

Generalized Significance in Scale Space: The GS3 Package

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Green House Gas (GHG) Emission Measurement

NIST developing technology & standards for remote sensing of GHG's

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DIAL for distributed sources

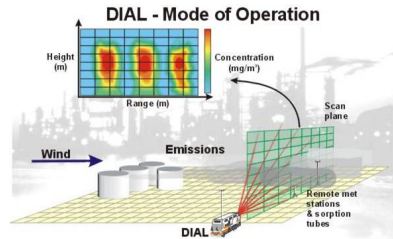
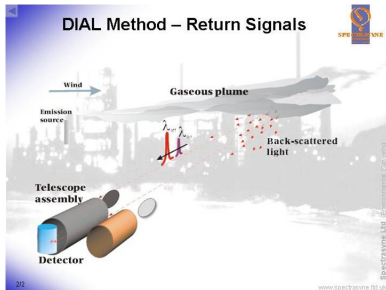
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- Range resolved, column integrated measurements

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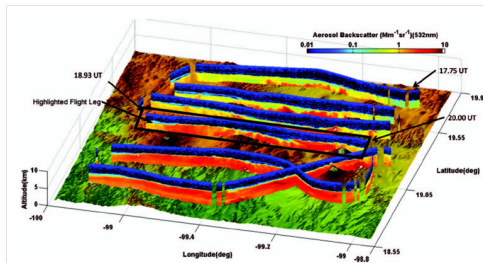
- **H**igh **S**pectral **R**esolution **L**IDAR
- Similar technology/data
- Validation of Calipso satellite measurements

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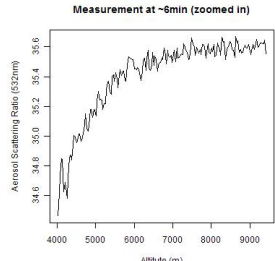
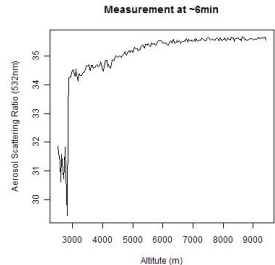
Hair et al. (2008)

Data graciously provided by NASA Langley Research Center

Challenges associated w/ HSRL & DIAL data

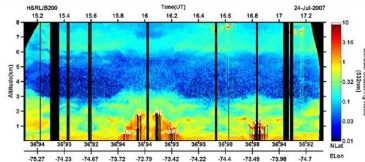
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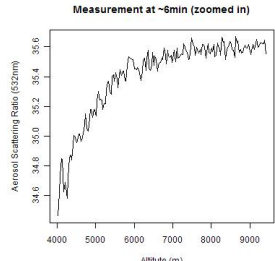
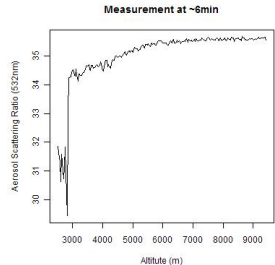


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- Highly variable
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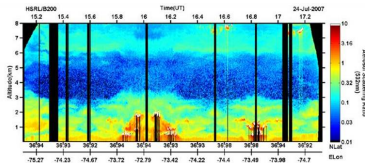


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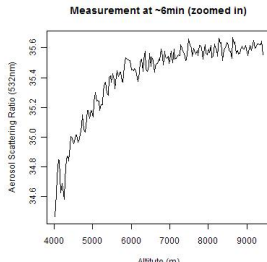
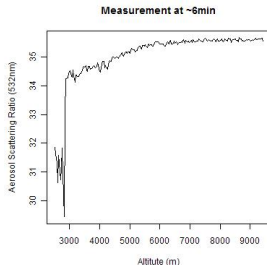
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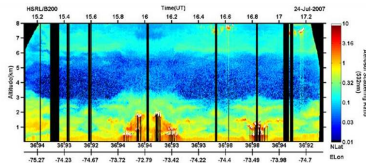
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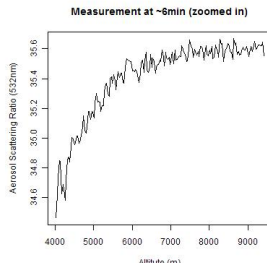
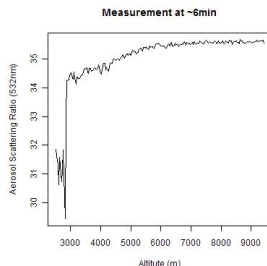


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Goals

- Estimate concentration (derivative)
- Calculate uncertainty



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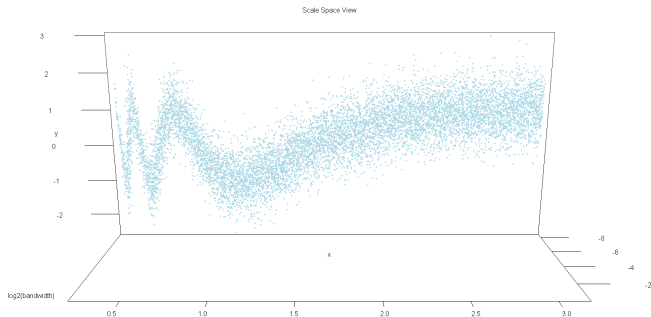
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The GS3 package provides a solution

Scale Space

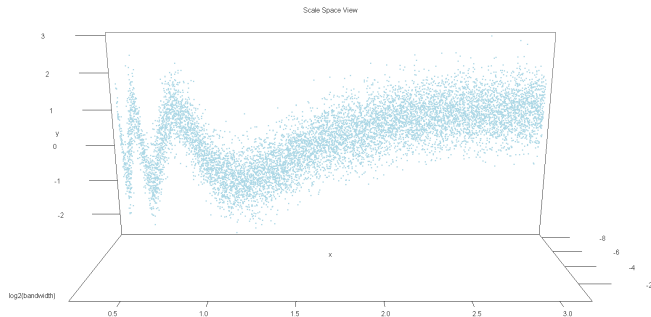
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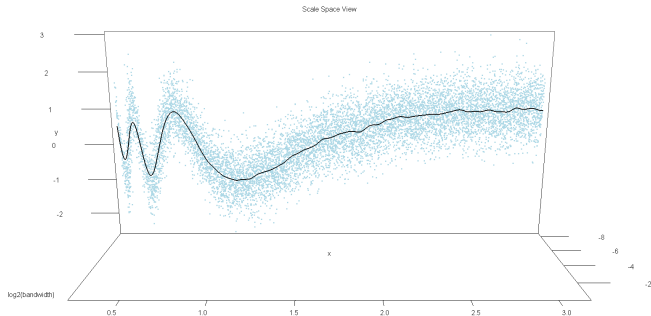
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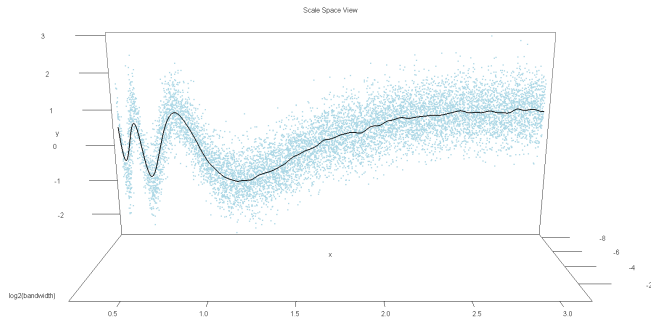
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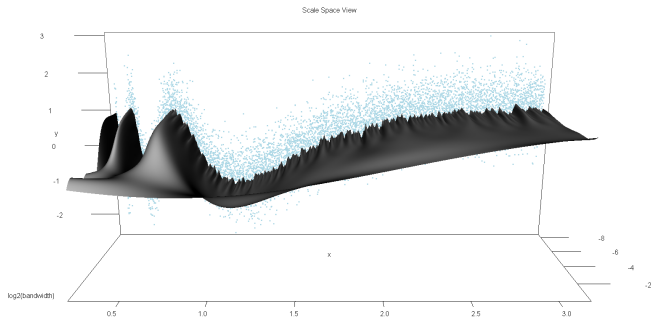
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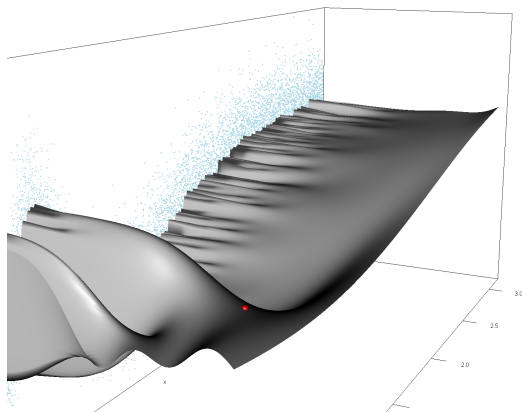
- Many instances where *a fit* desired
- However, good practice to look at multiple smooths
- Scale space studies a “family” of smooths



RODEO

RODEO (Wasserman & Lafferty (2008)) greedy algorithm for traversing "scale space surface"

Algorithm

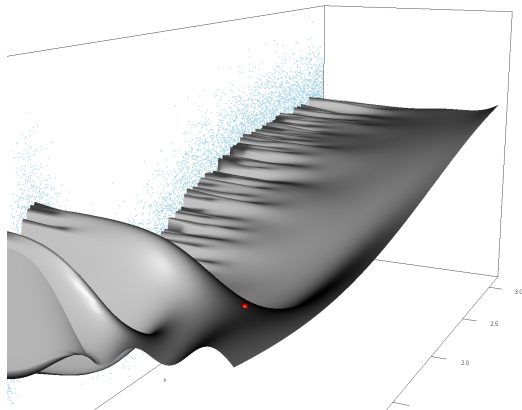


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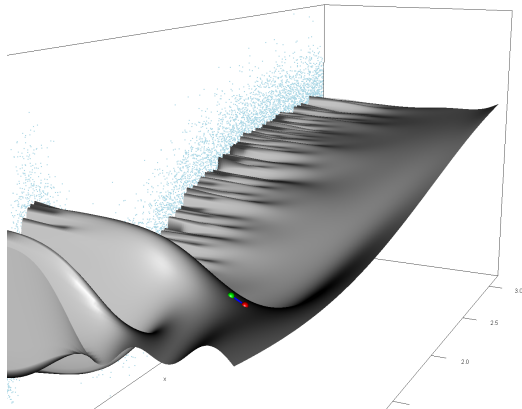


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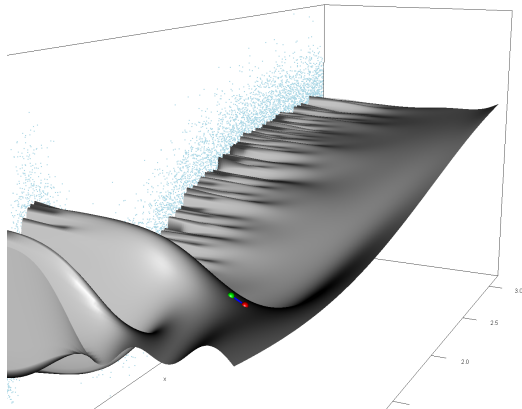


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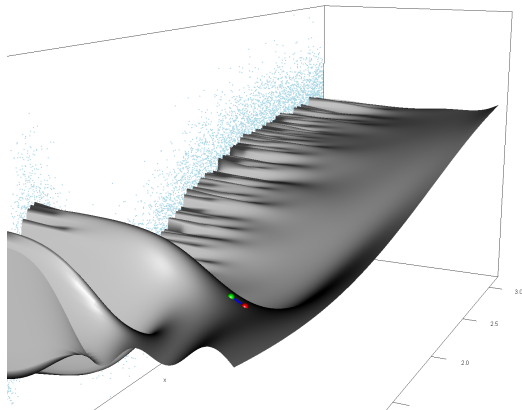


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- NB: $\text{Var}(Z) \sim \sigma^2$
 - σ^2 unknown population parameter

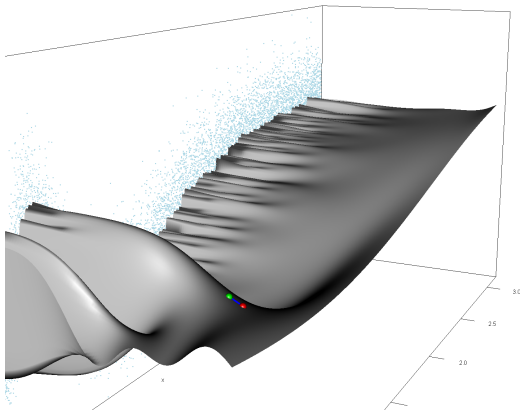
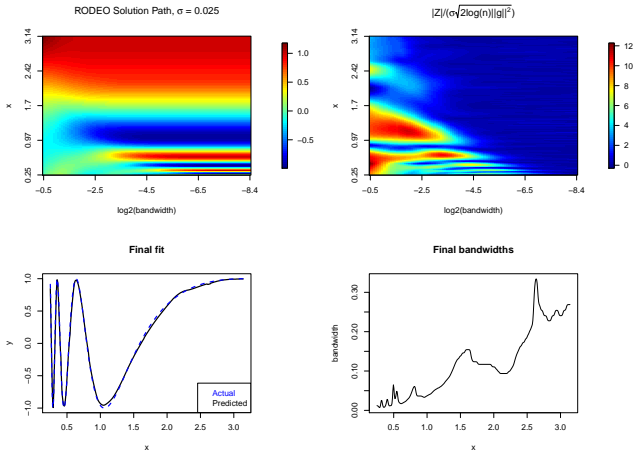


Illustration of RODEO in Scale Space

For $\sigma = 0.025$

Results

- Produces sensible smooth & bandwidths

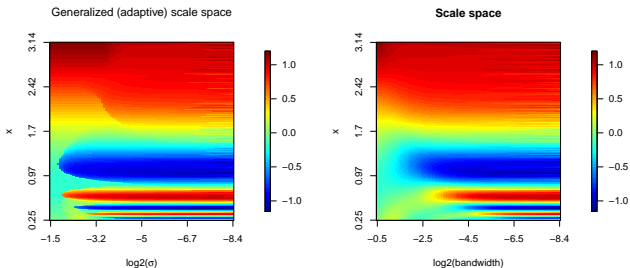


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- However, can also interpret σ in similar way to h



Higher dimensions

$d > 1$

- Straightforward, calculate $Z_j, j = 1, \dots, d$ & $\text{Var}(Z_j)$ ($\sim \sigma$)
- Same greedy approach used along each dimension

Generalized Scale Space

Scale Space

Computation

Speed of Bandwidth Selection

- Use linear binning ideas (Fan & Marron (1994), Wand (1995))
- $M_i, i = 1, \dots, d$ grid size & $T = \#$ candidate bandwidths
- Selection takes $O(dTM_1 \log M_1 \dots M_d \log M_d)$
- Compared to smooth w/ global bandwidth,
 $O(M_1 \log M_1 \dots M_d \log M_d)$

Illustration of Generalized Scale Space on HSRL data

Conclusions & Future Work

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- Provided R functions for 1, 2 & 3D binned LLR
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Future Work (currently in progress)

- Local variance function estimation
- Spatial dependence