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.

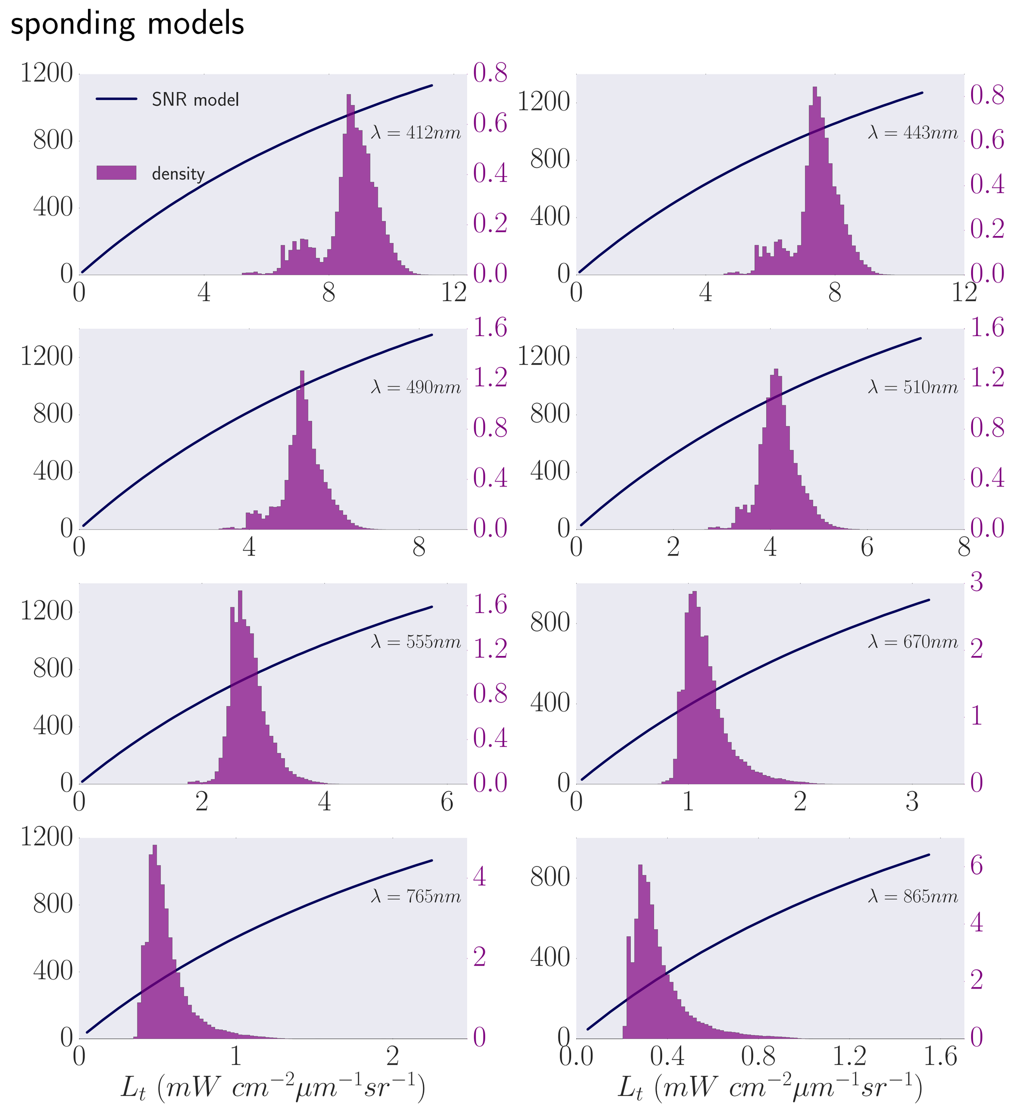
Introduction

- 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 mission.
- Generally, L_T is perturbed, resulting Rrs noise quantifies noise propagation.
- Using this characterization to estimate Rrs uncertainty is as follows.
- Signal-to-Noise-Ratio (SNR) modeled (Figure.1) as a function of measured L_T[4].
- Noise distribution spread: $\sigma = \frac{L_T}{SNR}$.
- Draw random $L_{T,noise}$ from $\mathcal{N}(L_T, \sigma)$.
- Monte-Carlo (MC) simulation: repeat the above to converge to Rrs uncertainty.
- Run experiments in variety of conditions; use select bands, different geographical areas, etc.

Figure 1: Modeling SNR as a function of L_T. Purple histogram illustrates relationship between data from eight SeaWiFS bands and corresponding models



Results

Perturbed	% change in Rrs					
Lt (+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 (not MC simulation) perturbation. Only perturbation at λ=412 does not result in Rrs uncertainty in the rest of the spectrum. 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-infra red bands, $L_T(765)$ and $L_T(865)$, that are instrumental in the atmospheric correction applied to obtained Rrs.

Figure 2: Difference in Rrs response between an MC simulation with visible and near infra-red bands are perturbed and one where only visible bands are perturbed.

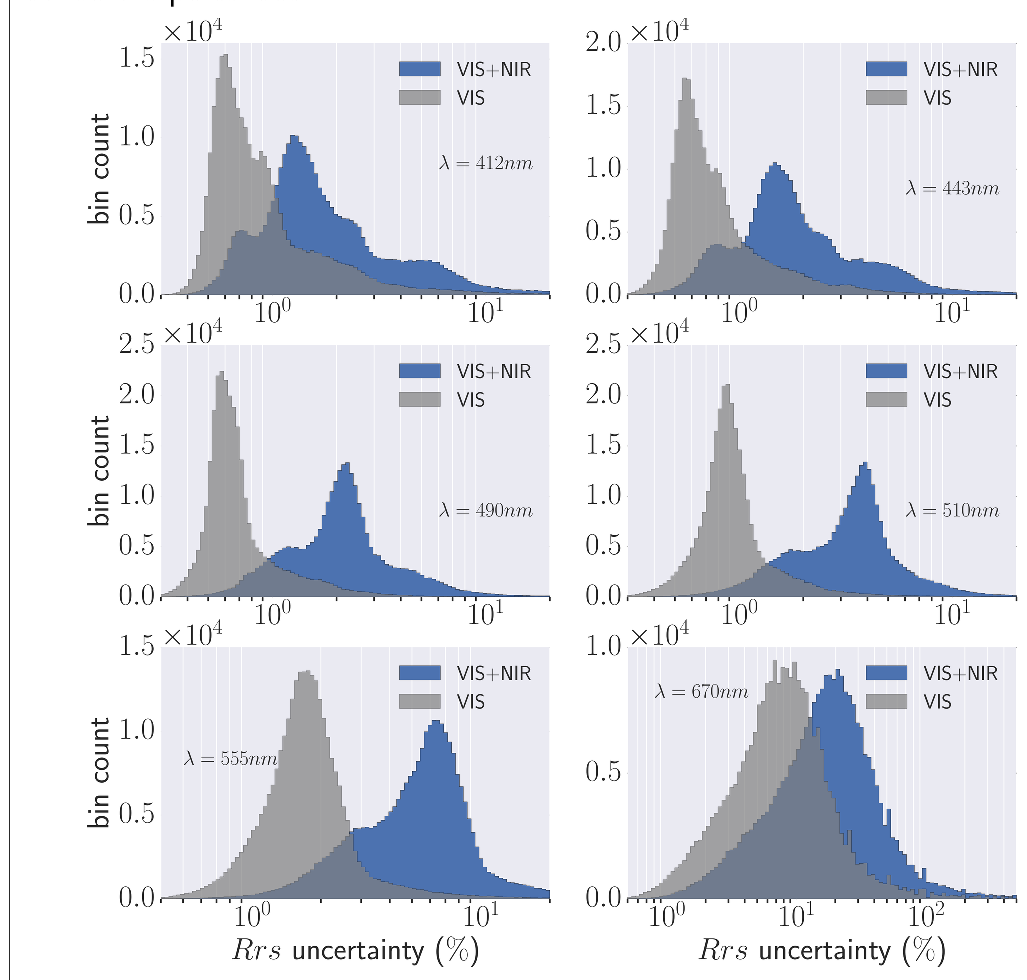
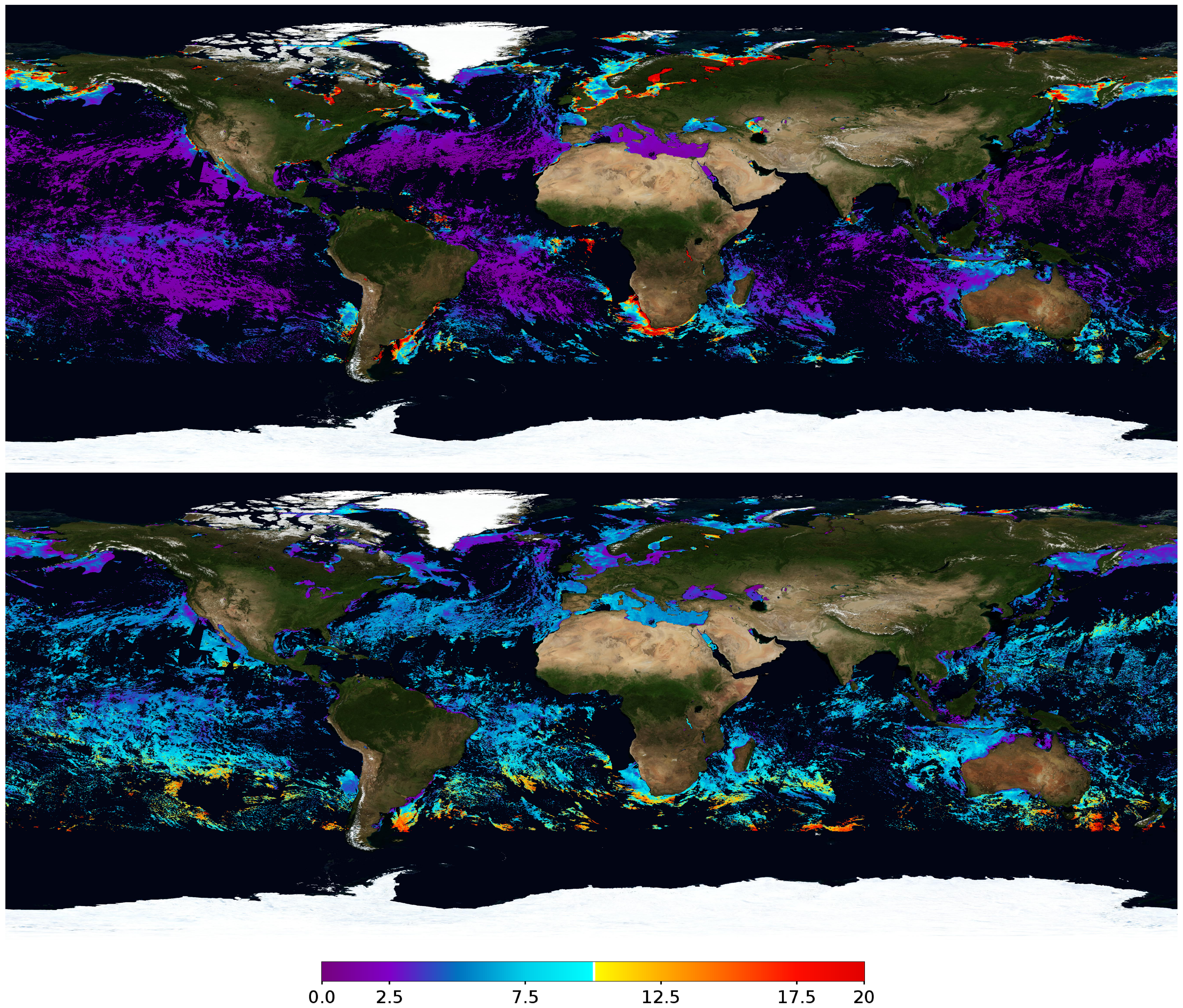


Figure 3: **Rrs % uncertainty** calculated for a global scene – date–, resulting from a 1000-run MC simulation. Top panel: $Rrs(412 - blue)$ uncertainty. Bottom panel: $Rrs(555 - yellow/green)$ uncertainty. Both images are on the same scale (*cf.* color bar). Areas of high radiance in the corresponding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



Summary

- L_T noise amplifies $10\times - 70\times$ as it is propagated to Rrs.
- Noise propagation is subject to cross-band contamination.
- NIR bands (atmospheric correction) contribute significantly noise amplification.
- MC simulation converges successfully to yield Rrs uncertainty.
- Rrs uncertainty for most of the world ocean hovers around 1-10%.
- Higher uncertainty found in complex coastal waters.

Next...

- Extend MC simulations to other sensors.
- Incorporate uncertainty in ancillary inputs (pressure, windspeed, humidity, ozone)
- MC simulations computationally costly;
  - Finding an alternative to build on this work is a priority.
  - One possible solution: 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

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