

How is Remote Sensing used to observe the oceans?



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NTUA PH [] T []
GRAMMETRIC
COMPUTER VISION

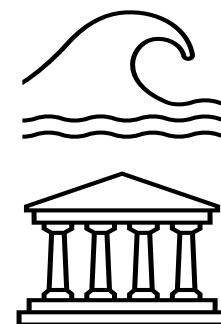
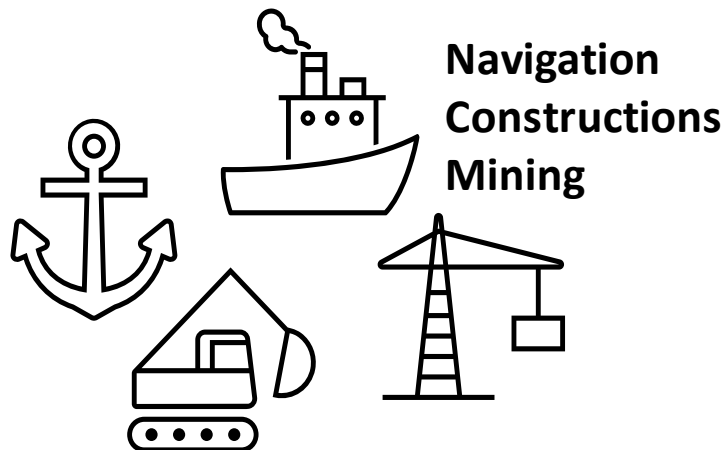


3[Deep]Vision
Research Group



RS platforms can "see the sea" in ways that are otherwise impossible

Why?

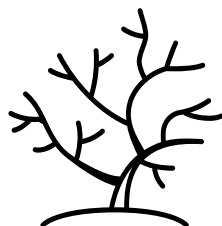
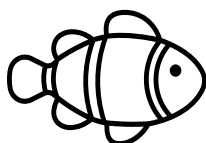


Cultural Heritage

Marine litter
detection



Support action
for climate



Map/monitor marine animal
forests

Tourism



What kind of platforms and data?



Satellites, occupied airborne or unoccupied airborne (drones)

- RGB+MS imagery
- LiDAR
- SAR Radar Altimeter
- Other special payload instruments (radiometers etc.)

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Satellites, occupied airborne or unoccupied airborne (drones)

- **RGB+MS imagery**
- LiDAR
- SAR Radar Altimeter
- Other special payload instruments (radiometers etc.)

How can we get this information?

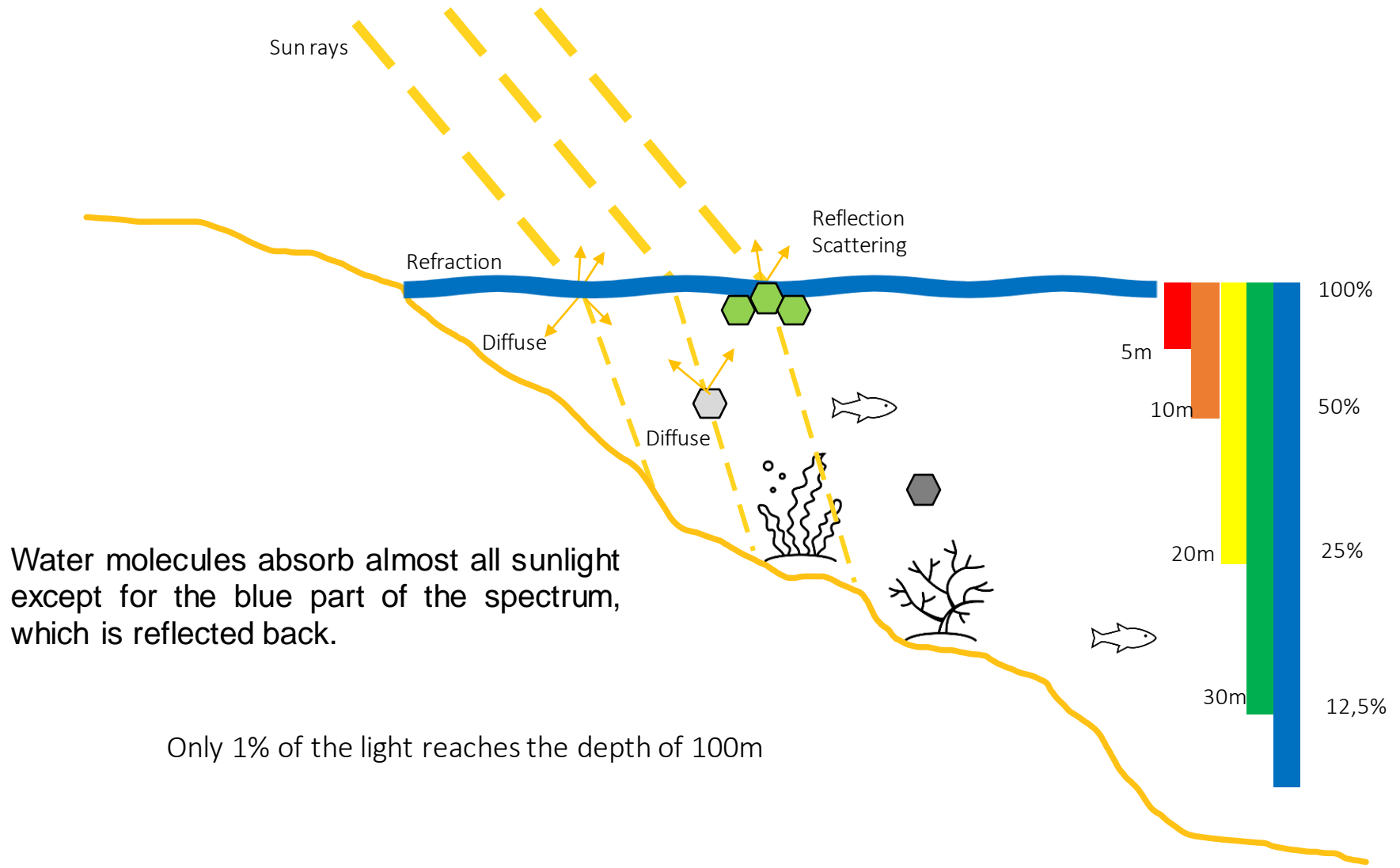
- **Exploiting the RADIOMETRIC information of the scenes**
- **Exploiting the GEOMETRIC information of the scenes**

What info can we get using RGB and MS Remote Sensing Ocean data?



- Biogeochemical indices (chlorophyll, nitrates)
- Sea ice coverage and state
- Sea surface temperature
- Marine debris detection/ tracking
- Pollution/ oil spill detection/ tracking
- Shallow water bathymetry
- Shallow seabed cover maps

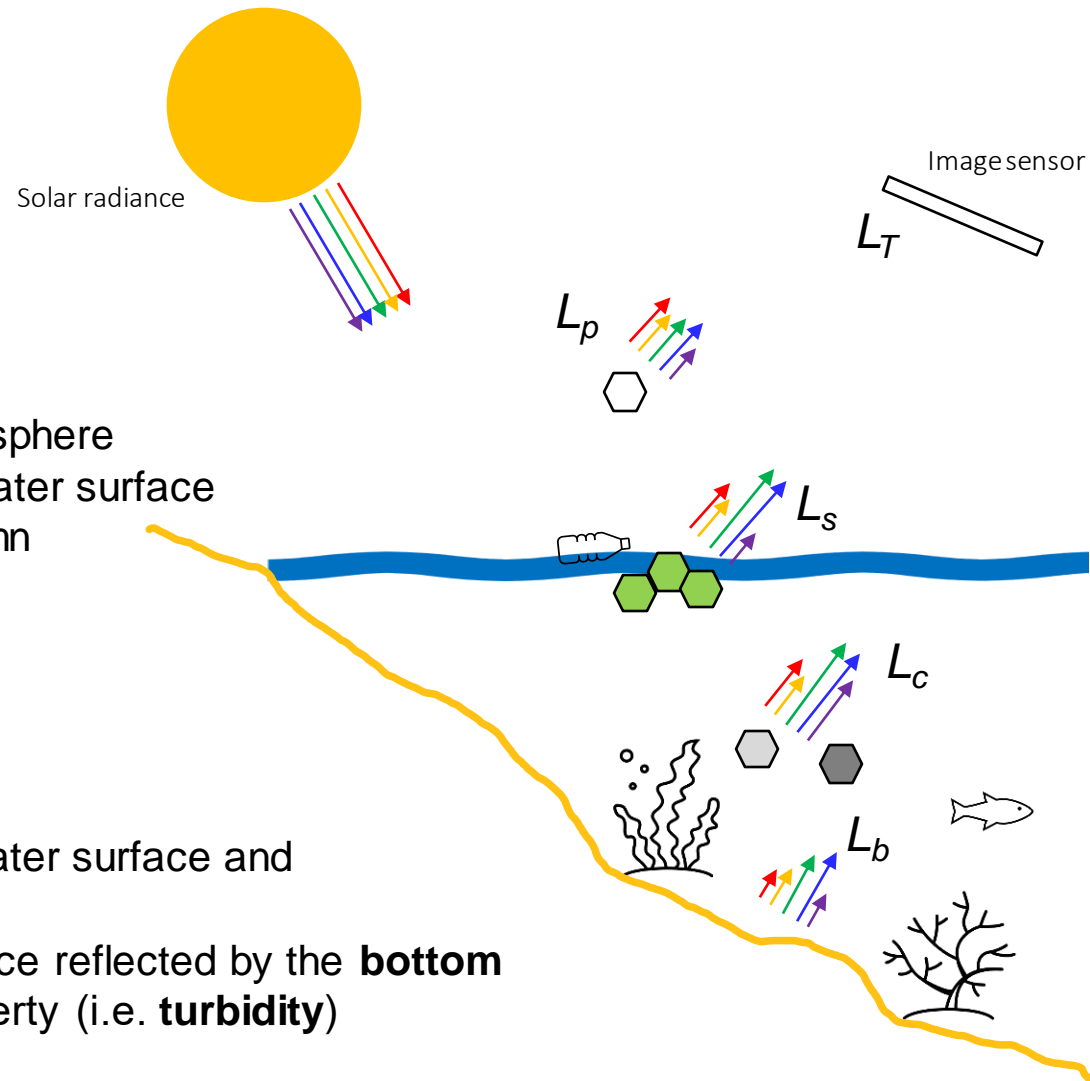
Light absorption in water column



Water molecules absorb almost all sunlight except for the blue part of the spectrum, which is reflected back.

Only 1% of the light reaches the depth of 100m

Basics of Spectral-based methods



$$L_T(\lambda) = L_p(\lambda) + L_s(\lambda) + L_c(\lambda) + L_b(\lambda)$$

L_T is the total upwelling radiance

L_p are the contributions from the atmosphere

L_s is the radiance reflected from the water surface

L_c is the radiance from the water column

L_b is the bottom-reflected radiance

L_s depends on the roughness of the water surface and sun position (**sun glint**)

L_b is related to **depth** and is the radiance reflected by the **bottom**

L_c is related to the water's optical property (i.e. **turbidity**)

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Biogeochemical indices

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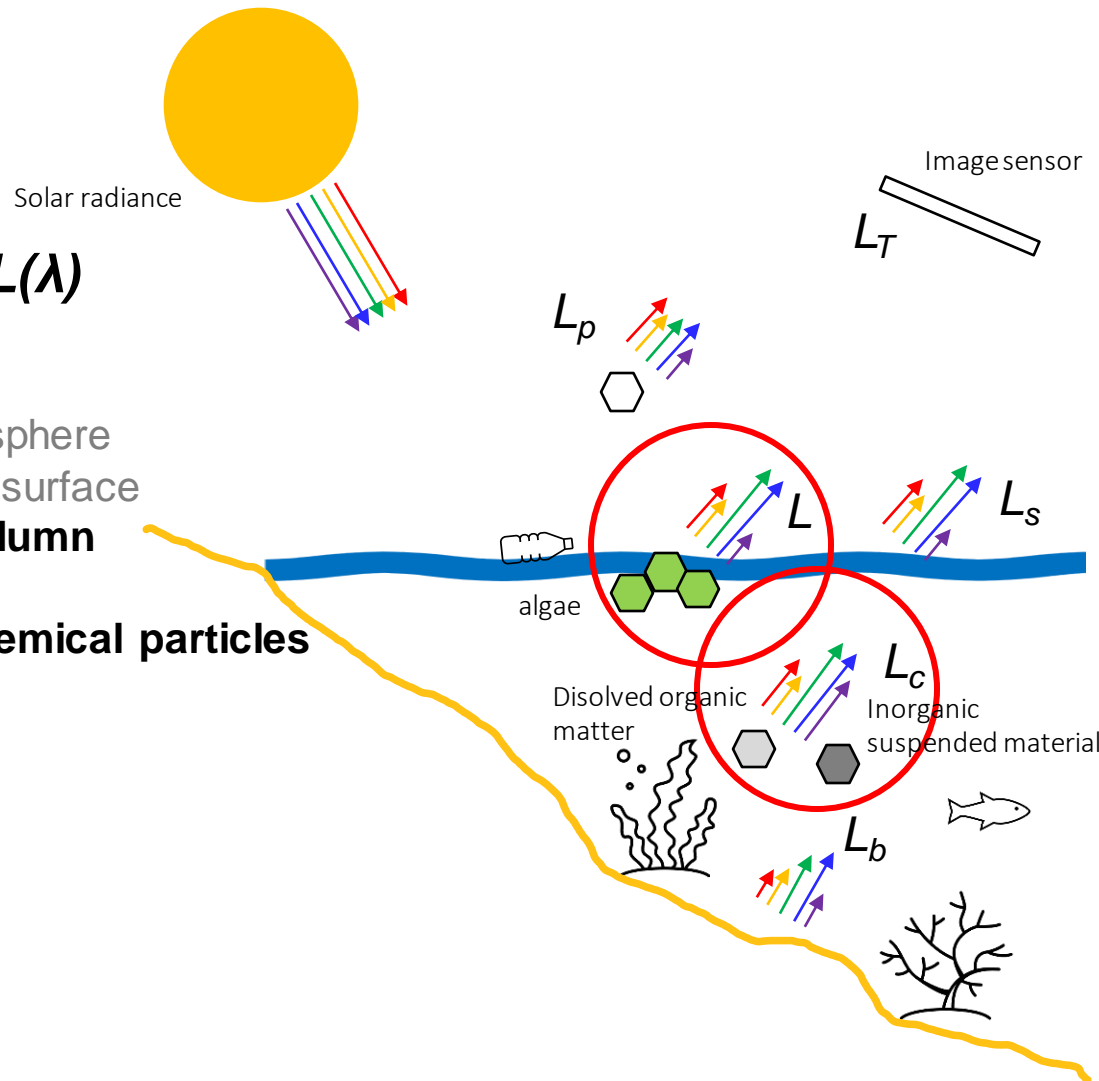
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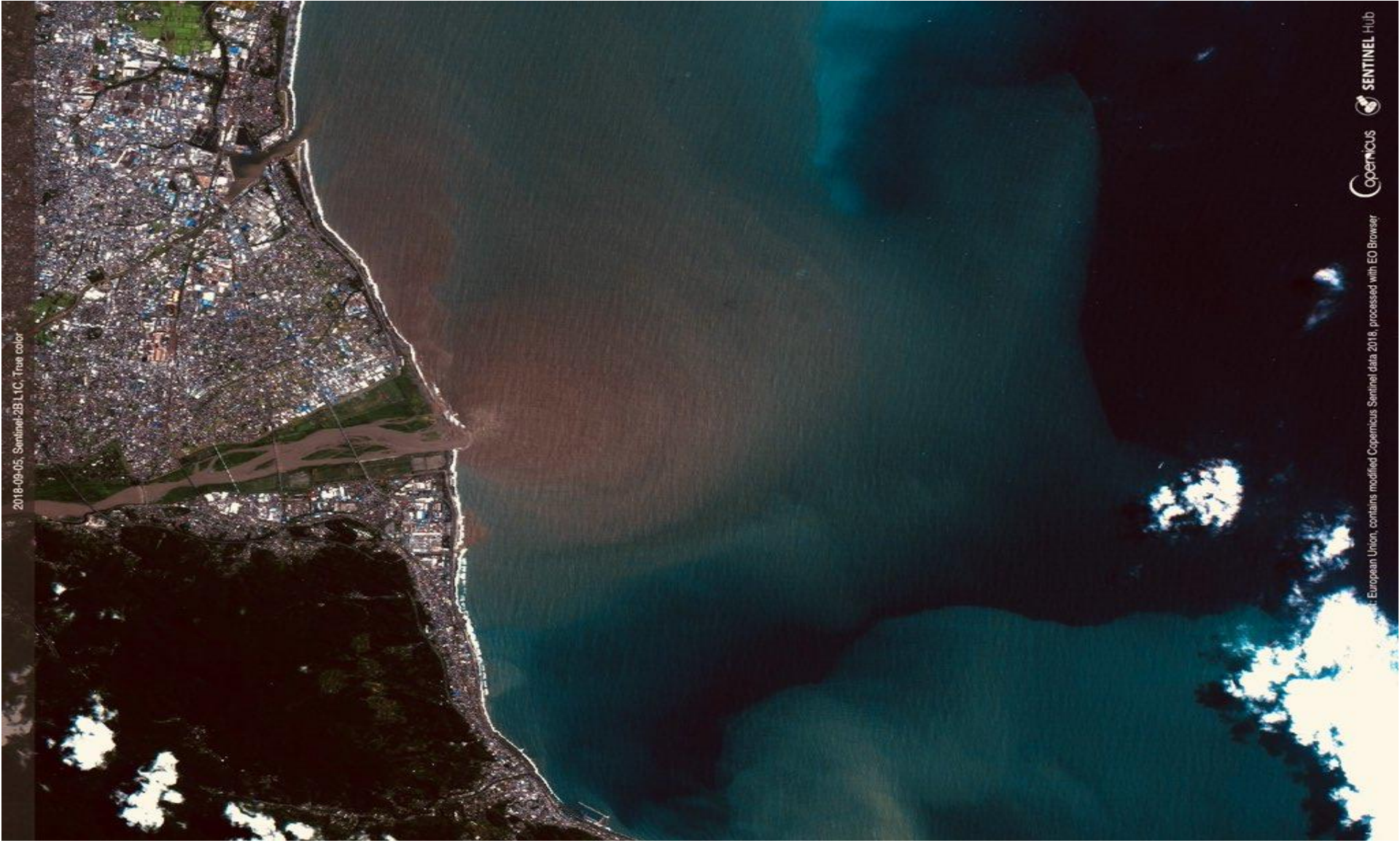
L is the radiance from the biogeochemical particles



Chlorophyll (algae)



Suspended matter (turbidity)



2018-09-05, Sentinel 2B L1C, True color

European Union, contains modified Copernicus Sentinel data 2018, processed with EO Browser

Copernicus SENTINEL Hub

Get biogeochemical indices



How?

Empirical algorithms

Statistically relate measurements of i.e. chlorophyll (CHL) or suspended matter and reflectance through regression, polynomial expressions or **Artificial Neural Networks**

Widely used bands:

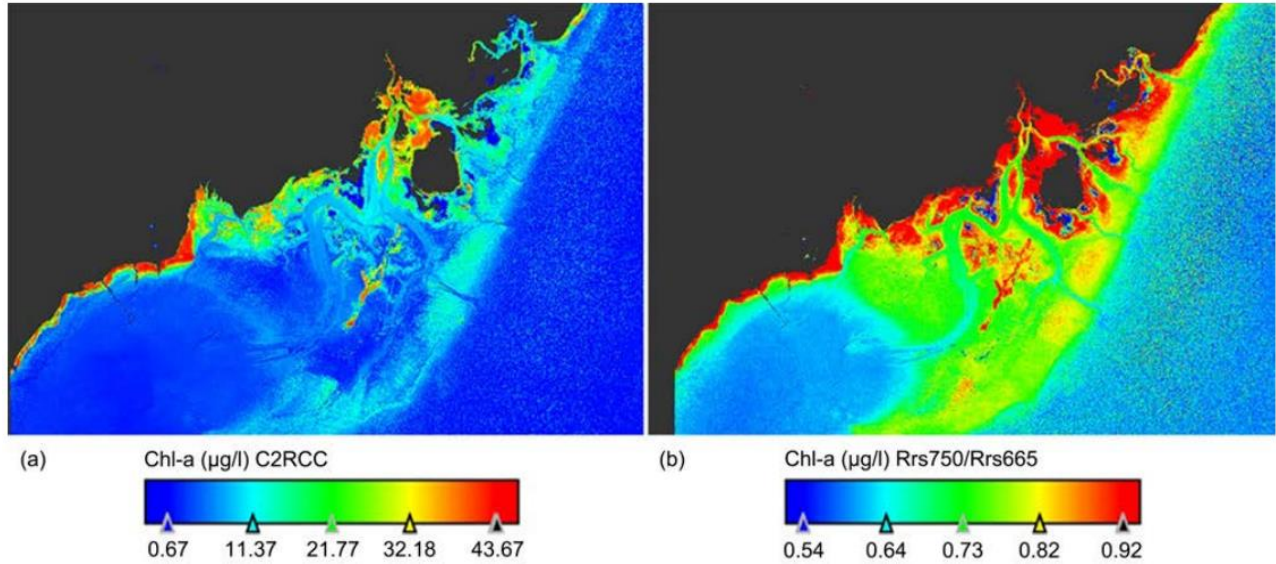
- Chlorophyll: Red, green and visible and near infrared (VNIR) bands
- Suspended matter: Red band

Semi-analytical algorithms

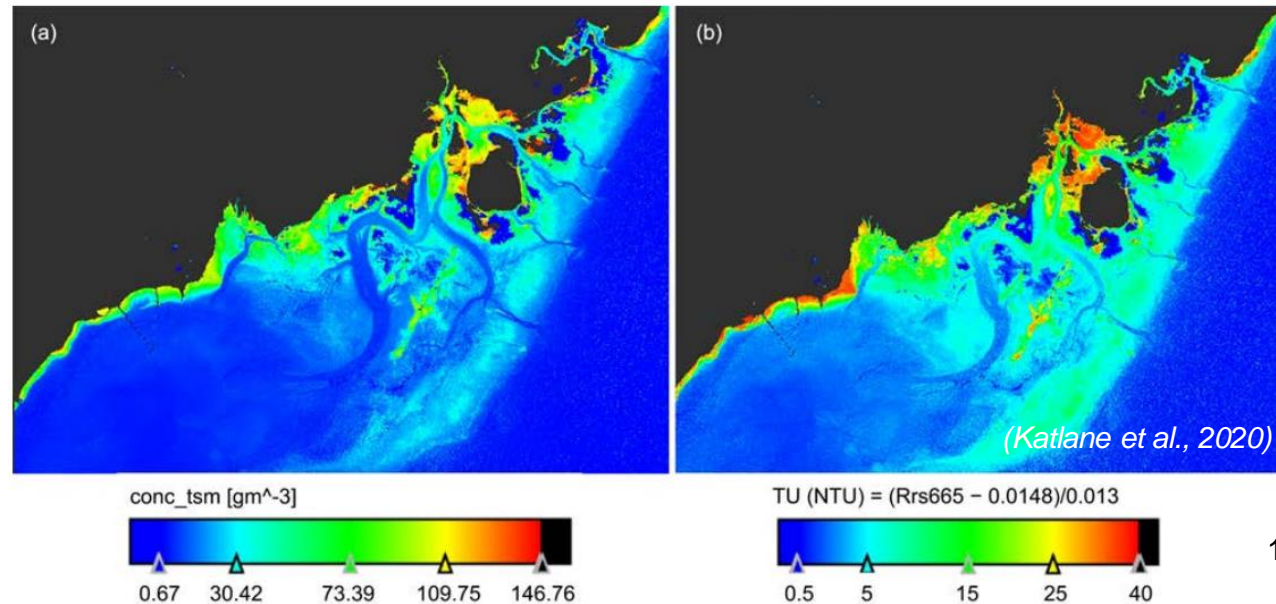
Estimate CHL via spectral absorption of phytoplankton, spectral backscattering by particles & the combined absorption by non-algal particles and colored dissolved organic material (*O'Reilly et al., 2019*)

Examples

Chlorophyll



Suspended matter

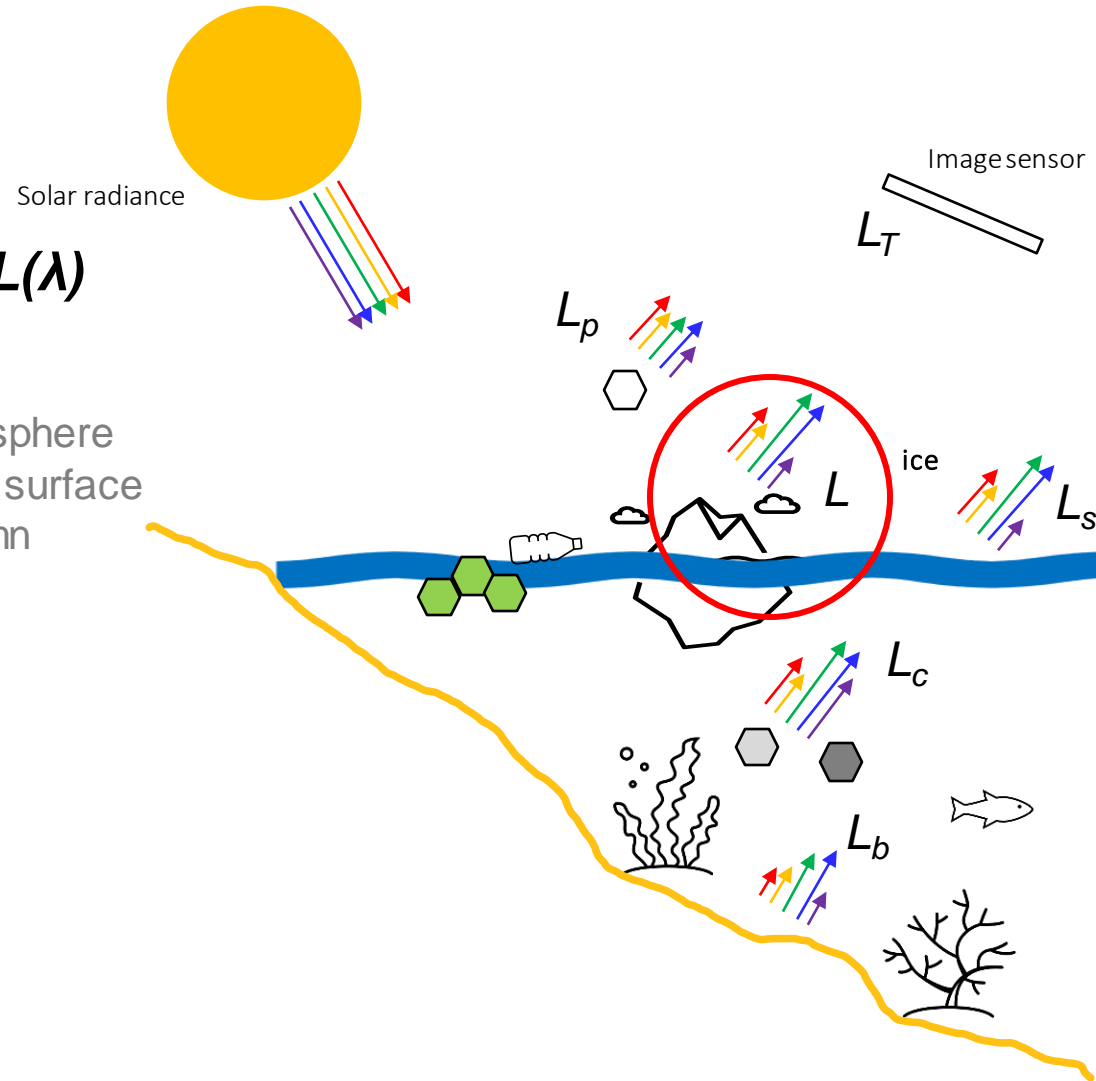


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Sea ice



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L_b is the bottom-reflected radiance

L is the ice-reflected radiance

Sea ice



PROGRAMME OF THE
EUROPEAN UNION



Ilulissat - Greenland, Sentinel-2, 1 May 2022



Ilulissat

Credit: European Union, Copernicus Sentinel-2 Imagery - Processed by @GCFIS, DJI

How?

Empirical algorithms

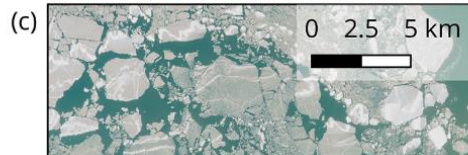
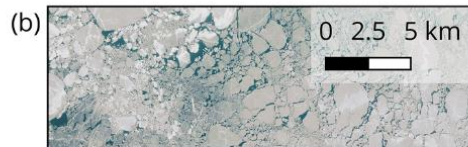
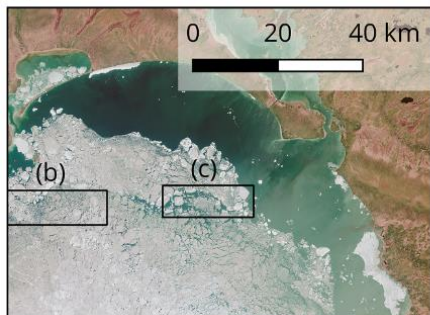
- Exploit spectral characteristics of snow, ice, & water in the visible and NIR
- Simple regression and polynomial models
- Support Vector Machines
- Gaussian Mixture Models
- Fully Conv. Neural Nets.

Major difficulties

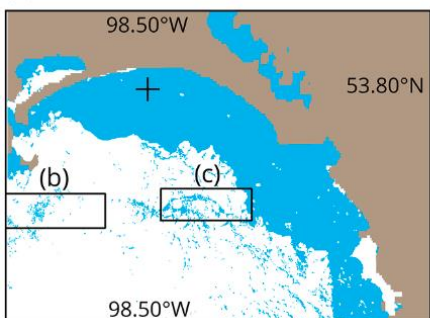
- Clouds: limited visibility & similar spectral characteristics
- Low light conditions: at high latitudes during polar night
- Thin ice at melting stage (black ice) is transparent and appears with the same color of the underlying water

Sea ice

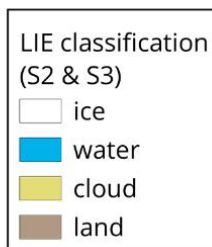
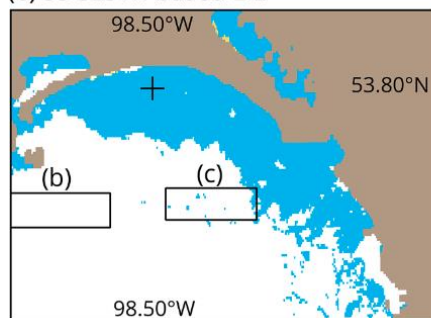
(a) S2 MSI true colour



(d) S2 MSI-based LIE



(e) S3 SLSTR-based LIE

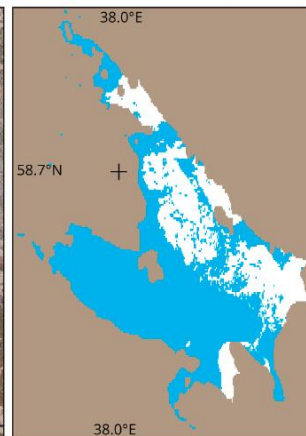


(Heinilä et al., 2021)

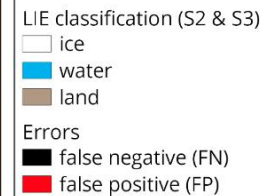
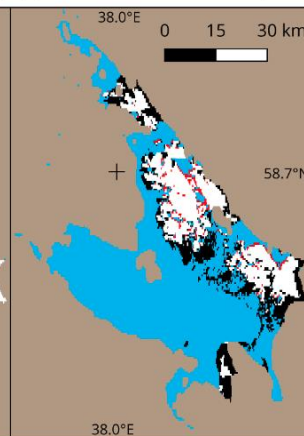
(a) S2 MSI (true colour)



(b) S2 MSI-based LIE (0.005°)



(c) S3 SLSTR-based LIE (0.005°)



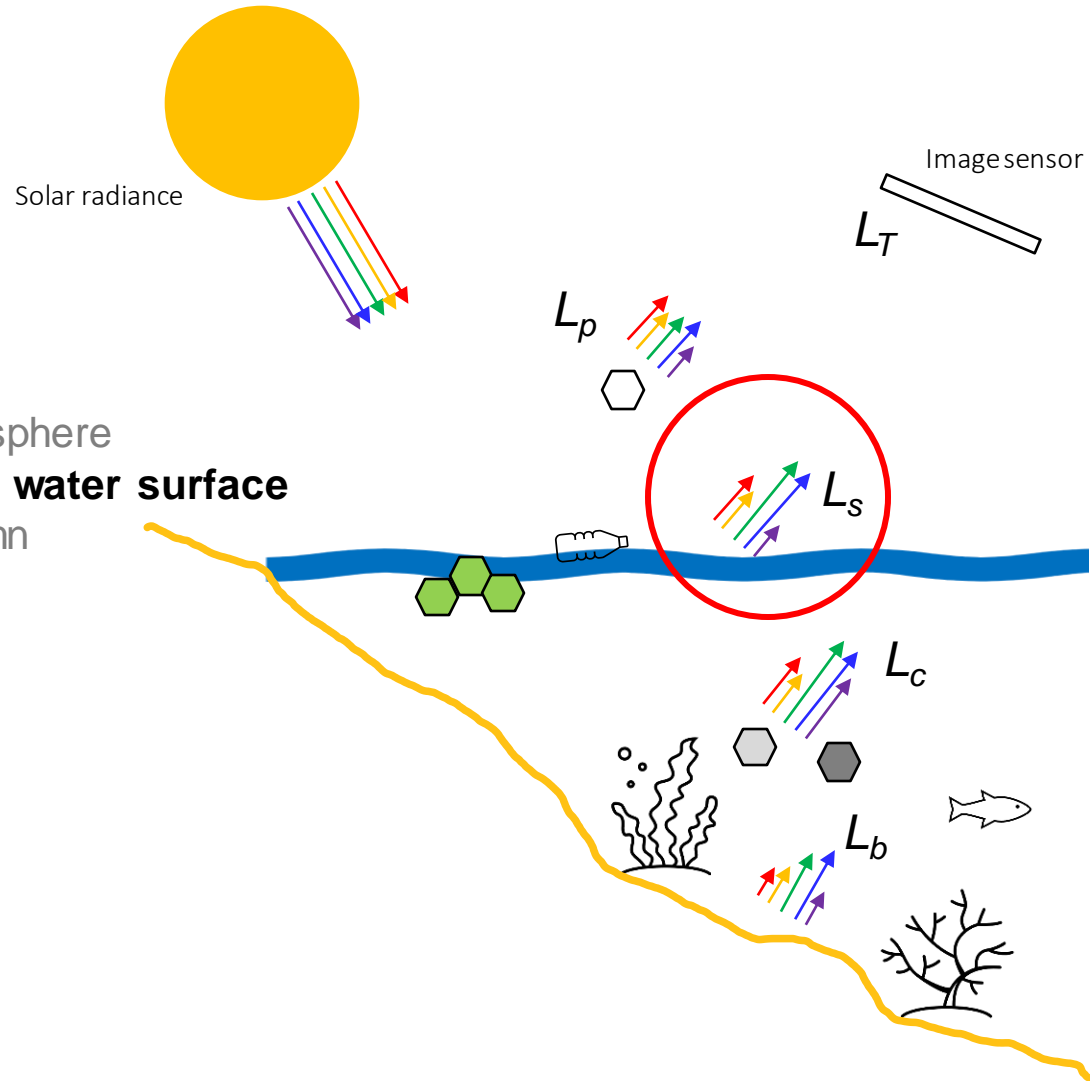
TP: 1057
 FP: 815
 TN: 2831
 FN: 1686
 Recall: 39 %
 Accuracy: 61 %
 Omission error: 61 %
 Commission error: 22 %

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Sea surface temperature (SST)



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L_T is the total upwelling radiance

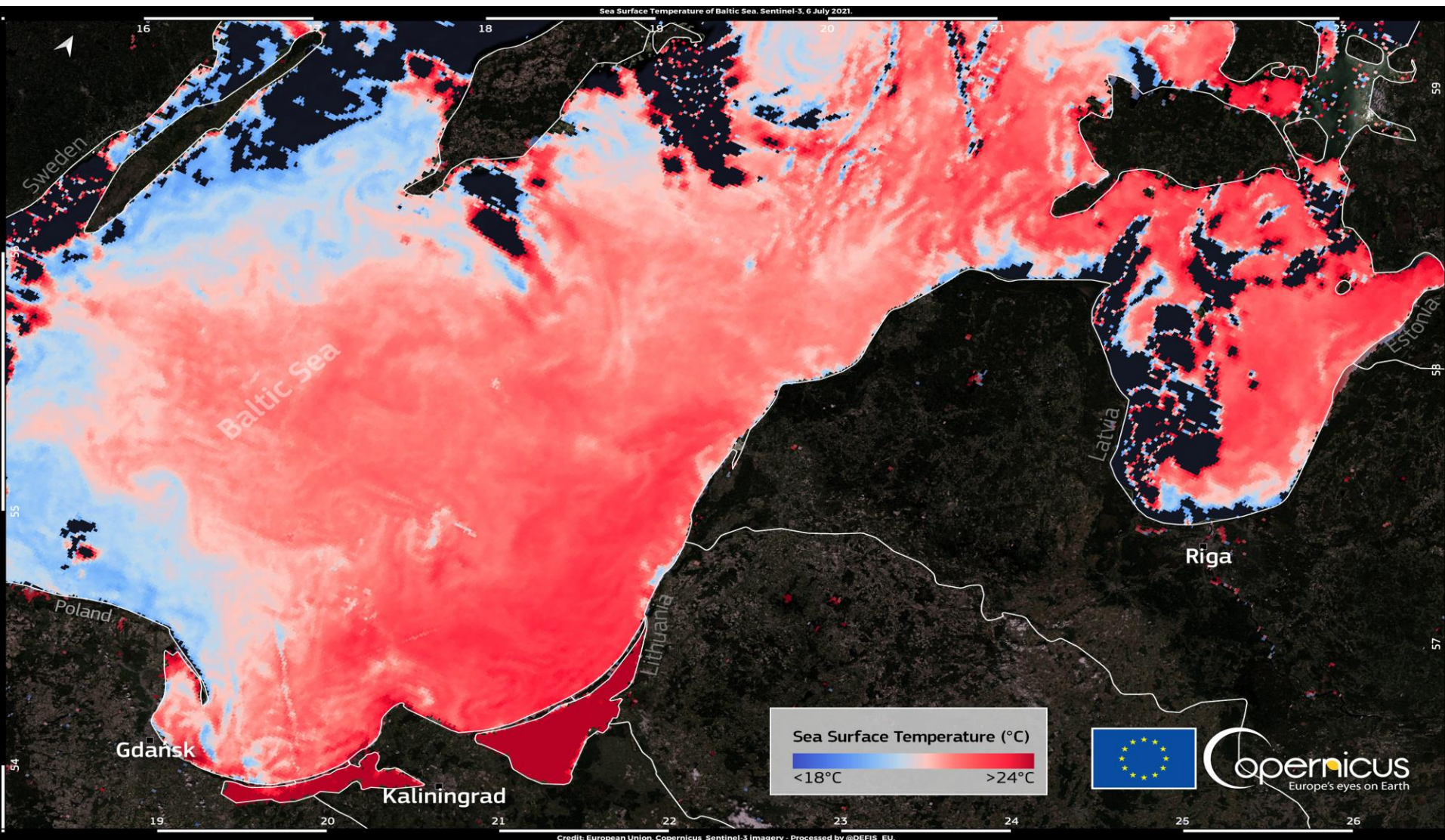
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Sea Surface Temperature (SST)



Sea Surface Temperature (SST)



How?

Highly accurate calibration of the three IR channels @ 3.74, 10.85 & 12 μm (S7-S8-S9) absorption & observation of the same on-ground pixel by means of two atmospheric path views for correction of aerosol effects.

Split-window algorithm

(SWA) that utilizes knowledge of land surface emissivity

$$T_s = a_{f,i,pw} + b_{f,i}(T_{11} - T_{12})^{\frac{1}{\cos(\theta/m)}} + (b_{f,i} + c_{f,i})T_{12} \quad (\text{Remedios et al., 2012})$$

Sentinel-3

Absolute accuracy >0.3 K

Spatial resolution 1 km

Facts

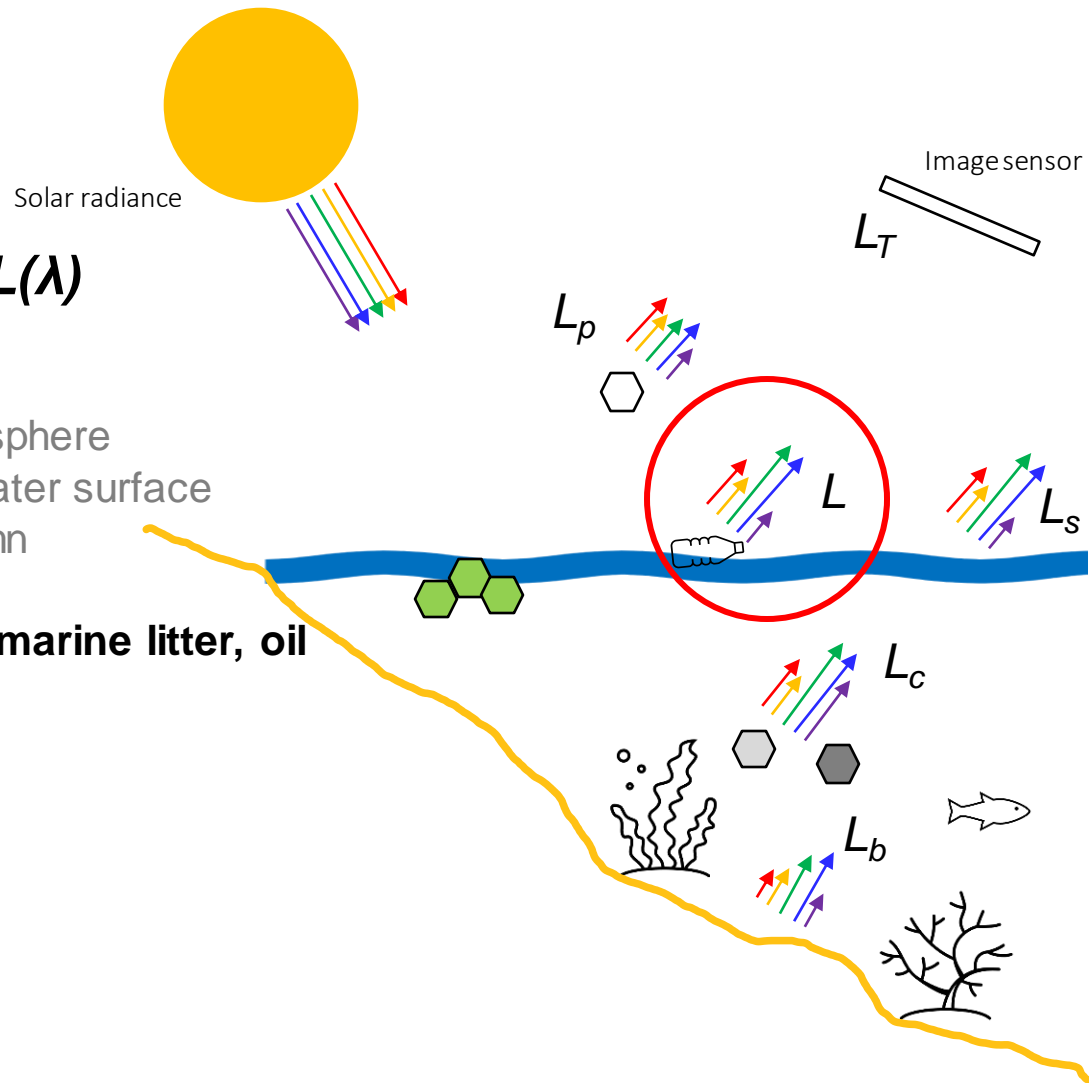
SST varies between -1.8°C
and +30°C

What info can we get using RGB and MS Remote Sensing Ocean data?



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- Sea surface temperature
- Renewable energy monitoring
- **Marine debris detection/tracking**
- **Pollution/ oil spill detection/tracking**
- Shallow water bathymetry
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Marine Debris



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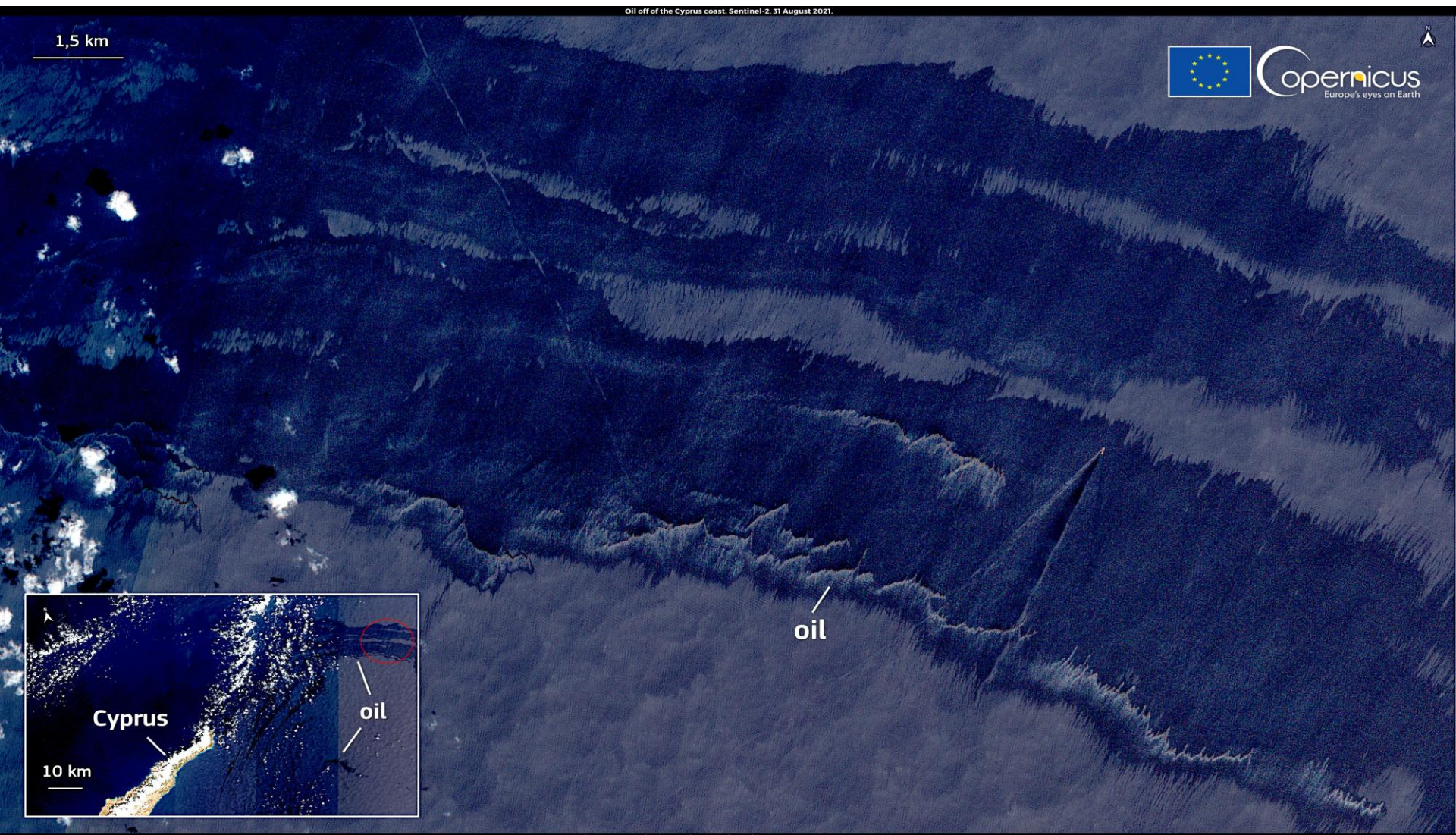
L_s is the radiance reflected from the water surface

L_c is the radiance from the water column

L_b is the bottom-reflected radiance

L is the radiance reflected from the marine litter, oil spills etc.

Pollution/oil spill detection



Credit: European Union, Copernicus Sentinel-2 Imagery - Processed by @DEFIS_EU.

Marine Debris



(Kikaki et al., 2022)

Marine Debris

How?

Empirical models

Statistically relate measurements marine debris (i.e. plastic) and reflectance through regression, polynomial expressions or **ML methods**

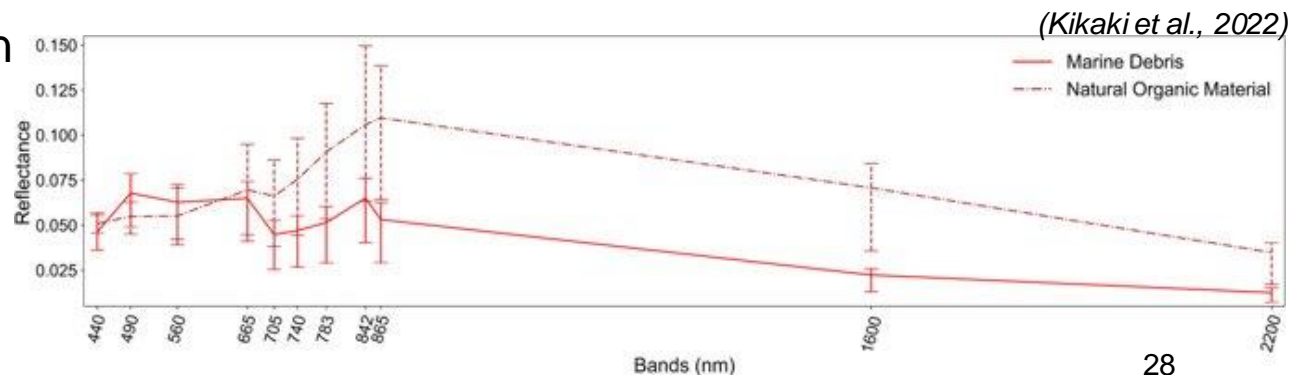
Some ML baselines

Weakly supervised semantic segmentation and multi-label classification:

- RF_{SS} (spectral signatures)
- RF_{SS+SI} (+ calculated spectral indices)
- $RF_{SS+SI+GLCM}$ (+ extracted Gray-Level Co-occurrence Matrix (GLCM) textural feat.)
- U-Net (11 Rayleigh reflectance S2 bands)

Multi-label classification

- ResNet



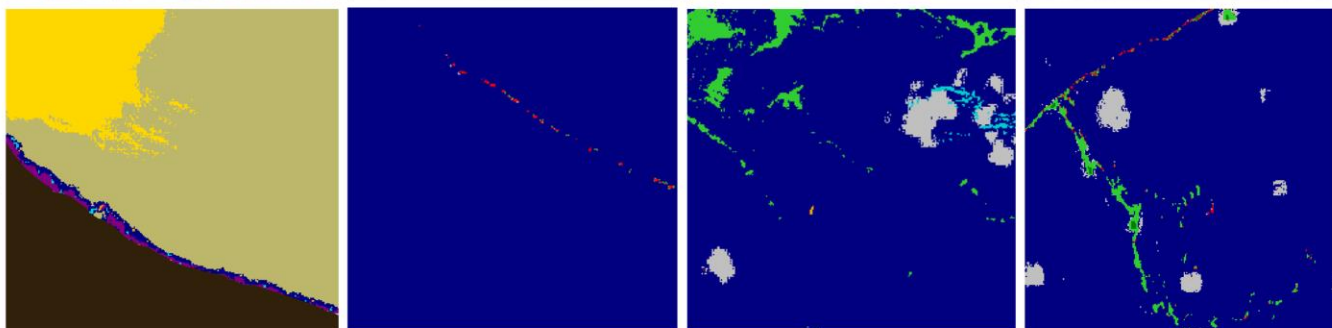
Marine Debris

A) S2_12-12-20_16PCC_6 B) S2_22-12-20_18QYF_0 C) S2_27-1-19_16QED_14 D) S2_14-9-18_16PCC_13

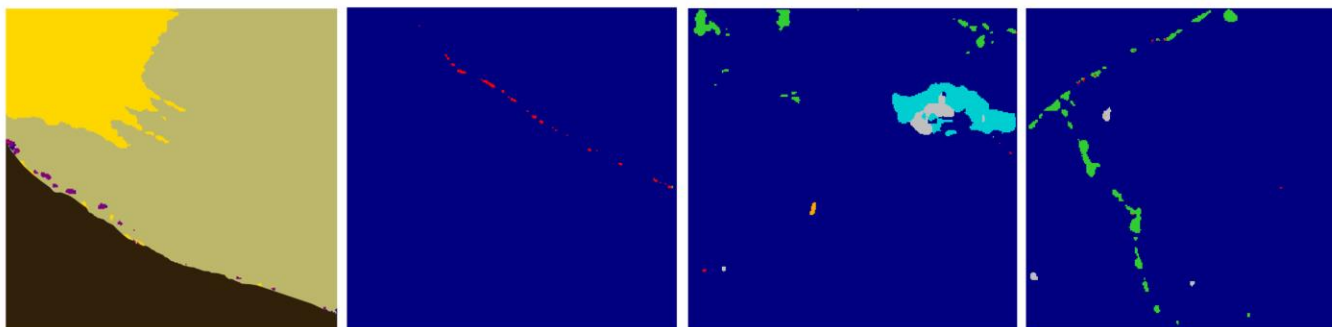
RGB



RF_{SS+SI+GLCM}



U-Net



Class

- MD
- DenS
- SpS
- Ship
- Clouds
- MWater
- SWater
- Foam
- TWater
- SLWater
- Land Mask

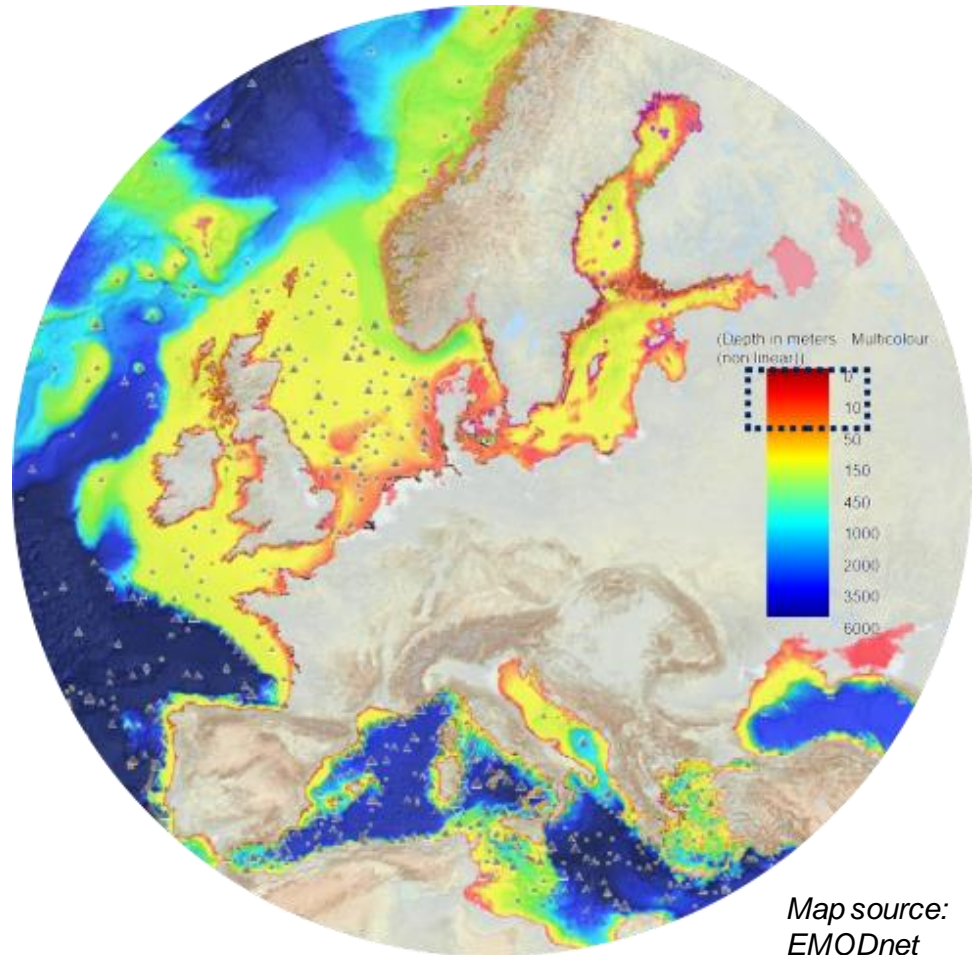
(Kikaki et al., 2022)

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- **Shallow water bathymetry**
- Shallow seabed cover maps

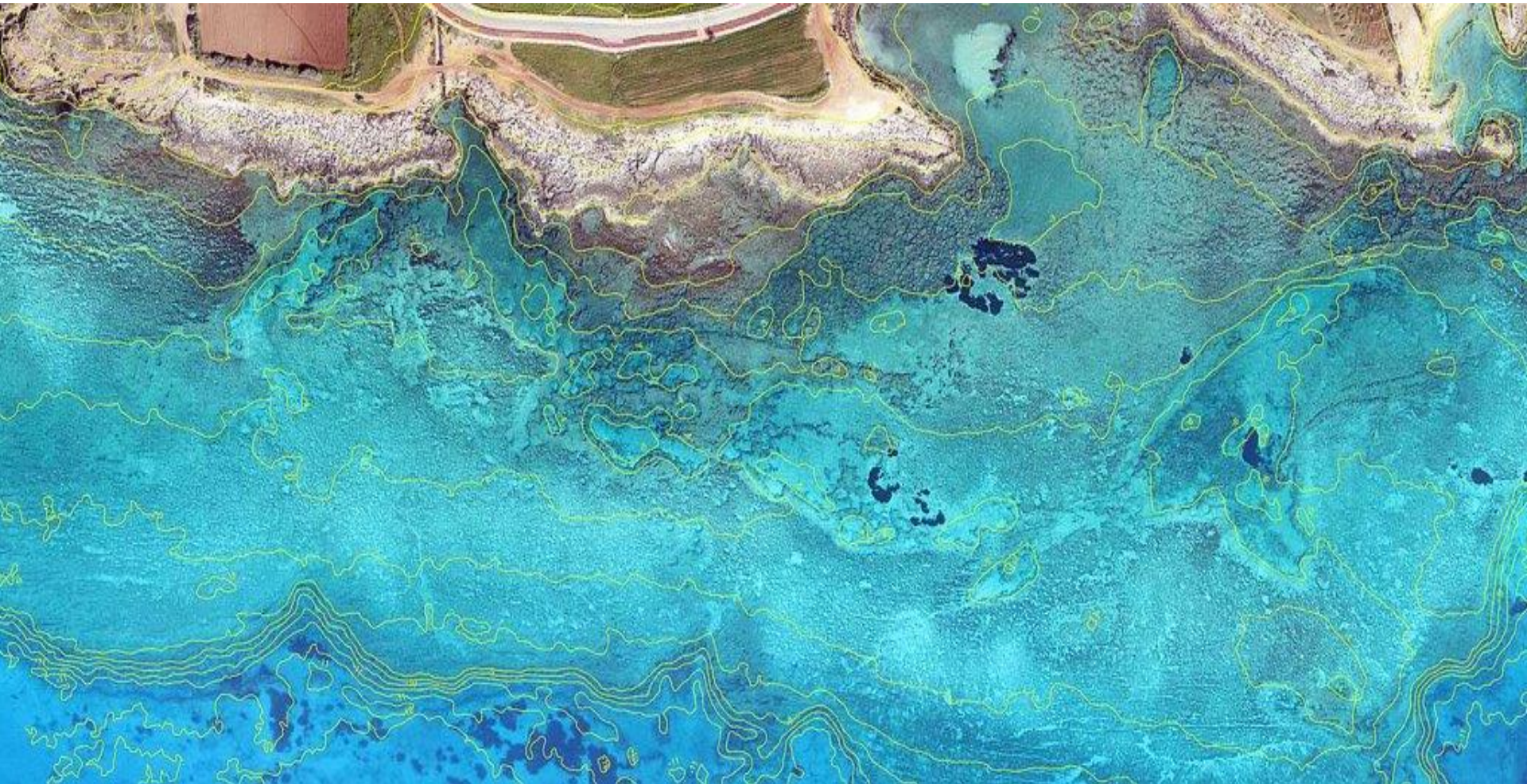
Shallow Water Bathymetry



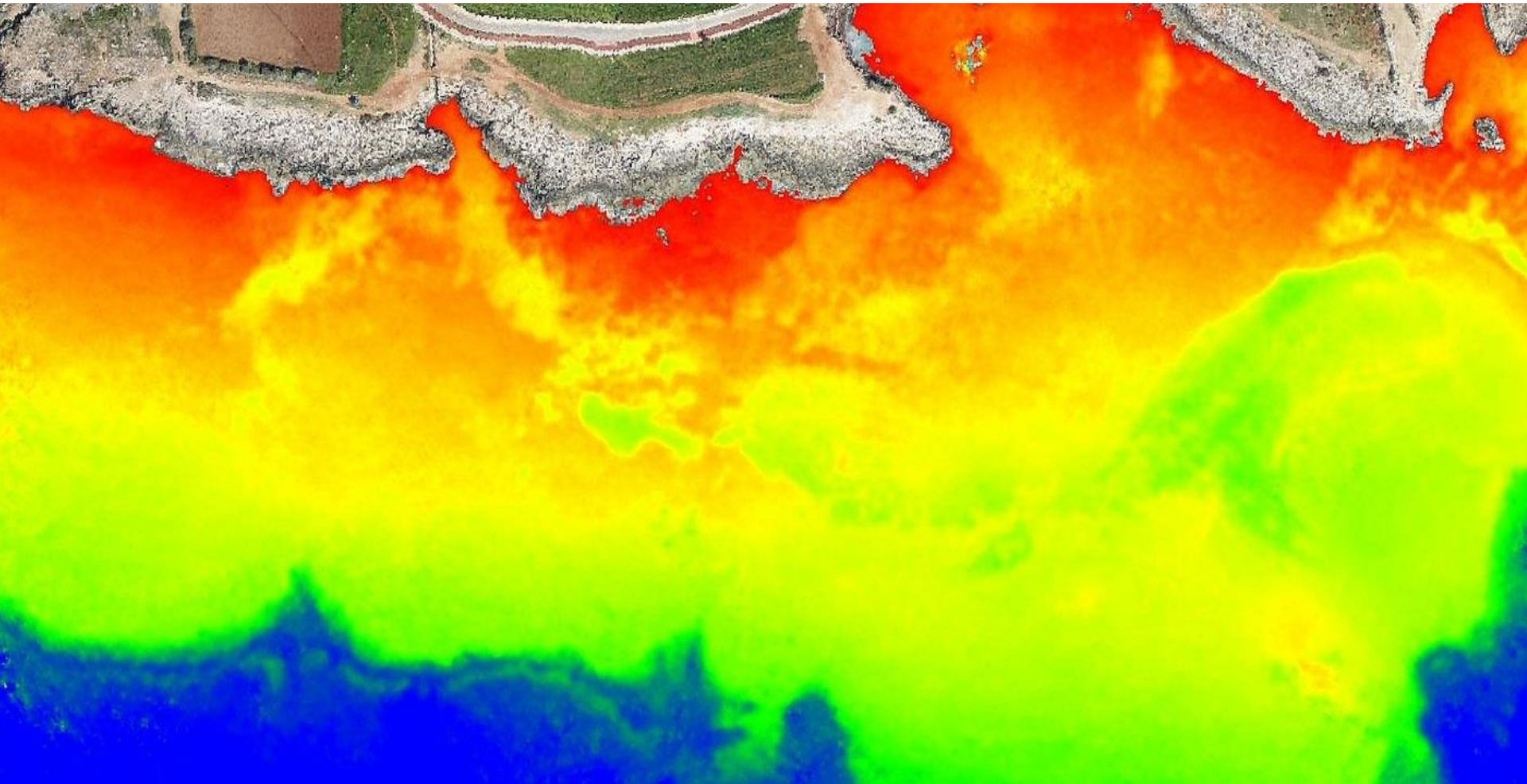
2.5% of the EU seabed is “shallow” (<20-25m depth) excluding lakes

Map source:
EMODnet

Shallow water Bathymetry



Shallow water Bathymetry

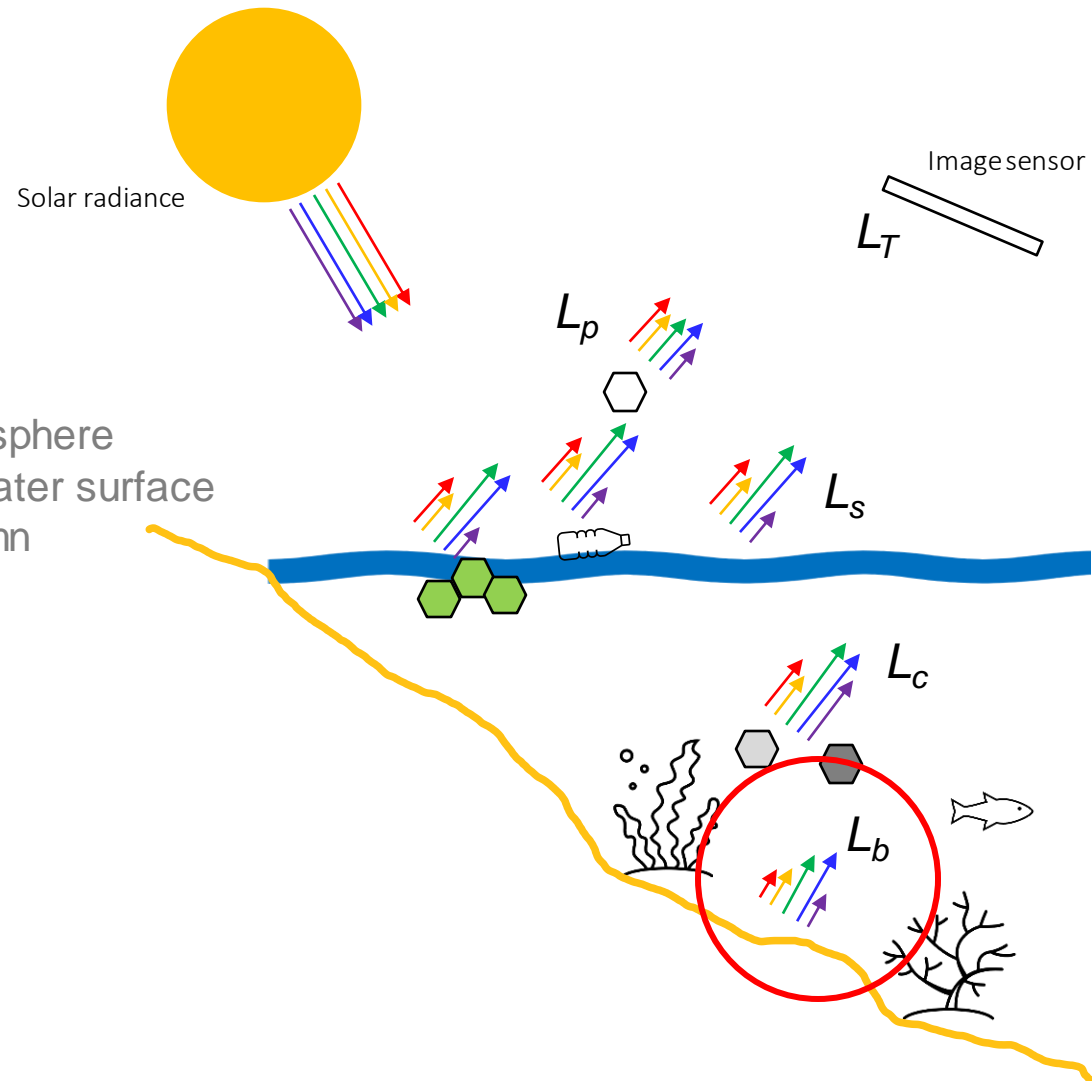


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- **Shallow water bathymetry**
 - **Spectral-based**
 - **Stereo-based**
- Shallow seabed cover maps

Basics of spectral-based bathymetry



$$L_T(\lambda) = L_p(\lambda) + L_s(\lambda) + L_c(\lambda) + L_b(\lambda)$$

L_T is the total upwelling radiance

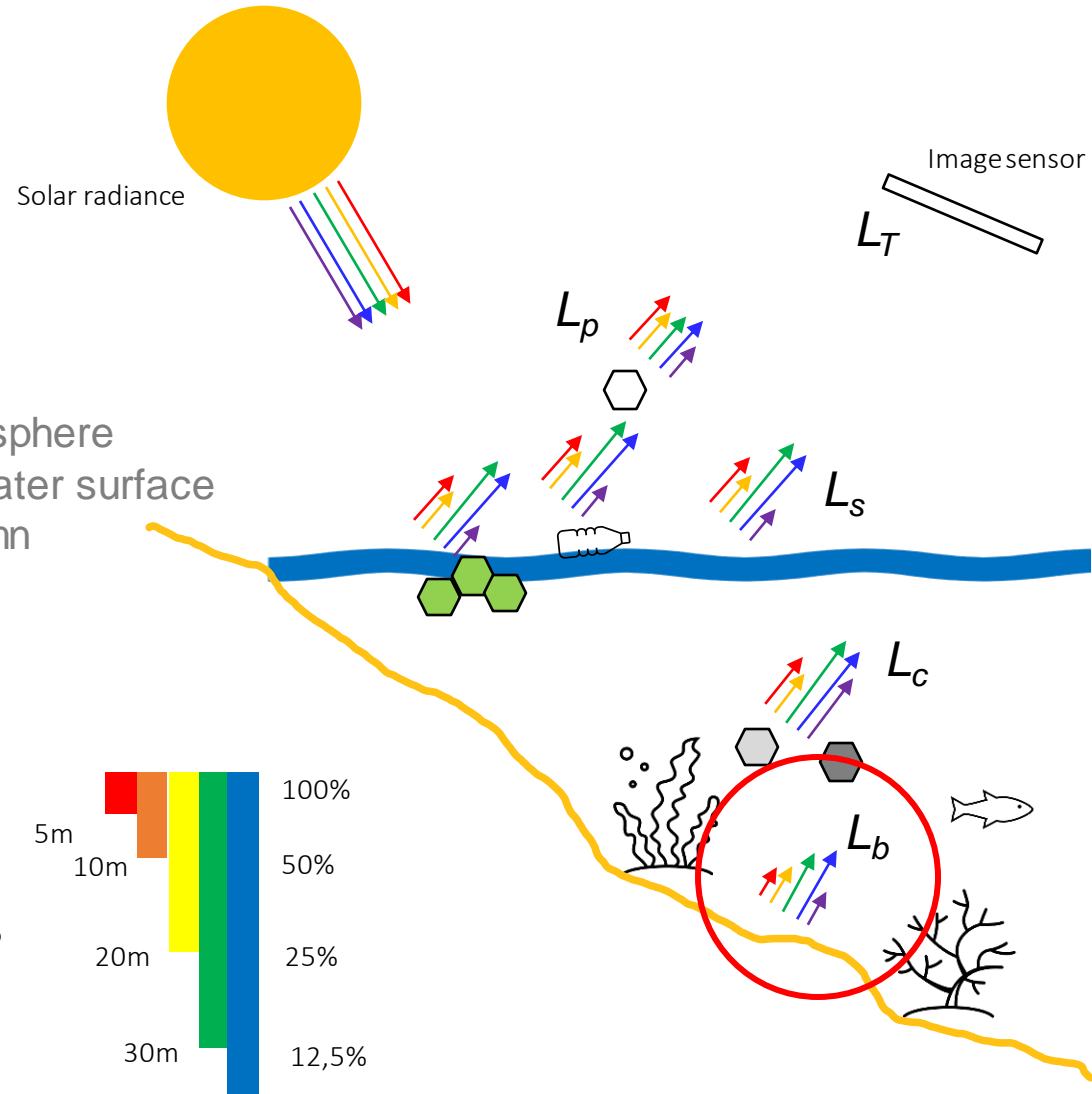
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Easy way

Correlate color loss and depth

What about different seabed classes ?

Spectral-based Bathymetry



How?

Statistical models: Statistically relate meas. depth and reflectance – need for ground truth data

- From simple linear regression to ML (RFs, SVMs) and DL (FCNs, GANs)

Physics-based radiative transfer models (bio + physio-optical):

- Inversion of a radiative transfer models (RTM) – no need for ground truth data
- Analytical
- Semi-empirical (band ratio, band difference, PCA, ANN, regression)
- Semi-analytical (direct linear inversion, spectral deconvolution)

Hybrid methods

Statistical models

Common approaches

- The standard linear algorithm (Lyzenga, 1978) assumes a log-linear relationship between reflectance ($R(\lambda_i)$) and water depth (z):

$$z = b \log R(\lambda_i) + c$$

- Stumpf et al., 2003 bathymetric algorithm

The method approximates “physics” of light in the water:

$$Z = m_1 \frac{\ln(nR_w(\lambda_i))}{\ln(nR_w(\lambda_j))} - m_0$$

pSDB “pseudo depth”

where m_1 is a tunable constant to scale the ratio to depth, n is a fixed constant for all areas, and m_0 is the offset for a depth of 0m

- Sample-specific multiple band ratio techniques (*Niroumand-Jadidi et al., 2020*)
- Physics-based radiative transfer model (RTM) inversion techniques
- **Shallow and Deep ML techniques (RFs, SVMs, FCNs)**

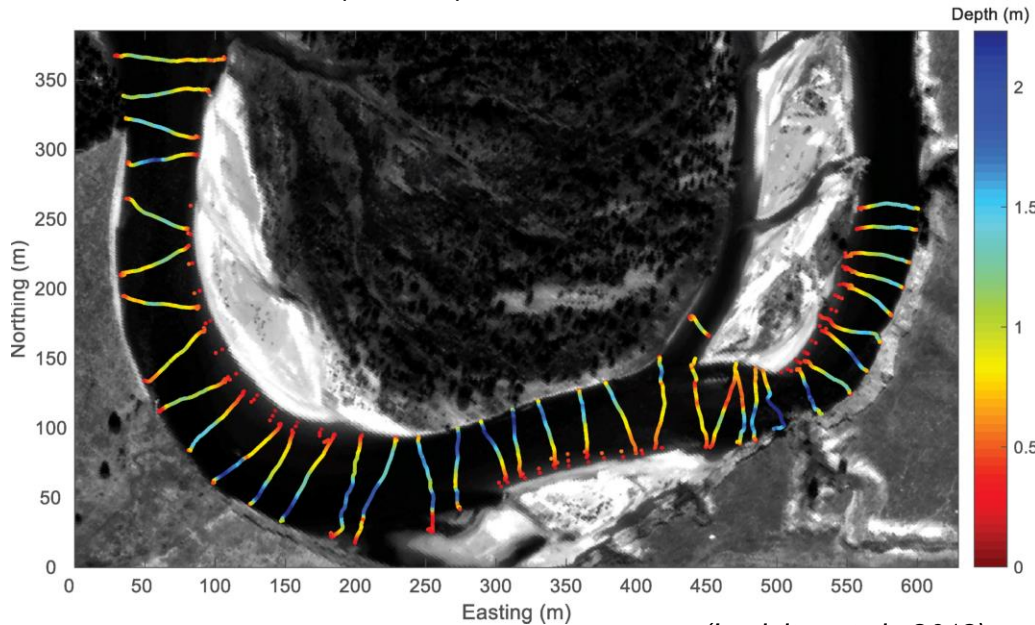
Statistical models

Examples

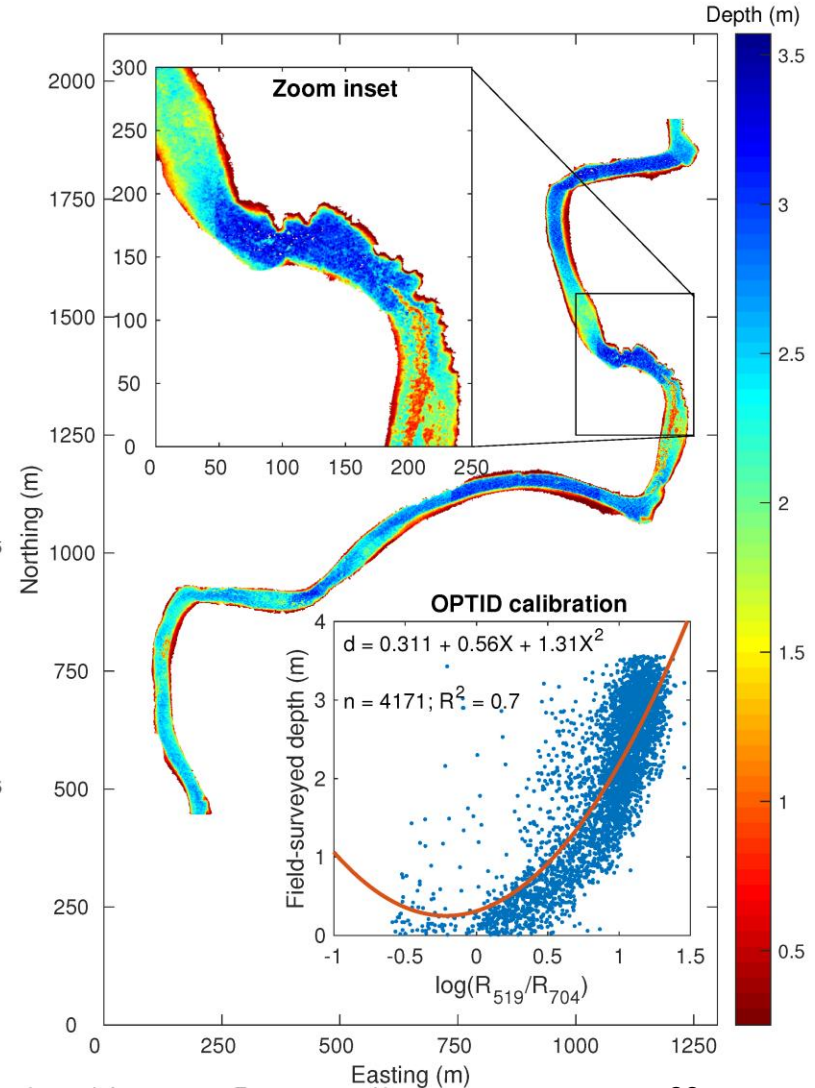
Airborne HS images

Polynomial regression

Ground truth bathymetric data used: Acoustic Doppler Current Profiler (ADCP)



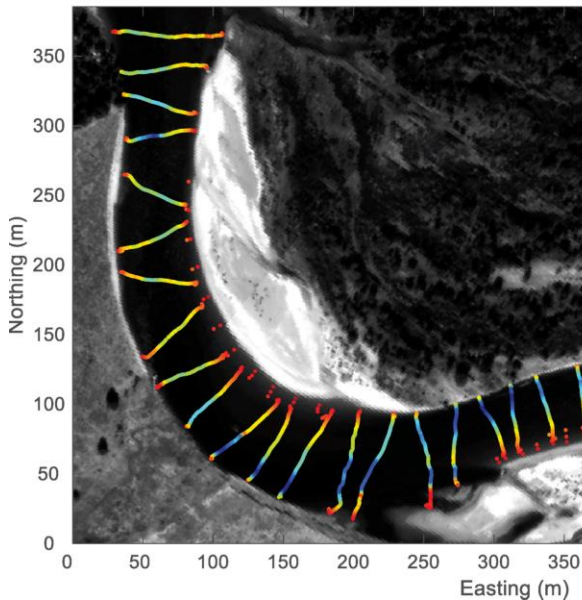
(Legleiter et al., 2018)



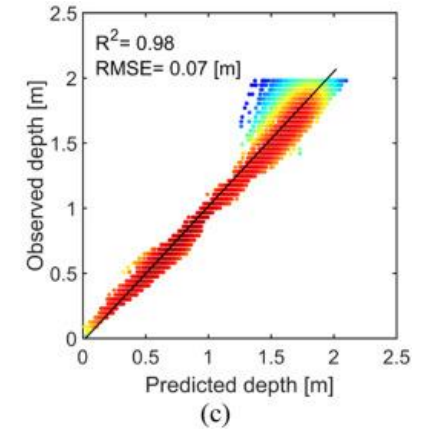
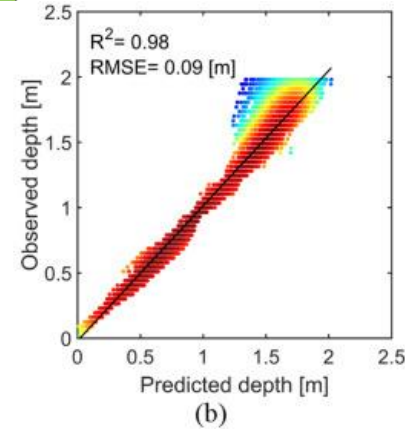
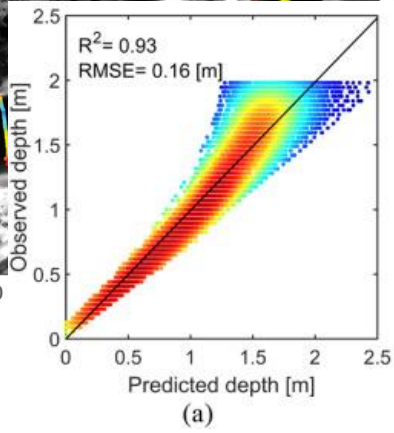
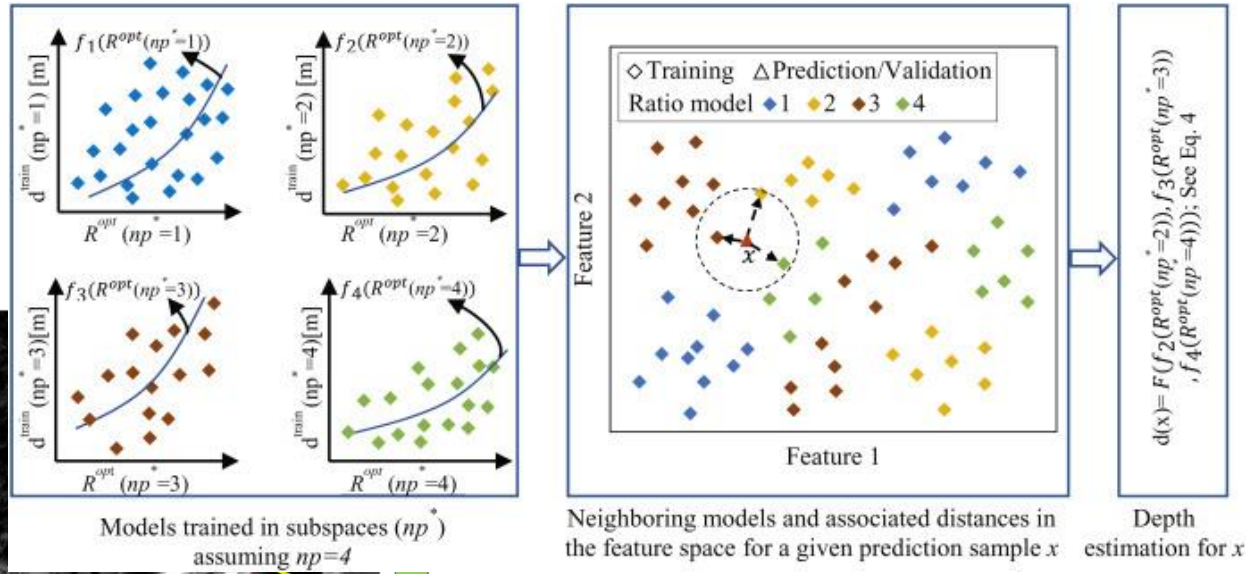
Statistical models

Examples

K-NN clustering + Polynomial regression



(Legleiter et al., 2018)



(Niroumand-Jadidi et al., 2020)

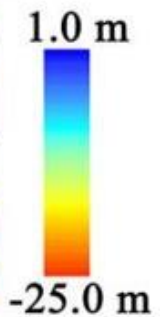
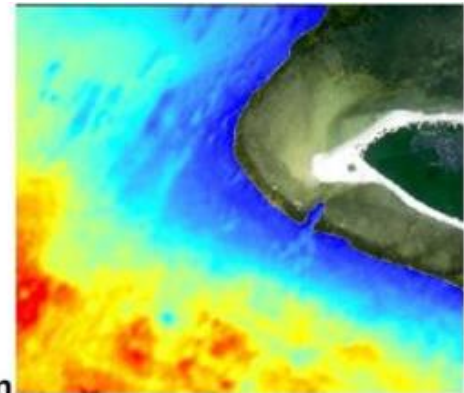
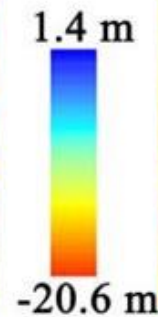
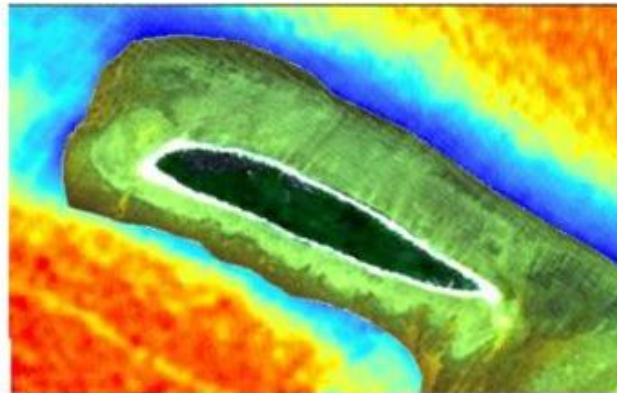
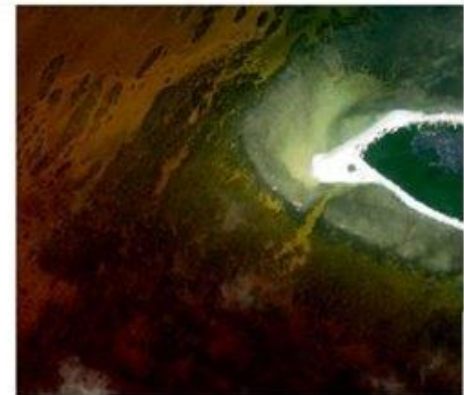
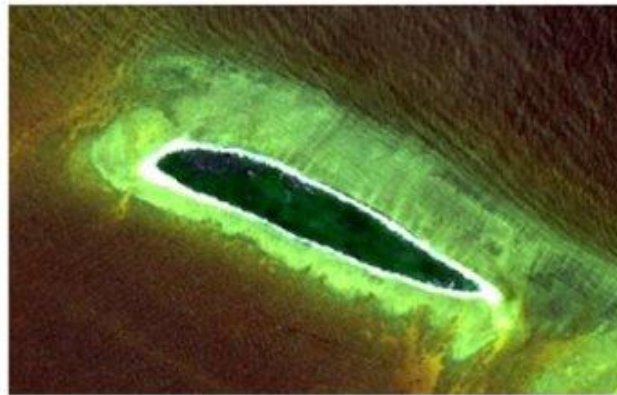
Statistical models

Examples

Worldview-2 (WV2) images

CNNs

Ground truth
bathymetric data
used: Airborne
LiDAR



(Ai et al., 2020)

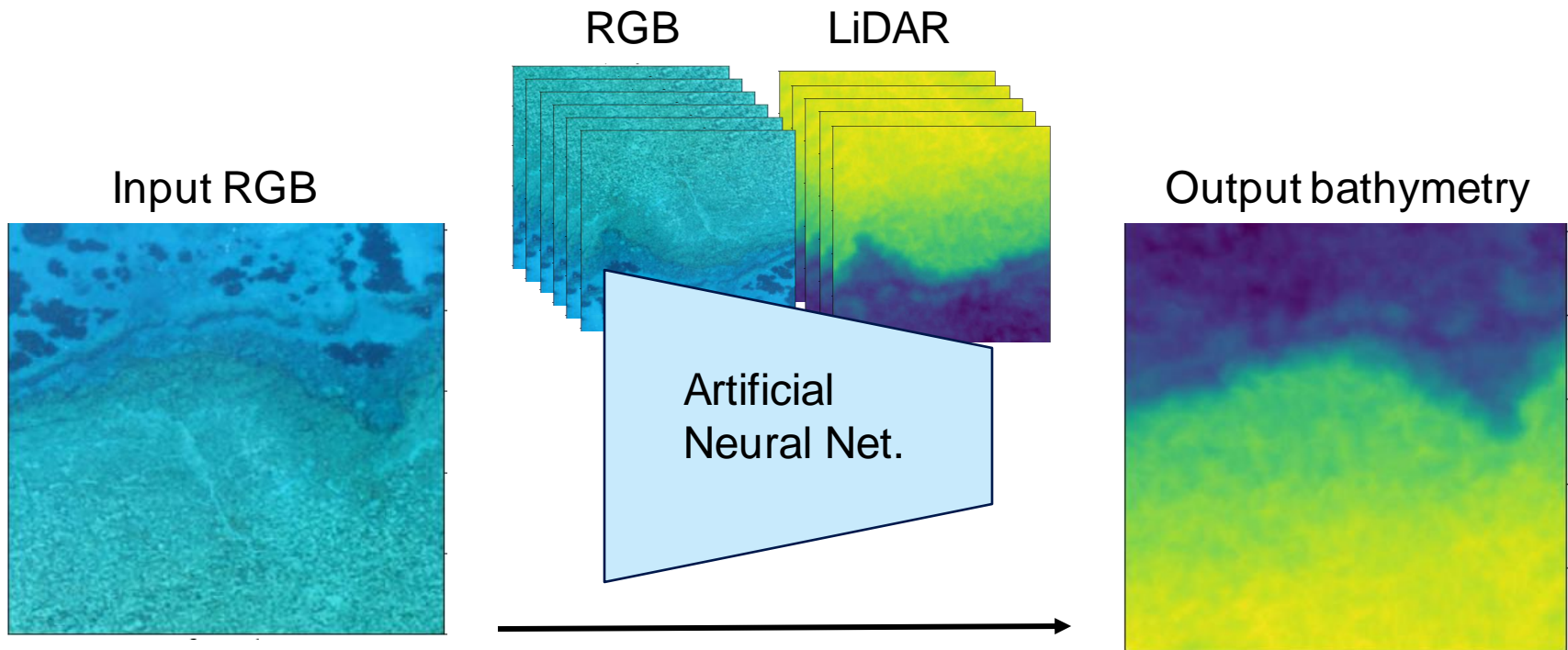
Statistical models

Examples

UAV RGB images

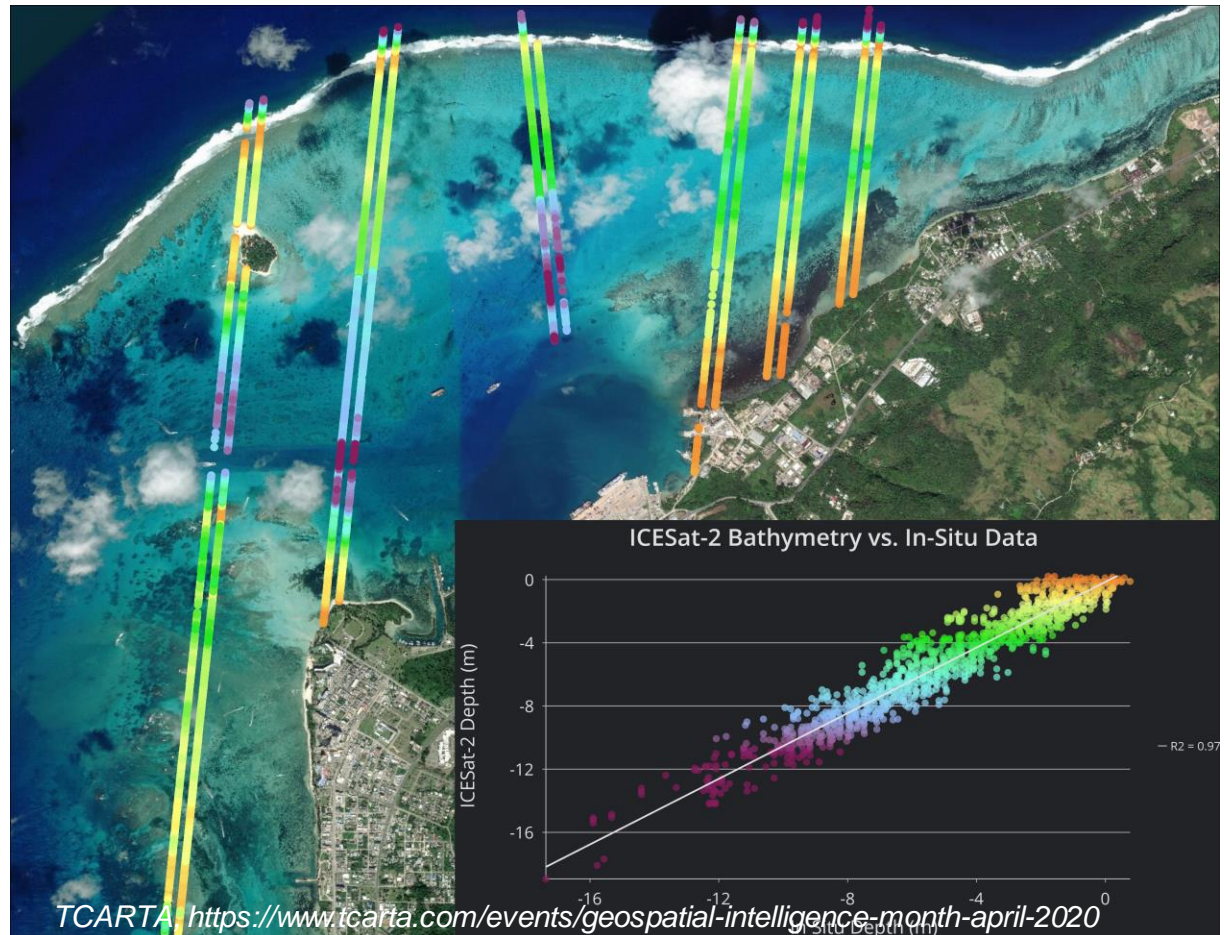
CNNs

Ground truth bathymetric data used: Airborne LiDAR



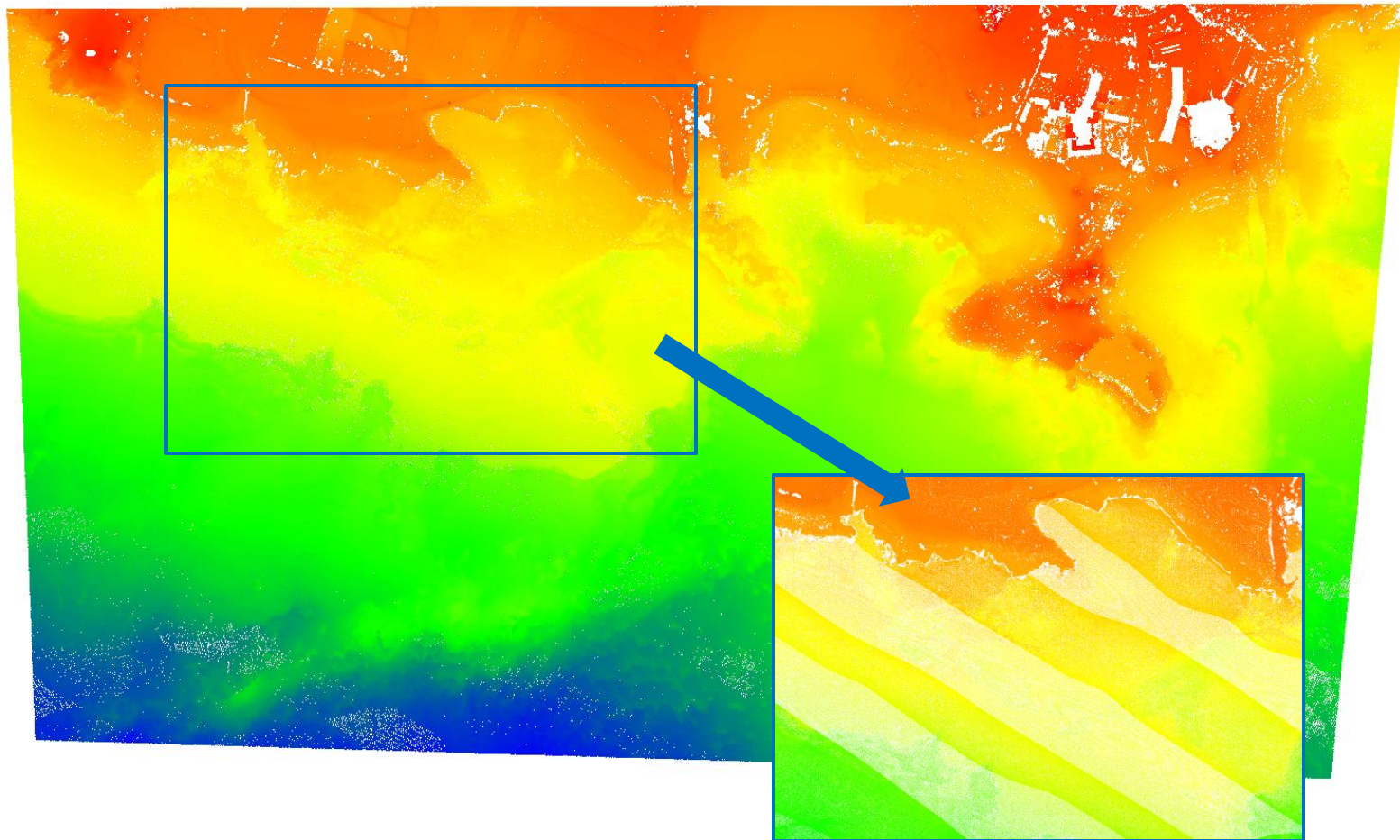
Ground truth data

ICE-Sat2 satellite or similar



Ground truth data

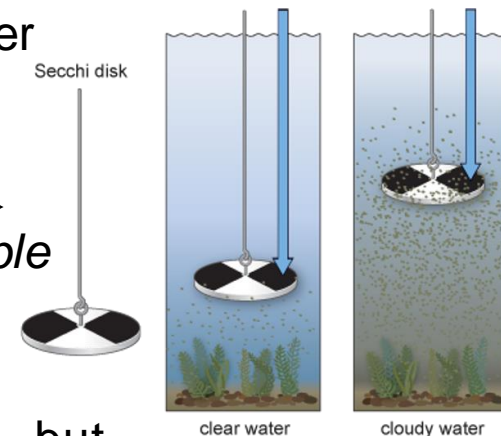
Airborne LiDAR or shipborne Echosounder



Spectral-based methods

Pros, Issues and Limitations

- No sophisticated geometry processing necessary
- Can handle certain differences in substrate type and water clarity
- Covers large areas (satellites)
- Max depth ~ 1 **Secchi** \longrightarrow
the max depth a disk 30cm is visible



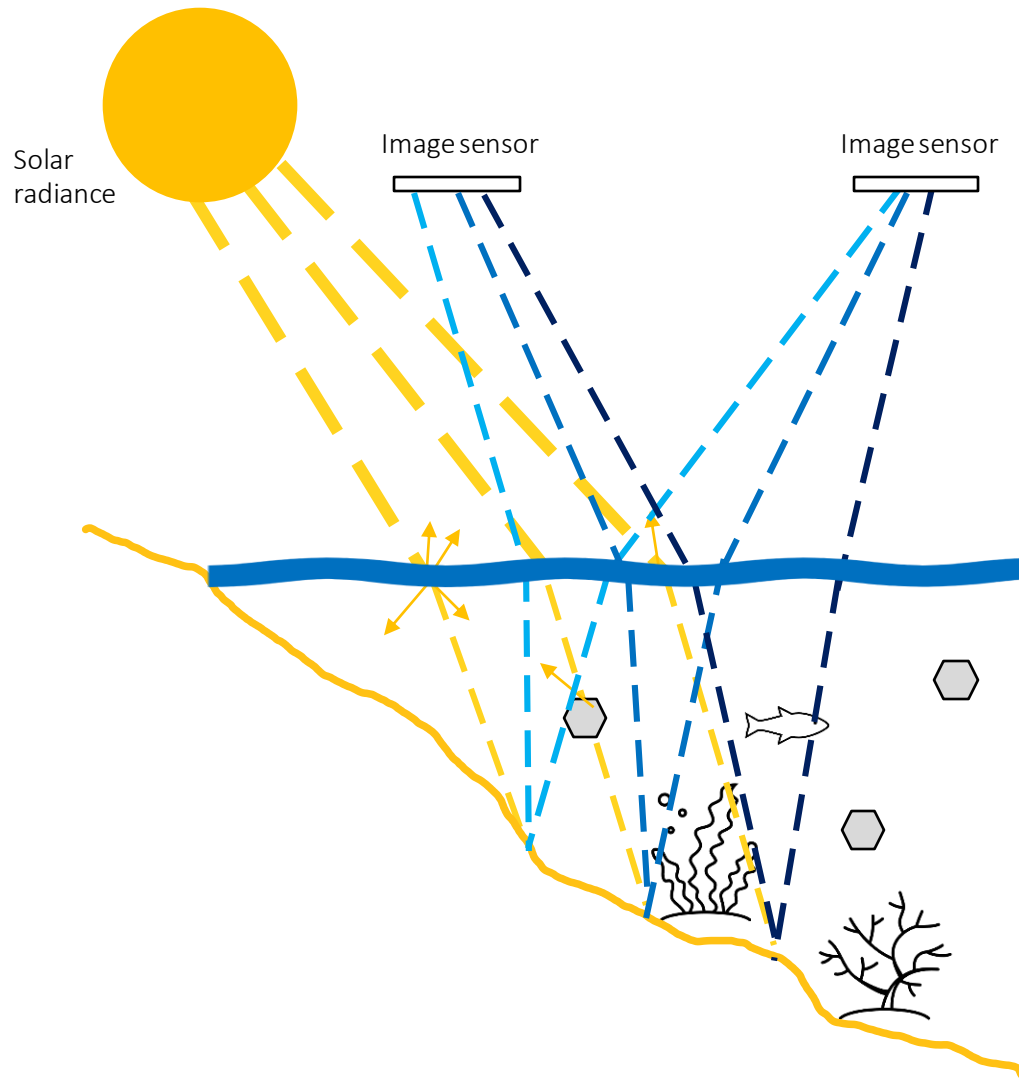
- Requires visibility of bottom features (similar to SfM-MVS, but not texture is required here)
- Work better on homogenous seabed
- **Requires ground-truth for calibrating coefficients**
- **Heavily affected by sun glint, high aerosol, turbidity etc.**
- **Lack of generalization potential** due to the daily/seasonal etc. variability of spectral values

What info can we get using RGB and MS Remote Sensing Ocean data?

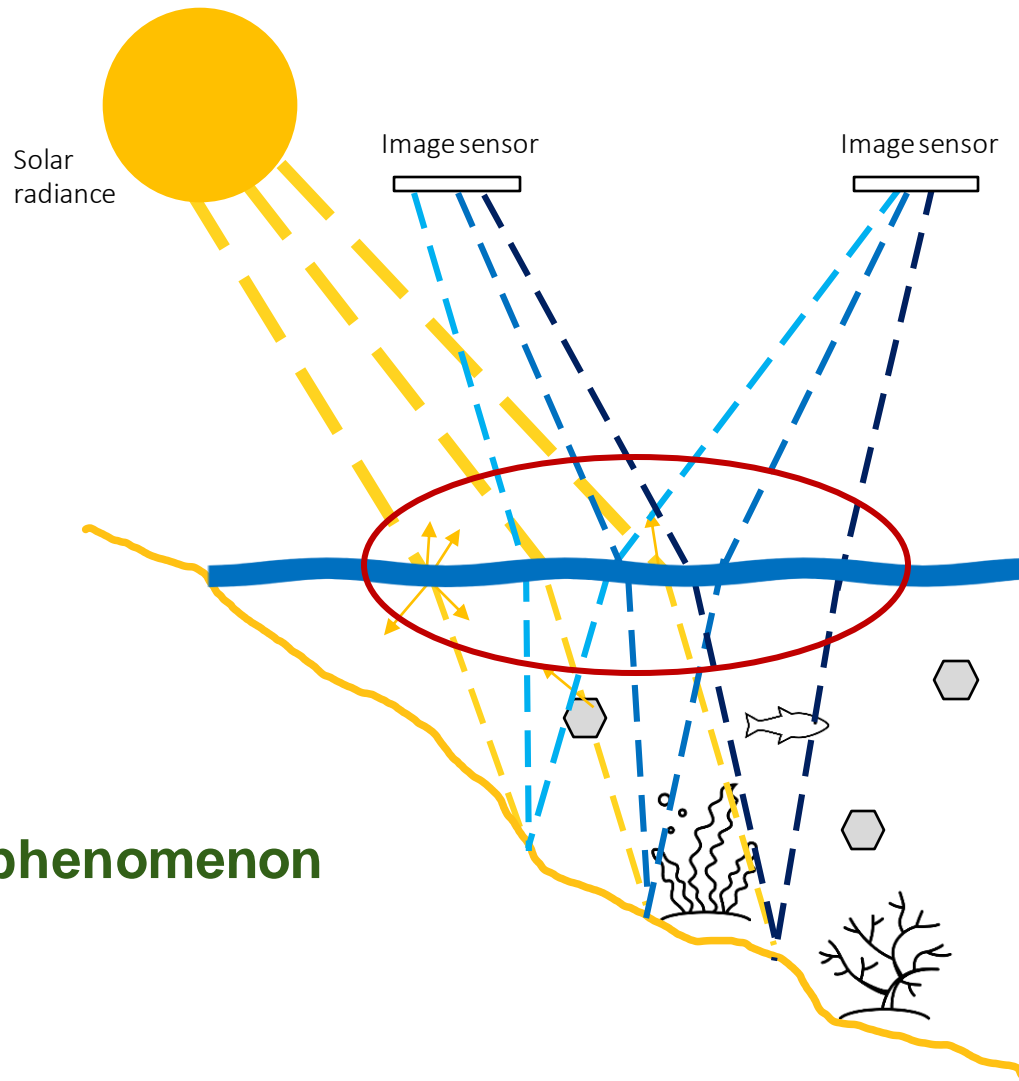


- Biogeochemical indices (chlorophyll, nitrates)
- Sea ice coverage and state
- Sea surface temperature
- Renewable energy monitoring
- Marine debris detection/ tracking
- Pollution/ oil spill detection/ tracking
- **Shallow water bathymetry**
 - Spectral-based
 - **Stereo-based**
- Shallow seabed cover maps

Basics of stereo-based models



Basics of stereo-based models



Refraction phenomenon

Refraction phenomenon

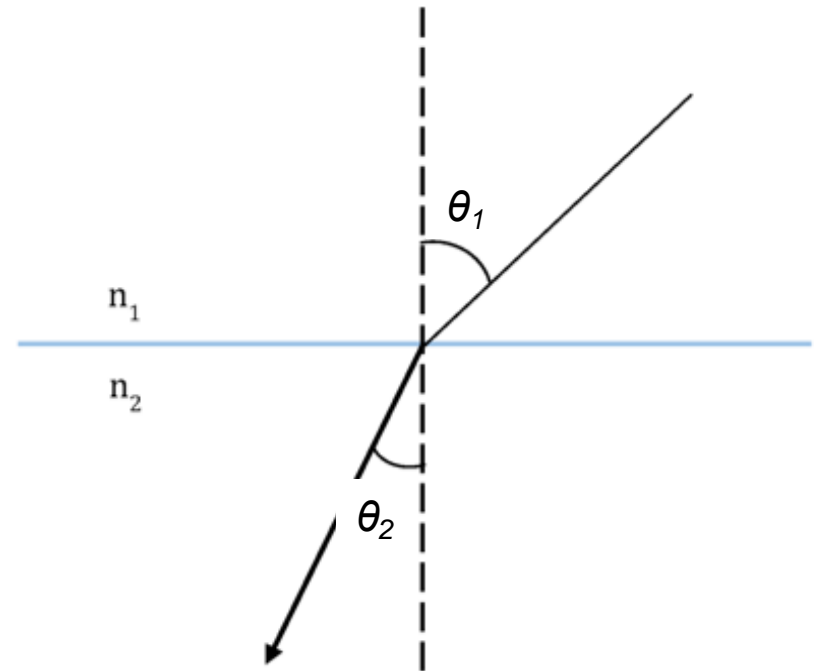
Snell's law

The ratio of the sines of the angles of incidence and refraction is equivalent to the ratio of phase velocities in the two media

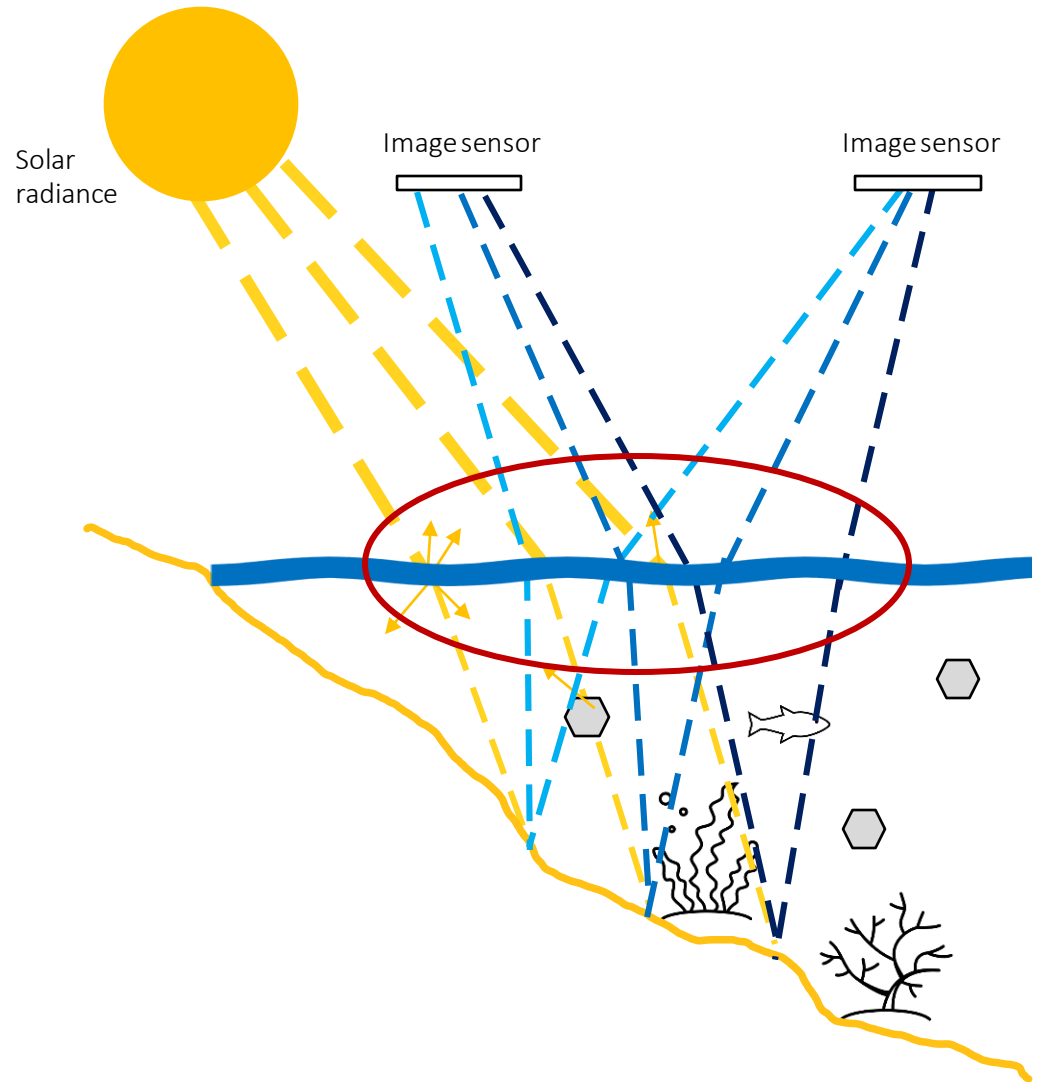
The law is based on **Fermat's principle**, also known as the principle of least time

Fermat's principle states that the path taken by a ray between two given points is the path that can be traversed in the least time.

$$\frac{\sin \theta_2}{\sin \theta_1} = \frac{v_2}{v_1} = \frac{n_1}{n_2}$$



Refraction phenomenon



Refraction effect is totally different for each image and each image point!

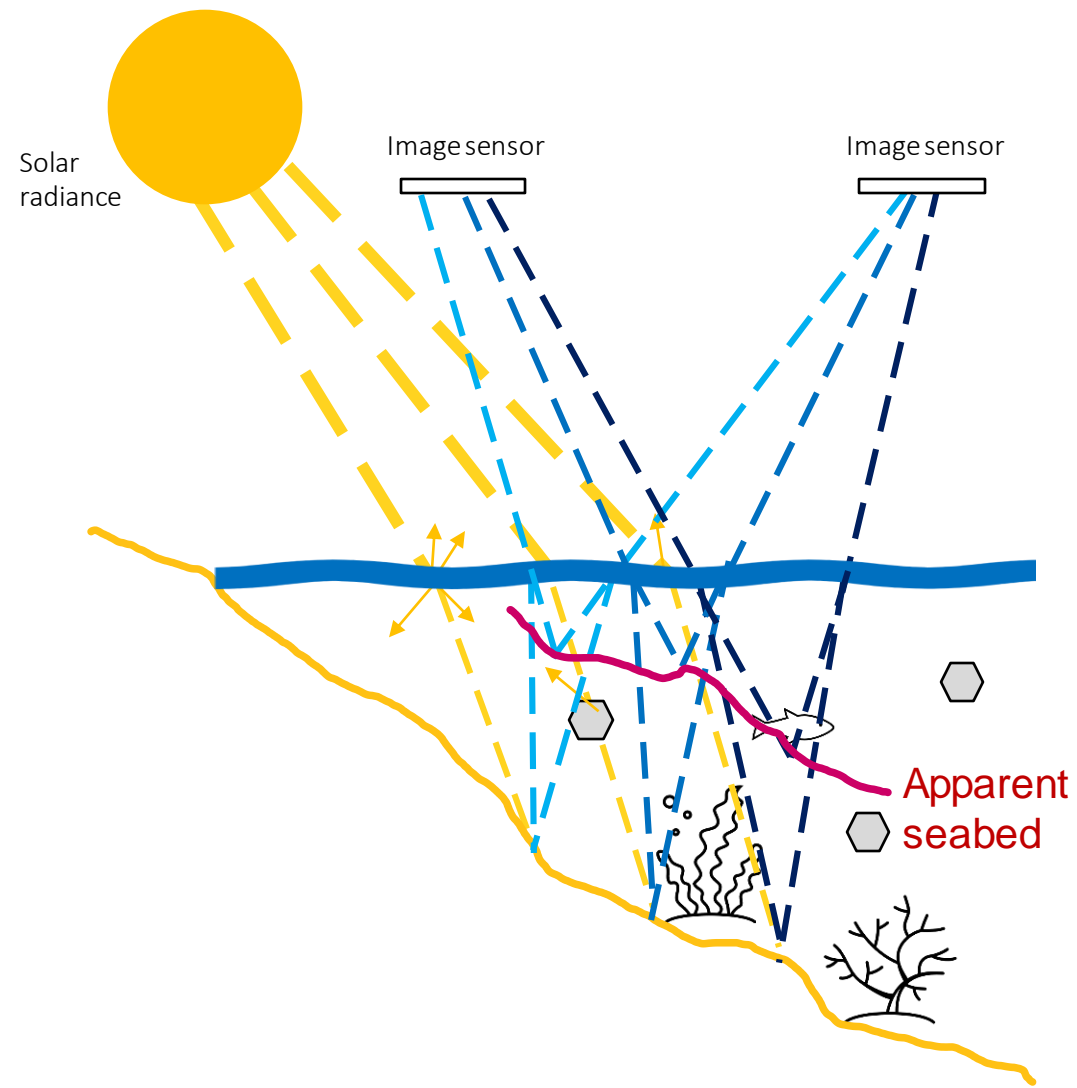
It depends on

- Depth
- Angle
- Camera position

Refraction phenomenon

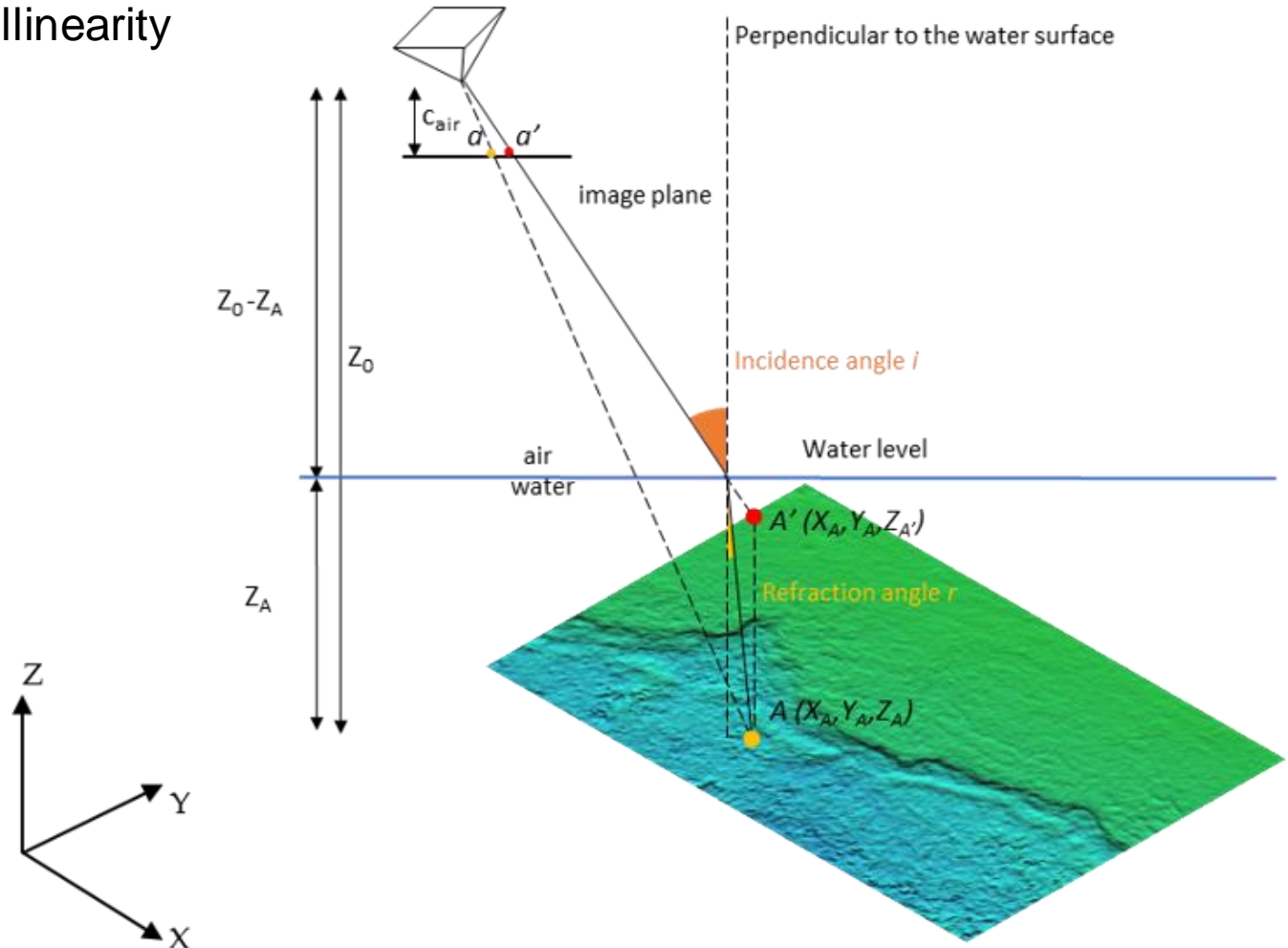
RMSE of about 30-40% of the real depth value!

Example:
A point at 13.5m depth would appear at 10m depth



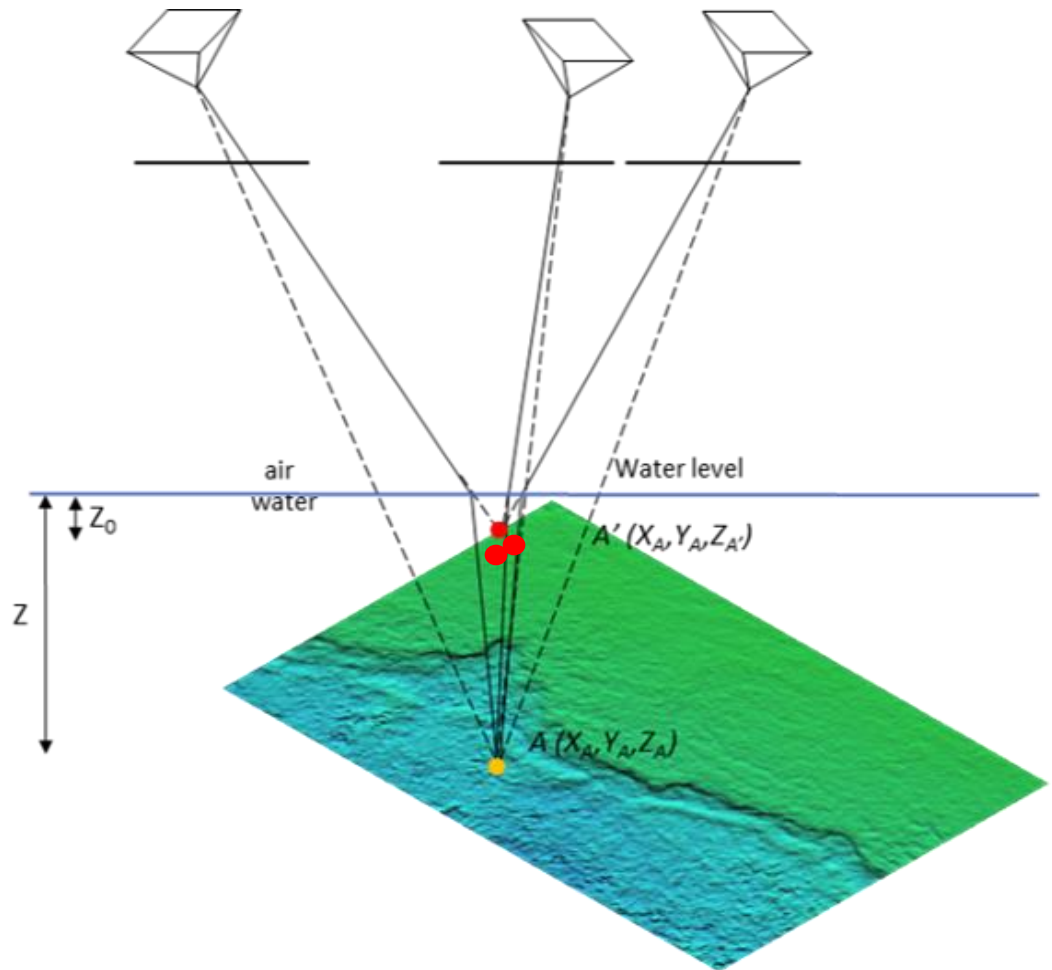
Single View Geometry

- Violation of the Collinearity Equation
- Apparent depths



Multiple-View Geometry

- Violation of the Collinearity Equation – different for each point -> for each image
- Apparent depths
- Increased noise in the 3D point clouds



Refraction correction basics



Since SfM-MVS software is delivering 3D point clouds even when refraction is ignored, can we skip it?

– **NO**, it's physics!

To deliver accurate SfM-MVS results, orthoimages, Digital Elevation Models etc., the correction of refraction effects is necessary!

Stereo-based bathymetry



How?

Structure from Motion – Multi-View Stereo + Refraction correction

Refraction correction

Analytical correction

Modification of the collinearity equation. (1950...)

Image-space correction

Re-projection of the original photo to correct the water refraction. (2018...)

Machine learning-based

Depends on machine learning models that learn the underestimation of depths and predict the correct depth knowing only the apparent one. (2019...)

Image Space Correction

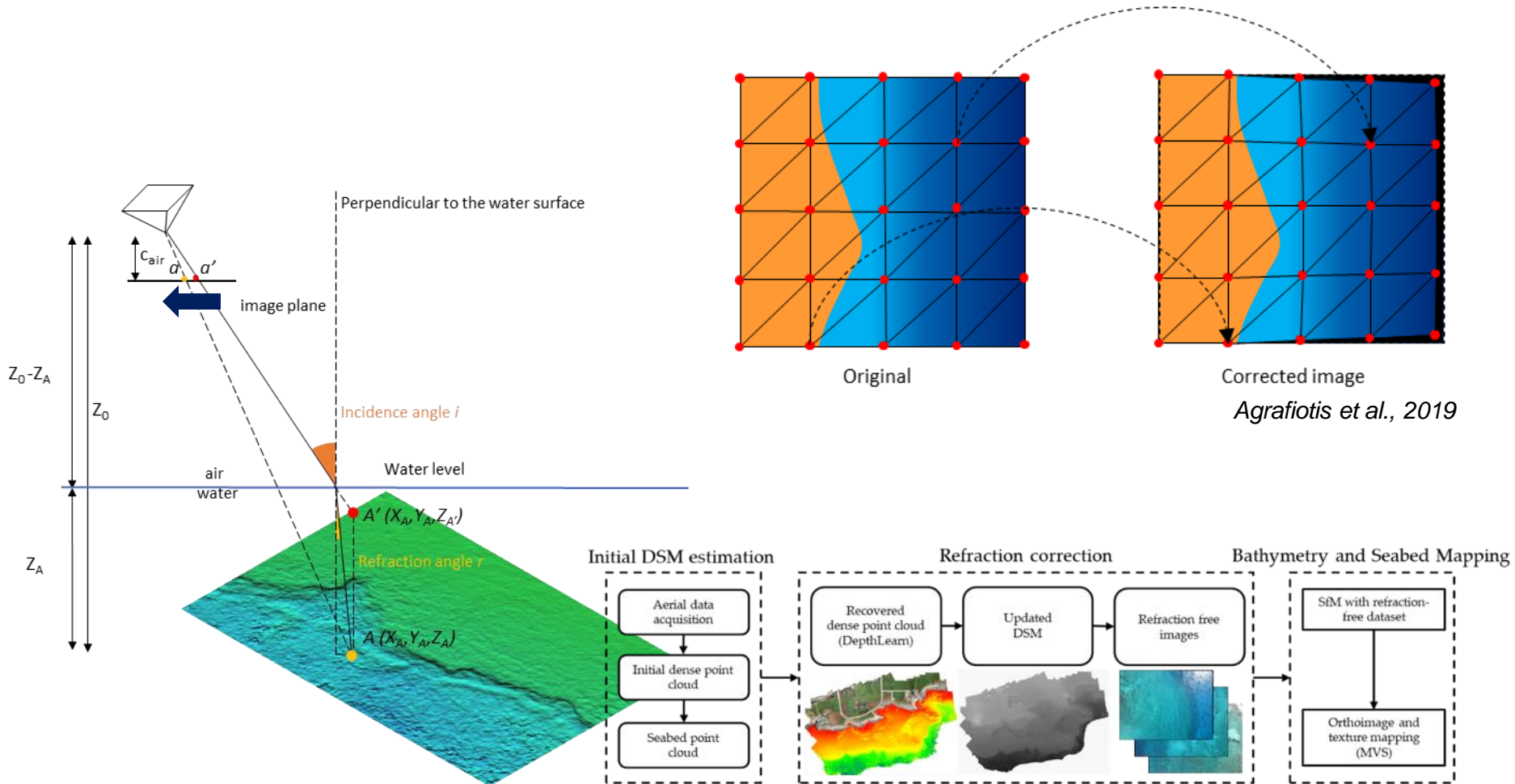


Image Space Correction



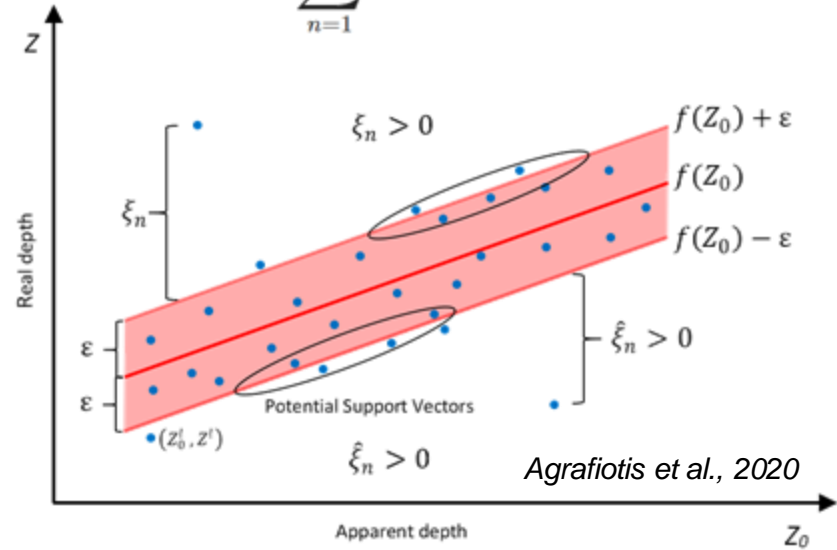
Image Space Correction



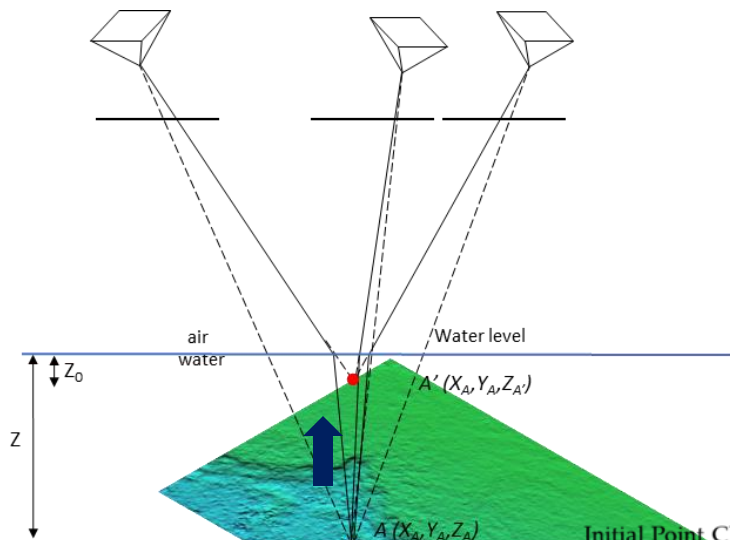
Corrected image

3D Space Correction

$$f(Z_0) = \sum_{n=1}^N (a_n + \hat{a}_n) k(Z_0, Z_{0n}) + b$$



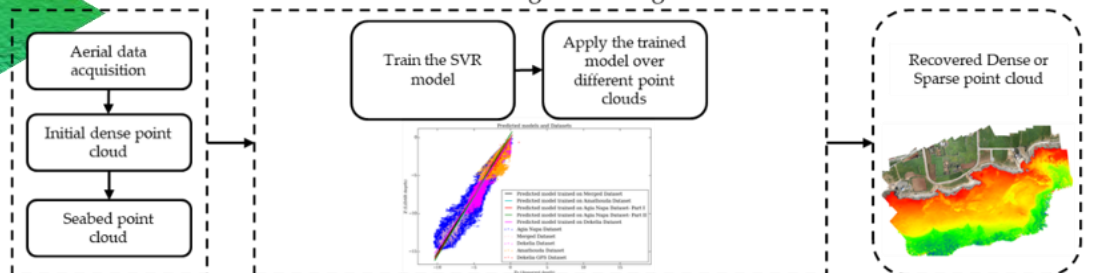
Agrafiotis et al., 2020



Initial Point Cloud Generation

Model training and testing

Recovered Point Cloud

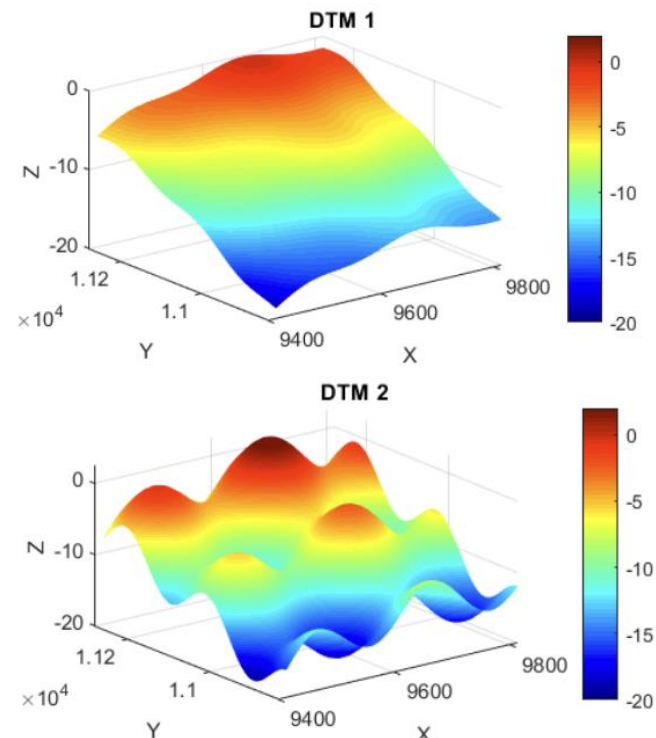


Need for synthetic data

Train ML models

- Avoid errors and limitations in image matching caused by the visibility restrictions (turbidity, caustics, sun glint)
- Avoid errors introduced by the wavy surface

The only unknown is the refraction effect



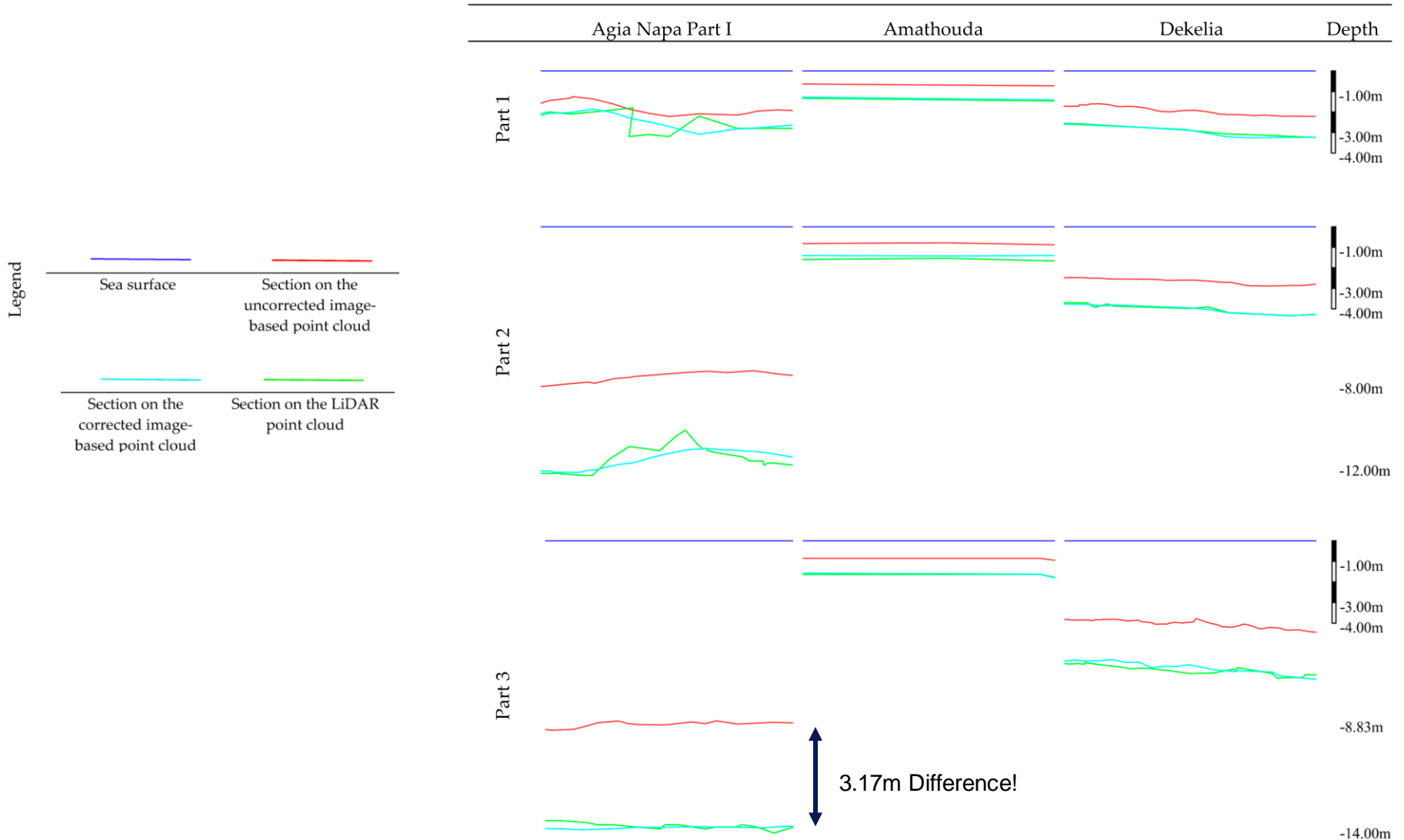
Agrafiotis et al., 2021

Results

65% RMSE reduction compared to the state of the art (LiDAR ground truth data used)
94% RMSE reduction in depth determination between corrected and uncorrected data (LiDAR ground truth data used)

Example

The respective parts of the cross sections



Stereo-based methods

Pros, Issues and Limitations

- Measured depth through triangulation & Delivers color information
- Delivers high 3D point density in shallow water areas
- Max depth ~ 1 Secchi
- Combined DEMs of emerged and submerged areas
- More accurate compared to spectral-based methods, WHEN refraction is corrected

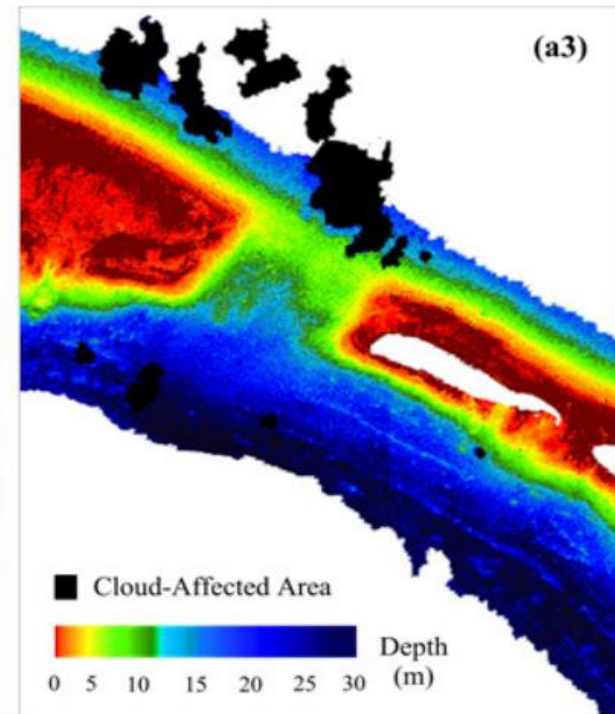
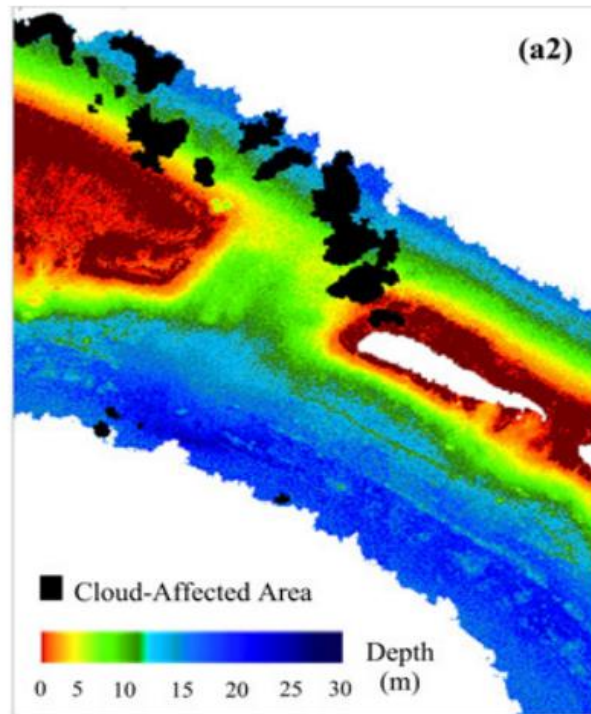
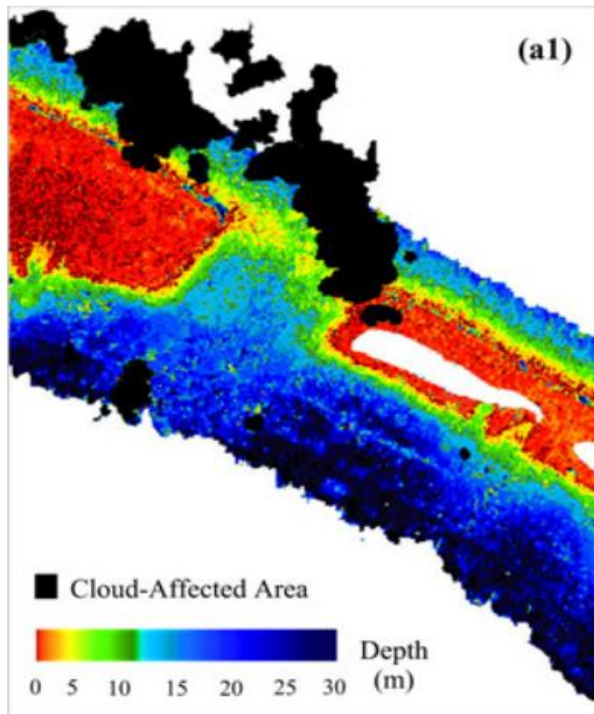
- **Refraction correction is necessary**
- Passive method
- Geometric
- **Requires texture** to perform SfM-MVS

Stereo VS Spectral-based

Stereo-based

Spectral-based
(left image)

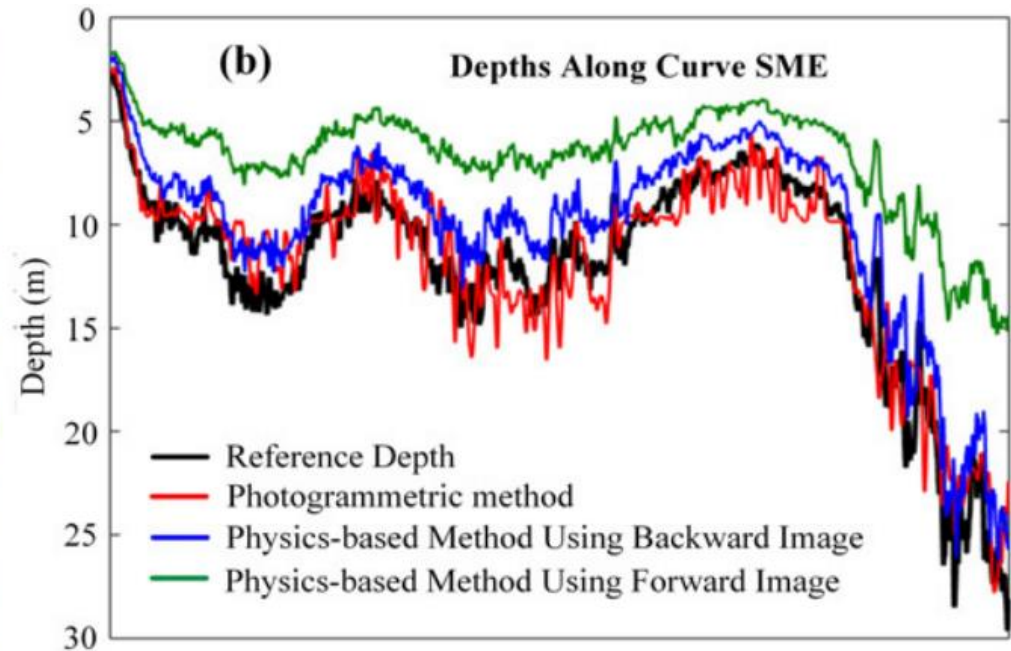
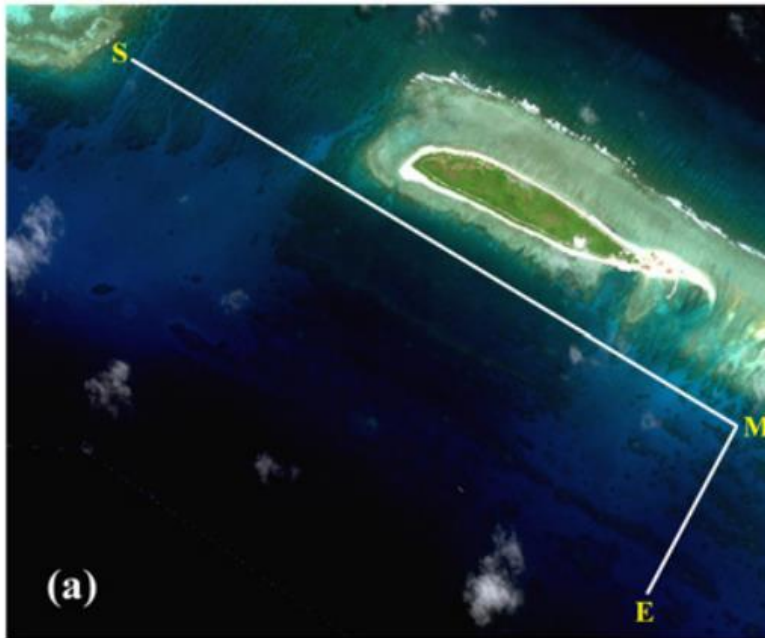
Spectral-based
(right image)



Cao et al., 2021

Stereo VS Spectral-based

Cross sections of the derived bathymetries



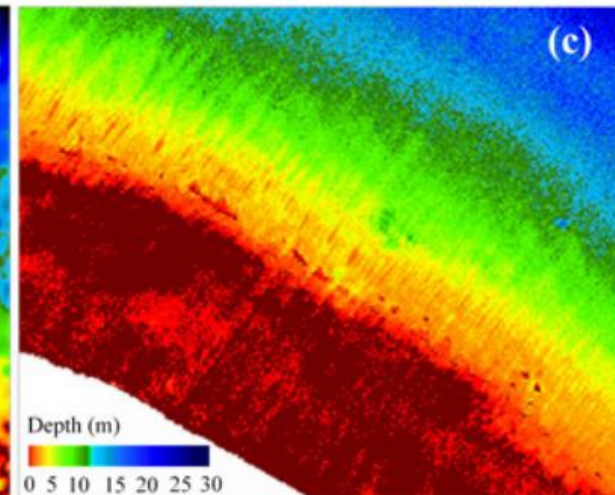
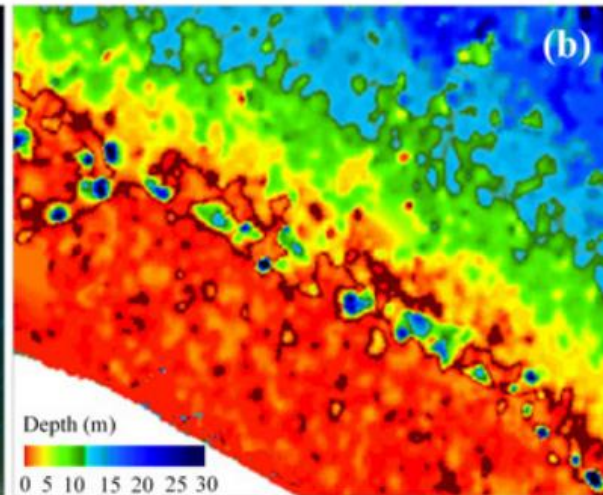
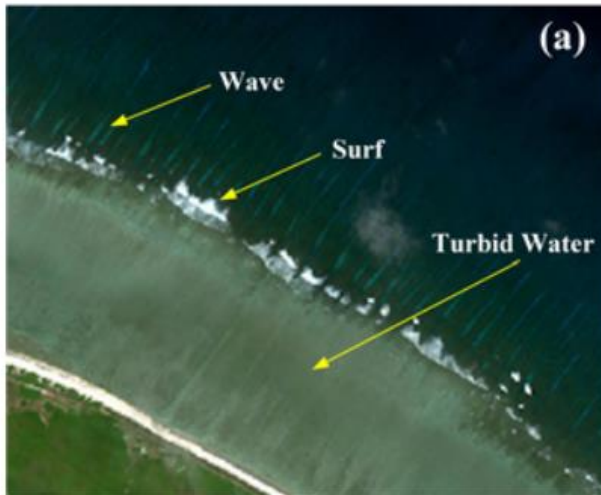
Cao et al., 2021

Stereo VS Spectral-based

Wave breaking and turbidity effects

Stereo-based

Spectral-based



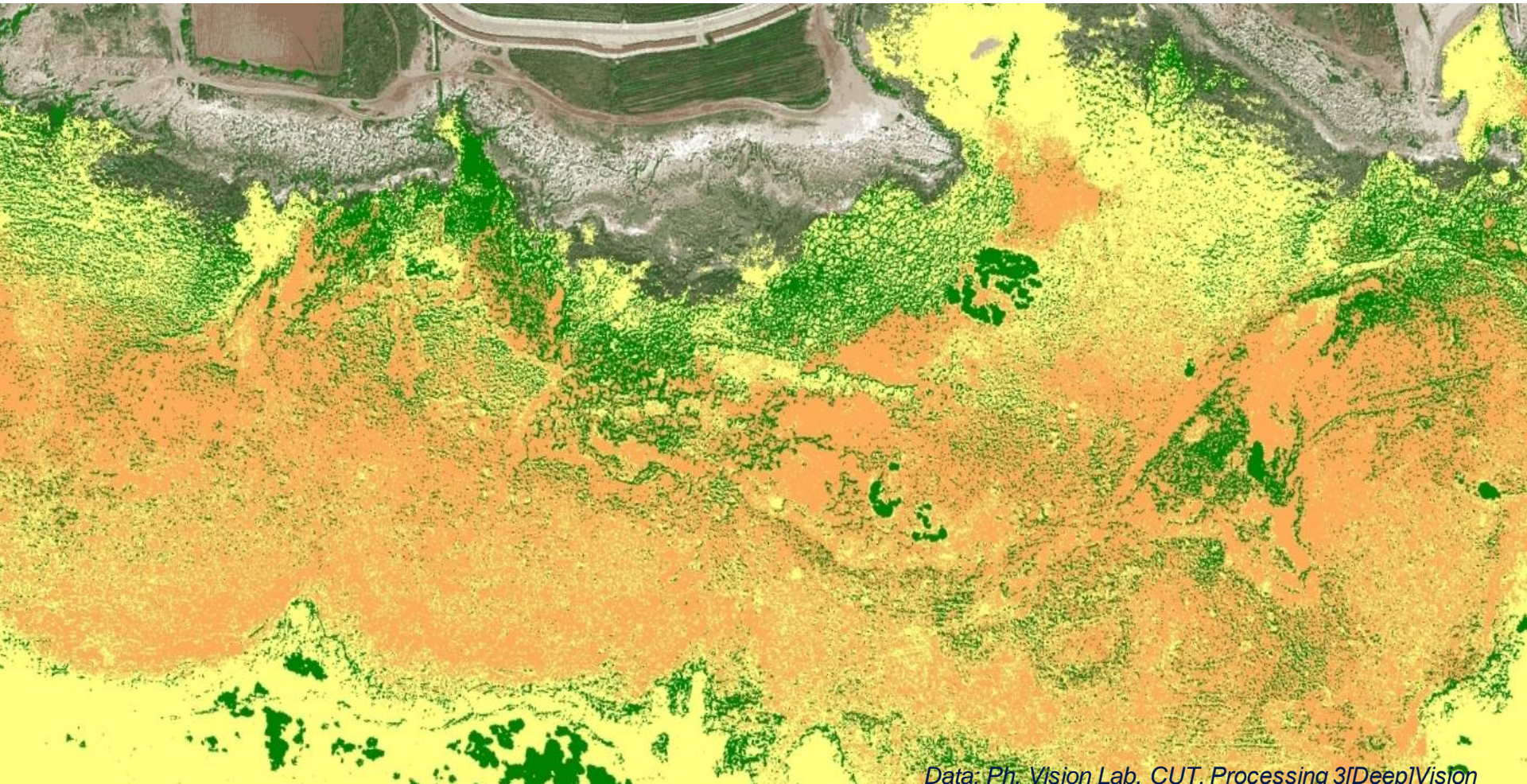
Cao et al., 2021

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- Shallow water bathymetry
- **Shallow seabed cover maps**

Shallow seabed cover maps



Data: Ph. Vision Lab. CUT, Processing 3[Deep]Vision

Shallow seabed cover maps



How?

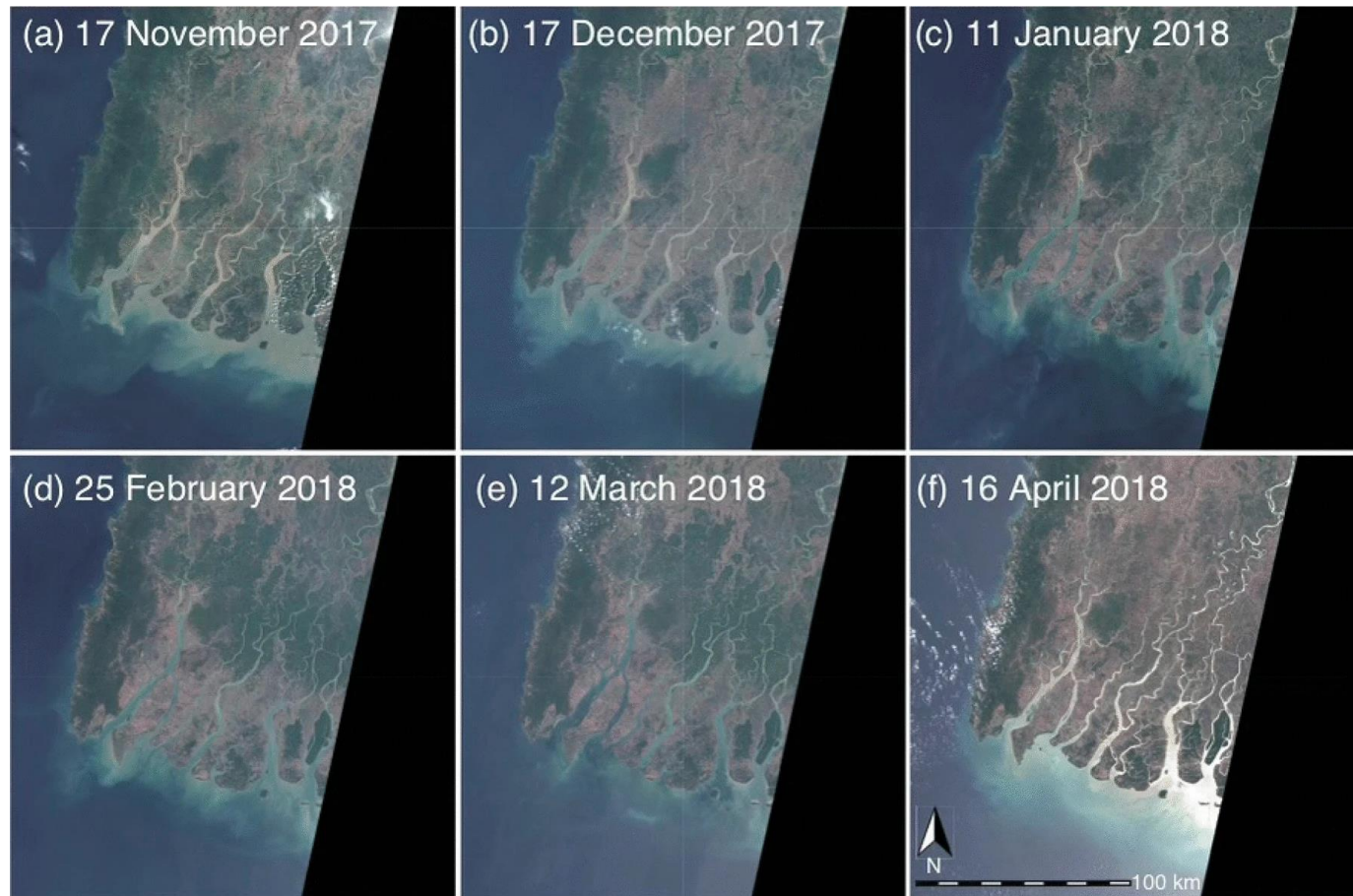
Statistical models: Statistically relate meas. seabed cover and reflectance – need for ground truth data

- From simple linear regression to ML (RFs, SVMs) and DL (FCNs etc.)

Seasonal/Monthly variation

MANY different spectral signatures for same pixels

- Limited generalization of trained models

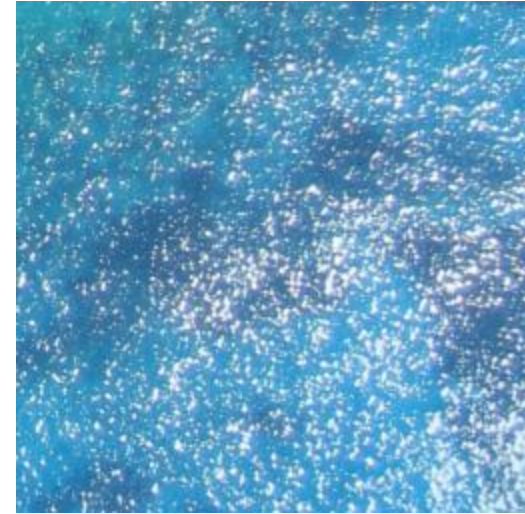


(Sakai et al., 2021)

Instant variation

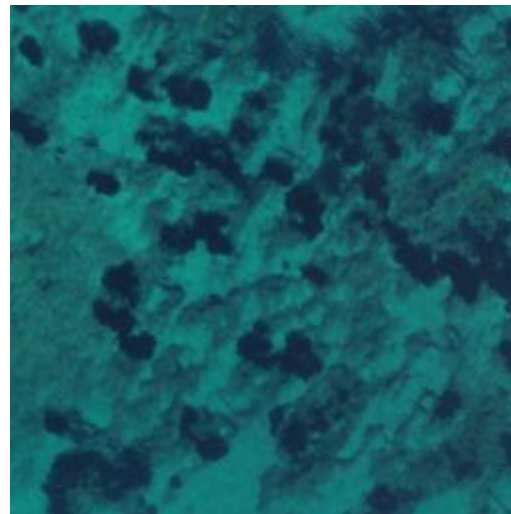
t

t+5sec OR different angle



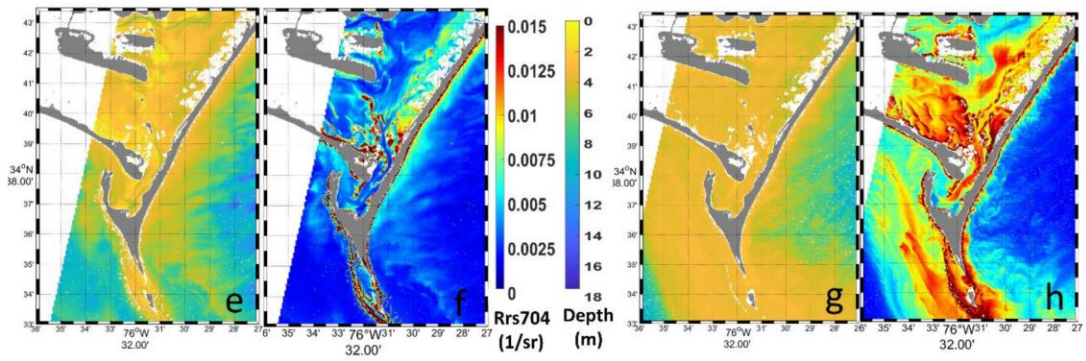
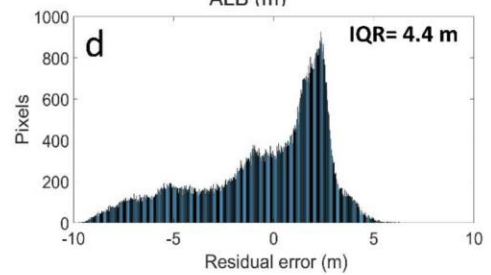
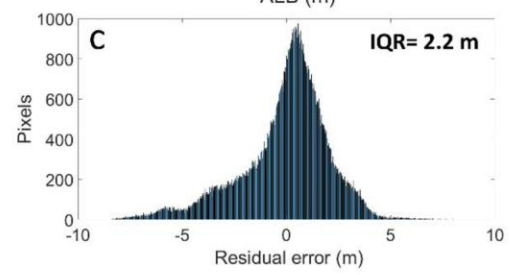
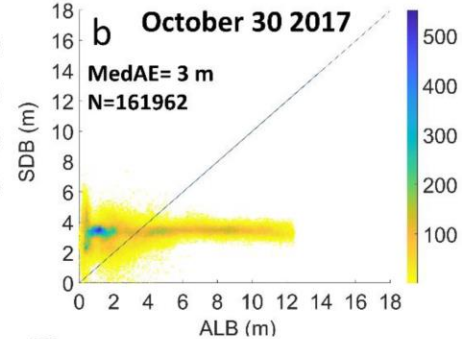
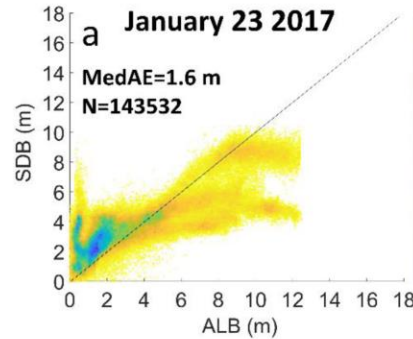
Caused by

- Change in point of view
- Sun glint
- Caustics
- Currents
- Ships and boats
- Clouds



Data: Ph. Vision Lab. CUT

Seasonal/Monthly variation



Caballero and Stumpf, 2020

MagicBathy MSCA PF HE Project



Multimodal **m**ultitask learning **G** for Multiscale **B**ATHYmetric mapping in shallow waters

Funding: HORIZON Europe MSCA Postdoctoral Fellowships - European Fellowships

Host: TU Berlin, RSiM group

Duration: 24 Months

Starting date: 1st of February 2023

Web: <https://www.magicbathy.eu/>

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