

Python as a Self-Teaching Tool: Insights into Gaussian Process Modeling using Python Packages

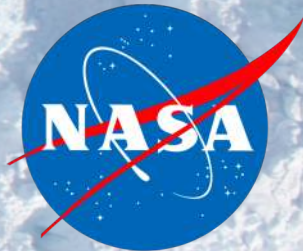
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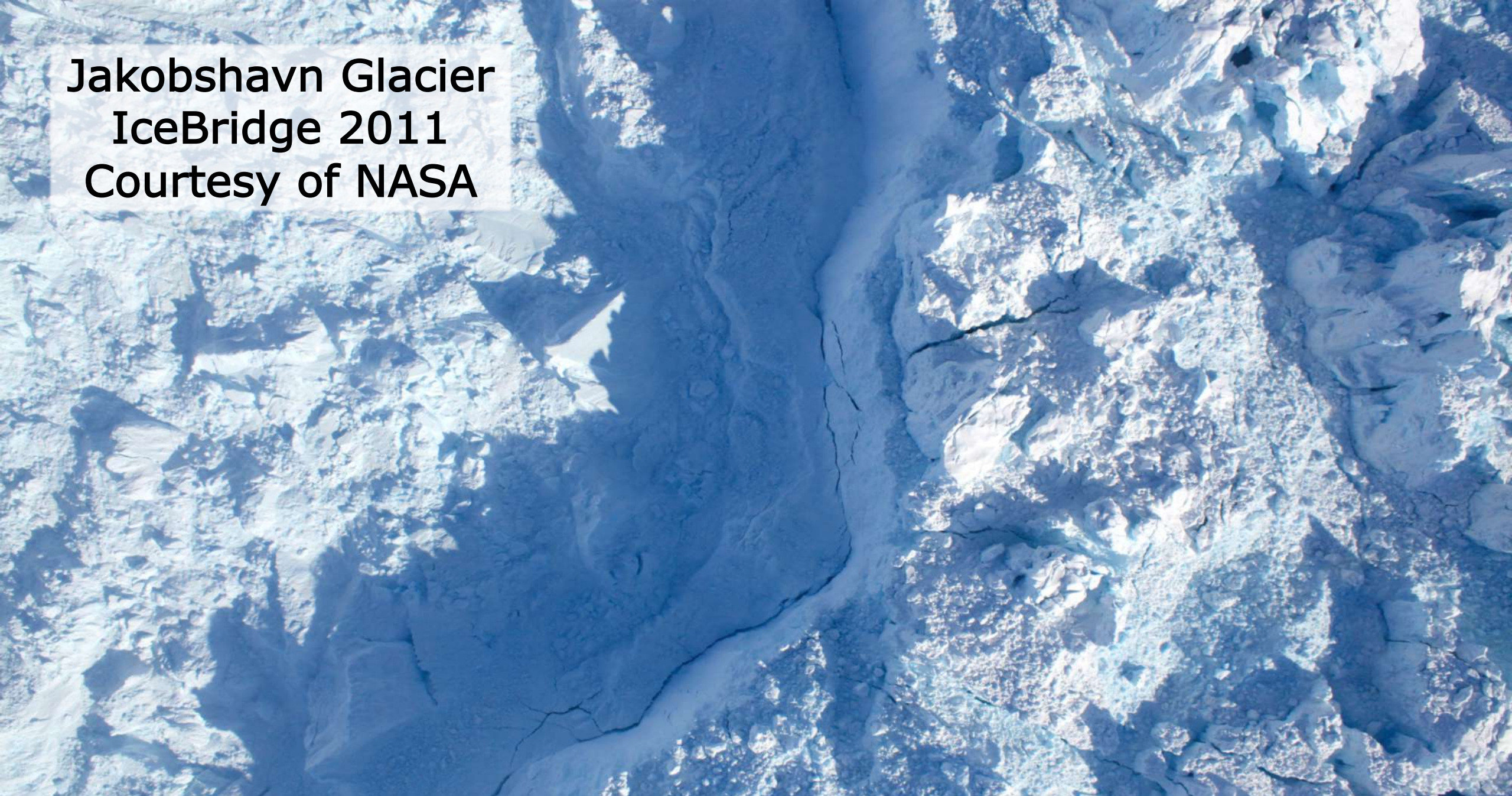
Collaborators: Robert Kopp, Erica Ashe, Rob DeConto, David Pollard, Anna Ruth Halberstadt, Ian Bolliger, Michael Delgado, Moon Limb

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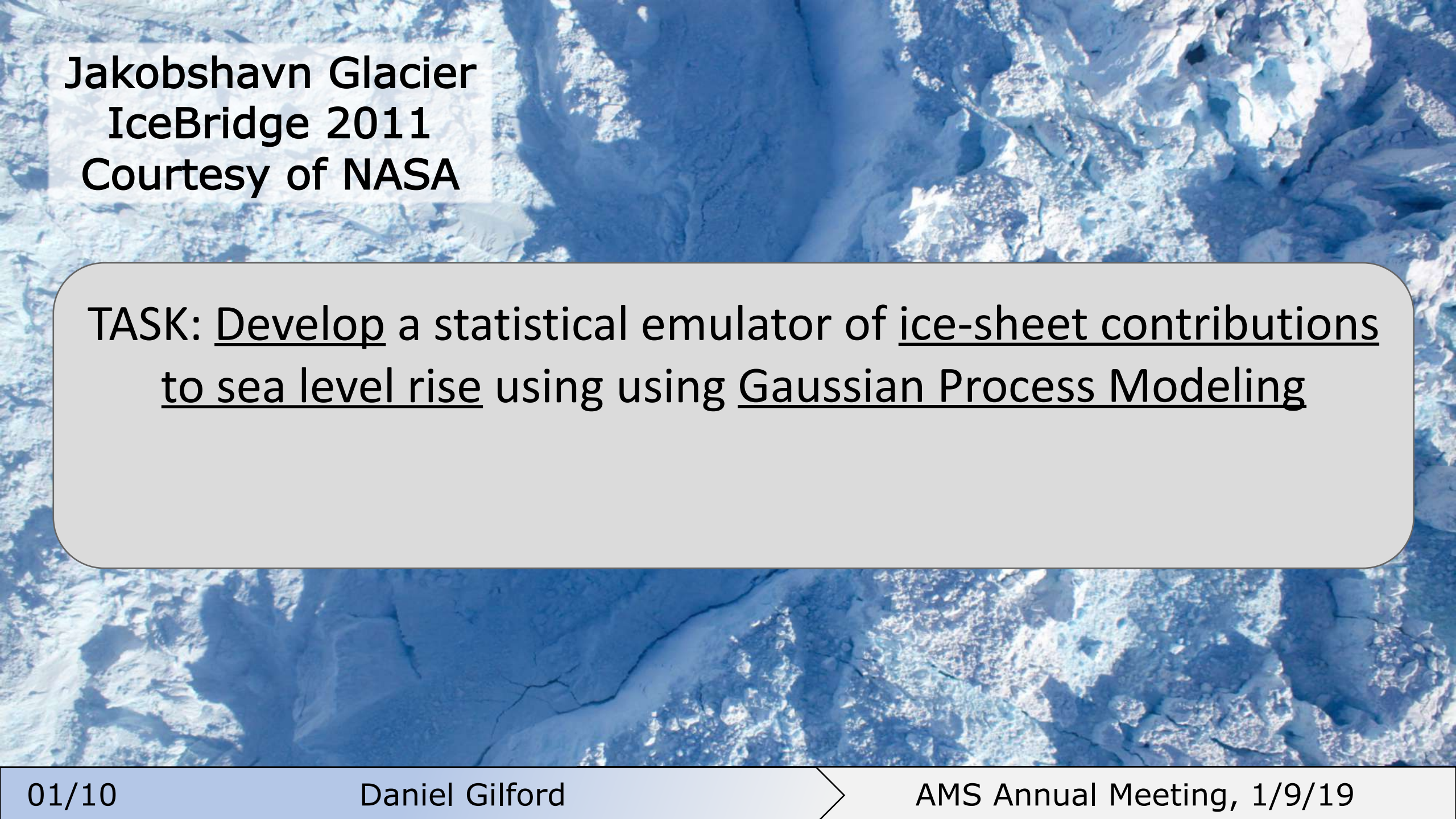
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Support From:





Jakobshavn Glacier
IceBridge 2011
Courtesy of NASA



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TASK: Develop a statistical emulator of ice-sheet contributions to sea level rise using Gaussian Process Modeling

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Python

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TASK: Develop a statistical emulator of ice-sheet contributions to sea level rise using Gaussian Process Modeling

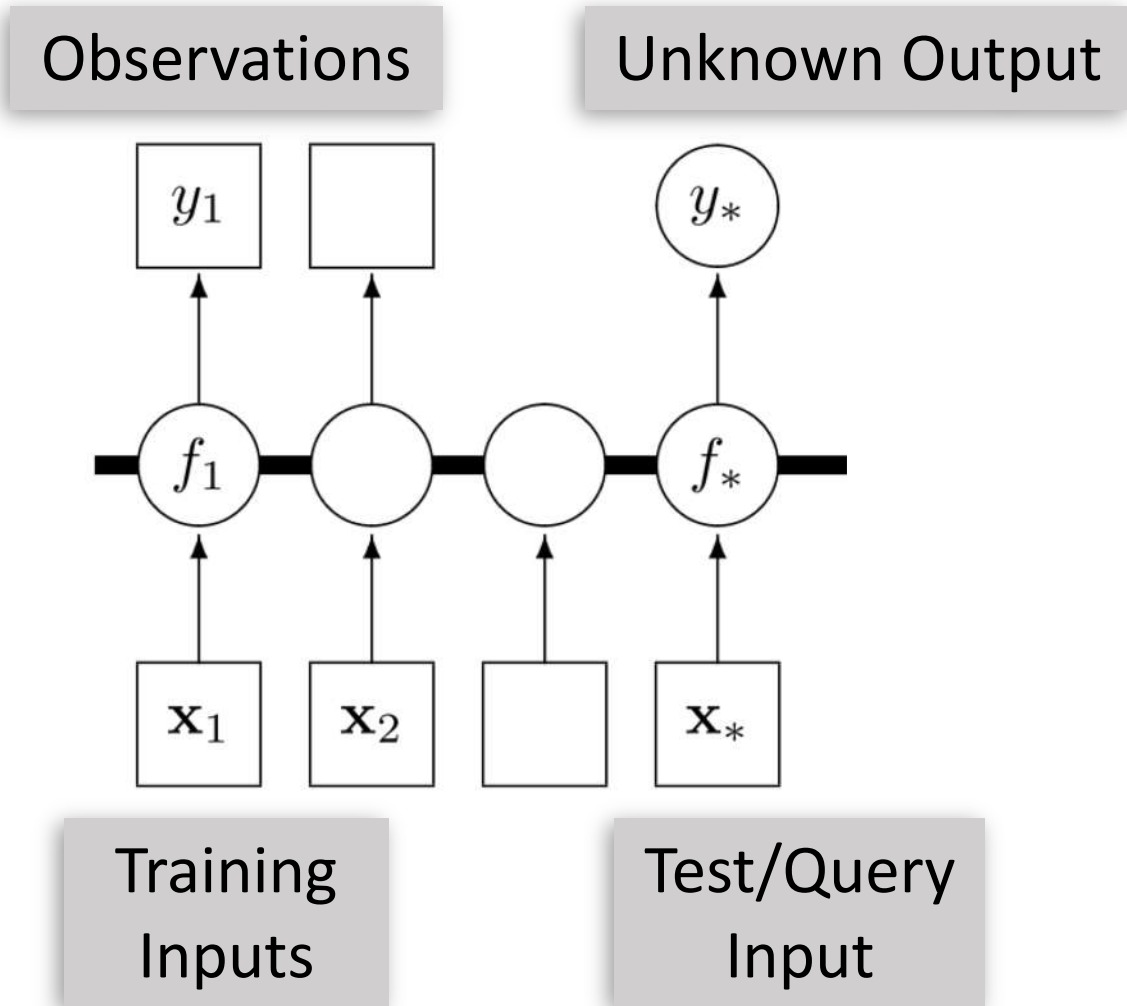
Read Literature

Jakobshavn Glacier
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TASK: Develop a statistical emulator of ice-sheet contributions to sea level rise using Gaussian Process Modeling

Python/Read

What is Gaussian Process Modeling?



- Non-parametric: there are a distribution of **functions** consistent with observations
- These functions are jointly Gaussian, e.g.
$$f = \mathcal{N}(\mu(x), k(x, x'))$$
- Uncertainty inherently provided

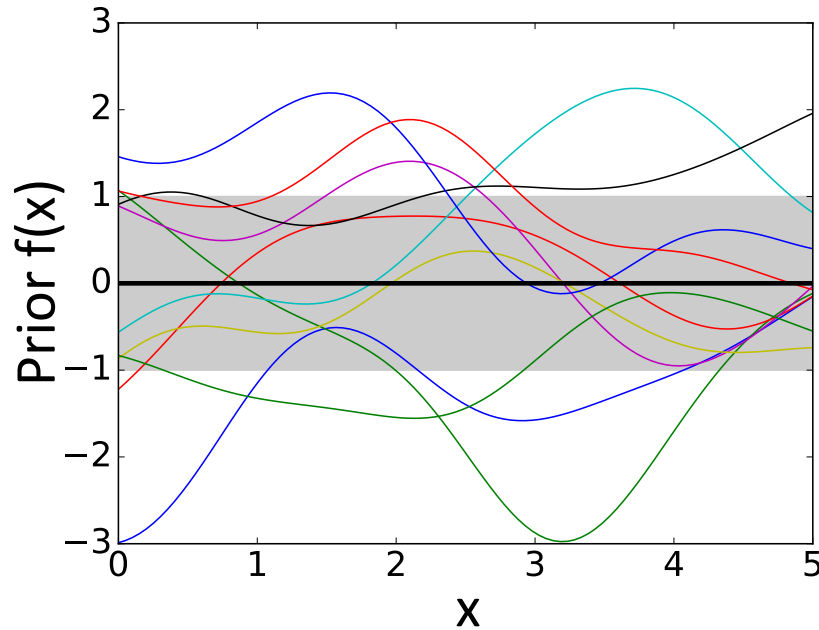
For more details: Rasmussen and Williams (2006),
<http://www.gaussianprocess.org/gpml/chapters/RW.pdf>

What is Gaussian Process Modeling?

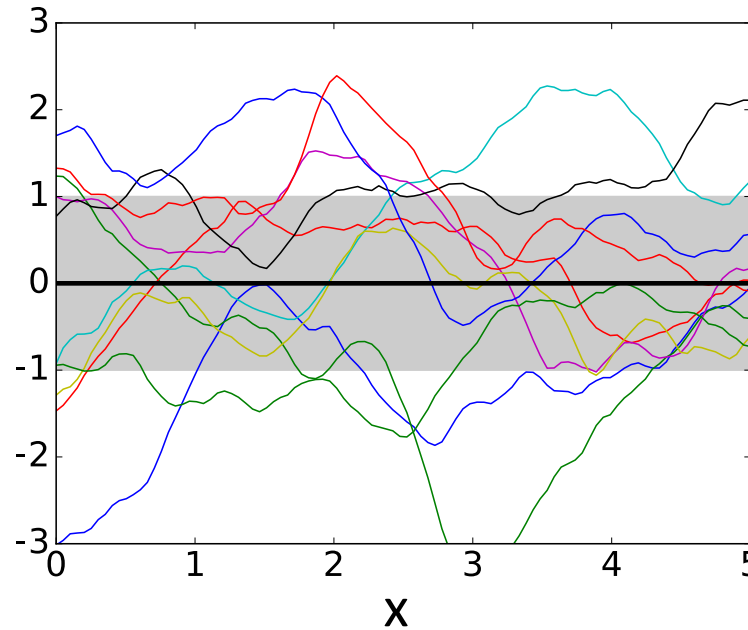
Covariance function
general form:

$$k = \textit{Amplitude} * F\left(\frac{\textit{distance}(x, x')}{\textit{Length Scale}}\right)$$

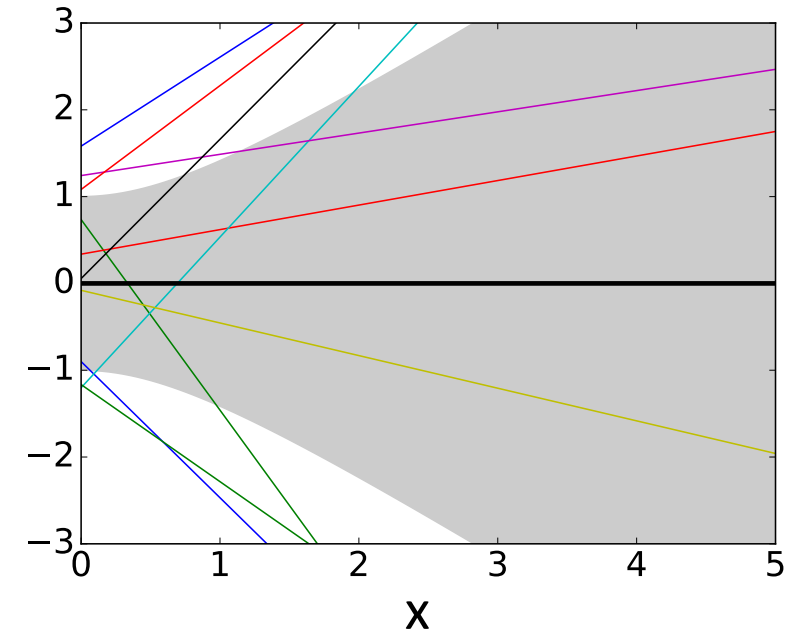
Squared-exponential (RBF)



Matern 1/2



Dot-product (Linear)

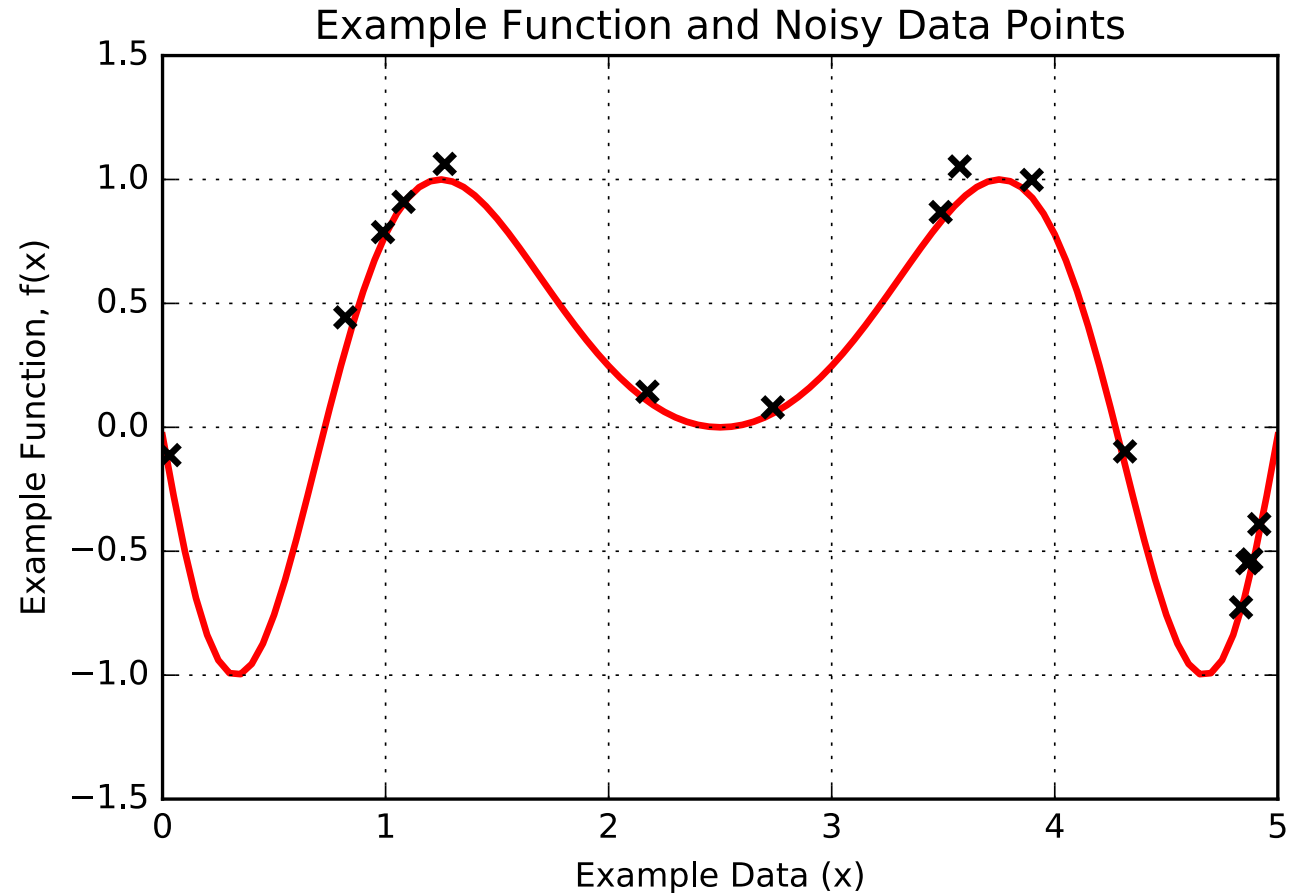


Example: Simple trigonometric curve

— $y = \sin((x - 2.5)^2)$

X training obs. + noise

- Use `gpflow` package to optimize the hyperparameters of the covariance function
- Try a squared-exponential k

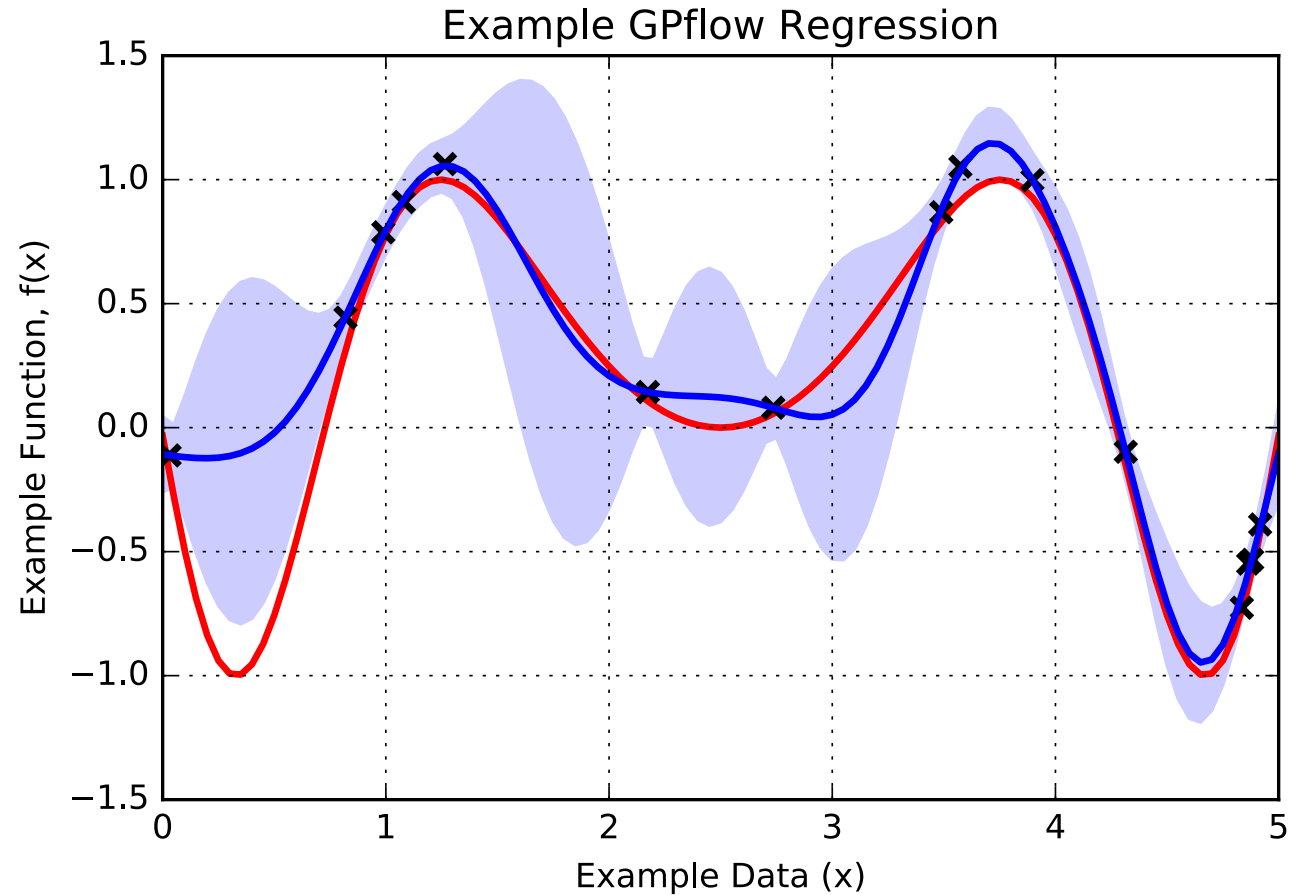


Example: Simple trigonometric curve






- $y = \sin((x - 2.5)^2)$
- X training obs. + noise
- μ of fit model
- 2σ of fit model

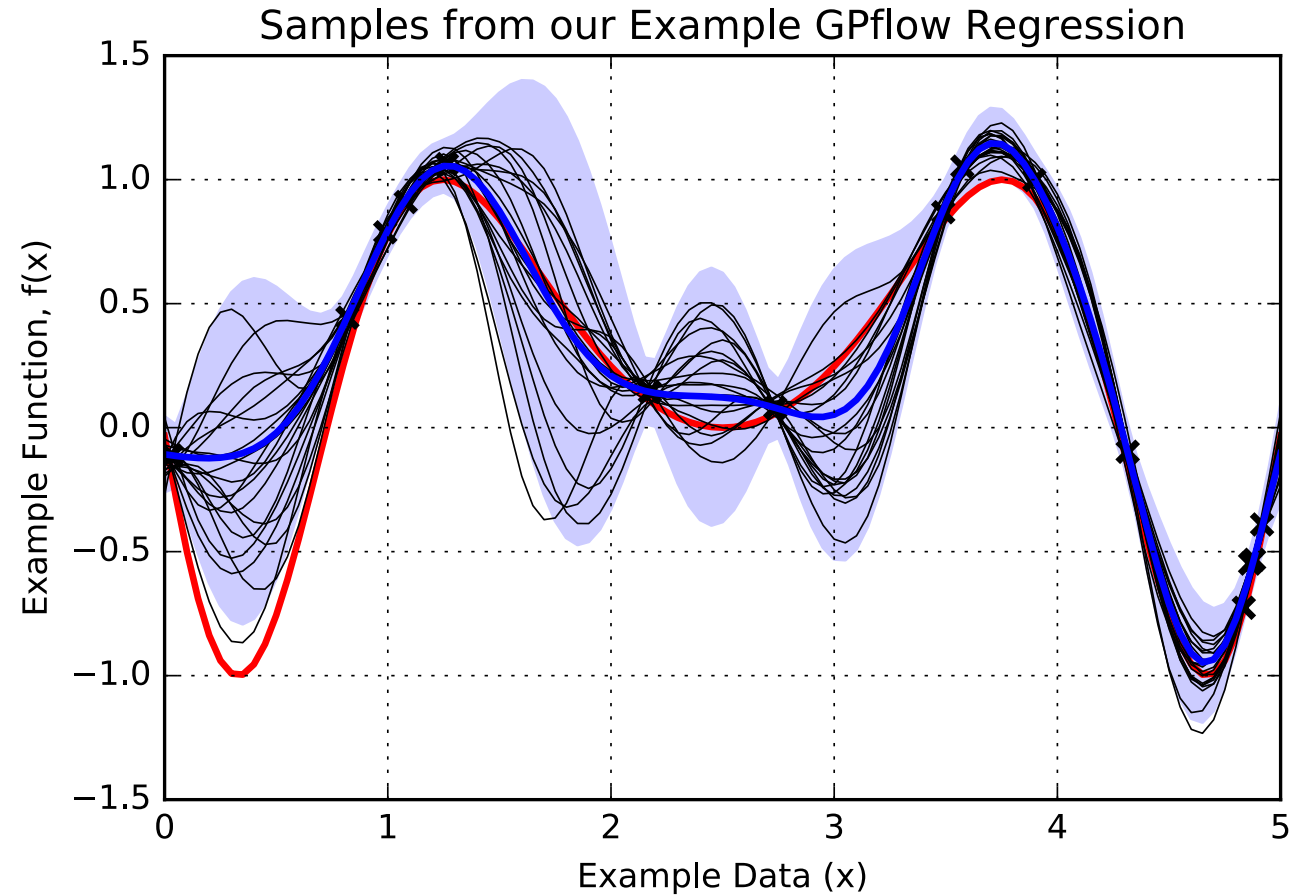
Amplitude = 0.38

Length Scale = 0.34

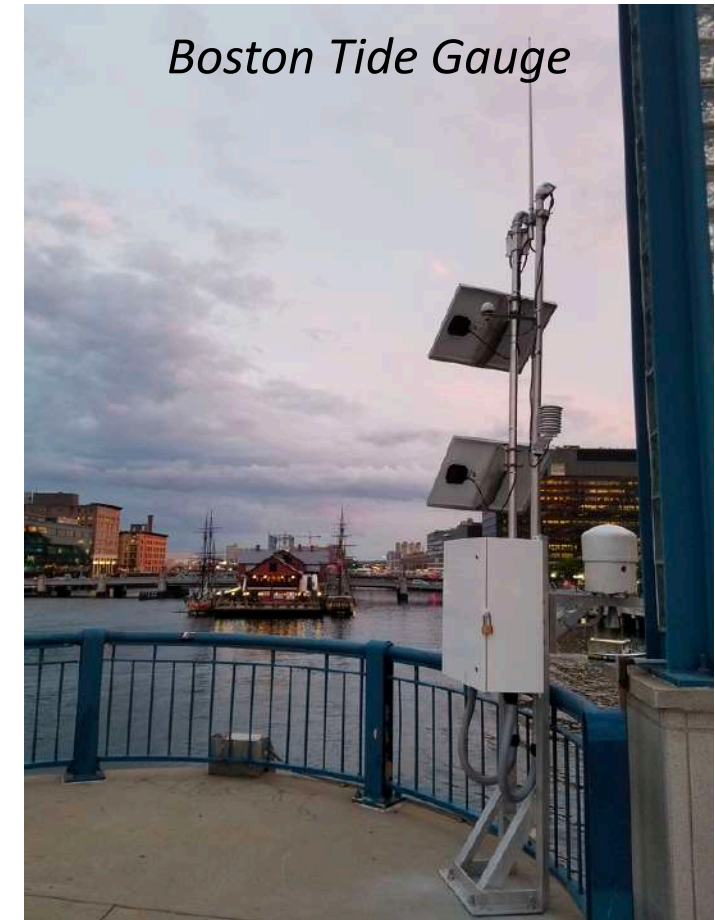
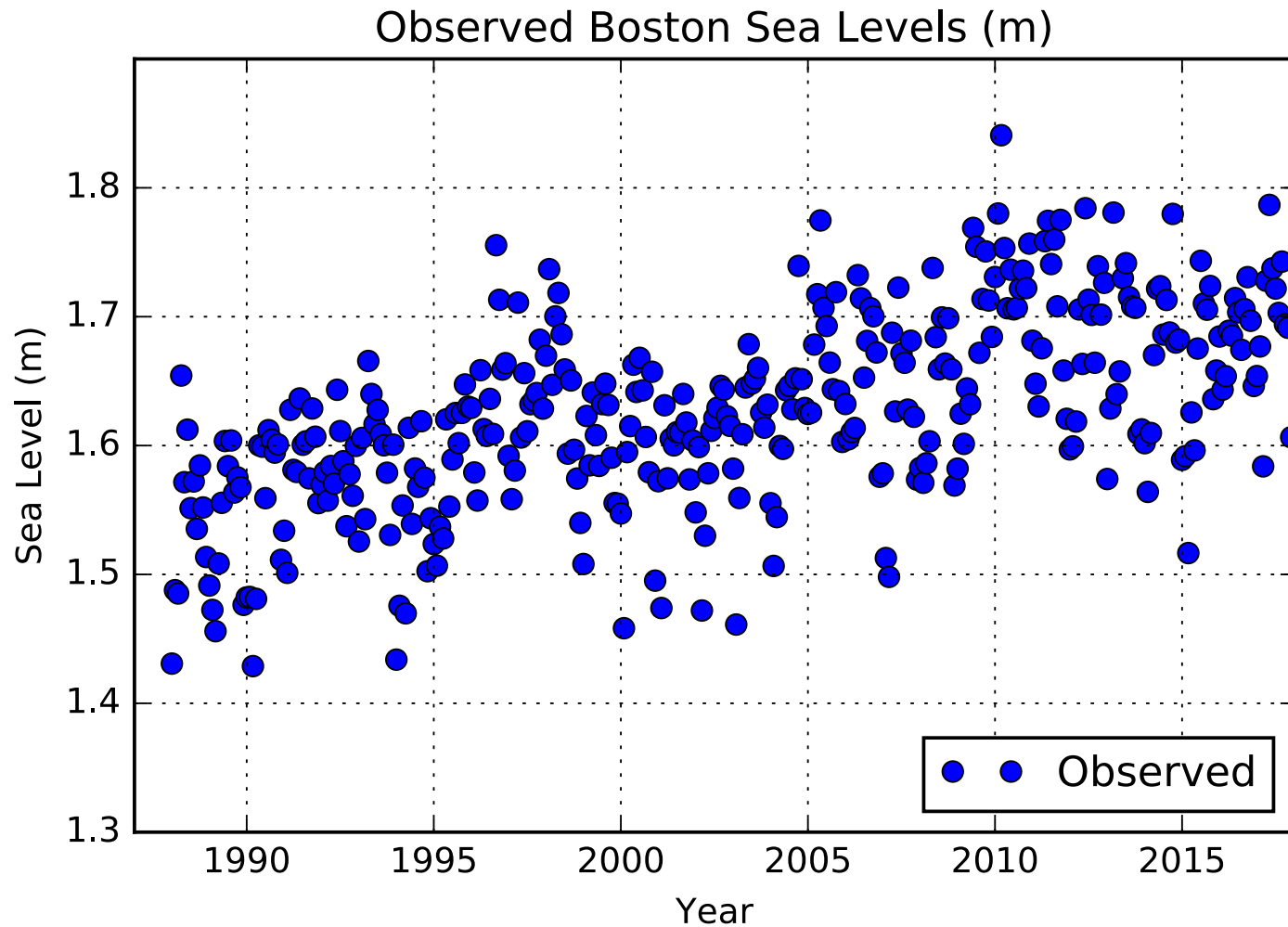


Example: Simple trigonometric curve

-  $y = \sin((x - 2.5)^2)$
-  training obs. + noise
-  μ of fit model
-  2σ of fit model
-  samples from model

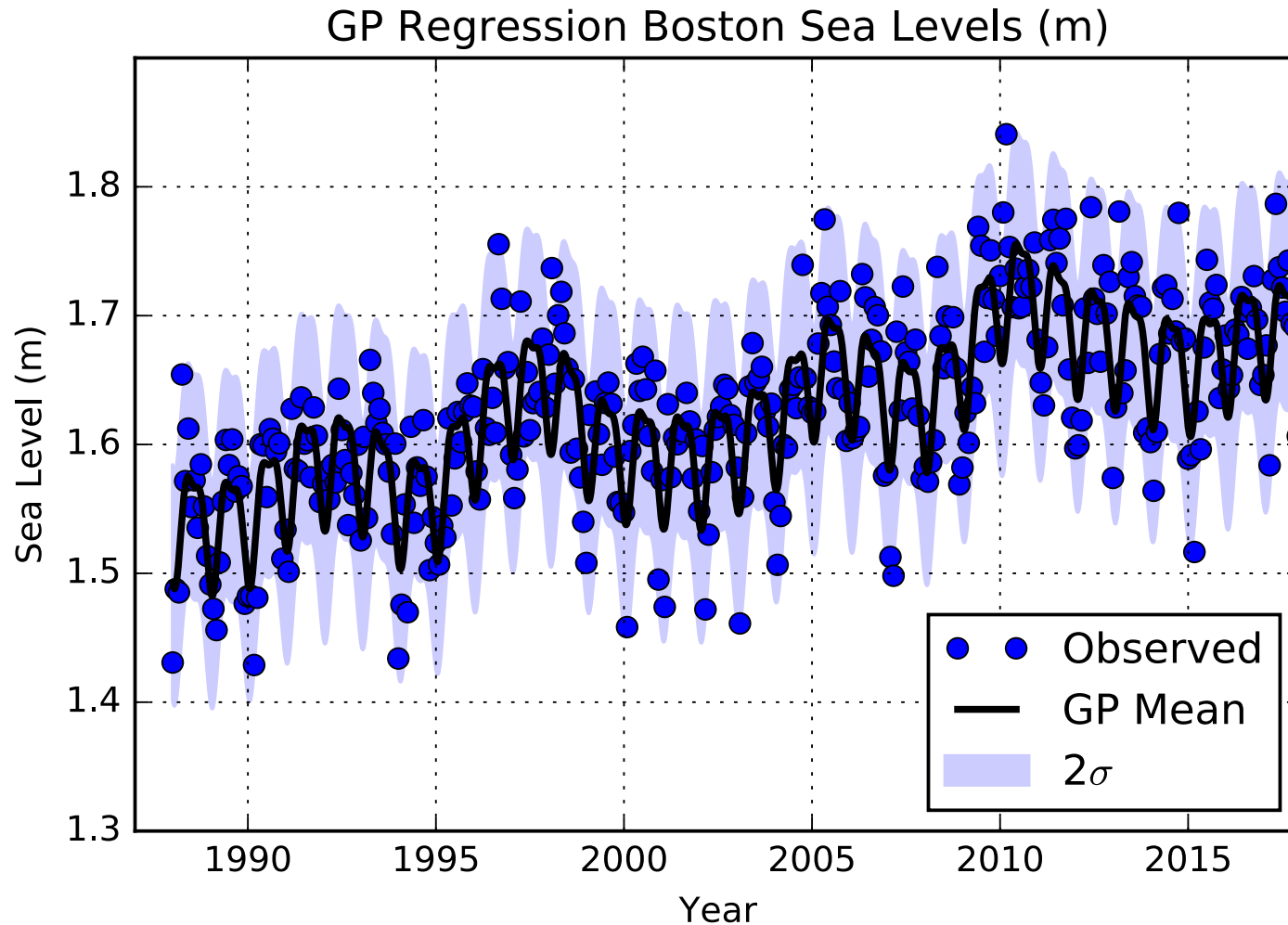


gpflow: GP Regression on Boston Sea Levels

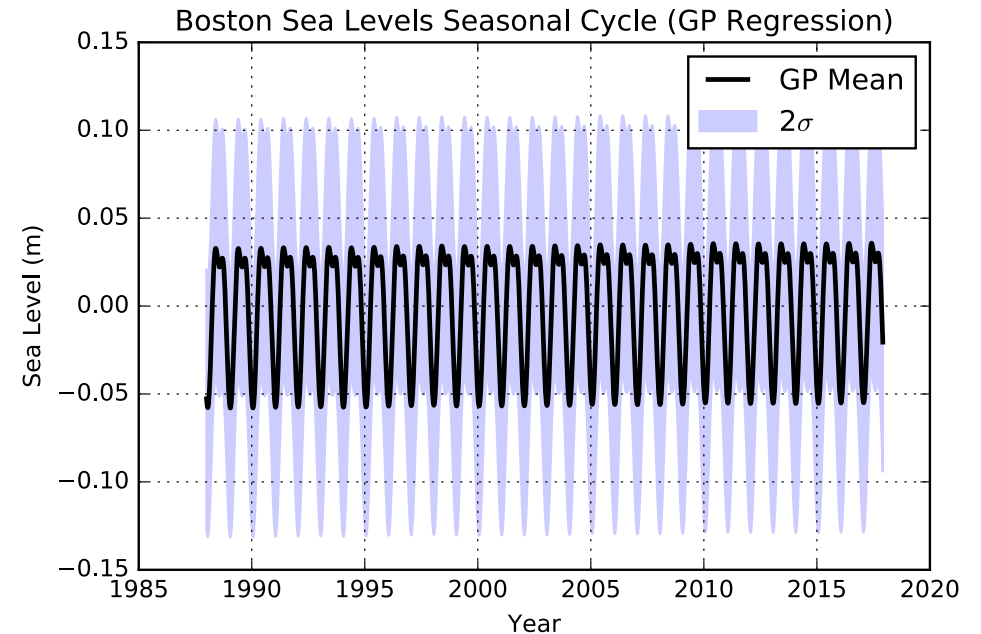


Courtesy of NOAA

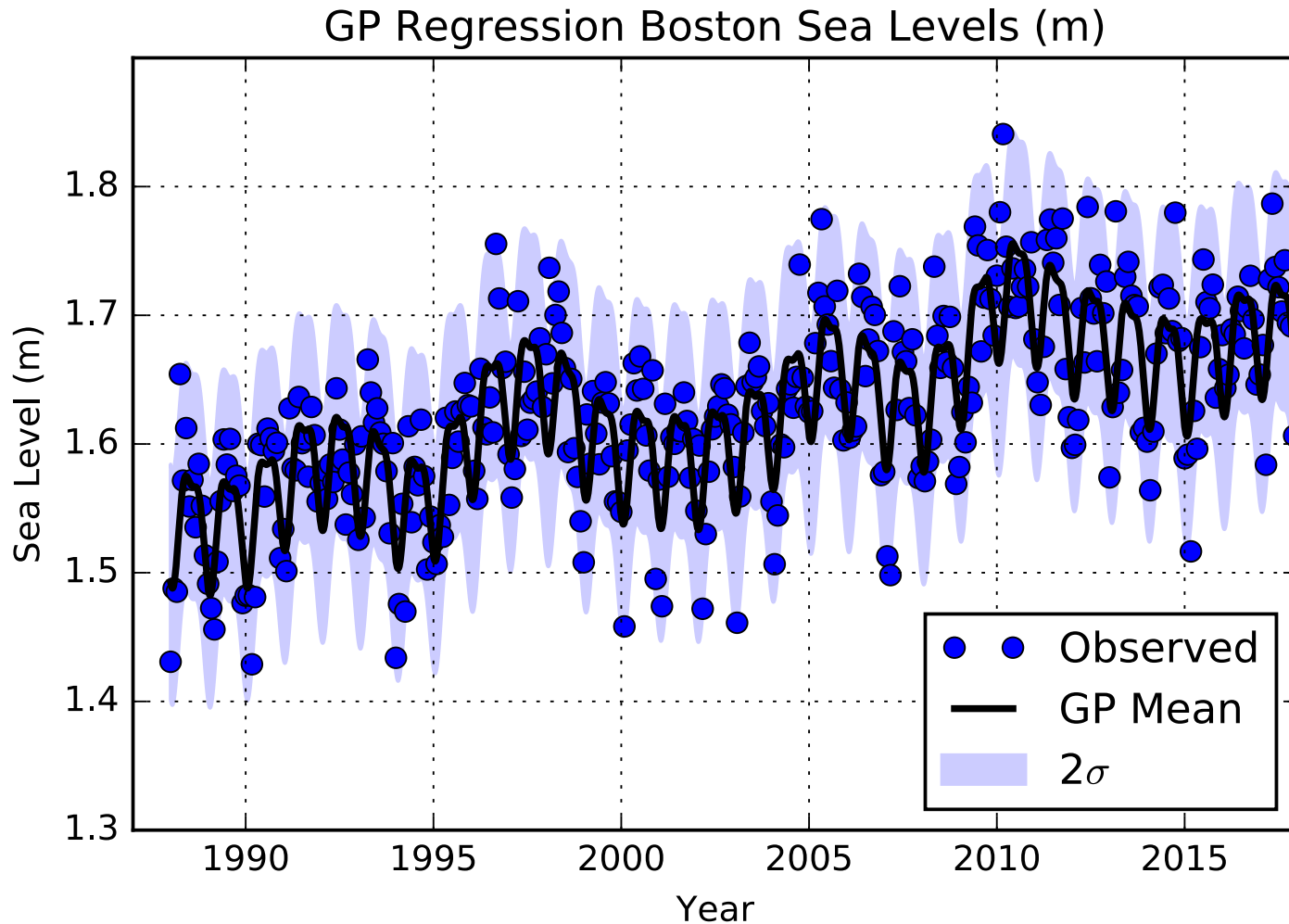
gpflow: GP Regression on Boston Sea Levels



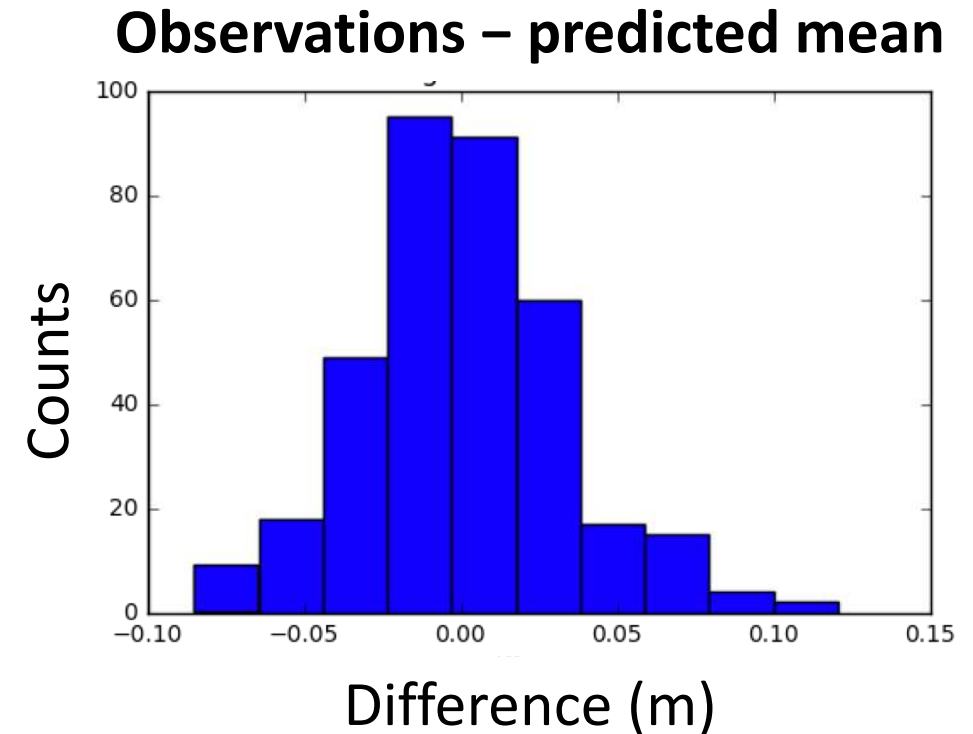
$$k = \text{Linear} + \text{Matern} + \text{Periodic} + \text{Constant}$$



gpflow: GP Regression on Boston Sea Levels

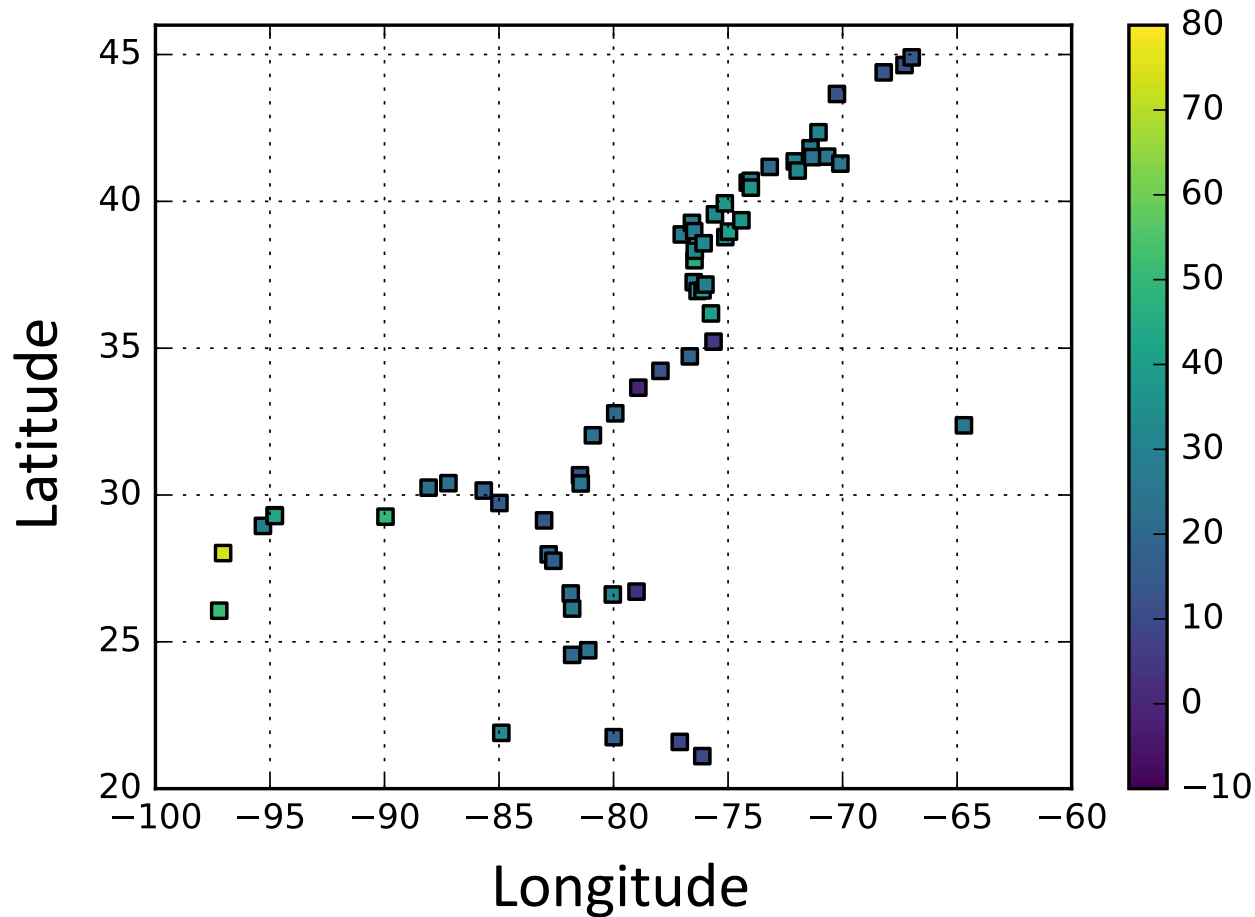


$k = \text{Linear} + \text{Matern}$
 $+ \text{Periodic} + \text{Constant}$



scikit-learn: Spatial Regression on a Sphere

Observed datum offsets at Tide Gauges (mm)



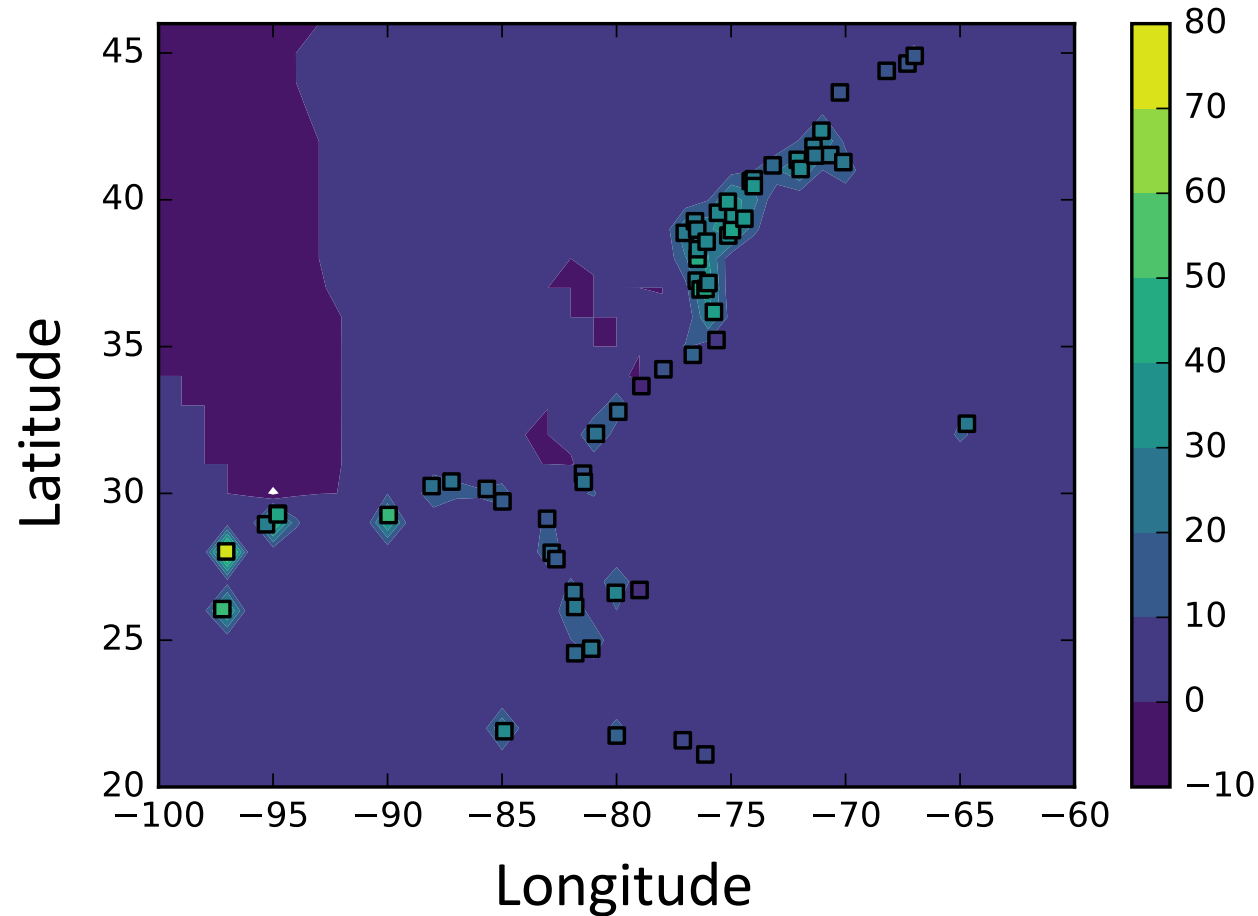
- Goal: Map geolocations (lat/lon) to “datum” differences across the east and gulf coasts
- How do we defined the distance, $d(x, x')$, in k for this model?

For more on datums, see:

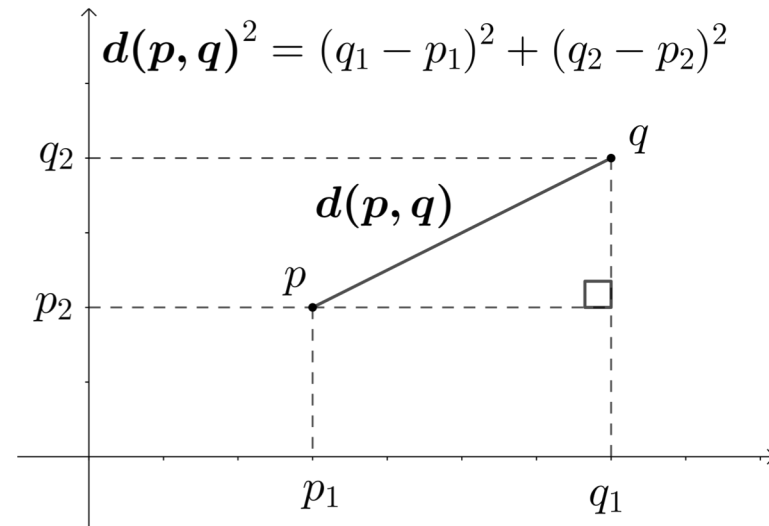
https://tidesandcurrents.noaa.gov/datum_options.html

scikit-learn: Spatial Regression on a Sphere

GP Regression μ with Euclidean distance (mm)

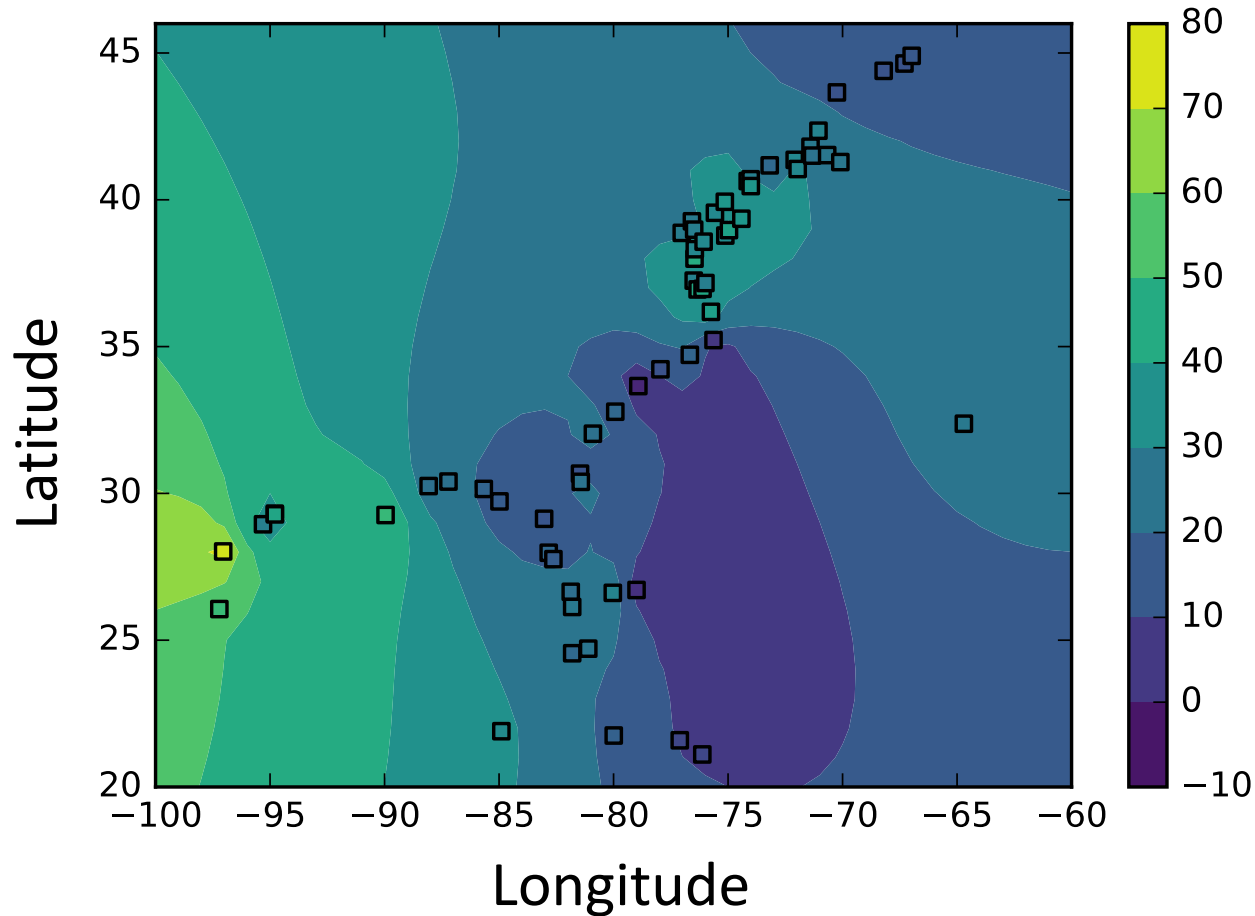


- Goal: Map geolocations (lat/lon) to “datum” differences across the east and gulf coasts

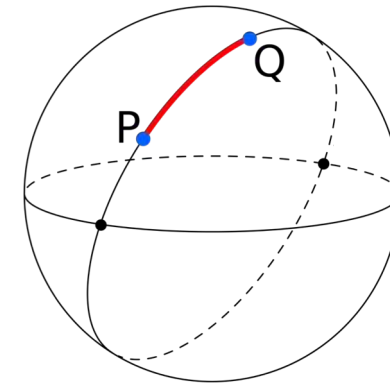


scikit-learn: Spatial Regression on a Sphere

GP Regression μ with Haversine distance (mm)



- Goal: Map geolocations (lat/lon) to “datum” differences across the east and gulf coasts

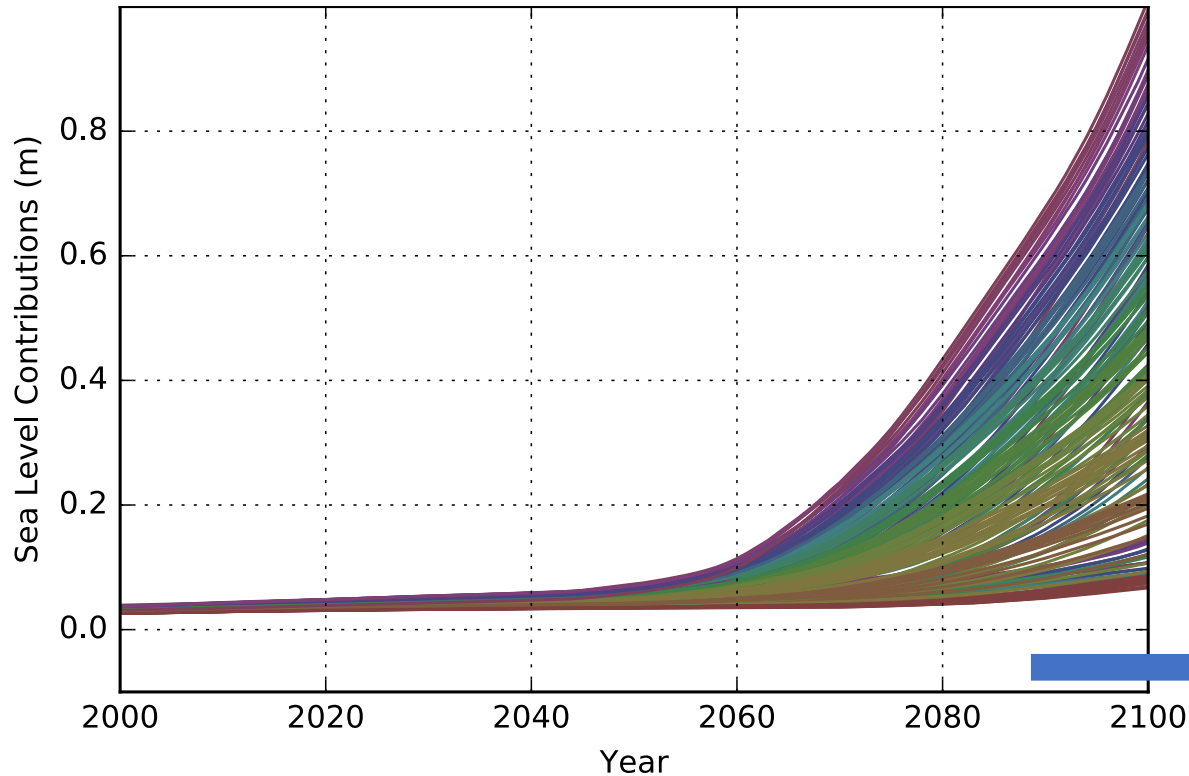


Haversine package:

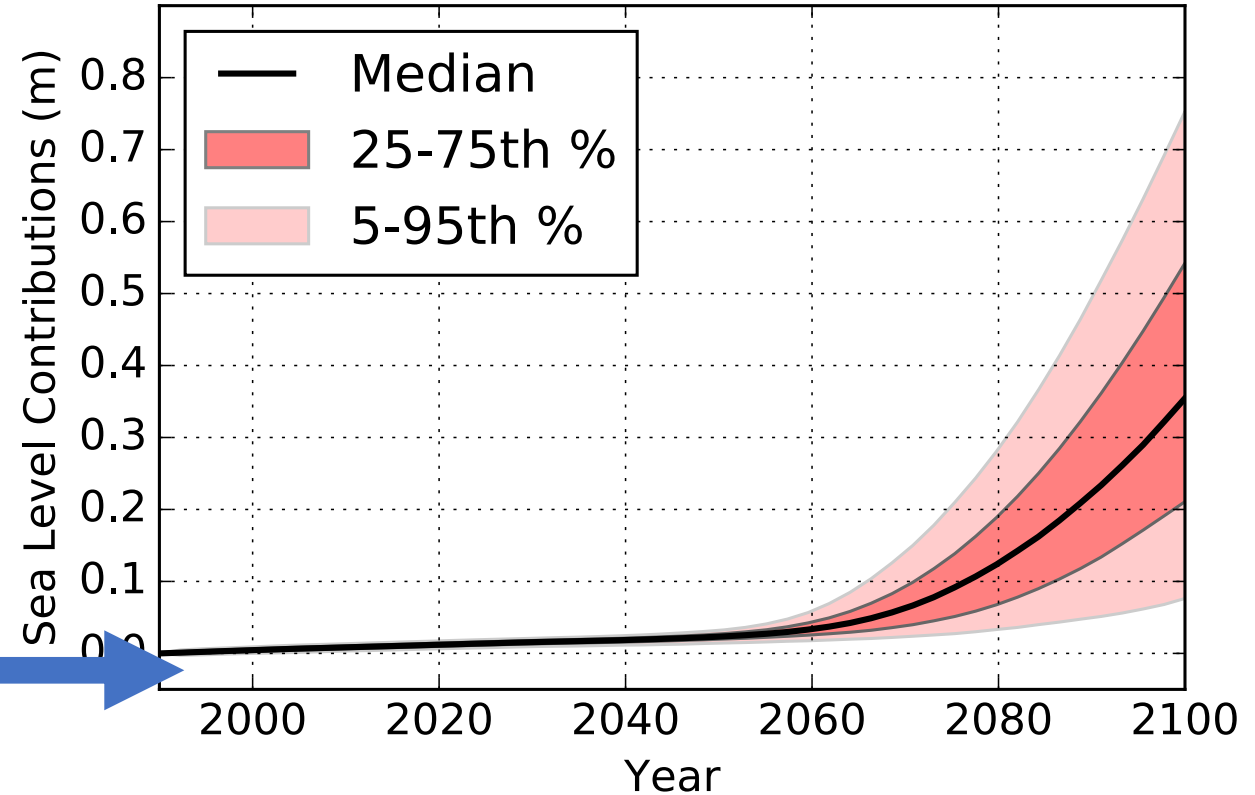
<https://github.com/mapado/haversine>

Ice-Sheet Model Emulator

RCP8.5 Antarctic Contributions (m)



Emulated Probabilities of Contributions (m)



Using `gpflow` to construct an emulator, we condition on modern and paleoclimate observations to construct a probability distribution of projections

Reflections on Python as a Self-Teaching Tool

1. Python is an effective tool for teaching oneself new concepts. It particularly excels in statistics, machine learning, or other subjects which may be intuitively explored through graphics



Want to learn and rapidly adopt a new tool?
Use Python!


2. Implementing a new package is easy to do, often requiring just a few lines of code to explore a working example

Reflections on Python as a Self-Teaching Tool

3. Many Python packages have flexibility and transparency, so they can be adapted as needed

 Take the leap... **Leaps facilitate learning!**

4. Don't rely on a single package. Explore as many as you have bandwidth for: push boundaries, discover gaps, develop ideas

 I often learned most when I realized a package out-of-the-box *wasn't* capable of what I wanted to do

Find this presentation, a simple `gpflow` tutorial,
and more resources at <http://danielgilford.com>



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[@danielgilford](https://twitter.com/danielgilford)

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Additional Resources

Rasmussen and Williams (2006):

<http://www.gaussianprocess.org/gpml/chapters/RW.pdf>

Gaussian processes for dummies, by Kat Bailey:

<http://katbailey.github.io/post/gaussian-processes-for-dummies/>

Kernel cookbook, by David Duvenaud:

<https://www.cs.toronto.edu/~duvenaud/cookbook/>