Machine Learning for Observing the oceans with Remote Sensing

Dr. Ing. Panagiotis Agrafiotis

Postdoctoral Researcher - Marie Skłodowska-Curie Fellow
agrafiotis@tu-berlin.de
https://rsim.berlin/
https://www.magicbathy.eu/

Course: Machine Learning for Remote Sensing Data Analysis

Faculty IV – Electrical Engineering and Computer Science
TU Berlin

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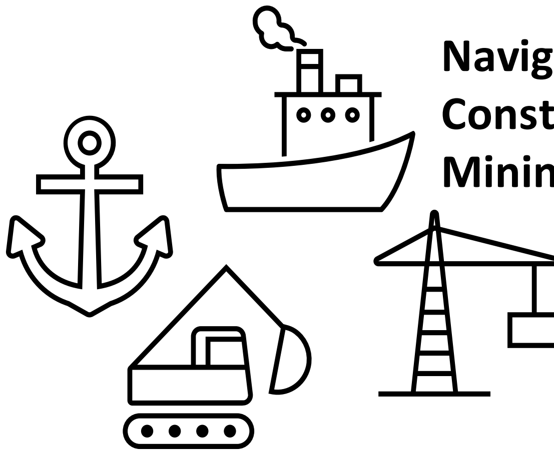
02.11.2023

Technische Universität Berlin

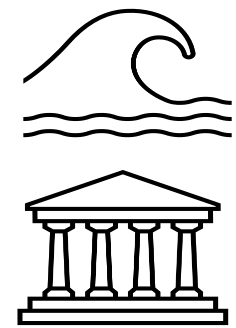
RSiM

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

Why?



Navigation
Constructions
Mining

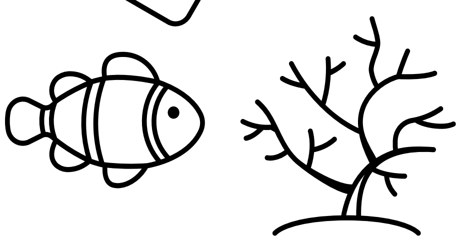


Cultural Heritage

Tourism

Marine litter detection

Support action for climate



Map/monitor marine animal forests

RSiM

What platforms and data?

Satellites, occupied airborne or unoccupied airborne (drones)

- RGB + Multispectral imagery
- LiDAR (LIght Detection And Ranging)
- Synthetic-aperture radar (SAR) altimeters
- Other special payload instruments (radiometers etc.)

What platforms and data?

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- **RGB + Multispectral imagery**
- LiDAR (LIght Detection And Ranging)
- Synthetic-aperture radar (SAR) altimeters
- Other special payload instruments (radiometers etc.)

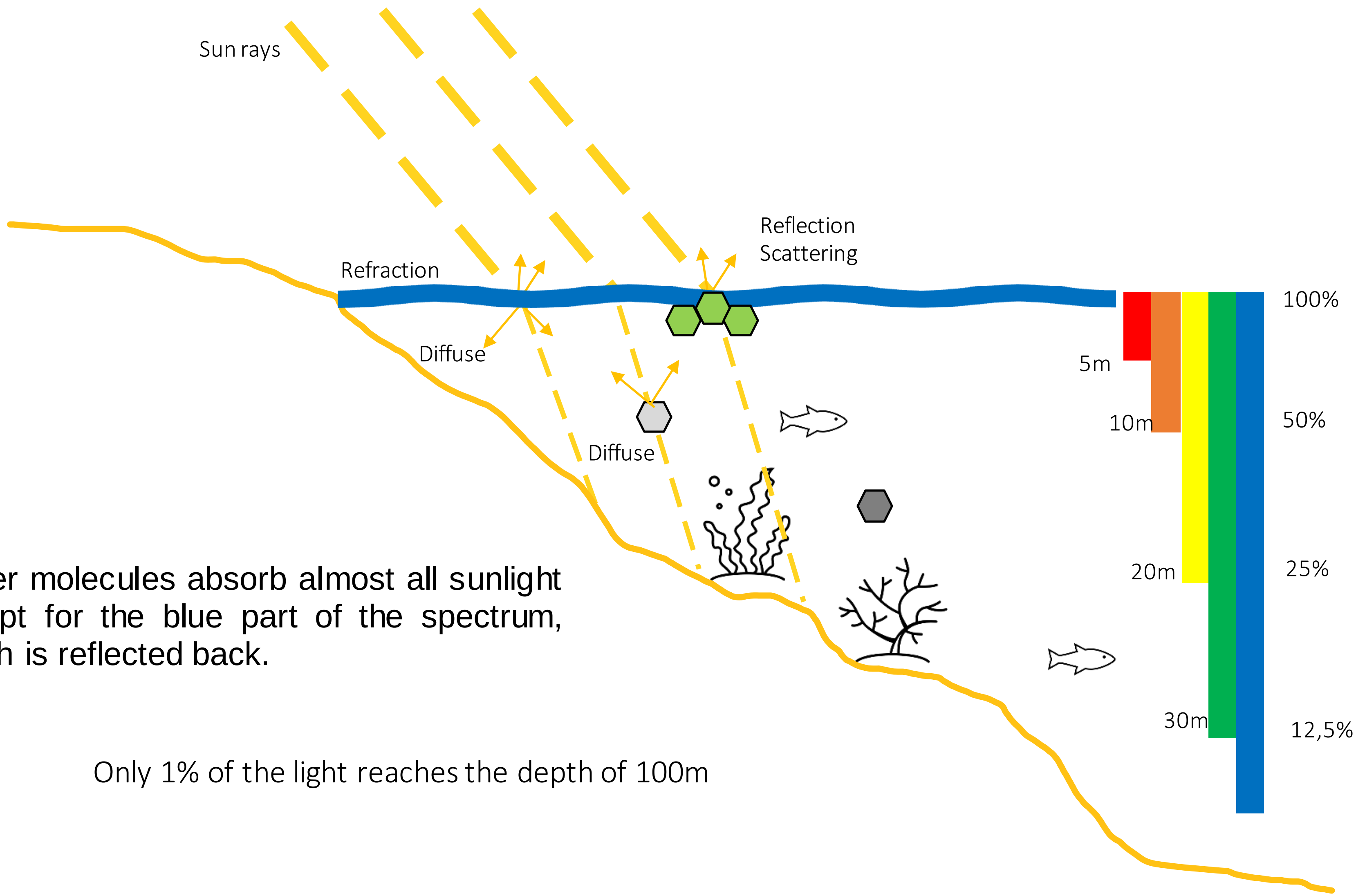
How can we get the required information?

- **Exploit the RADIOMETRIC information of one or more scenes**
- **Exploit the GEOMETRIC information derived by two or more scenes (stereo etc.)**

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

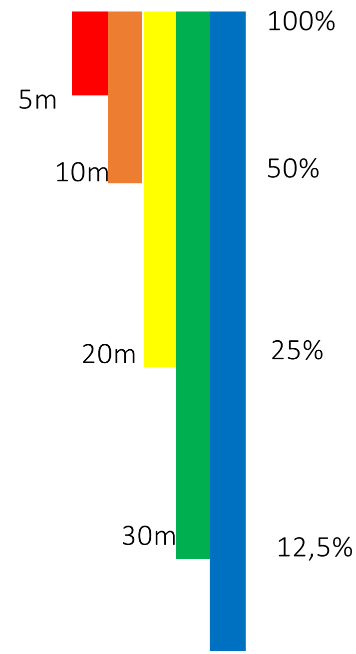


Water molecules absorb almost all sunlight except for the blue part of the spectrum, which is reflected back.

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

Light absorption in water column

Optically clear waters

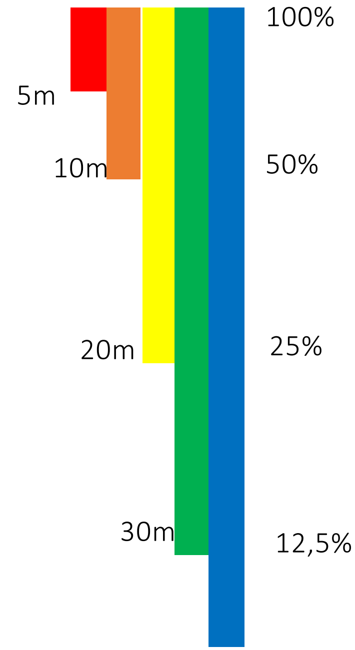


Bottom is visible till the depth of 20-25m

Image source:
Copernicus, https://dataspace.copernicus.eu/

Light absorption in water column

Optically clear waters but with higher chlorophyll etc. concentration and darker bottom



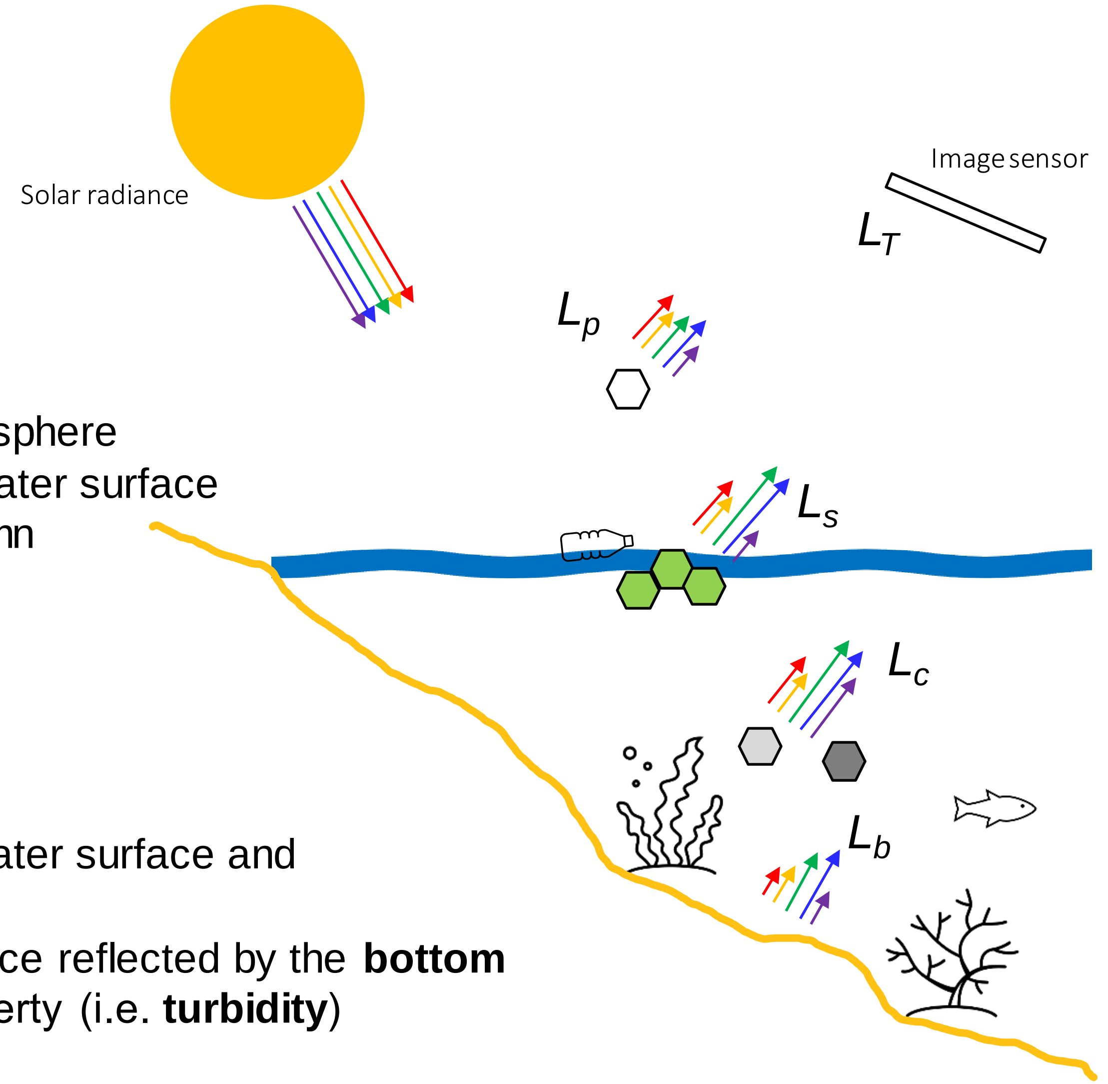
Bottom is visible till the depth of 4-5m

Image source:
Copernicus, https://dataspace.copernicus.eu/

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**)

ML applications using radiometric information

- Biogeochemical indices (i.e., chlorophyll)
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Biogeochemical indices

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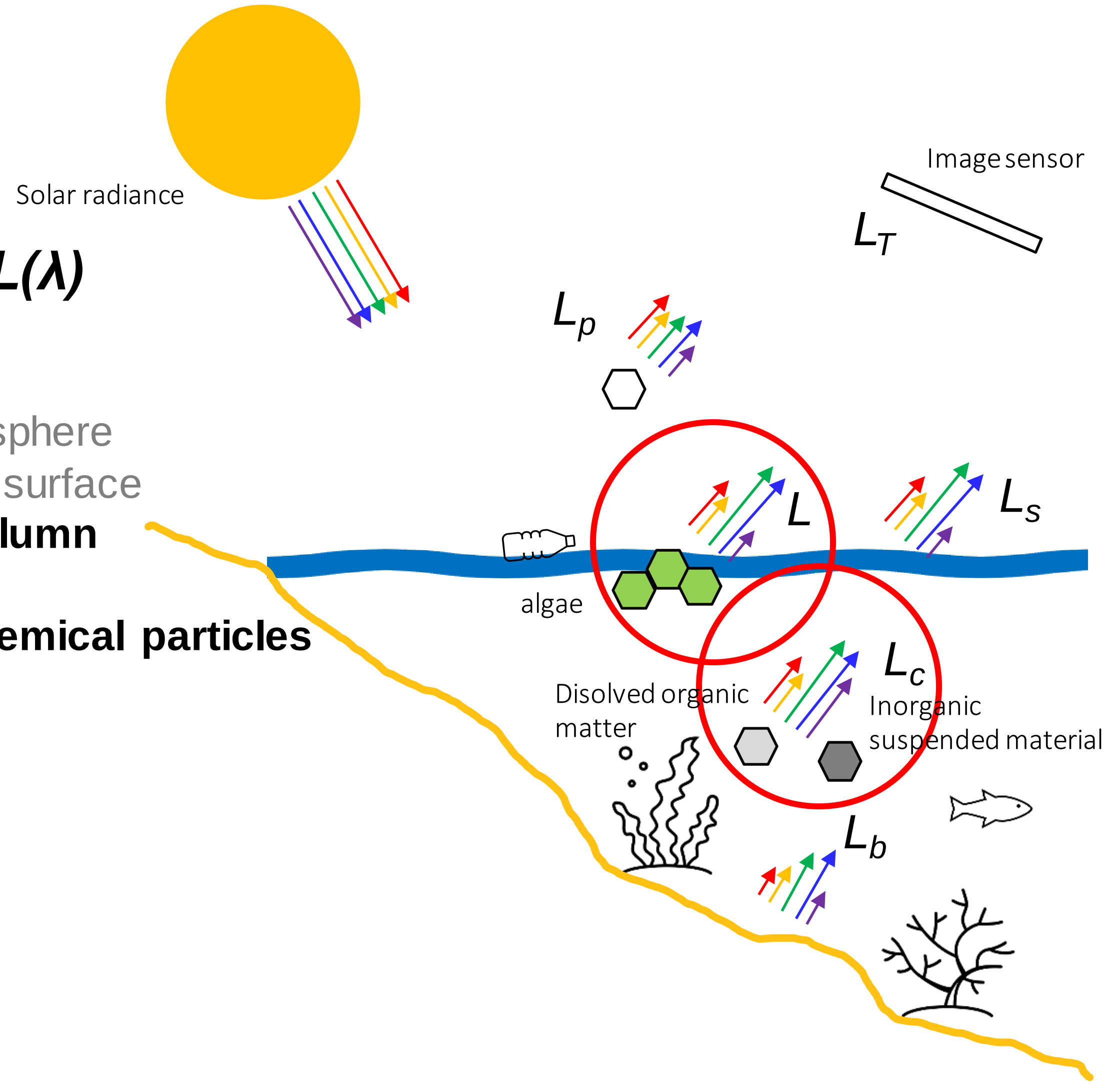


L_T is the total upwelling radiance
L_p are the contributions from the atmosphere
L_s is the radiance reflected from water surface
L_c is the radiance from the water column
L_b is the bottom-reflected radiance
L **is the radiance from the biogeochemical particles**

Suspended matter (turbidity)

Chlorophyll (algae)

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:

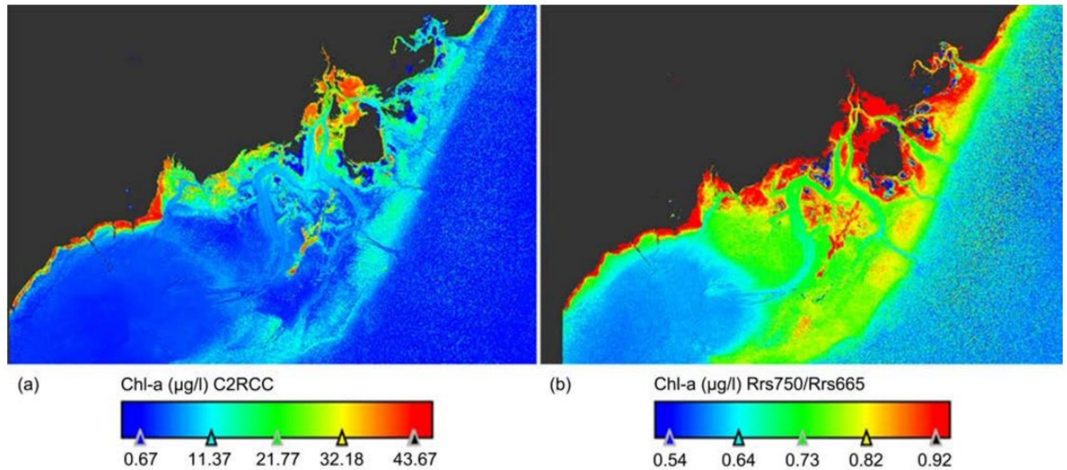
- Chlorophyll: Red, green and visible and near infrared (VNIR) bands
- Suspended matter: Red band

Semi-analytical algorithms

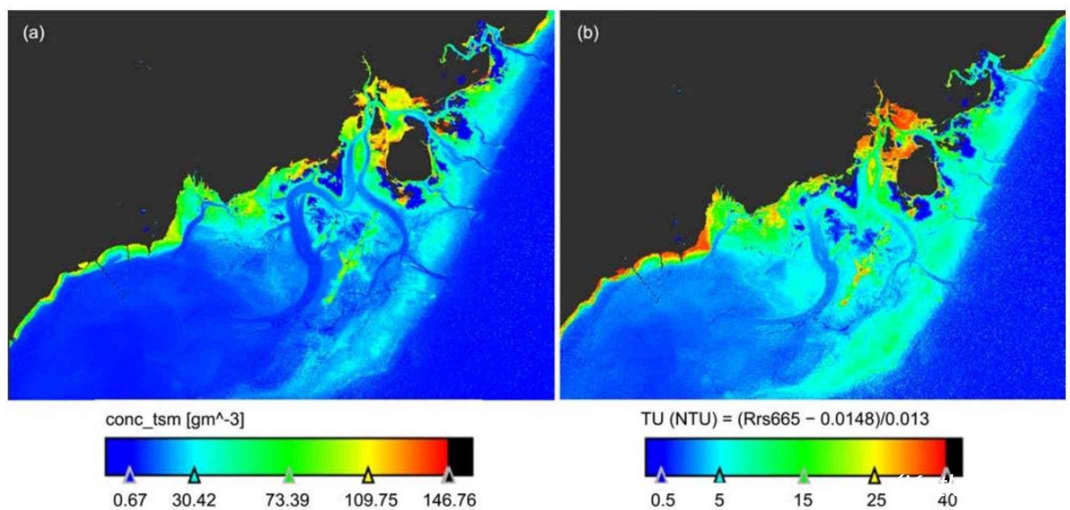
Estimate CHL via spectral absorption of phytoplankton, spectral backscattering by particles & the combined absorption by non-algal particles and colored dissolved organic material *(O'Reilly et al., 2019)*

Examples

Chlorophyll

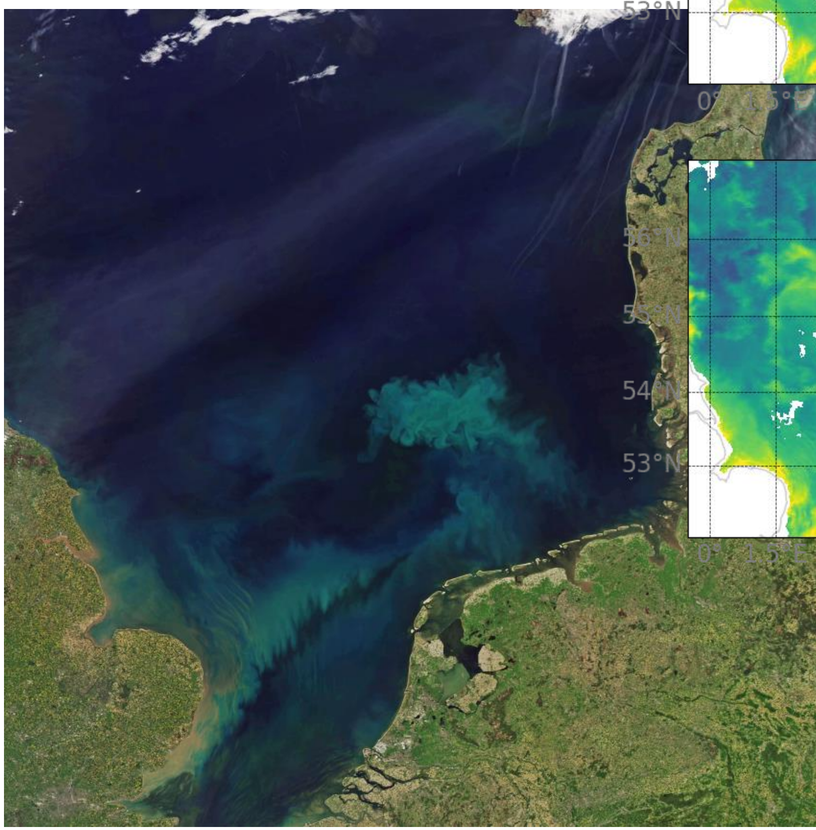


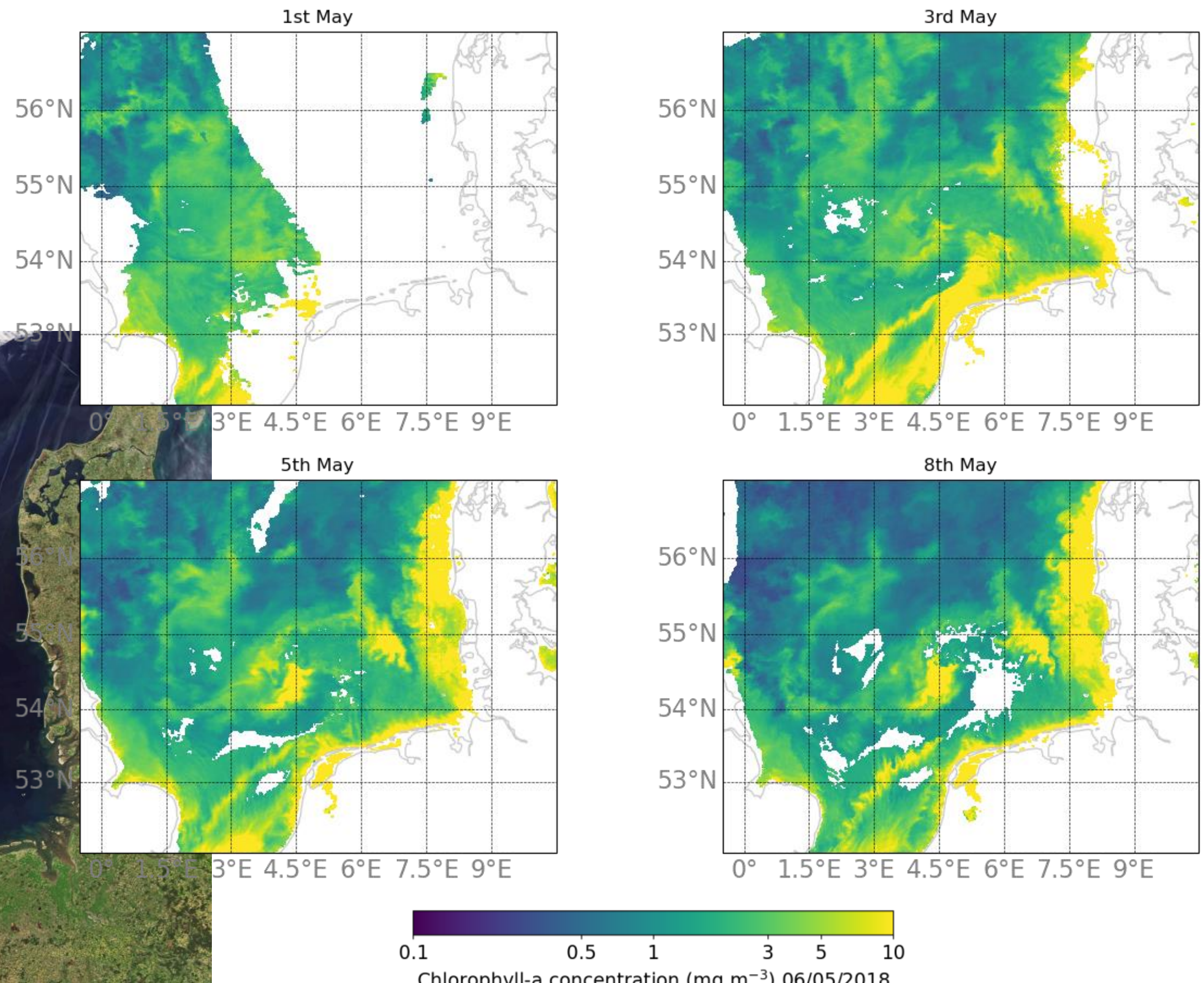
Suspended matter



Examples

Chlorophyll daily variation





Data source: Copernicus Marine Service Online Training Workshop 2020 (Mercator Ocean international, UK Met Office, Plymouth Marine Laboratory, German Federal Maritime, and Hydrographic Agency)

ML applications using radiometric information

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- **Sea ice coverage and state**
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Sea ice

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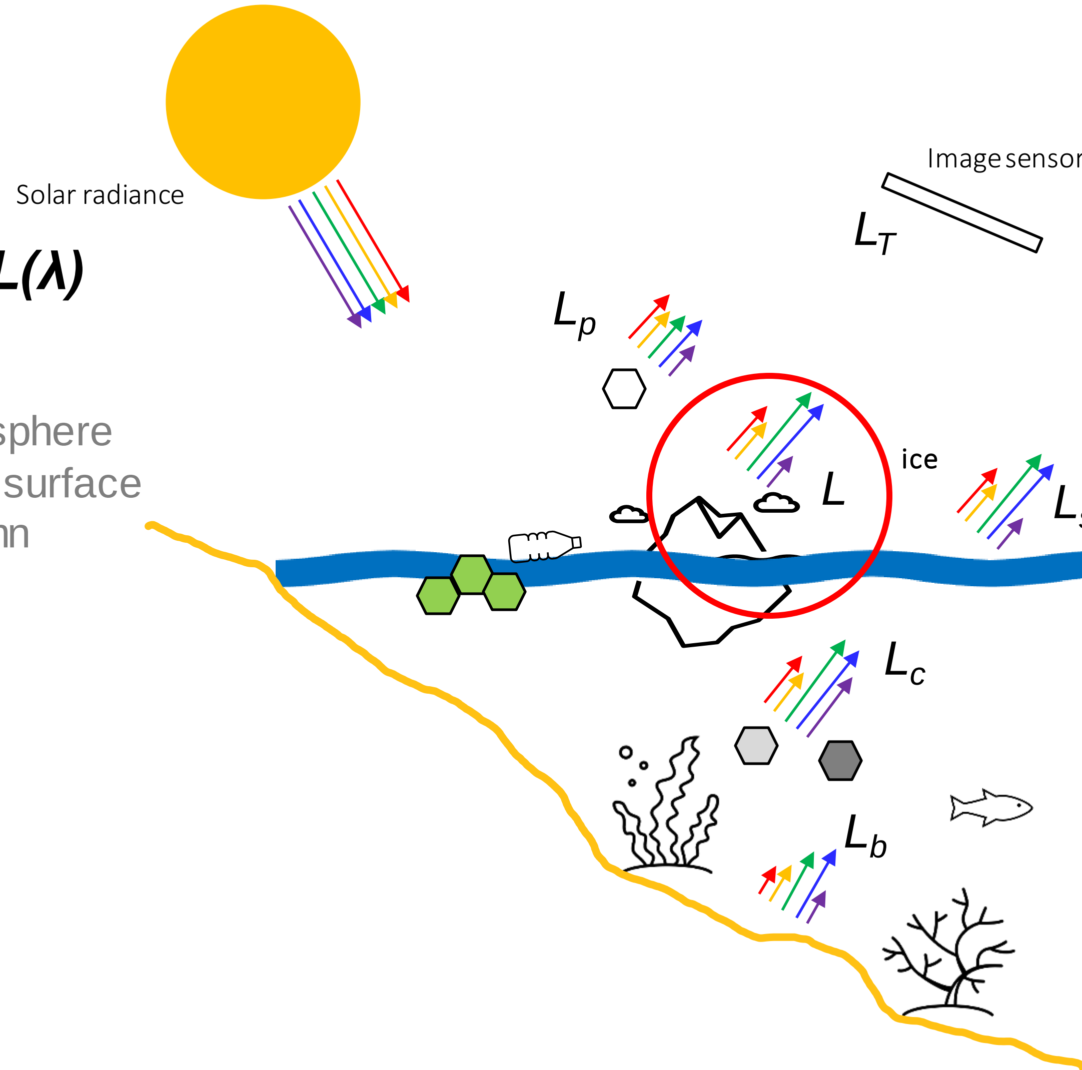
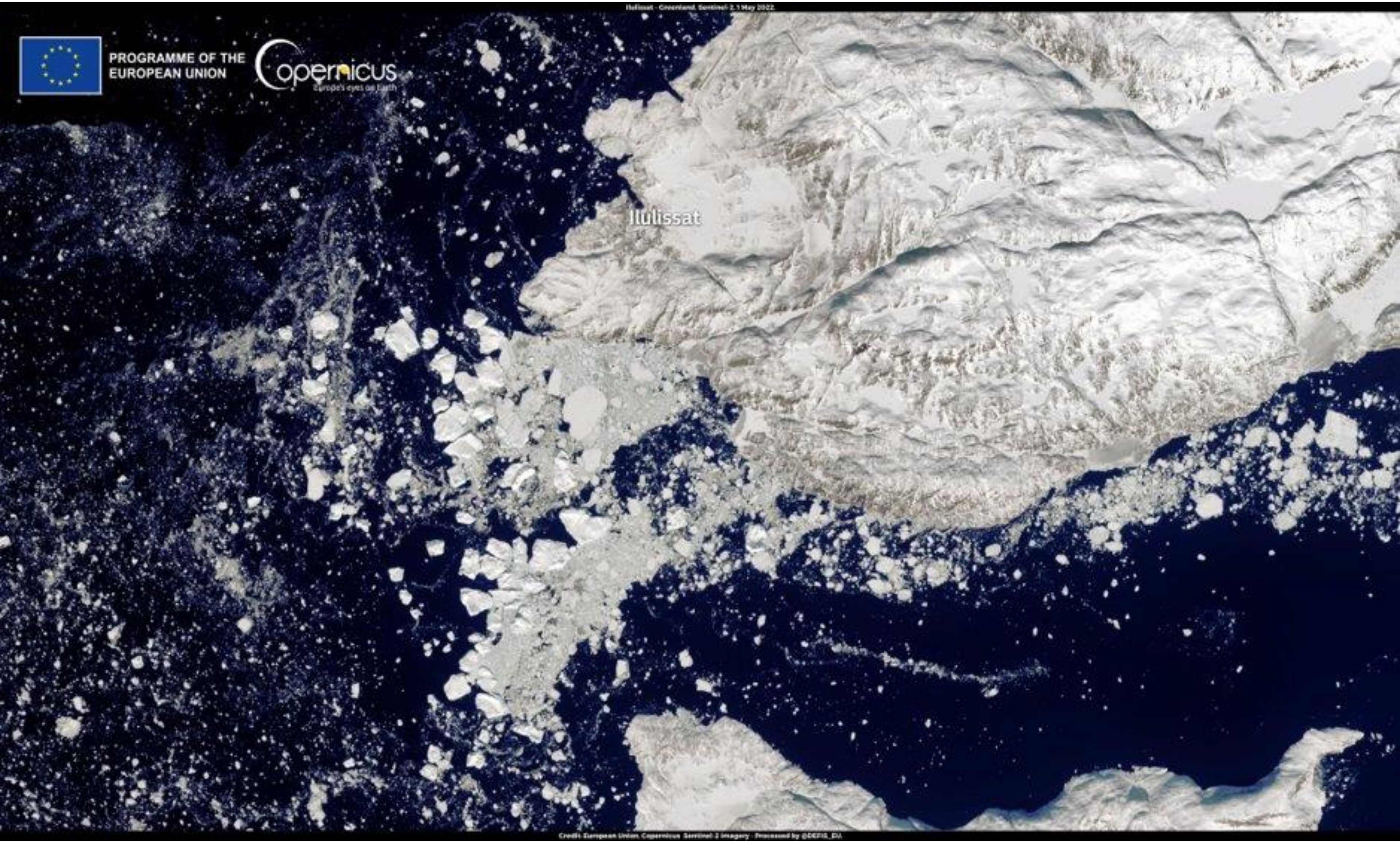
L is the ice-reflected radiance



Sea ice



Ilulissat - Greenland, Sentinel-2, 1 May 2022
PROGRAMME OF THE EUROPEAN UNION
Copernicus
Ilulissat

Sea ice

How?

Empirical algorithms

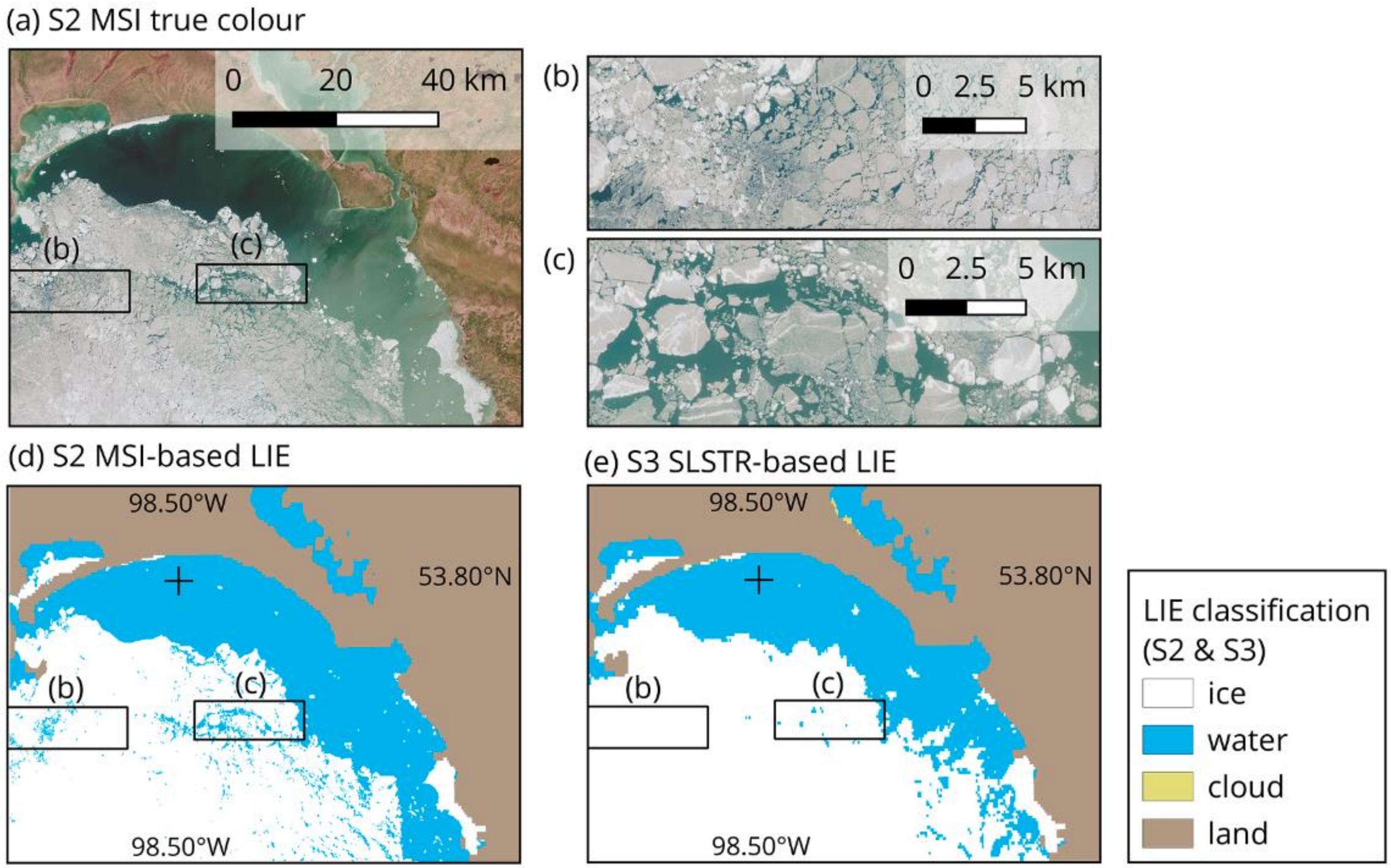
- Exploit spectral characteristics of snow, ice, & water in the visible and NIR
- Simple regression and polynomial models
- Support Vector Machines
- Gaussian Mixture Models
- Fully Conv. Neural Nets.
- ...

Major difficulties to deal with

- 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

Results of a trained Gaussian Mixture Model on S2 optical data



(Heinilä et al., 2021)

ML applications using radiometric information

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- **Pollution/ oil spill detection/ tracking**
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Marine Debris

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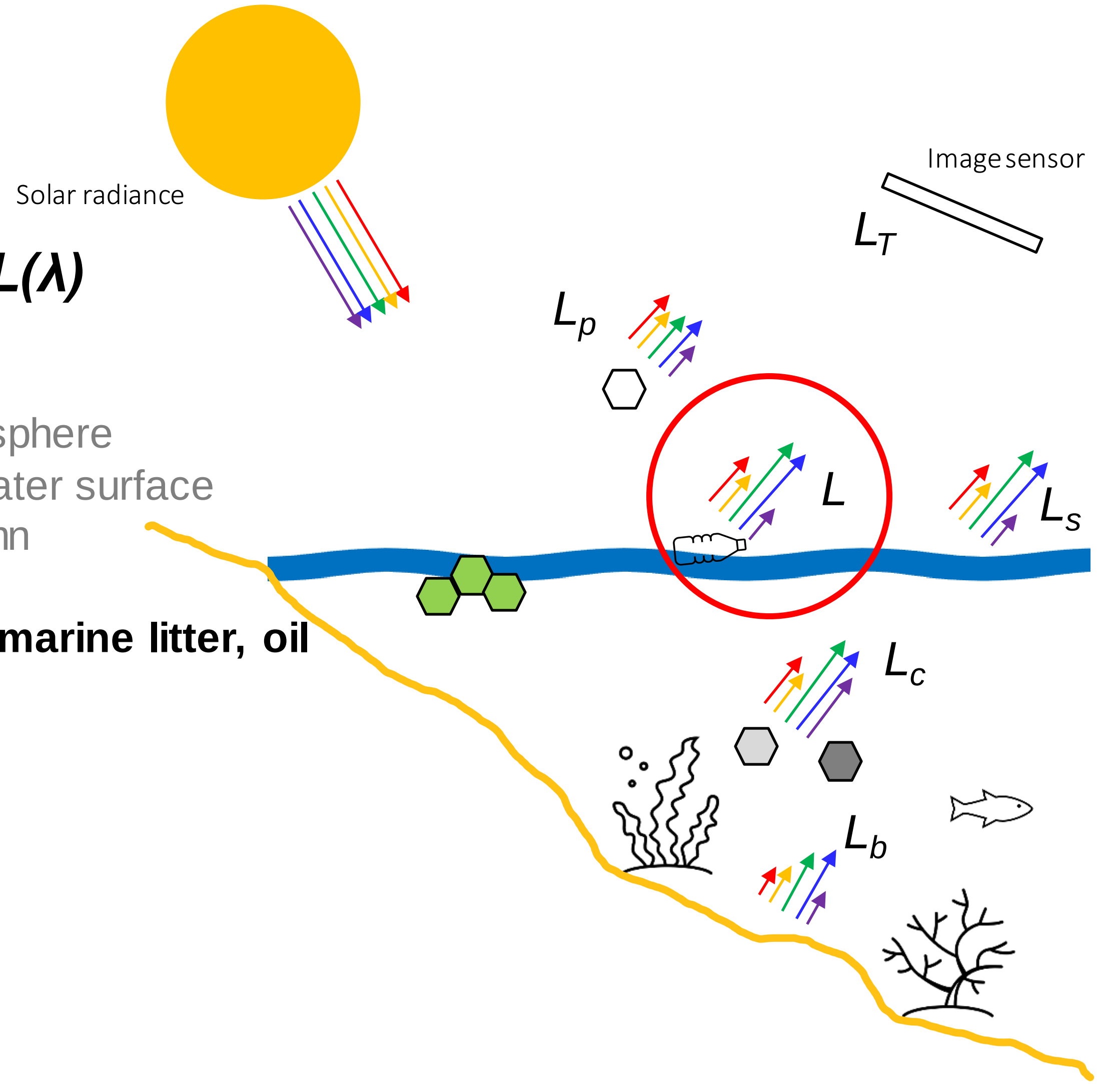
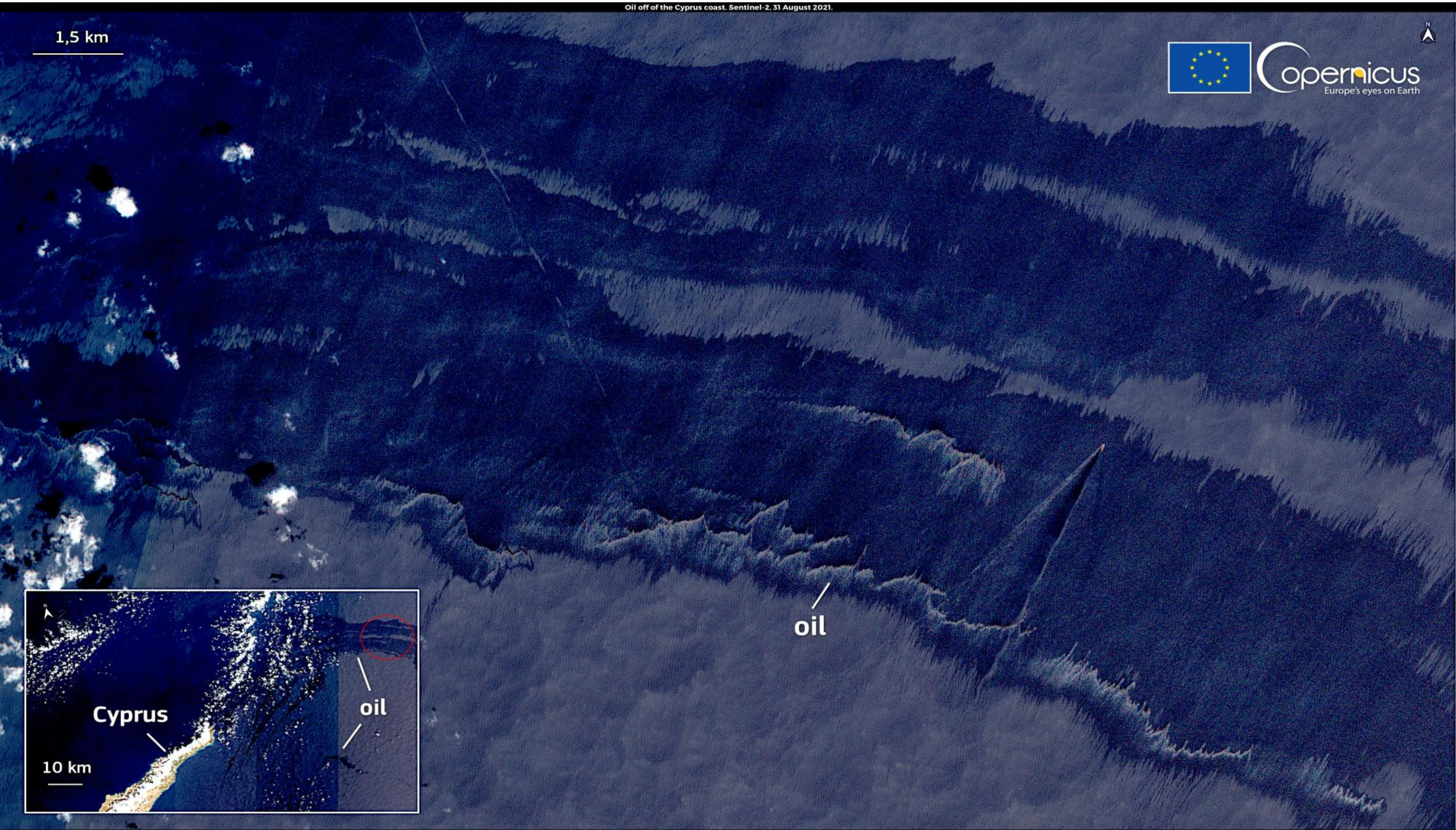
L_b is the bottom-reflected radiance
L is the radiance reflected from the marine litter, oil spills etc.



Pollution/oil spill detection

Oil off of the Cyprus coast. Sentinel-2, 31 August 2021.



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

Marine Debris

(Kikaki et al., 2022)

Marine Debris

How?

Empirical models

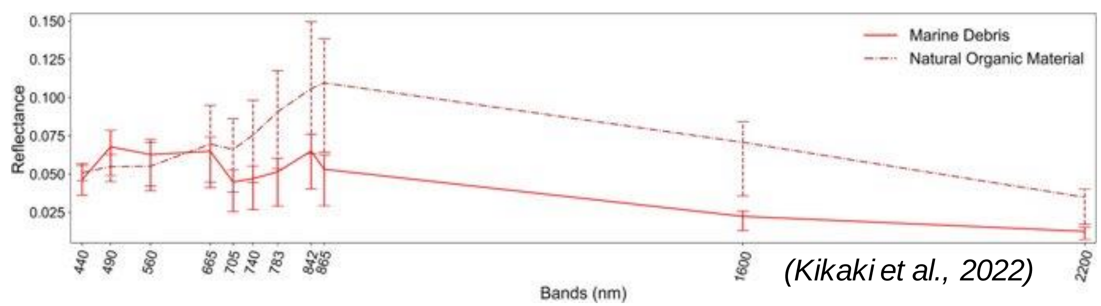
Statistically relate measurements marine debris (i.e. plastic) and reflectance through logistic regression, polynomial expressions or more complex **ML methods**

Some ML baselines

Weakly supervised semantic segmentation and multi-label classification:

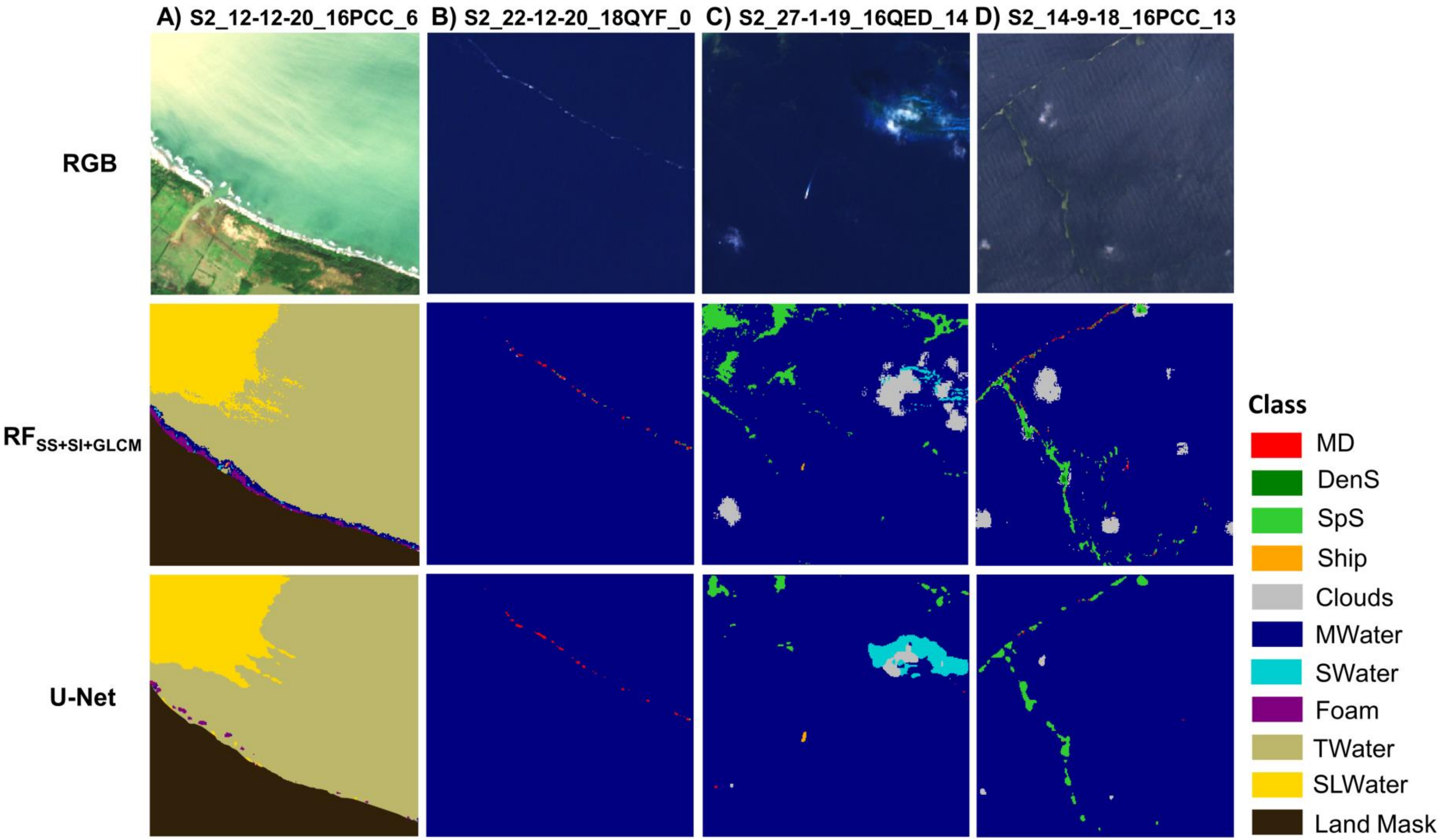
- RF_{SS} (spectral signatures)
- RF_{SS+SI} (+ calculated spectral indices)
- $RF_{SS+SI+GLCM}$ (+ extracted Gray-Level Co-occurrence Matrix (GLCM) textural feat.)
- U-Net (11 Rayleigh reflectance S2 bands)

- Multi-label classification:
- ResNet
- ...



(Kikaki et al., 2022)

Marine Debris



(Kikaki et al., 2022)

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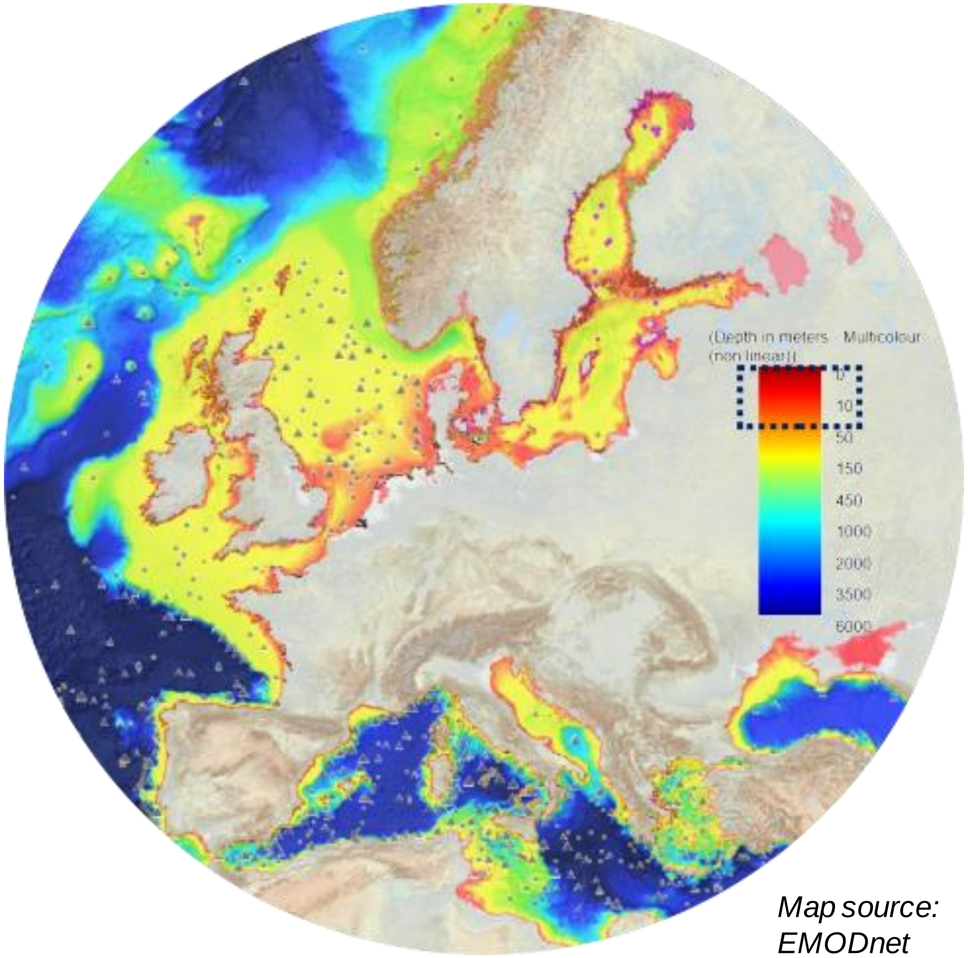
- Shallow seabed cover maps

Shallow Water Bathymetry



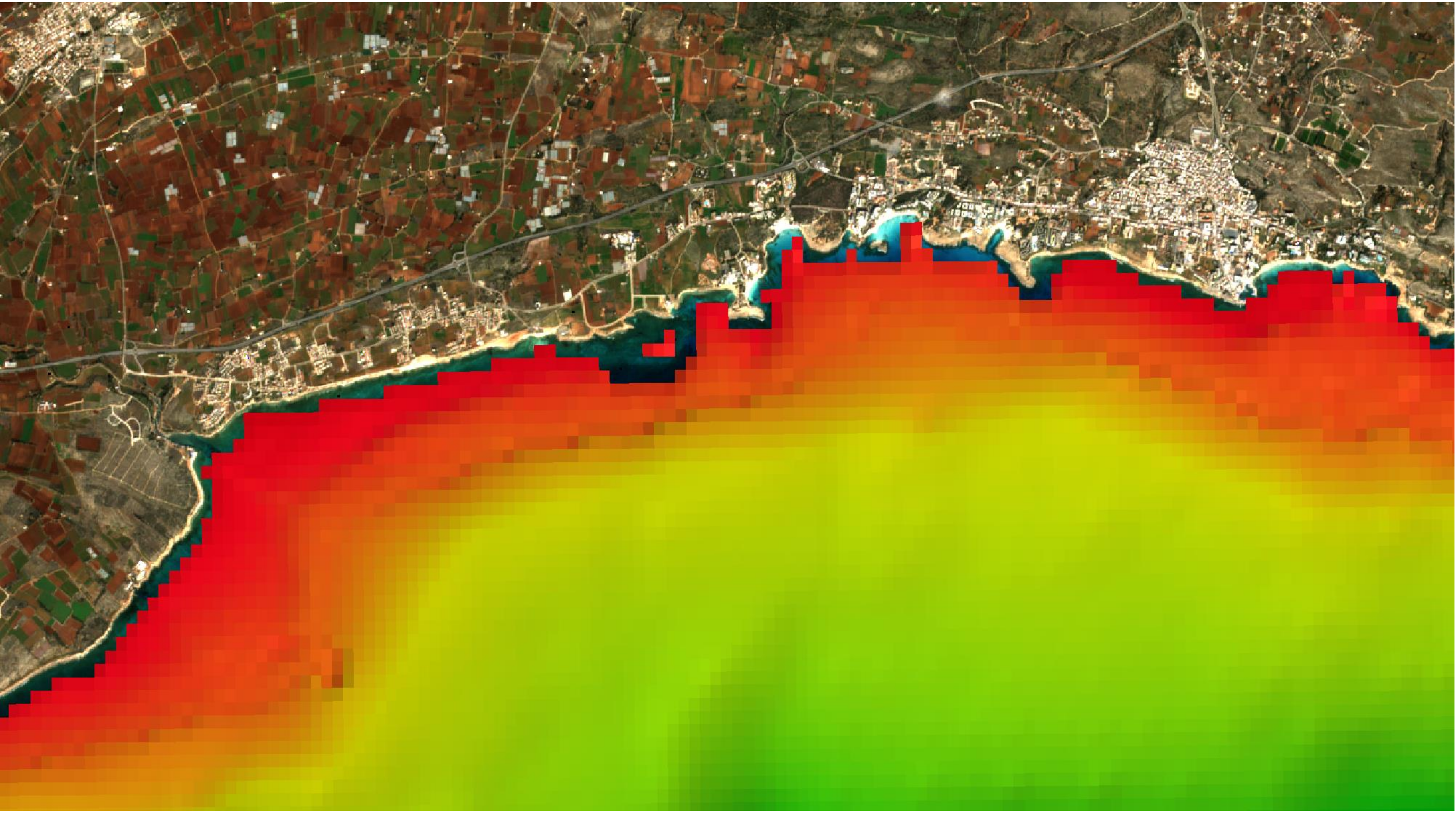
2.5% of the EU seabed is "shallow" (<20-25m depth) excluding lakes

Map source: EMODnet

Shallow Water Bathymetry

Image source:
Copernicus, https://dataspace.copernicus.eu/

Shallow Water Bathymetry



Satellite Image source: Copernicus - Bathymetry Source: EMODNet (spectral based)

Shallow Water Bathymetry

Satellite Image source: Copernicus - UAV Image source *Ph. Vision Lab. CUT*

RSiM

Shallow Water Bathymetry

Satellite Image source: Copernicus - UAV depths source *Ph. Vision Lab. CUT/ 3DeepVision Research (stereo based and corrected for water refraction using Agrafiotis et al., 2019, 2020, 2021 methods)*

ML applications using radiometric information

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

Basics of spectral-based bathymetry

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

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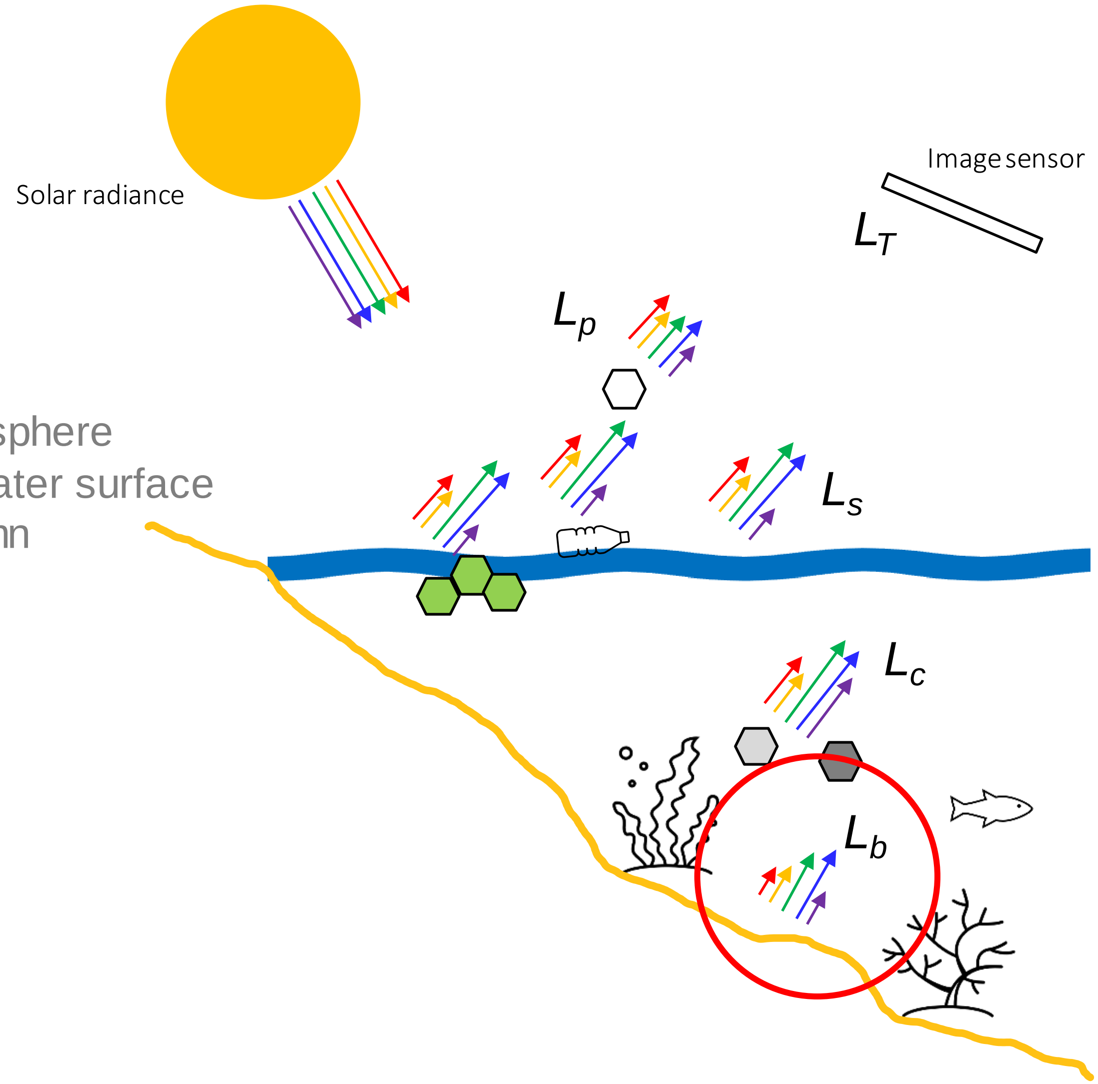

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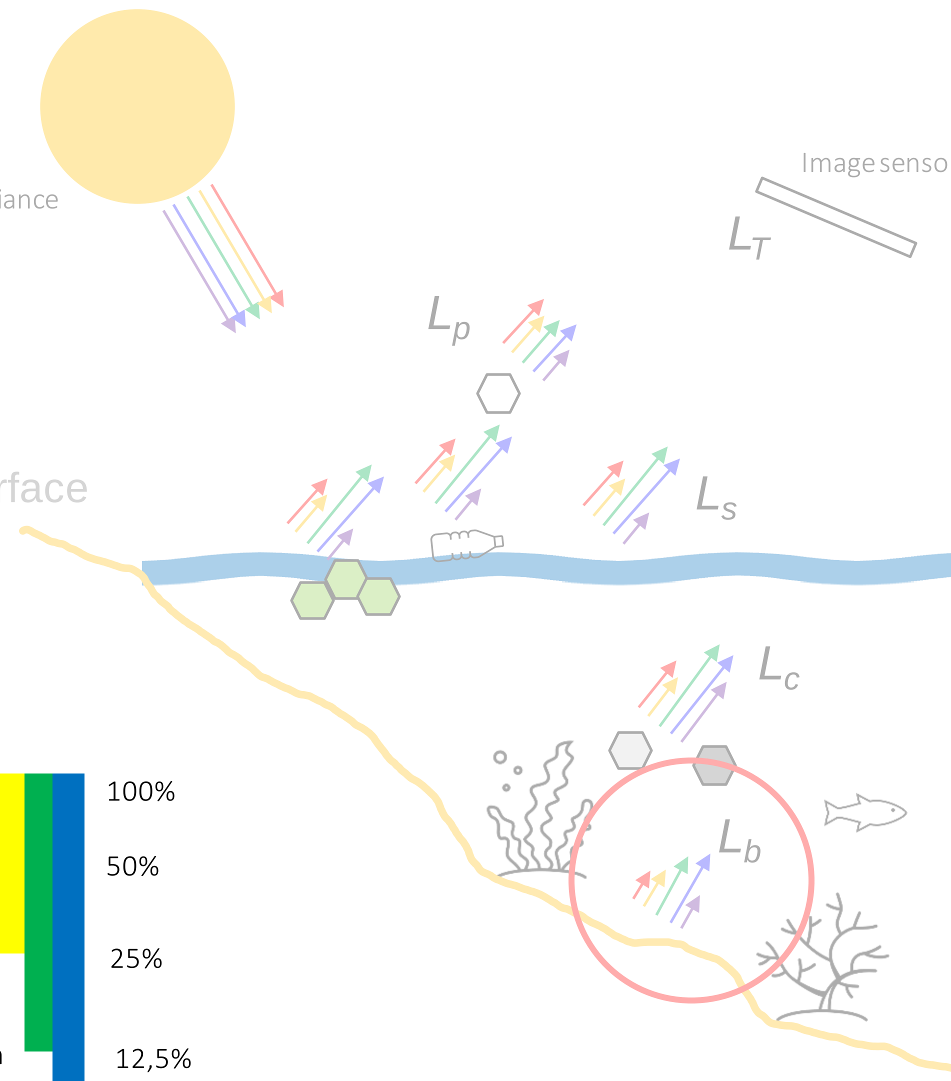
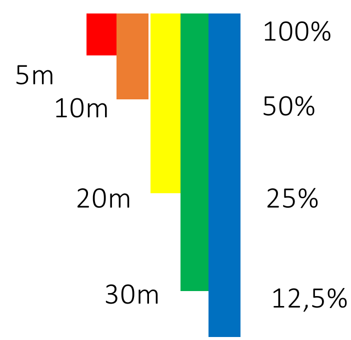


Easy way
Correlate color loss and depth



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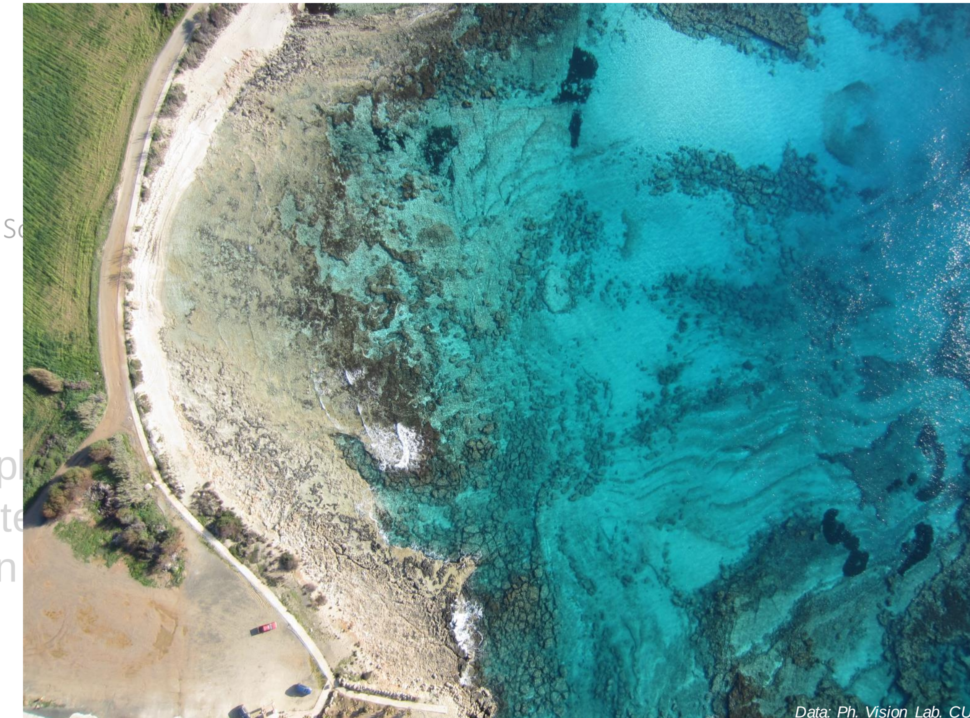
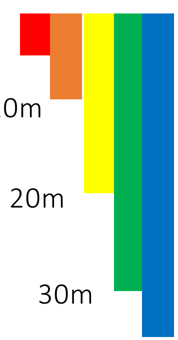
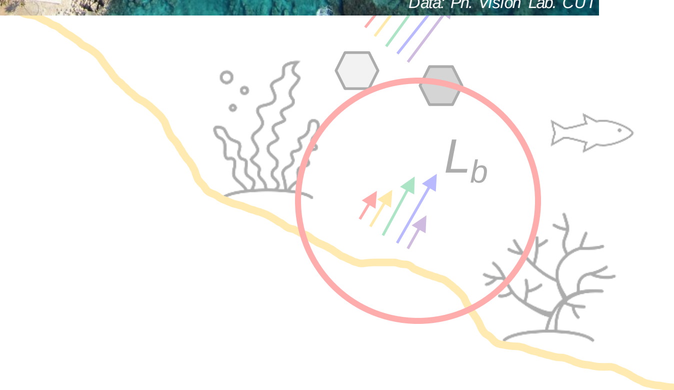


Easy way
Correlate color loss and depth

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 etc.)

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(λi)) 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:

pSDB "pseudo depth"

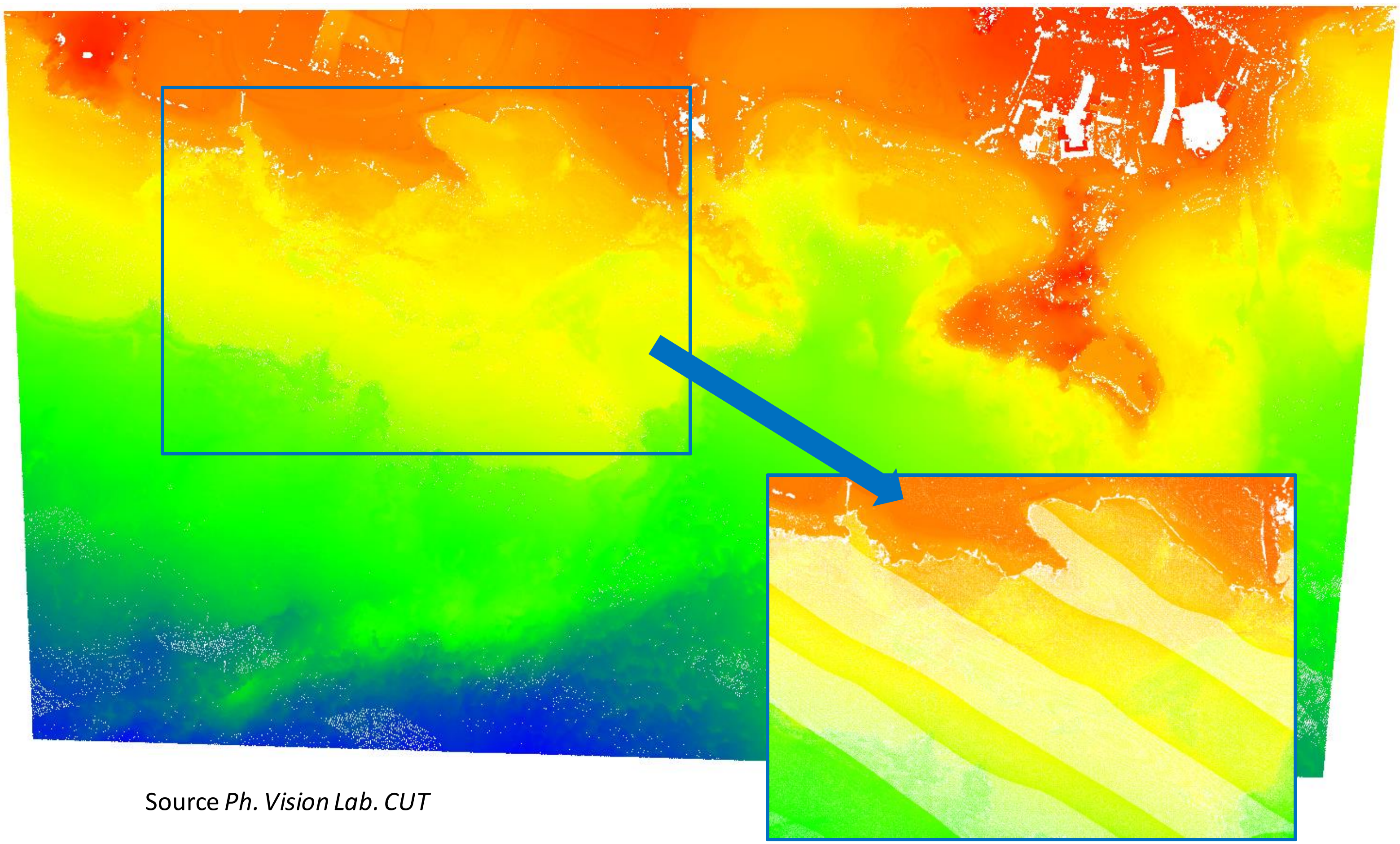
$$Z = m_1 \boxed{\frac{\ln(nR_w(\lambda_i))}{\ln(nR_w(\lambda_j))}} - m_0$$

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 techiques (RFs, SVMs, FCNs)**

Ground truth data for ML

Airborne LiDAR or shipborne Echosounder



Source *Ph. Vision Lab. CUT*

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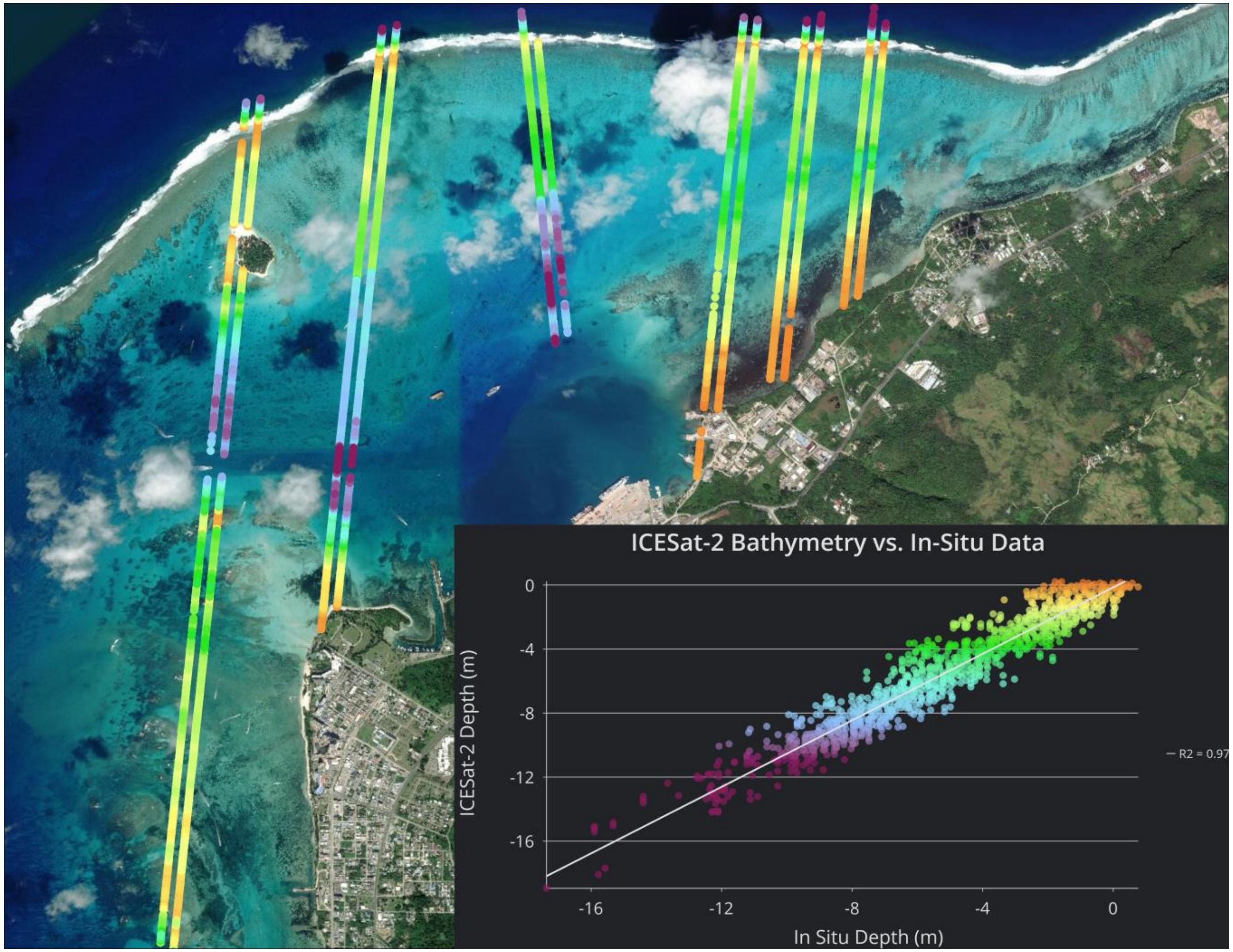
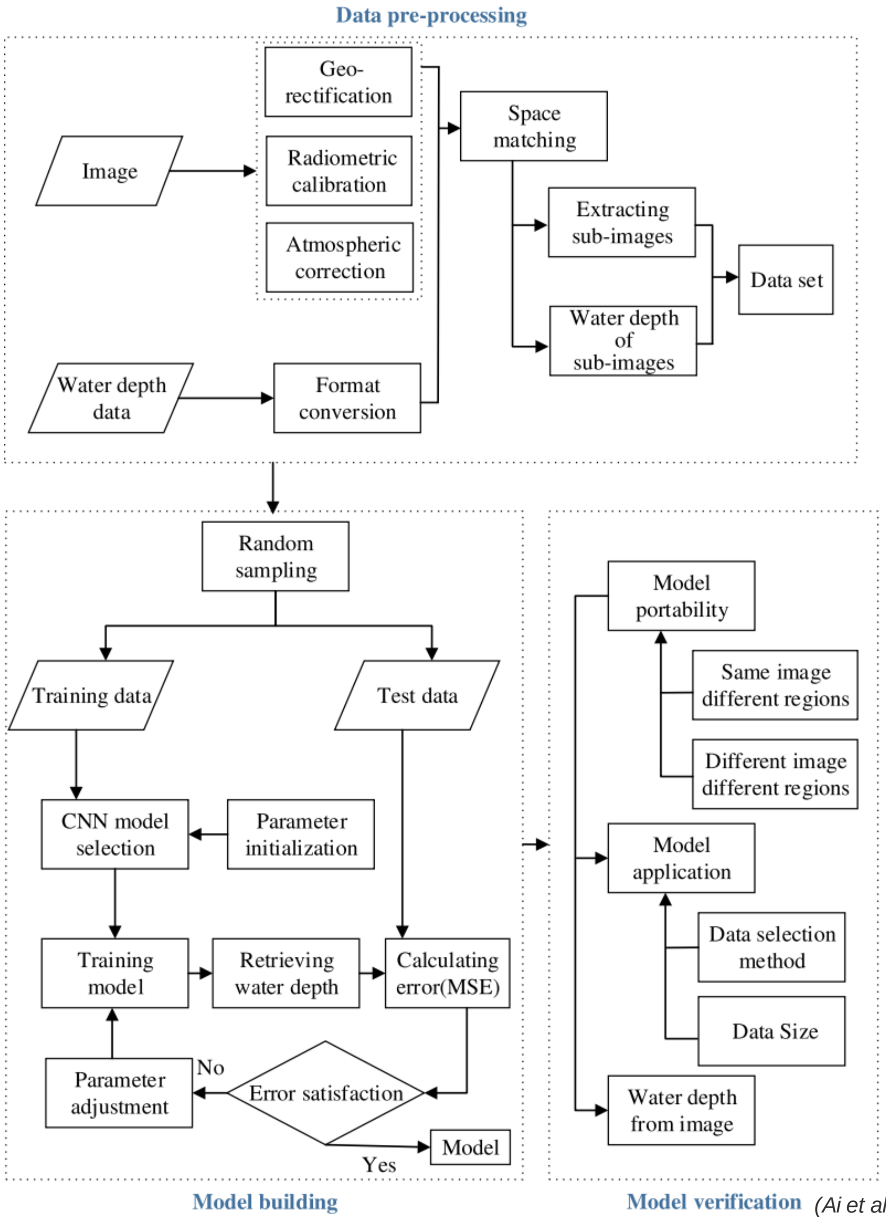
Ground truth data for ML

ICESat-2 satellite or similar



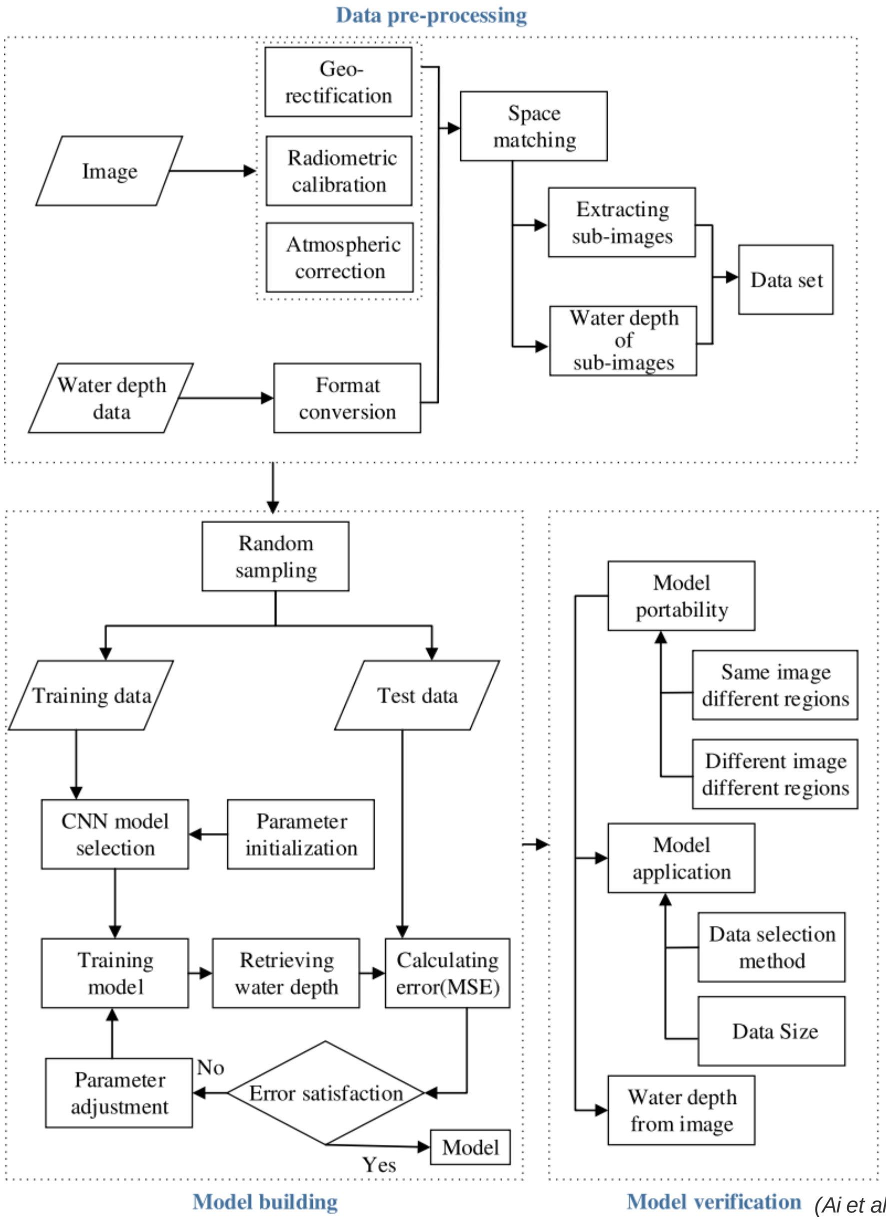
TCARTA, https://www.tcarta.com/events/geospatial-intelligence-month-april-2020

General depth retrieval flowchart



(Ai et al., 2020)

General depth retrieval flowchart



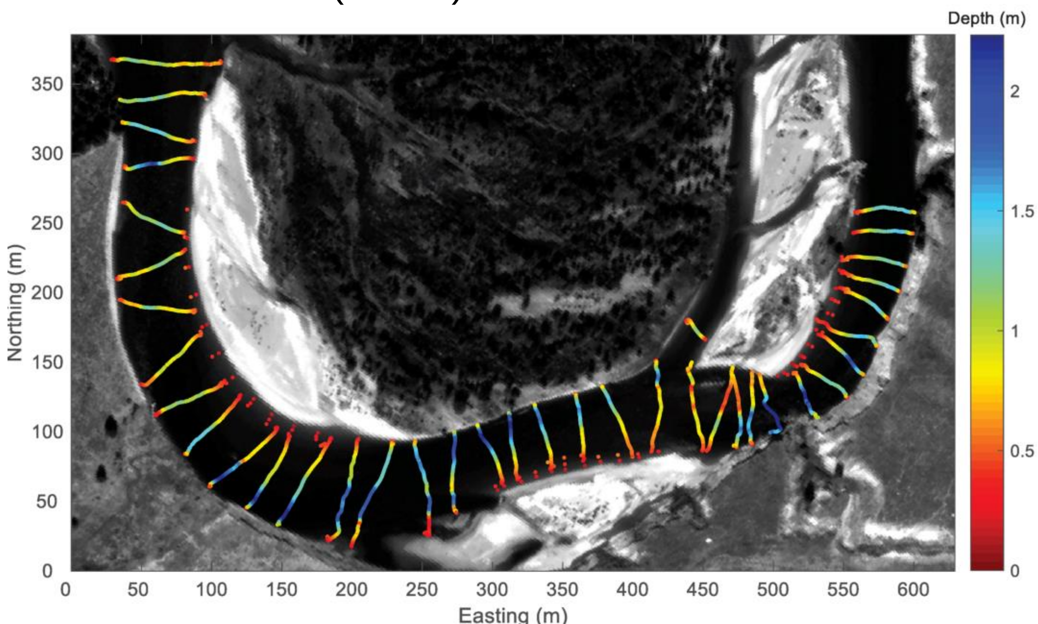
(Ai et al., 2020)

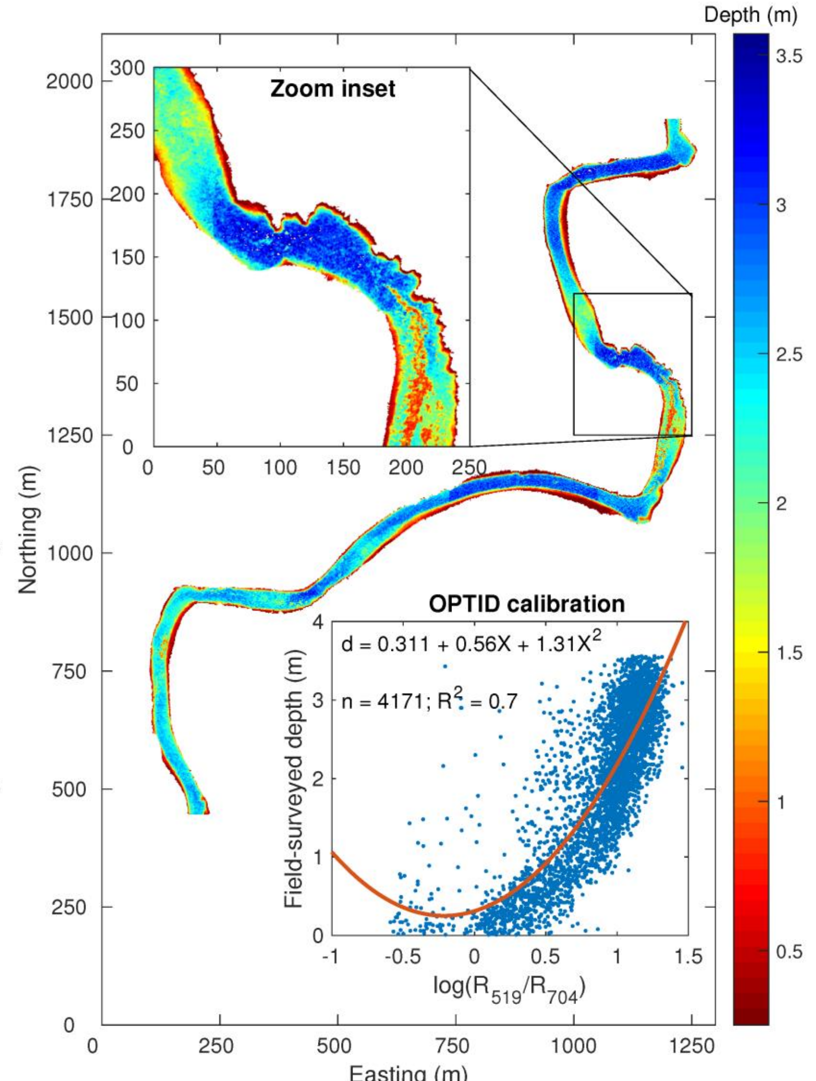
Examples

Statistical models

Examples
Airborne HS images

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



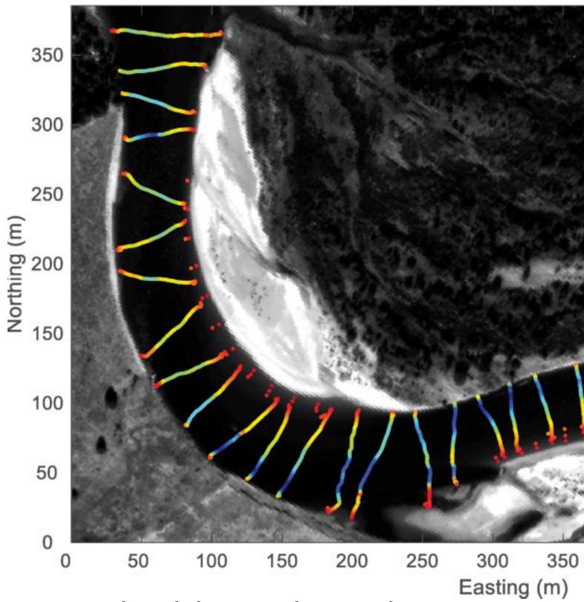


(Legleiter et al., 2018)

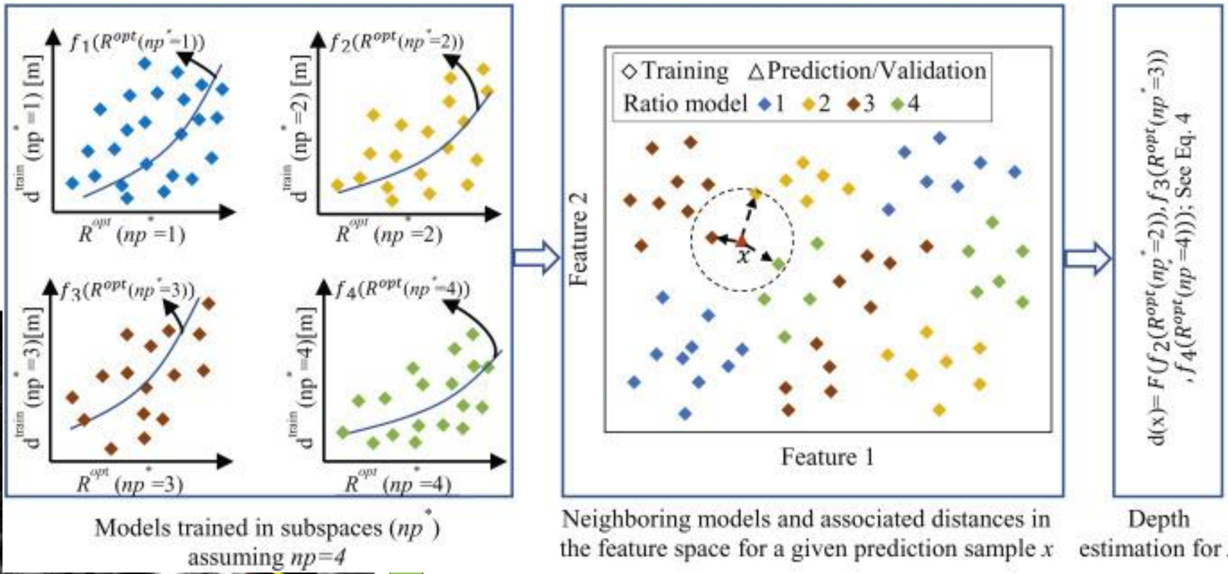
Statistical models

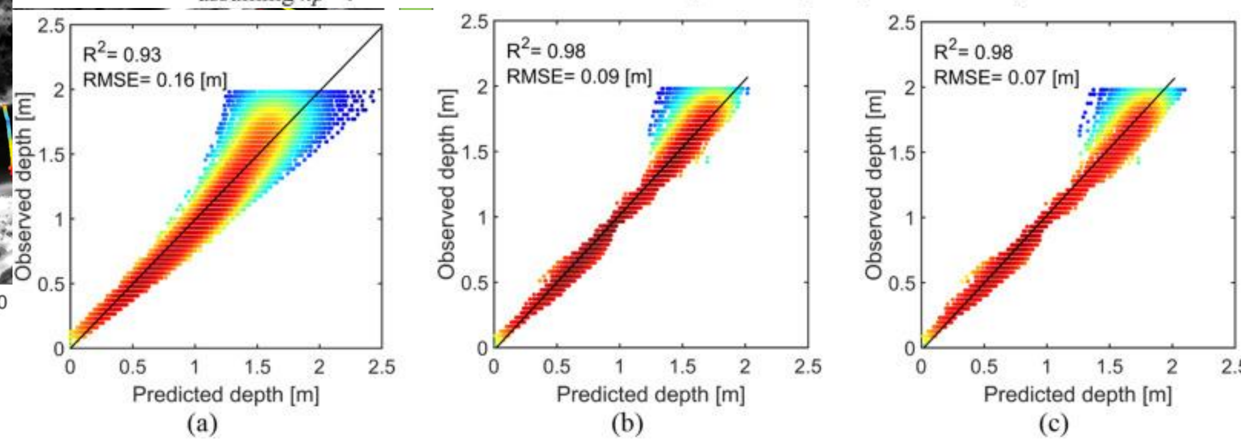
Examples

K-NN clustering + Polynomial regression



(Legleiter et al., 2018)



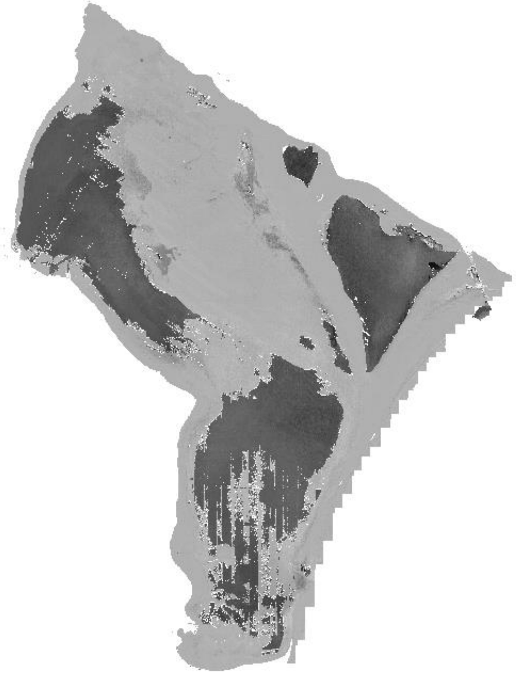


(Niroumand-Jadidi et al., 2020)

Statistical models

Examples
SPOT6 MS Image

Random Forests
Ground truth bathymetric data used: LiDAR + Singlebeam acoustic Profiler



Statistical models

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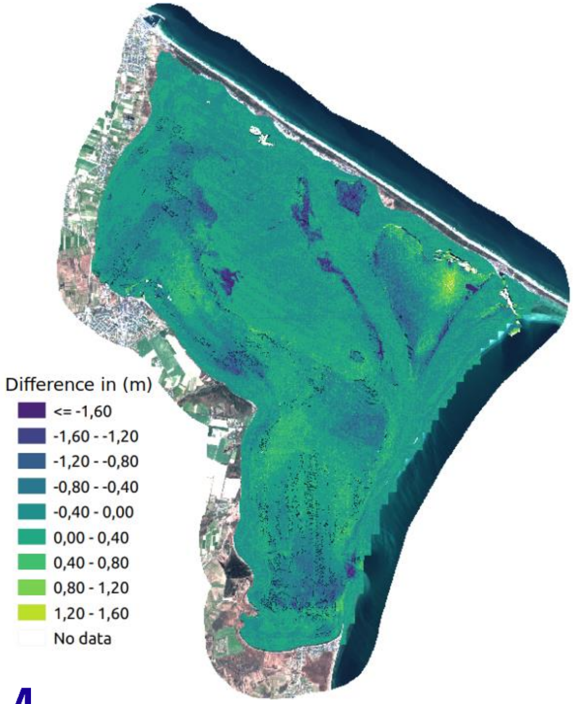
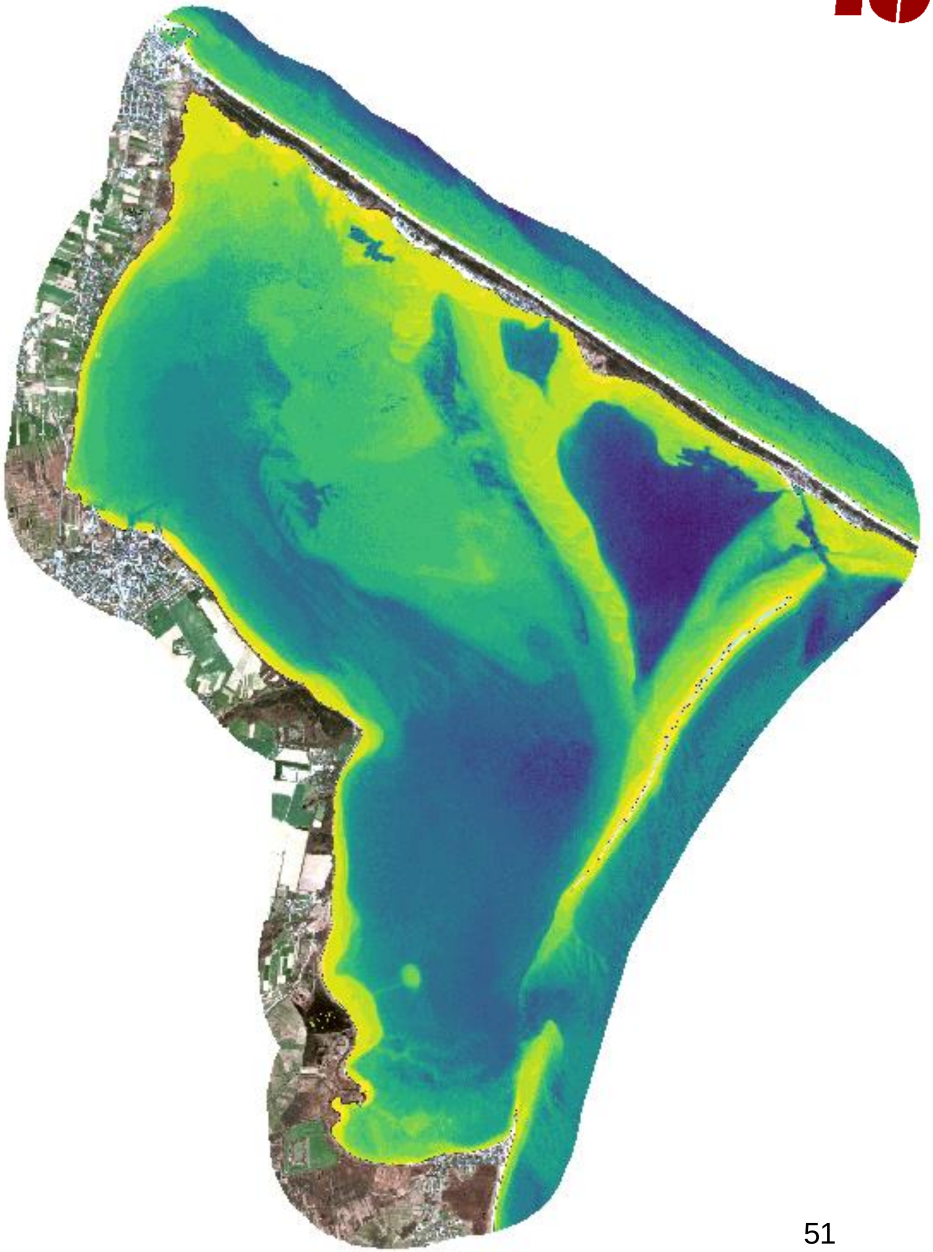
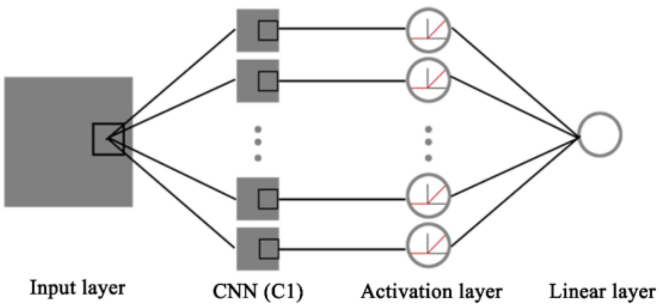


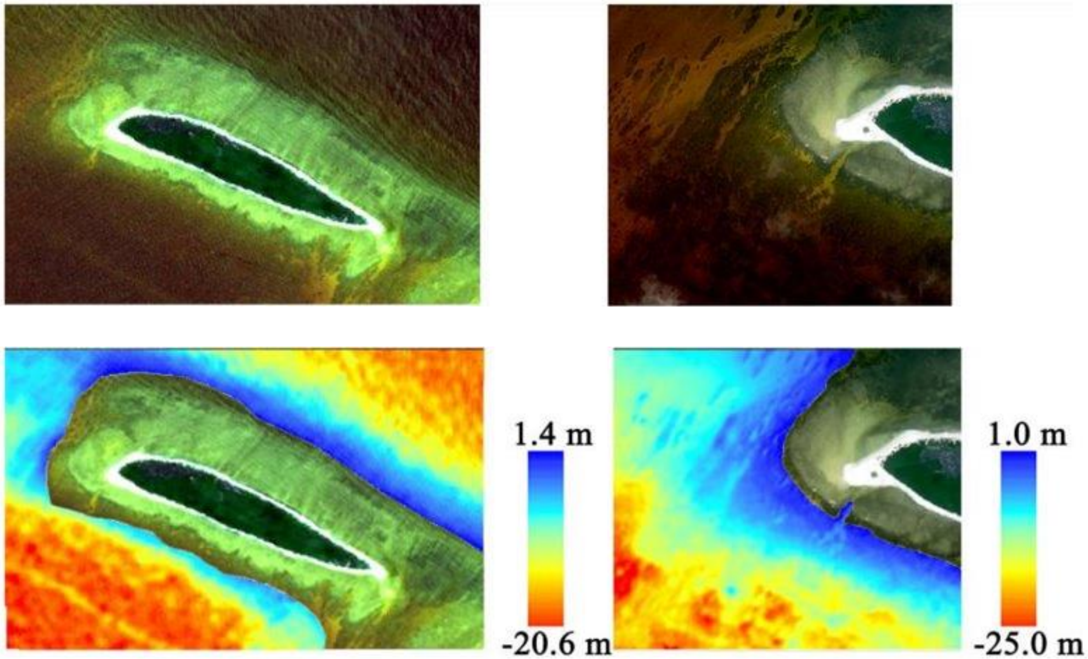


Statistical models

Examples
Worldview-2 (WV2) images

CNNs
Ground truth bathymetric data used:
Airborne LiDAR





(Ai et al., 2020)

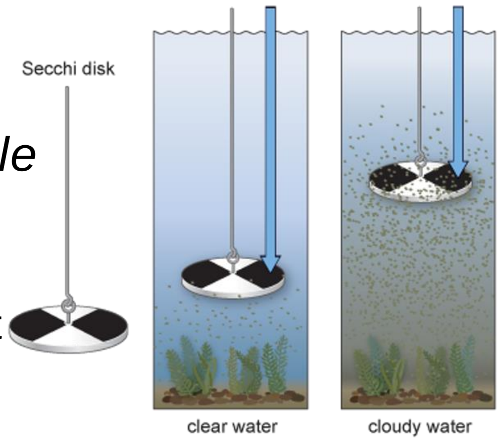
CNN with only one convolutional layer to perform the retrieval work adapted to regression tasks

Dataset here cannot reach a larger dimension in terms of structure and data volume and is not suitable for deeper networks.

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** → *the max depth a disk 30cm is visible*

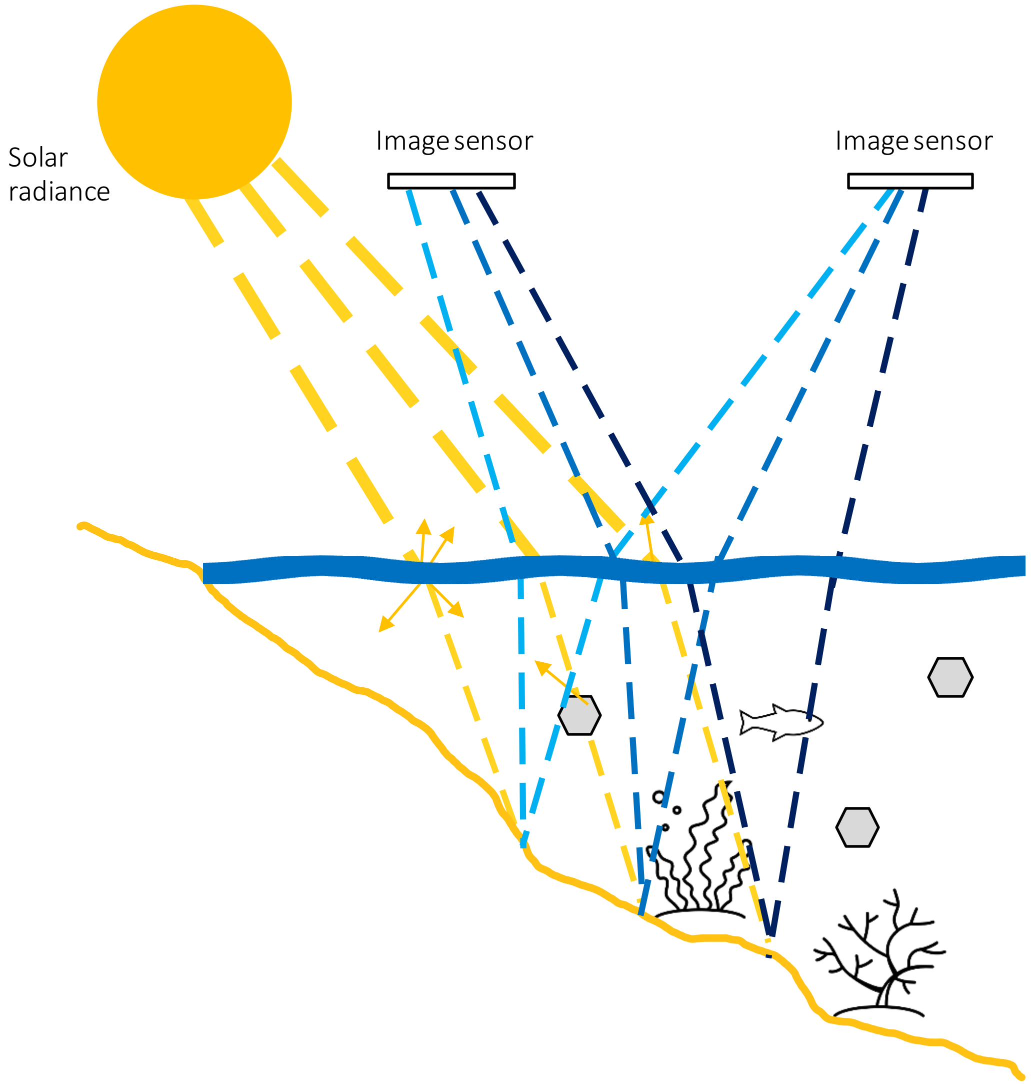


- Requires visibility of bottom features (similar to SfM-MVS, but not texture is required here)
- Work better on homogenous seabed
- **Requires ground-truth for calibrating coefficients**
- **Heavily affected by sun glint, high aerosol, turbidity etc.**
- **Lack of generalization potential** due to the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

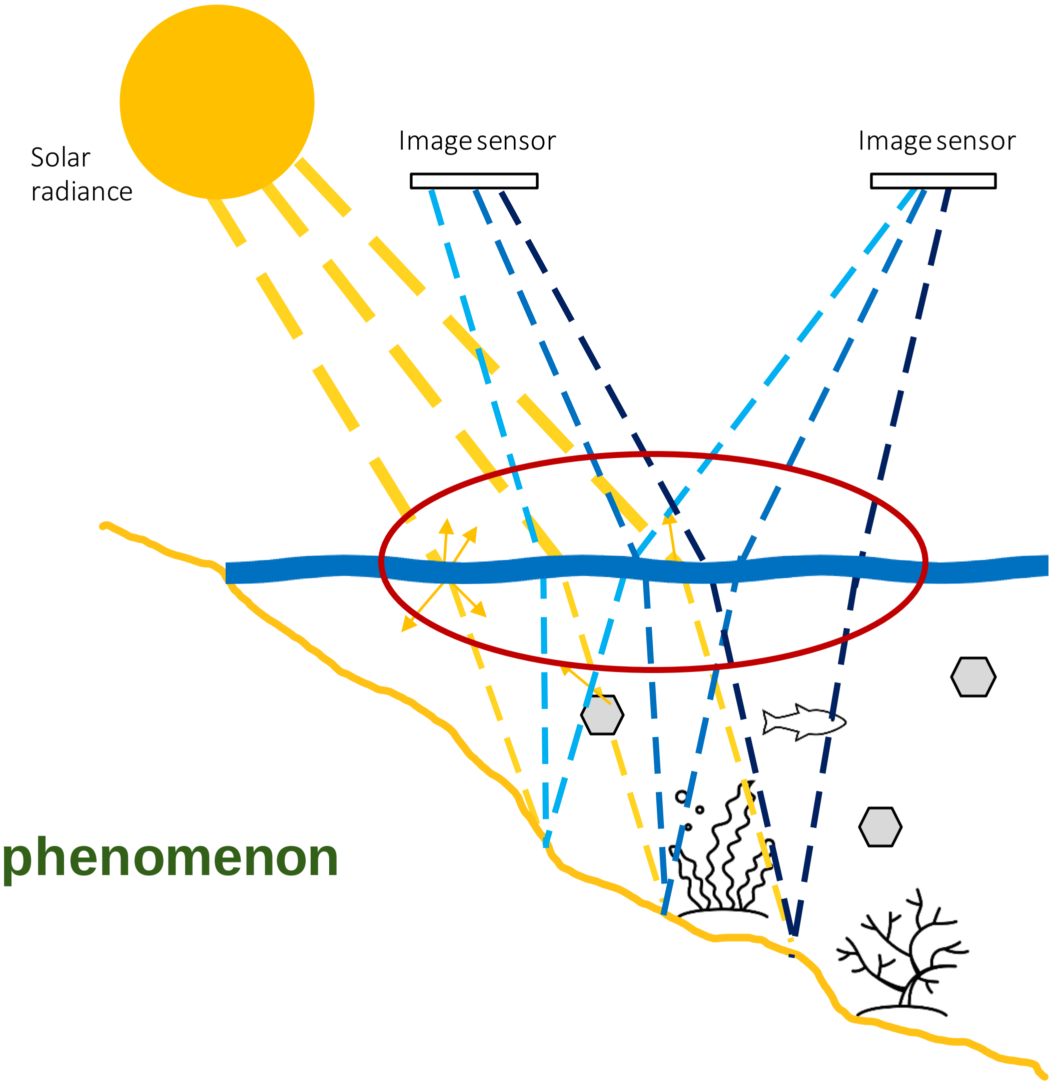
ML applications
using geometric information

- 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



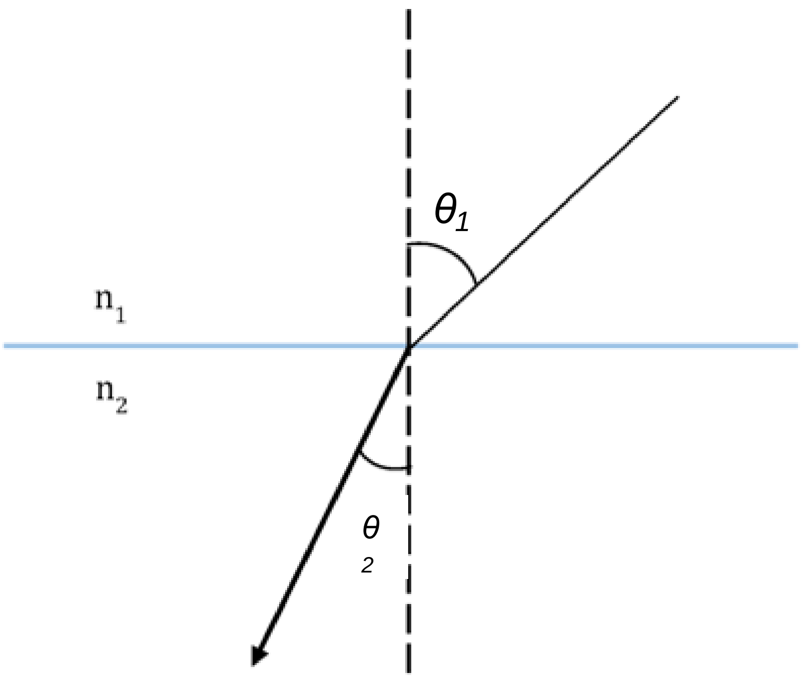
Refraction phenomenon

Refraction phenomenon

Snell's law

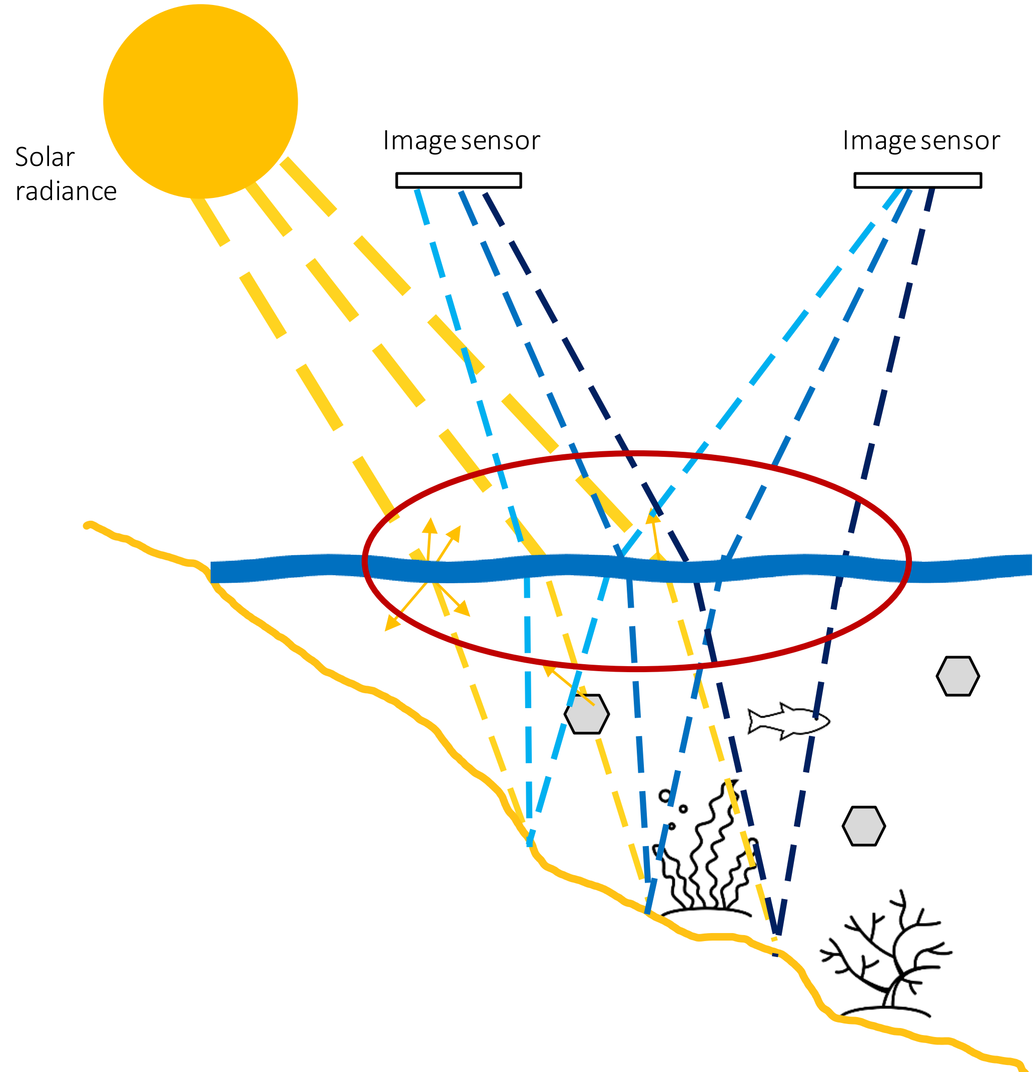
The ratio of the sines of the angles of incidence and refraction is equivalent to the ratio of phase velocities in the two media

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



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.

Refraction phenomenon



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

It depends on

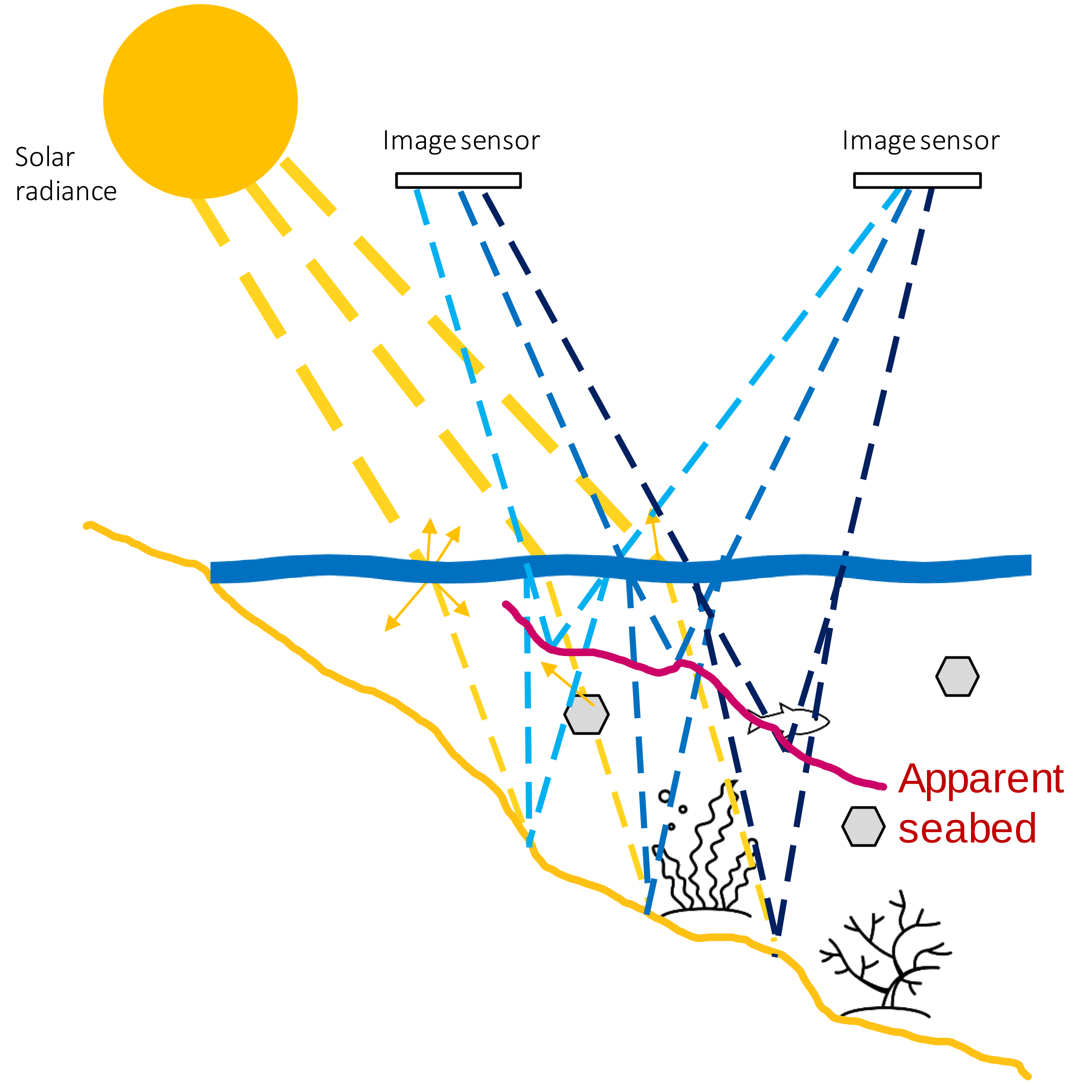
- Depth
- Angle
- Camera position

Refraction phenomenon

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

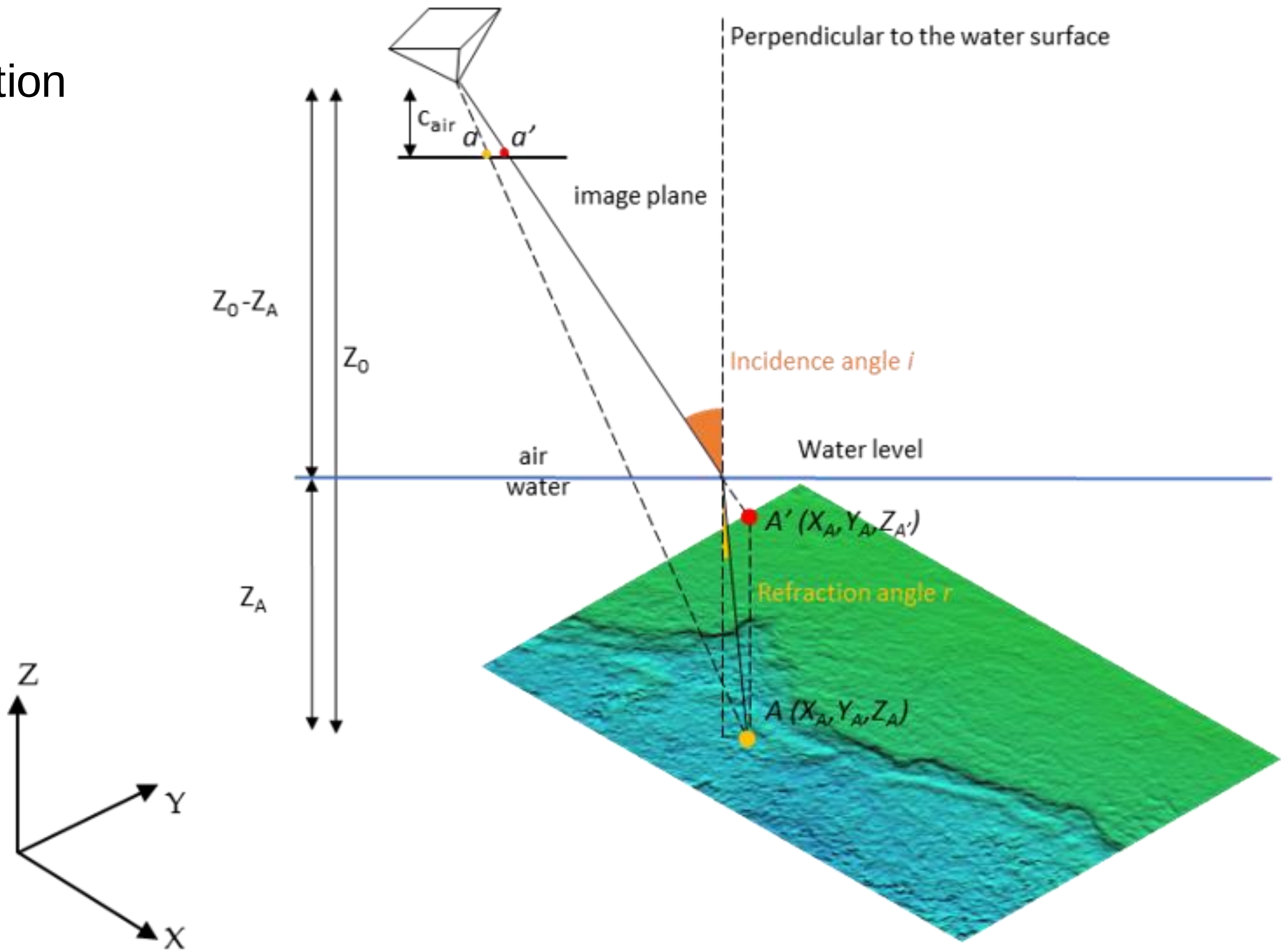
Example:

A point at 13.5m depth would appear at 10m depth!!!



Single View Geometry

- Violation of the Collinearity Equation
- Apparent depths



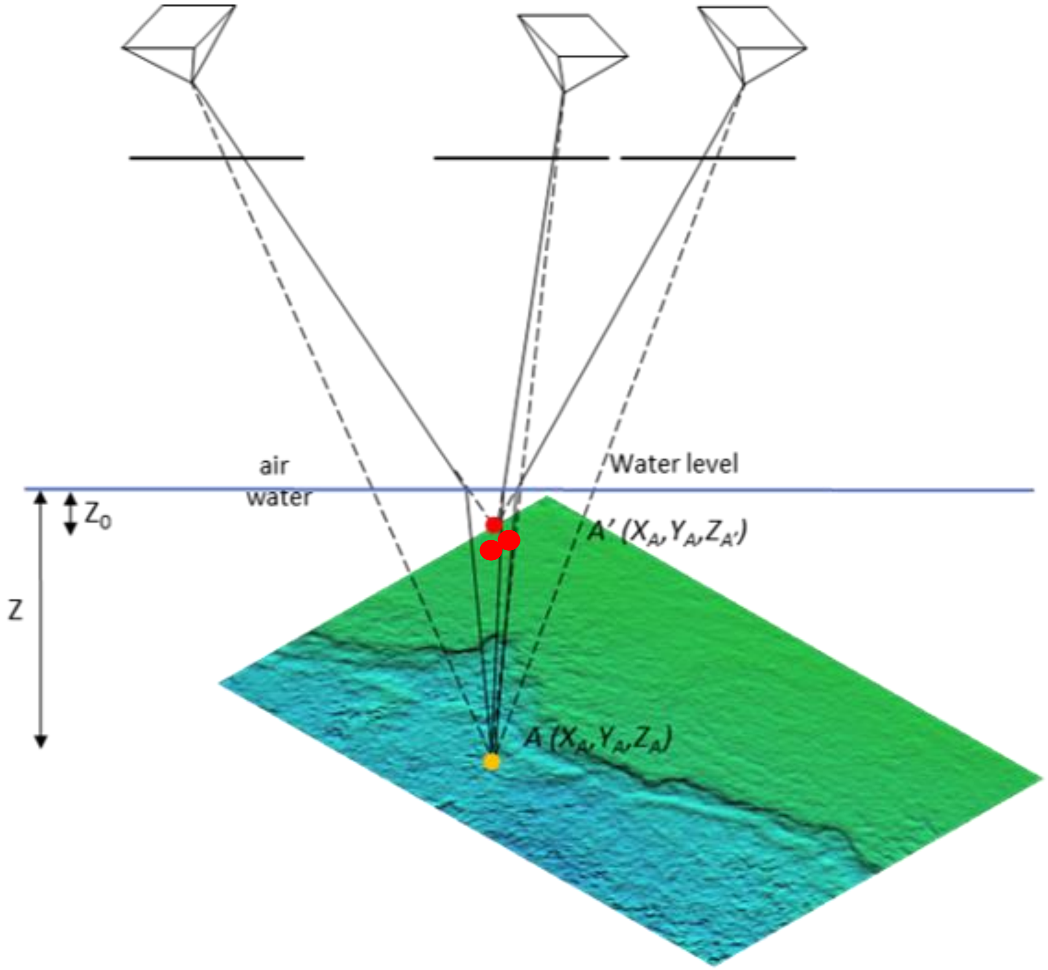
RSiM

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., <u>the correction of refraction effects is necessary</u>!

Stereo-based bathymetry

How?

Structure from Motion – Multi-View Stereo + Refraction correction

Refraction correction

Analytical correction

Modification of the collinearity equation. (1950…)

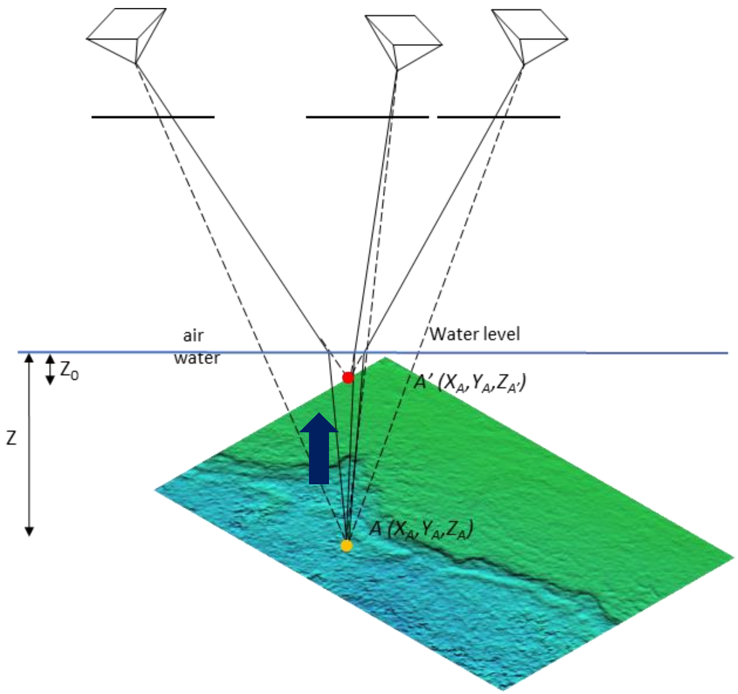
Image-space correction

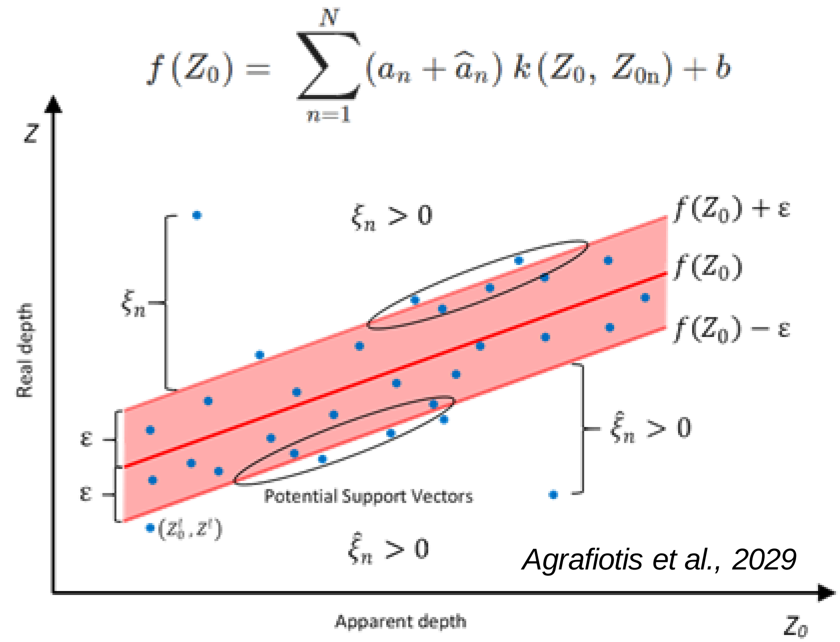
Re-projection of the original photo to correct the water refraction. (2018…)

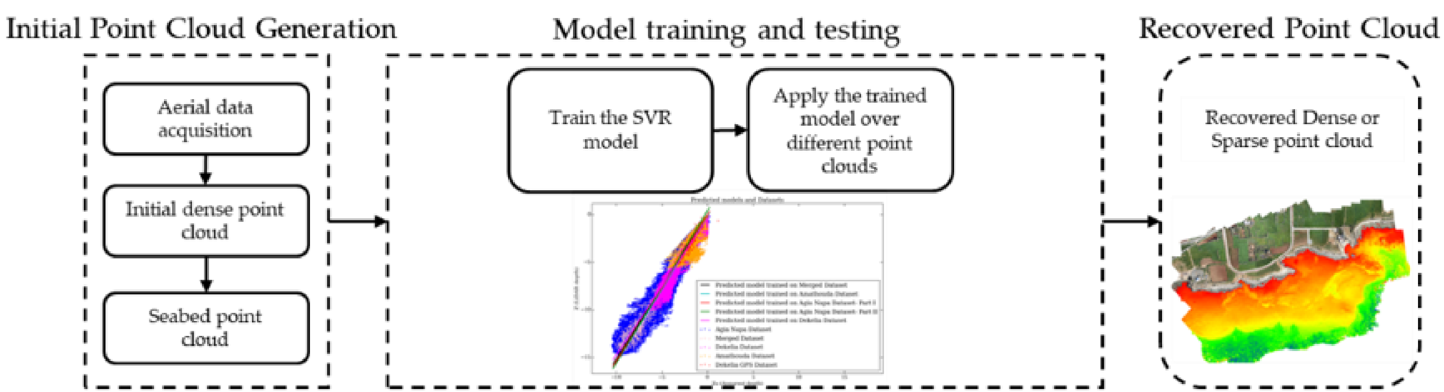
Machine learning-based

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

3D Space Correction







Agrafiotis et al., 2029

Need for synthetic data

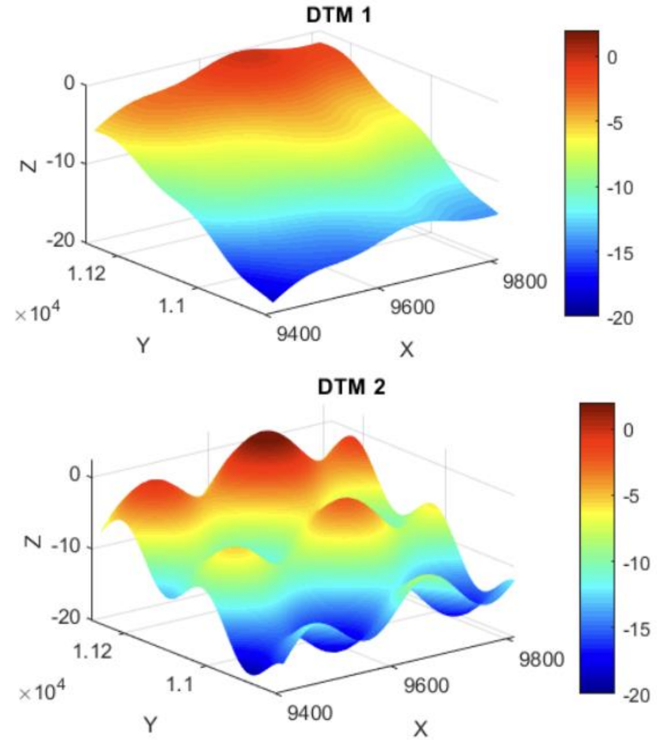
Train ML models

- 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

- 8 datasets – 4 with refraction and 4 without
- Flying height from 150m-2800m
- Various sensors
- Camera constant from 3.6mm to 100.5mm



Agrafiotis et al., 2021

Need for synthetic data

Train ML models

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- Avoid errors introduced by the wavy surface

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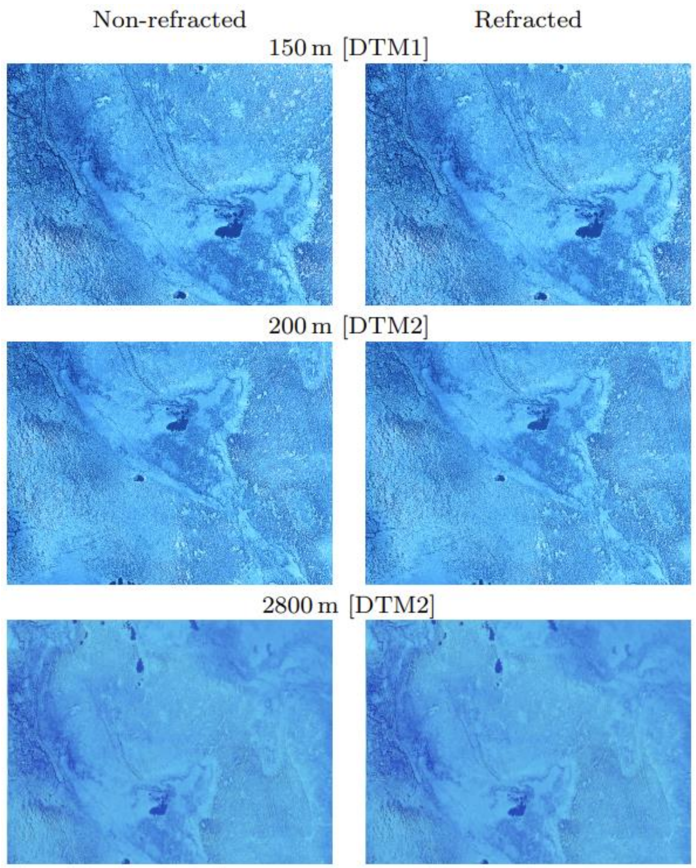


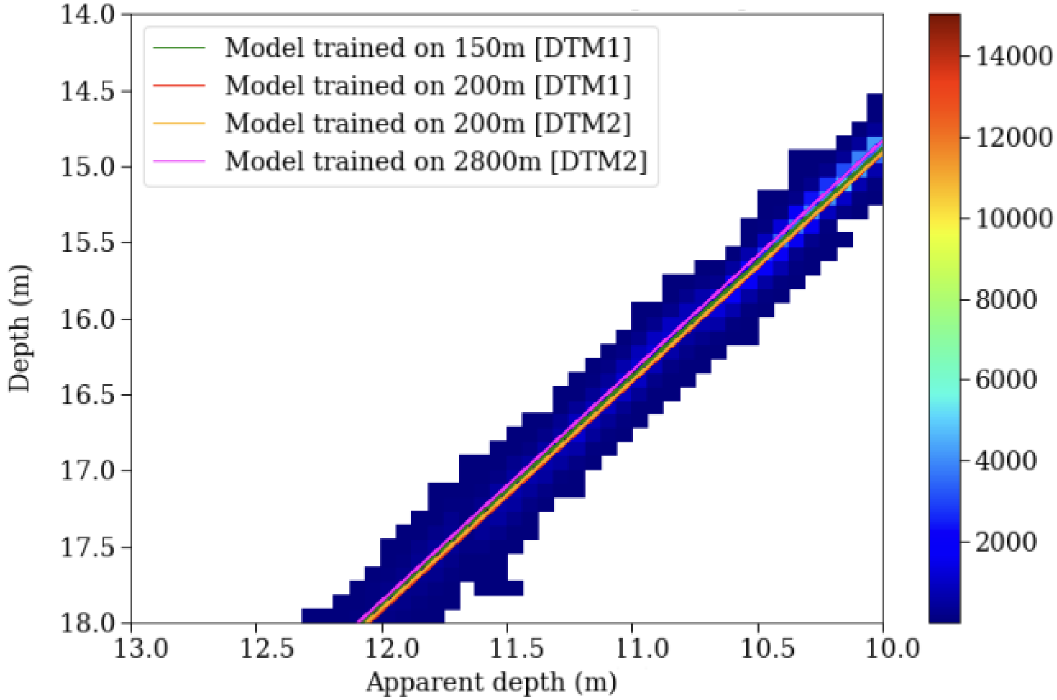
Agrafiotis et al., 2021

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)

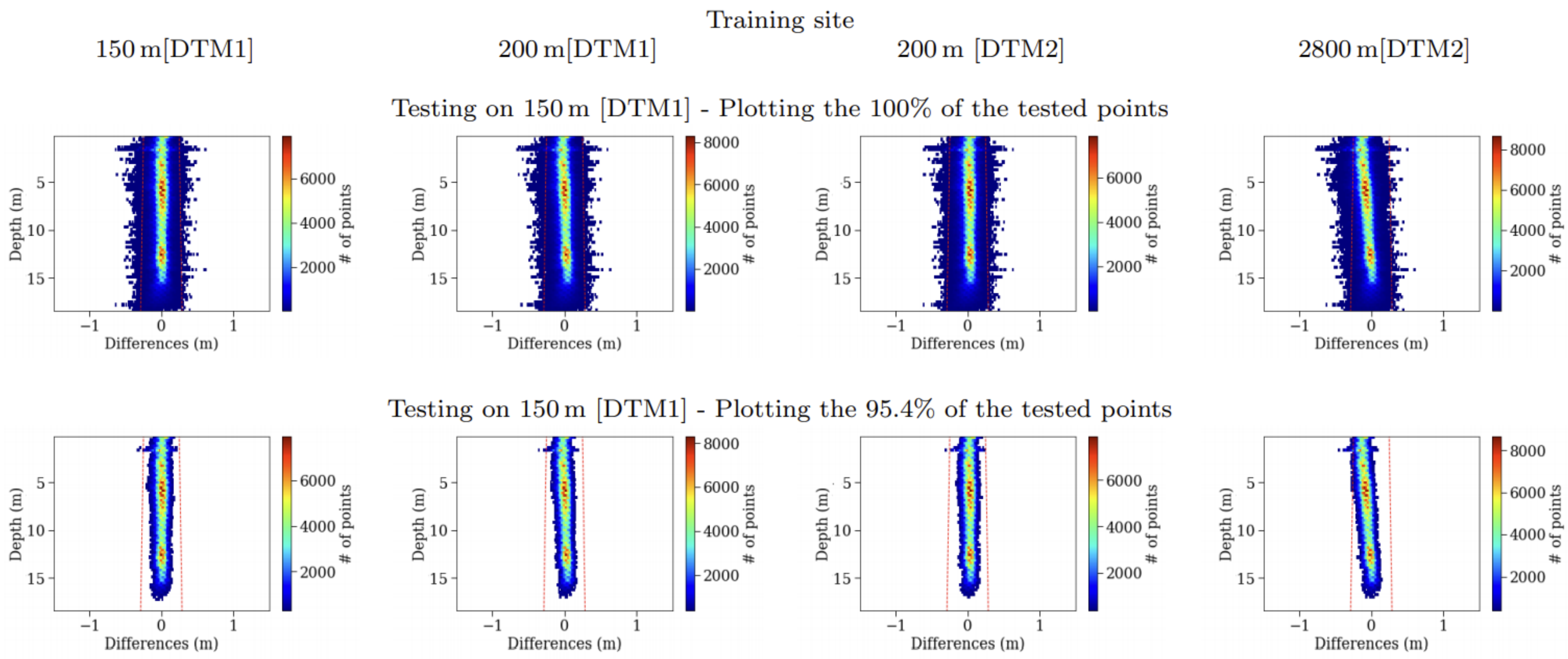
Need for synthetic data

Training the ML models
only on synthetic data



Agrafiotis et al., 2021

Differences between the real and corrected depths – synthetic data



Agrafiotis et al., 2021

UAV synth. data: RMSE of 3.34m reduced to **0.09m**!

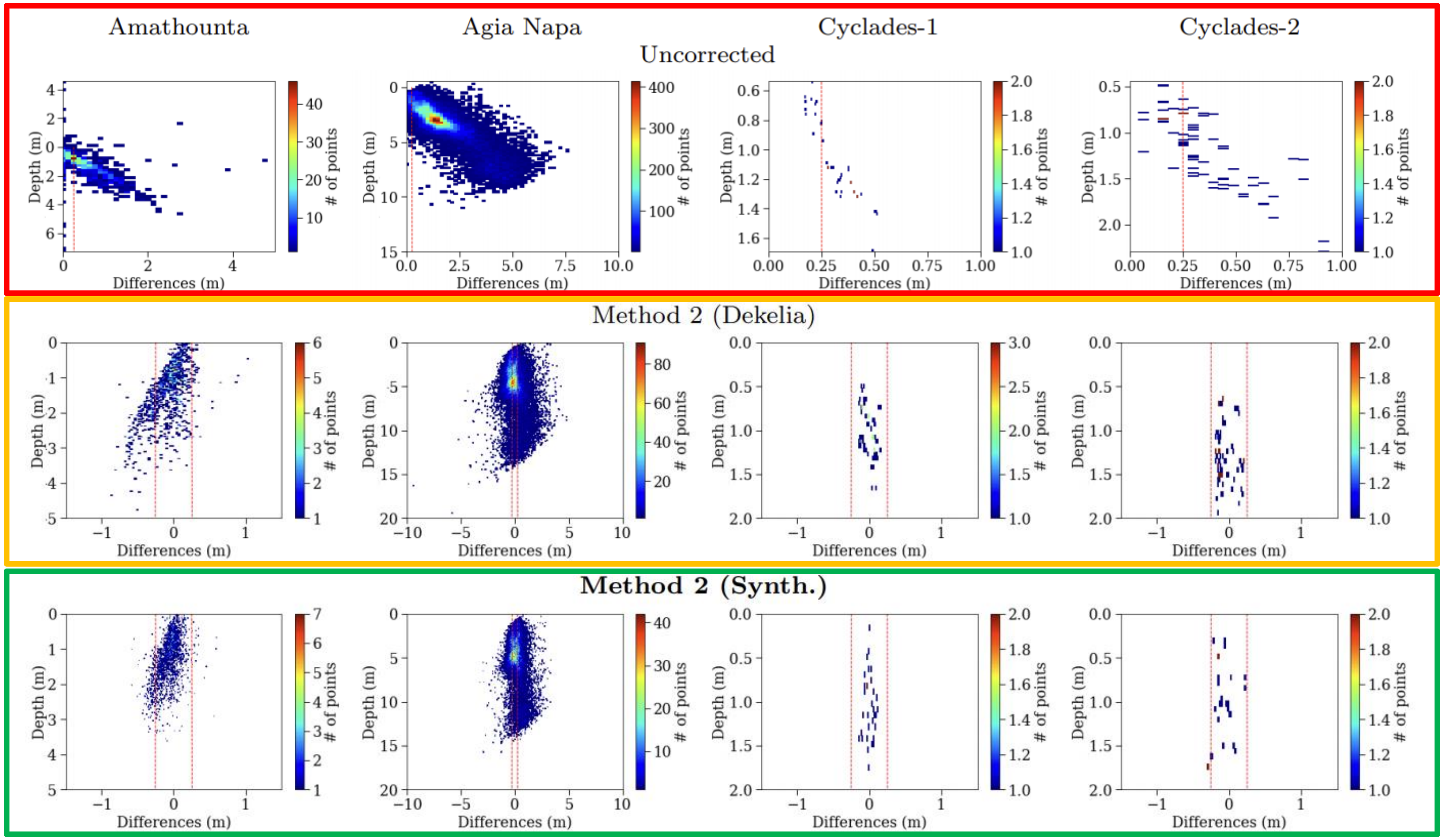
Aircraft-borne synth. data: RMSE of 6.38m reduced to **0.20m**!

Differences between the real and corrected depths – real data

Uncorrected data

Corrected/trained on real-world data

Corrected/trained on **synthetic** data



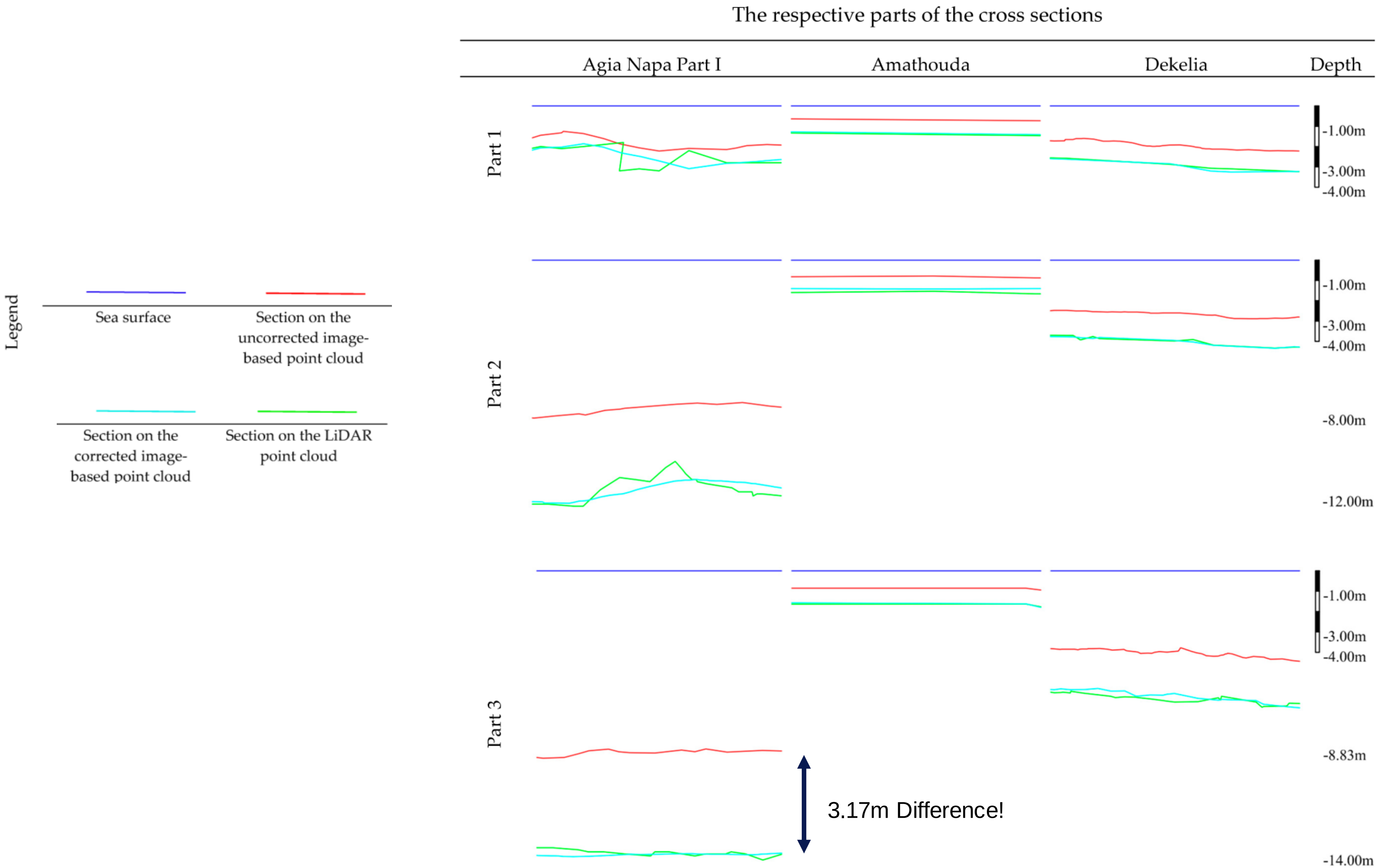
Agrafiotis et al., 2021

Differences between the real and corrected depths – real data

Test site												
	Amathounta			Agia Napa			Cyclades-1			Cyclades-2		
Check points	1K			75K			23			34		
Max/Min depth (m)	5.57/0.10			14.8/0.20			6.9/0.0			4.05/0.0		
Point clouds from different methods	Statistical analysis [m]											
	$\bar{x}$	σ	$RMSE_Z$	$\bar{x}$	σ	$RMSE_Z$	$\bar{x}$	σ	$RMSE_Z$	$\bar{x}$	σ	$RMSE_Z$
Uncorrected images	0.67	2.19	2.28	1.71	1.18	2.08	0.32	0.10	0.33	0.54	0.29	0.62
Method 3	−0.27	0.40	0.49	0.63	1.02	0.98	−0.08	0.10	0.12	−0.23	0.26	0.34
Method 4	0.49	0.54	0.73	−1.55	1.49	1.75	0.38	0.25	0.46	−0.15	0.24	0.28
Method 4 (filt.)	0.22	0.40	0.45	0.43	0.72	0.84	−0.06	0.09	0.10	−0.20	−0.30	0.36
Method 1 (Dekelia)	−0.09	0.18	0.28	−0.13	0.51	0.55	0.02	0.09	0.09	−0.01	0.21	0.21
Method 1 (Synth.)	−0.04	0.13	0.14	0.06	0.41	0.42	−0.05	0.06	0.07	−0.05	0.12	0.13
Method 5	−0.39	0.88	0.96	−0.05	0.74	0.74	0.15	0.42	0.46	−0.28	0.36	0.46
Method 2 (Dekelia)	−0.19	0.28	0.31	−0.04	0.37	0.38	−0.02	0.09	0.09	−0.06	0.14	0.15
Method 2 (Synth.)	−0.04	0.12	0.13	−0.03	0.21	0.23	0.00	0.06	0.07	−0.05	0.06	0.09

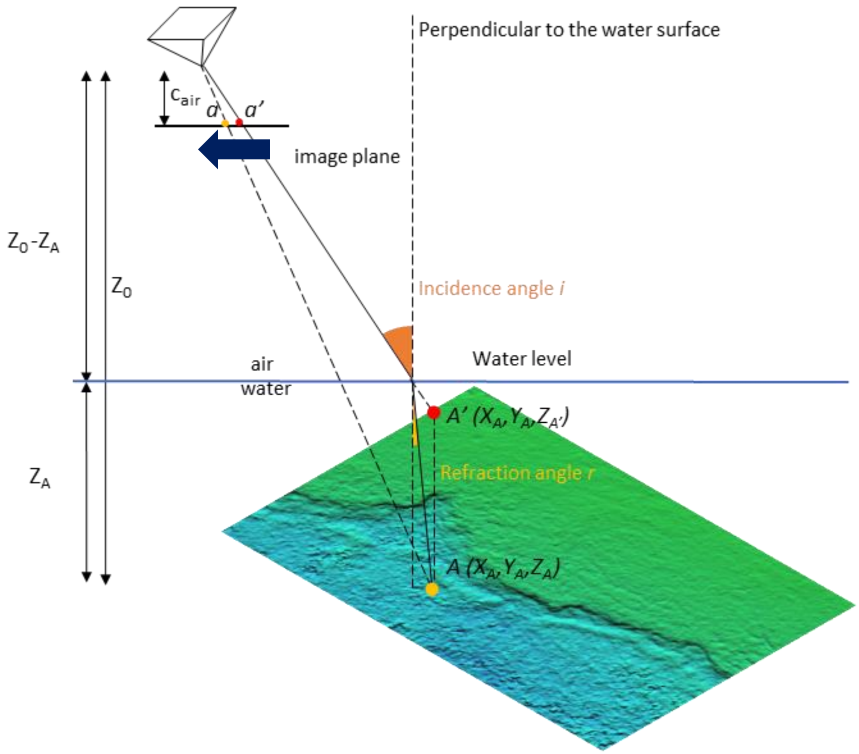
Agrafiotis et al., 2021

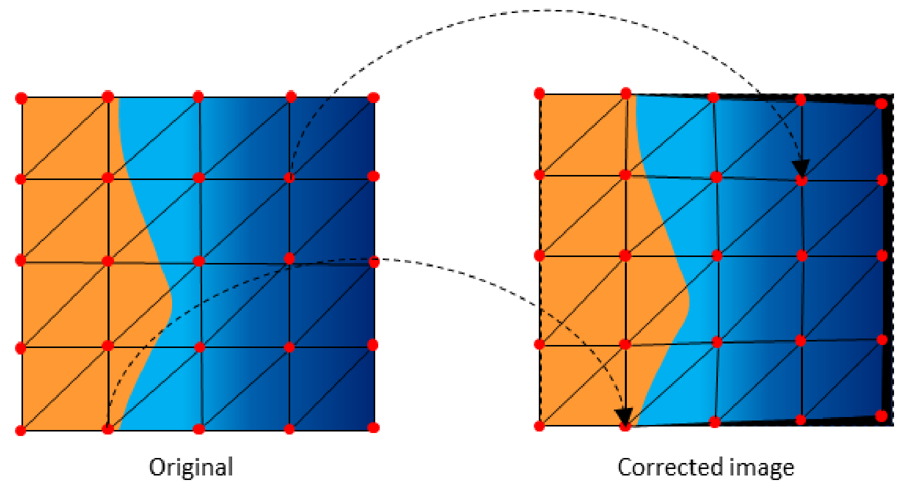
Cross sections

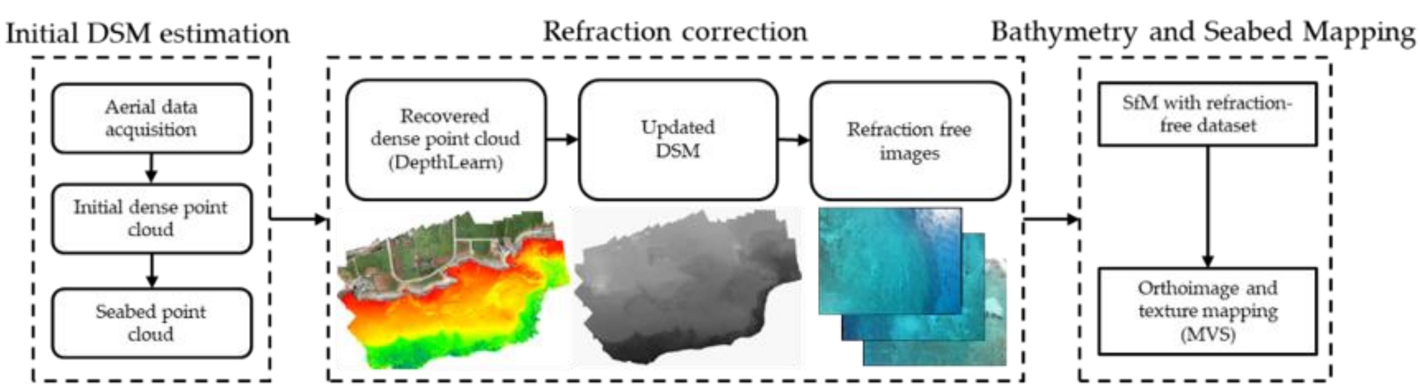


Agrafiotis et al., 2019

Image Space Correction







Agrafiotis et al., 2020

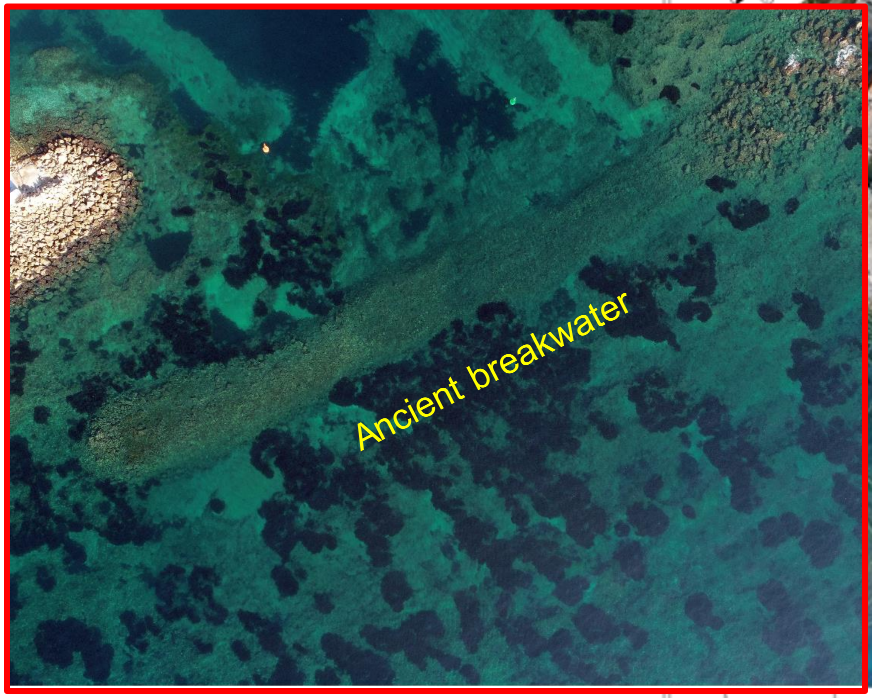
Image Space Correction

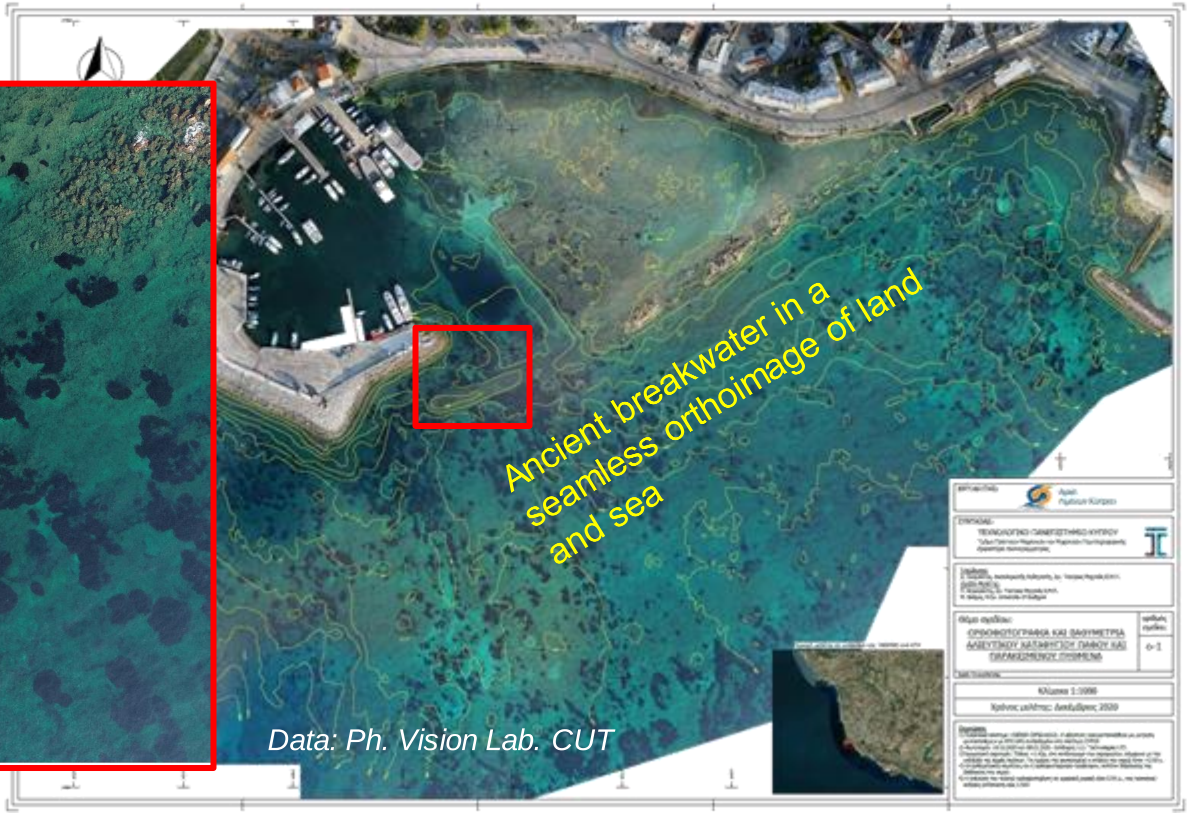
Uncorrected image

Image Space Correction

Corrected image

Deliverable example





Stereo-based methods

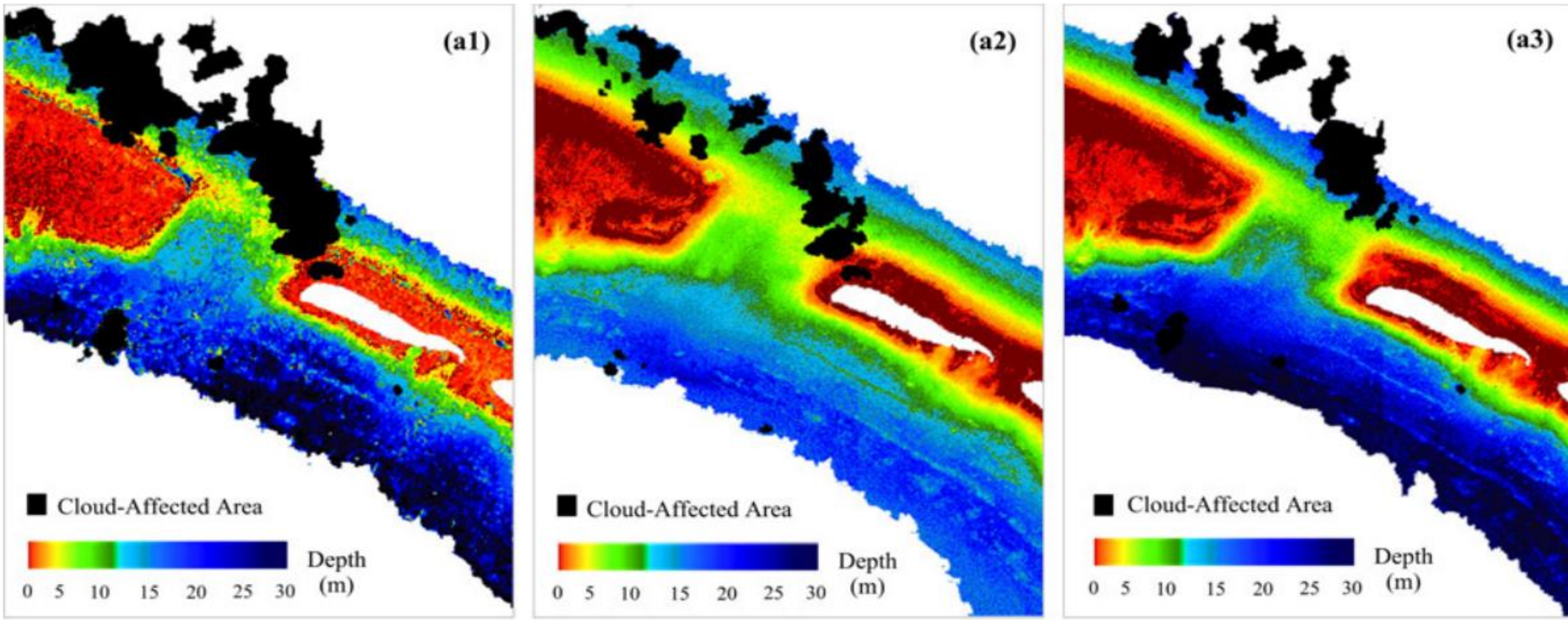
Pros, Issues and Limitations

- Measured depth through triangulation & Delivers color information
- <u>Delivers high 3D point density in shallow water areas</u>
- 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)**



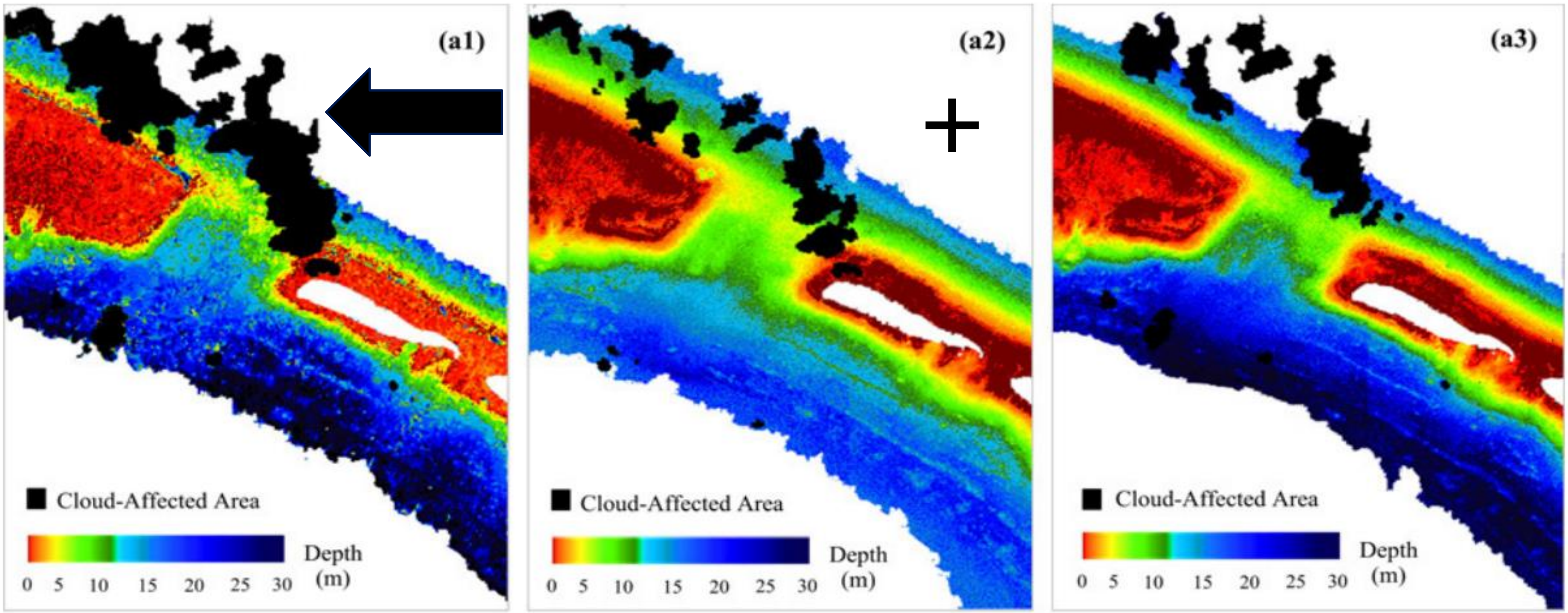
Cao et al., 2021

Stereo VS Spectral-based

Stereo-based

Spectral-based (left image)

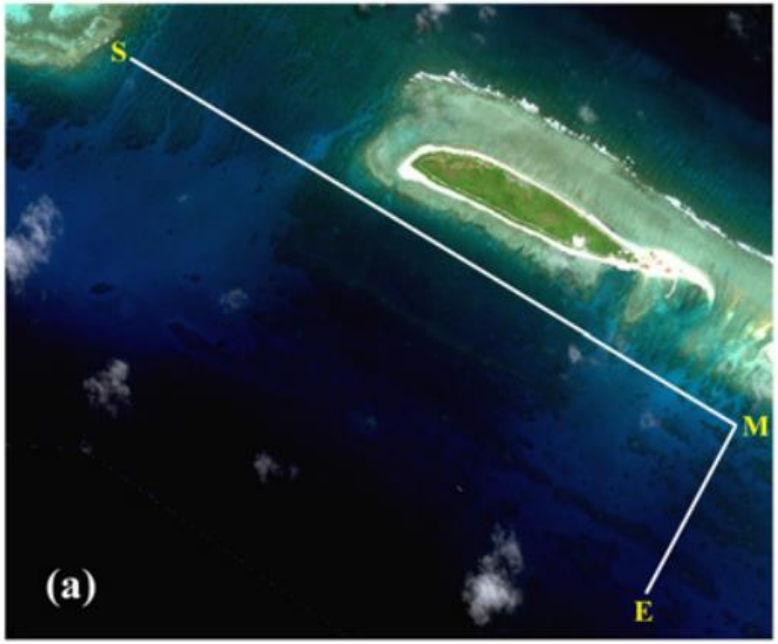
Spectral-based (right image)

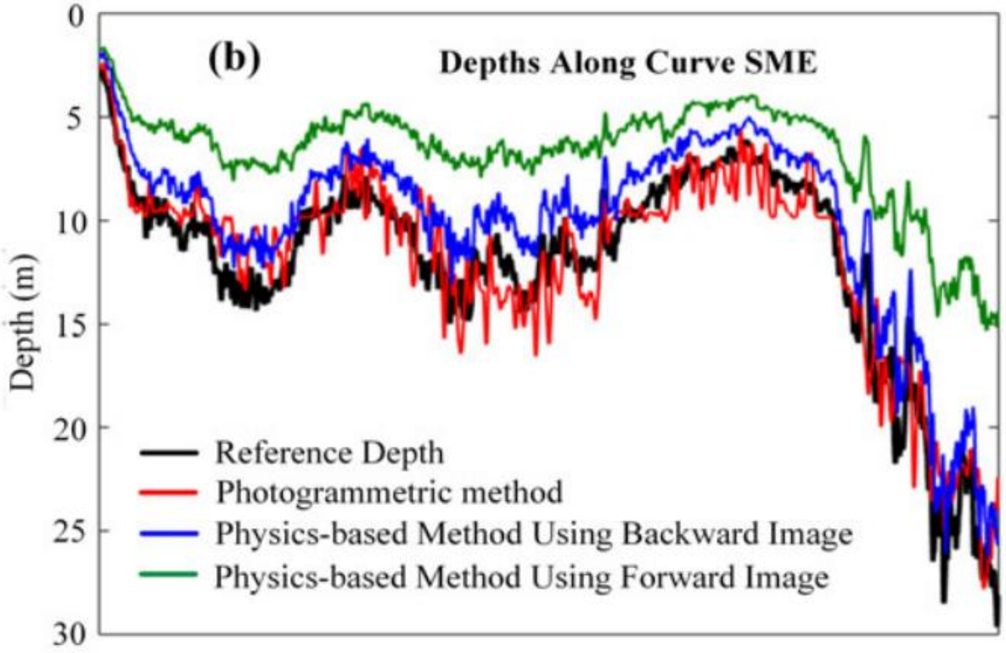


Cao et al., 2021

Stereo VS Spectral-based

Cross sections of the derived bathymetries





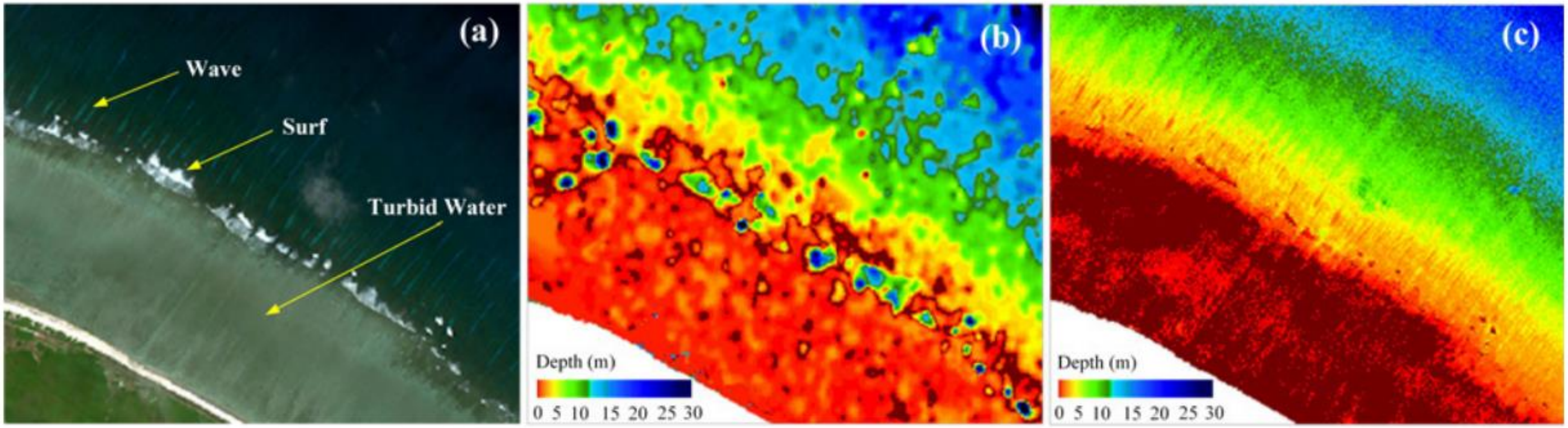
Cao et al., 2021

Stereo VS Spectral-based

Wave breaking and turbidity effects

Stereo-based

Spectral-based

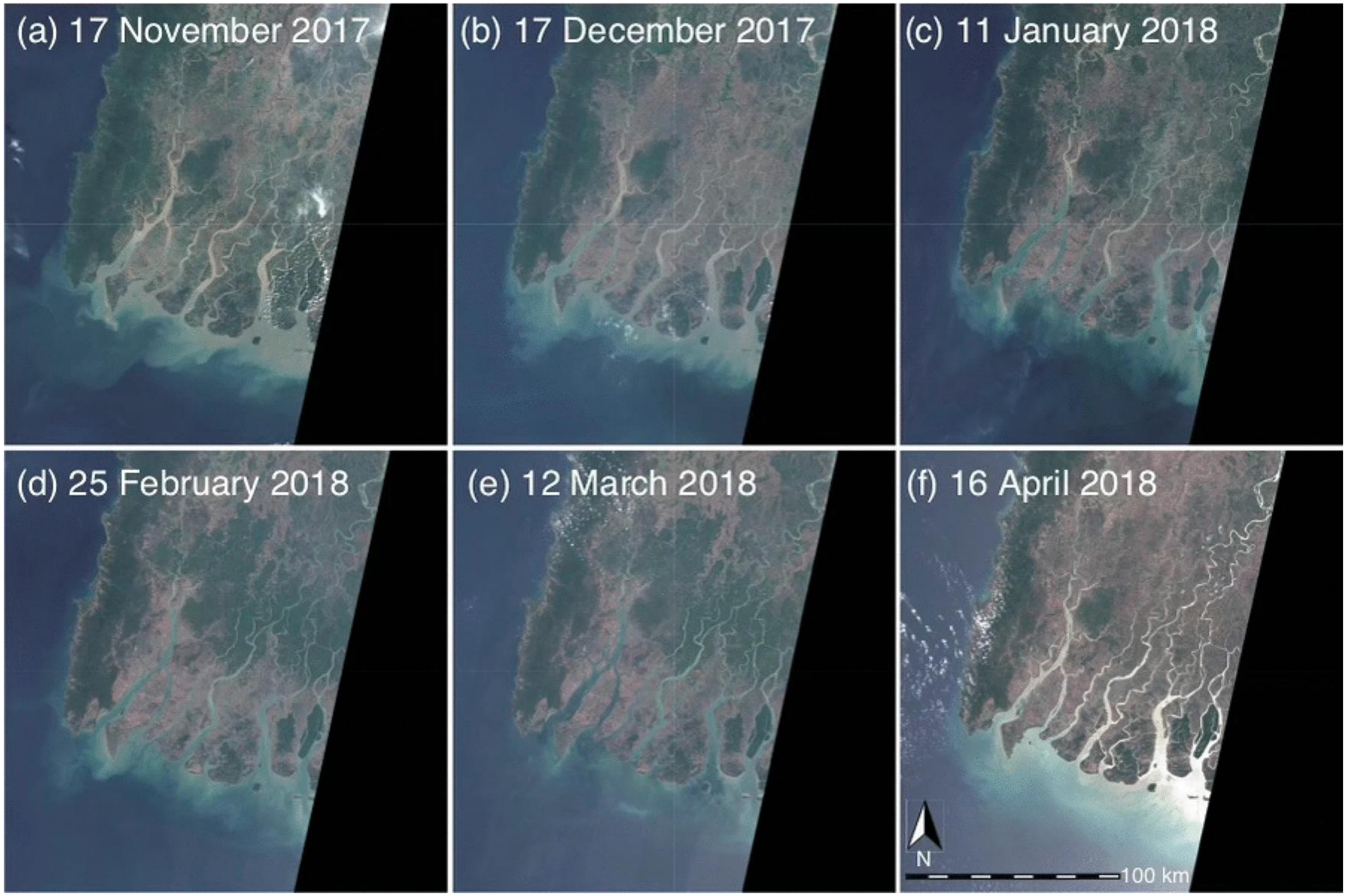


Cao et al., 2021

Seasonal/Monthly variation

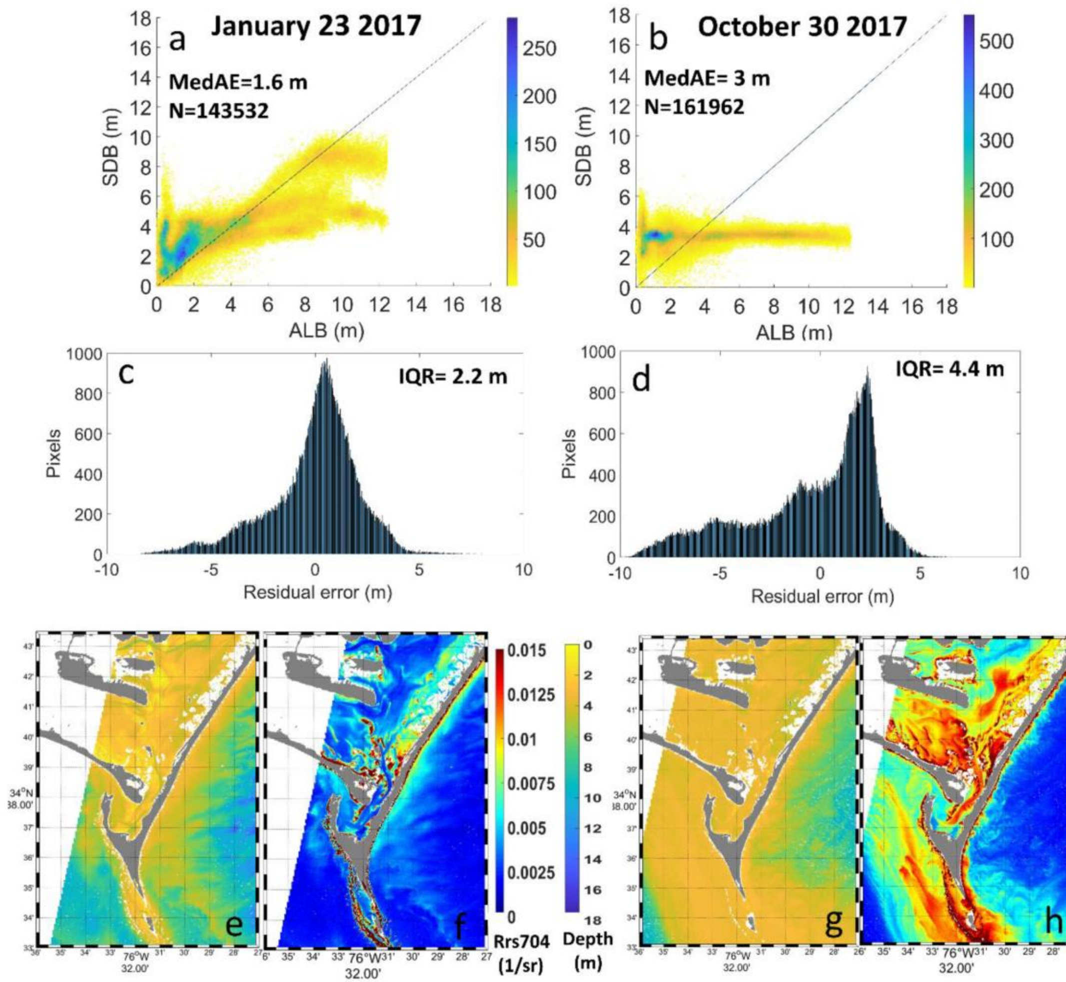
MANY different spectral signatures for same pixels

- Limited generalization of trained models



(Sakai et al., 2021)

Seasonal/Monthly variation



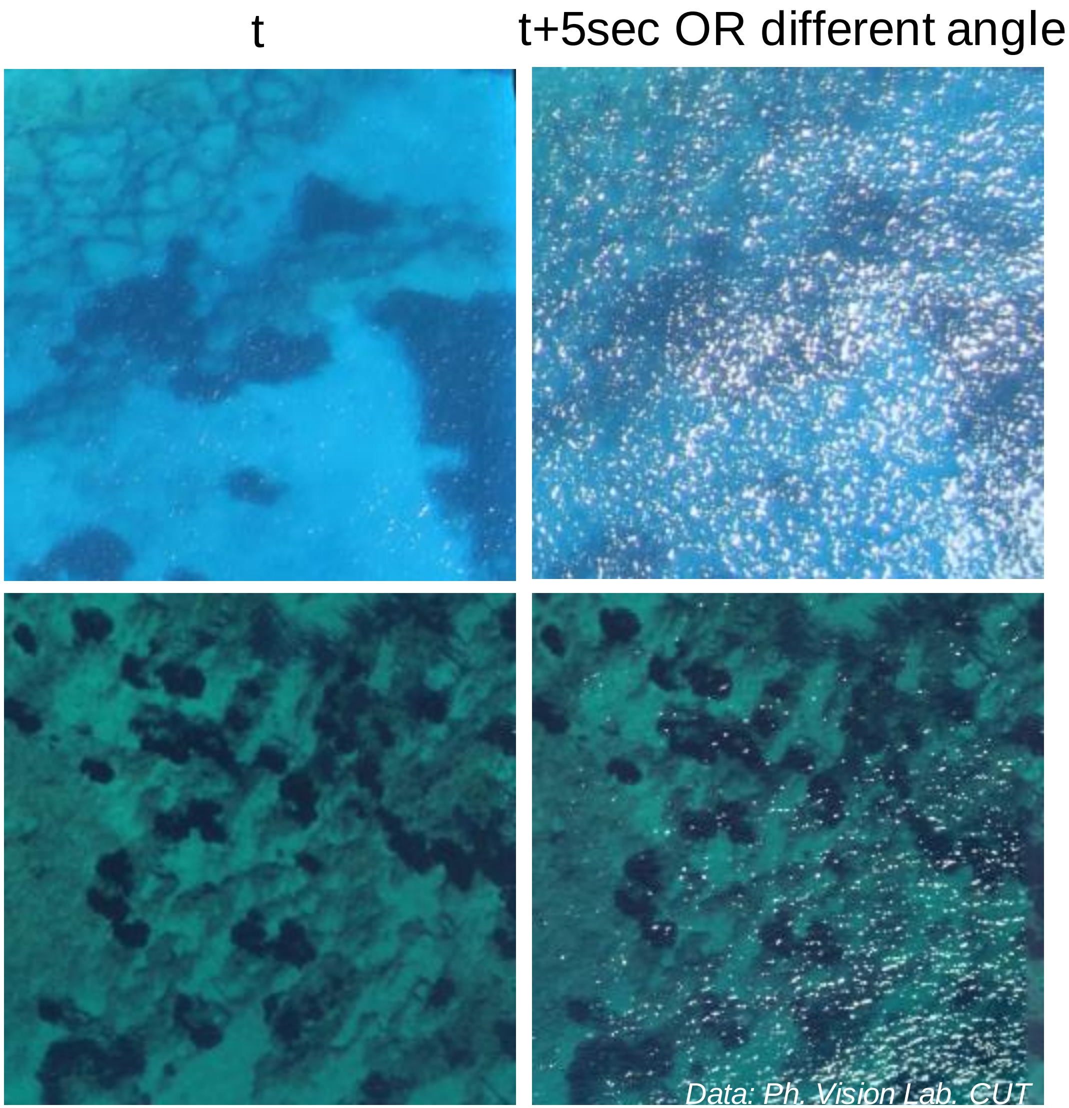
Caballero and Stumpf, 2020

RSiM

Instant variation

Caused by

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



ML applications using radiometric information

- 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
- **Shallow seabed cover maps**

Shallow seabed cover maps

How?

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

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

Shallow seabed cover maps

Examples

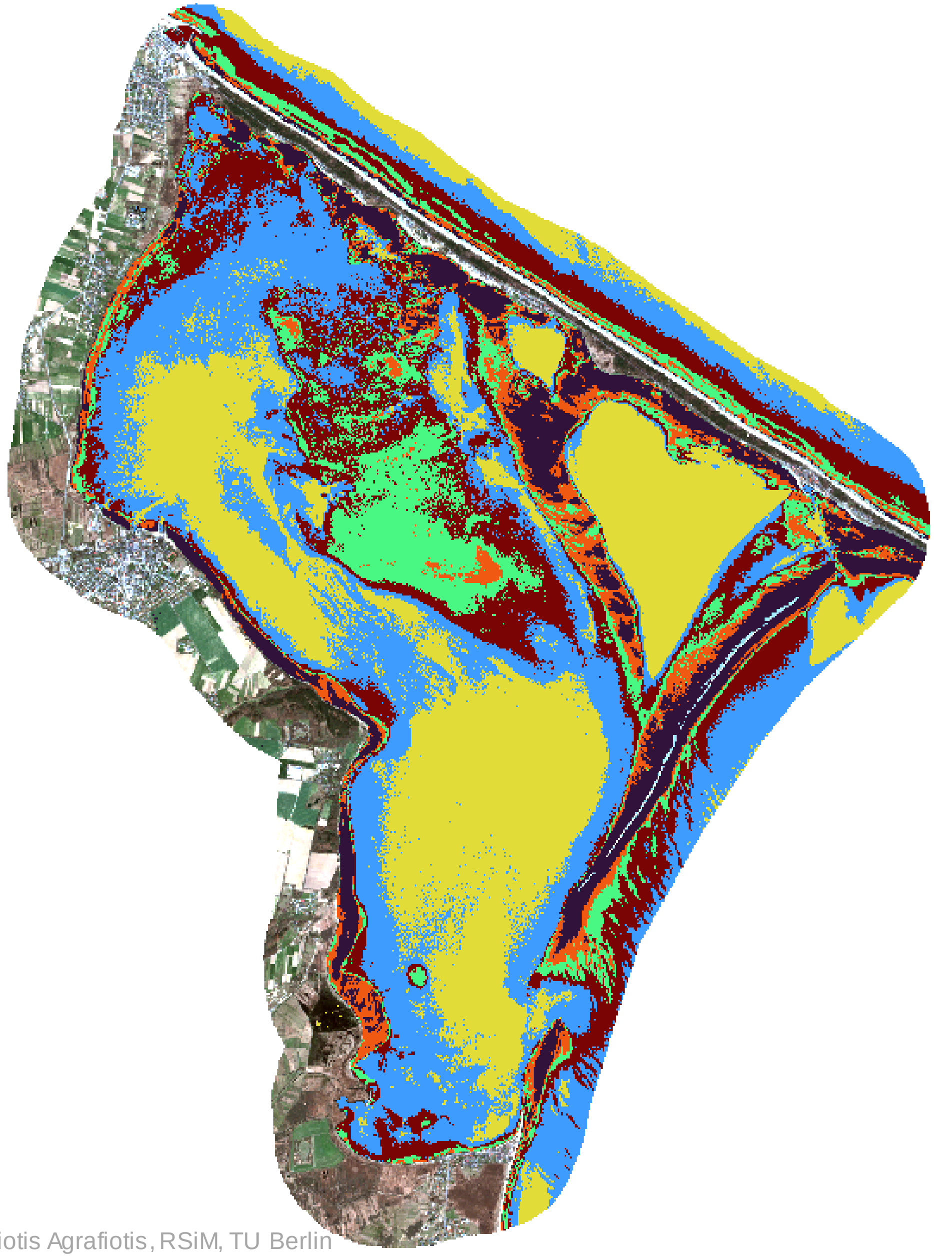
SPOT6 MS Image

Shallow seabed cover maps

Examples
SPOT6 MS Image

FCN+ResNet101

Weakly supervised semantic segmentation and multi-label classification



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