

A Monte-Carlo based approach for estimating remote sensing reflectance uncertainty

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Objectives

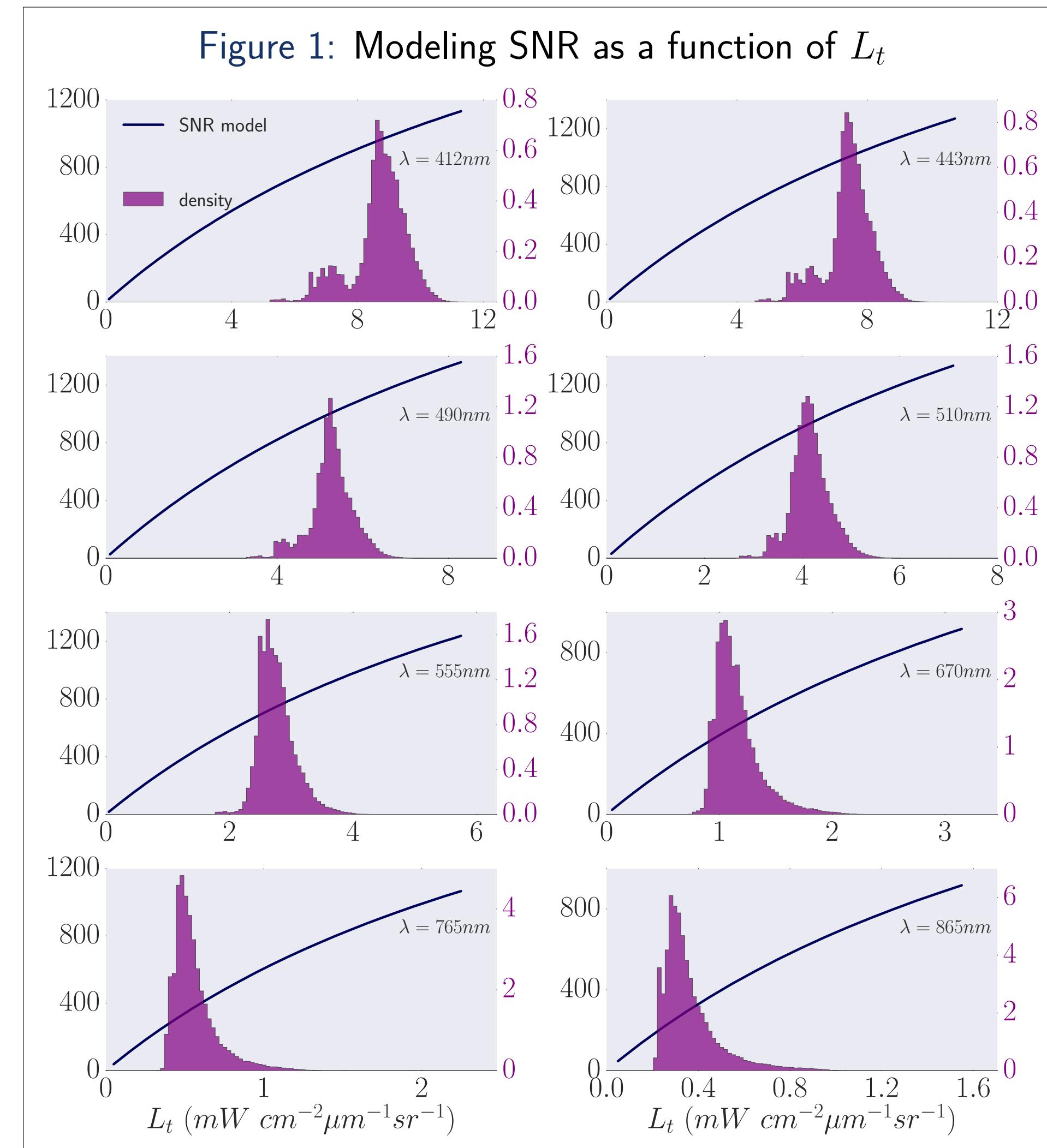
- Implement self-contained sensor-dependent (SeaWiFS showcased) noise model.
- Characterize noise propagation due to atmospheric correction.
- Characterize impact of noise in near-infrared bands
- Generate remote sensing reflectance uncertainty product.

Introduction

- Satellite borne ocean color remote sensors measure **top-of-the-atmosphere radiance** (L_t)
- L_t is used to derive **remote sensing reflectance** (Rrs), from which other properties of interest are obtained.
- Typical uncertainty estimation done using potentially problematic comparisons with in-situ data or other remote sensing missions[1, 2, 3].
- Consequently a product characterizing Rrs uncertainty has remained illusive.

Approach

- All data shown is from the SeaWiFS sensor.
- Signal to noise Ration (SNR) is modeled (Fig.1) as a function of measured L_t
- Spread in noise distribution is given by $\sigma = \frac{L_t}{SNR}$.
- A perturbed $L_{t,noise}$ is drawn from $\mathcal{N}(L_t, \sigma)$



Results

Perturbed	% change in Rrs					
$L_t (+0.1\%)$	412	443	490	510	555	670
Lt(412)	1.14	—	—	—	—	—
Lt(443)	0.22	0.97	0.21	0.22	0.22	0.53
Lt(490)	0.22	0.21	0.79	0.22	0.23	0.93
Lt(510)	0.97	0.62	0.41	1.0	0.35	0.84
Lt(555)	0.23	0.22	0.23	0.24	1.6	1.2
Lt(670)	0.51	0.38	0.27	0.32	0.31	5.0
Lt(765)	0.90	0.92	0.95	1.5	2.4	7.5
Lt(865)	0.66	0.65	0.65	1.0	1.5	4.3

Table 1: Average Rrs response to single-band one-time perturbation. Note that for $\lambda > 412$ there Predictably, the main diagonal shows larger responses in each row, reflecting the band that was perturbed. However, some of the largest responses can be observed across all bands following perturbations of near-infrared bands ($L_t(765)$ and $L_t(865)$). These are instrumental in the atmospheric correction applied to obtained Rrs %endtable

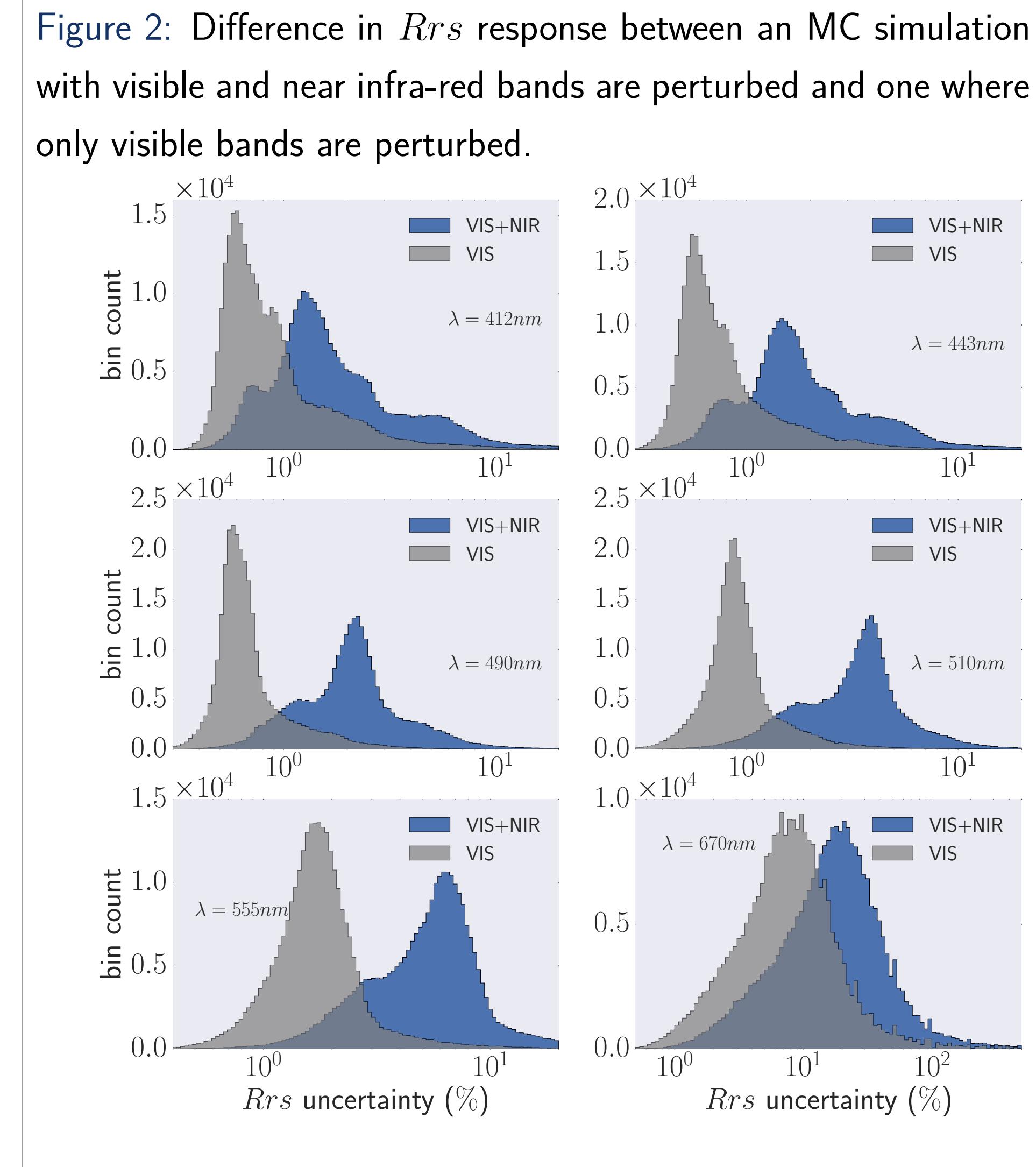
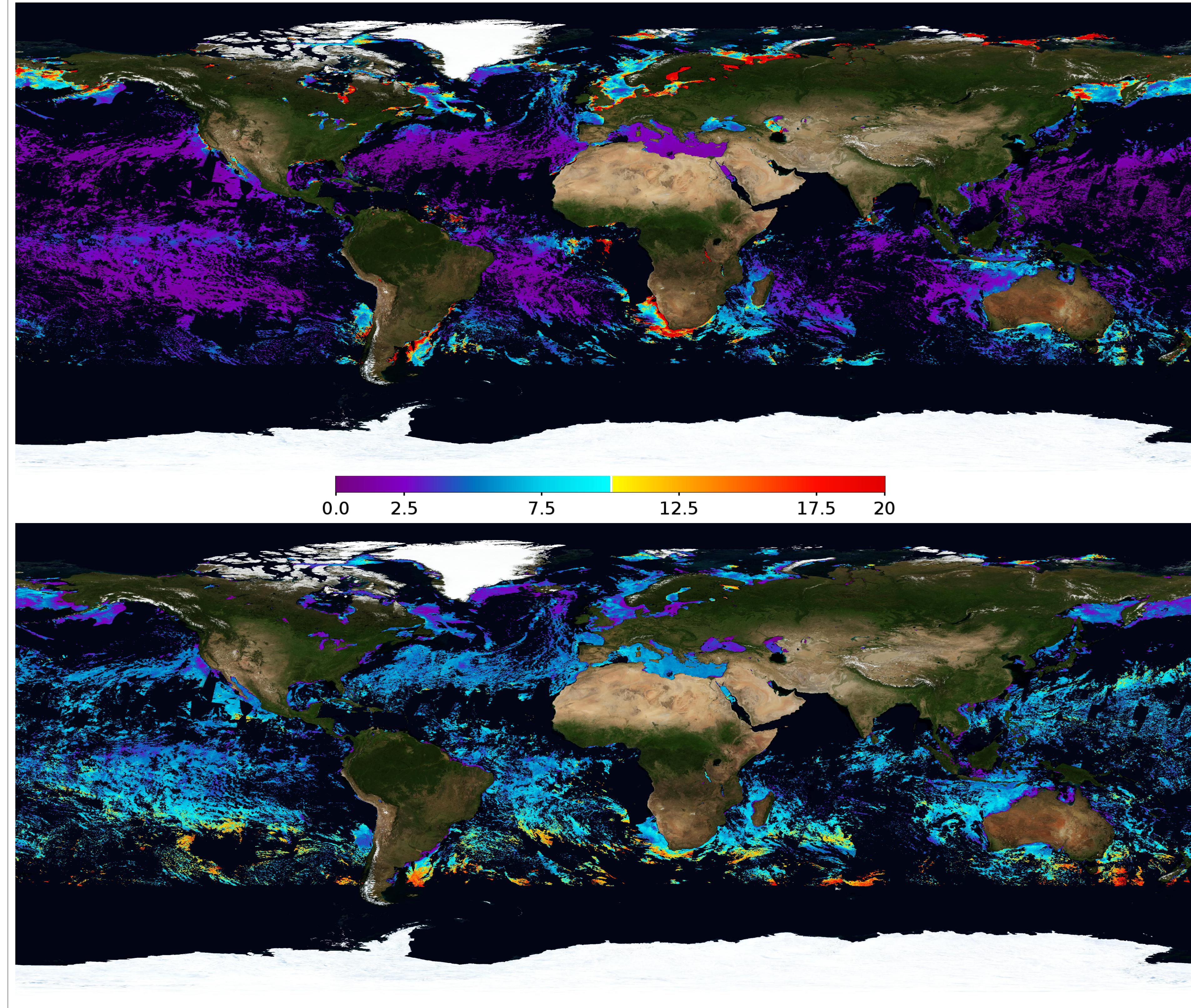


Figure 3: Rrs uncertainty calculated for a global scene – date-, resulting from a 1000-run MC simulation. Top panel: $Rrs(412)$ uncertainty. Bottom panel: $Rrs(555)$ uncertainty. Both images are on the same scale (cf. color bar). Areas of high radiance in the corresponding band (e.g. open ocean in the case of $Rrs(412)$) are more likely to result in lower uncertainty and vice versa.



Summary

- atmospheric correction contributes on average to

Next...

- Extend MC simulations to other sensors.
- MC simulations computationally costly;
 - Finding an alternative to build on this work, a priority
 - Develop machine learning (ML) approach (e.g. neural network);
 - Identify uncertainty drivers in MC as potential inputs to ML;
 - Use ML to shorten uncertainty product generation to one run.

References

- [1] S. Bailey and P. Werdell, “A multi-sensor approach for the on-orbit validation of ocean color satellite data products,” *Remote Sensing of Environment*, vol. 102, no. 1-2, pp. 12–23, 2006.
- [2] D. Toole, D. Siegel, D. Menzies, M. Neumann, and R. Smith, “Remote-sensing reflectance determinations in the coastal ocean environment: impact of instrumental characteristics and environmental variability,” *Applied Optics*, vol. 39, no. 3, pp. 456–469, 2000.
- [3] C. Hu, L. Feng, and Z. Lee, “Uncertainties of seawifs and modis remote sensing reflectance: Implications from clear water measurements,” *Remote Sensing of Environment*, vol. 133, pp. 168–182, 2013.
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