High image resolution NASA CALIOP extinction denoising / inference

Constructive insights for future space-based missions

Willem J. Marais, Robert E. Holz, Mark A. Vaughan, Charles R. Trepte, John W. Hair, Chris A. Hostetler

12/04/2023

Langley NASA CALIOP

Langley NASA CALIOP

Noisy total attenuated backscatter (Horizontal 1km, Vertical 30m)

Clouds are masked out, since we specifically interested in denoising aerosols

Denoised total attenuated backscatter (Horizontal 1km, Vertical 60m)
2016-08-10 (nighttime)
Altitude (km)
8
6
4
2
0
38
39
40
41
Latitude [degree]
total attenuated backscatter [1/km 1/sr]
5e-3
4e-3
3e-3
2e-3
1e-3
5e-4
1e-4

The basic ingredients of denoising methods

- CALIOP noisy image: y
- Attenuated scattering ratio: x
- CALIOP forward model: $F(x)$
- CALIOP noise model: $\ell(y \mid F(x))$
- A priori assumption about attenuated scattering ratio: $p(x)$

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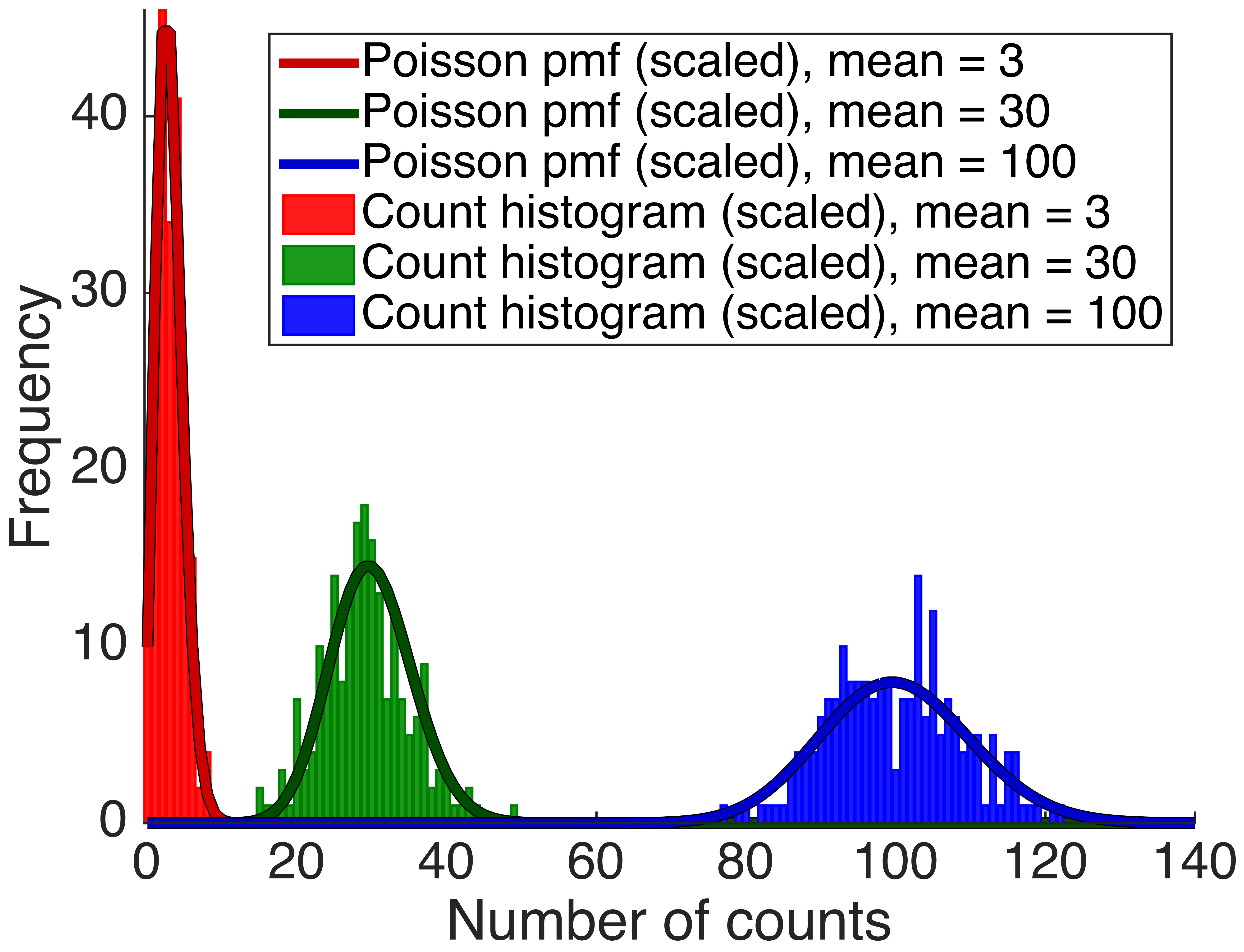
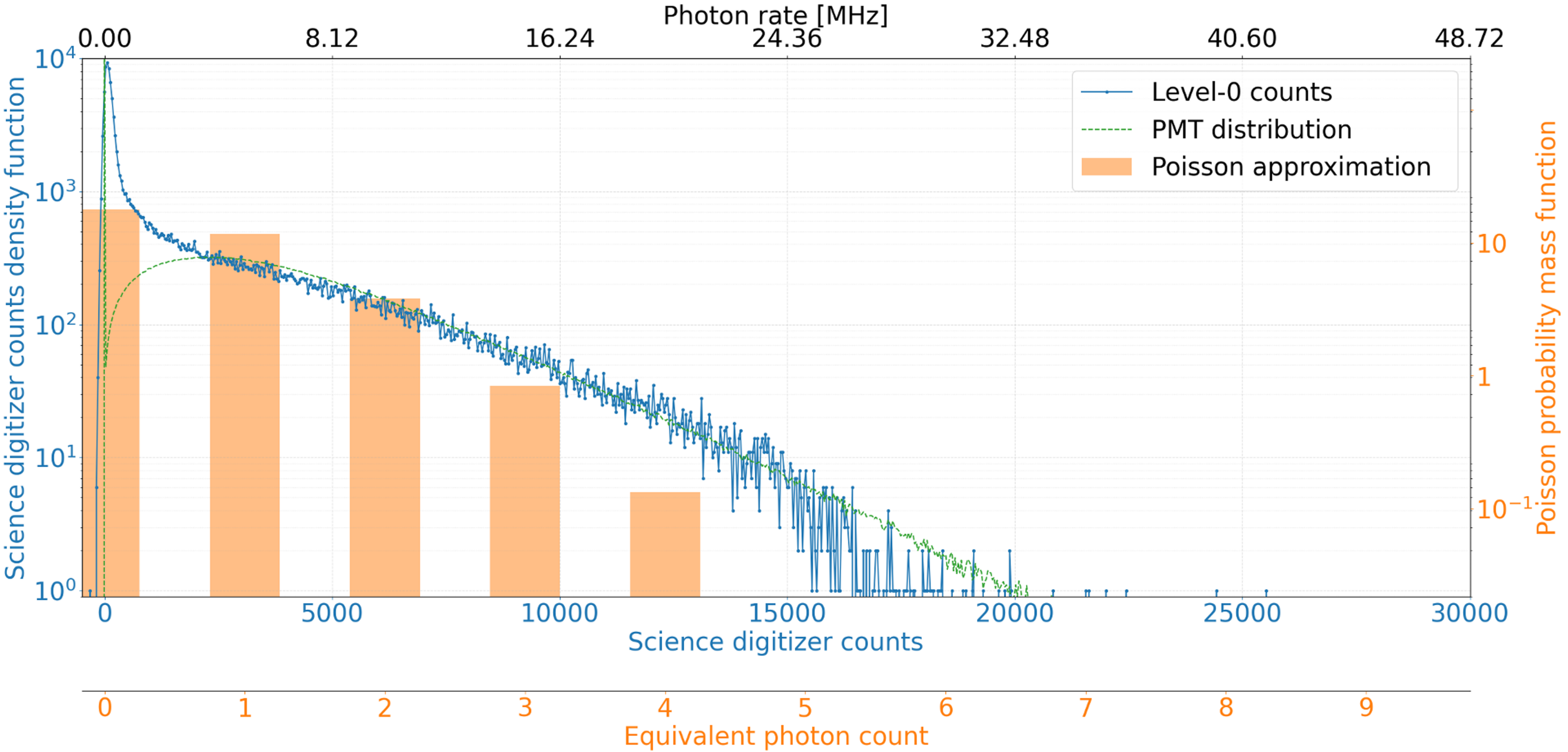
- Model noise statistical properties

The noise model

Spatially-varying and signal-dependent noise variance



CALIOP noise probability distribution



Starting with something familiar

The formulation of optimal estimation

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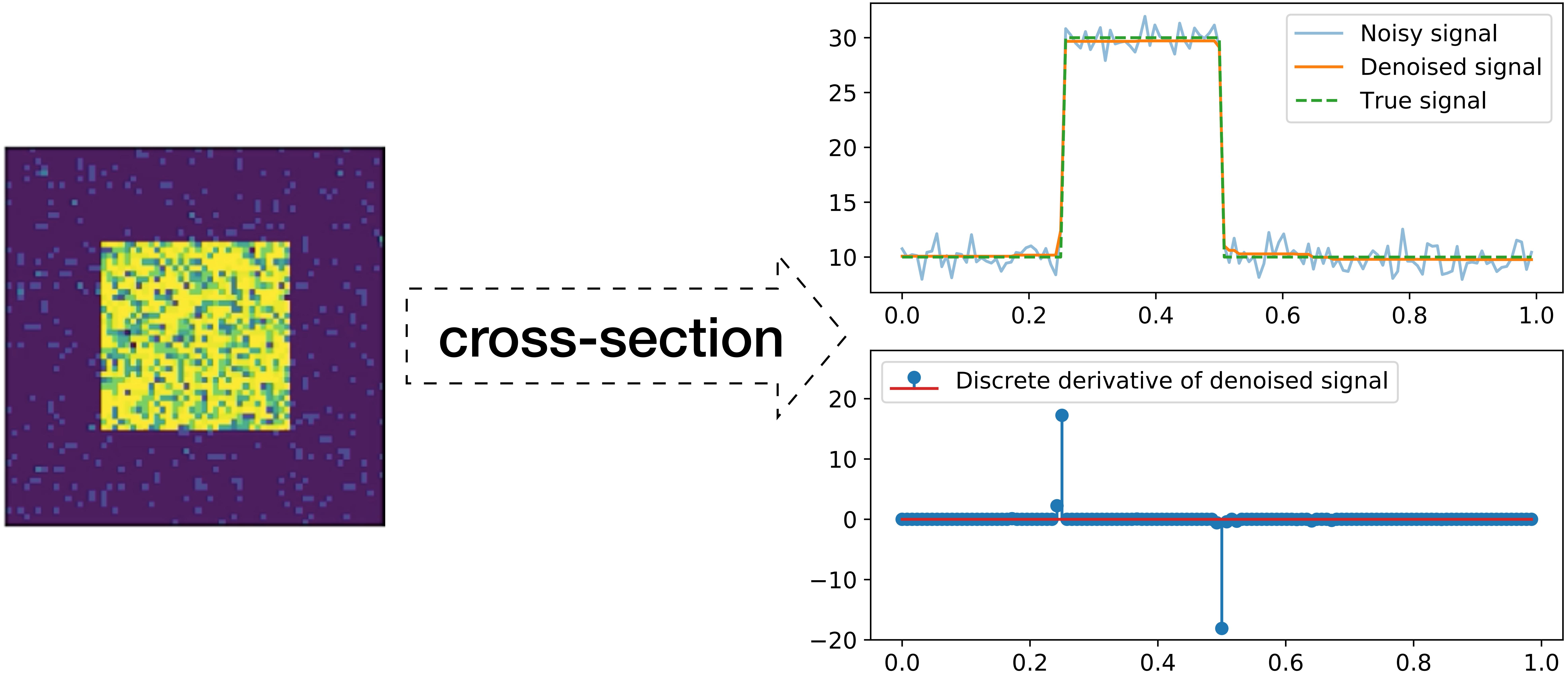
- The raw level-0 digitizer counts
- Estimate parl. & perp. separately
- Model expected value of y
- Model noise statistical properties
- Promote structure / spatial + temporal correlation in image

Poisson total variation (PTV)

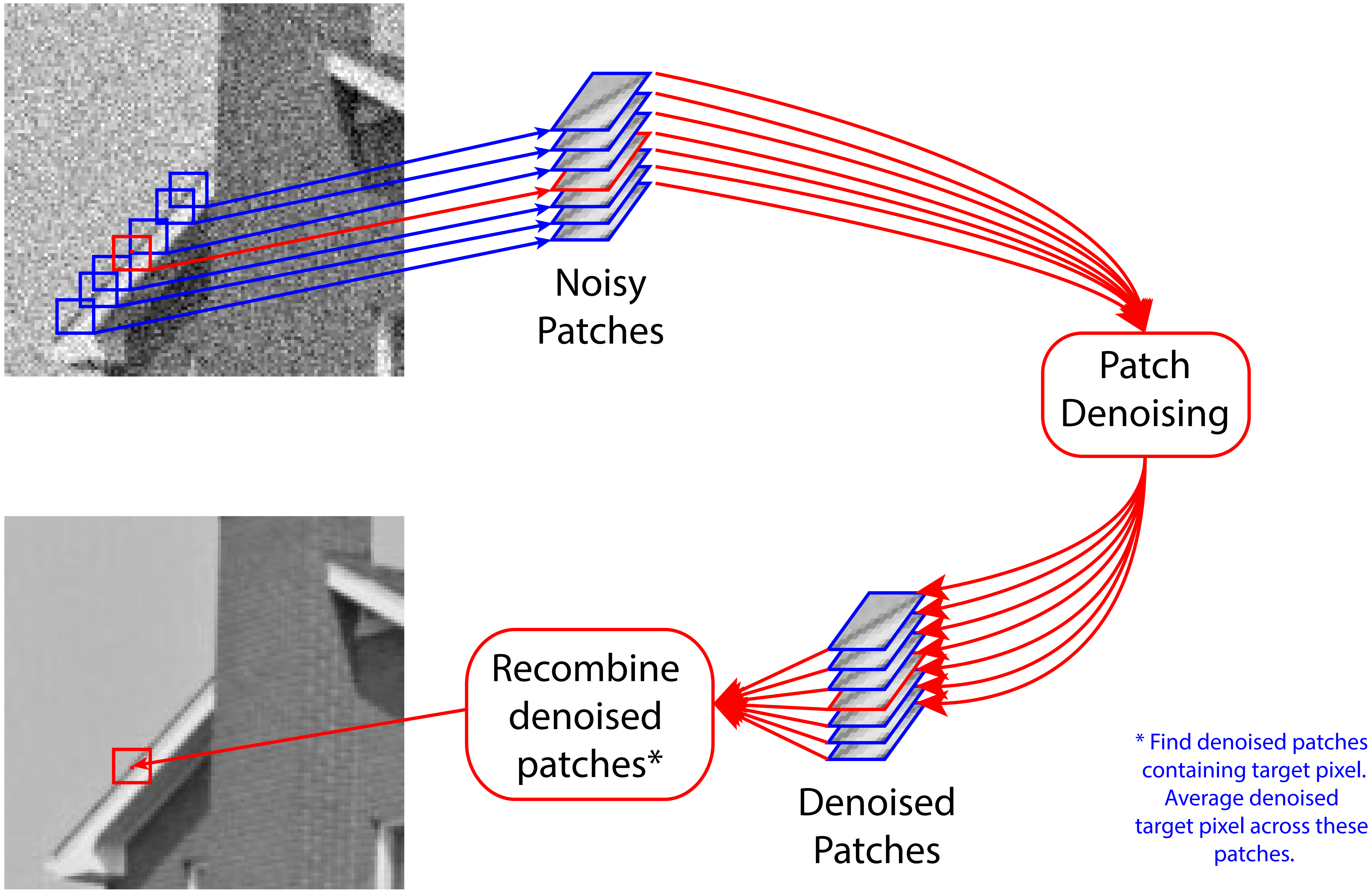
PTV approximates the image as piecewise constant



Willem J. Marais, et. al., "Approach to simultaneously denoise and invert backscatter and extinction from photon-limited atmospheric lidar observations" (2016)

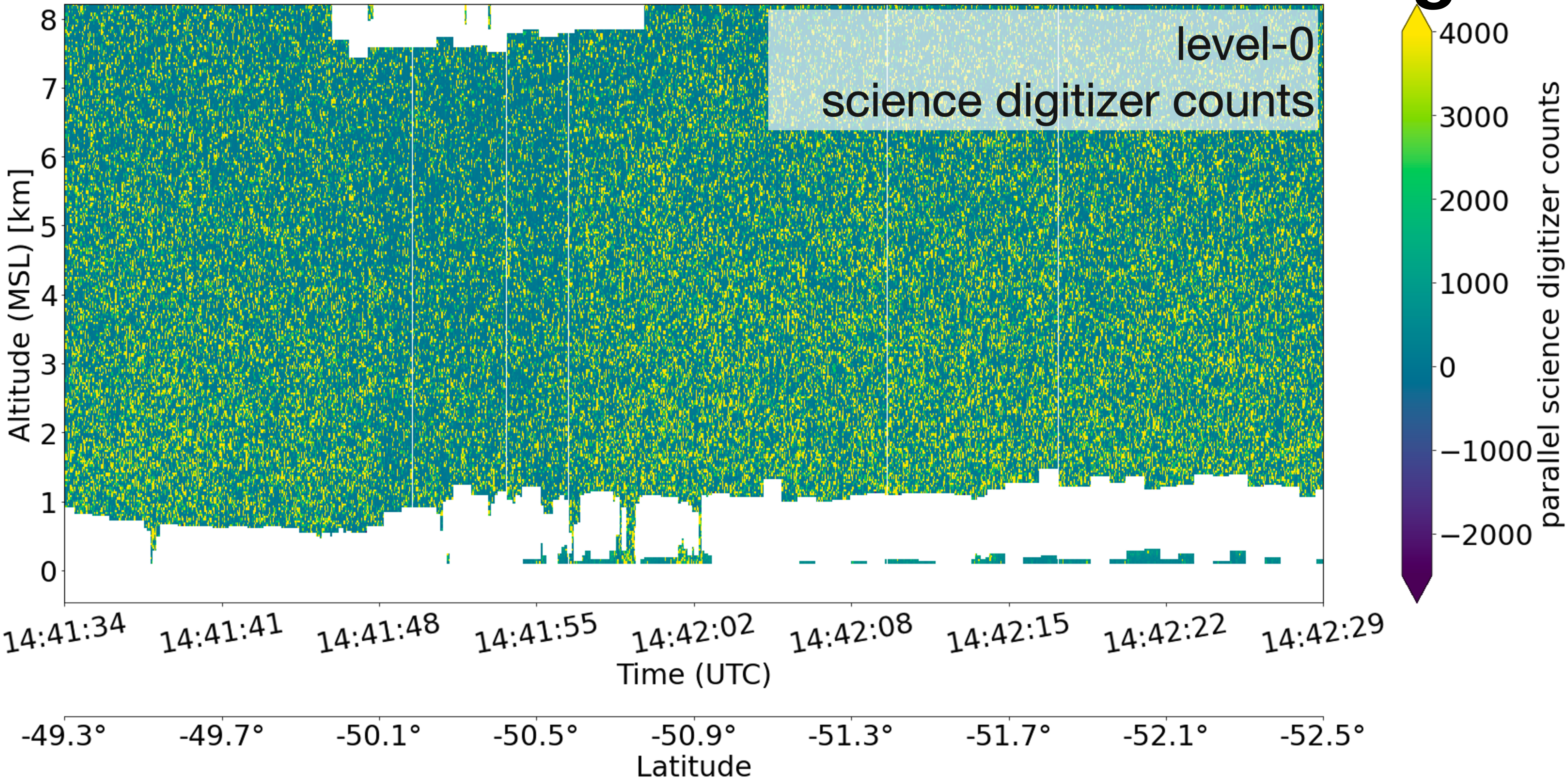
Patch based denoising

Exploit redundancy in image that allows for accurate approximation of a richer class of images



Marais, Willem, and Rebecca Willett. "Proximal-gradient methods for Poisson image reconstruction with bm3d-based regularization." In 2017 IEEE 7th International Workshop on Computational Advances in Multi-Sensor Adaptive Processing (CAMSAP), pp. 1-5. IEEE, 2017.

@ 2022 CALIPSO science team meeting



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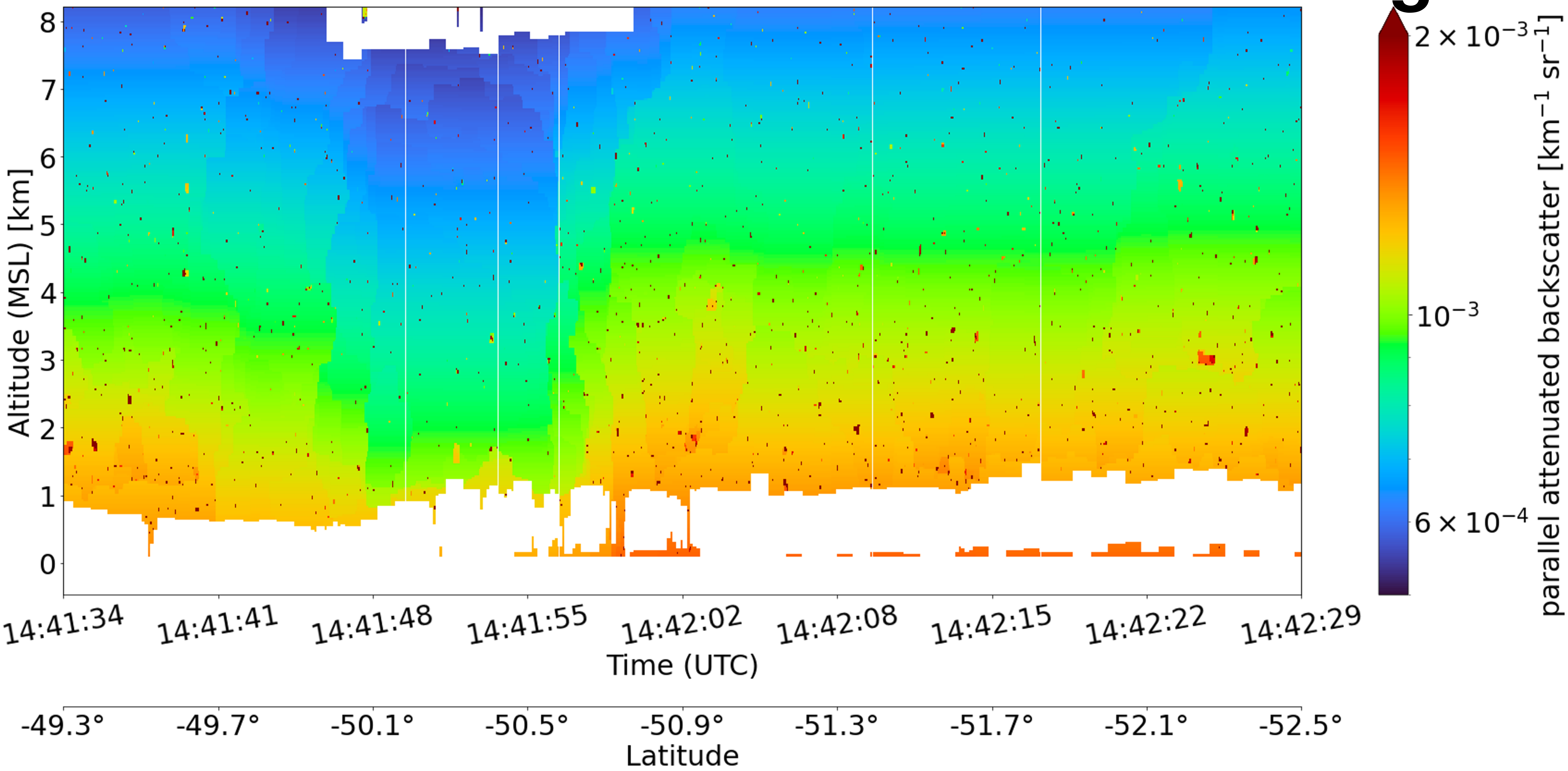


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Denoised total attenuated backscatter (Horizontal 1km, Vertical 60m)

HSRL2 total attenuated backscatter (Horizontal 1/3km, Vertical 30m)
2016-08-10 (nighttime)
Altitude (km)
0
2
4
6
8
38
39
40
41
Latitude [degree]
A - 37.29°
B - 40.37°
total attenuated backscatter [1/km 1/sr]
5e-3
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5e-4
1e-4

Profile A - 37.29°

Profile B - 40.37°

Backup slides

Cross-validation: Choosing the regularization parameter

Step 1: Holdout pixels

Complete CALIOP noisy image

Image <u>without</u> holdout pixels

Image <u>with</u> holdout pixels

Cross-validation: Choosing the regularization parameter

Step 2: Denoise and interpolate over holdout pixels

1) For regularization parameter λ denoise & interpolate

2) Choose estimate with regularization parameter λ which best fits holdout pixels

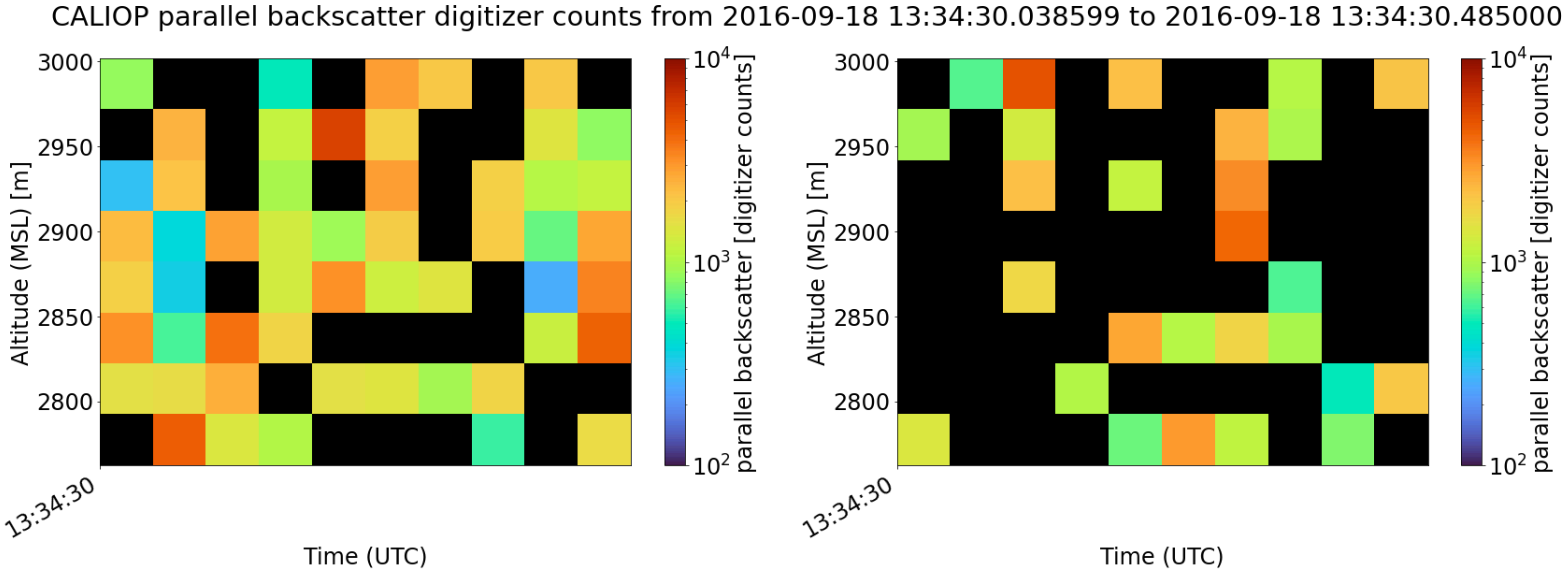


Image without holdout pixels

Image with holdout pixels

The three keys ideas

that OE shares with regularized maximum likelihood estimation

1) Noise model quantifies goodness of fit between $F(x)$ and y

2) Regularizer function that promotes a priori about x

$$\ell\,(y \mid F(x)) + \lambda p(x)$$

3) Regularization parameter sets the degree to which the a priori of x is promoted

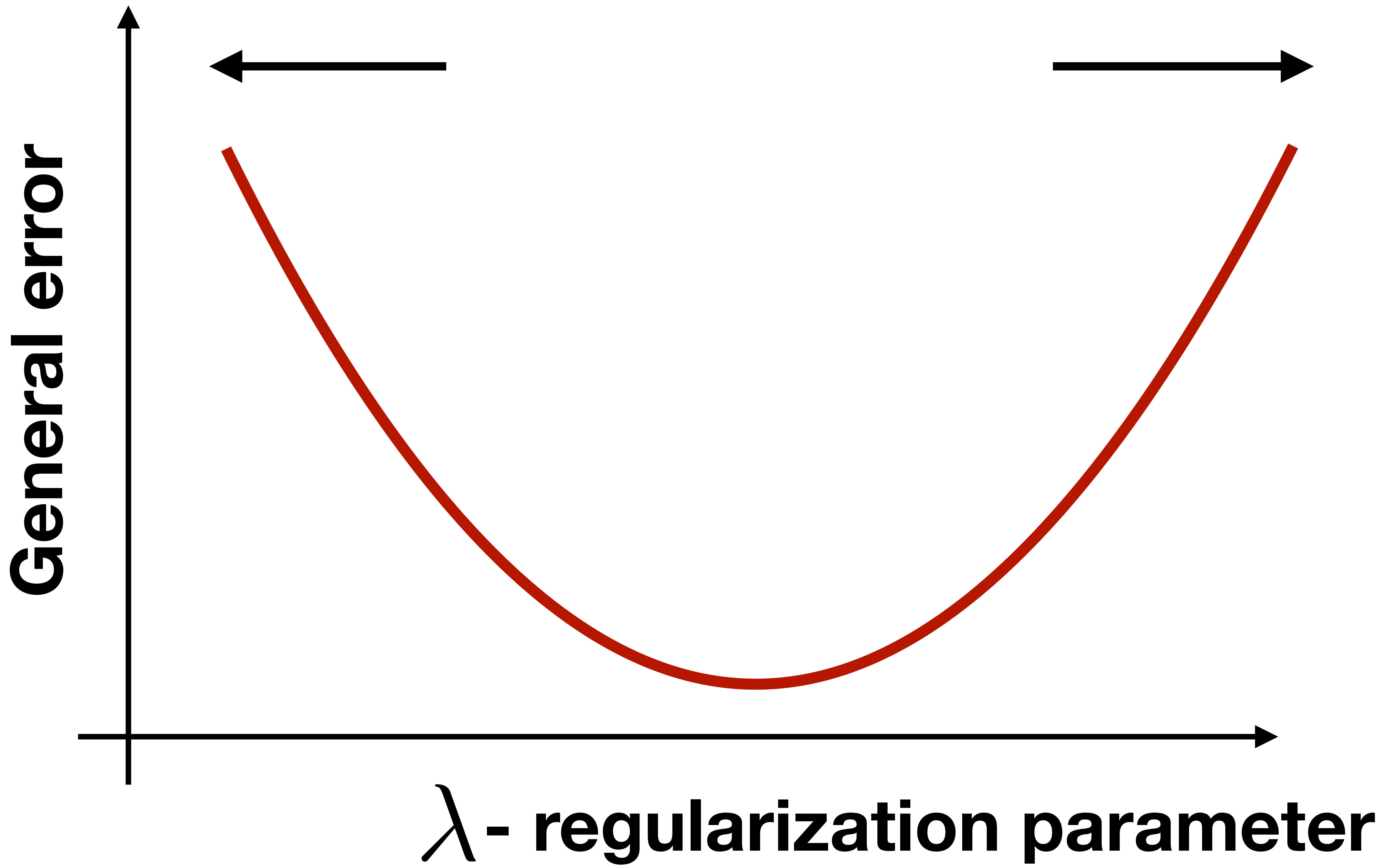
Error vs the regularization parameter

Intuition behind the regularization parameter

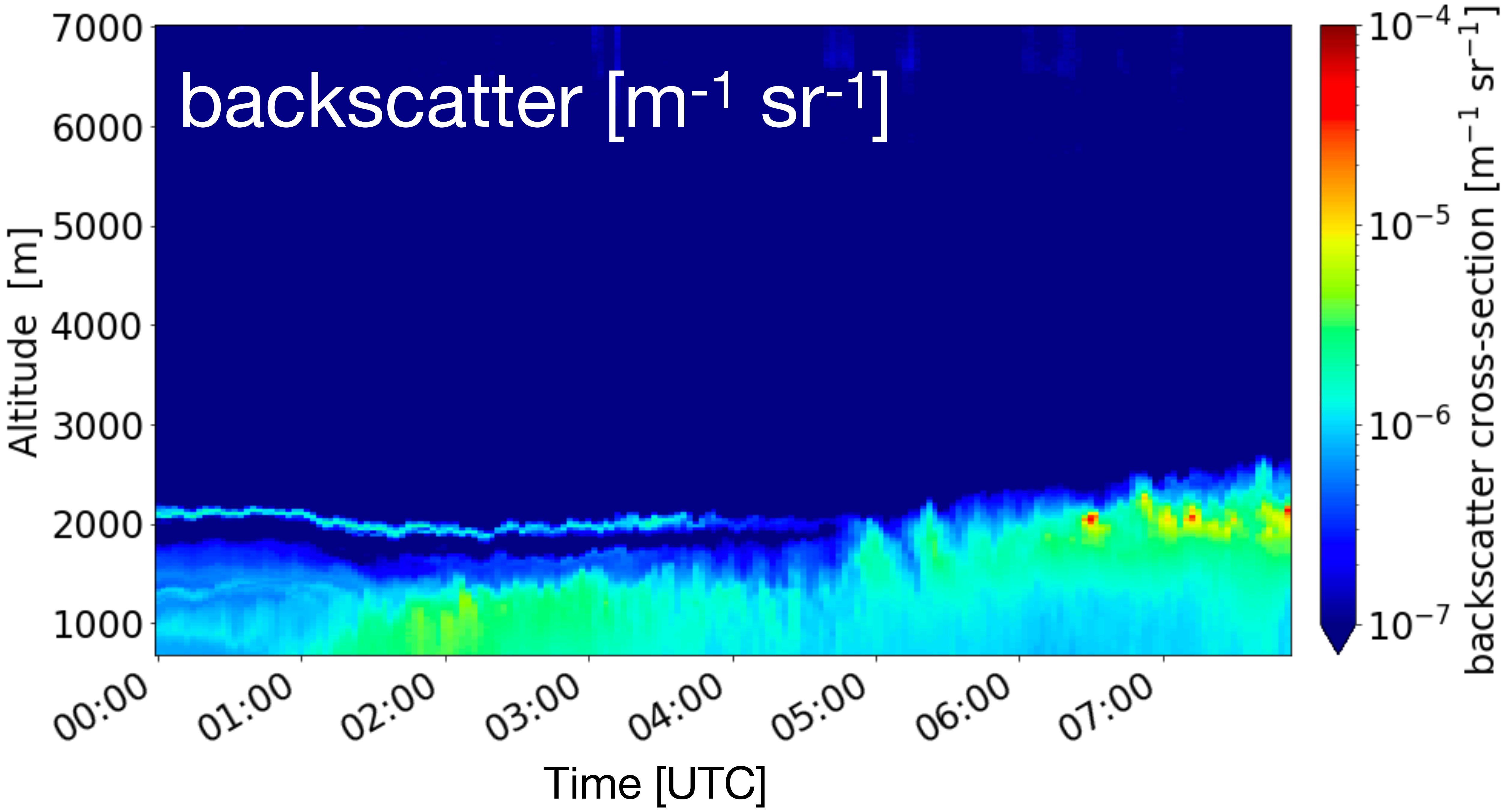
$\ell_g\left(y \mid F(x)\right)$

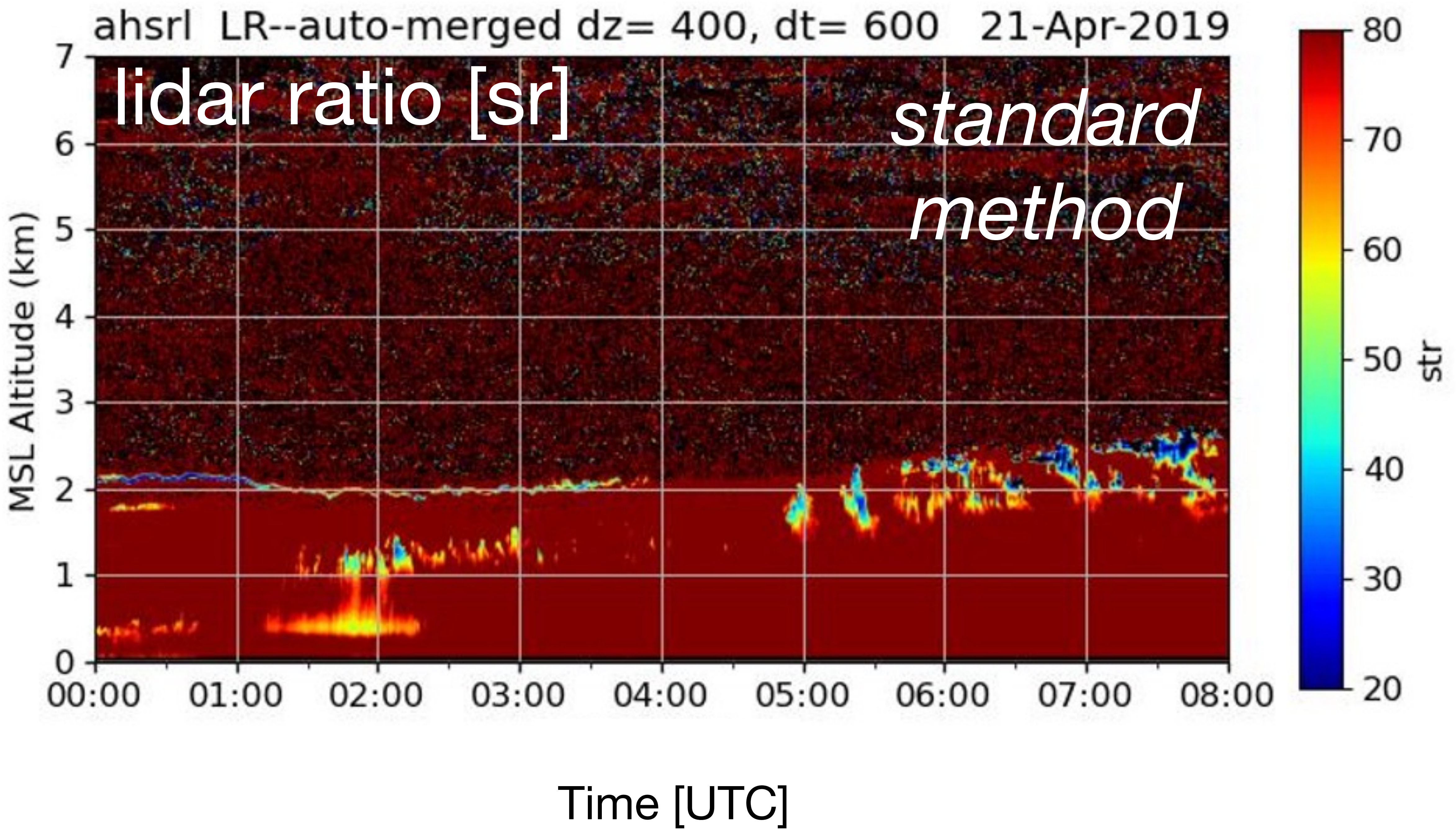
Low bias
High variance (e.g. residual noise)

High bias (e.g. smoothing) $\tilde{p}_g(x)$
Low variance



Denoising UW High Spectral Resolution Lidar data





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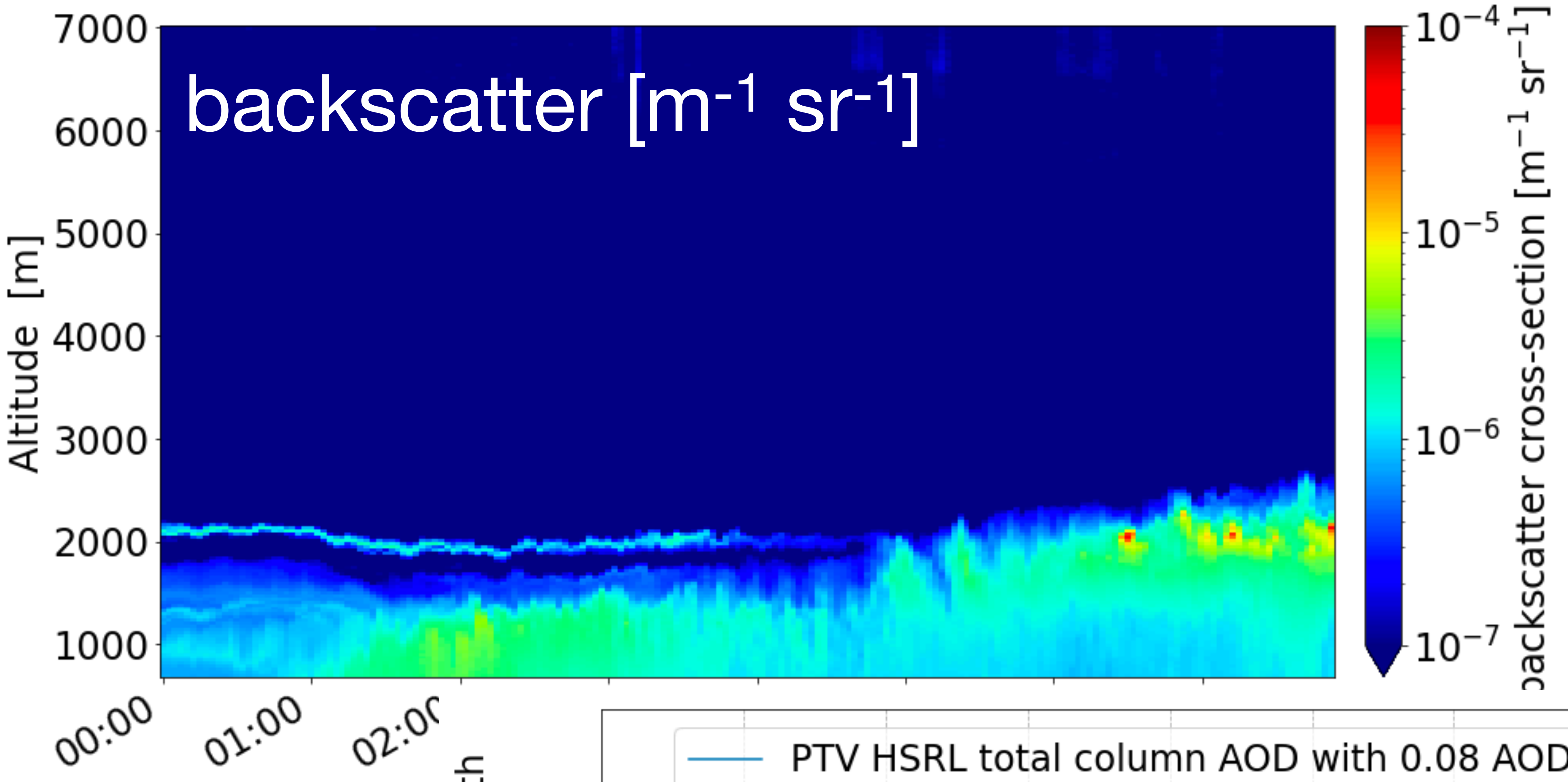

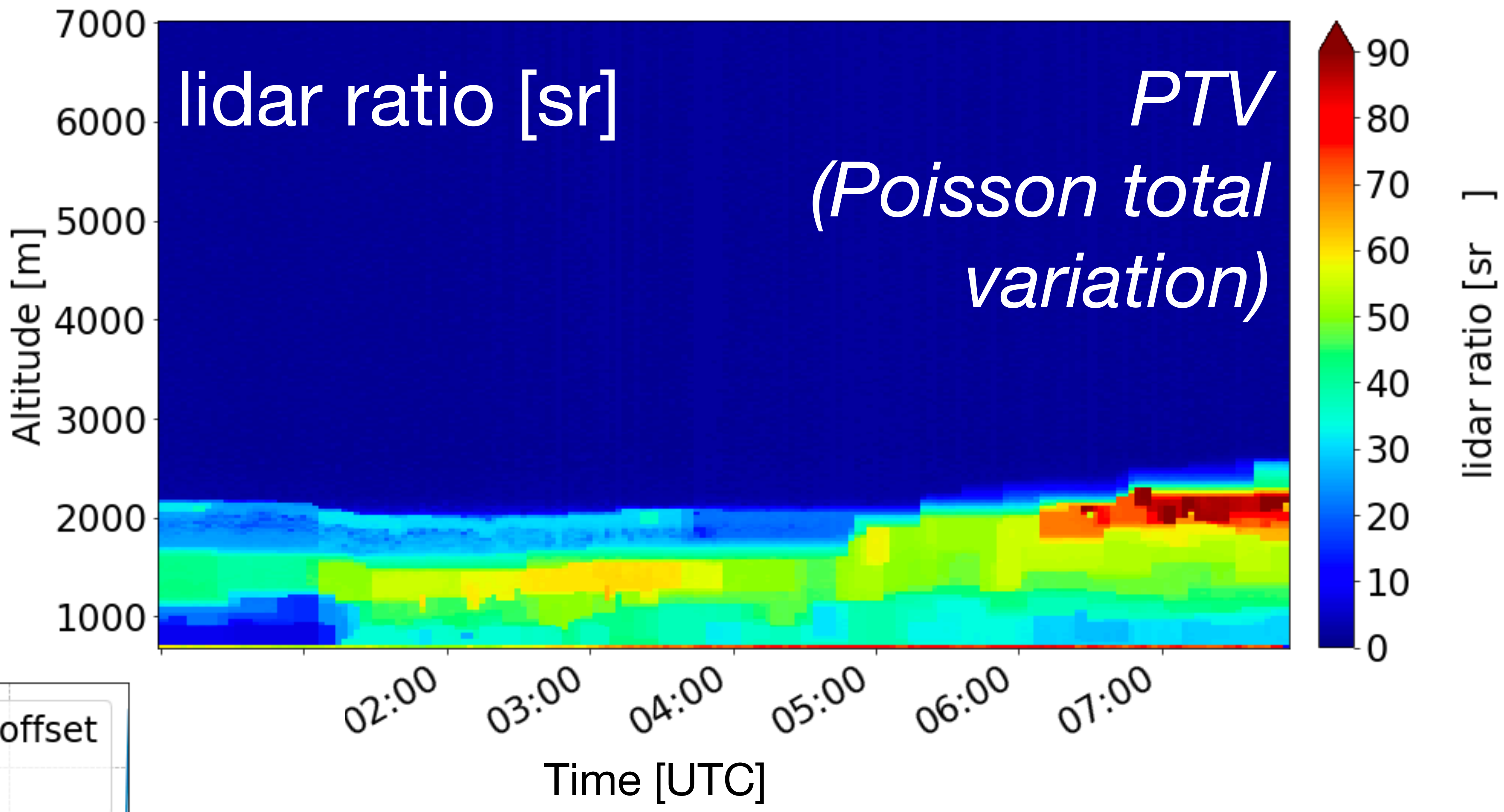

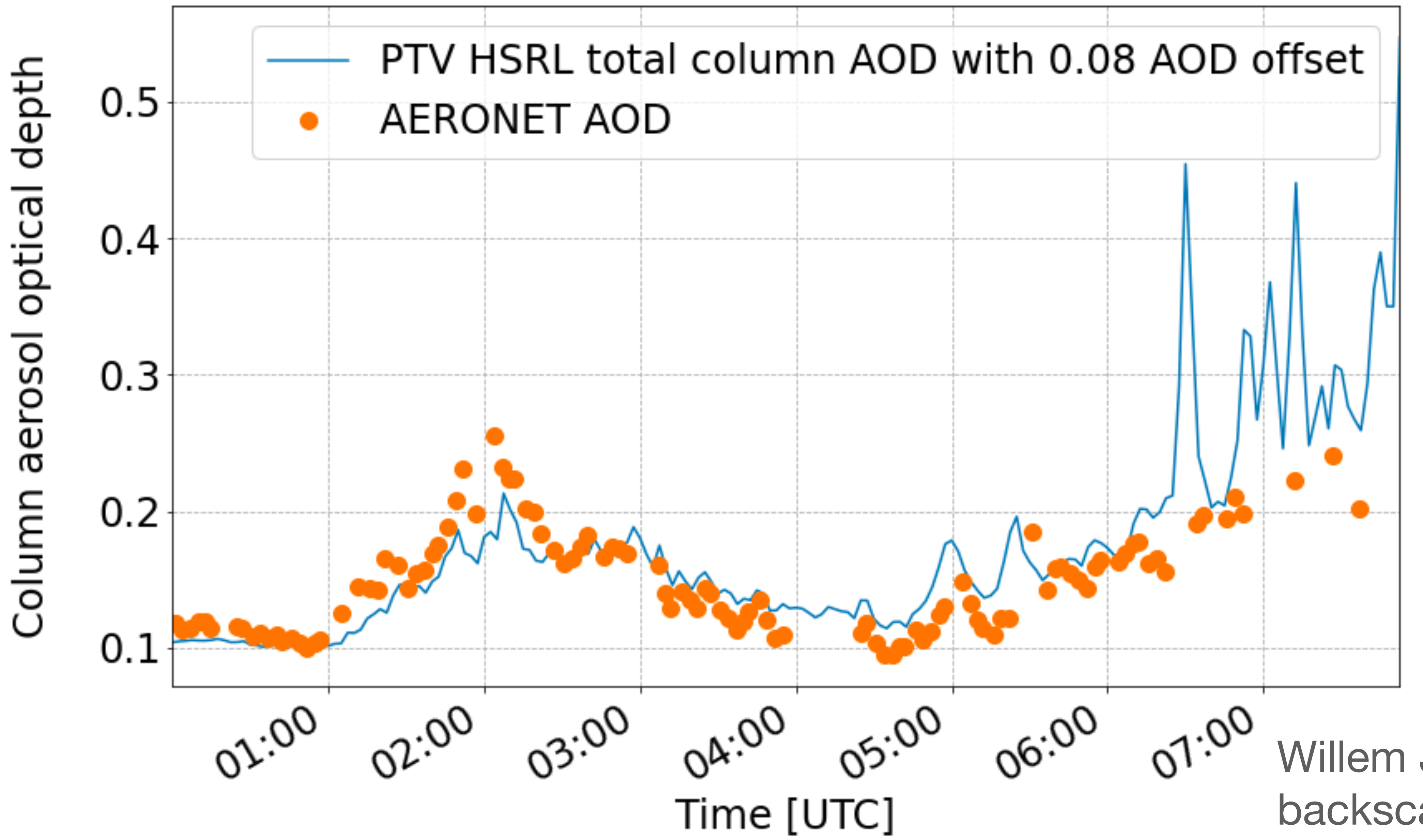

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Denoising NCAR Micro Pulse DIAL (MPD) data

Willem J. Marais, and Matthew Hayman. "Extending water vapor measurement capability of photon limited differential absorption lidars through simultaneous denoising and inversion." Atmospheric Measurement Techniques (2022)