SQOOP (Spaceborne Quantification of Ocean micrO-Plastics)

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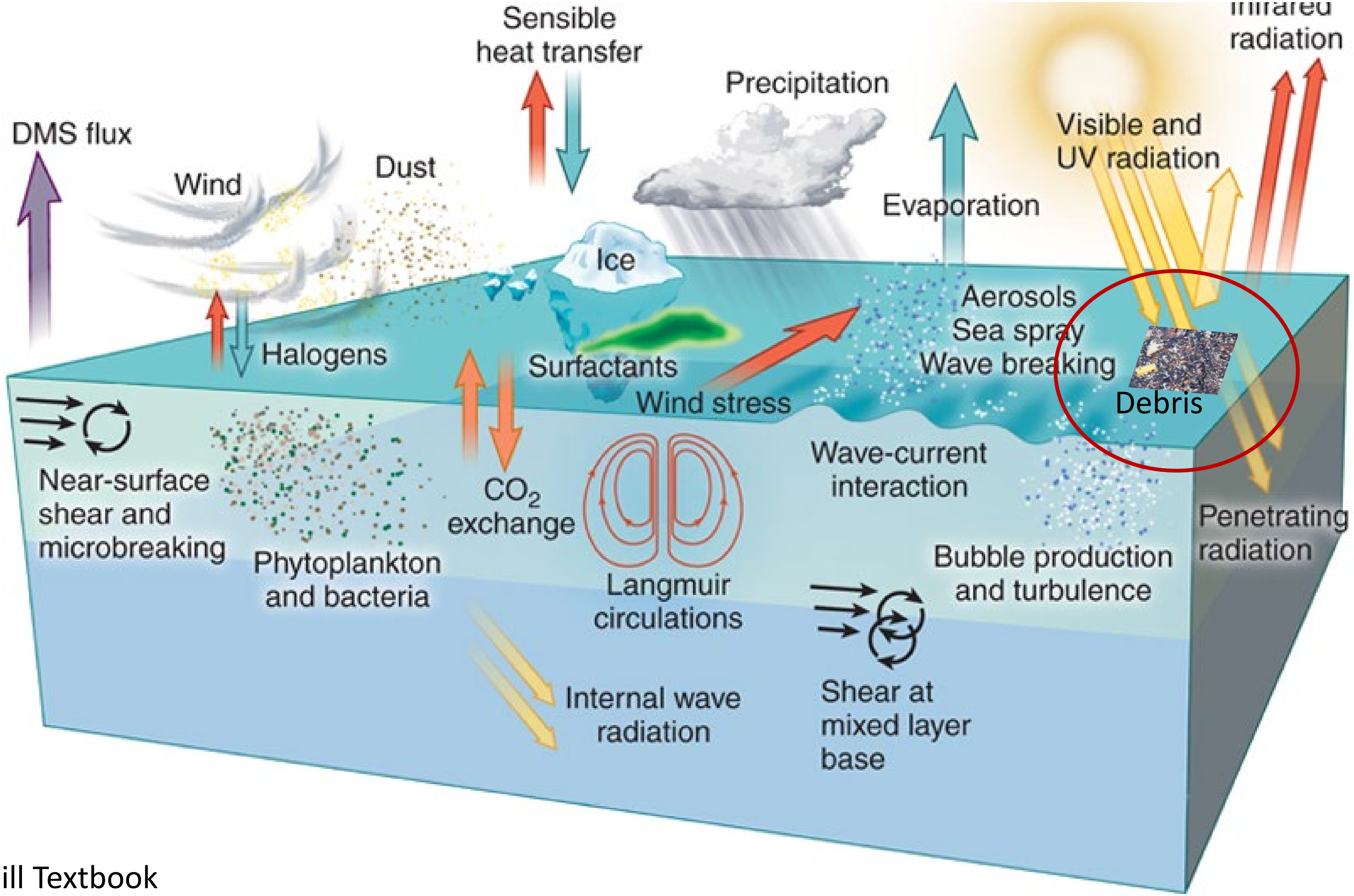
Photo: Oskar Landi

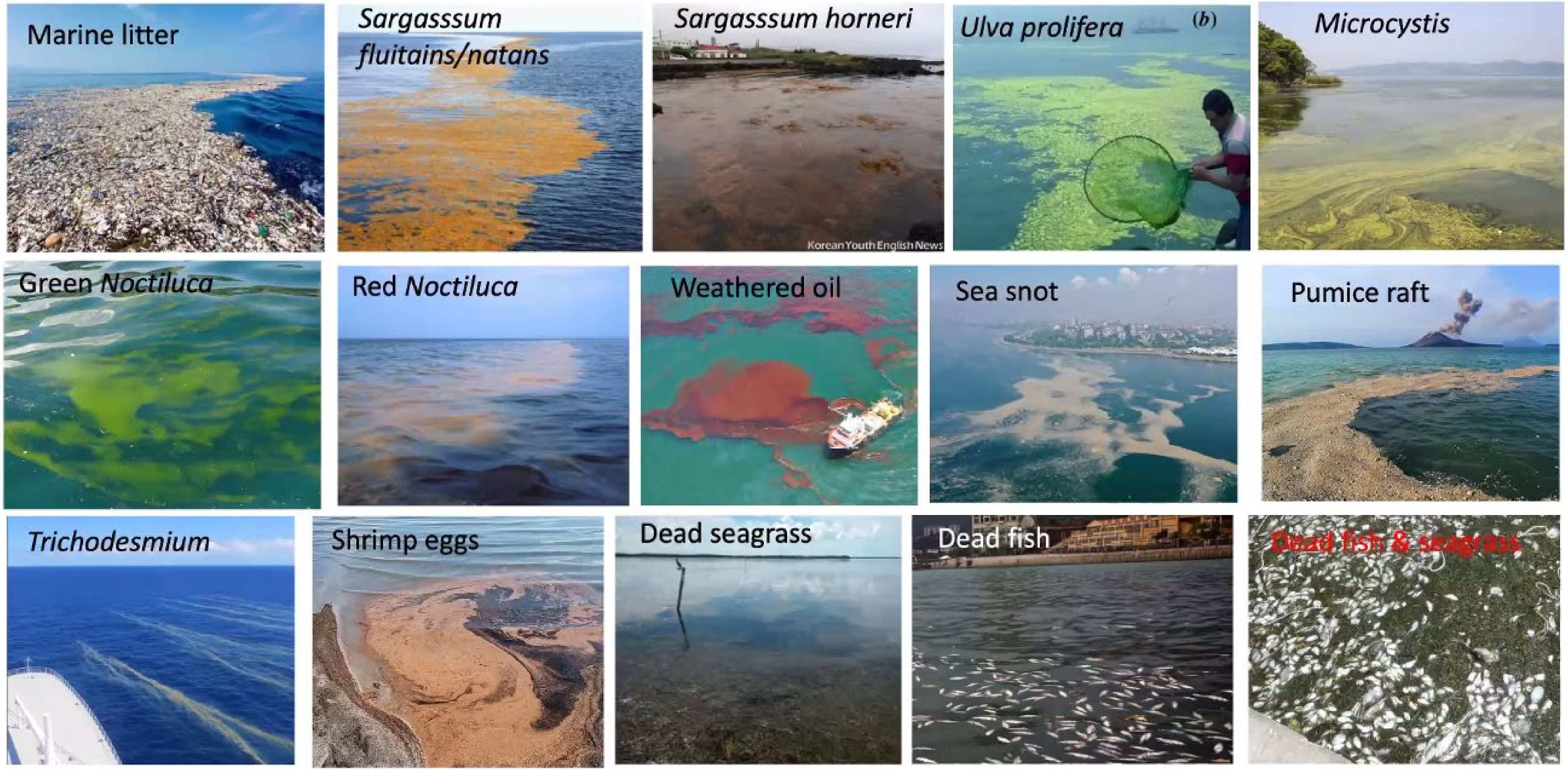
Many constituents influence the sea surface



How to detect Plastic Debris from sea spray, dust, foam, surfactants, glint?

McGraw Hill Textbook

Chuanmin Hu: Types of Floating Matter



Microplastics < 5mm

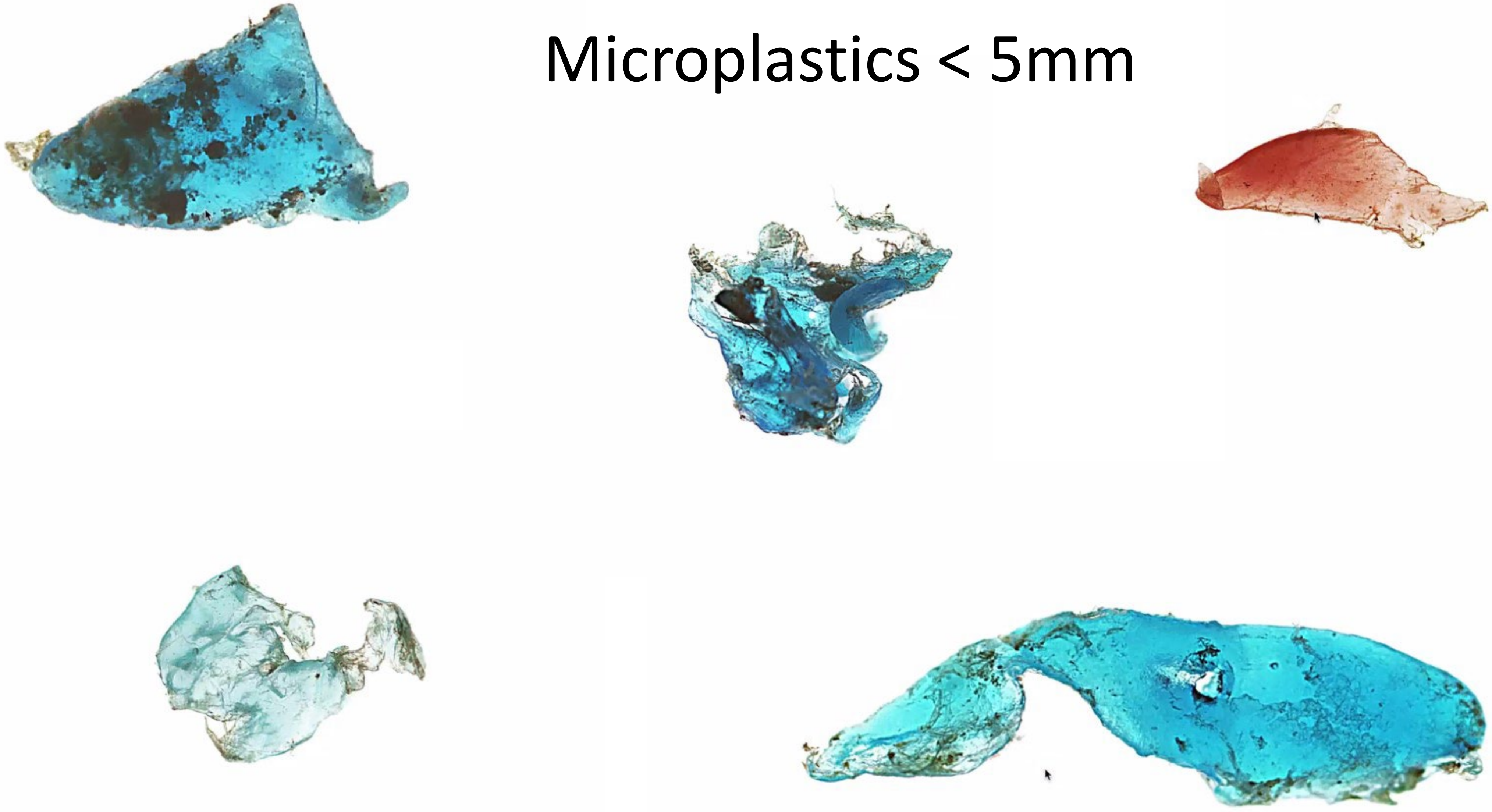
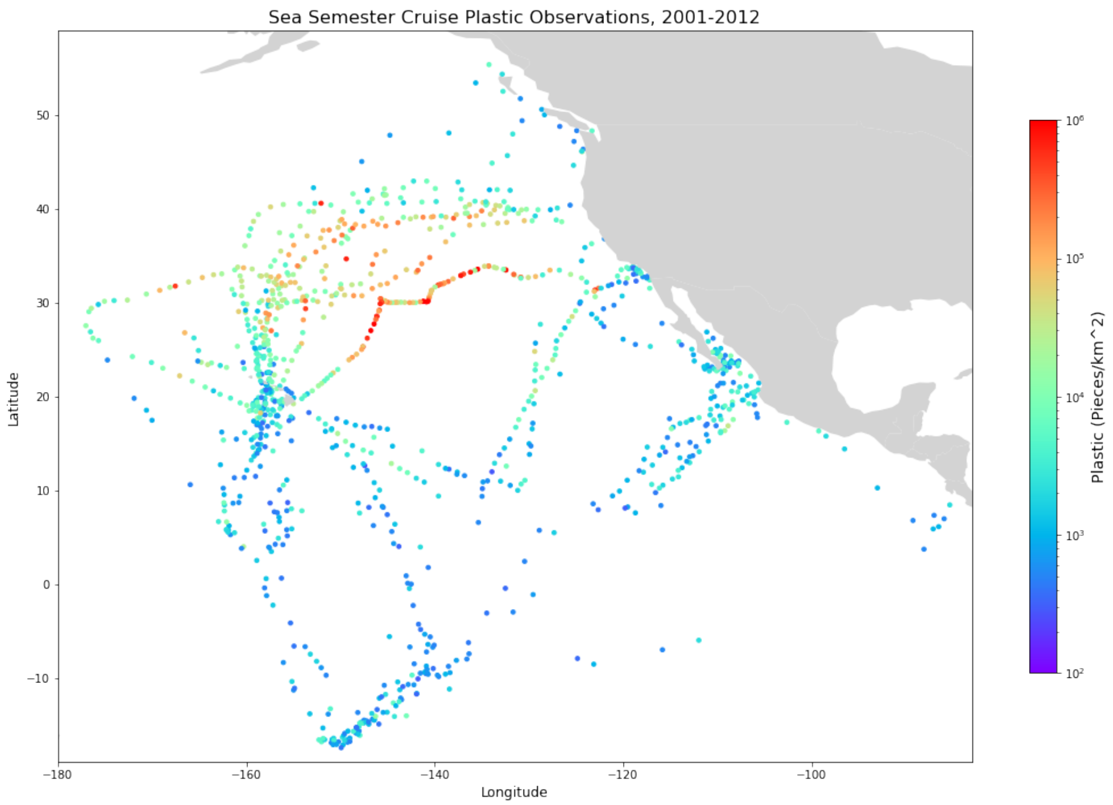


Photo Credit: Oskar Landi

Microplastics in the Great Pacific Garbage Patch

- **8% of the total mass** but
- **94% of the estimated 2 trillion floating pieces**
- up to **1,000,000 pieces km^{-2}**.

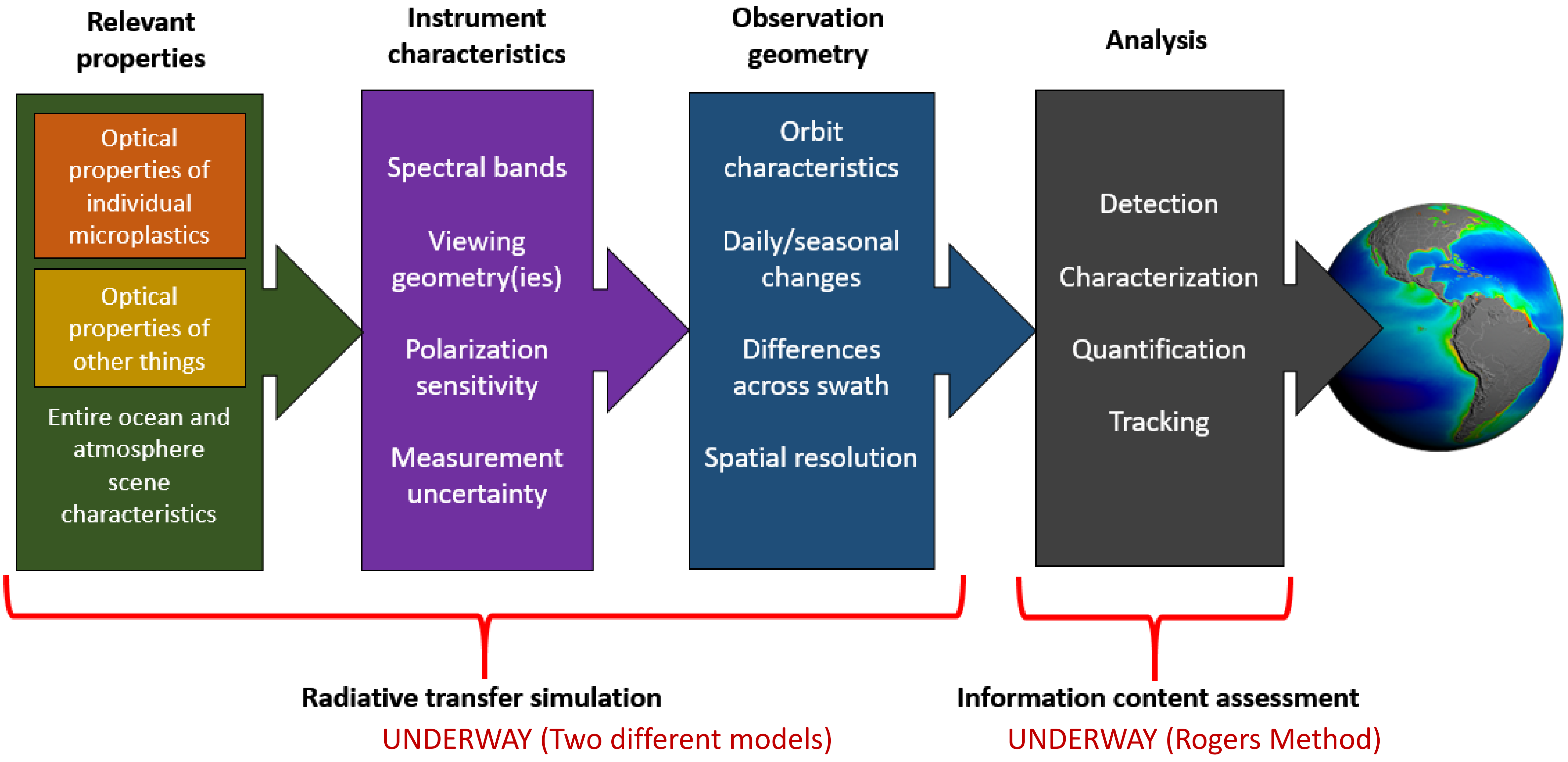


A QUEST…

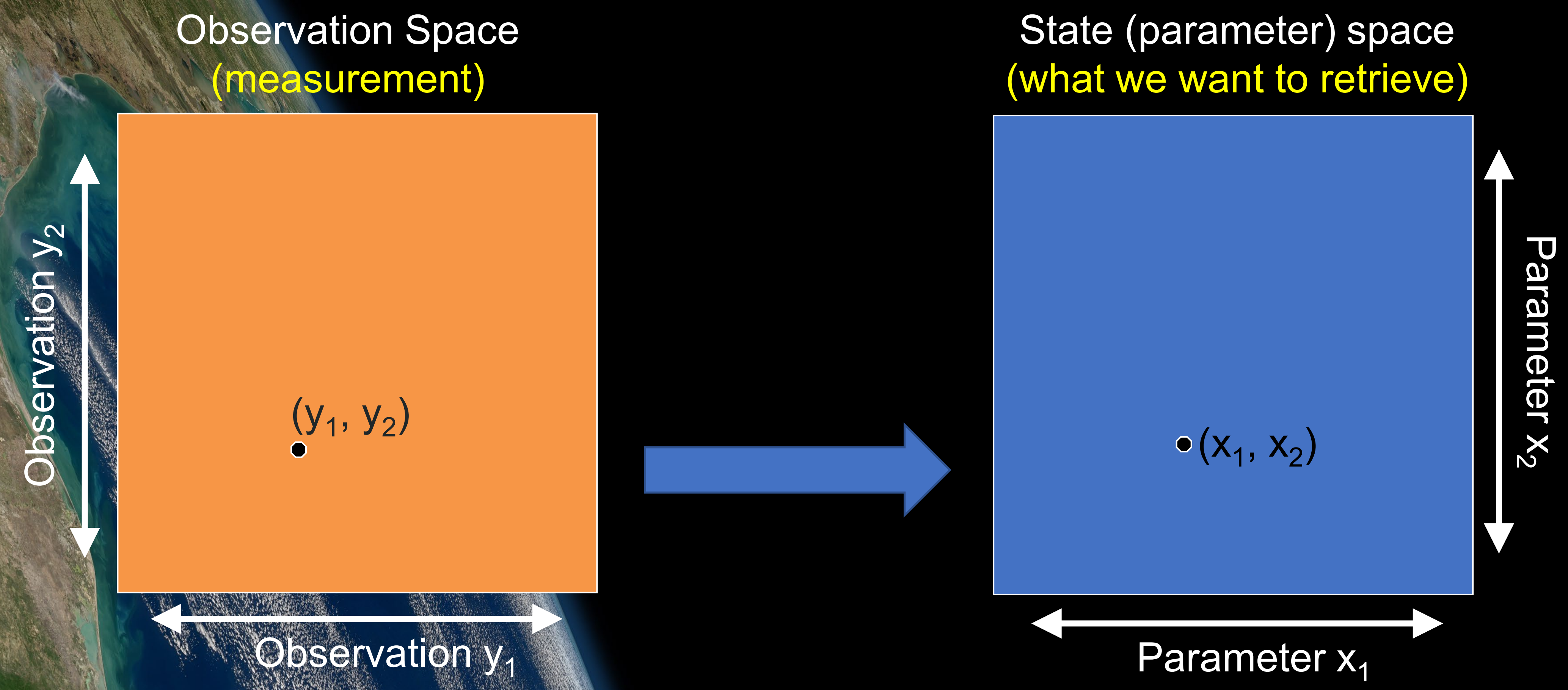
- *From a radiative transfer perspective, it is still unclear at* ***what concentrations surface floating microplastics will have a detectable influence*** *on sea spectral reflectance and the ocean refractive index.*

- a feasibility study of remote detection of surface microplastics:
  - different surface particle properties
  - uncertainties in atmospheric correction
  - with hyperspectral and polarimetric approaches

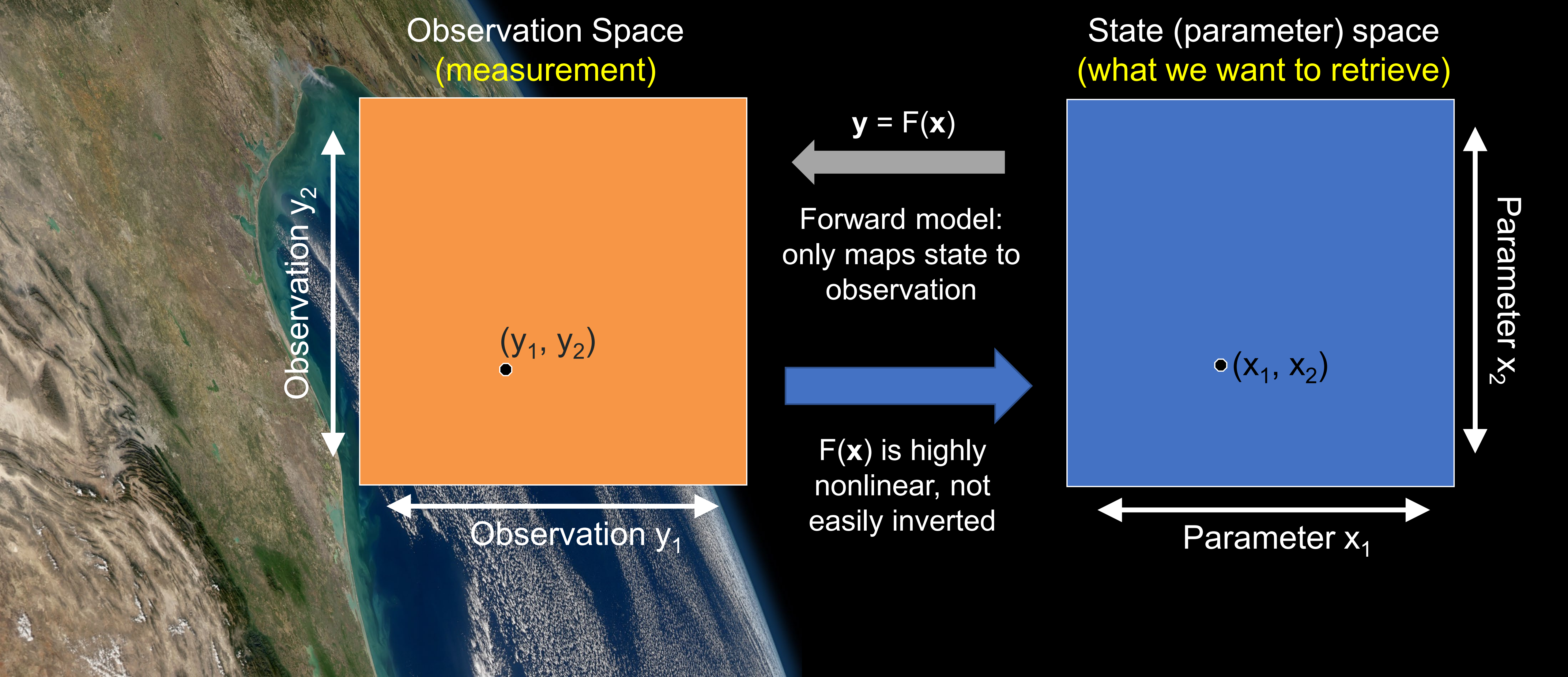
Components of a successful microplastic retrieval



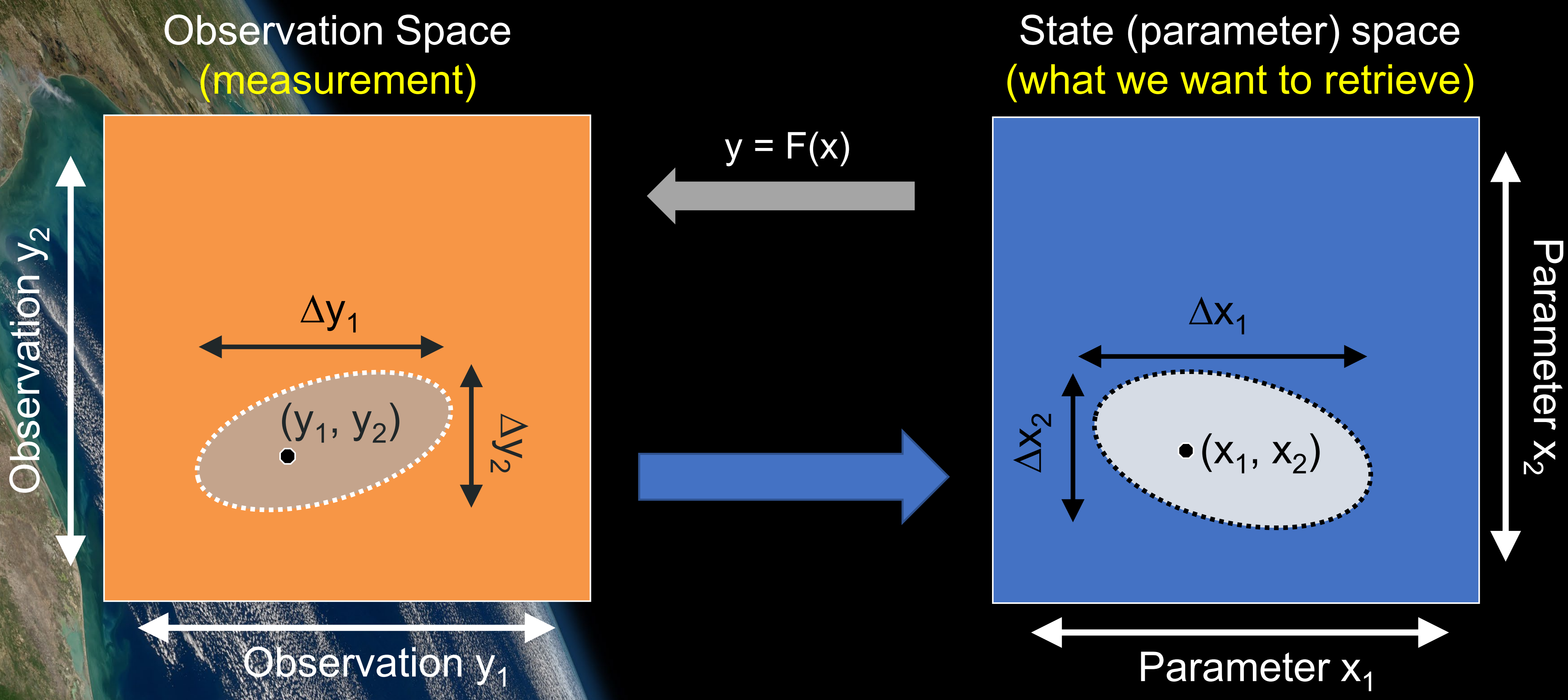
There is a connection between state (parameter) space and observation space



Forward model = radiative transfer simulation



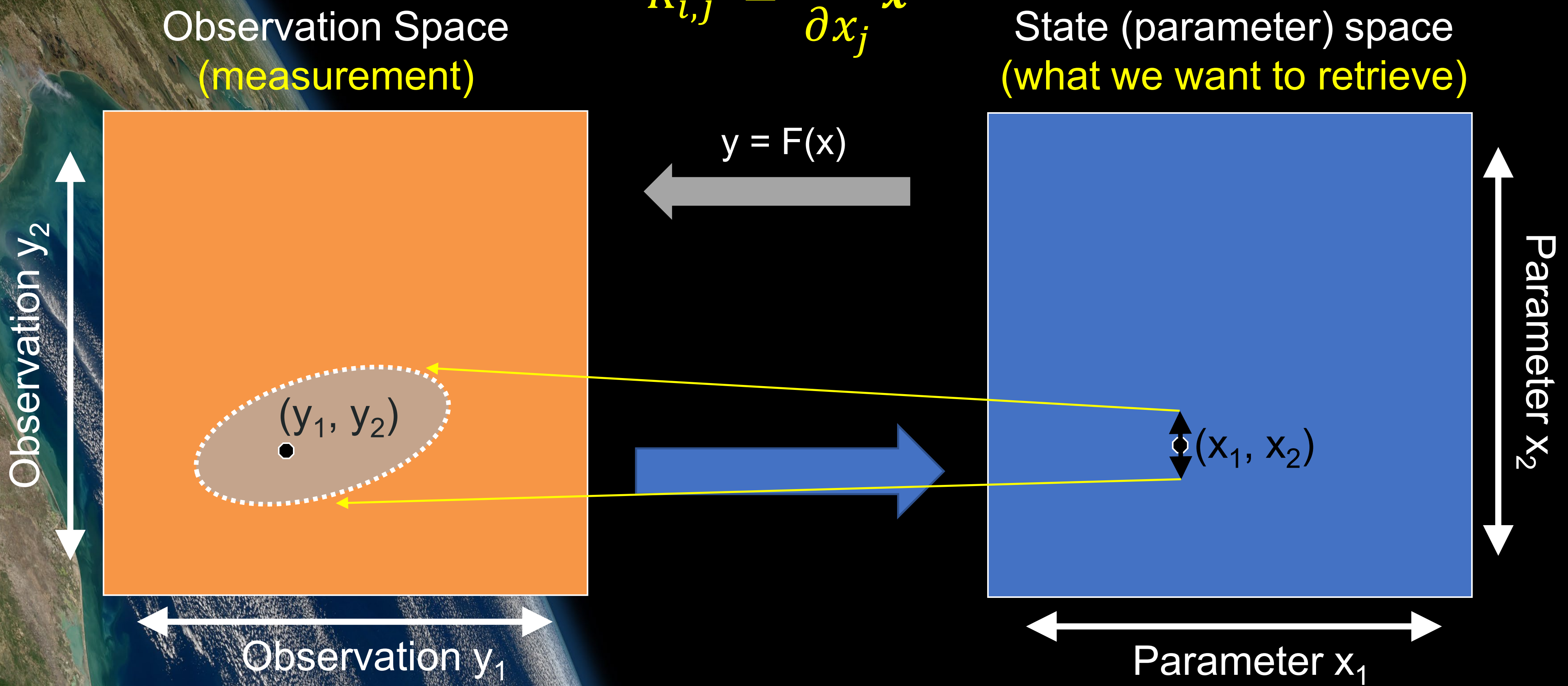
Volumes represent measurement, model uncertainty



We want to know how uncertainty in observation space maps to state space

Mapping uncertainty assessed with Jacobian matrix (K)– sensitivity of model to perturbation

$$K_{i,j} = \frac{\partial F_i}{\partial x_j}\boldsymbol{x}$$

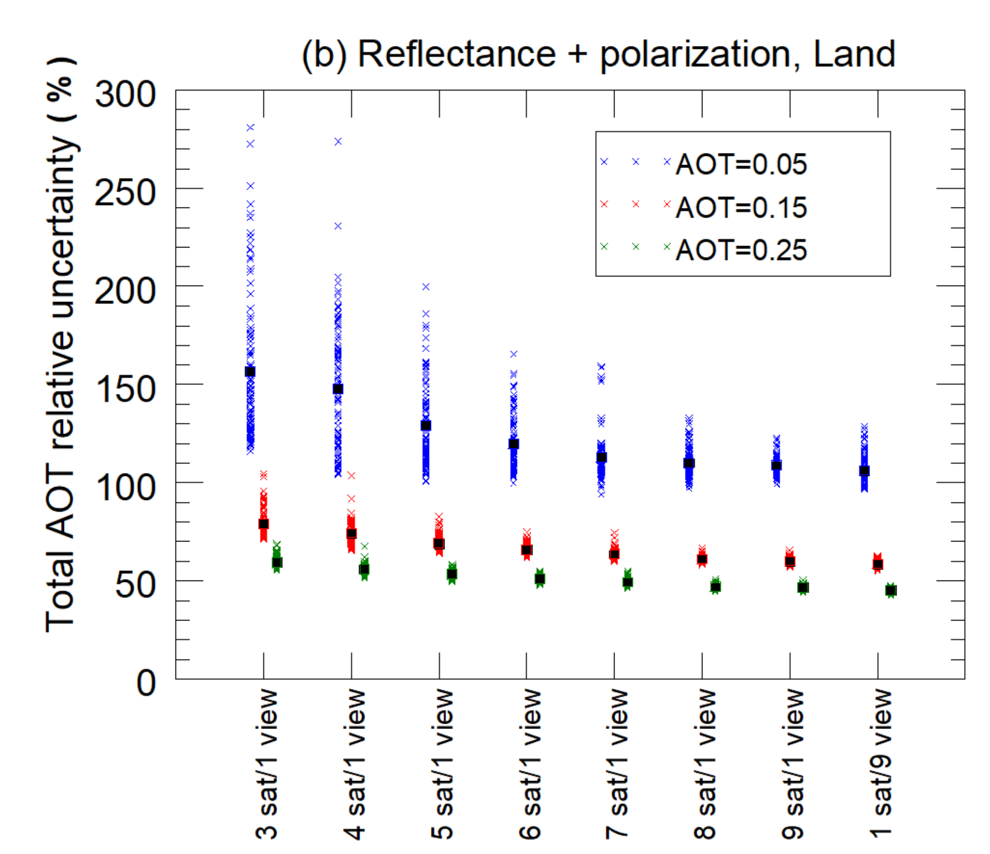


Jacobian helps us map uncertainty from one space to another

This is the “Rodgers method” of information content assessment

$$\hat{\mathbf{S}}^{-1} = \mathbf{K}^T \mathbf{S}_\epsilon^{-1} \mathbf{K} + \mathbf{S}_a^{-1}$$

Simulated uncertainty   Jacobian   Measurement uncertainty   Prior knowledge



From: 10.5194/amt-11-3935-2018

Must test this for an ensemble of scenes: parameter values

Best case scenario

Represents ‘known unknowns’ and assumes a perfect retrieval algorithm

Doesn’t account well for multiple potential solution – just represents sensitivity surrounding state/obs space.

Good for high dimension cases, simple to implement

Progress by Kirk Knobelspiesse

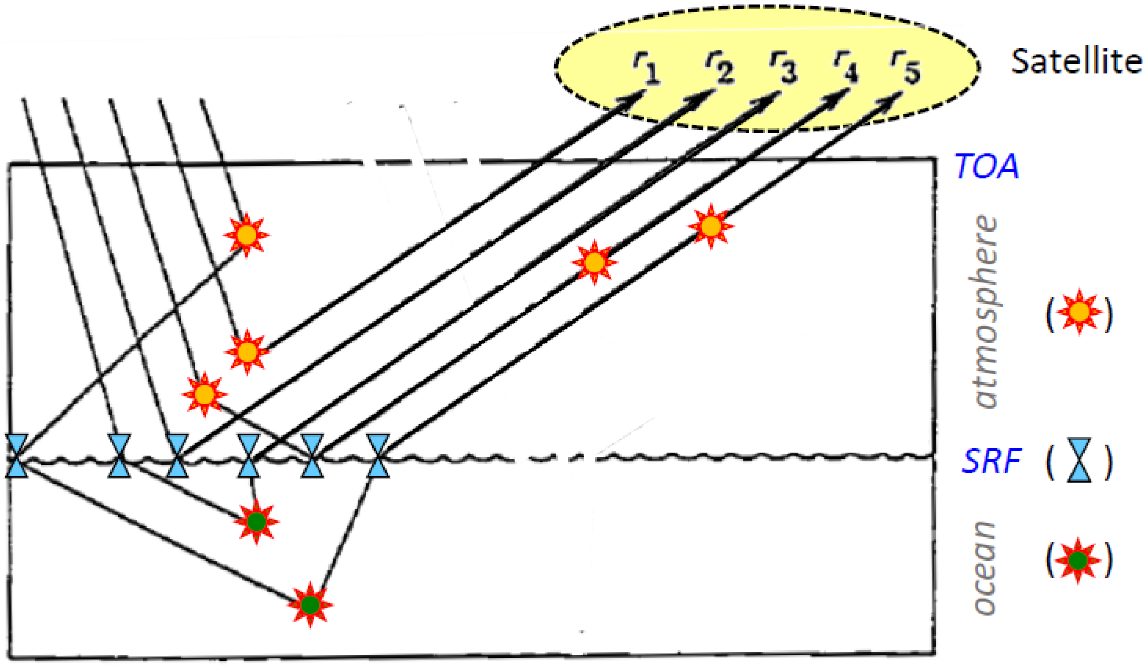
- a python example notebook of how the Rodgers information content analysis works

- Implementation of approach using simulation

- Code to be uploaded
- https://github.com/knobelsp

scattering decomposition

Radiative Transfer Simulations -→ Chowdhary et al. 2019



Satellite observations: $R_{satellite} = r_1 + r_2 + r_3 + r_4 + r_5$

Benchmark Comparison of two models:

1) Simplified RT model (Ibrahim)
2) Full radiative transfer simulations with polarization (Chowdhary)

atmosphere scattering

ocean body scattering

ocean surface R/T

r_1 = only atmo scattering contribution

r_2 = only surf reflection contribution

r_3 = only **ocean** scattering contribution §

r_4 = atmo scattering + surf interaction

r_5 = atmo scattering + surf interaction + **ocean** scattering

$r_3 + r_5$: provides ocean scattering

§ includes transmission into and out of ocean body by surface

Photo Credit: Oskar Landi

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Simplified Radiative Transfer Approach with “Wet” Microplastic Reflectance

We simulated the TOA reflectance as follows: $\rho_{TOA} = F(Pr,, RH, WS, WV, O_3, chl-a, f_{plastic}, fmf, \tau_a)$

$$\rho_{TOA} = (\rho_r + \rho_a + T\rho_{surf}) \times T_{gsol} \times T_{gsen}$$

$$T\rho_{surf} = (1 - f_{plastic}) \times T\rho_g + (1 - \rho_{plastic}) \times T\rho_w + T\rho_{plastic}$$

$$T\rho_{plastic} = f_{plastic} \times \rho_{plastic} \times t_{sen}$$

$$T\rho_w = \rho_w \times t_{sen}$$

Example condition

Pr (mbar)	RH (%)	WS (m/s)	WV (cm)	O_3 (DU)	$chl-a$ (mg/m3)	$f_{plastic}$	fmf	τ_a
1013	55	5	1	300	0.1	0-1 (logspace)	50	0.1

Run 100,000 cases varying pressure, wind speed, relative humidity, ozone, optical depth, fine mode fraction, water vapor, chl-a,plastics fraction, and orbit geometries

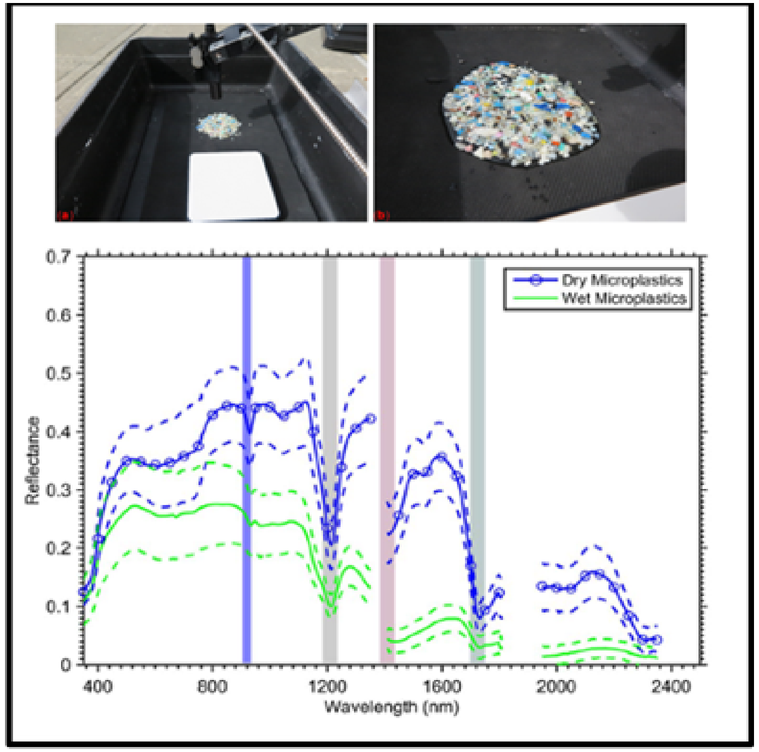

Fig. 2. Pictures of a sample of harvested marine microplastics and the resulting mean and standard deviation reflectance spectrum dry and wet (Garaba and Dierssen 2018)

Microplastics Influence Near Infrared Reflectance and Aerosol Retrieval at the TOA

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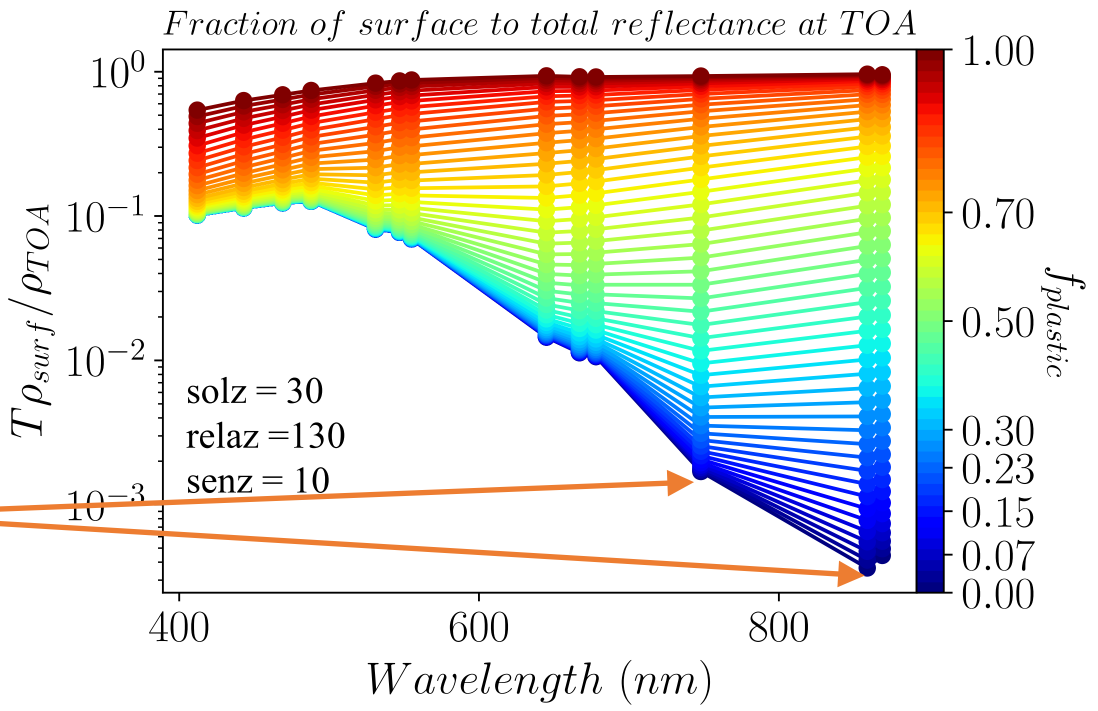
Increasing microplastics influences the Near Infrared Reflectance at the Top of the Atmopshere and Aerosol Retrievals that use the ratio of 869 and 748 nm bands



Amir Ibrahim, NASA GSFC

aerosol model selection & application

select the two sets of 10 models (10 size fractions) with relative humidity (RH) that bound the RH of the observation.

find the two models that bound the observed epsilon within each RH model family.

$$\varepsilon^{obs}(748,869) = \frac{\rho_a(748)}{\rho_a(869)} \rightarrow \varepsilon^{\text{mod}}(748,869)^*$$

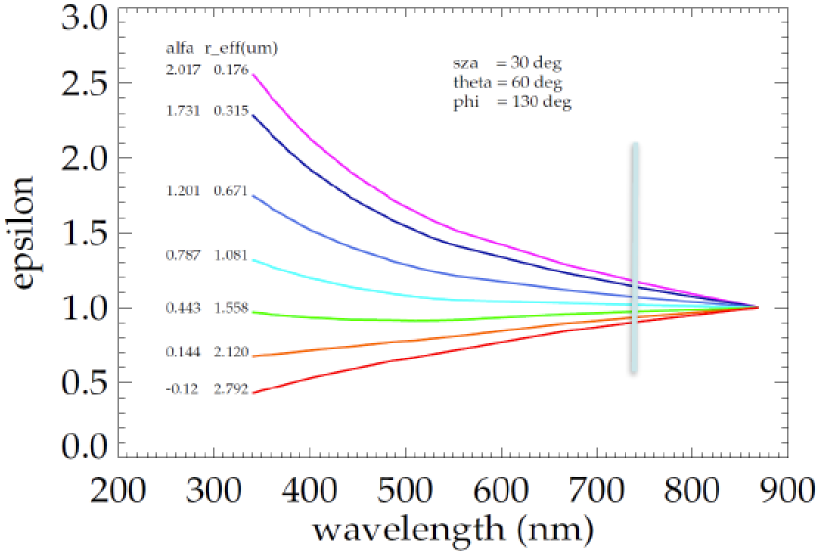
use model epsilon to extrapolate to visible.

$$\rho_a(\lambda) = \rho_a(869)\varepsilon^{\text{mod}}(\lambda,869)$$

compute weighted average, $\overline{\rho}_a$, between models within each RH family, and then again between bounding RH solutions.

$$[L_a + L_{ra}] = \overline{\rho}_a(\lambda)\frac{F_0\cos(\theta_0)}{\pi}$$

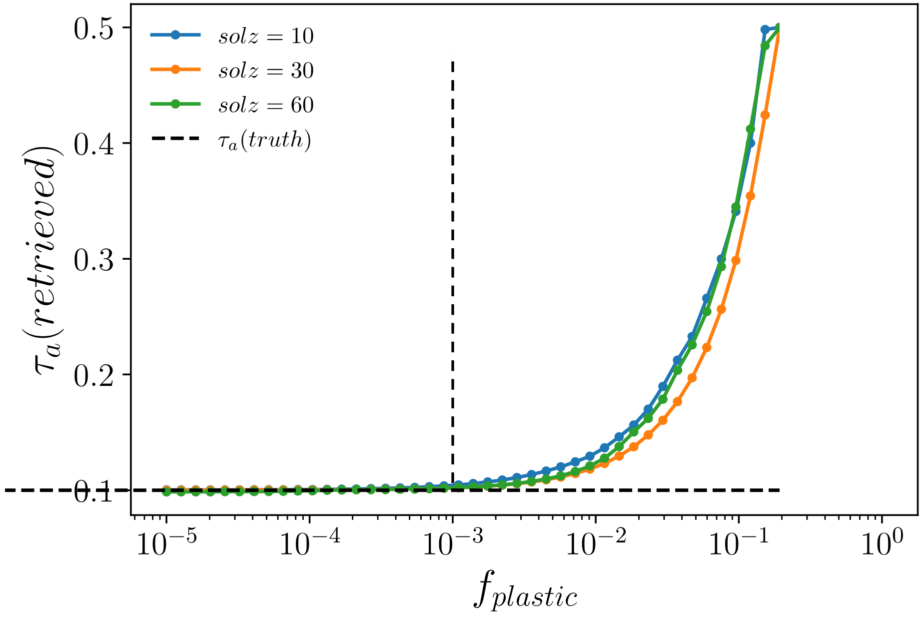
model epsilon

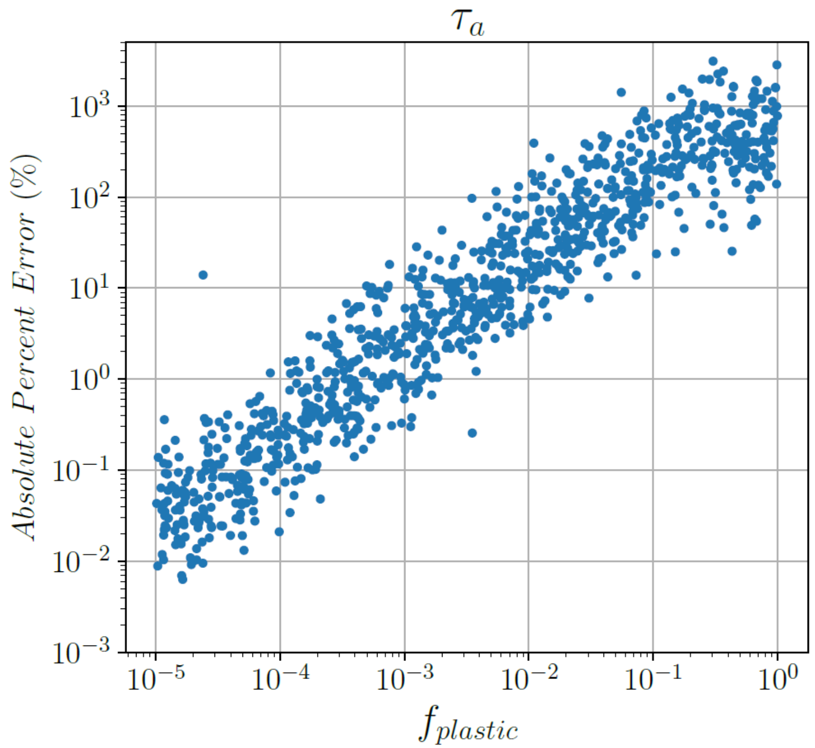


**actually done in single scattering space and transformed to multi-scattering*

Bryan Franz

Initial simulations show ~0.1% fractional coverage of microplastics produce >10% error in aerosol retrievals (50 times higher than measurements)



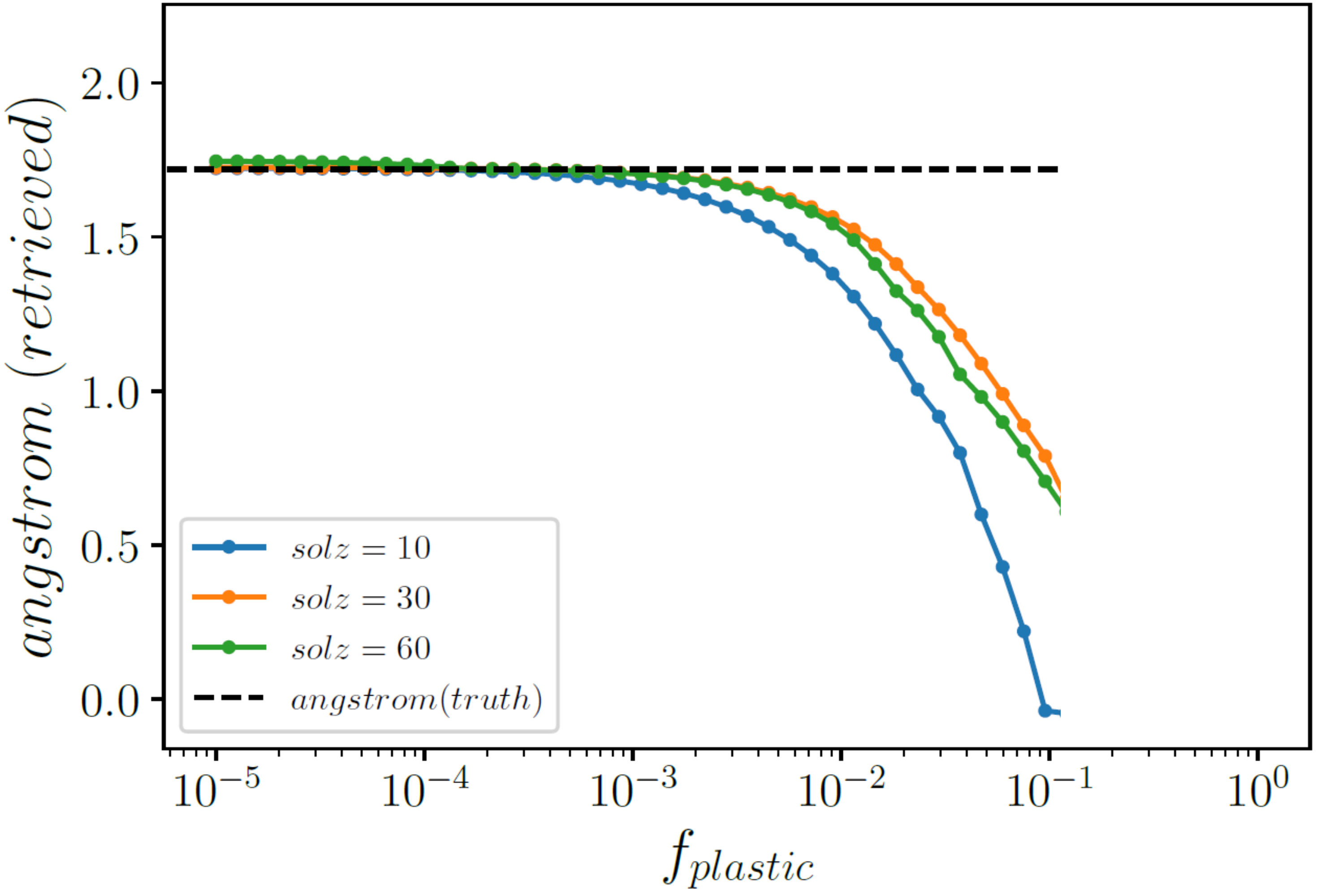


For this specific condition, $f_{plastic}$ < 0.1% has no effect on either the aerosol optical depth or the fine-mode fraction.

1000 different simulations showing an increase in error in retrieval of aerosol optical depth

Field data showing highest fraction of a 1 km^2 pixel covered by surface borne microplastics is 0.002% -- 50 times less than would be detectable in aerosol retrieval

Plastic particles may artificially decrease the angstrom coefficients



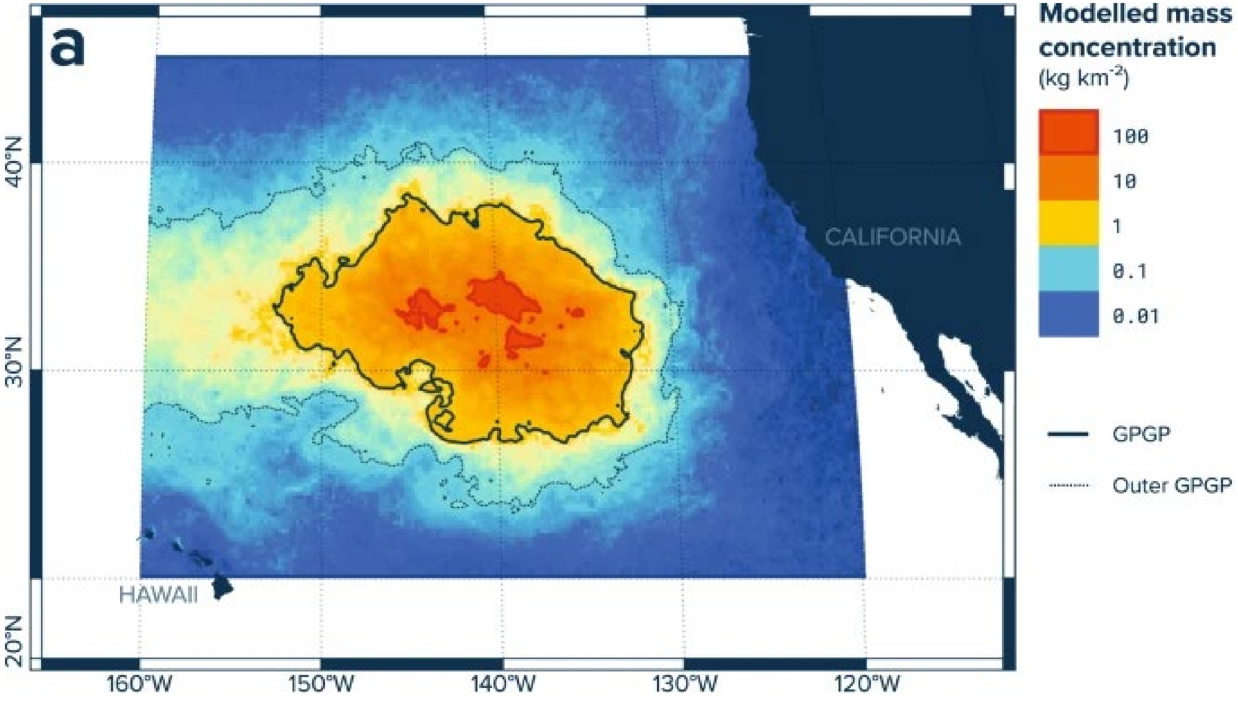
What fraction of microplastics is detectable?

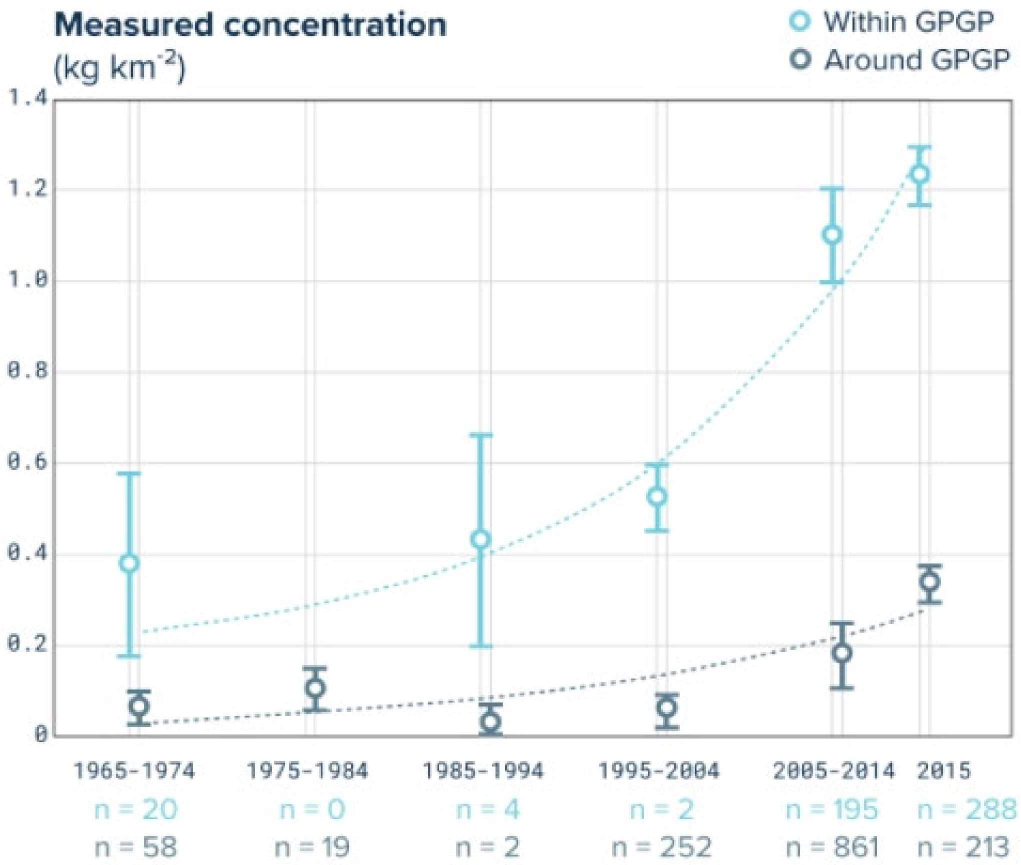
- Initial simulations suggest that microplastics could be detectable in atmospheric retrievals if they represent greater than **0.001 fraction of the sea surface** using standard approaches

- For the scale of 1 km^2 pixel,
  - Field data up to ~20 m^2/pixel (1,000,000 pieces/km^2)
  - **0.00002 highest fraction microplastics observed**
  - Initial analysis suggests microplastics would need to be **~50x more concentrated** at the sea surface than we find in net tows

- For smaller scale pixels
  - We do not know how patchy and concentrated microplastics can get along fronts.

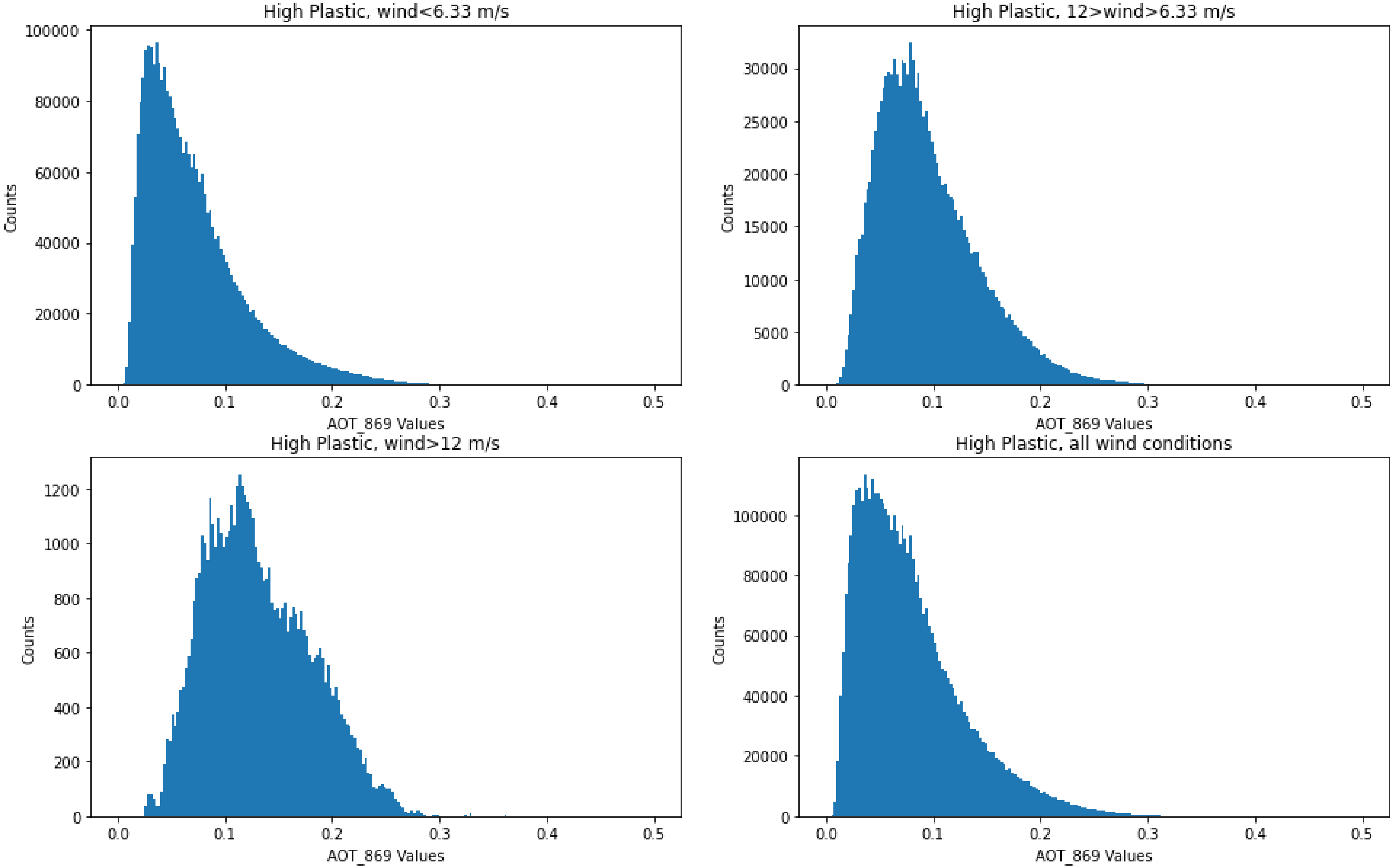
Is Plastic Accumulation Visible in Ocean Color Imagery from the GPGP?





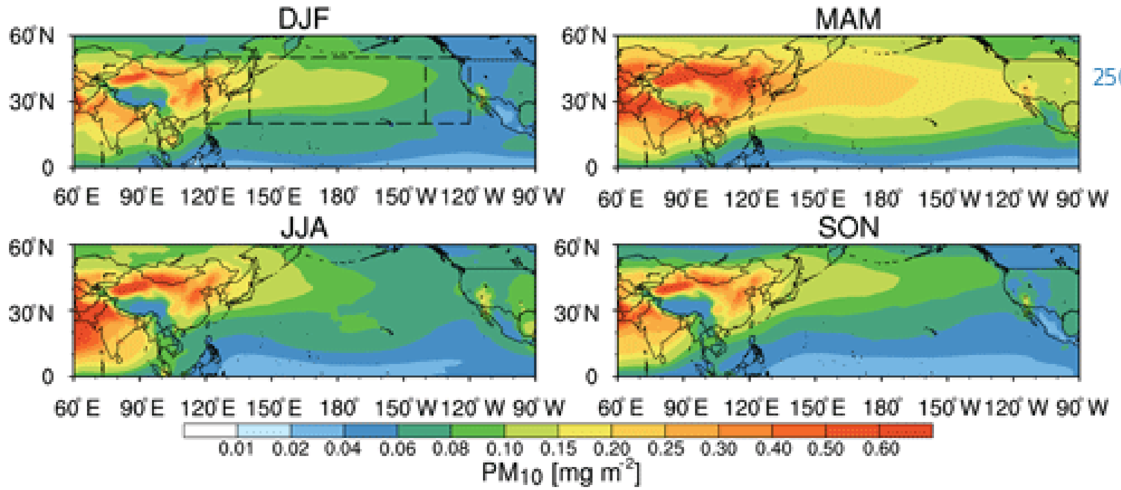
Lebreton et al 2018

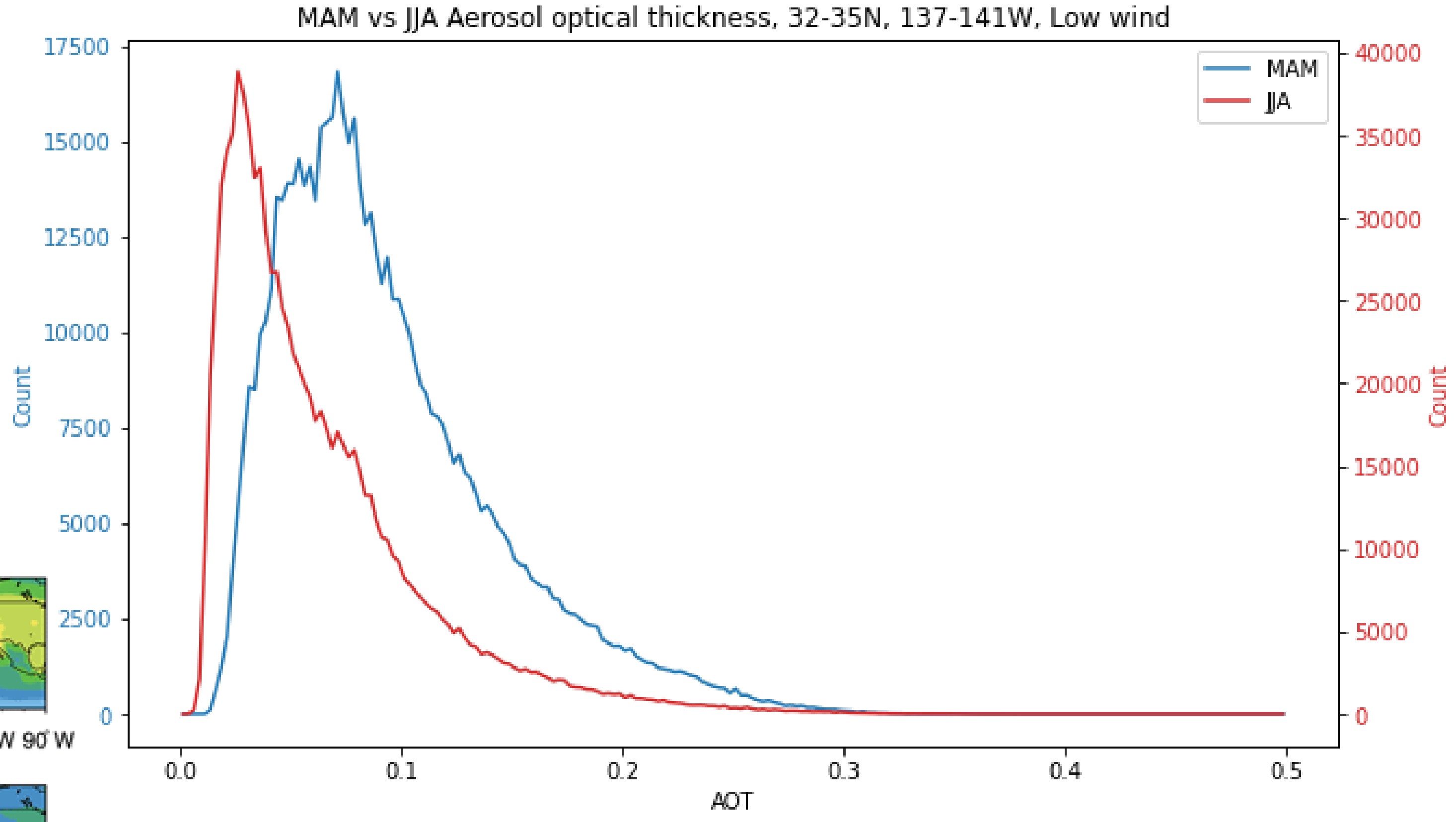
Impact of Wind on the Aerosol Retrievals



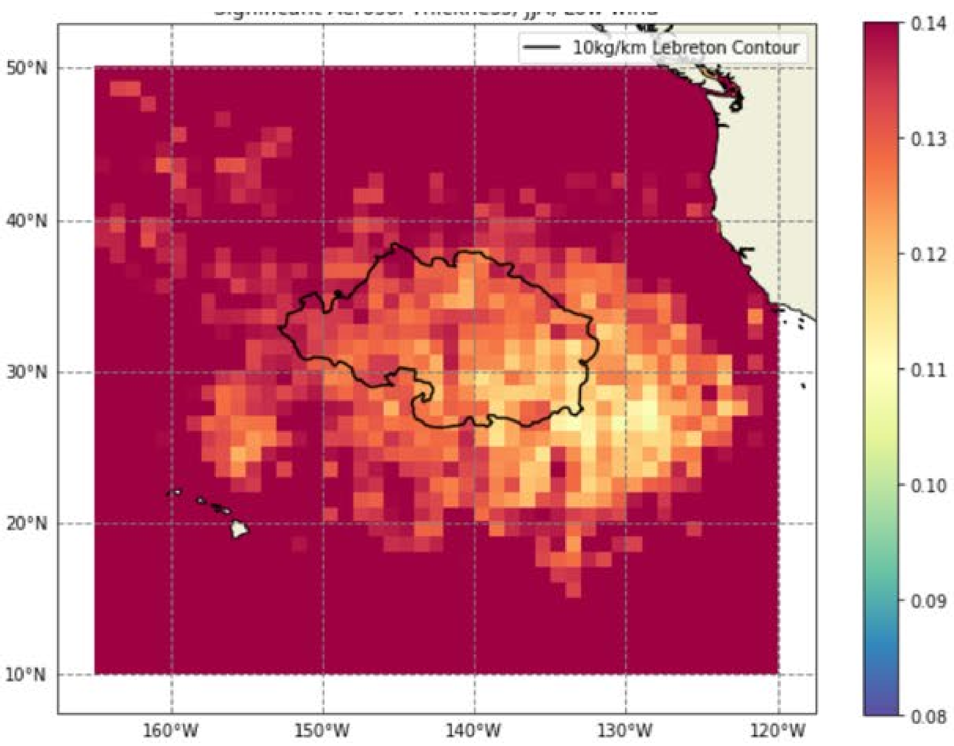
Visualizing the Seasonal Asian Aerosol Plume

- Clear histogram shift towards higher AOT values during peak Asian aerosol input

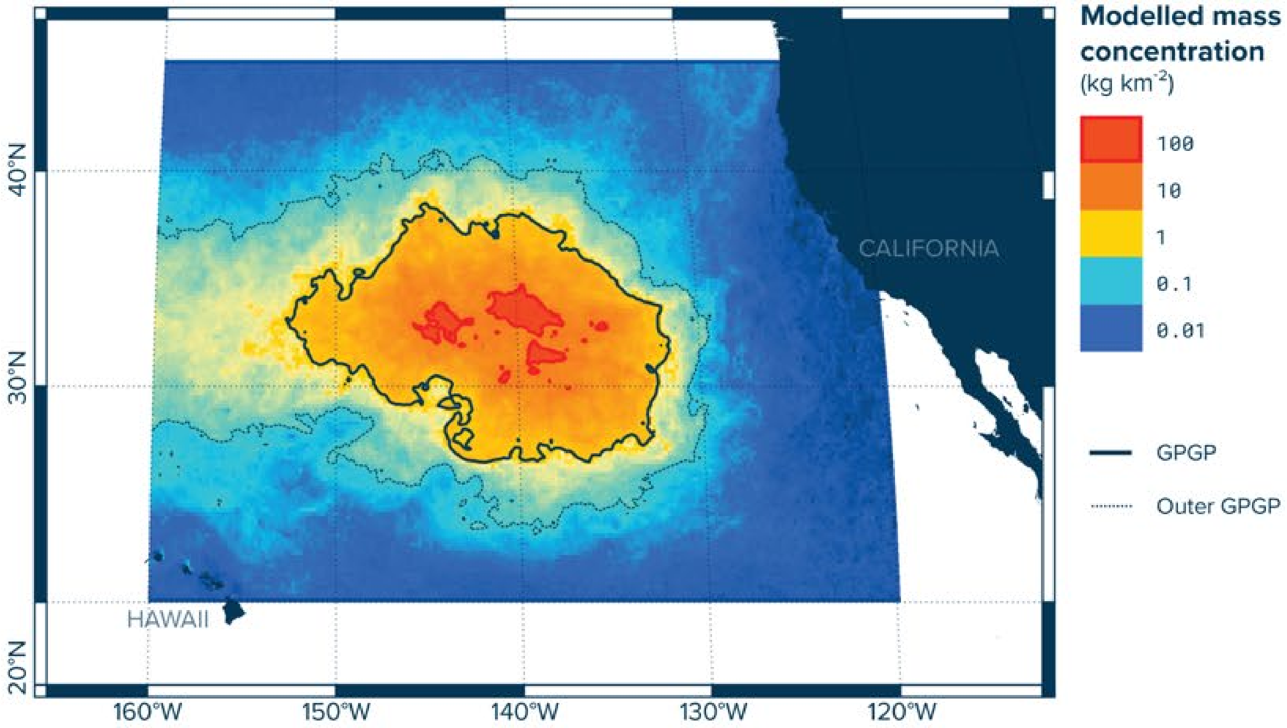




MODIS Aerosol Anomalies in “Great Pacific Garbage Patch” (GPGP)

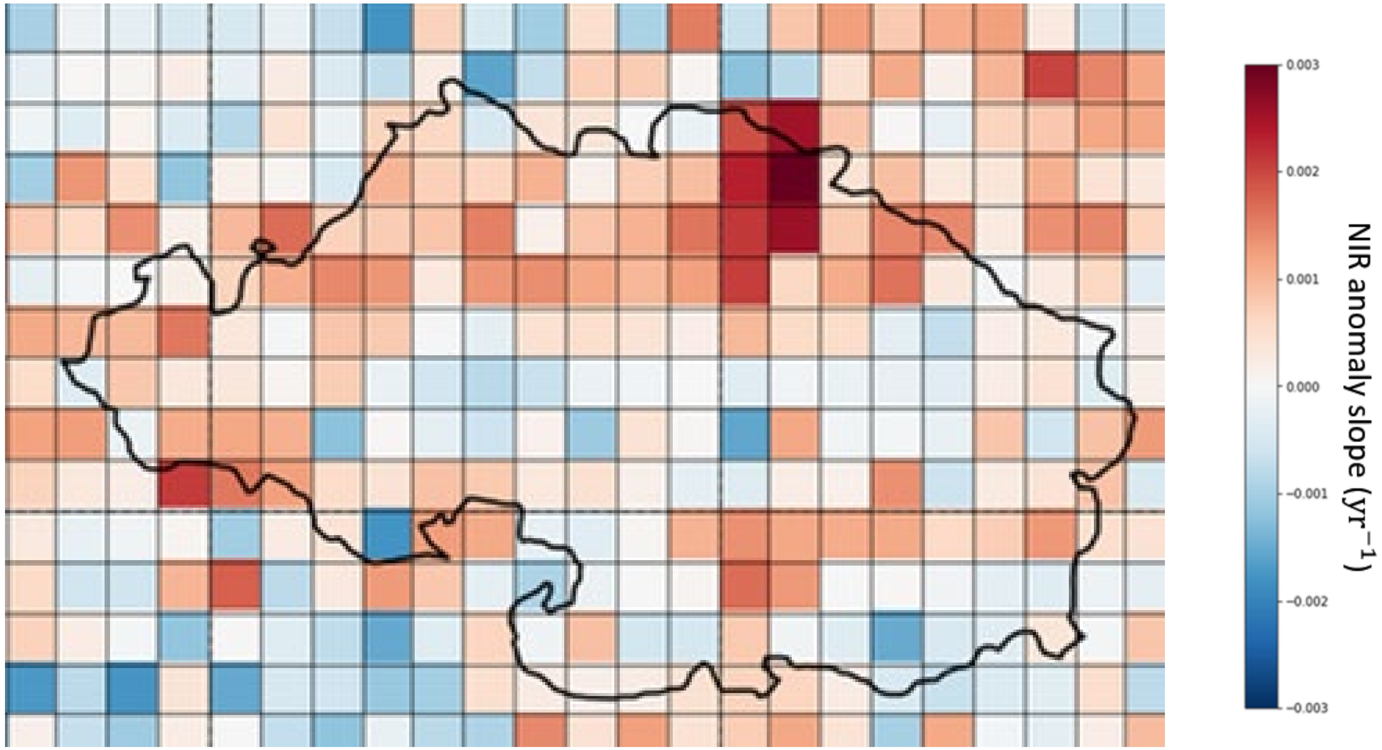


Example of MODIS Aqua Anomalies in GPGP



Simulations of GPGP from Lebreton et al. 2018

Some initial results:
NIR anomaly trend over 18 year time series



- Parts of GPGP show increasing NIR anomalies during 18 year MODIS time series, but not all

Stay Tuned for Polarimetry Results

To the extent floating materials modify the surface-averaged refractive index of seawater, the polarization signatures of the TOA signal will be first and foremost affected around the specular reflection region, as described by the Fresnel laws

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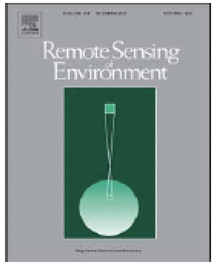

Remote sensing of the ocean surface refractive index via short-wave infrared polarimetry

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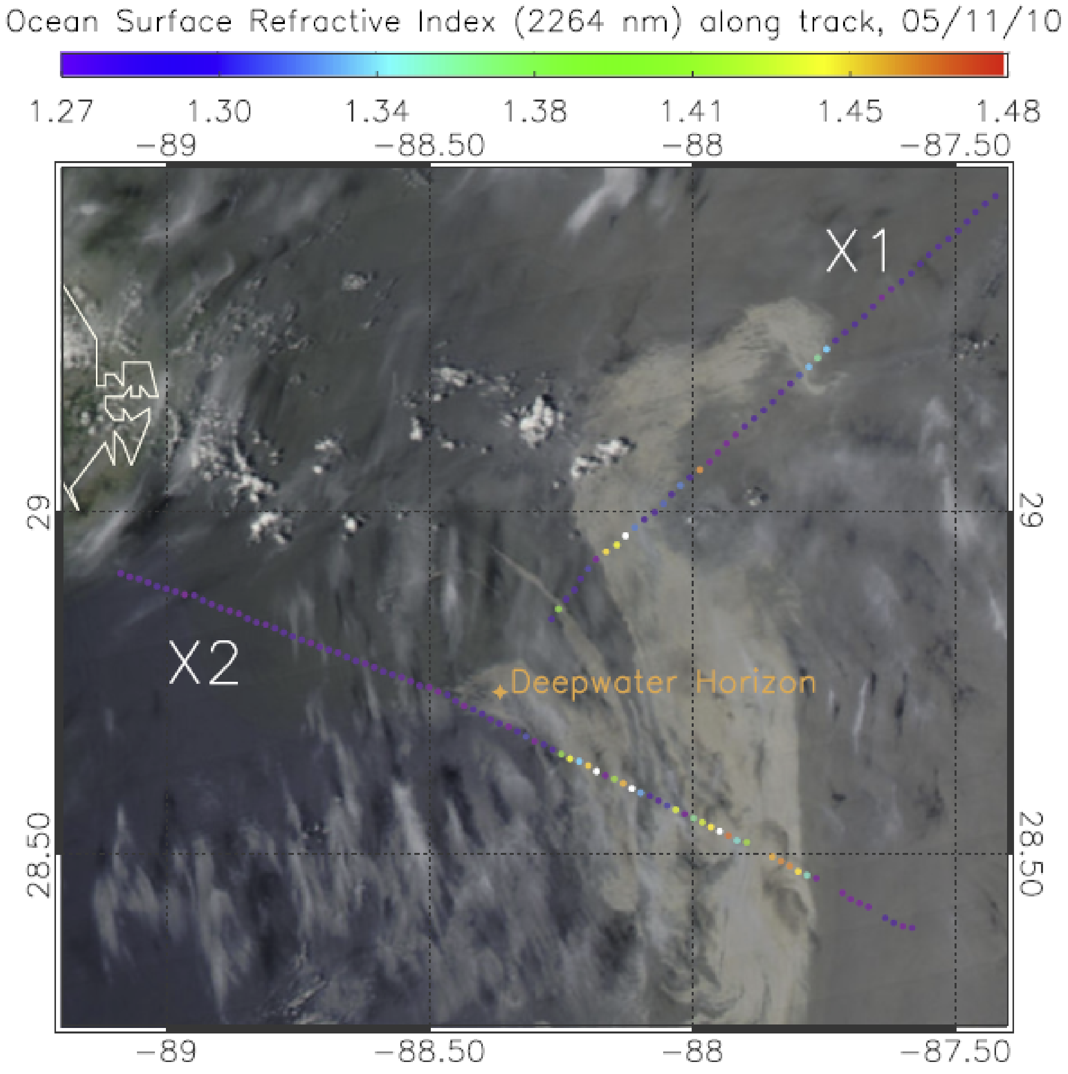
Sensitivity studies underway to investigate the concentrations of floating microplastics needed to appreciably change the polarimetric retrieval of surface-averaged refractive indices



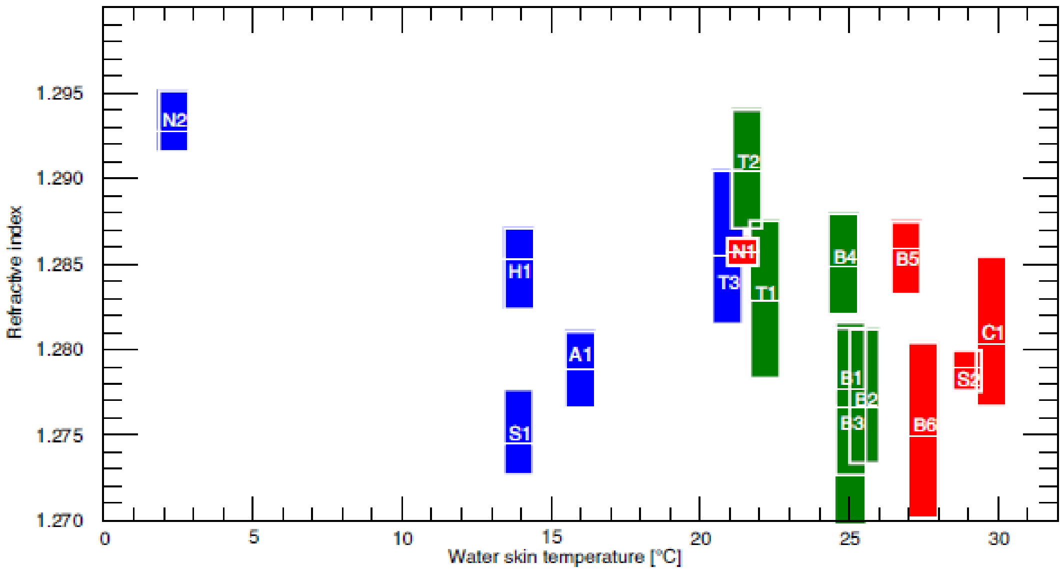


Fig. 8. Boxplot of the refractive indices retrieved for all analyzed transects (excluding X1 and X2 over oil) as a function of the water skin temperature. The vertical extension of each box spans the range of the quartiles; the median is indicated by the white horizontal line. Each box is colored with the associated values of low (< 33 PSU, blue), average (33 ≤ PSU ≤ 37) or highly variable (green) and high (> 37 PSU, red) salinity as obtained from the Aquarius satellite measurements closest in space and time. The resulting behavior is compatible with the modulation by salinity variations of the expected decrease in refractive index predicted for increasing seawater temperatures. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

THANK YOU