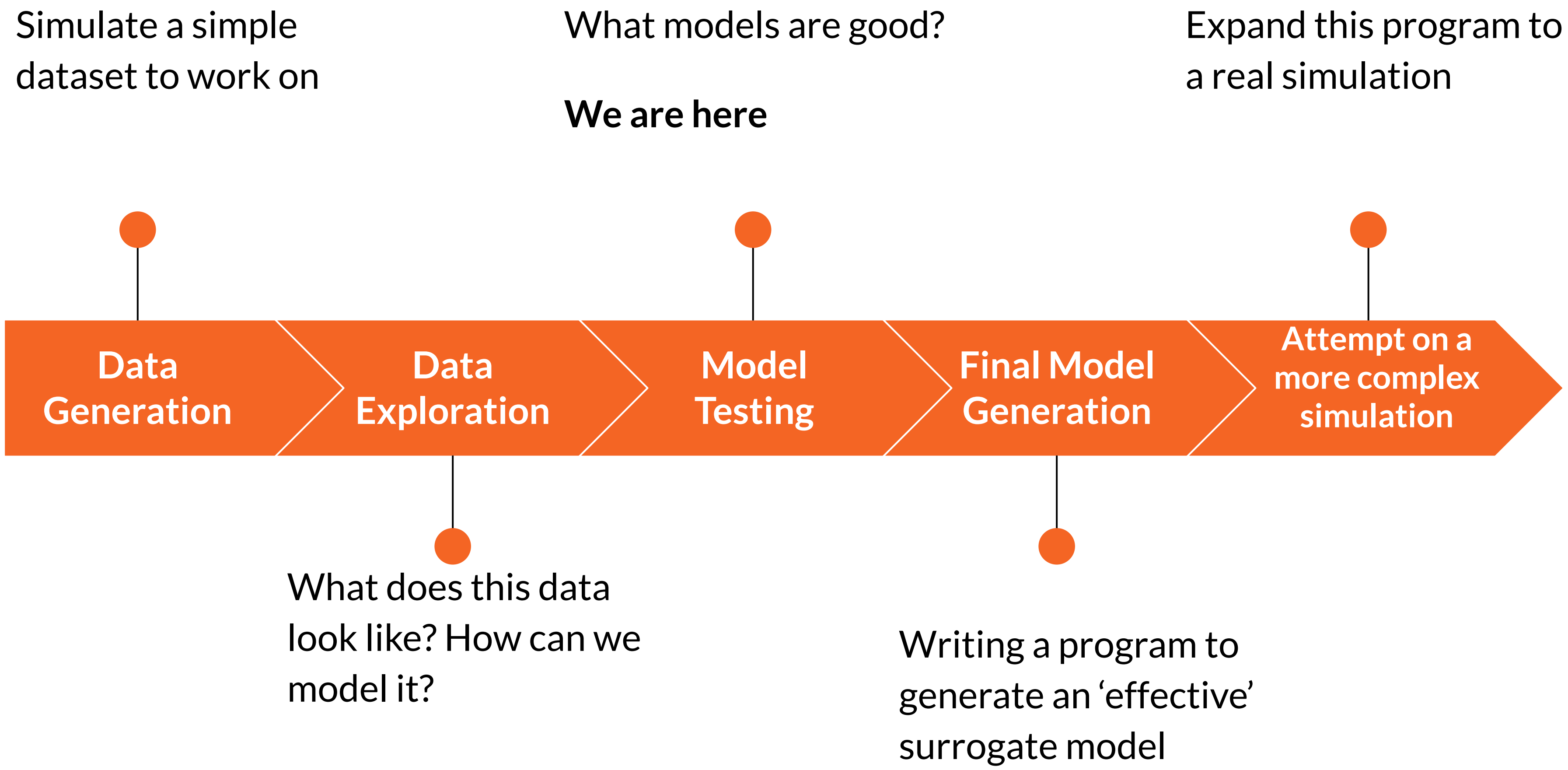


Diagram from Dr. Hunt's paper



Simulate a simple dataset to work on
What models are good?
We are here
Expand this program to a real simulation
Data Generation
Data Exploration
Model Testing
Final Model Generation
Attempt on a more complex simulation
What does this data look like? How can we model it?
Writing a program to generate an 'effective' surrogate model

Specifics of the problem

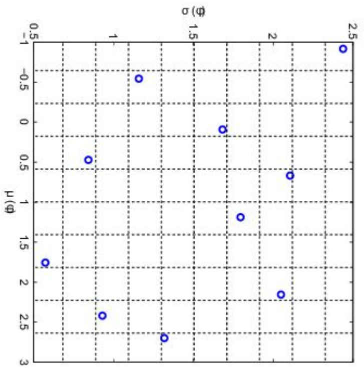
What makes the model complex?

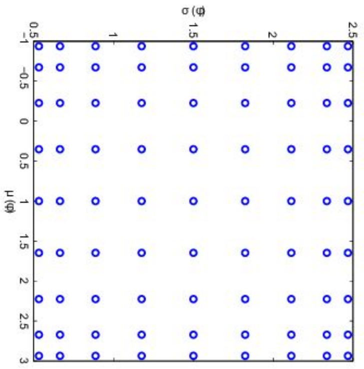
- Things act very strange at these speeds
- There are a TON of variables to consider, and lots of things that can go wrong

Why don’t we just test it?

- Testing is very expensive and hard
- It’s much easier to run a program than risk your many million dollar plane

Data Creation and Exploration





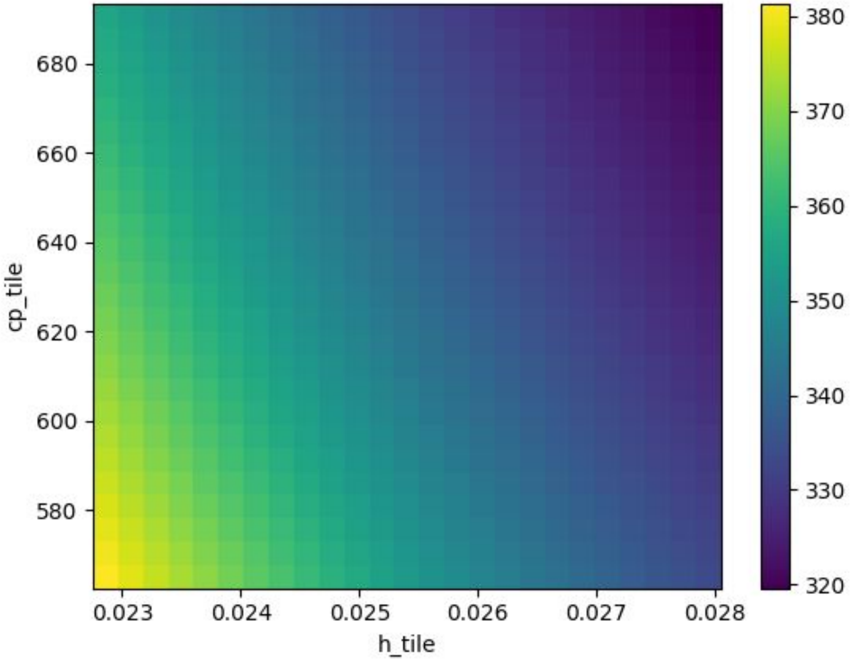
Random Data

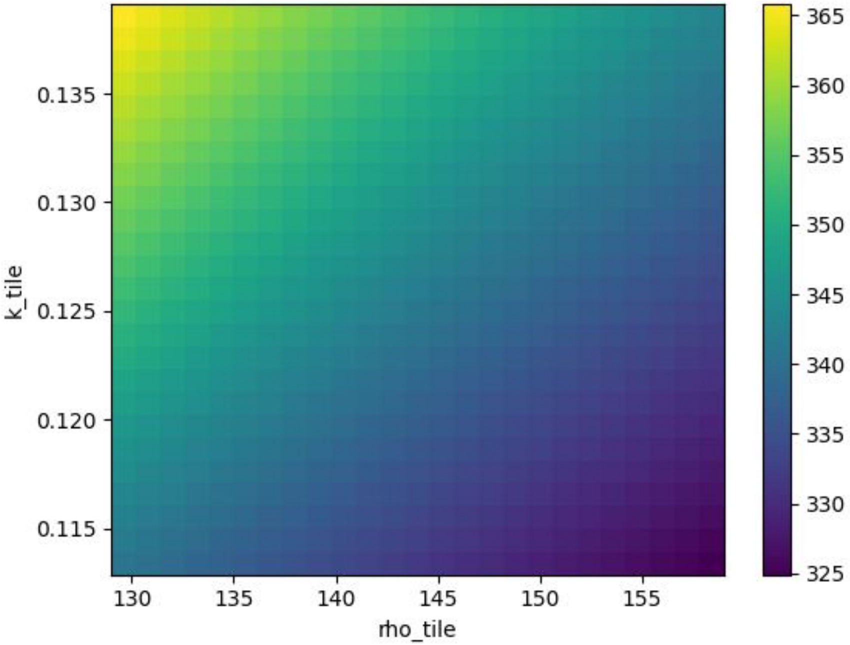
- 1000 data points where each parameter was randomly sampled from a +-10% range of baseline

Latin Hypercube Data

- Build a latin hypercube to generate specific data points
- This should lead to less data points that each provide more information

Heatmaps: Show linear shape





Three ML Models

Random Forest Regression (RFR)

Gaussian Process Regression (GPR)

Lasso Regression

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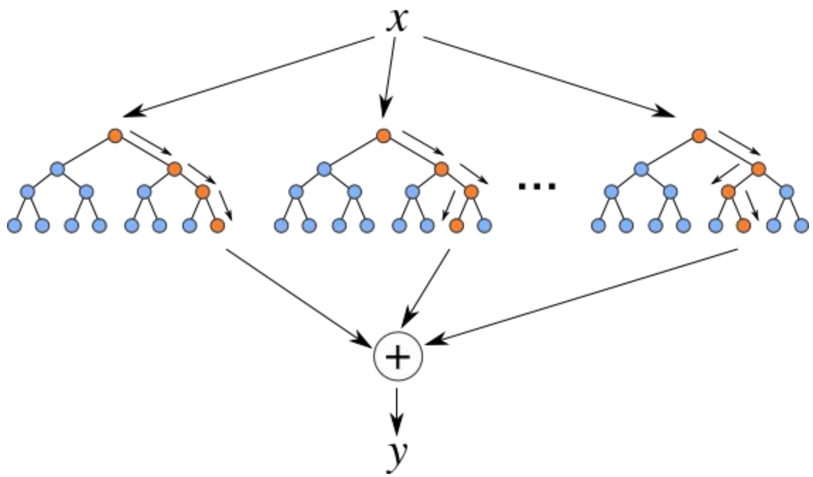
Random Forests

- A ‘forest’ of decision trees that are each trained on bootstrapped data
- Each tree is unique and random
- Pros:
  - VERY hard to overfit
  - Does not suffer strongly from high dimensions
- Cons:
  - Slower*
  - ‘Greybox’
  - Hard to select out dimensions



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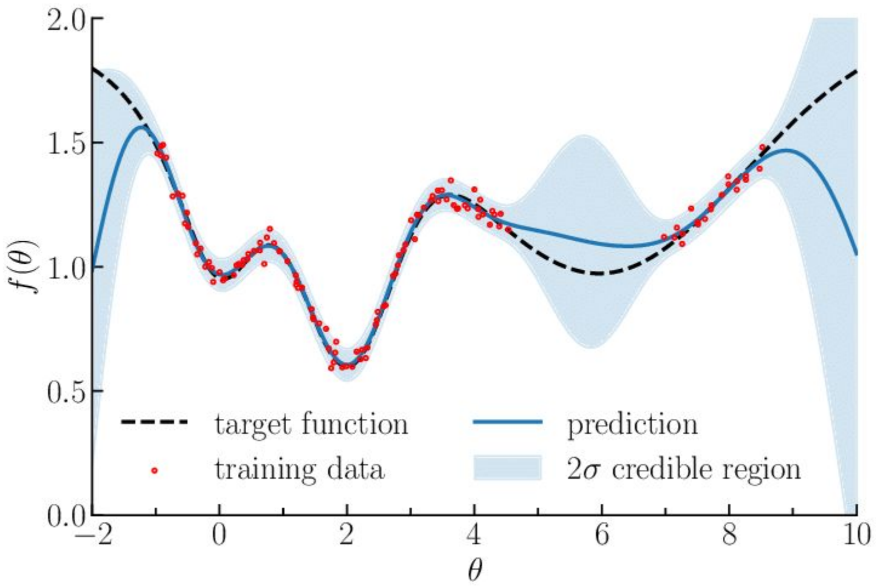
Gaussian Processes

- Used Radial Basis Functions
- Very flexible, can fit many functions
- Pros:
    - Creates automatic uncertainties for each point
    - Interpolation between points
    - Doesn't need a lot of training data
- Dimensionality concerns



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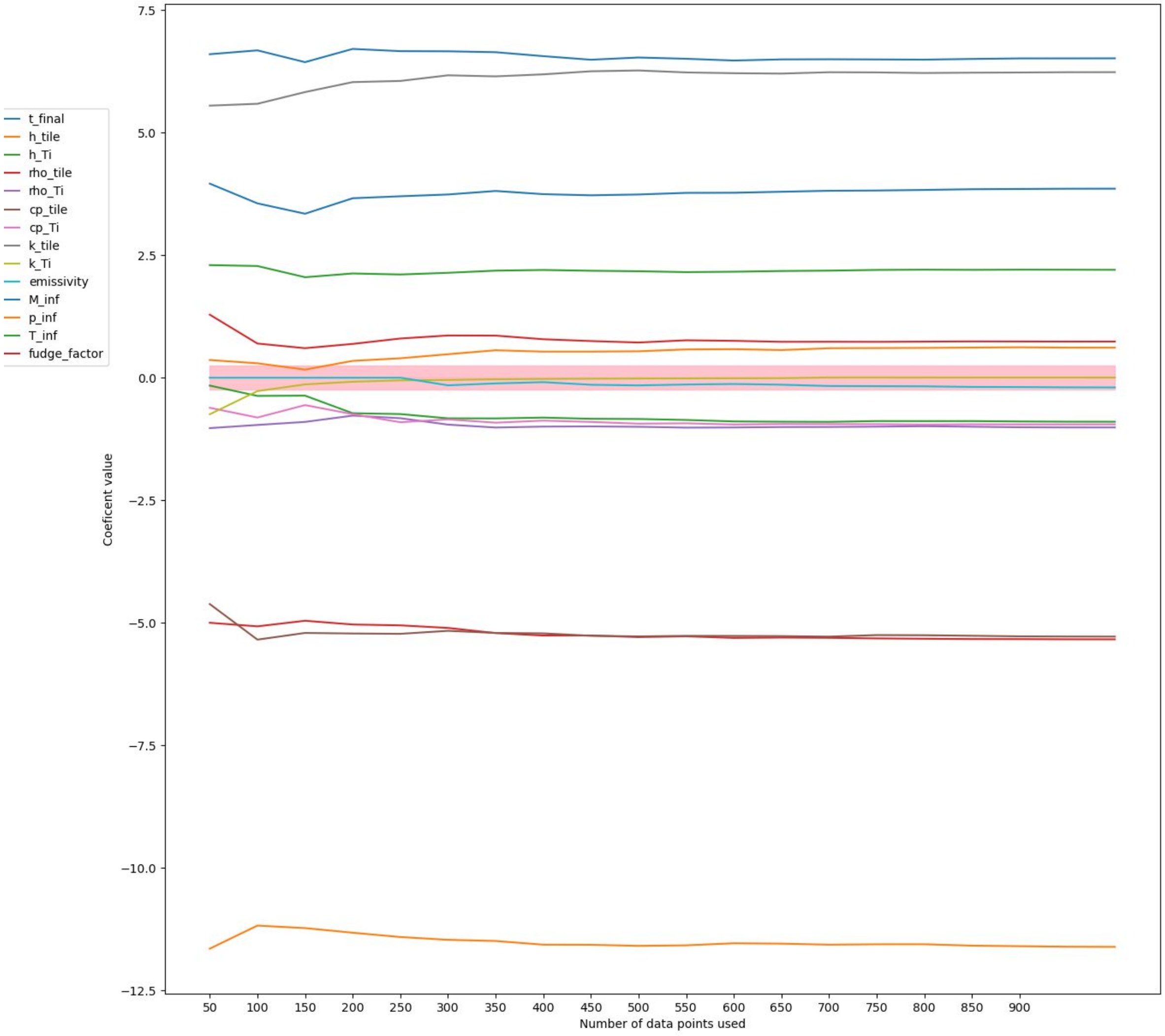
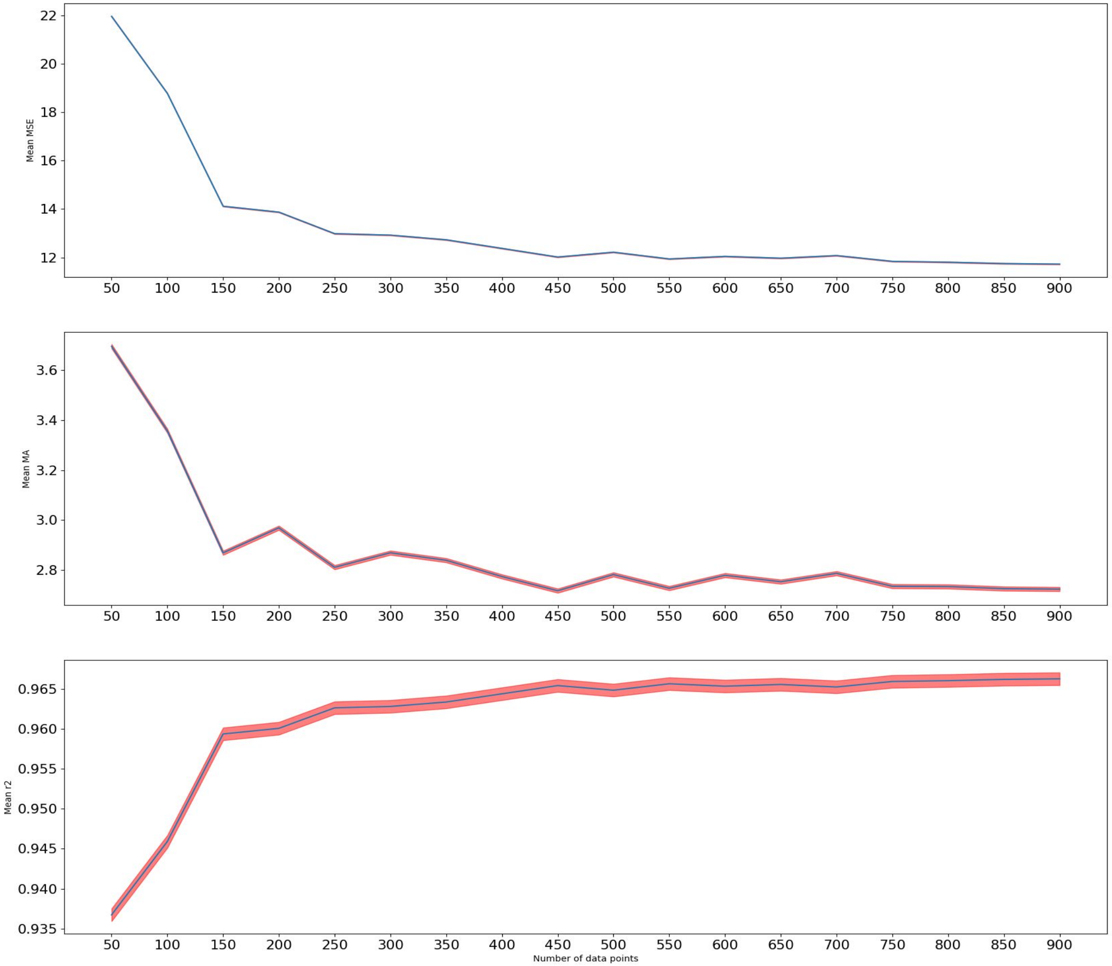
Lasso

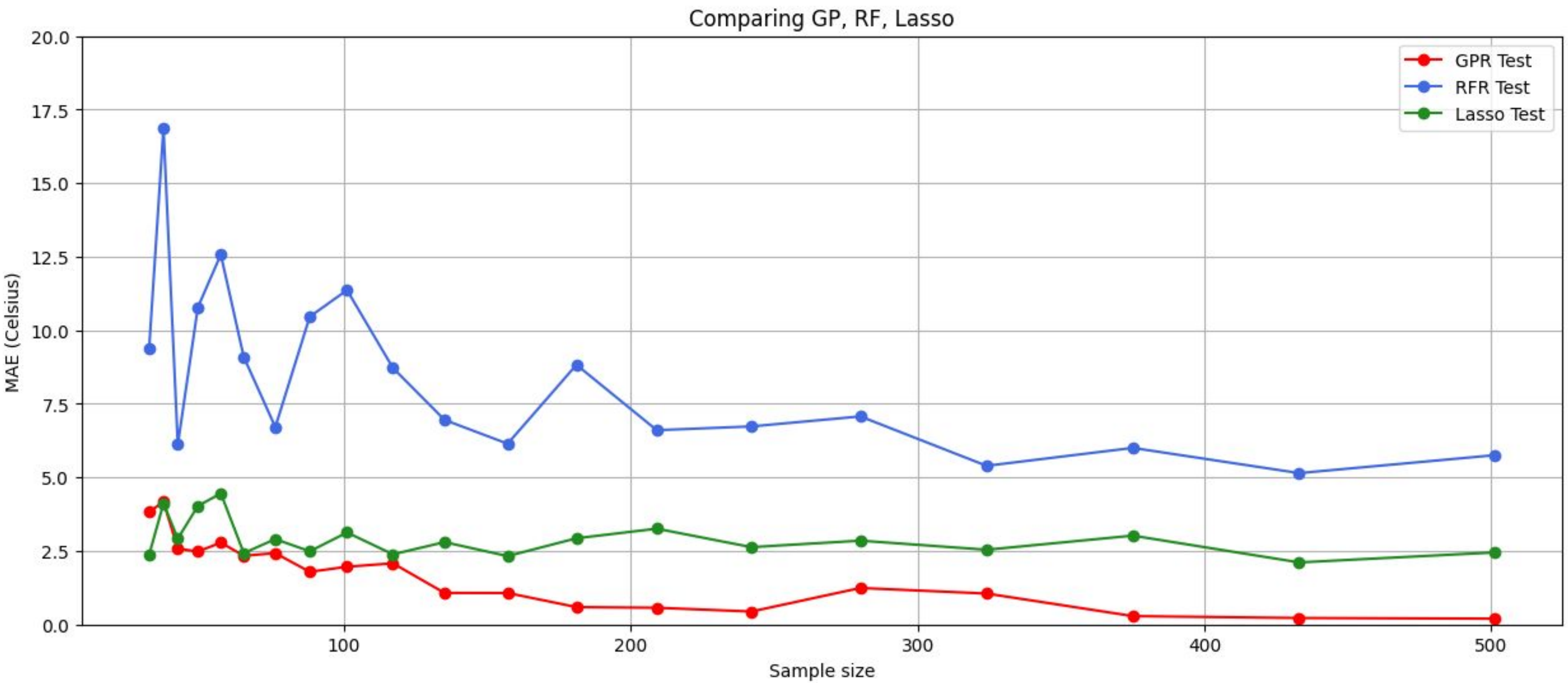
- Extensions of OLS that adds a penalty to minimize RSS
- Requires standardization
  - We used a Standard Scalar (z = [x - u] / s)
- Pros:
  - Coefficients can be 0
  - Very easy to plot and interpret
  - Does not need much data
- Cons:
  - Can be overfit easily
  - Suffers at higher dimensions



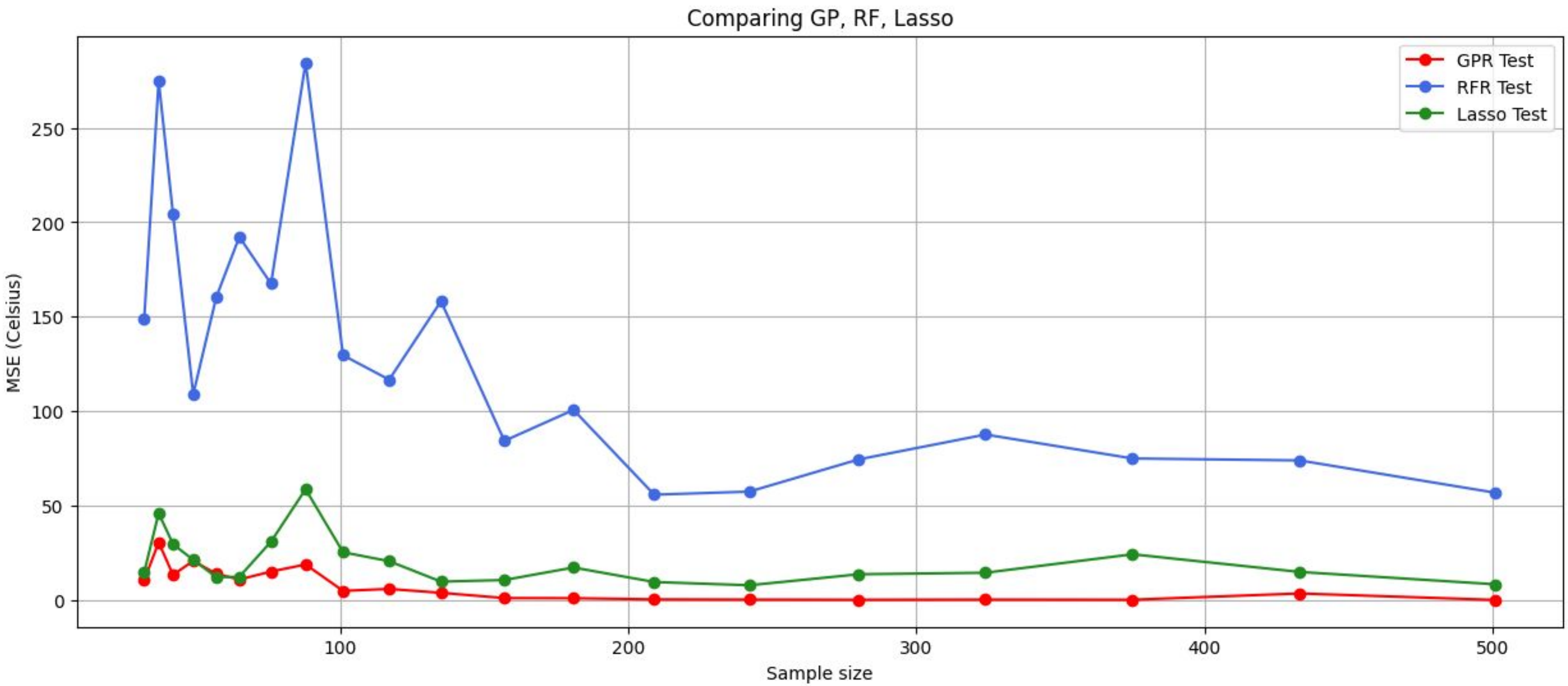
Lasso Performance

- Model Performance
  - MSE: 11.72 ℃
  - MA: 2.72 ℃
  - r2: 0.95
- Monte Carlo Performance
  - KS: 0.045 / 0.621
  - Wasserstein distance 0.670



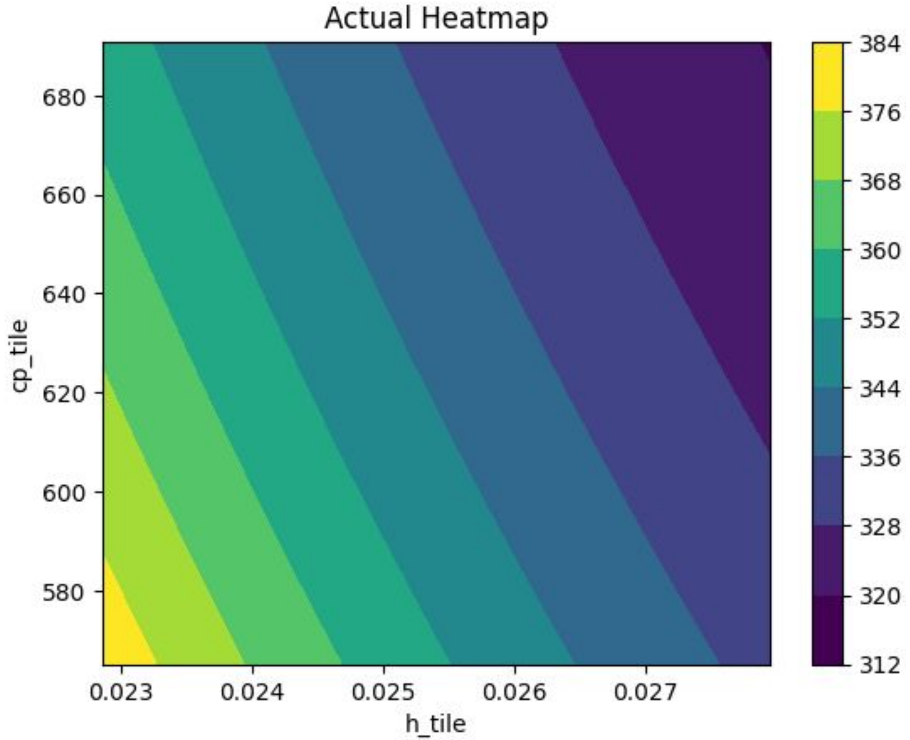


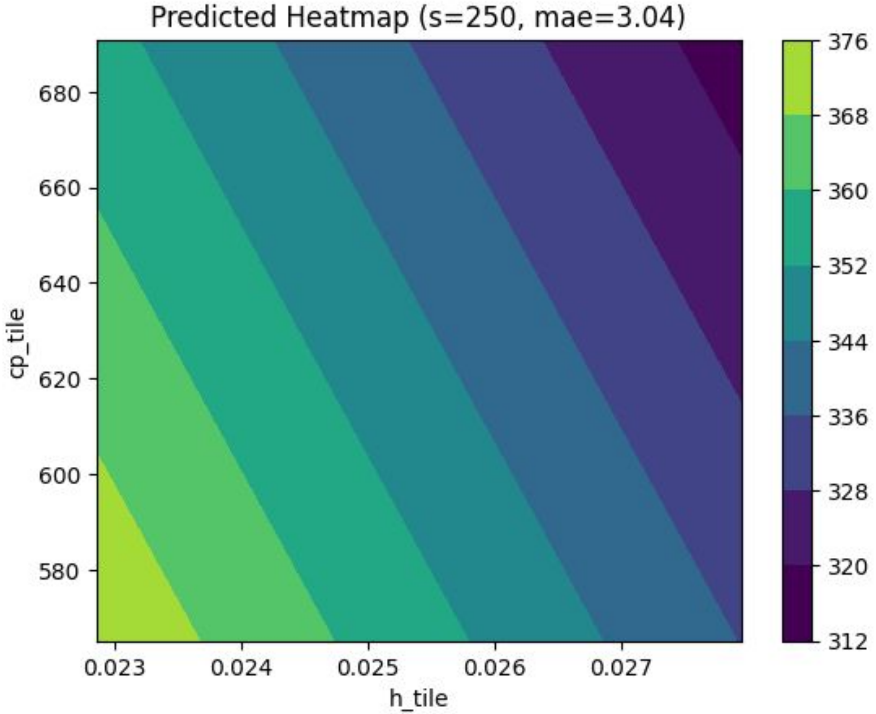
Comparison: Mean Absolute Error



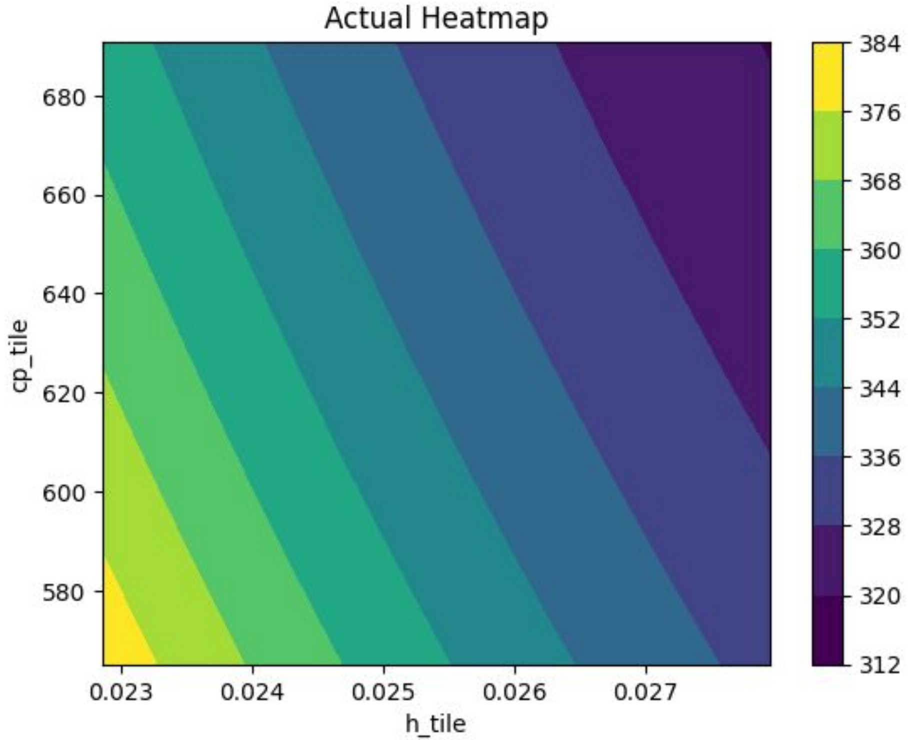
Comparison: Mean Squared Error

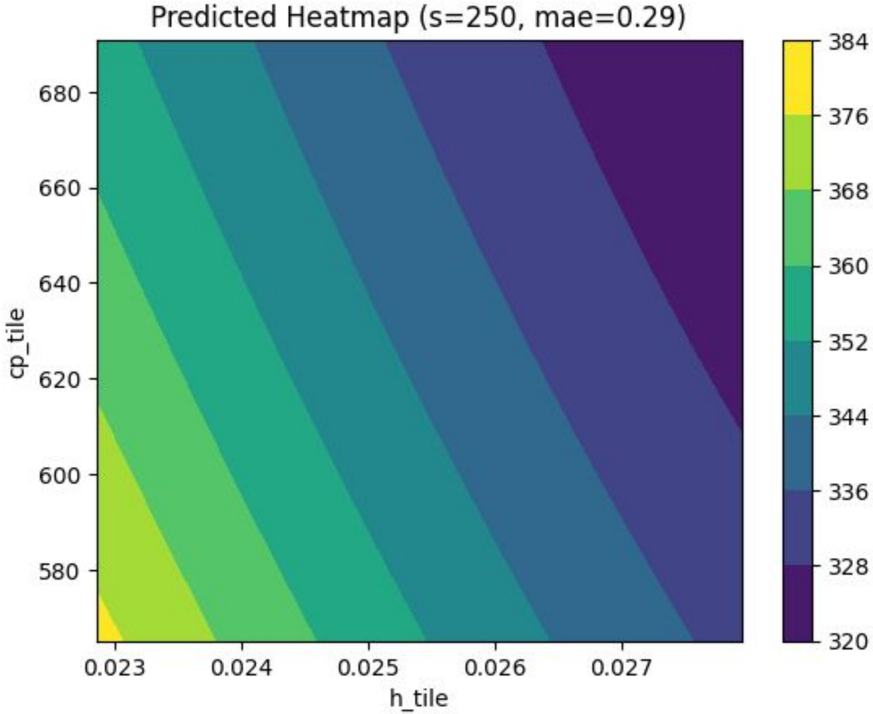
Heatmaps: Lasso





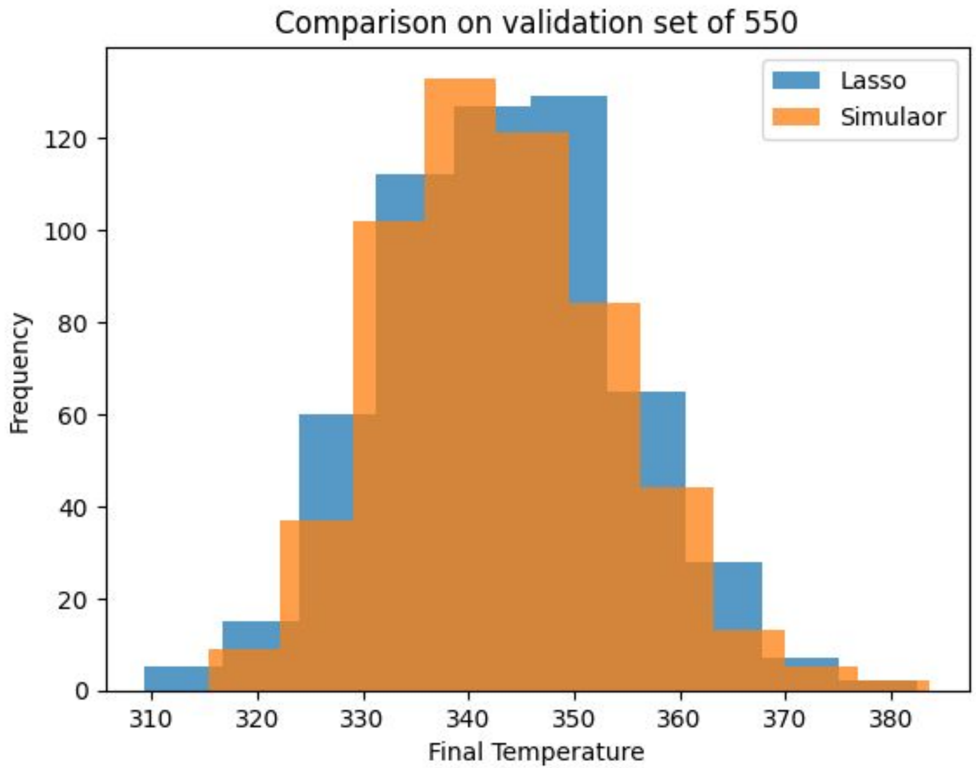
Heatmaps: GPR





Lasso UQ Performance

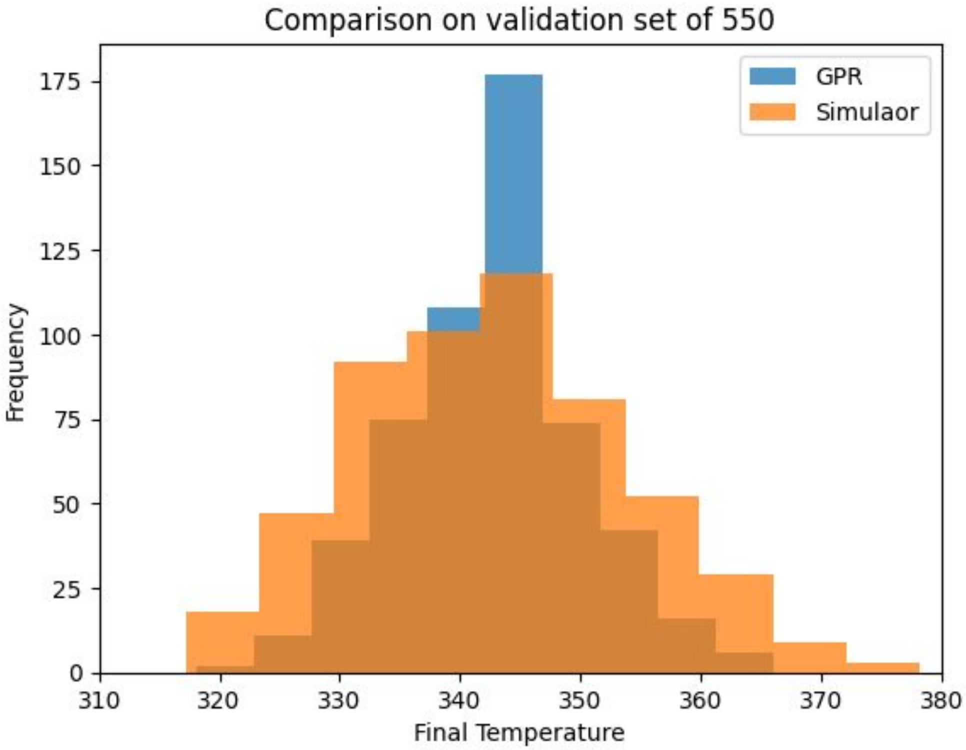
- Monte Carlo Performance
  - KS: 0.045 / 0.621
  - Wasserstein Distance: 0.671



With time exposure ('t_final') as the uncertain variable

GPR UQ Performance

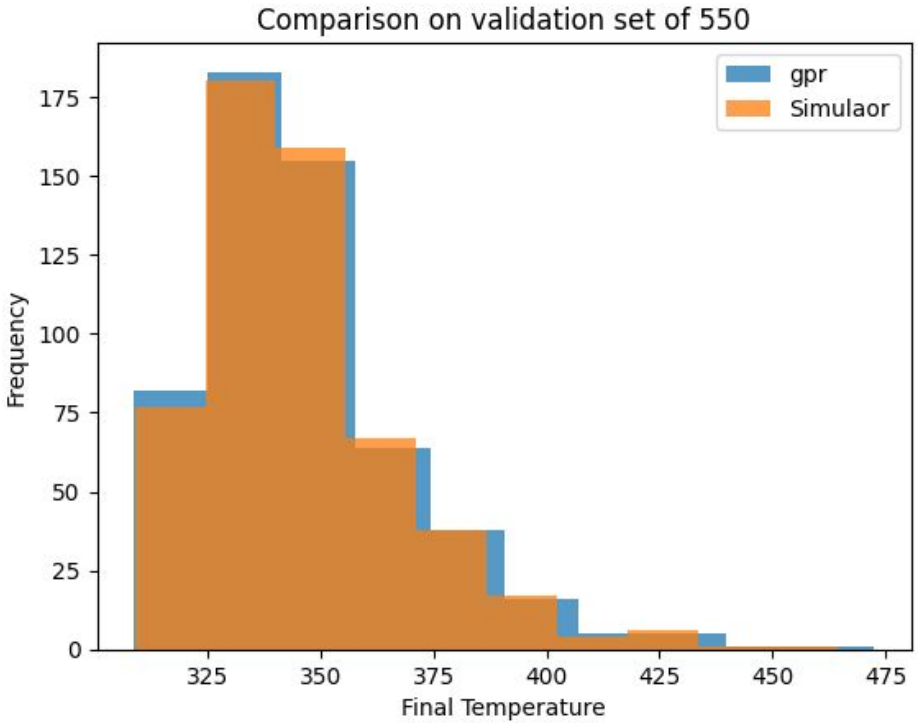
- Monte Carlo Performance
  - P-value=0.001 (they are different)
  - Wasserstein Distance: 3.3
- Hypothesis:
  - GPR will perform better with variables that result in non-normally distributed temperatures.



With time exposure ('t_final') as the uncertain variable

GPR UQ Performance

- Monte Carlo Performance
  - P-value=0.96 (they are the same)
  - Wasserstein Distance: 1.07
- GPR is more accurate depending on the uncertain variable. This leads us to believe that UQ vary based on the variables and models used.



With exterior tile height ('h_tile') as the uncertain variable

What comes next

1. Compare and finalize model
2. Perform uncertainty analysis on mini-simulator
3. Expand process to more complex models