Satellite Remote Sensing of Surface Albedo of the Cryosphere Using Scientific Machine Learning Models

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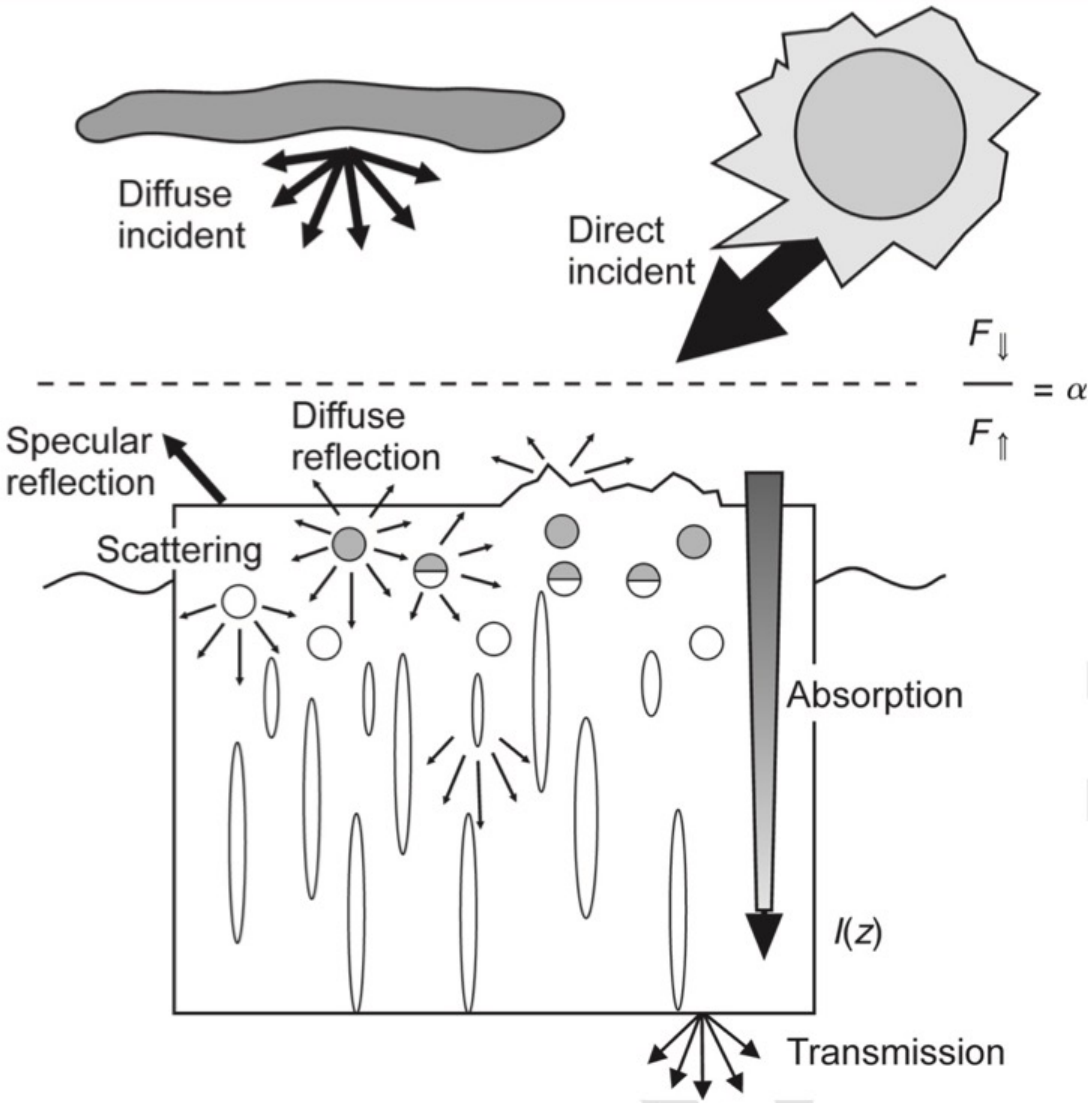
Components of 'Cryosphere'

Focus of this research: the flat 'sea-ice' surface, including:

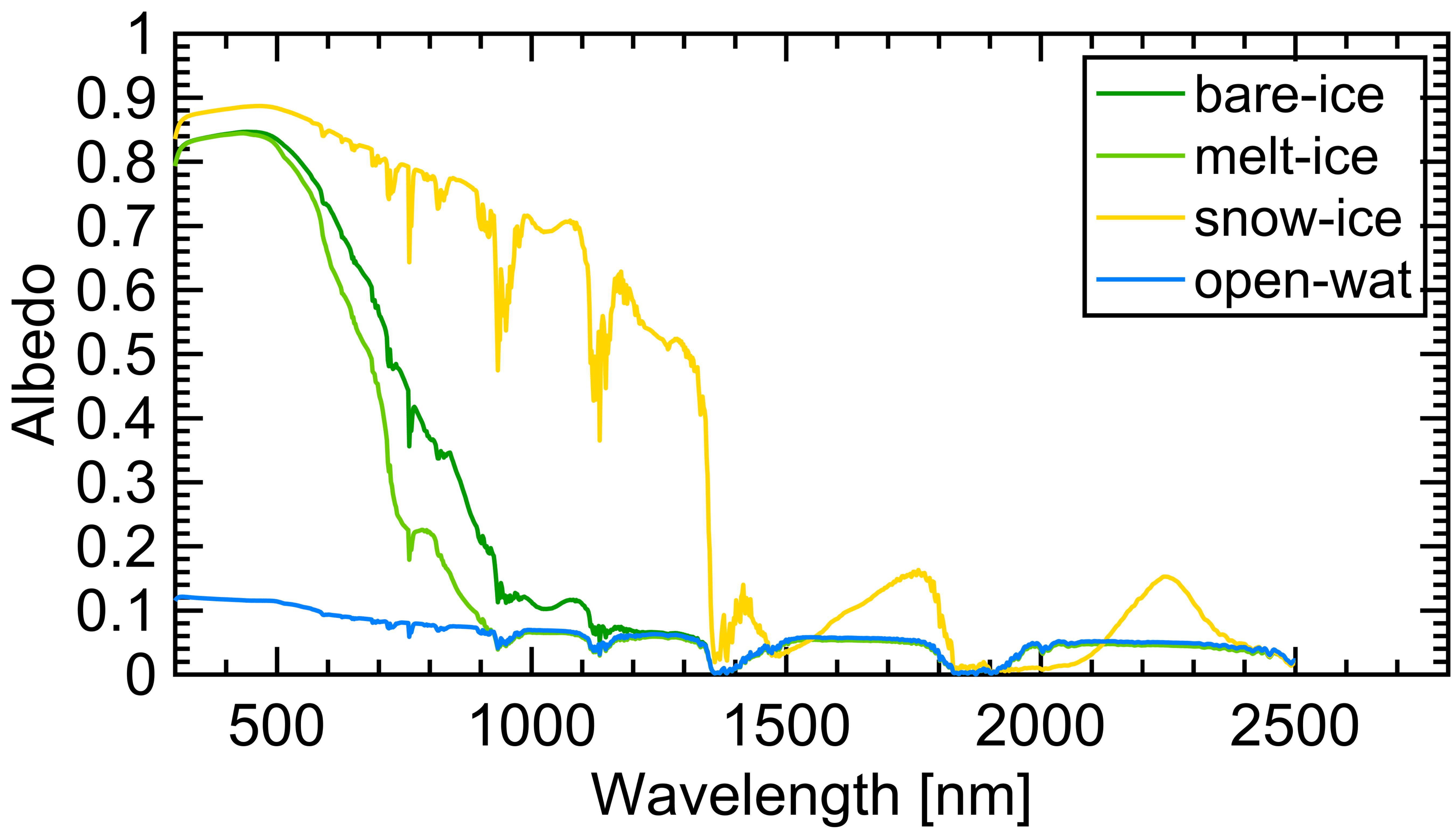
open-ocean
melt-pond
bare sea-ice
snow-covered ice

The sea ice areas: Arctic, Sea of Okhotsk, Bohai Sea, Antarctica

Retrieve the surface albedo of sea ice



Spectral albedo $$\alpha(\lambda) = \frac{F^{+}(\lambda)}{F^{-}(\lambda)}$$



Broadband albedo

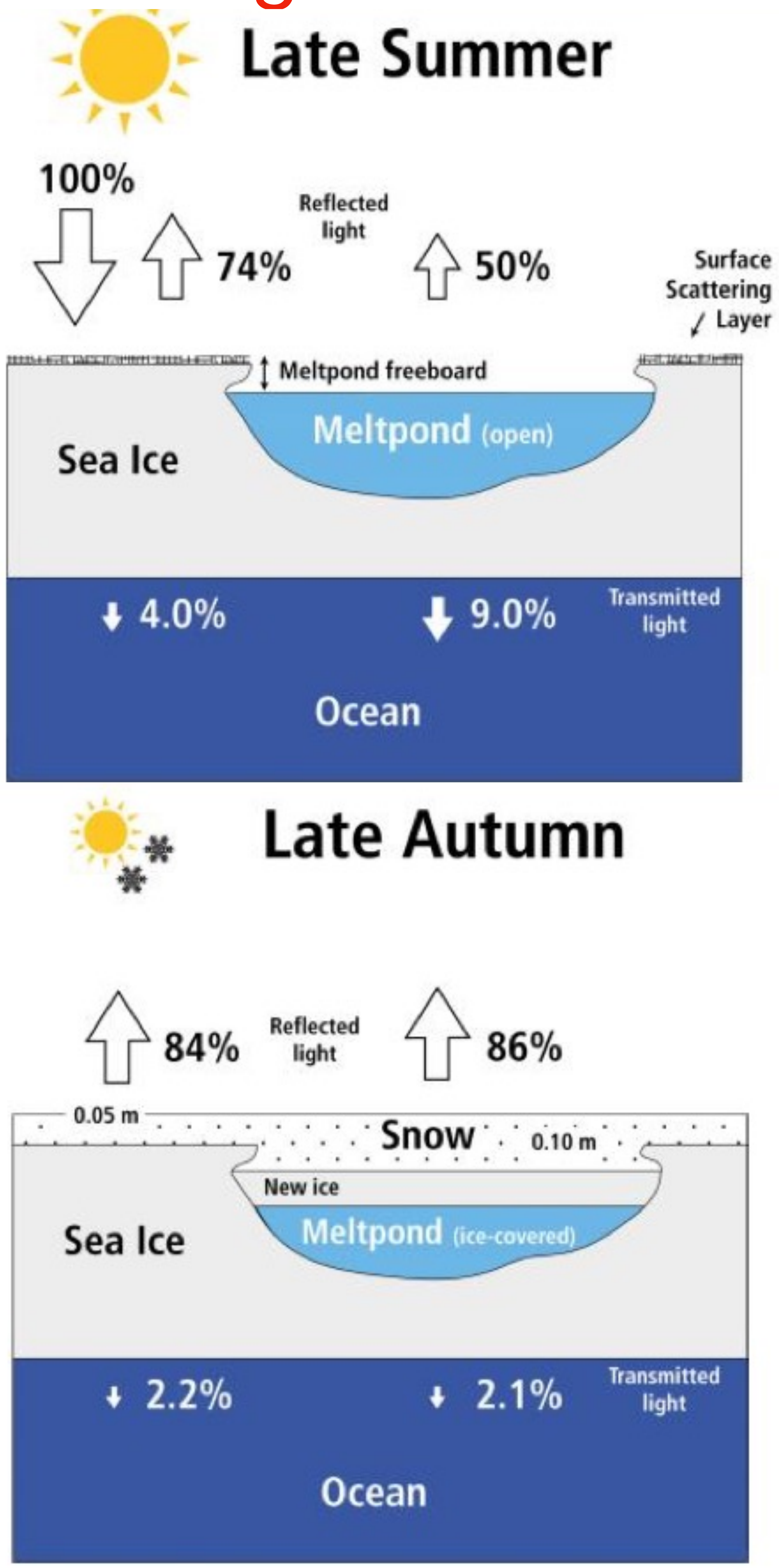
$$\alpha_{i-j} \equiv \frac{F^{+}}{F^{-}} = \frac{\int_{\lambda_i}^{\lambda_j} F^{+}(\lambda)d\lambda}{\int_{\lambda_i}^{\lambda_j} F^{-}(\lambda)d\lambda}$$

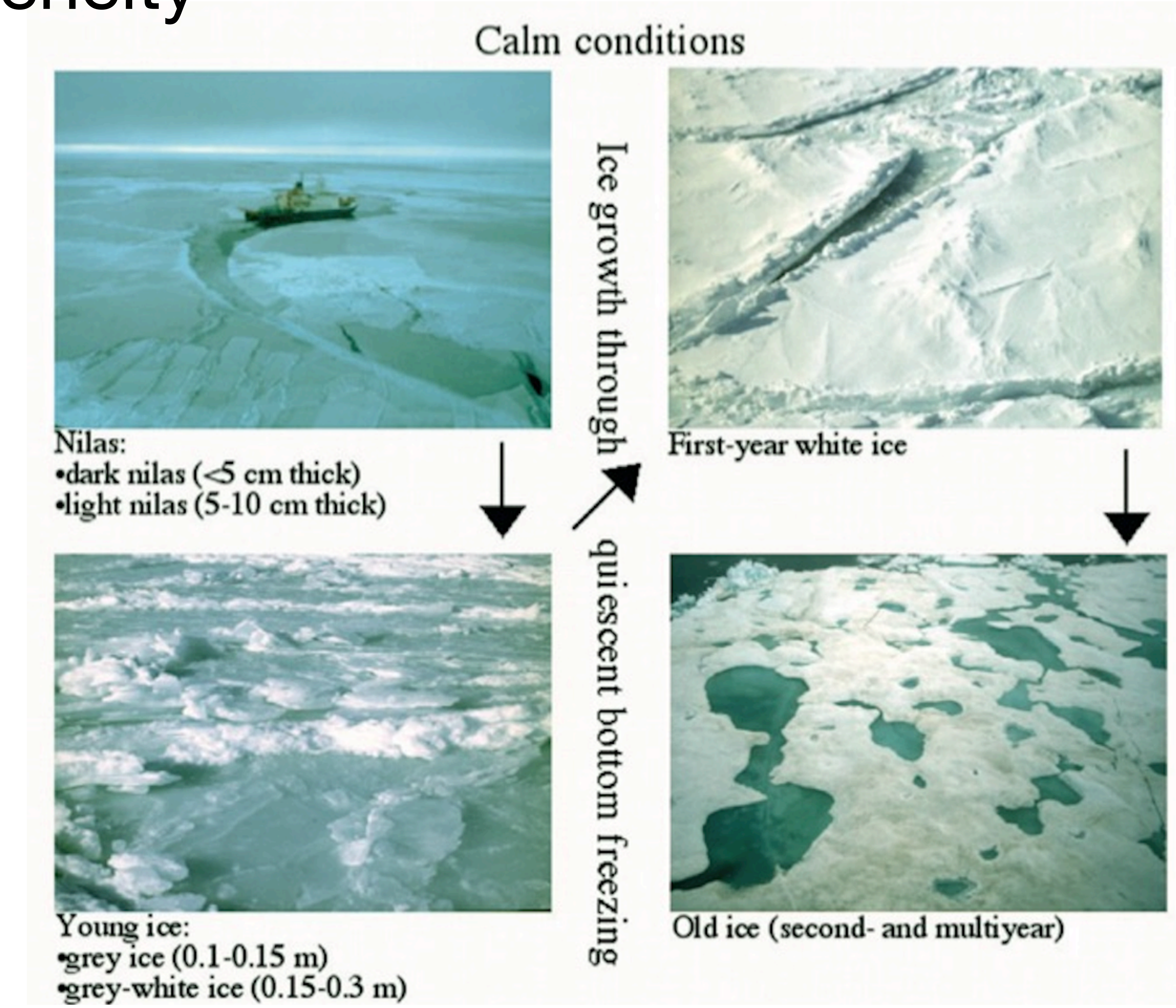
α_{VIS} **300~700 nm**

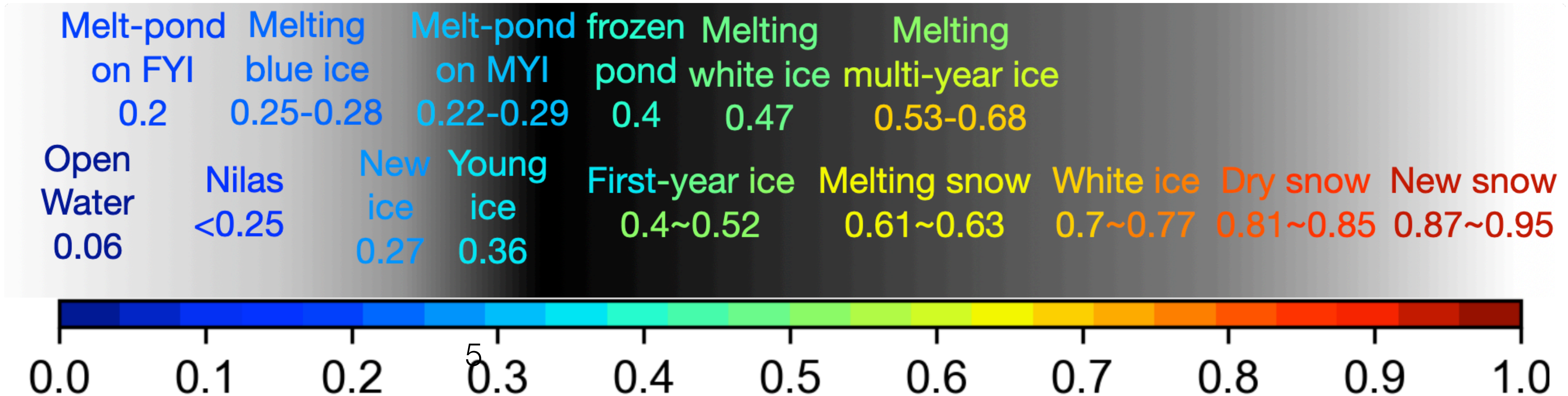
α_{NIR} **700~2500 nm**

α_{SW} **300~2500 nm**

Challenge #1: surface heterogeneity

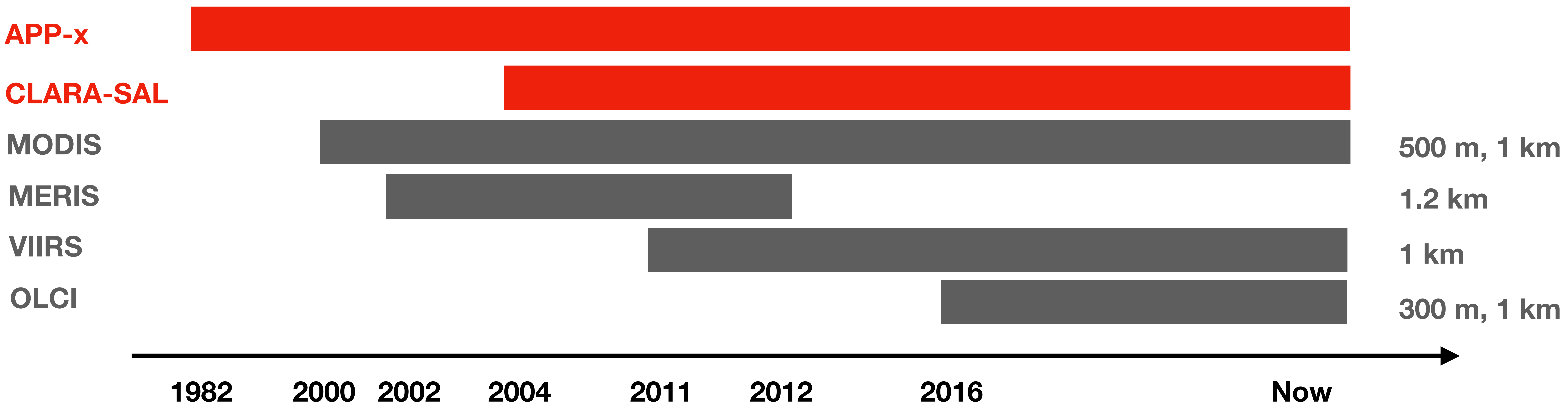






Problem #1: insufficient spatial/temporal resolution

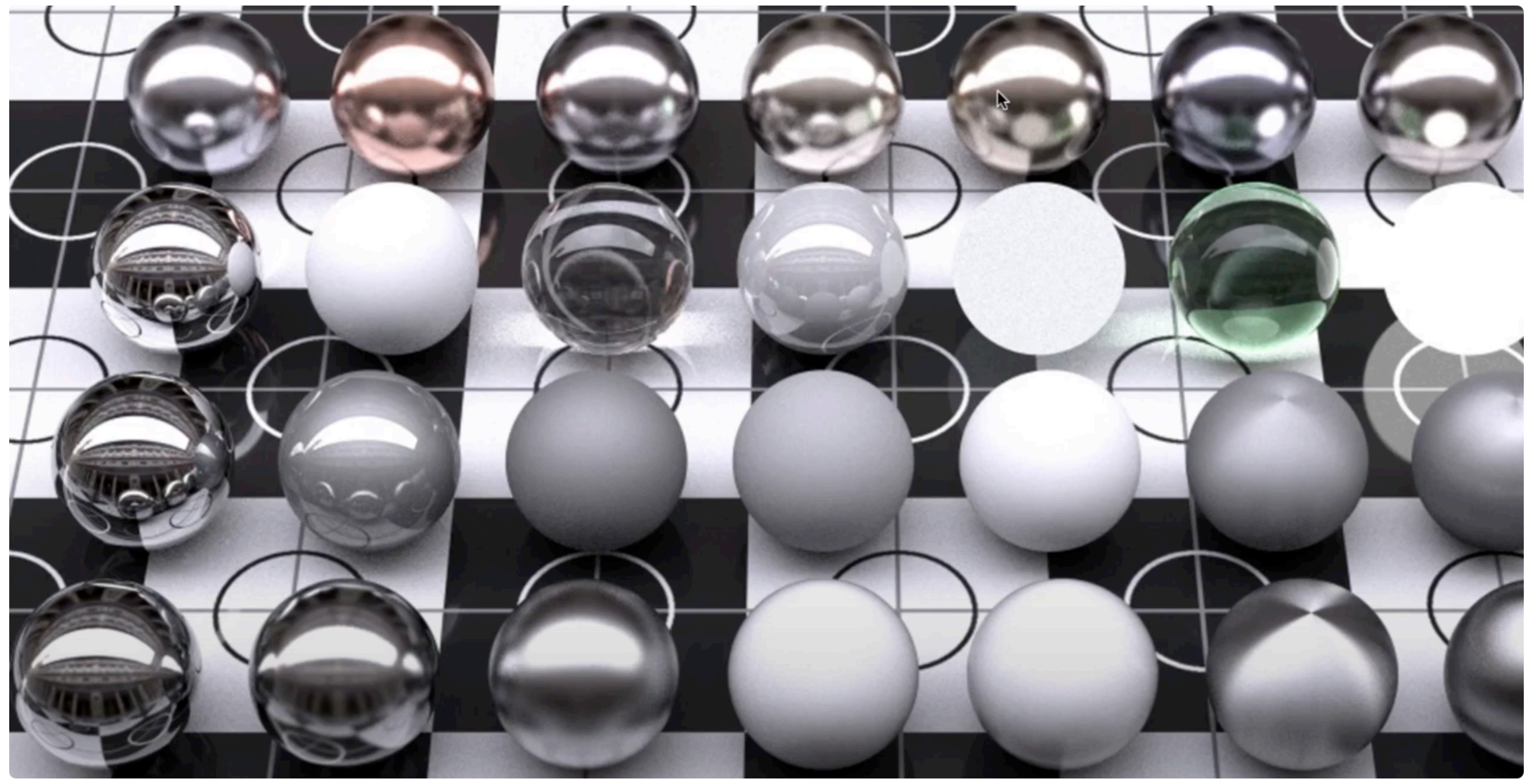
Satellite sensors & algorithms that can retrieve sea-ice albedo values



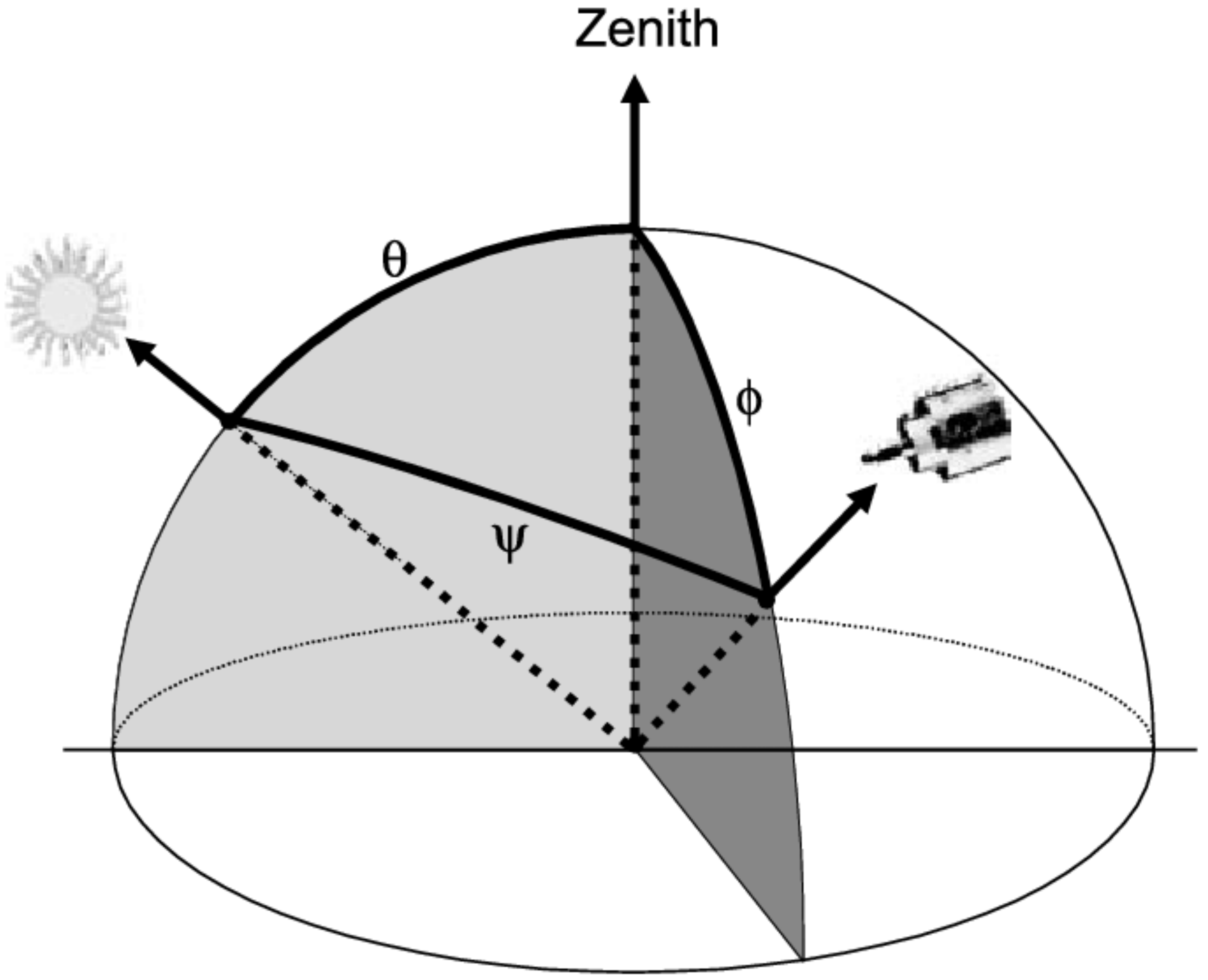
Albedo Product (sensor)	Description
APP-x (AVHRR)	25-km spatial resolution, monthly temperal resolution,
CLARA-SAL (AVHRR)	25-km spatial resolution; weekly temporal resolution, only contains data in southern of 80N

Challenge #2: reflection anisotropy

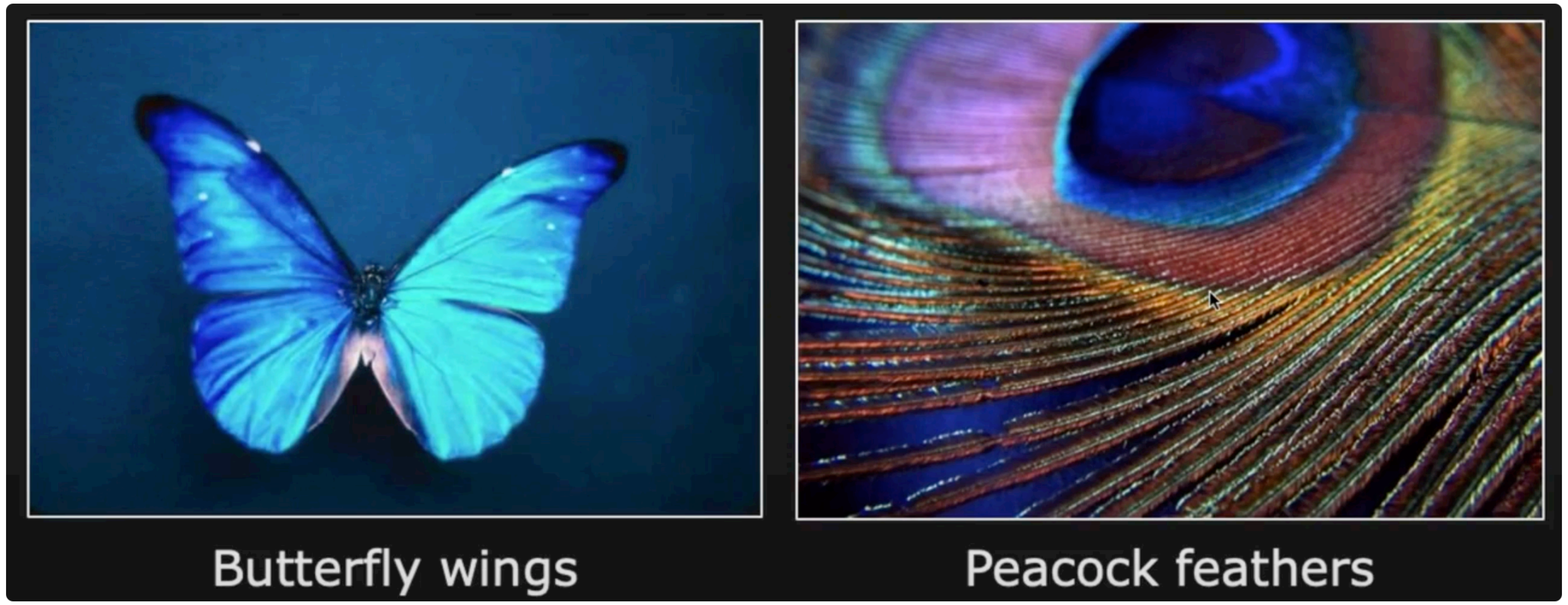
Reflectance properties
are determined by the surface appearance



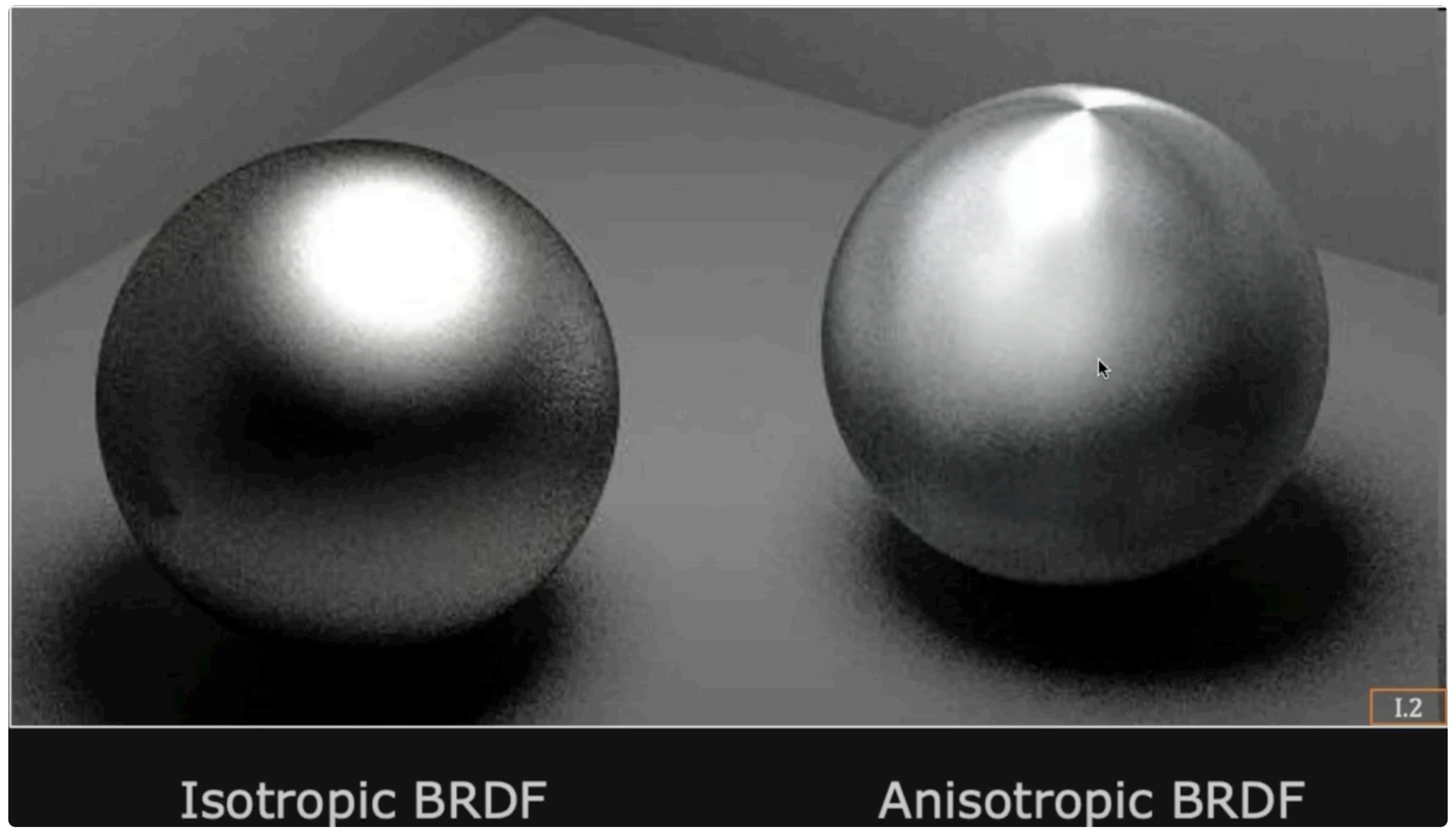
$R(\theta, \phi, \varphi, \lambda)$ The spectral bi-directional reflectance distribution function (BRDF)



Examples of anisotropic BRDF in nature



Reflection on snow / ice surface is anisotropic

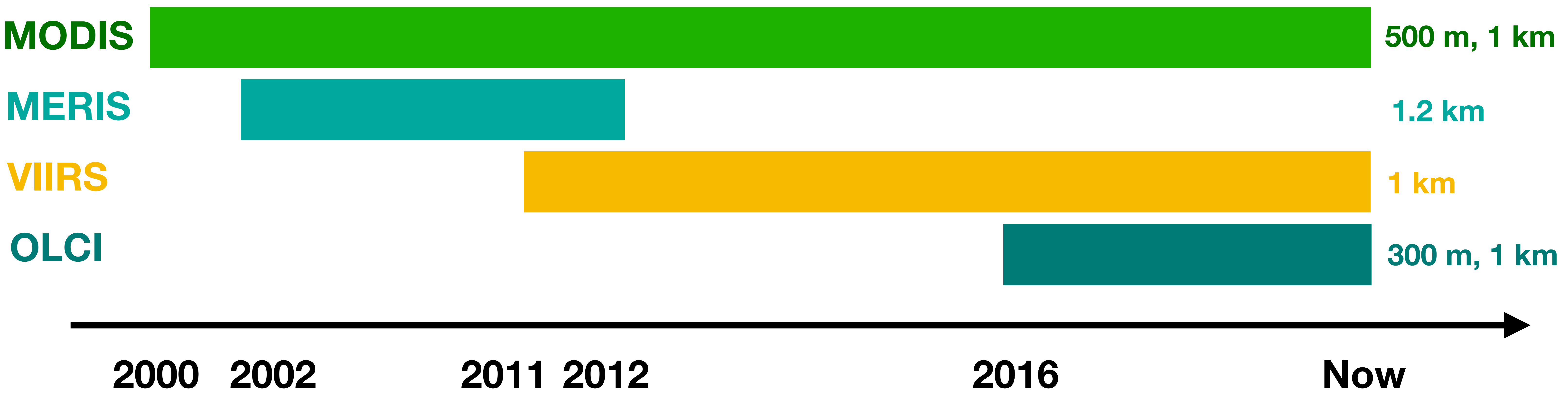


Problem #2: surface BRDF estimations

Current estimation approaches

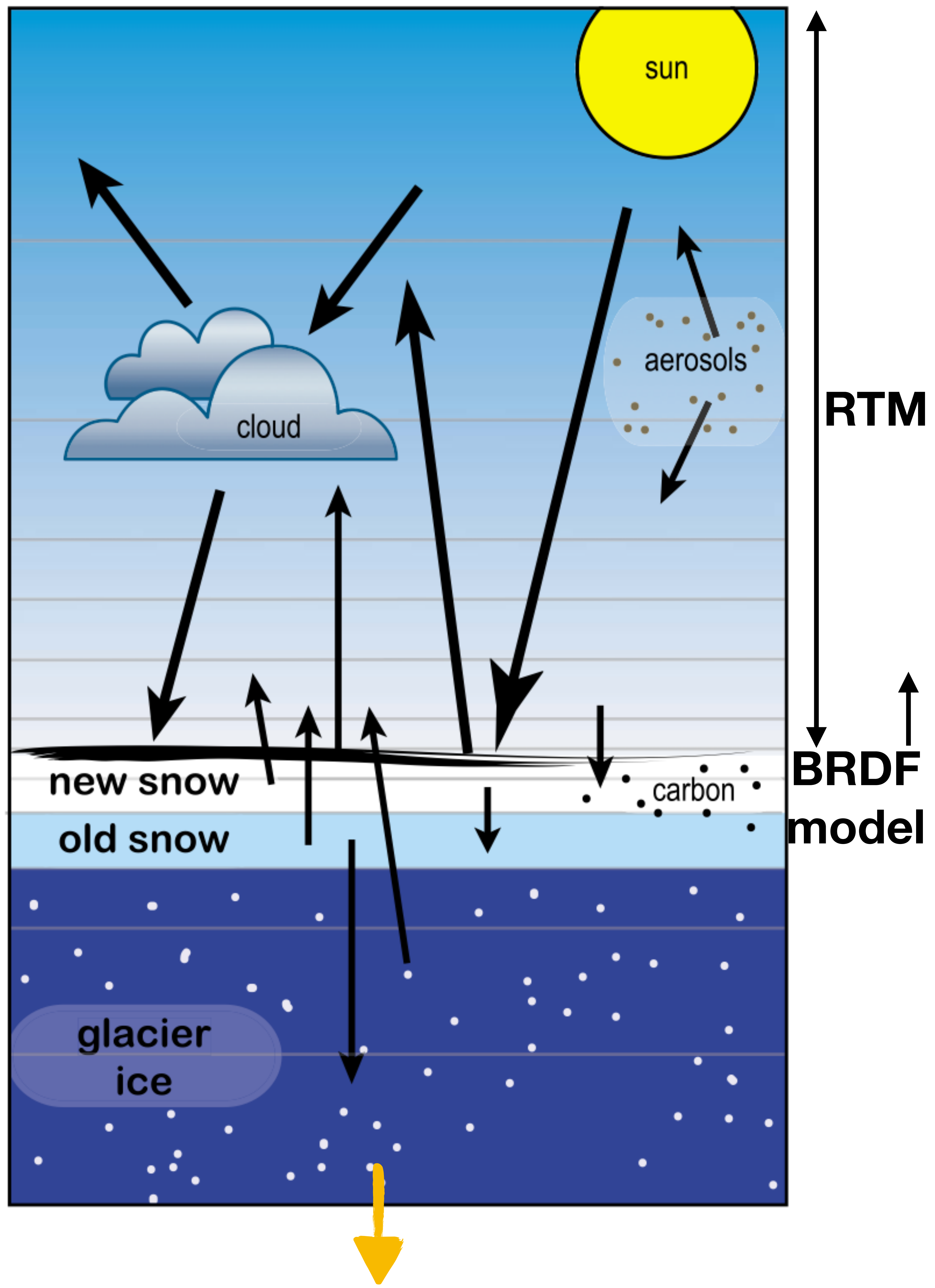
1. Require 16-day BRDF observations for retrieval of each day
   → ~~temporal variations~~
2. Only include BRDF of limited surface types or sea-ice conditions
   → ~~crude estimations~~
3. Need empirical relations to determine the surface type prior to BRDF-value assignments
   → ~~errors cascade~~

Satellite sensors & algorithms that can retrieve sea-ice albedo values



Methodology	Product (sensor)	Problems
BRDF angular modeling	MCD43 (MODIS)	1
Analytical solution of RTM	MPD-based algorithm (MERIS, OLCI)	2, 3
LUT-based direct-estimation	Qu's (MODIS), Peng's (VIIRS)	2

Problem #3: decouples the atmosphere

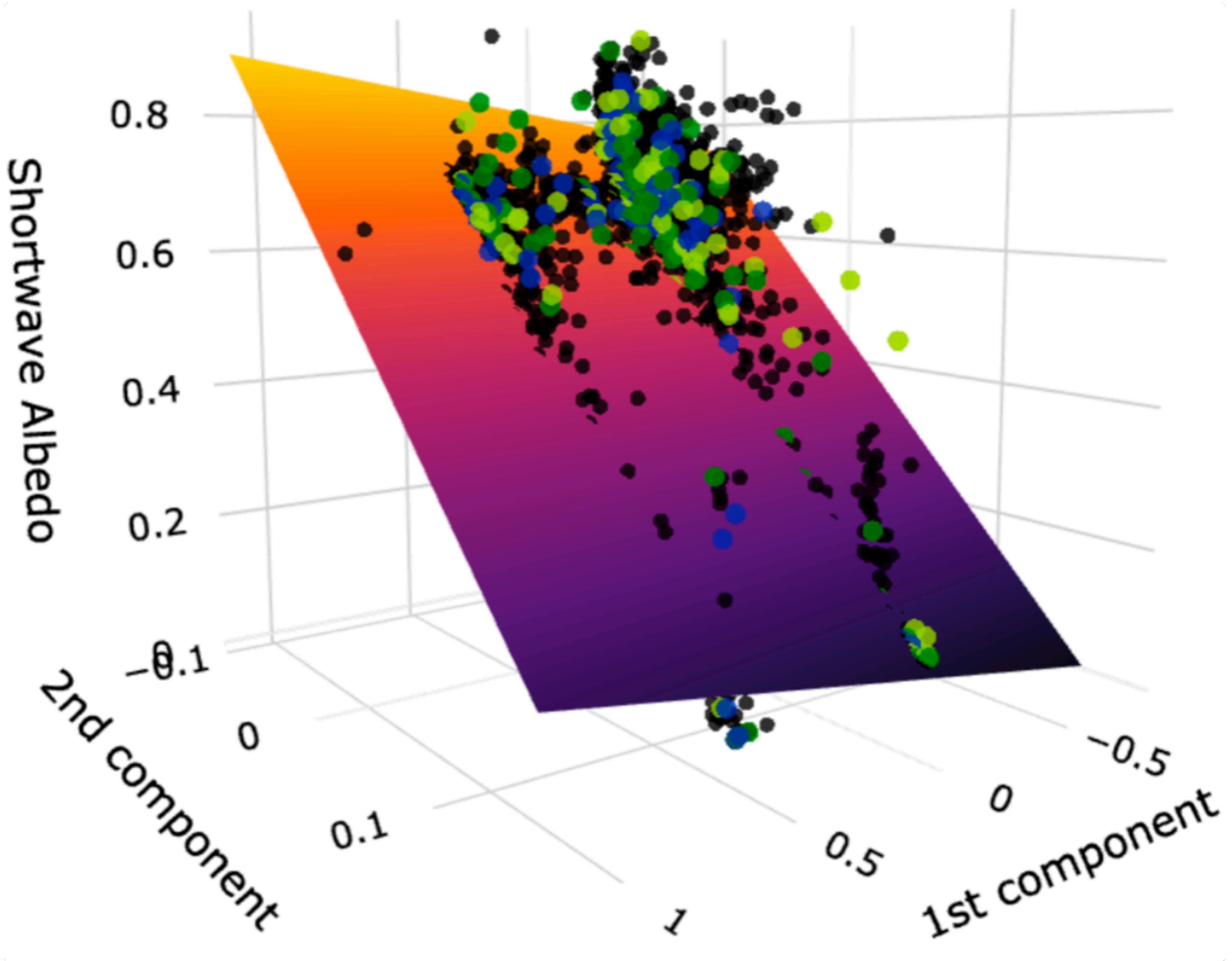


relies on a look-up-table (LUT) to obtain linear relations between TOA radiance and surface albedo

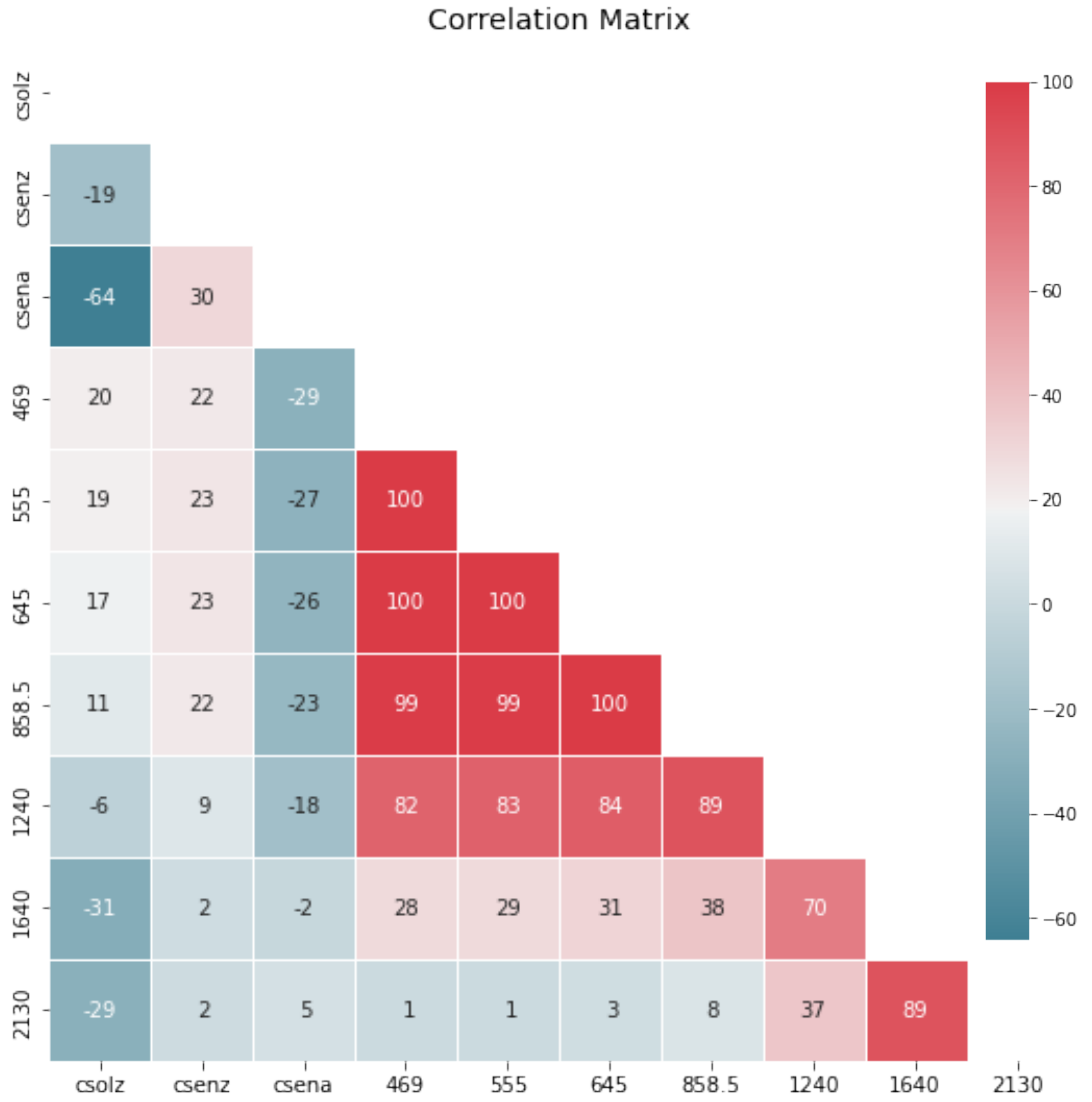
Problem #4: not able to obtain the non-linear relations

A simple linear regression model

Weight?	Feature
+0.385	645
+0.330	858.5
+0.302	1240
+0.211	555
+0.169	469
+0.098	2130
+0.083	csenz
+0.064	1640
-0.044	csena
-0.683	csolz
-1.128	<BIAS>



Radiance values (esp. visible band) have a high correlation



Assumptions that cannot be fulfilled:

- Lack of multicollinearity
- Linearity

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Problem #2: BRDF estimations
Problem #3: Uncoupled RTM

→ Accurate and coupled radiative transfer model (RTM)

Problem #1: Insufficient resolution
Problem #4: a simple regression model

→ Train SciML models to learn the RT processes & deploy to satellite sensors

An Accurate Radiative Transfer Model—— correctly solve the ‘forward’ problem

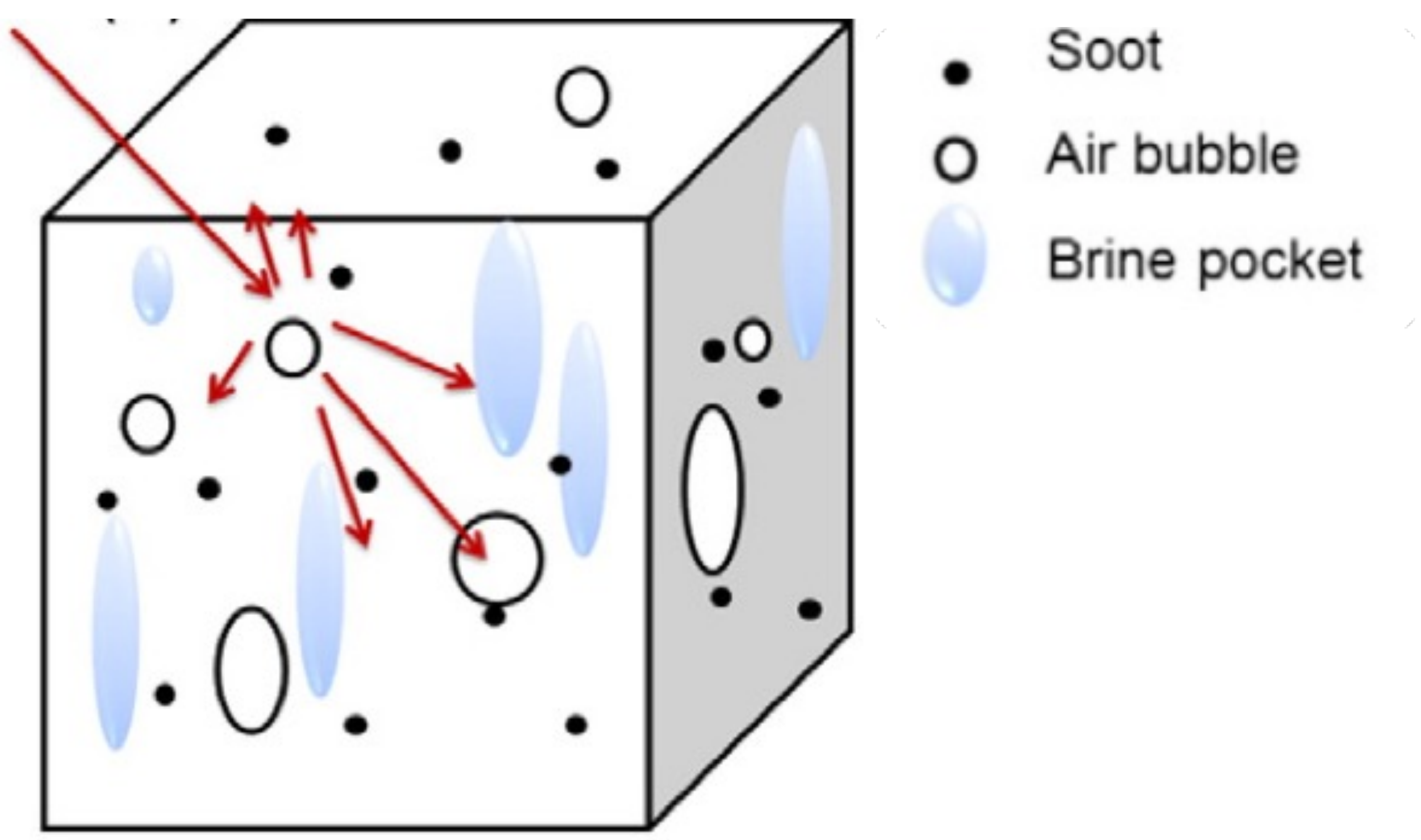
1: A coupled RTM to solve the forward problem:

Angular radiance at TOA level
Spectral irradiance and albedo at the surface

Represent the optical properties of sea-ice / snow / water correctly, with their ‘Inherent optical properties’ (IOPs)

- absorption coefficients
- scattering coefficients
- scattering phase function

IOPs of sea-ice



IOPs of all surfaces & atm.

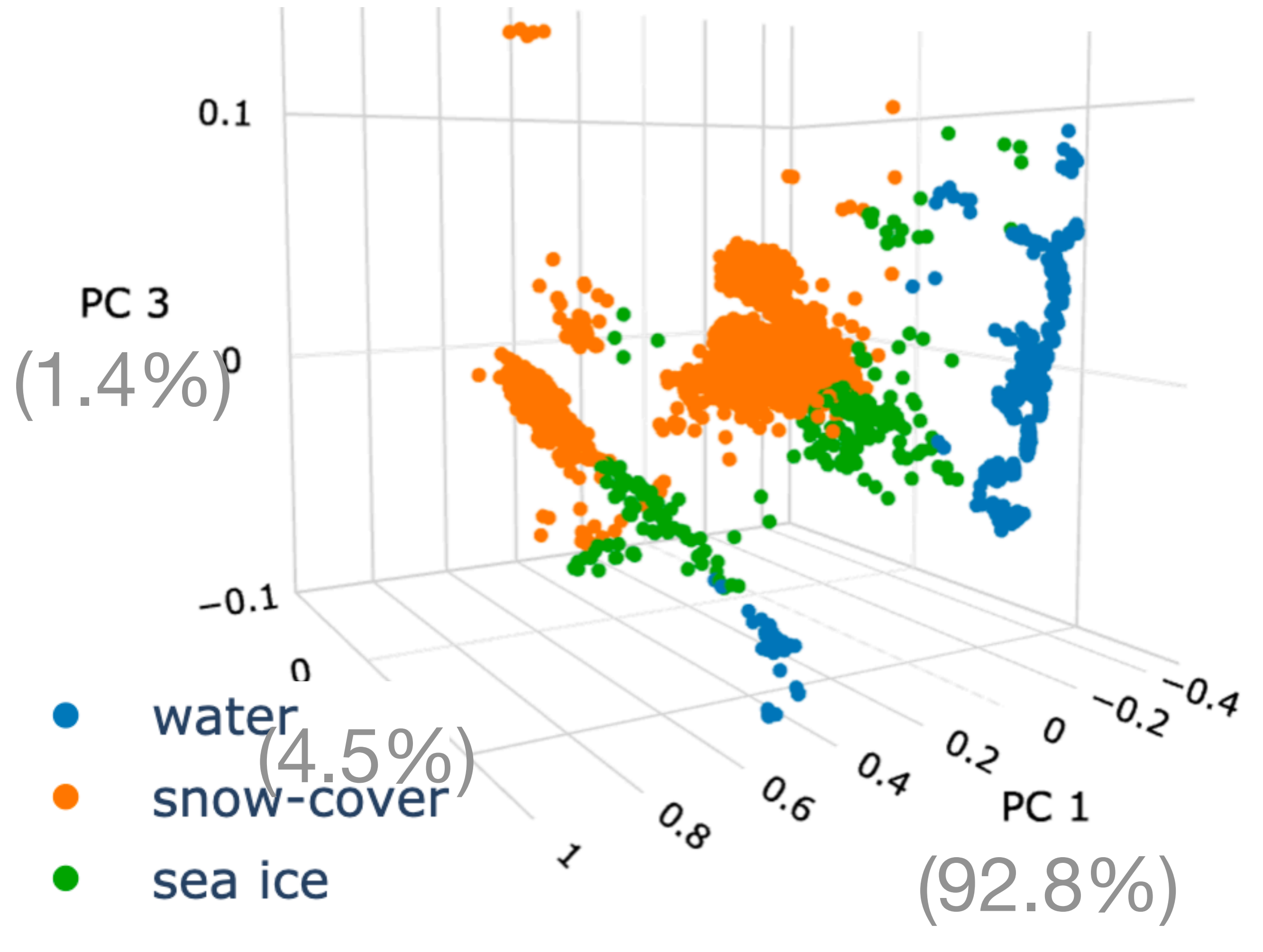
Type	Parameter	Properties	Comments
bare ice	X_{ice}	h	sea ice thickness
		V_{br}	brine pocket volume fraction
		r_{br}	brine pocket radius
		V_{bu}	air bubble volume fraction
		r_{br}	air bubble radius
		$f_{\mathrm{bc,i}}$	black carbon impurity fractions in ice
		X_{water}	physical properties of the ocean water beneath the sea ice layer
snow-covered ice	X_{snow}	r_{e}	effective grain size of snow particles
		ρ_{s}	snow density
		h_{s}	snow depth
		$f_{\mathrm{bc,s}}$	black carbon impurity fractions in snow
		X_{ice}	physical properties of the sea ice below the snow-cover layer
		X_{water}	physical properties of the ocean water beneath the sea ice layer
ocean water	X_{water}	h_{w}	open-water depth
		f_{chl}	chlorophyll-a concentration
		f_{CDOM}	colored dissolved organic matter (CDOM) concentration
melt-pond	X_{melt}	h_m	melt pond thickness
		X_{ice}	physical properties of the sea ice below the melt pond layer
		X_{water}	physical properties of the ocean water below sea ice layer
aerosol	$X_{aerosol}$	τ_{aero}	aerosol optical depth in the atmospheric layer

Step 2: A comprehensive dataset that includes all conditions, and use any appropriate SciML models to solve the ‘inverse’ problem

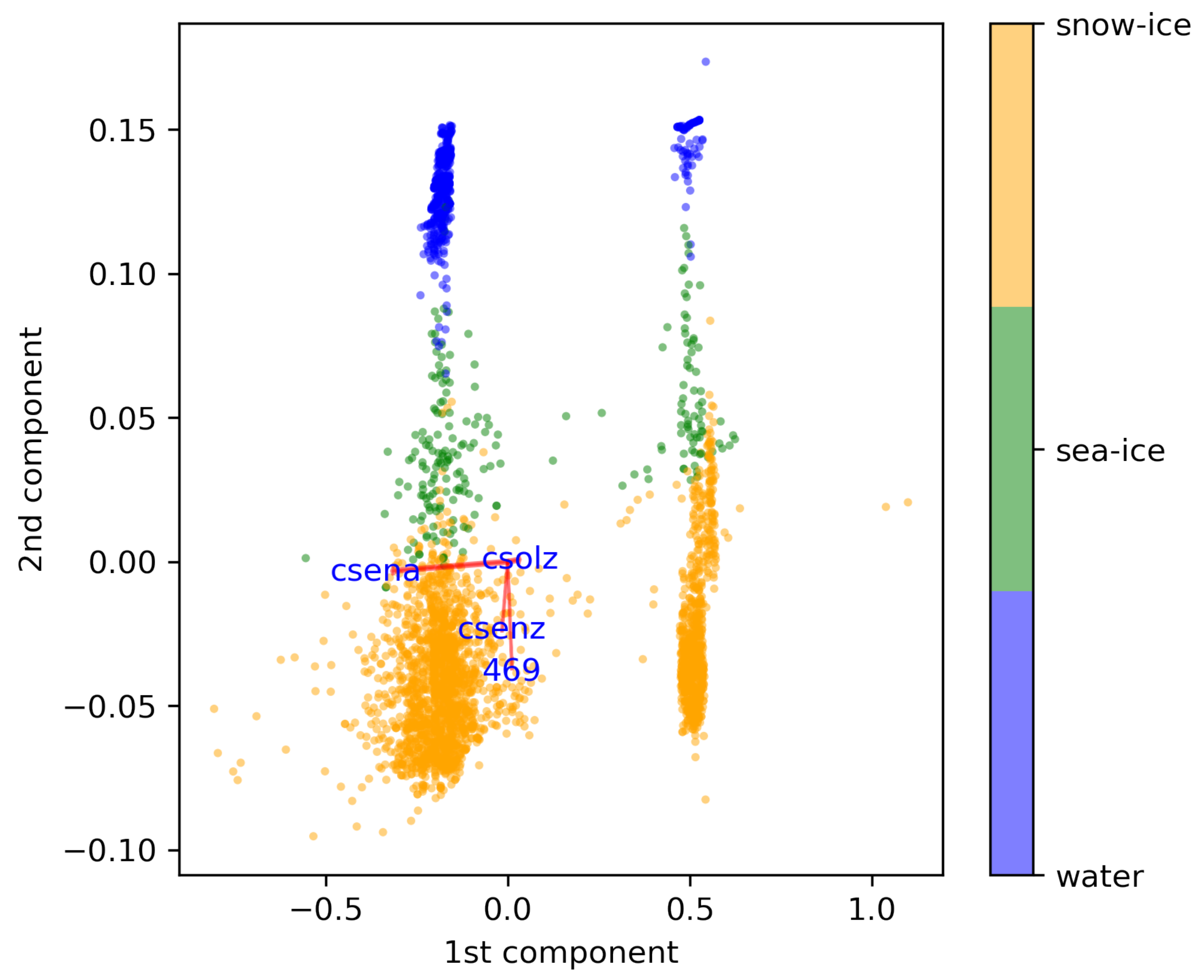
Surface condition
Atmospheric condition
Geometry angle combinations

Use SciML models to solve the 'inverse' problem
—— with the Principal Component Analysis (PCA) as an example

Project the input data onto three PCs
(PCA, with 3 principal components)

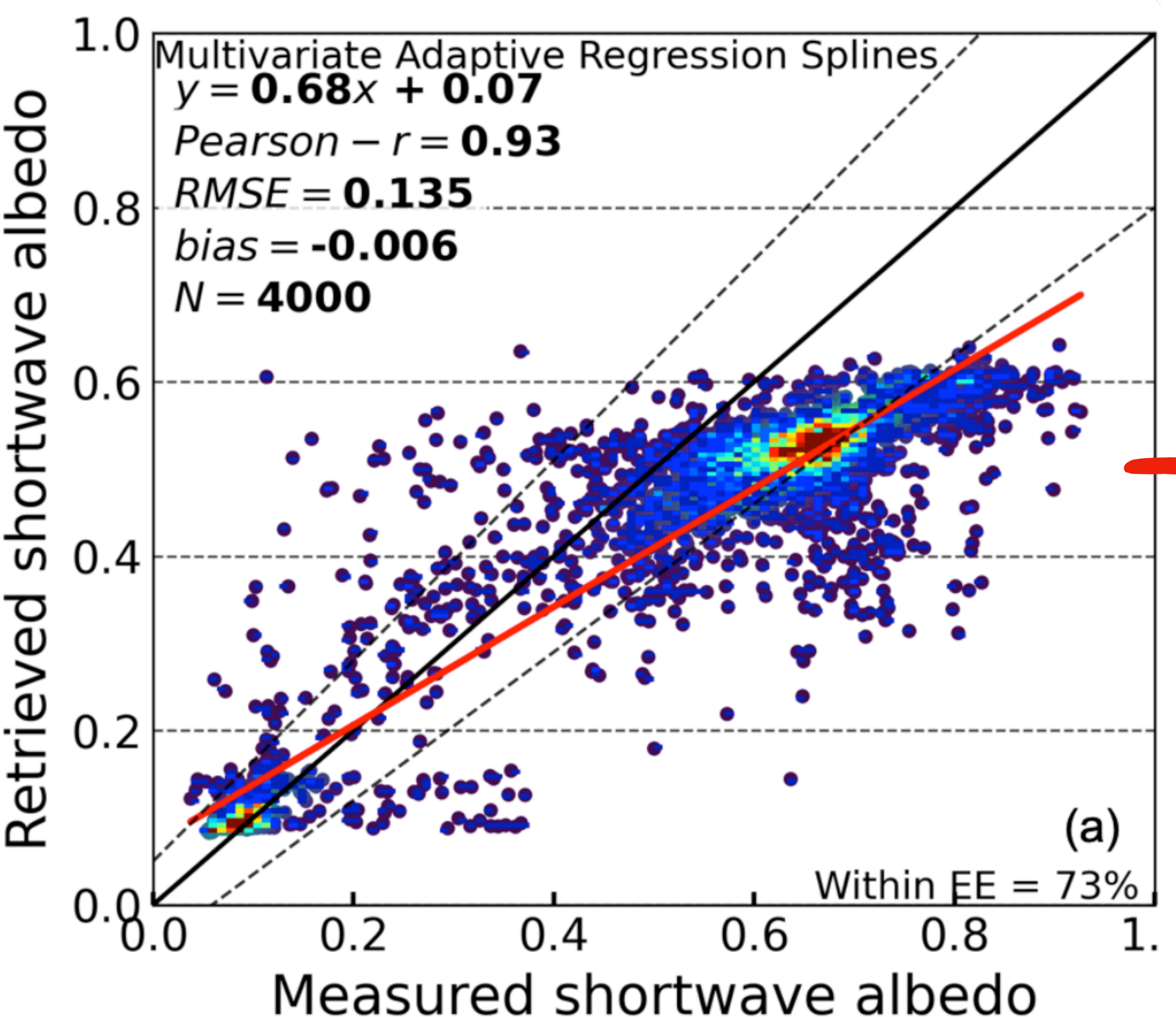


Project the input data onto two PCs
(PCA, with 3 principal components)

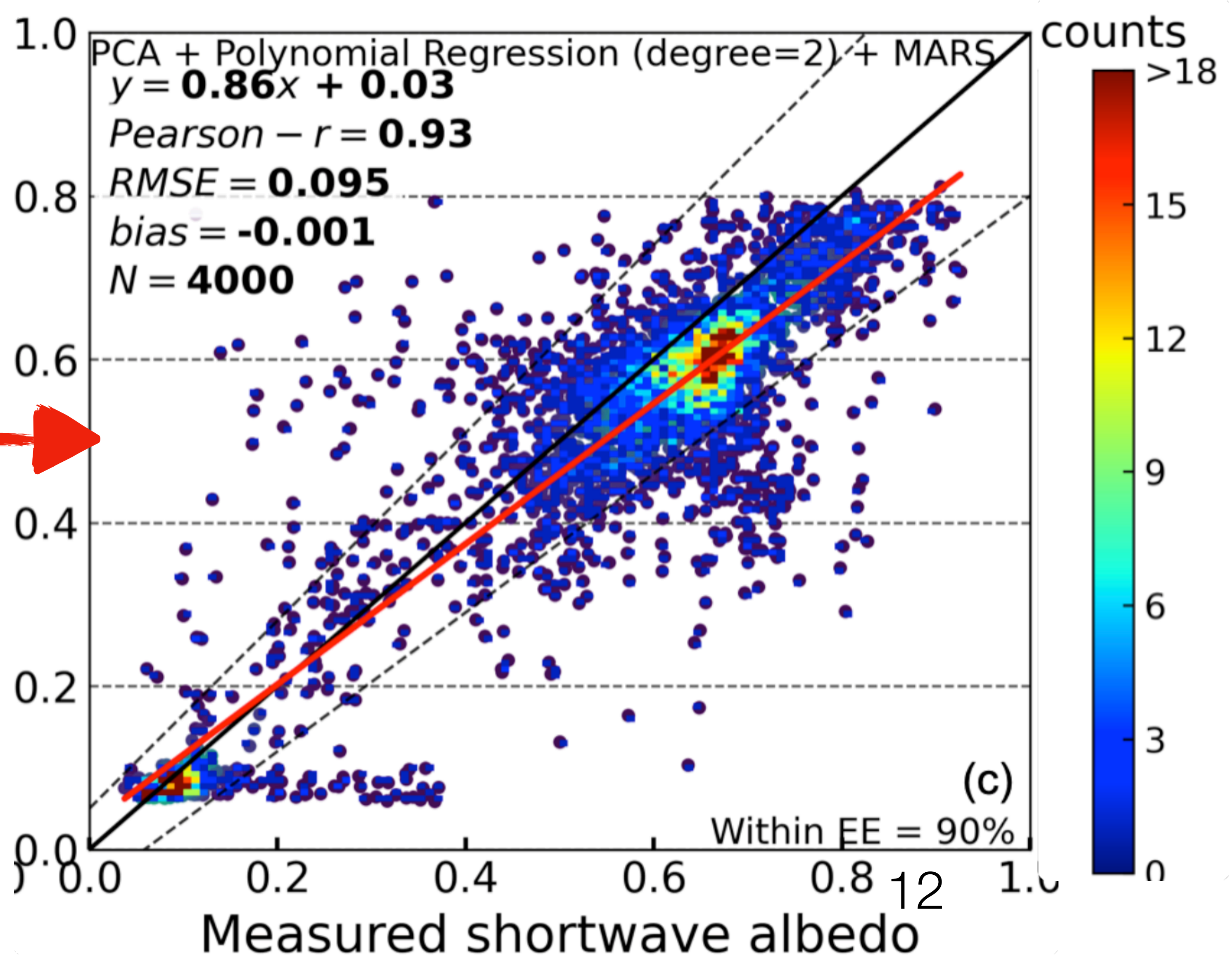


'dot product' operation can already assist to distinguish the surface types

Piecewise linear regression



PCA-engineered piecewise linear regression



and thereby improves the regression on 'albedo' values

Use SciML models to solve the 'inverse' problem

During SciML model training:

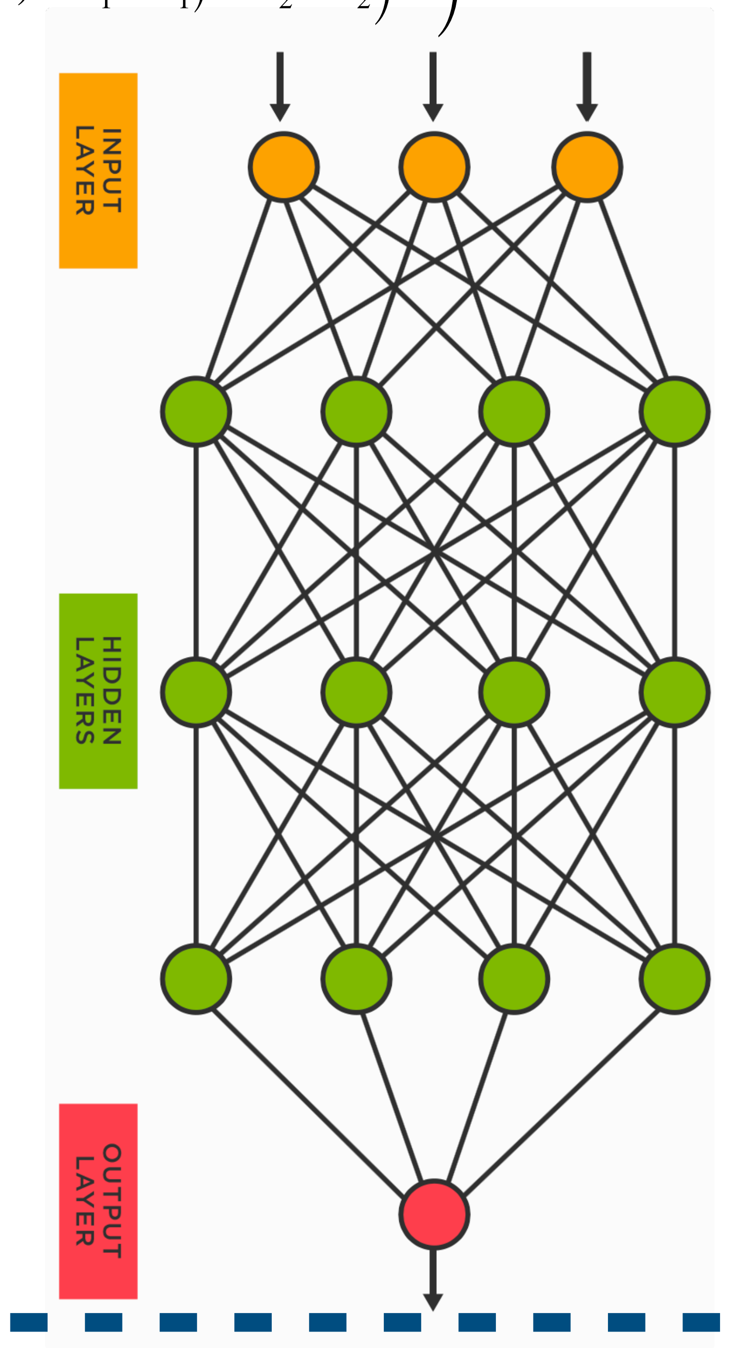
Inputs (from the synthetic dataset)

Randomly-generated sun-sensor geometry angles

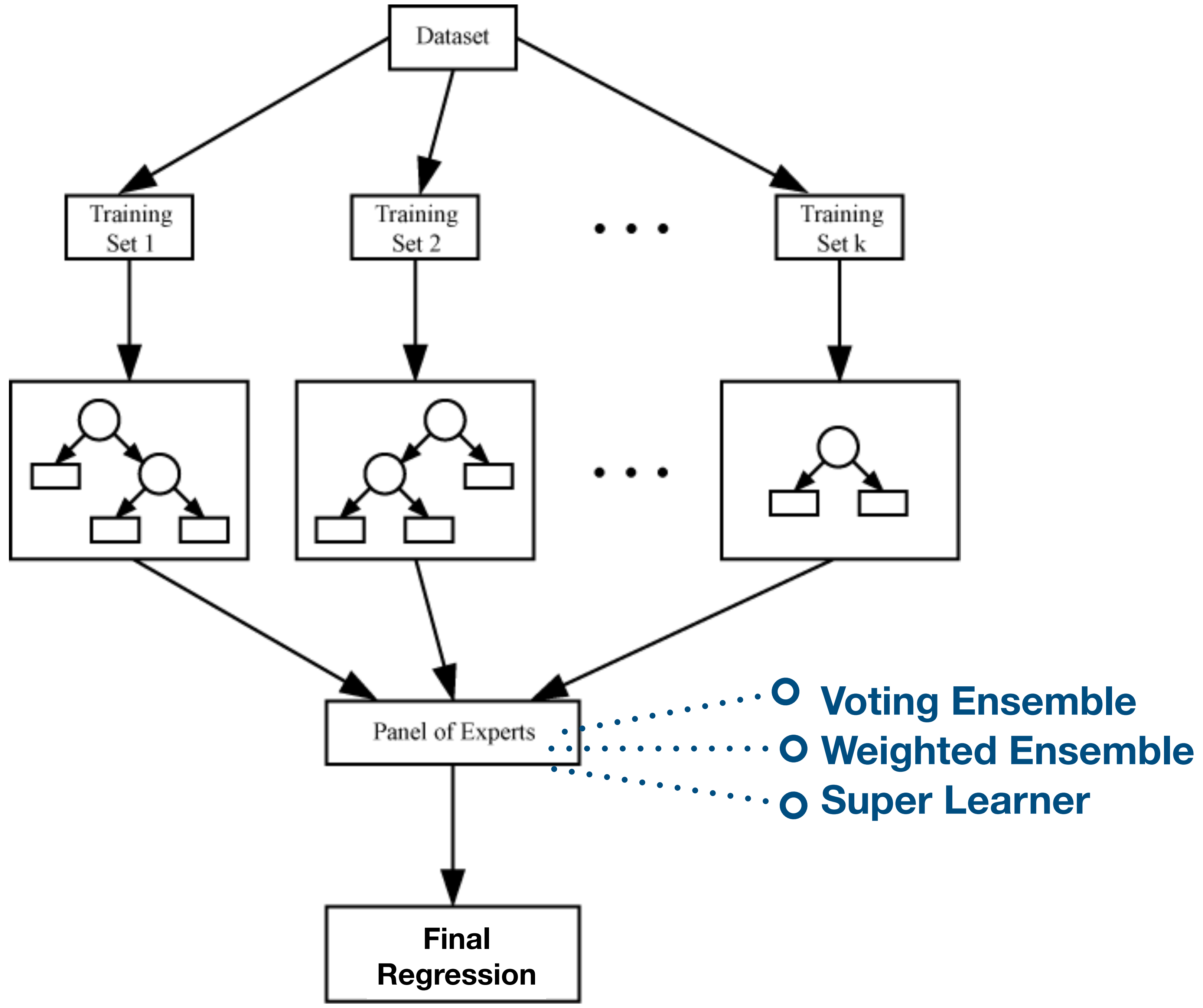
Seven TOA radiance from RTM computation

Multi-layer Artificial Neural Network

$$F(x) = f_n\left(\dots f_3\left(f_2\left(f_1(x)\times w_1 + b_1\right)\times w_2 + b_2\right)\dots\right)$$



Ensemble models



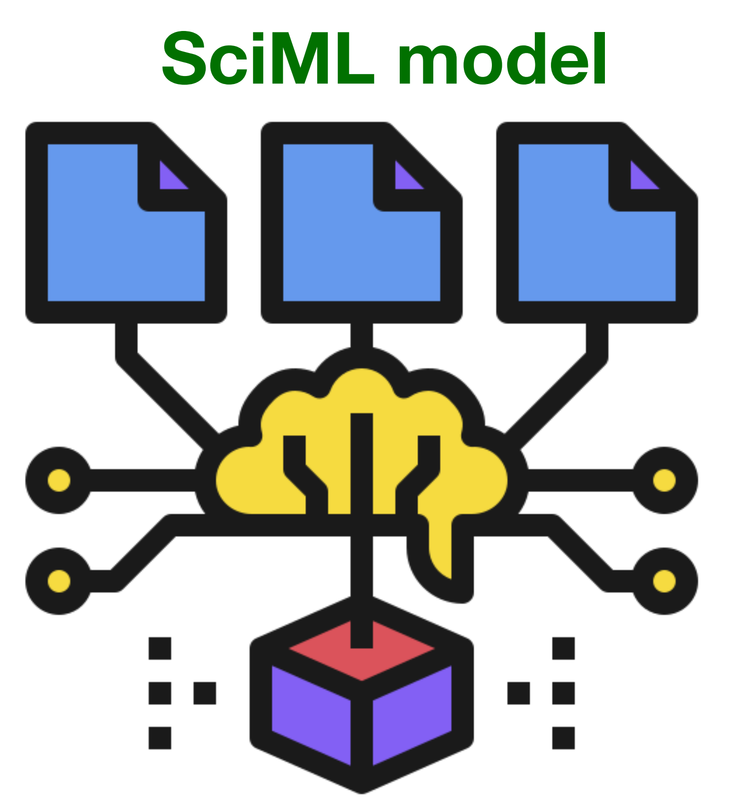
Outputs:

Three broadband **albedo**

During deployment:

Inputs (from sensor)

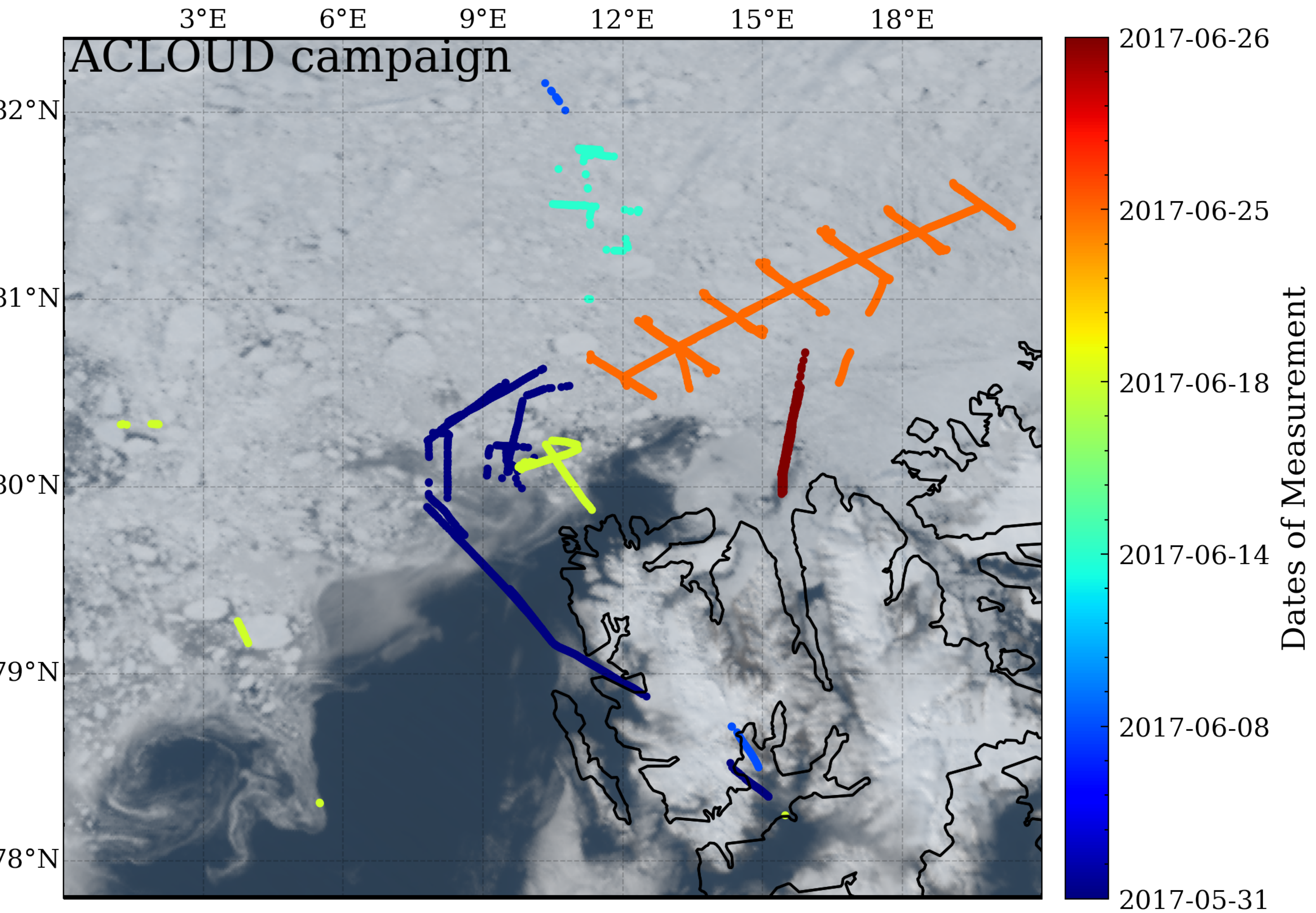
1. Seven **TOA radiance**
2. Sun-sensor **geometry**



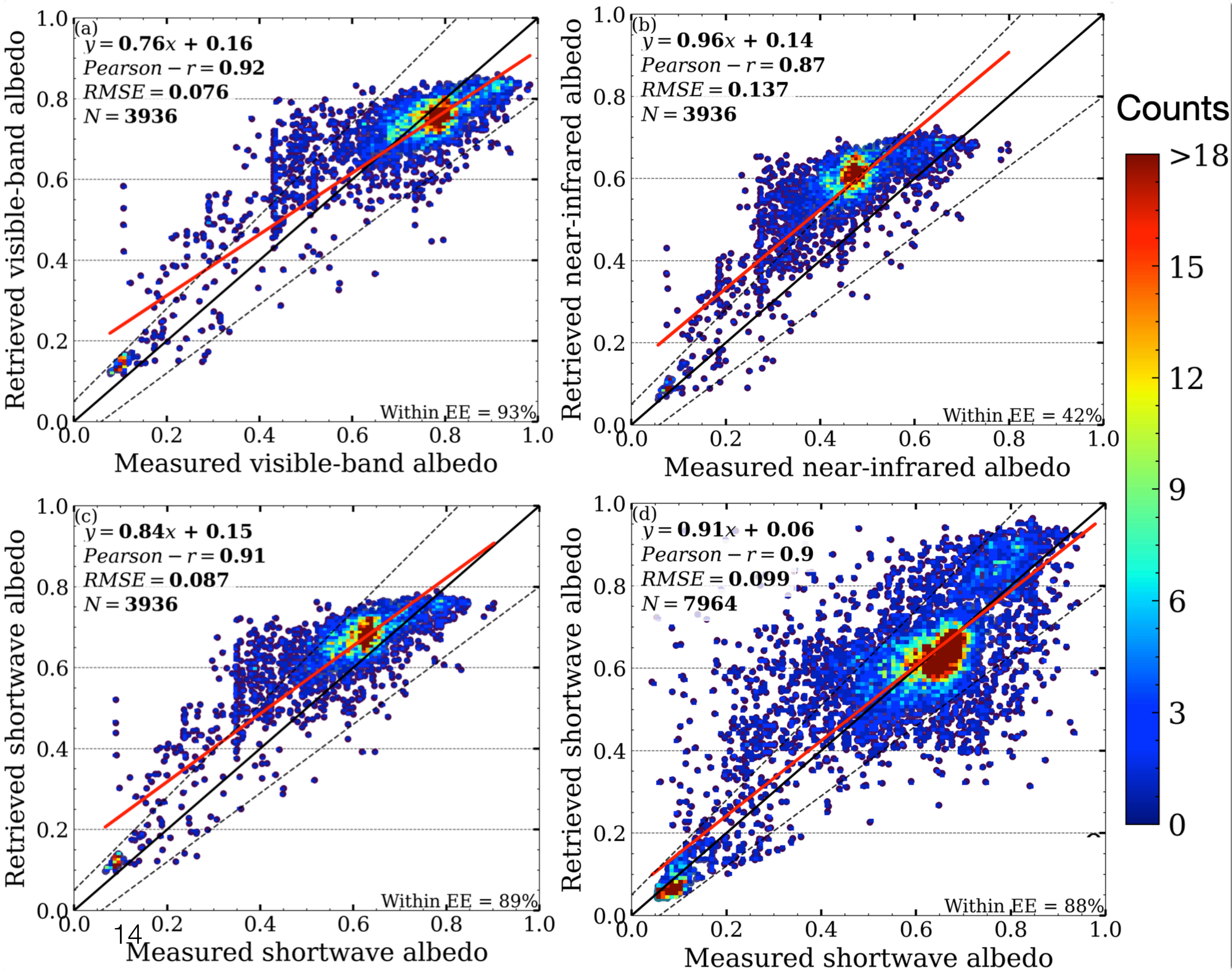
Outputs:

Three broadband **albedo**

Evaluation on the retrieval model with aircraft measurements, with $\delta_t \leq 5h$



Good agreement, considering the numerous uncertainties



Data

- albedometer (~4000)
  $\alpha_{SW}, \alpha_{VIS}, \alpha_{NIR}$
- pyranometer (~8000)
  α_{SW}

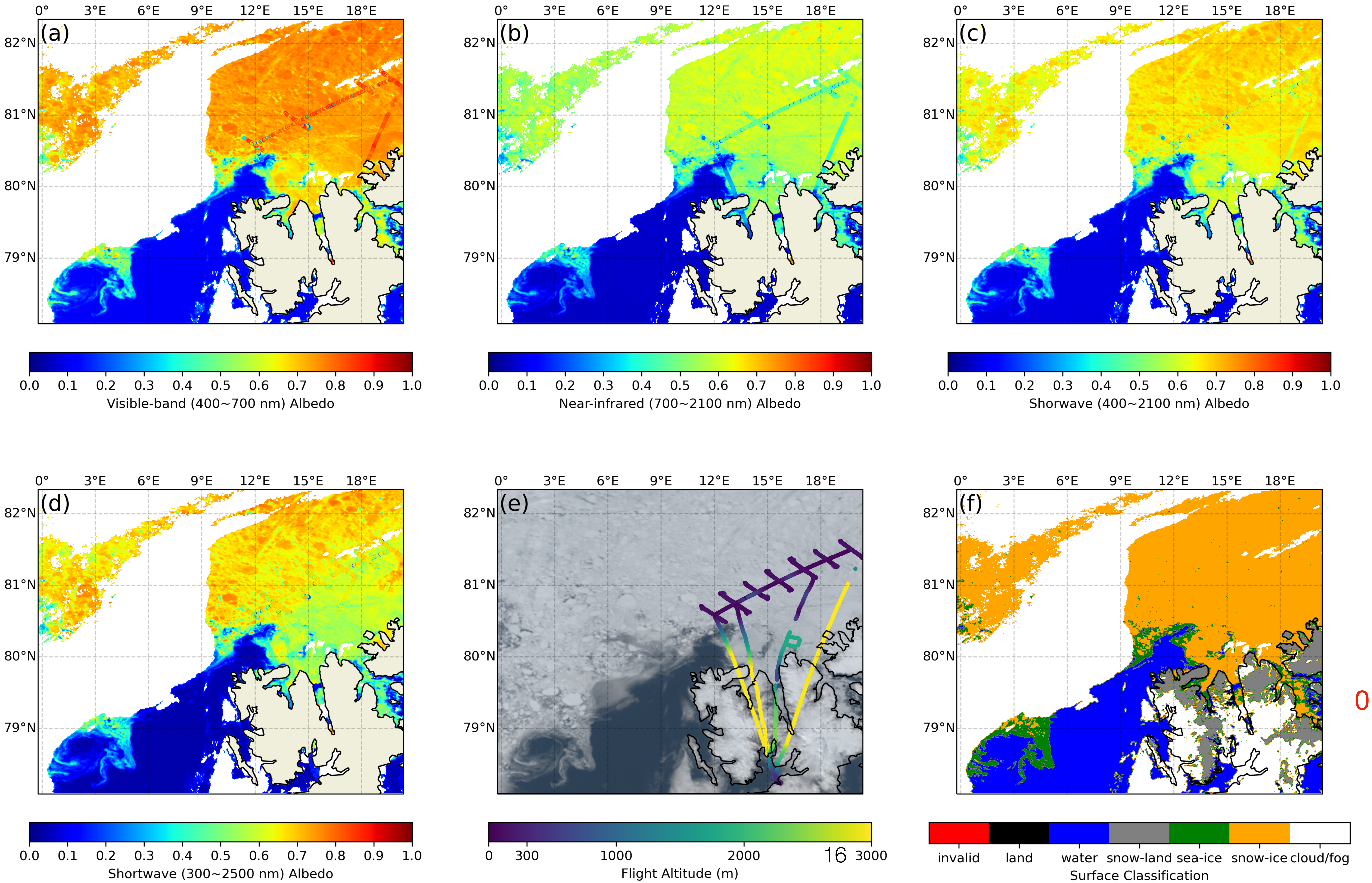
Metrics

$$\text{error} = \frac{1}{n}\sum_{i=1}^{n} \left| y_i - \hat{y}_i \right|$$

$f_{EE\leq 15}, f_{above}, f_{below}$

Evaluation on the retrieval model with aircraft measurements, with $\delta_t \leq 1.5h$

Evaluation on the retrieval model with aircraft measurements, on a cloud-free image



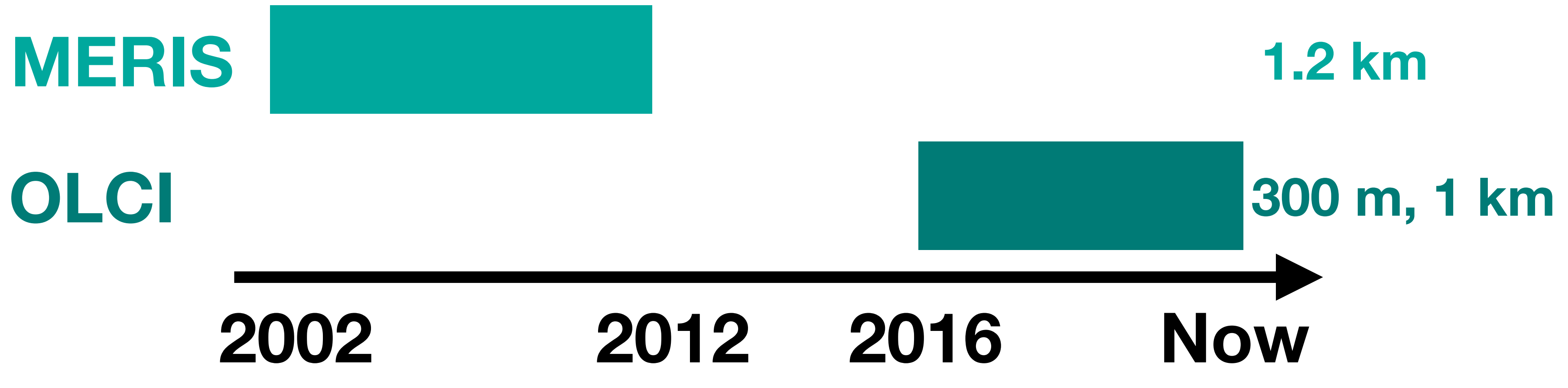
0.047 means absolute error, compared to the *in-situ* measurements

Compared to the MODIS-albedo product (MCD43)

Methodology	Product	Problems
BRDF angular modeling	MCD43	1. Requires BRDF in 16-day window (unable to capture the temporal variation) 2. Only functions at shallow shores (near coastlines)

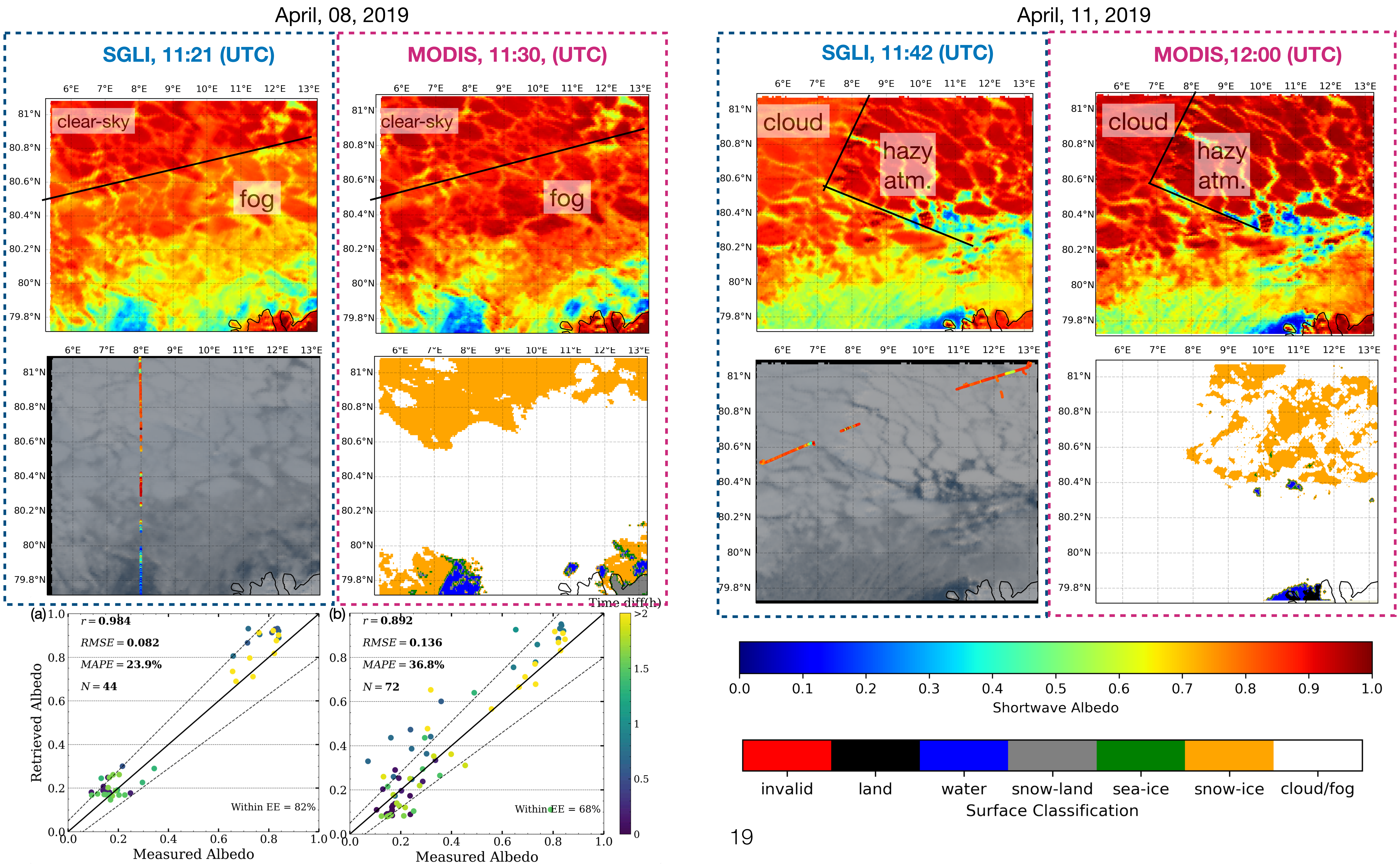
Compared to the MERIS/OLCI-albedo product (MPD-based retrieval)

Methodology	Problems
Analytical solution of RTM based on the ‘melt-pond detector’ algorithm	1. Only functions during late May to early Sept. 2. Imprecise retrieval results in some situations 3. Unavailable open-water retrieval



The retrieval method (coupled-RTM + SciML) can be applied to any optical sensor

Allows for sensor-to-sensor comparison of the retrieval results, or for increasing spatial/temporal retrieval-coverage



Summary

Developed an albedo-retrieval algorithm that provides

✅ Reliable retrieval results

- Mean absolute error = 0.047
- Physically consistent with f_{ice} , r_e

✅ Better spatial-temporal resolution

- Consistent with L1B radiance of the sensor
- Up to 4 retrievals / day

✅ Sensor-agnostic results

- SGLI, MODIS, VIIRS …

✅ Better performance than all existing albedo products

- MCD43 product
- 'Melt pond detector'-based products

Zhou, Y., Li, W., Chen, N., Fan, Y., and Stamnes, K.: A sensor-agnostic albedo retrieval method for all sea ice surfaces: Model and validation, The Cryosphere (submitted).


Q
A