Spatial Precision Working Group
Yeah, but, what is **Spatial Precision**?

Peter Cornillon

University of Rhode Island

GHRSST Spatial Precision Working Group

Outline

1. Selected Shorts – Some Things to Think About

2. The Error Budget of Satellite-Derived SST Fields.
   - Introduction
   - Two Approaches to Determining the *Instrument Noise*

3. Conclusion


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Bugs Bunny
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Bitcoins

- One bitcoin transaction consumes as much energy as nine American households consume in one day.
- The aggregate computing power of the bitcoin network is estimated to be 100,000 times larger than the world's 500 fastest supercomputers combined.

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- Alpha developed a machine based Go playing program, AlphaGo Zero
  - Trains only on itself – no human games used
  - Progressively learned the game of Go from scratch,
    given only the rules of Go.
  - Training is not constrained by the limits of human knowledge
  - Training to reach human world champion level took 3 days.
  - Discovered new knowledge, developing unconventional strategies and creative new moves.
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Overview – Measures of SST Uncertainty in Satellite-Derived Fields

- The uncertainty of satellite SST data products is determined from in situ matchups.
  - Standard measure is rms difference between buoy and satellite SSTs.
  - Typical values for AVHRR, MODIS . . . range from 0.4 to 0.6 K.
  - But these are based on match-ups widely separated in space and time
    - A significant contributor to these uncertainties are atmospheric fluctuations
    - Which vary over large scales.
- But these measures are not representative of small scale uncertainties,

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  Because large scale variability is relatively unimportant re fronts and gradients.

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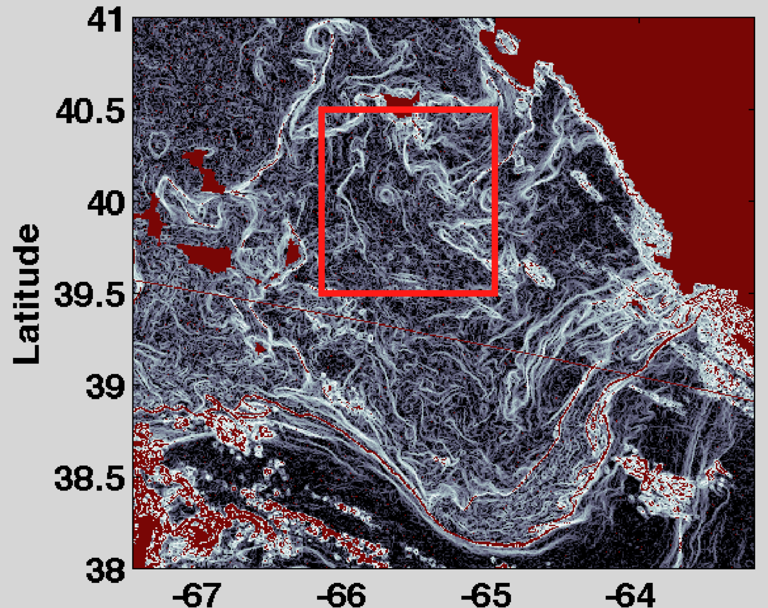
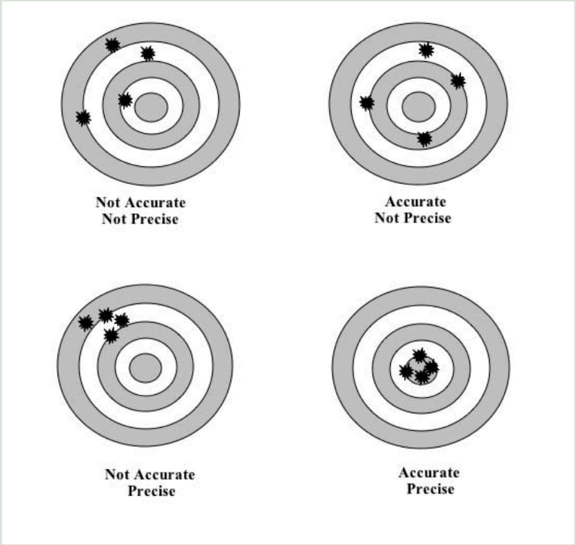
VIIRS SST



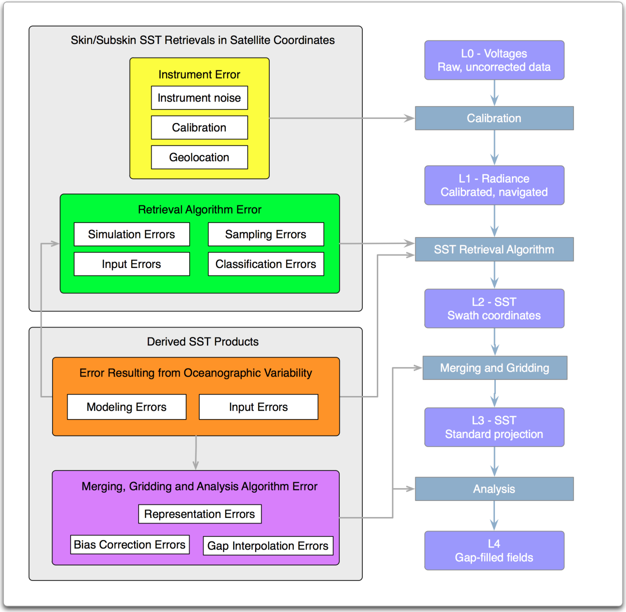
Accuracy versus Precision



The Error Budget

Let's take a step back and look at the error budget for SST products.

Error Budget for Satellite-Derived SST Fields (NASA SST Science Team)



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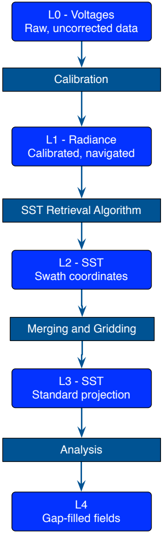

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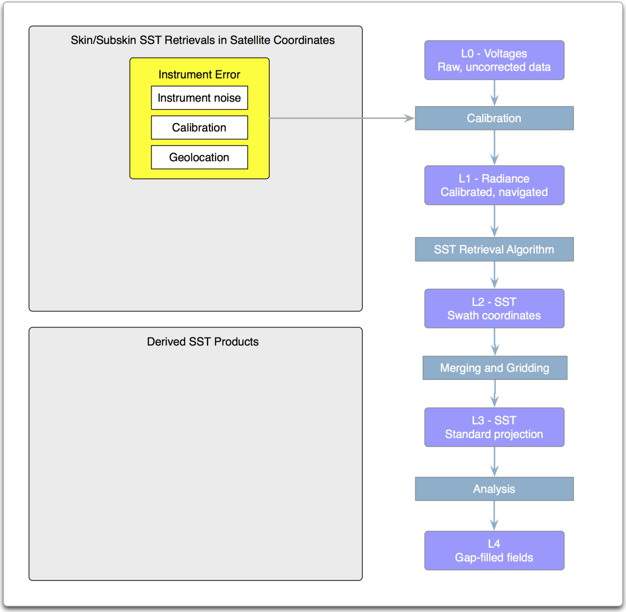

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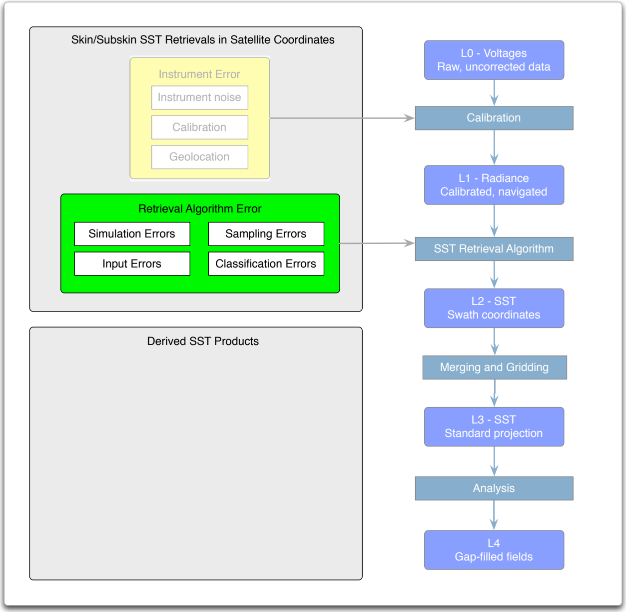

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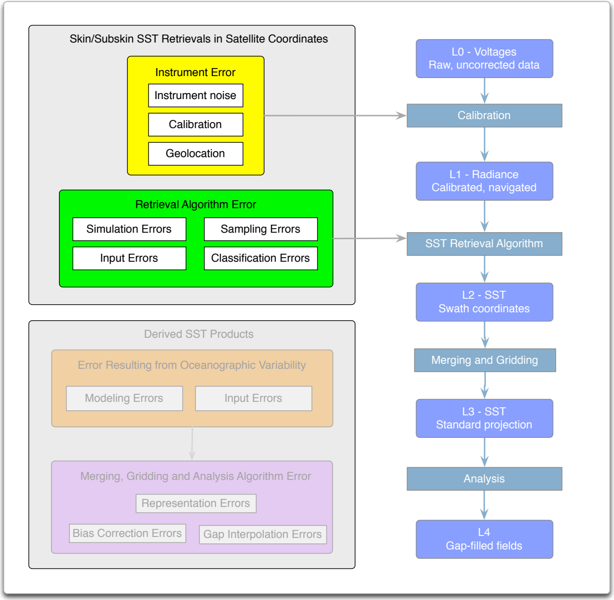

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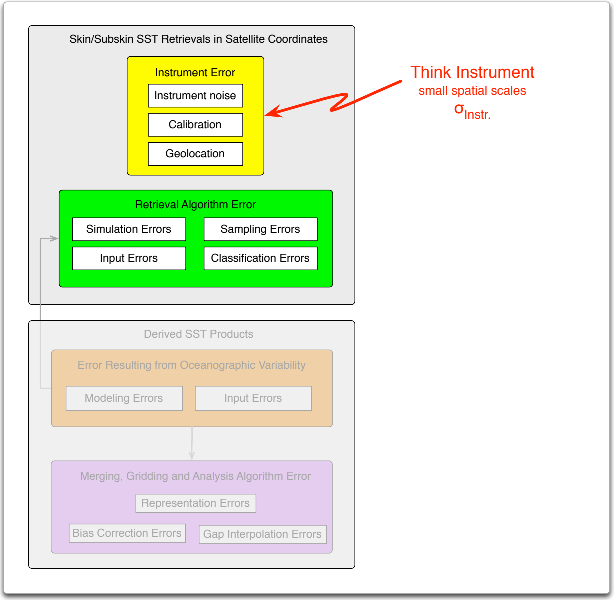

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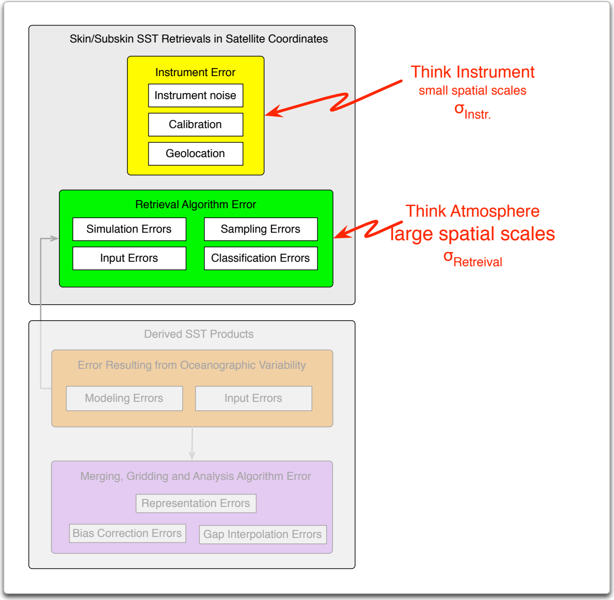

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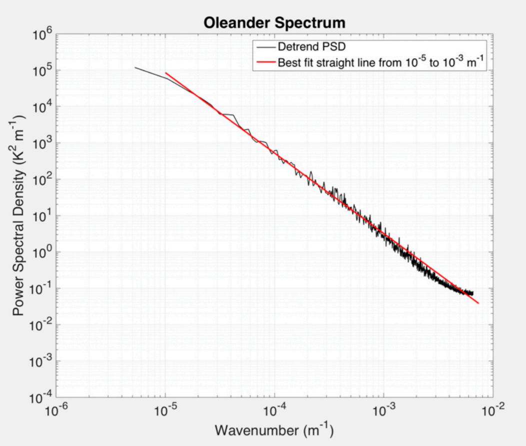

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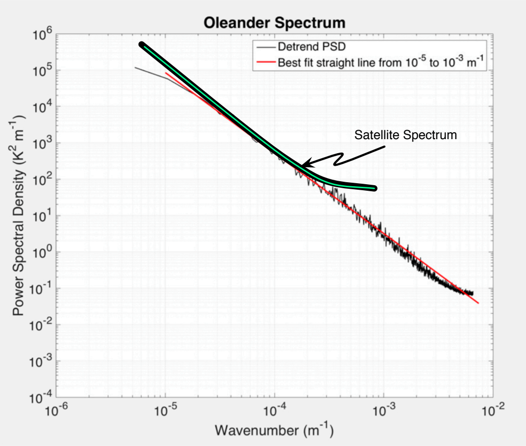
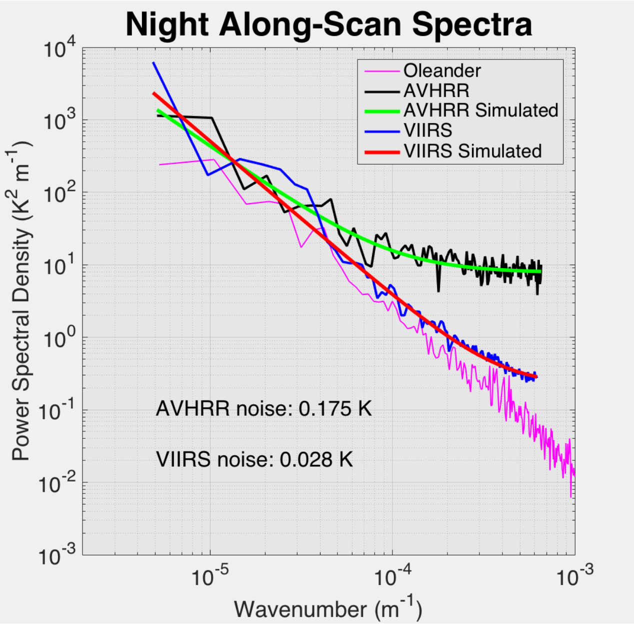


AVHRR and VIIRS Nighttime, Along-Scan Compared



The Variogram Approach

$$\text{Semivariance}: \quad \hat{\gamma}(\Delta) = \frac{1}{2N(\Delta)} \sum_{i=1}^{N(\Delta)} [SST(i+\Delta) - SST(i)]^2$$

where Δ is the separation of SST samples and
$N(\Delta)$ is the number of pairs for the given separation.

- It's a measure of the variance between pairs of points as a function of point separation.
- The value of a curve representing the variogram and $\Delta = 0$ is the variance of the underlying data.
- The curve may be of the form (the *exponential* model in this case):

$$\gamma(\Delta) = \sigma_o^2 + \sigma^2 \left(1 - e^{-\frac{\Delta}{L}}\right)$$

where σ_o^2 the *nugget*, the variance at zero-lag,
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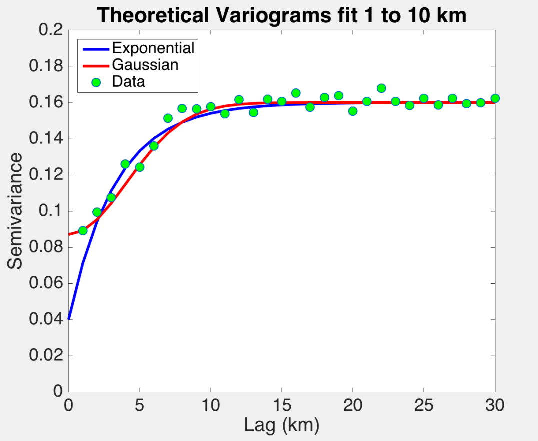
The Variogram Approach continued

$$\text{Exponential}: \gamma(\Delta) = \sigma_o^2 + \sigma^2 \left(1 - e^{-\frac{\Delta}{L}}\right) \qquad \text{Gaussian}: \gamma(\Delta) = \sigma_o^2 + \sigma^2 \left(1 - e^{-\frac{\Delta^2}{L^2}}\right)$$



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Instrument Noise

	Method	Day (K)		Night (K)	
		Along-Scan	Along-Track	Along-Scan	Along-Track
AVHRR	Spectral	0.172 (5)	0.209 (7)	0.173 (2)	0.209 (4)
	Variogram	0.185 (5)	0.219 (7)	0.183 (2)	0.219 (4)
VIIRS	Spectral	0.046 (4)	0.076 (10)	0.021 (24)	0.032 (14)
	Variogram	0.081 (4)	0.097 (10)	0.042 (24)	0.056 (14)

Uncertainties of estimates $\approx 0.004\,\mathrm{K}$

- These results apply only to instrument noise

  i.e., no contribution from misclassification errors.

- We used the *stable variogram* for this work.

$$\mathrm{StableVariogram}: \quad \gamma(\Delta) = \sigma_o^2 + \sigma^2 \left(1 - e^{-\left(\frac{\Delta}{L}\right)^{w}}\right)$$

  where parameter w ranges from (1) exponential model to (2) Gaussian model.

- Misclassification errors are likely to be spatially dependent.

  making their determination a bigger project.

  This is likely to be especially true for L3 and L4 products.

- Determining the contribution of misclassifcation errors is problematic.

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	Variogram	0.185 (5)	0.219 (7)	0.183 (2)	0.219 (4)
VIIRS	Spectral	0.046 (4)	0.076 (10)	0.021 (24)	0.032 (14)
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Uncertainties of estimates $\approx$ 0.004 K

- These results apply only to instrument noise

  i.e., no contribution from misclassification errors.

- We used the *stable variogram* for this work.

$$\text{StableVariogram} : \quad \gamma(\Delta) = \sigma_o^2 + \sigma^2 \left(1 - e^{-\left(\frac{\Delta}{L}\right)^{w}}\right)$$

  where parameter w ranges from (1) exponential model to (2) Gaussian model.

- Misclassification errors are likely to be spatially dependent.

  making their determination a bigger project.

  This is likely to be especially true for L3 and L4 products.

- Determining the contribution of misclassifcation errors is problematic.

Instrument Noise

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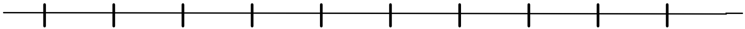
That's all Folks!
66

The Data – Preprocessing – Nearest Neighbor Resampling

- The sections were resampled to equal spacing.
  - To minimize interpolation, spacing chosen = to mean spacing on the section
  - Nearest neighbor interpolation was used.



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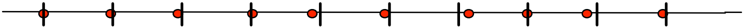

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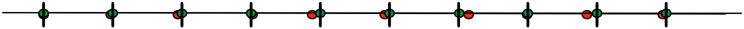

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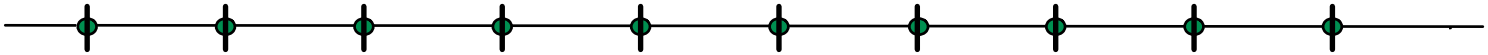

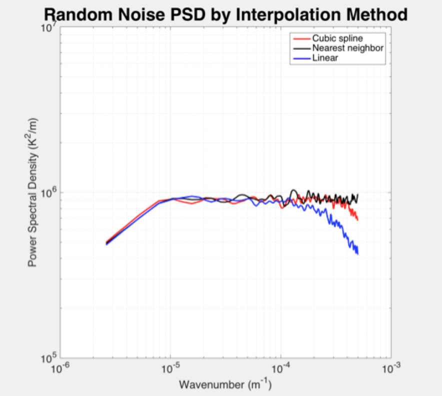

An Example of the Importance of the Spatial Precision

How does noise impact satellite-derived SST gradients?

- Consider 10,000 3×3 pixel squares for a fixed gradient in x, $\frac{\partial T}{\partial x}$, 0 in y.
- Add Gaussian white noise, σ, to each of the elements.
- Apply the 3×3 Sobel gradient operator in x and y.
- Determine the μ and σ of the resulting gradient magnitude
- Perform the above for:

$$0.01\,\mathrm{K\,km^{-1}} < \frac{\partial T}{\partial x} < 0.3\,\mathrm{K\,km^{-1}}$$

$$0.001\,\mathrm{K} < \sigma < 0.3\,\mathrm{K}$$

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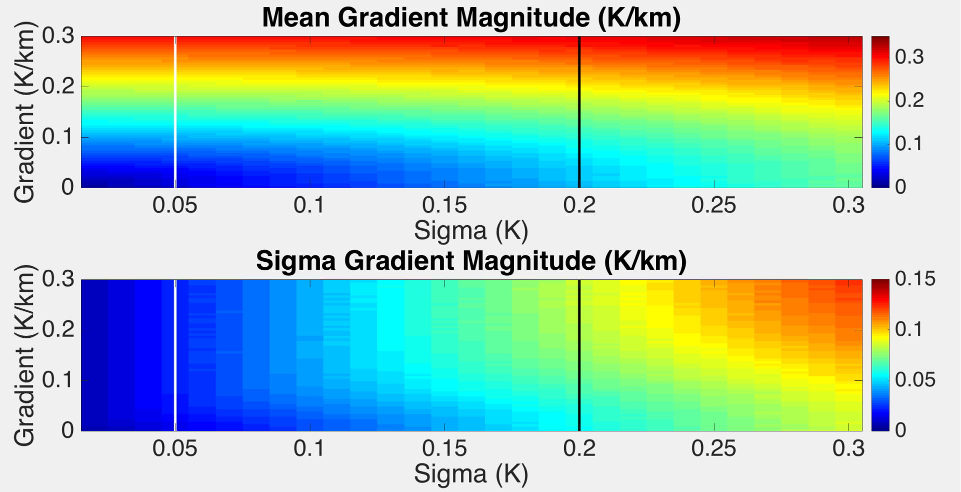

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Including me – GULP!

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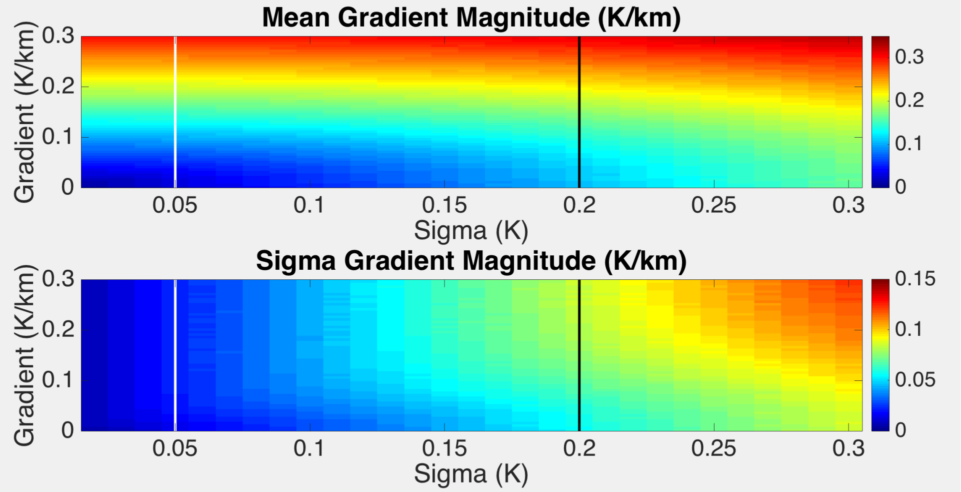

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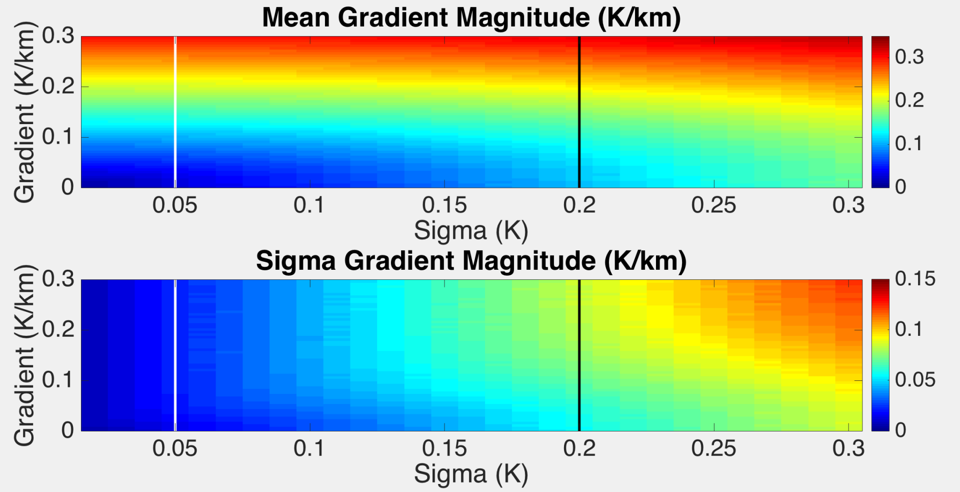

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