Learning-based bathymetric mapping for shallow coastal waters using RGB imagery

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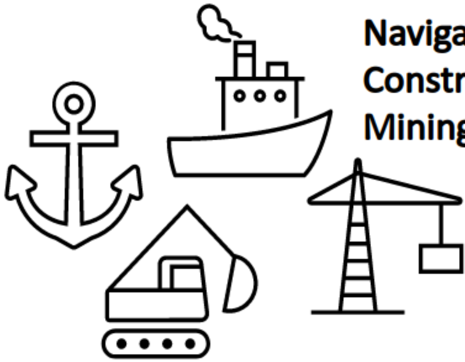
NTUA PHOTOGRAMMETRIC COMPUTER VISION

3[Deep]Vision Research Group

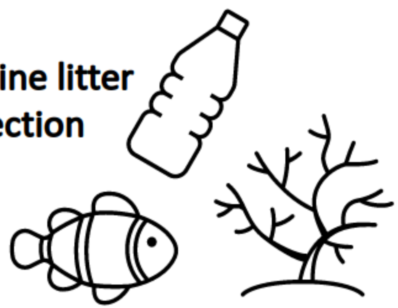
Seabed mapping in shallow waters



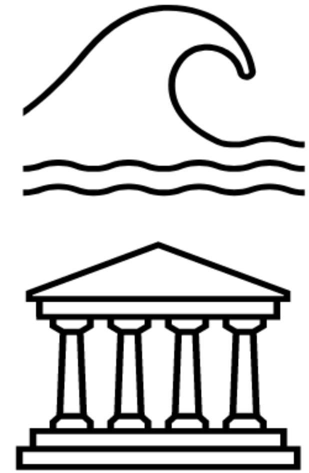
Navigation
Constructions
Mining

Tourism

Marine litter
detection



Marine animal
forests



Underwater Cultural Heritage at risk

***Bathymetric information

***Semantic information

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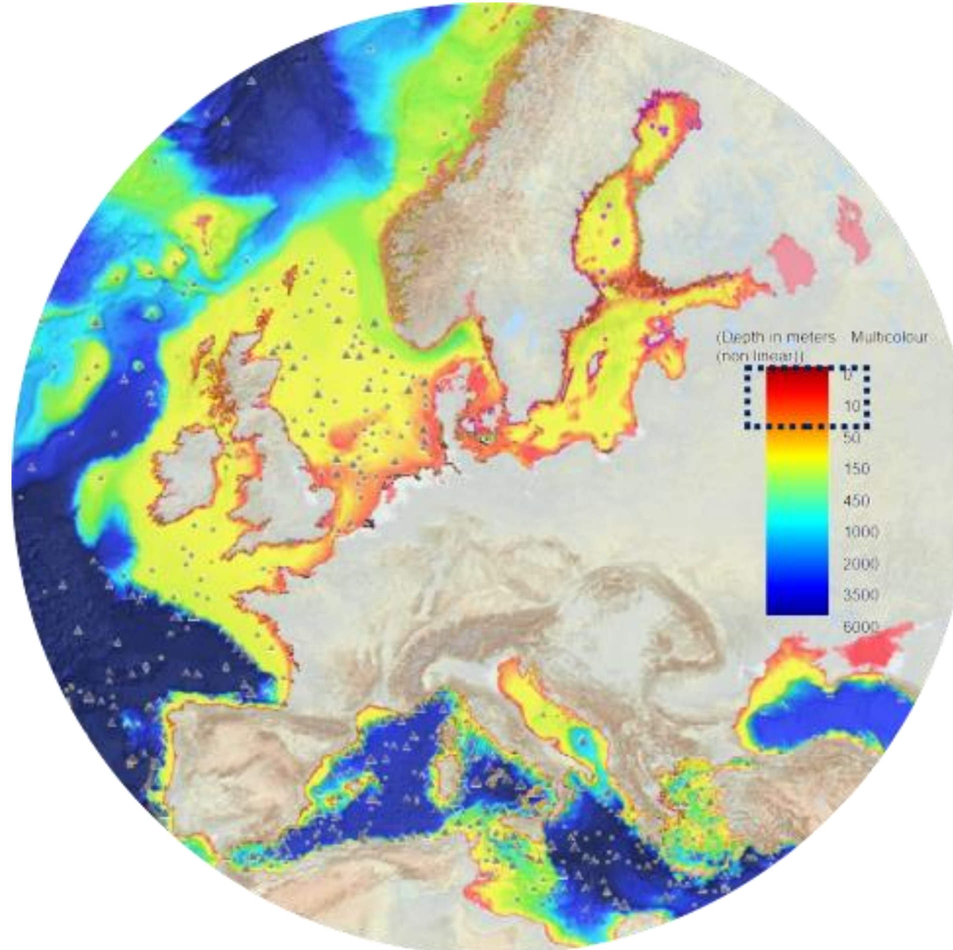
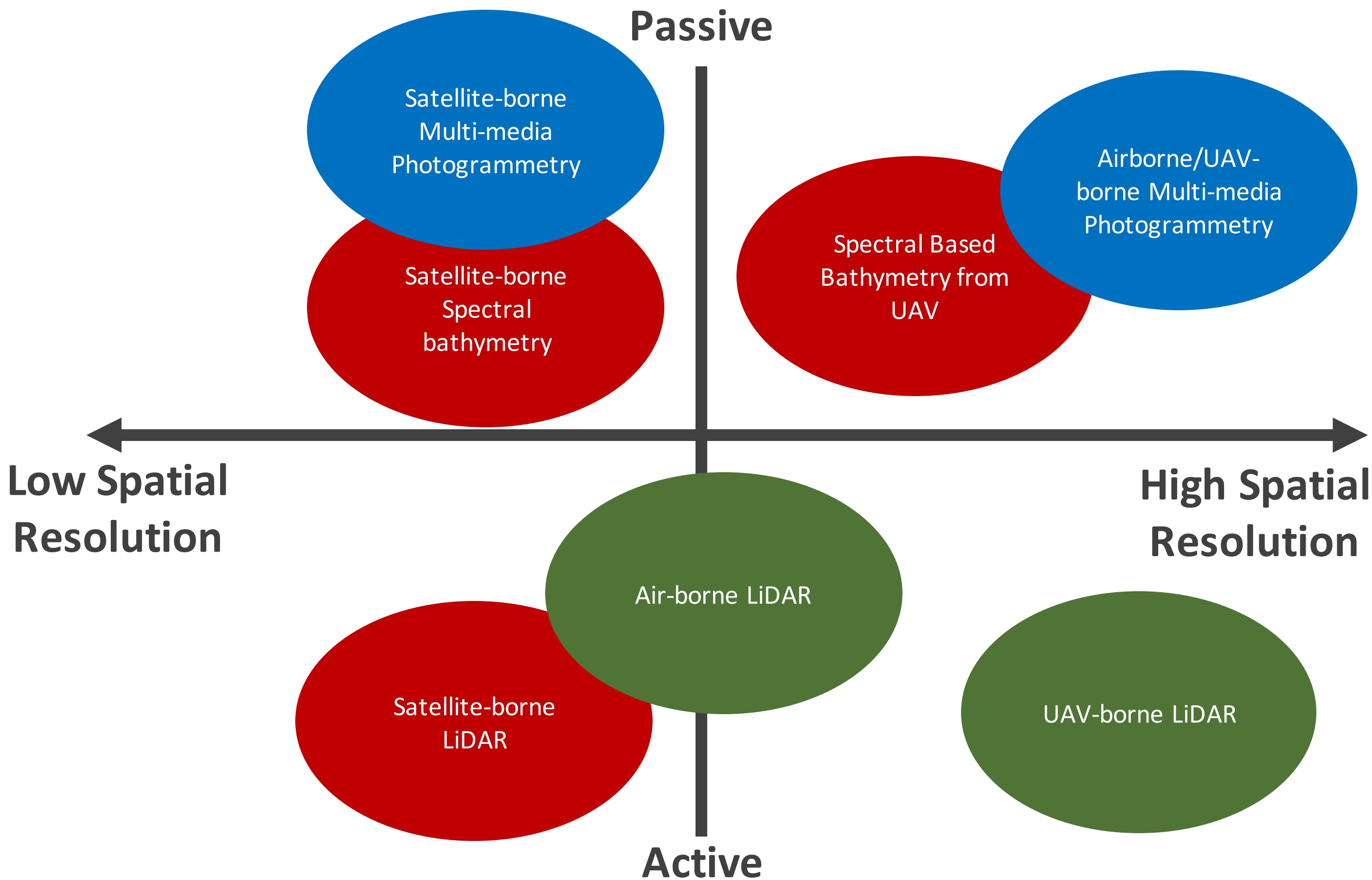
Shallow waters in EU

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



Map source: EMODnet

Bathymetry via active and passive airborne remote sensing



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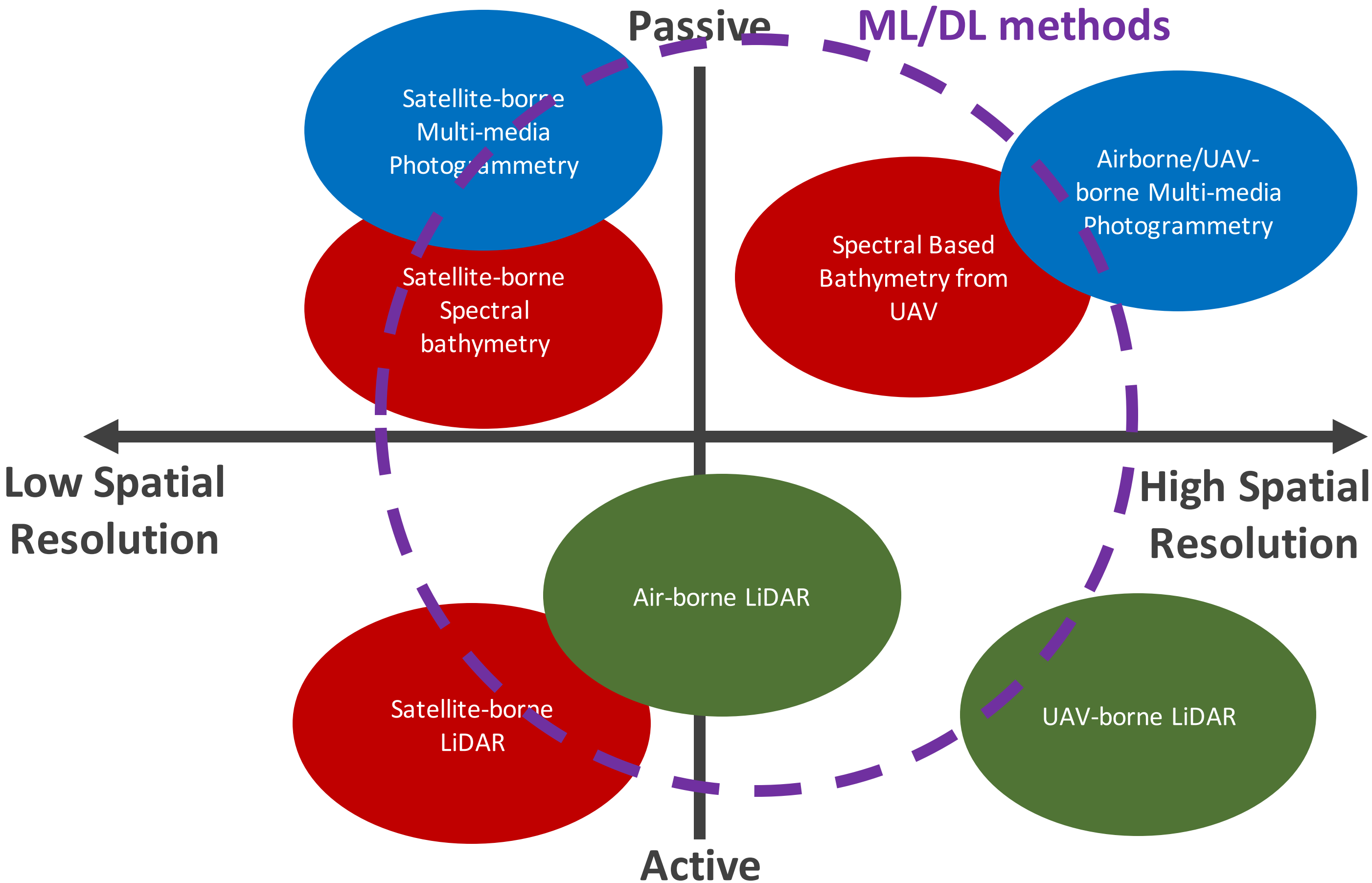
Bathymetry via active and passive airborne remote sensing



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PASSIVE Airborne/Satellite-borne image-based bathy-mapping

- Can provide a **cheap alternative** to traditional (LiDAR-SONAR etc.) and expensive shallow seabed mapping techniques

- Offer important **visual information** and high detail

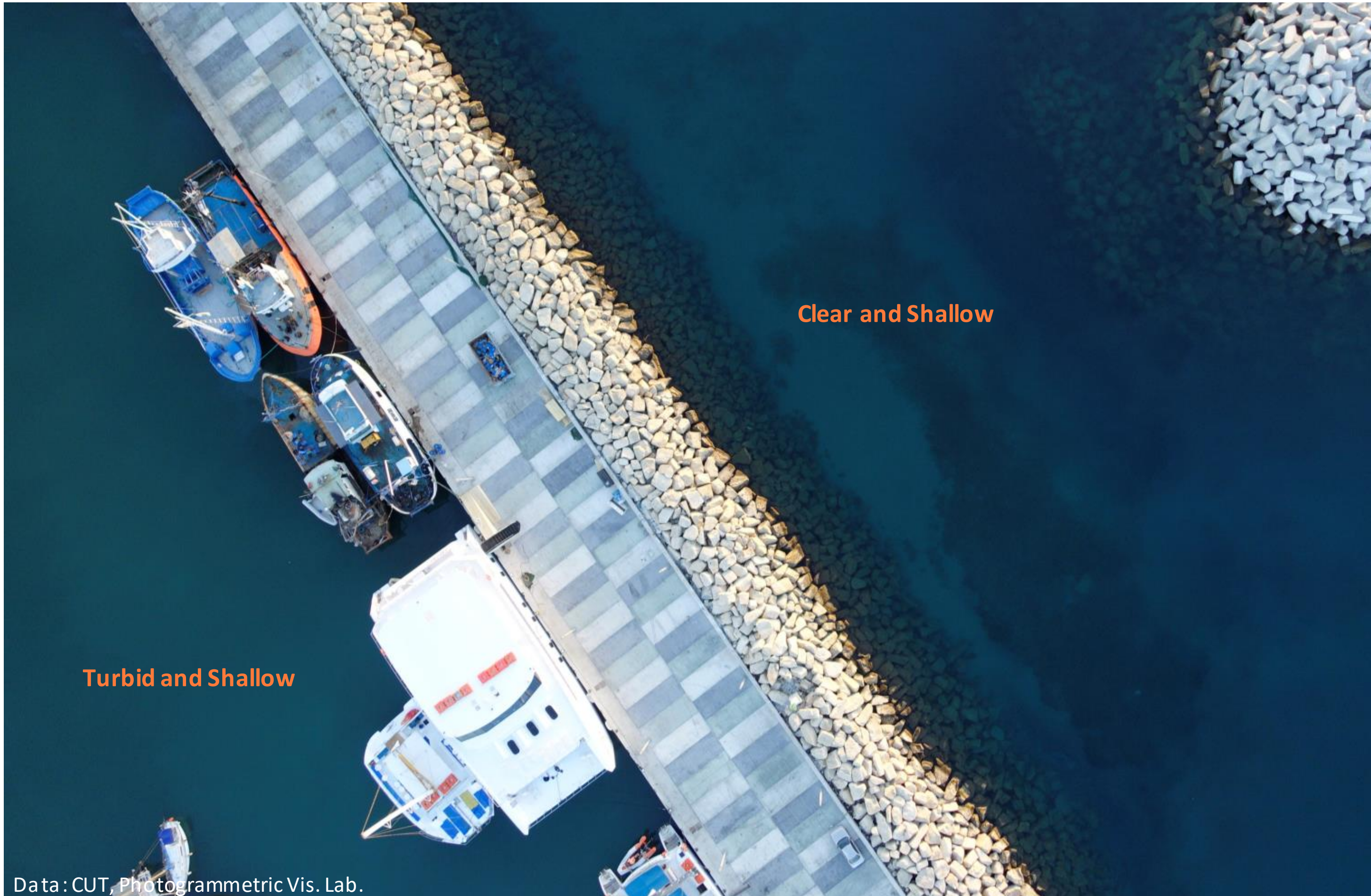
- Offer high density **3D point clouds** and meshes

- Facilitate **"easier" semantic segmentation** approaches with known FCNs (dealing with images)

- Cover **large areas in reduced time and cost**

- **Useful for mapping & reconnaissance of submerged CH in high resolution and extended coverage, enabling CH risk assessment and risk mitigation**

Shallow waters examples: Limassol marina, Cyprus



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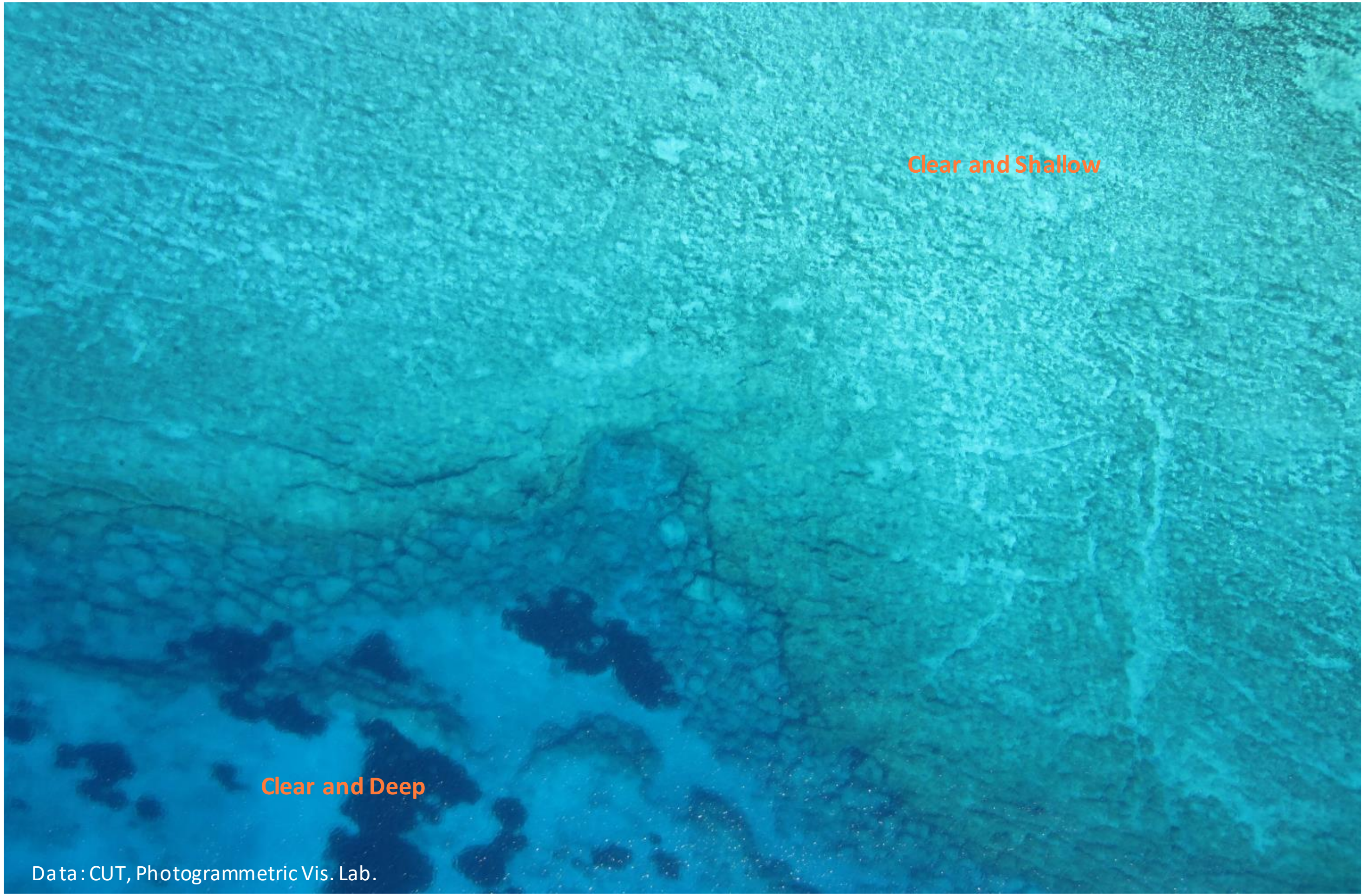
Shallow waters examples: Latsi, Cyprus

Shallow waters examples: Agia Napa, Cyprus



Submerged CH examples: Pafos, Cyprus

Submerged CH examples: Amathus, Cyprus

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Submerged CH examples: Epidavros, Greece

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Submerged CH examples: Epidavros, Greece

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Submerged CH examples: Epidavros, Greece

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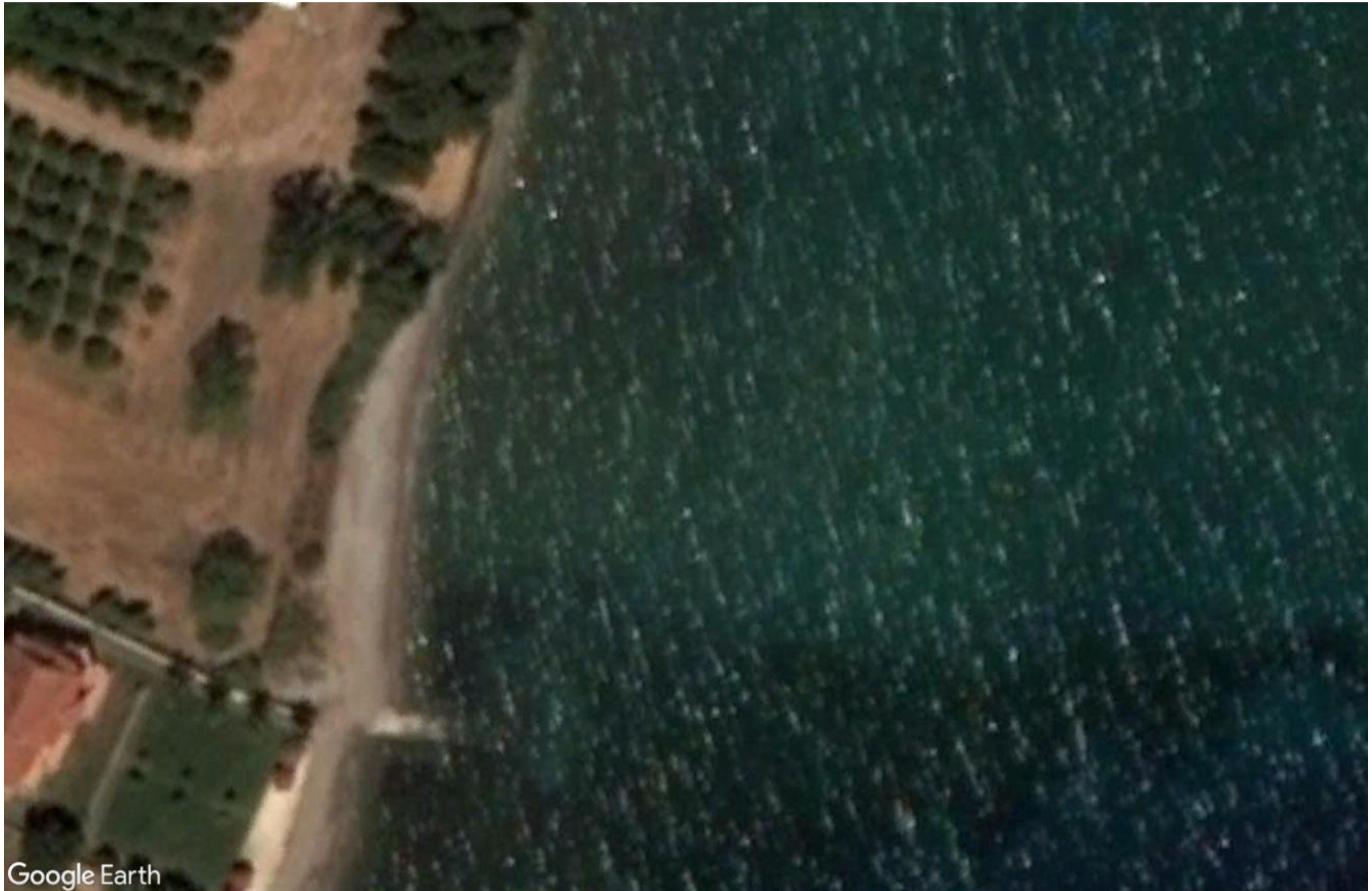
Submerged CH examples: Epidavros, Greece



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Shallow waters examples: Lemnos island, Greece

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Shallow waters examples: Andros island, Bahamas

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Shallow waters examples: Wadden Sea, Netherlands-Germany

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Shallow waters examples: Ionian Sea, Greece

Varying conditions and water column characteristics due to:

- **Weather (or extreme weather)**
- **Seasonal changes**
- **Anthropogenic activities**

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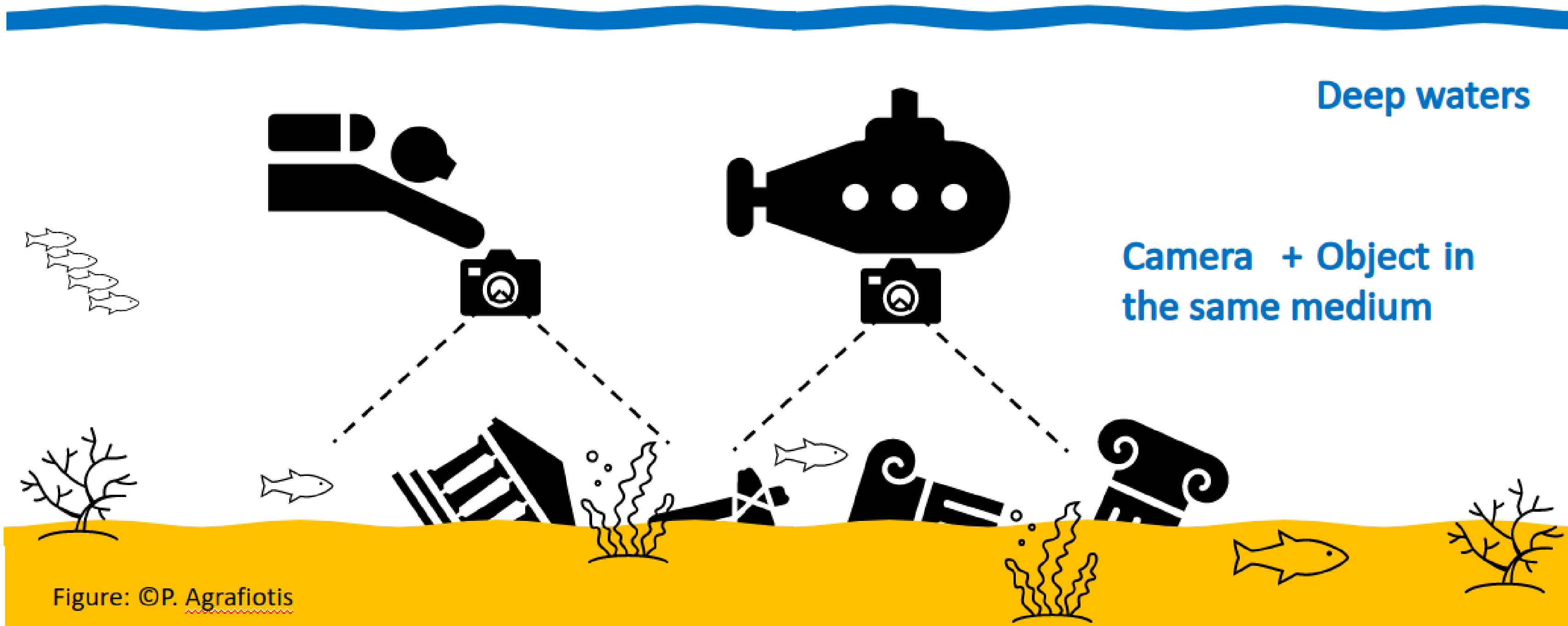
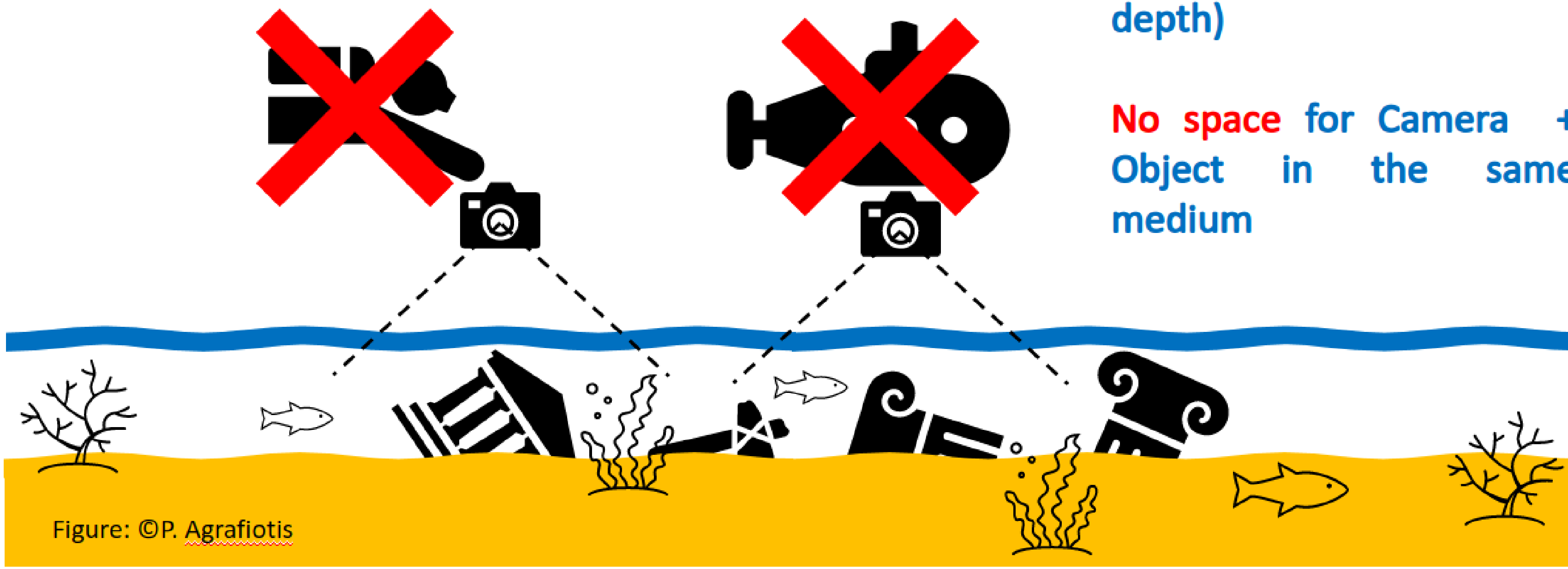
Necessity of Airborne/Satellite-borne image-based bathy-mapping in CH applications [1]



Agrafiotis P.: Learning-based bathymetric mapping for shallow coastal waters using RGB Imagery,

Necessity of Airborne/Satellite-borne image-based bathy-mapping in CH applications [2]



Very shallow waters (<1m depth)

No space for Camera + Object in the same medium

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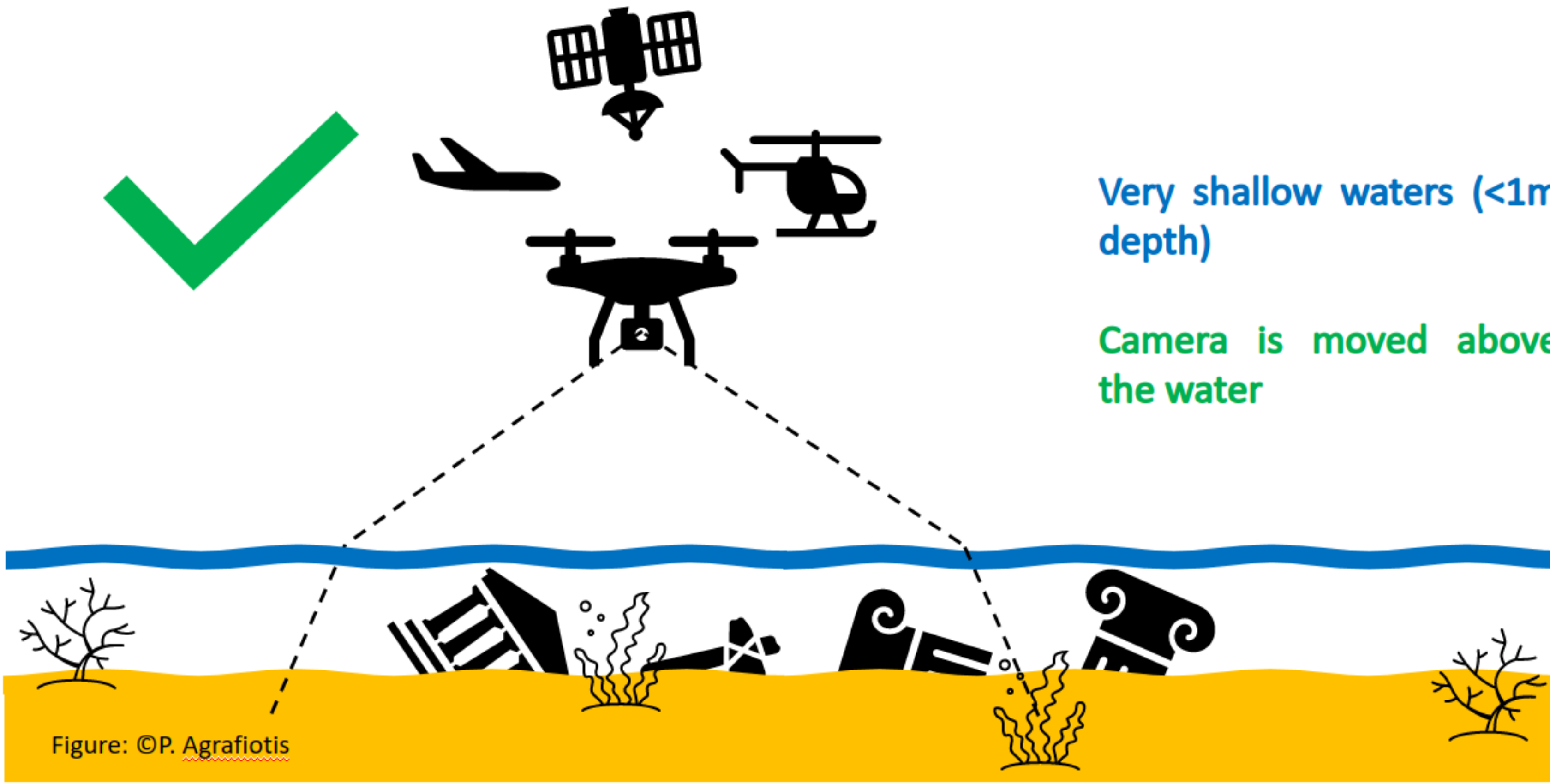
Necessity of Airborne/Satellite-borne image-based bathy-mapping in CH applications [3.1]



Very shallow waters (<1m depth)

Camera is moved above the water

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Necessity of Airborne/Satellite-borne image-based bathy-mapping in CH applications [3.2]

Shallow waters (1 – 15m depth)

Even when it is feasible to dive, extra effort is required when there is not enough space OR a large area should be mapped

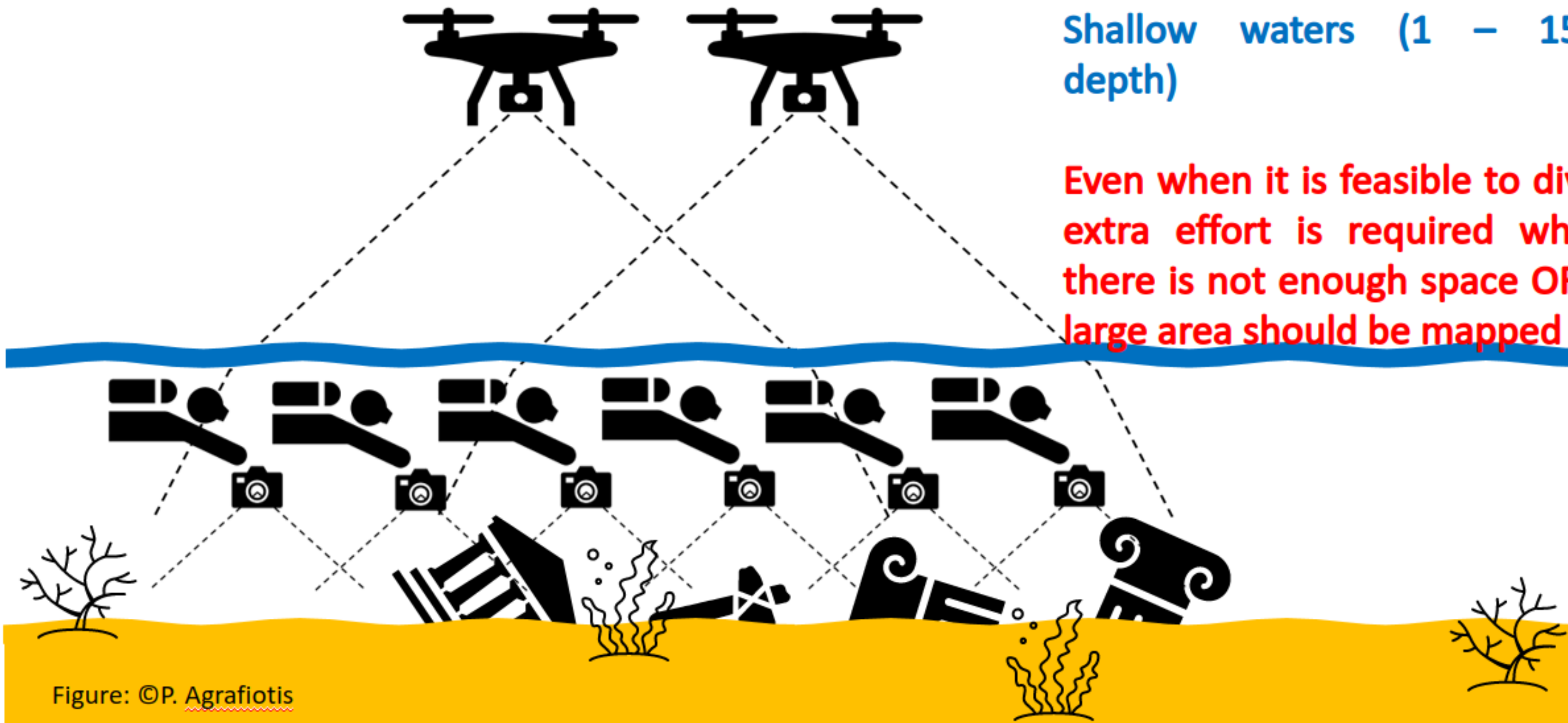

Figure: ©P. Agrafiotis

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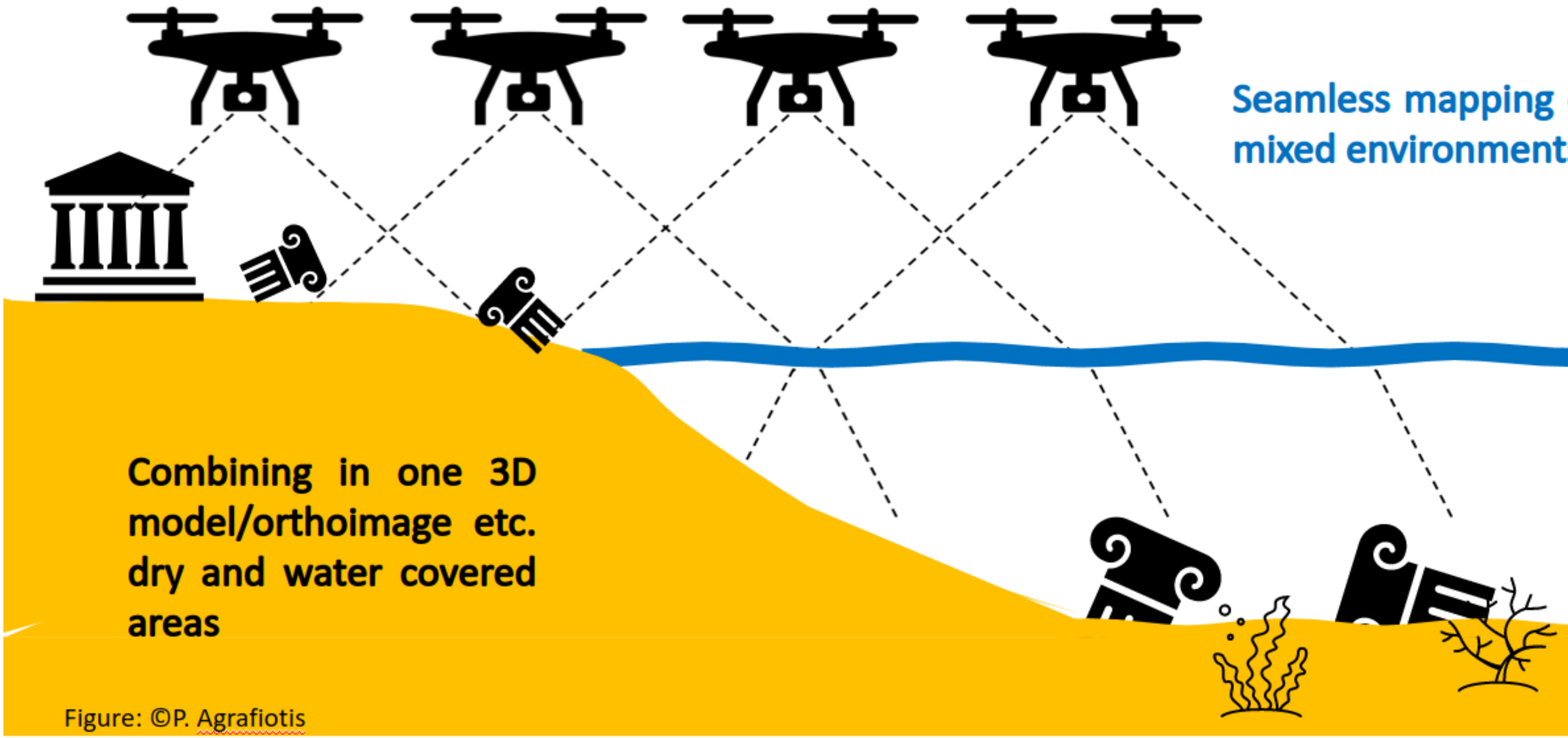
Necessity of Airborne/Satellite-borne image-based bathy-mapping in CH applications [3.3]



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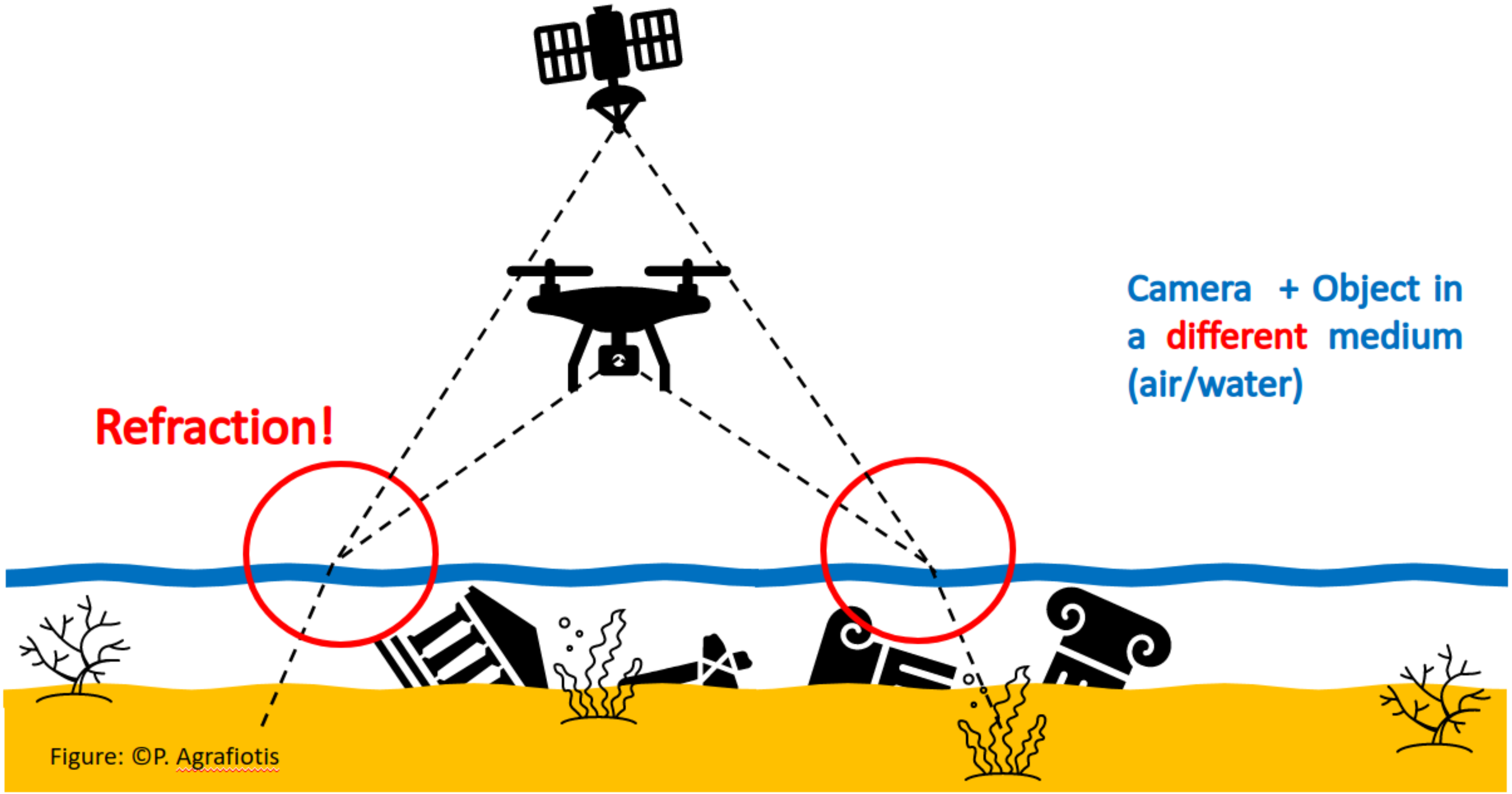
Why are they special cases of mapping ?



Camera + Object in a different medium (air/water)

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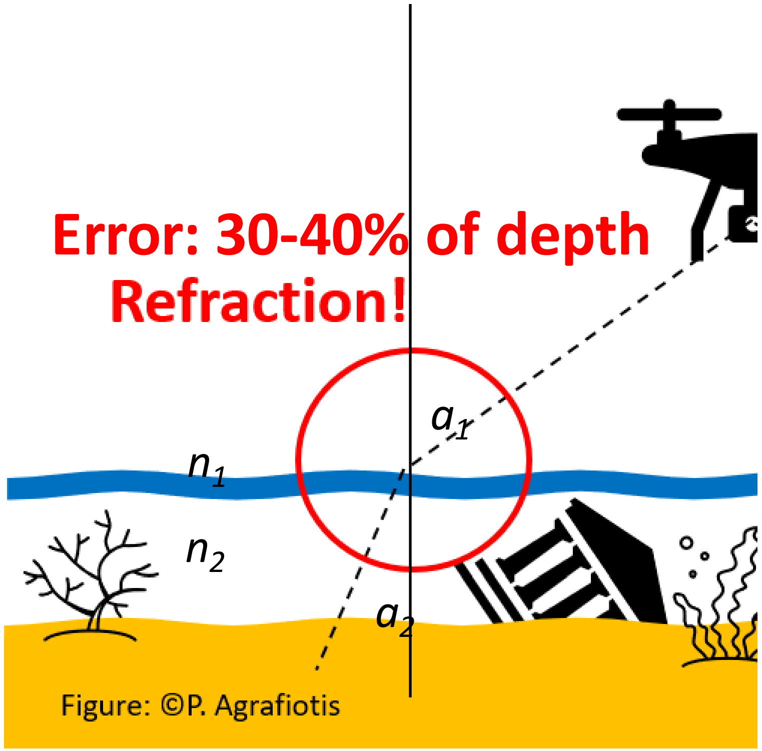
Info - Refraction effect

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, or equivalent to the reciprocal of the ratio of the indices of refraction

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.



- **Violates the Collinearity Equation**
- Generate **apparent depths**
- Roughly, acts like a non-uniform radial distortion, depending on the incidence angles and the depth
- In SfM-MVS **adds noise** in the **de-facto erroneous generated depths**

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Geometry – based methods

(SfM-MVS + refraction correction)

Multi-media Photogrammetry – Single View Geometry

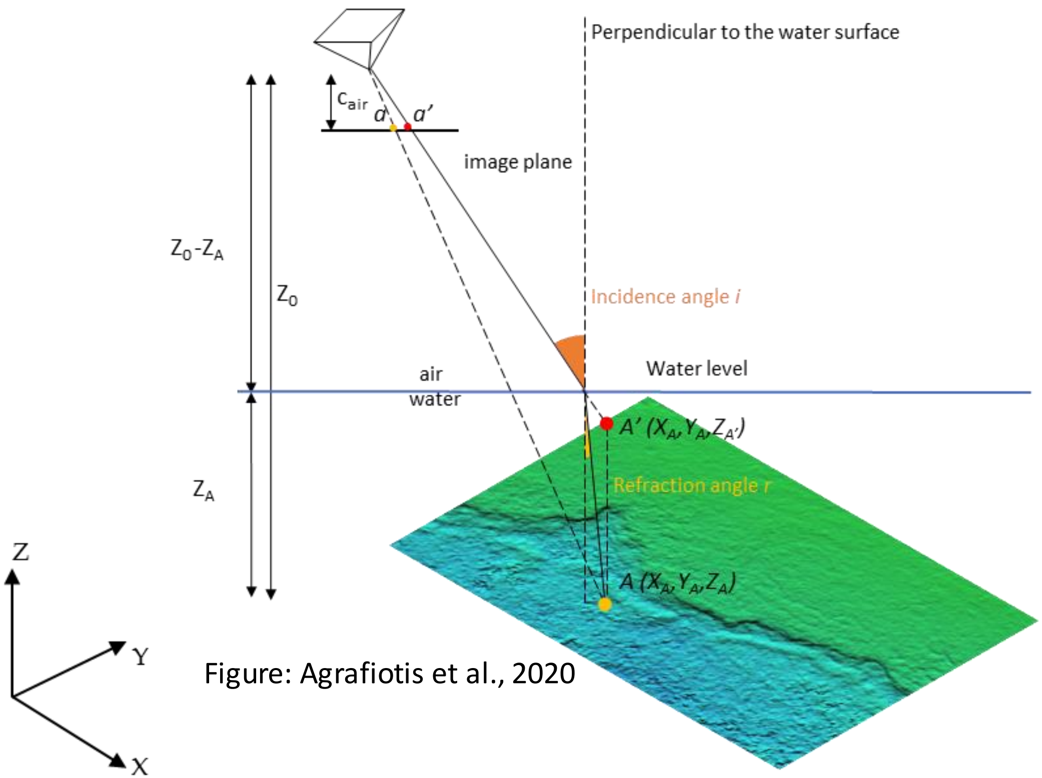

Figure: Agrafiotis et al., 2020

- Violation of the Collinearity Equation
- Apparent depths

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Multi-media Photogrammetry – Multiple View Geometry

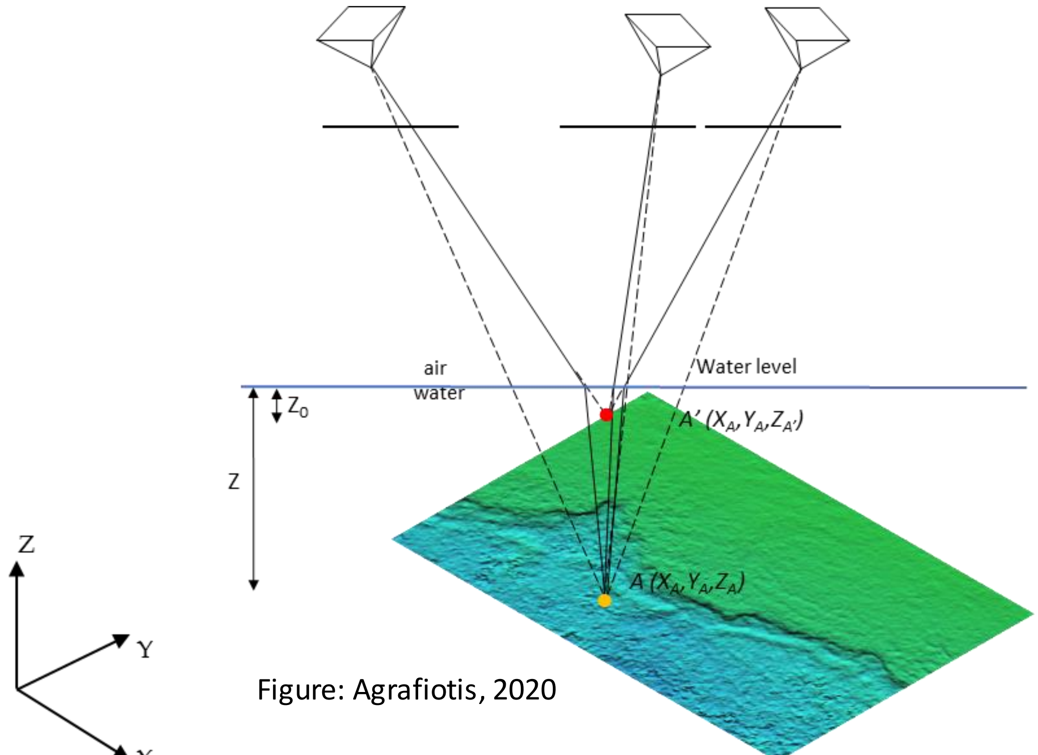

Figure: Agrafiotis, 2020

- Violation of the Collinearity Equation
- Apparent depths
- **Increased noise in the point clouds**

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Multi-media Photogrammetry – Correction Basics

- **Analytical correction:** modification of the collinearity equation.
- **Image-space correction**: re-projection of the original photo to correct the water refraction.
- **Machine/Deep Learning-based**: depends on models that learn the underestimation of depths and predict the correct depth knowing only the apparent one or the spectral values.

Other methods: multiplying the apparent depth with a constant number, which in most of the cases is the refraction index of the water the use of this form of correction might be acceptable in the very shallow waters, however, ***remarkable errors are expected after 2-3 m depth.***

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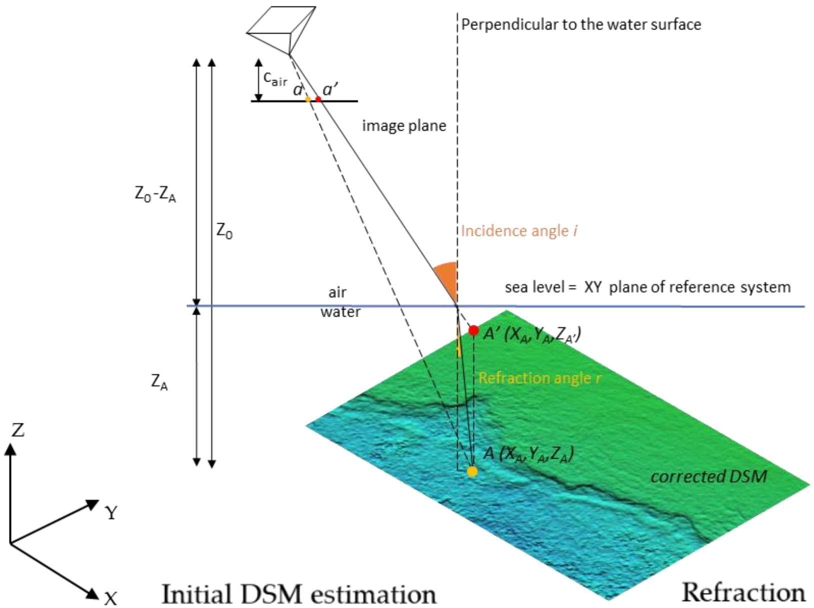
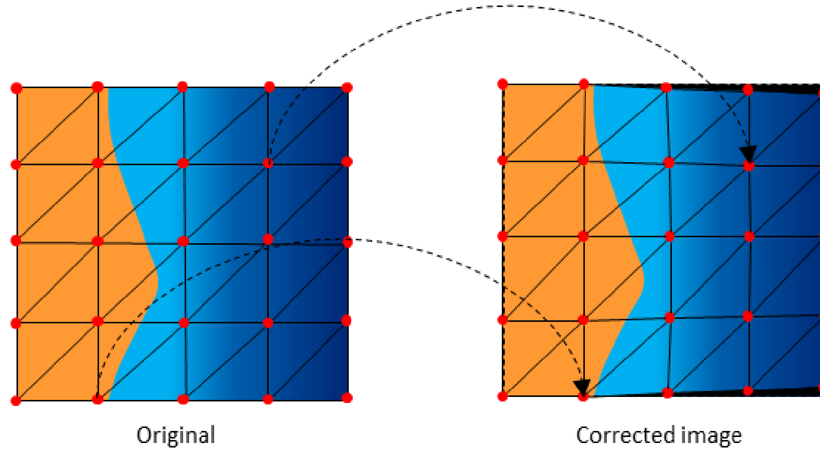
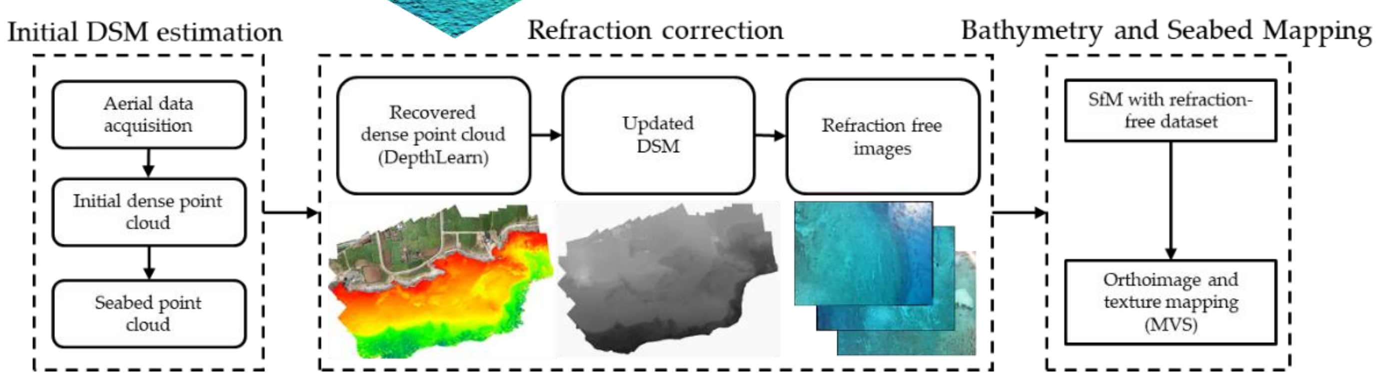
Multi-media Photogrammetry – Image Space Correction







Figures: Agrafiotis et al., 2020

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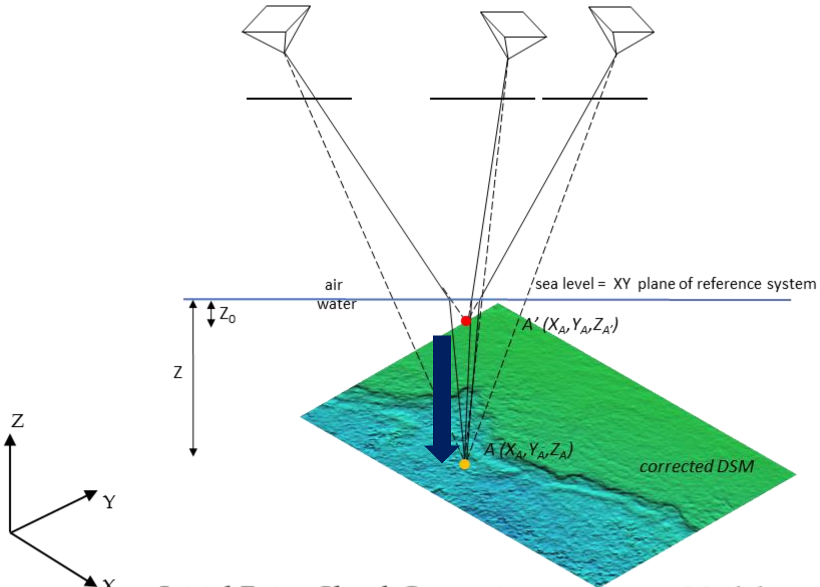
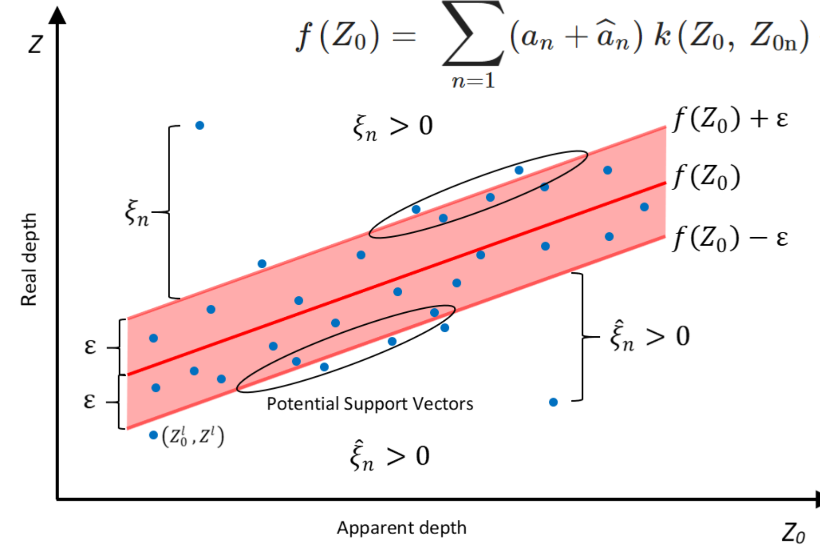
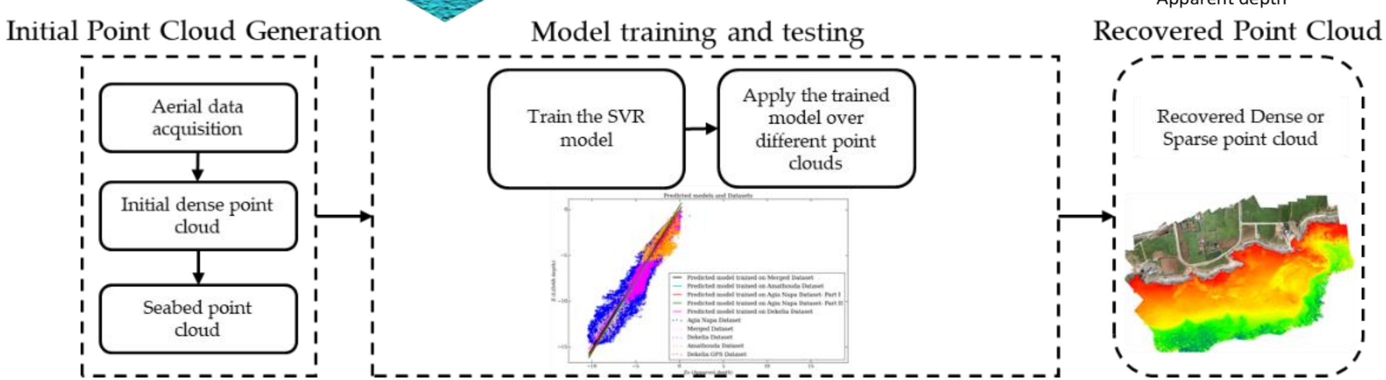
Multi-media Photogrammetry – ML-based Correction



Agrafiotis et al., 2019:

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





Figures: Agrafiotis et al., 2020

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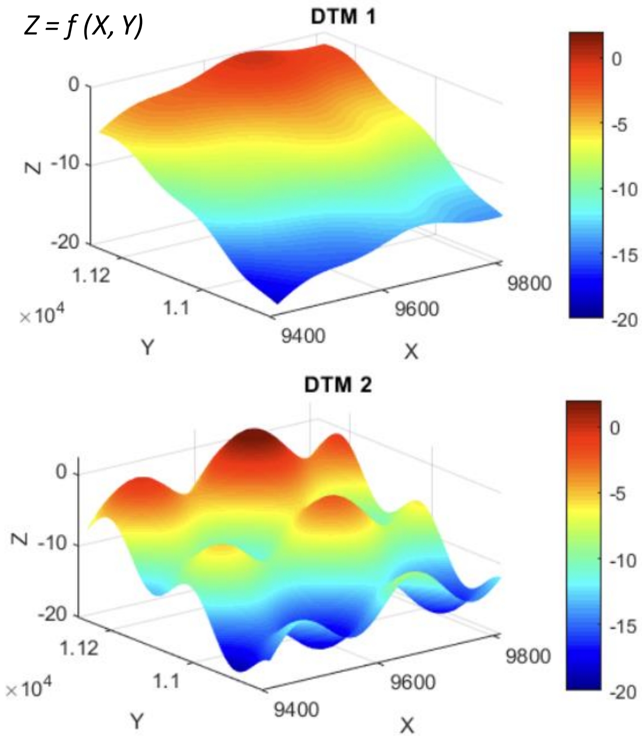
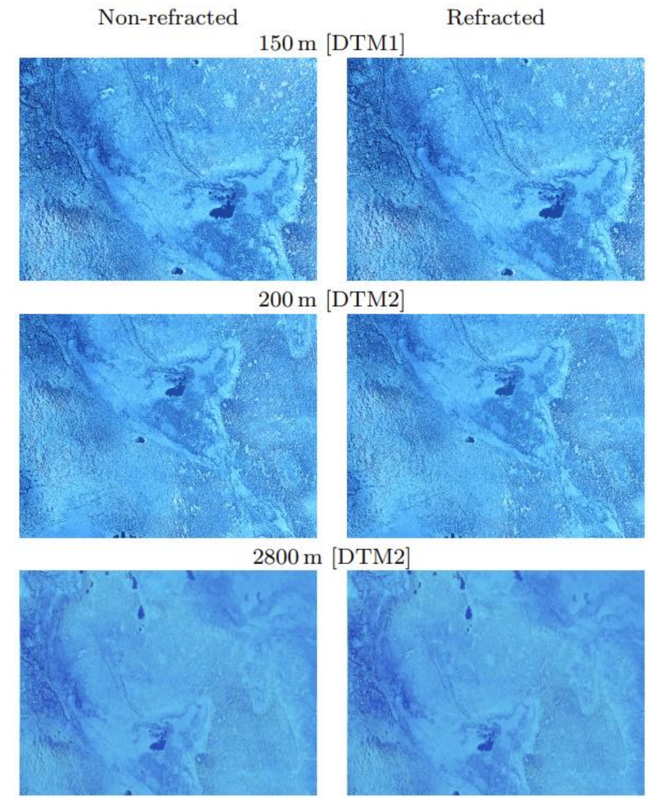
Need for synthetic data & generated data

- Accuracy & reliability of depths
- Known EO & IO
- 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, P., Karantzalos, K., Georgopoulos, A., & Skarlatos, D. (2021). Learning from Synthetic Data: Enhancing Refraction Correction Accuracy for Airborne Image-Based Bathymetric Mapping of Shallow Coastal Waters, *PFG, 144, doi:* 10.1007/s41064-021-00144-1

A deeper look into Multimedia Photogrammetry
Errors due to refraction

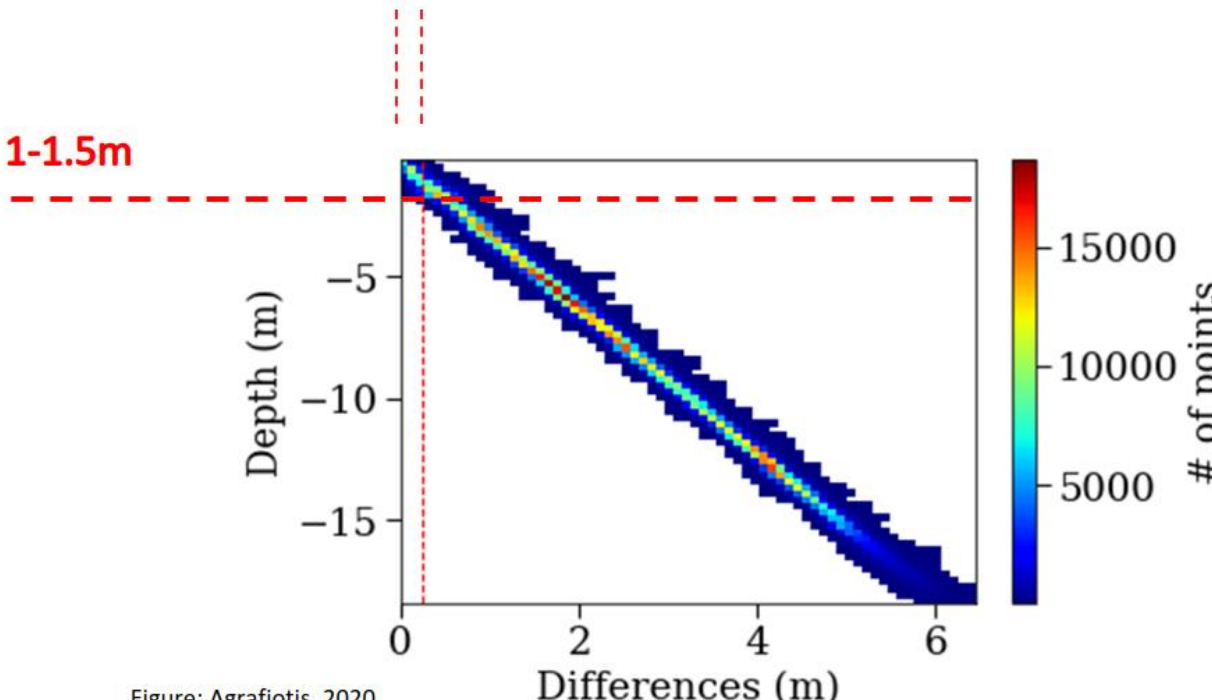


Figure: Agrafiotis, 2020

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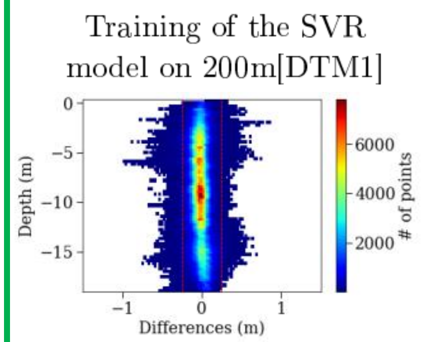
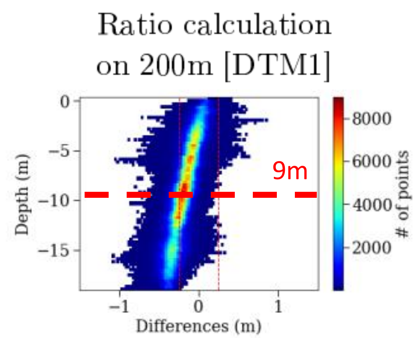
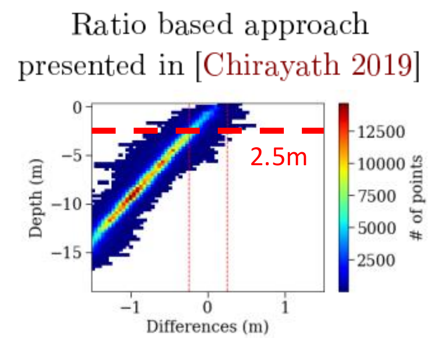
Ratio-based VS ML-based refraction correction methods







Dataset [training %]	Evaluation Site [testing %]	Max /Min depth of test site	Evaluation points	Uncorrected data			SVR corrected data			Ratio corrected data		
				$\bar{x}$ [m]	s [m]	$RMSE_Z$ [m]	$\bar{x}$ [m]	s [m]	$RMSE_Z$ [m]	$\bar{x}$ [m]	s [m]	$RMSE_Z$ [m]
150m [DTM1]	150m [DTM1]	18.7/0	2.461.488	2.48	1.47	2.874	**0.006**	**0.070**	**0.073**	-0.088	0.121	0.149
200m [DTM1]	200m [DTM1]	18.7/0	1.409.673	2.49	1.49	2.883	**0**	**0.109**	**0.109**	-0.108	0.164	0.197
200m [DTM2]	200m [DTM2]	19.05/0	2.097.713	2.96	1.54	3.337	**0.001**	**0.090**	**0.077**	-0.079	0.116	0.140
200m [DTM1]	200m [DTM2]	19.05/0	2.097.713	2.96	1.54	3.337	**-0.014**	**0.090**	**0.093**	-0.181	0.166	0.247
Cross site approach			Overall Average	2.643	1.500	3.031	**-0.002**	**0.090**	**0.088**	-0.114	0.142	0.183
			s	0.224	0.029	0.216	**0.009**	**0.016**	**0.016**	0.046	0.027	0.049

Figures and Table: Agrafiotis, 2020

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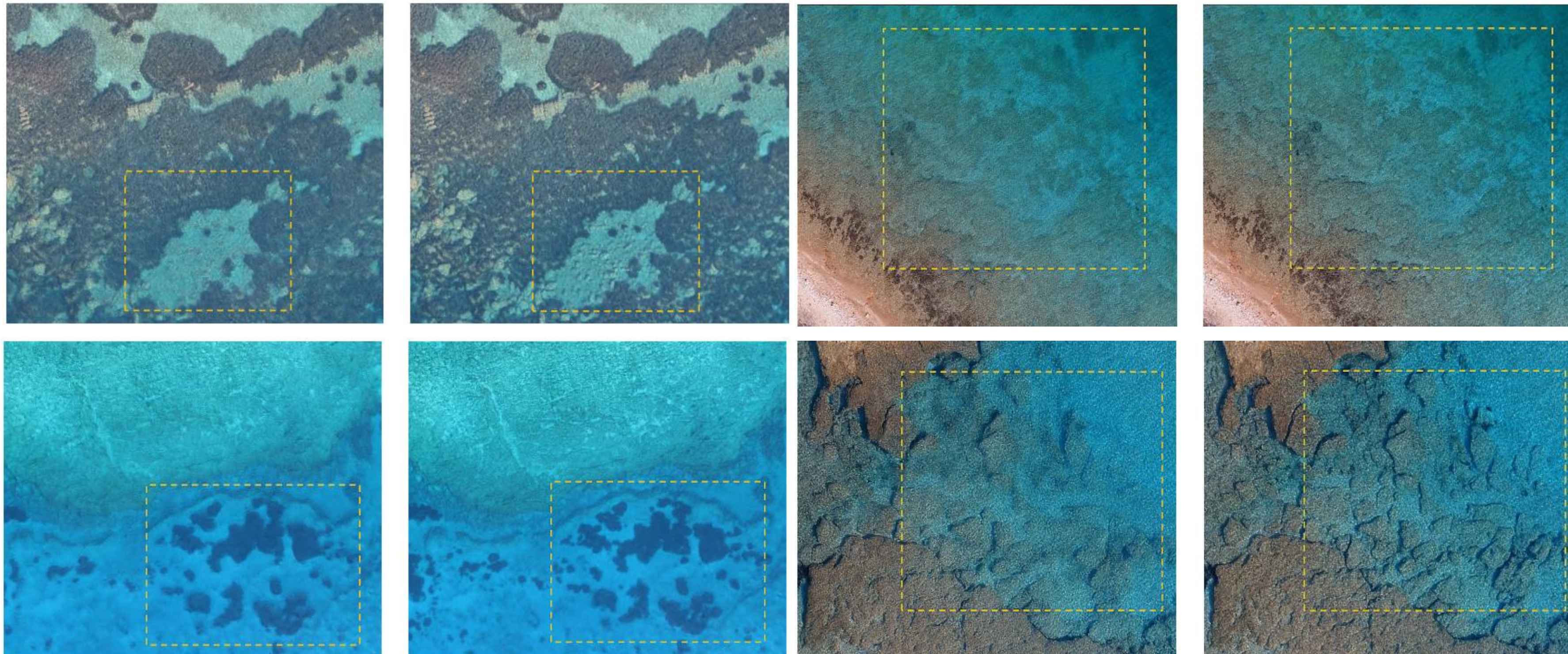
Improvement in texture

Uncorrected | Corrected | Uncorrected | Corrected



By correcting the images from refraction, the texture of the 3D model is improved

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Bathymetry Examples – Real world applications [1]

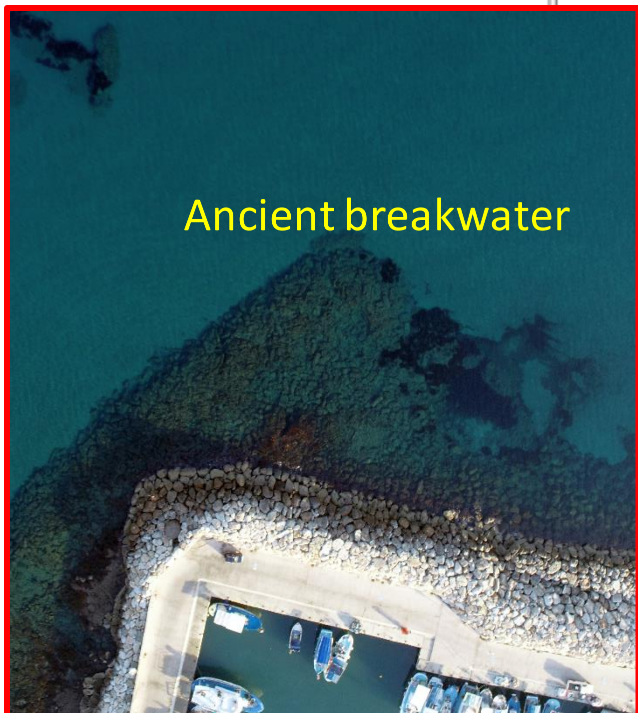


Figure: Photogrammetric Vision Lab, Cyprus University of Technology

Bathymetry Examples – Real world applications [2]

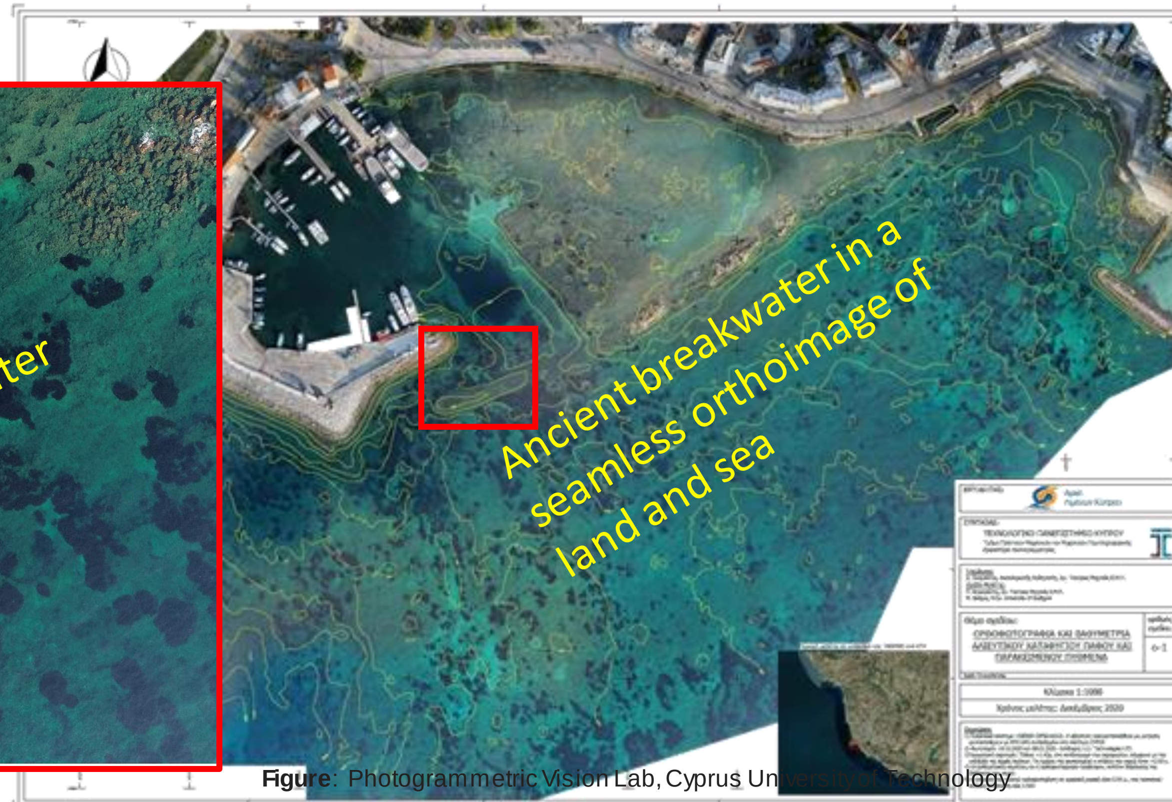
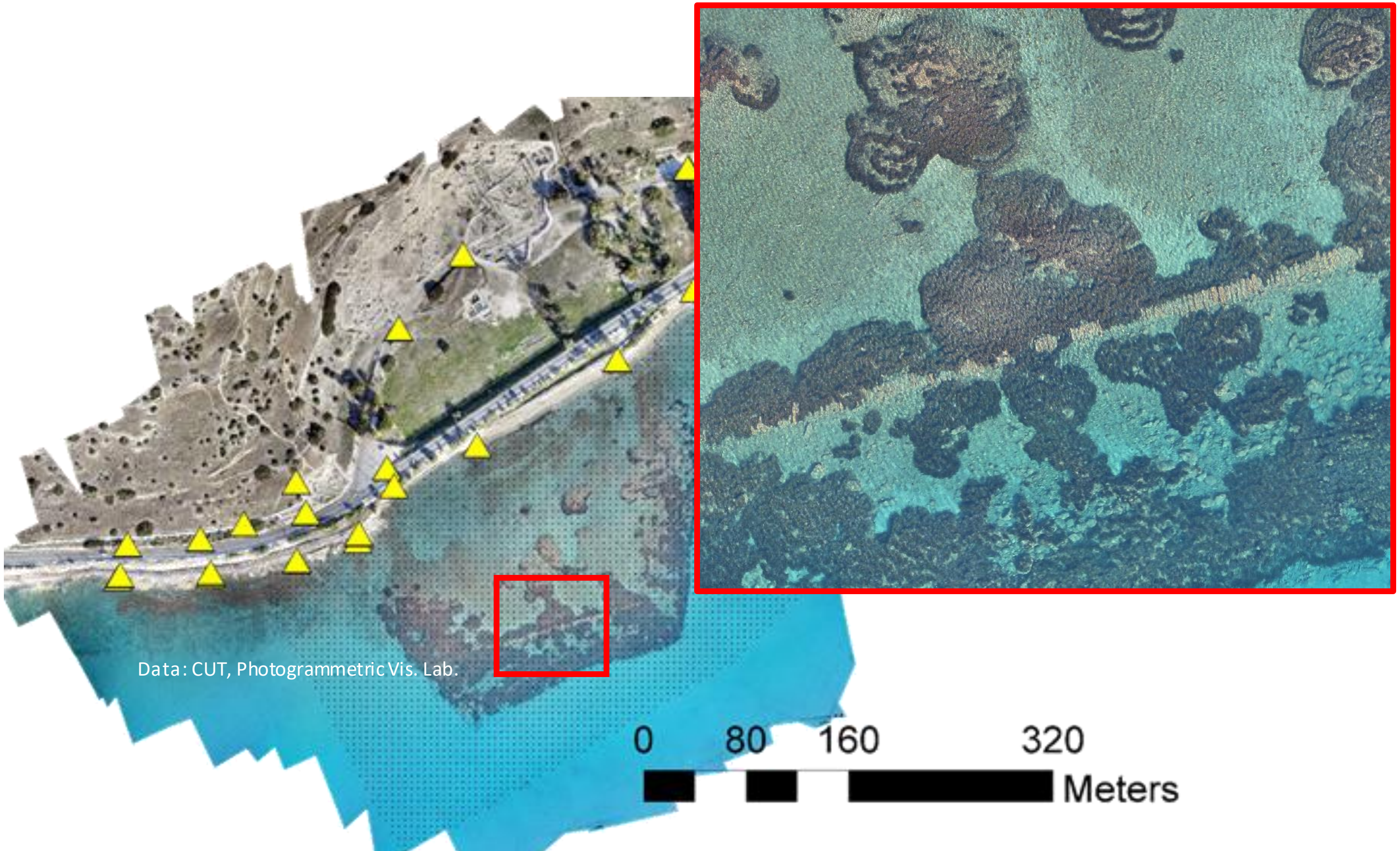
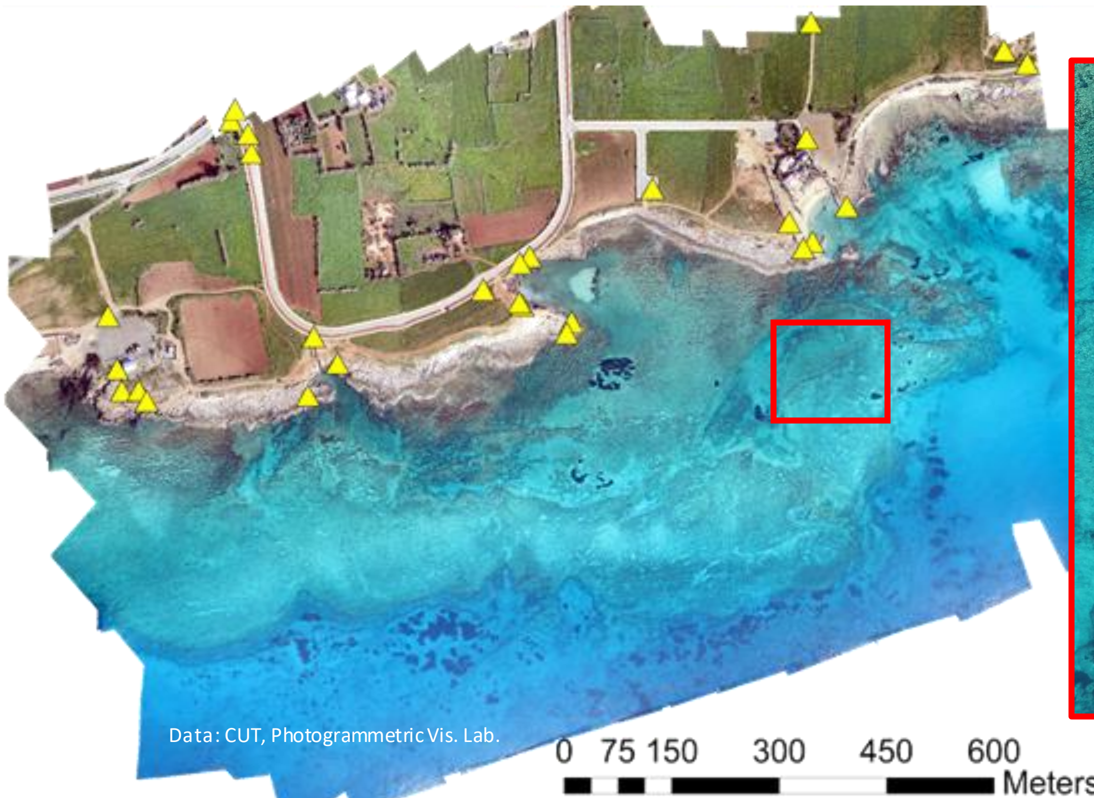


Figure: Photogrammetric Vision Lab, Cyprus University of Technology

Bathymetry Examples – Real world applications [3]



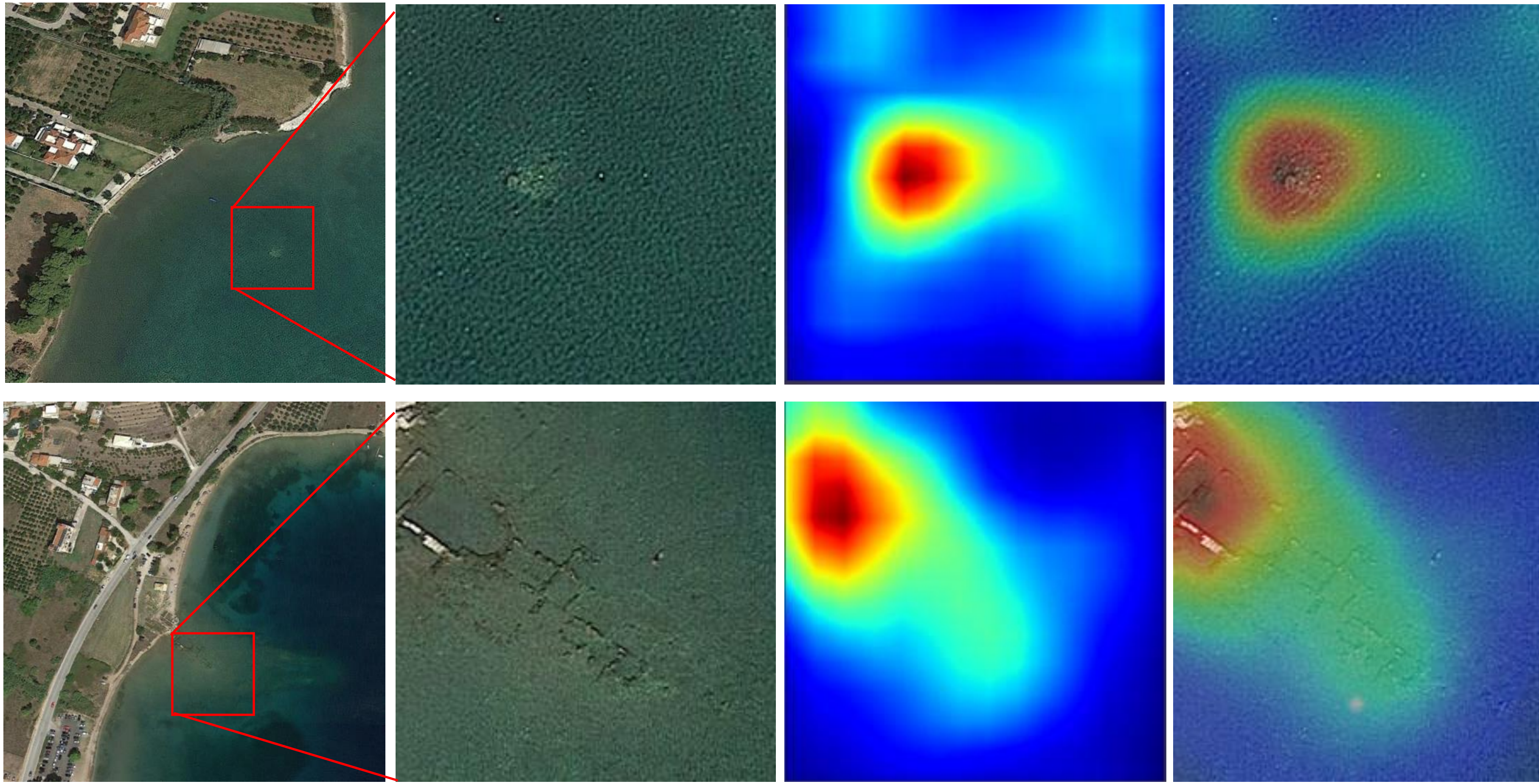
Bathymetry Examples – Real world applications [4]



Semantics Examples - Submerged CH detection with Deep Learning

Satellite images

CNN-based detection and localization of submerged Cultural Heritage sites



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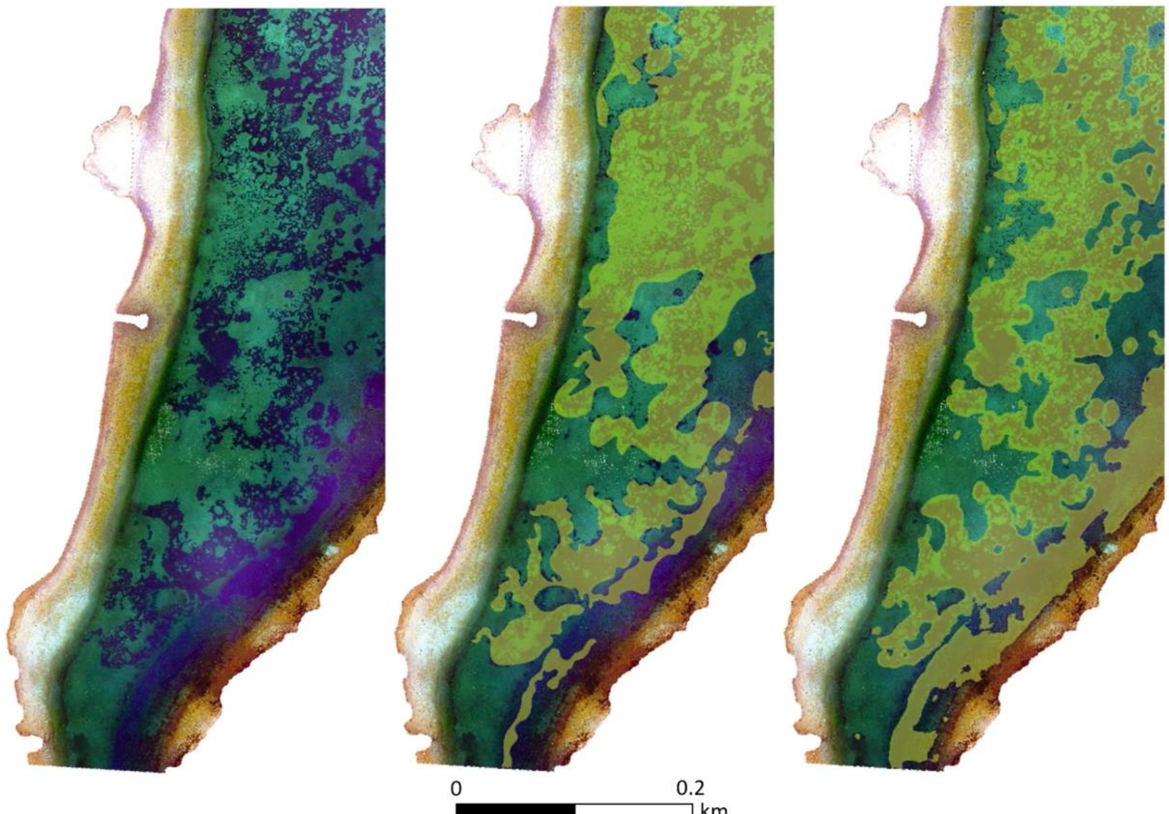
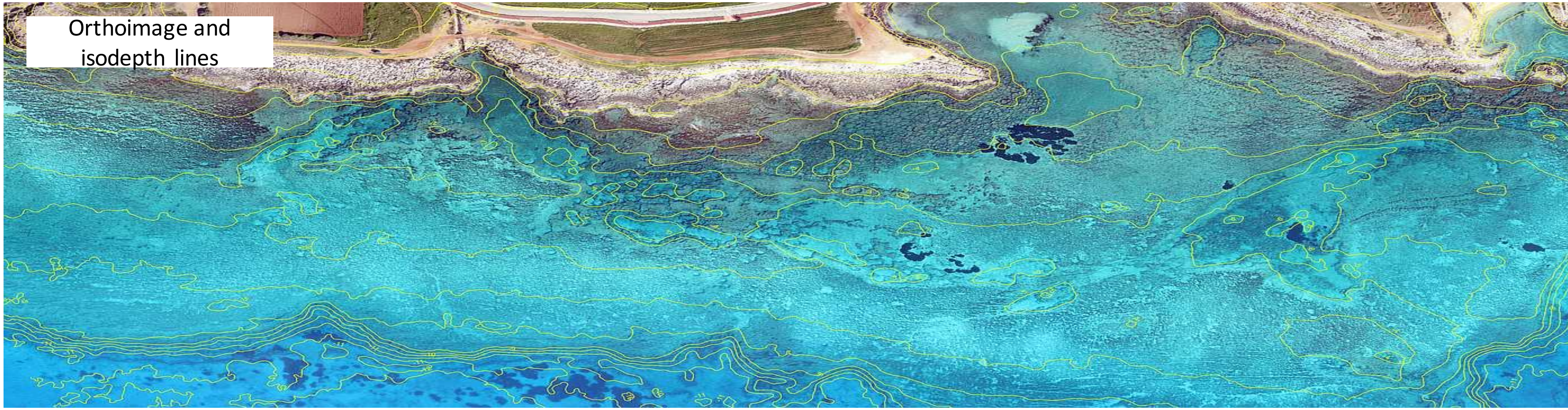
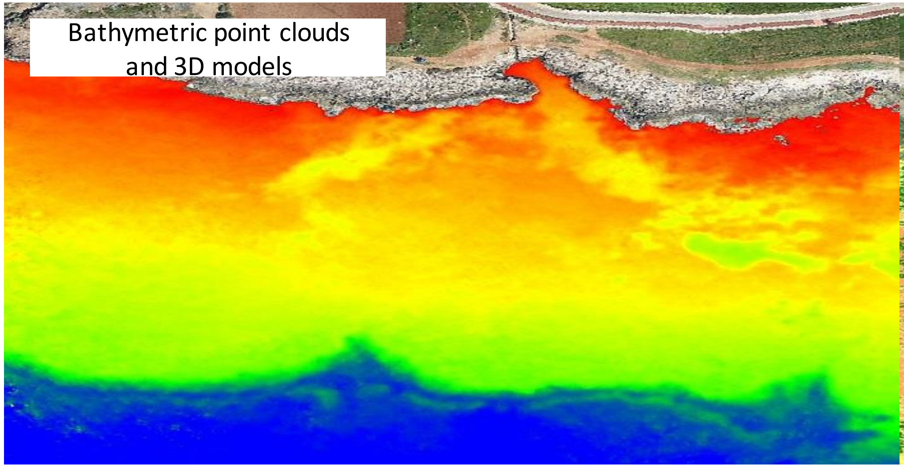
Semantics Examples – Seagrass semant. segm. with Deep Learning

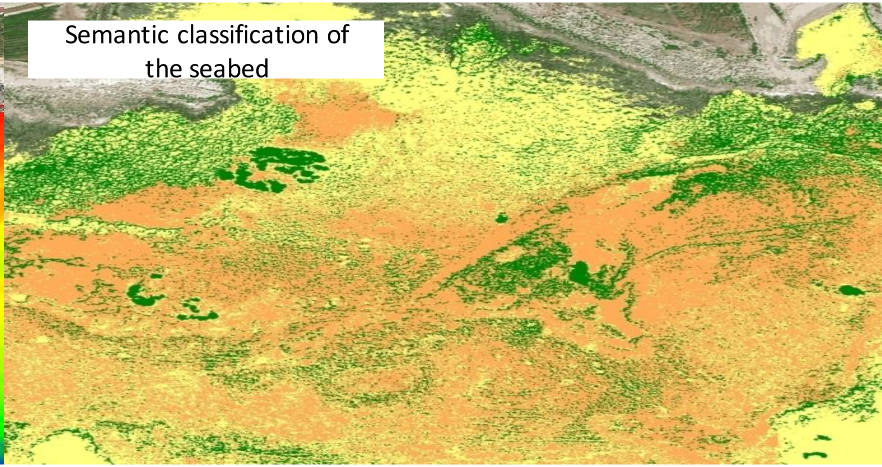


Mandlburger, G., Kölle, M., Nübel, H. *et al.* BathyNet: A Deep Neural Network for Water Depth Mapping from Multispectral Aerial Images. *PFG* **89,** 71–89 (2021).

Semantics/Bathymetry Examples with Deep Learning







Data: CUT, Photogrammetric Vis. Lab., 3[Deep]Vision

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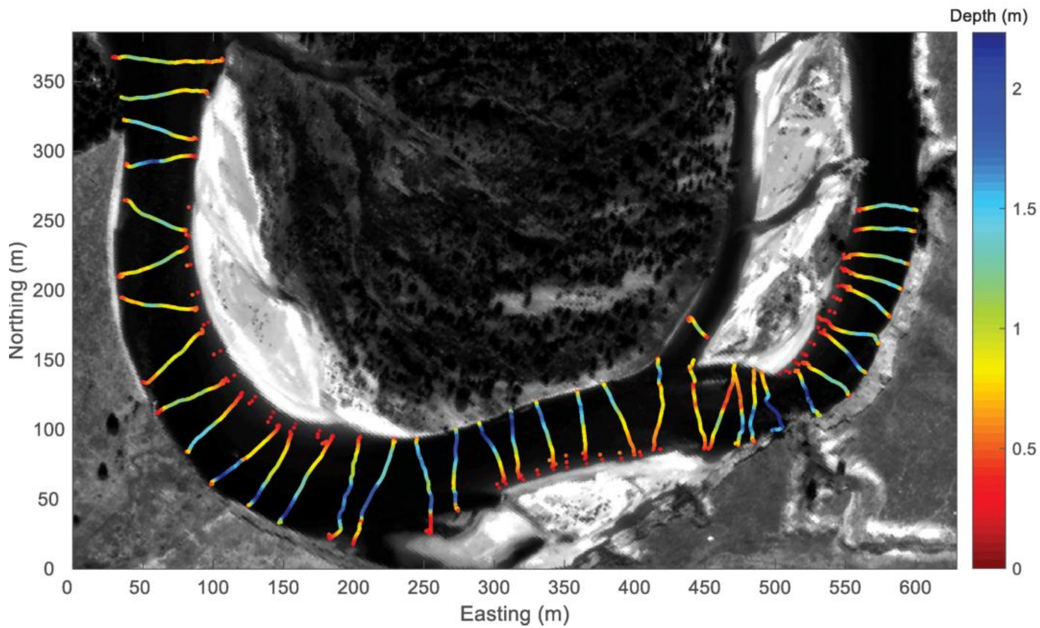
Spectral – based methods

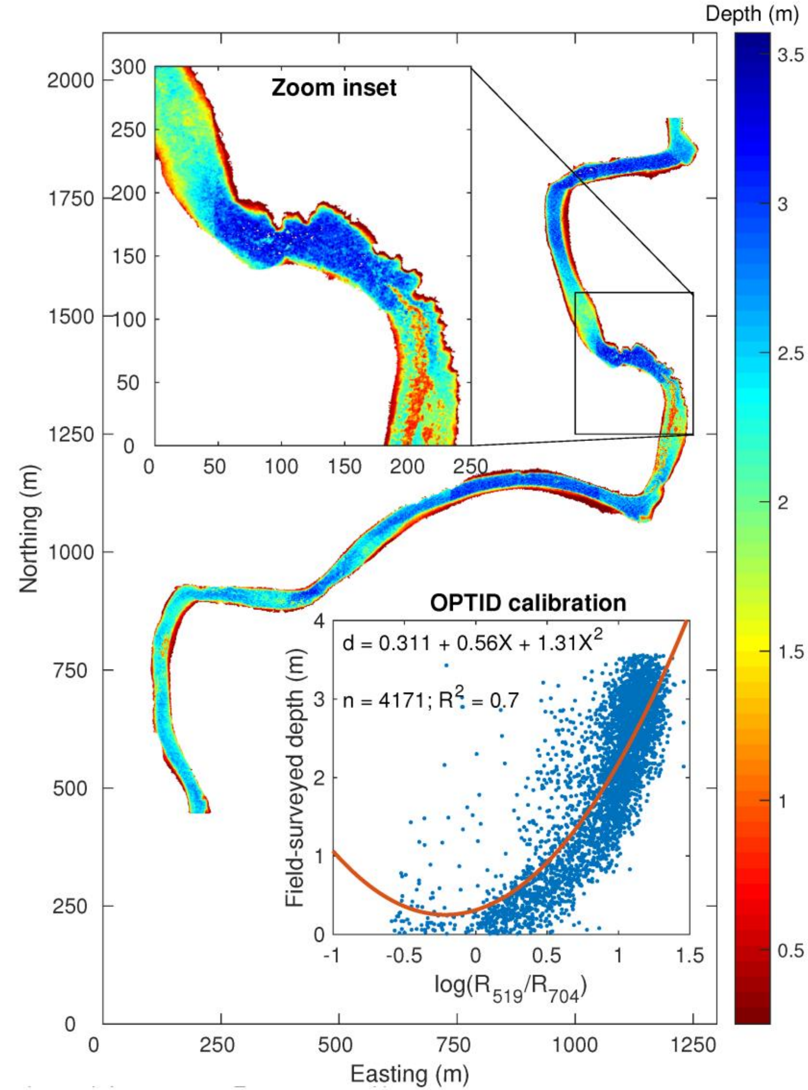
Spectral-based bathymetry (SBB)

No geometry – Only spectral values for bathymetry

No generalized method – sensitive to different types of seabed



Figures: Legleiter et al., 2018,



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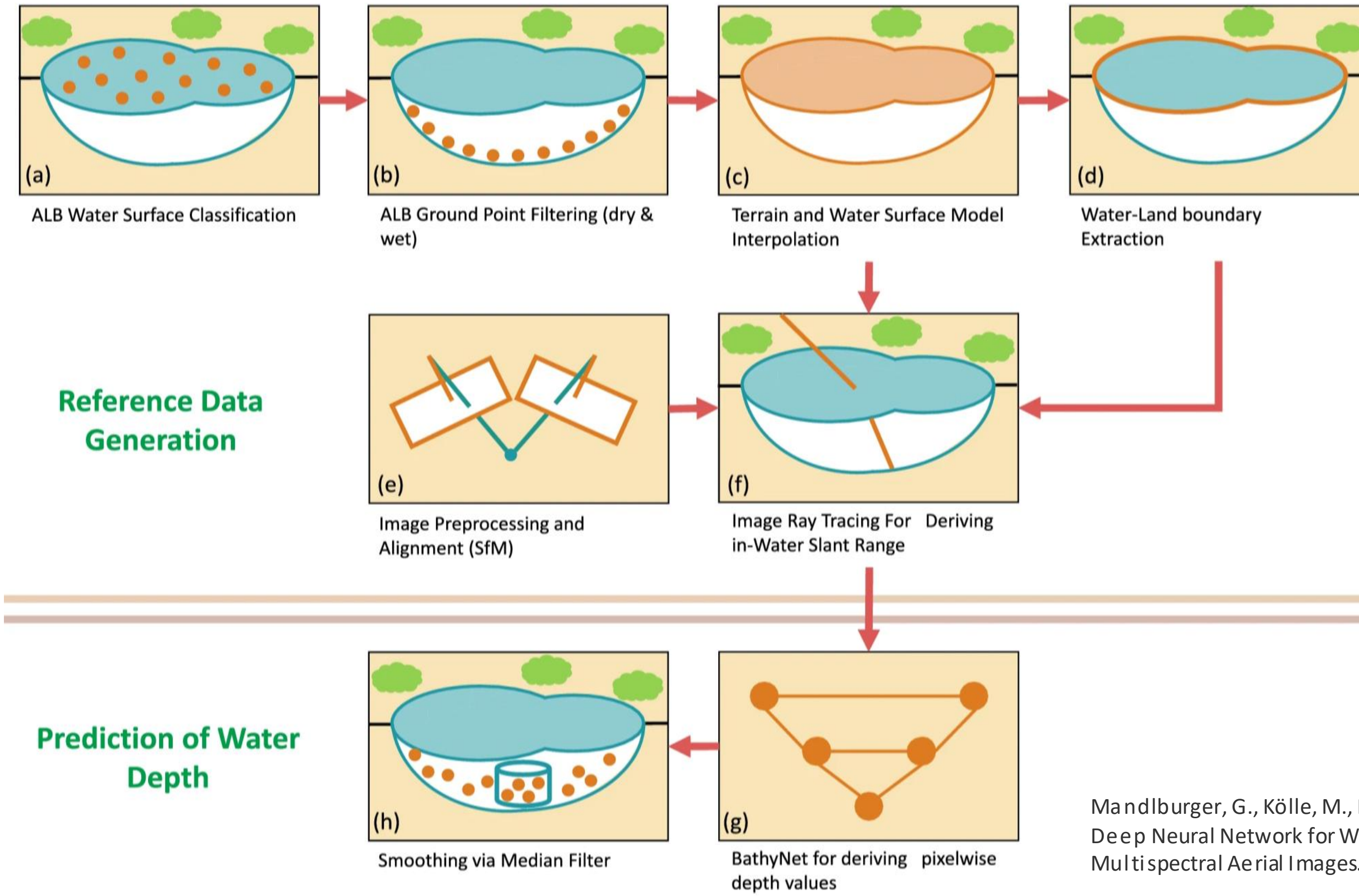
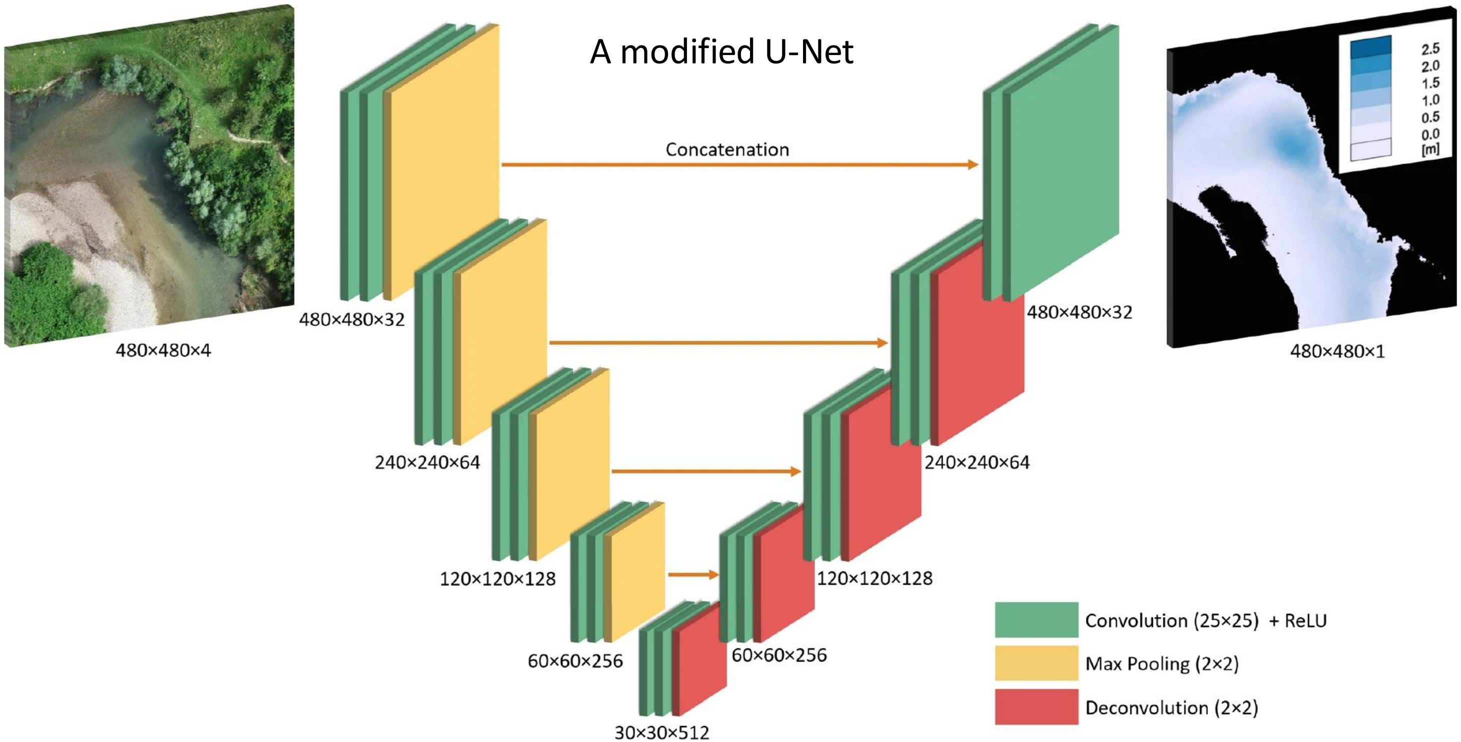
Multi-media Photogrammetry – DL-based Correction [1]



Mandlburger, G., Kölle, M., Nübel, H. *et al.* BathyNet: A Deep Neural Network for Water Depth Mapping from Multispectral Aerial Images. *PFG* **89,** 71–89 (2021).

Multi-media Photogrammetry – DL-based Correction [2]



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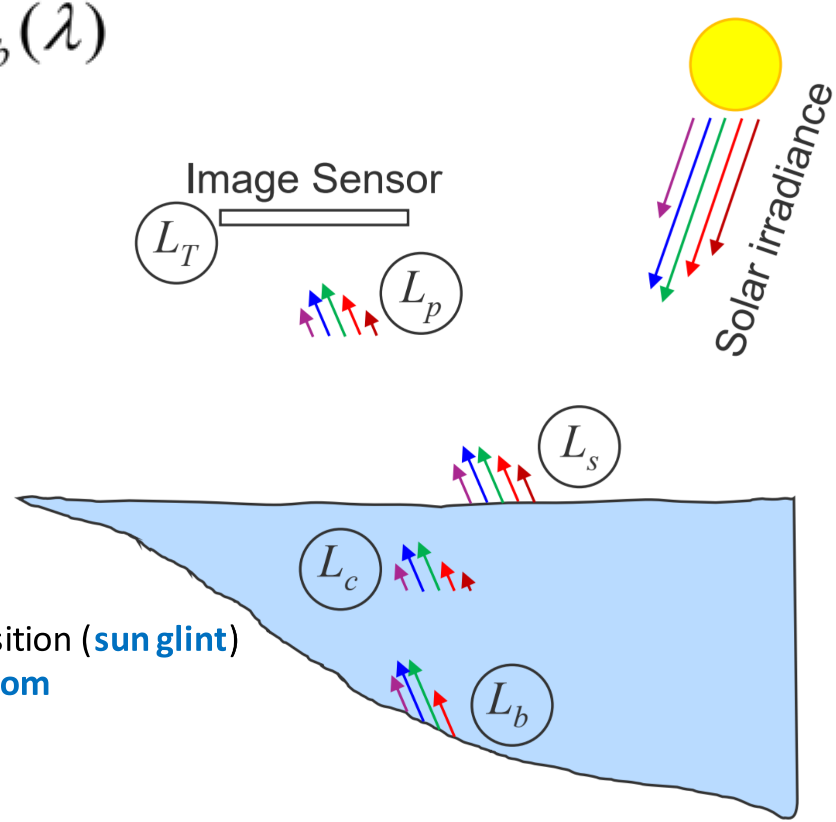
Basics of SBB

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

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**)

Slide retrieved from Mandlburger 2017, "Bathymetry from active and passive airborne remote sensing – looking back and ahead"

Colour loss – light absorption

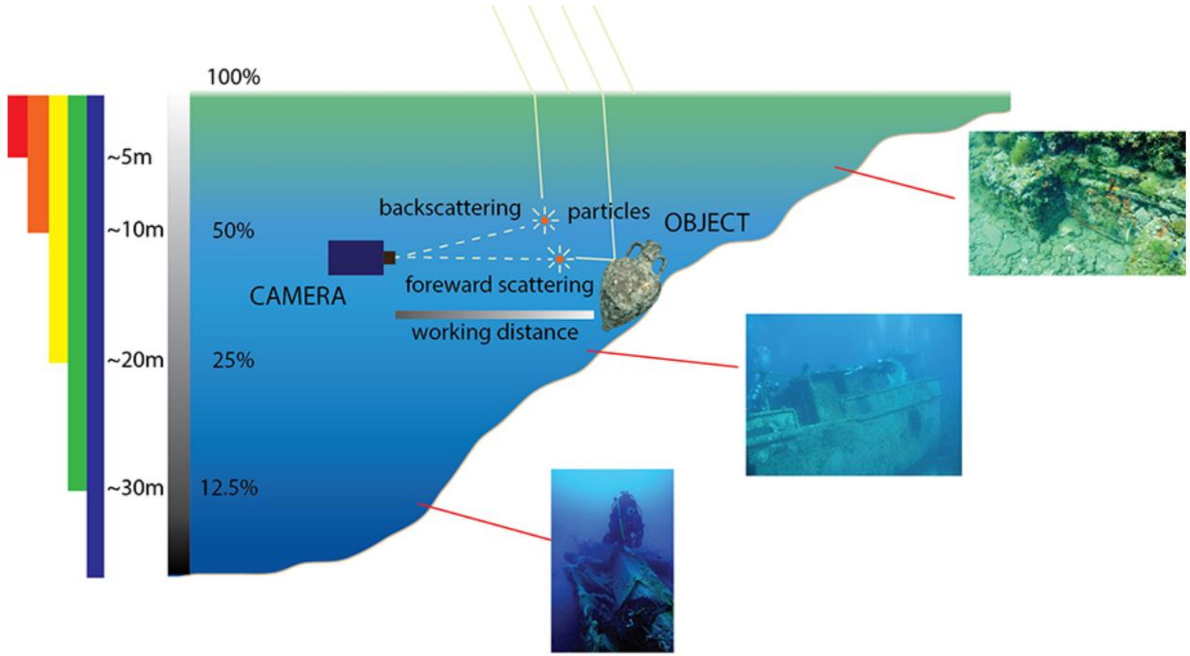


Figure: Bianco et al., 2015

Colour loss – light absorption

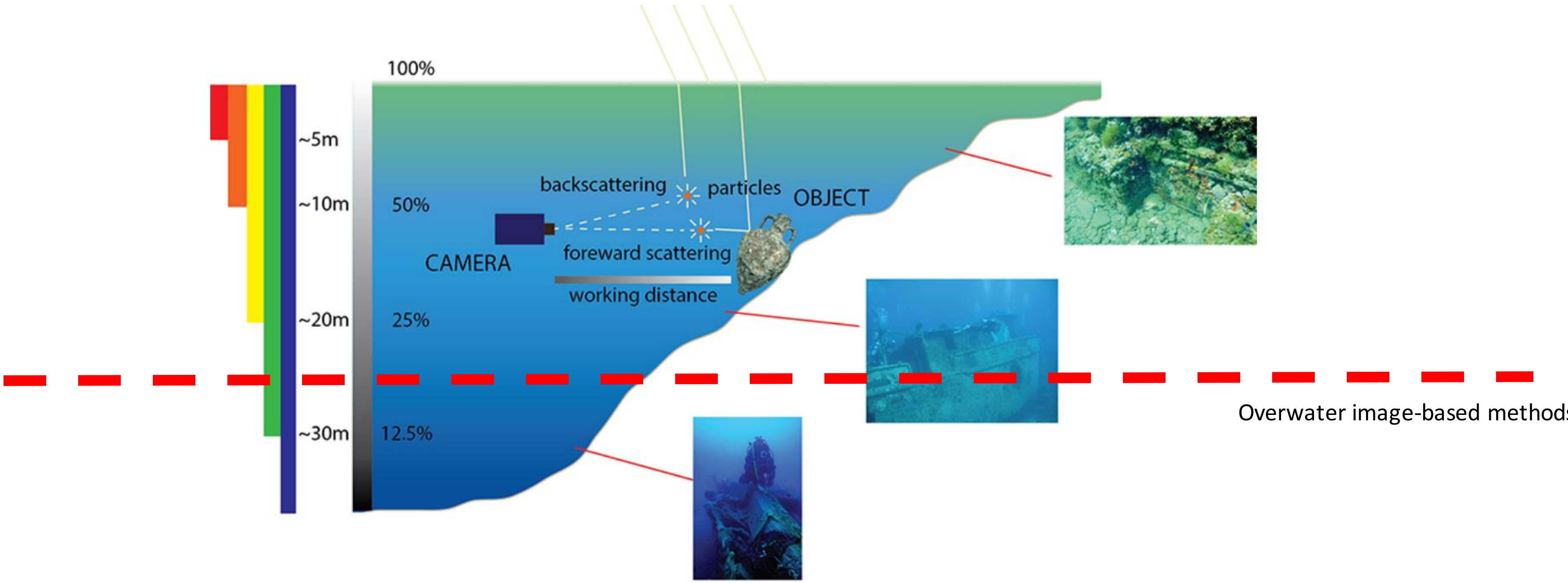


Figure: Bianco et al., 2015

Common colour-to-depth relation/methodology in SBB

- 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 0 m

- Empirically tune coefficients
- Tuning successful with chart soundings/LiDAR etc.
- Generalized model

- Cluster-Based Method (CBR)
- SVMs
- CNNs

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Factors affecting SBB (UAV or satellite)

Sun glint - Turbidity - High Aerosol

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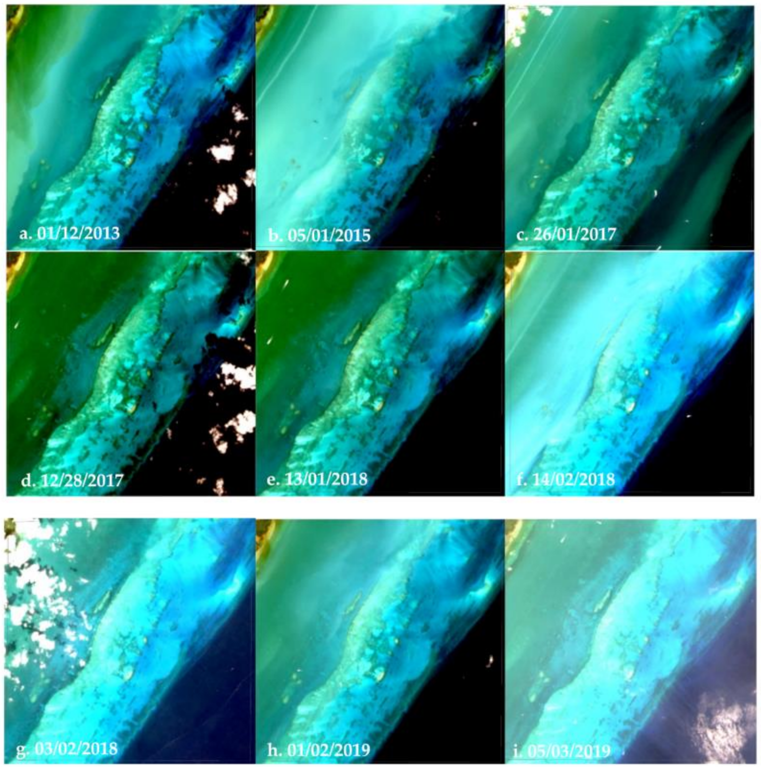
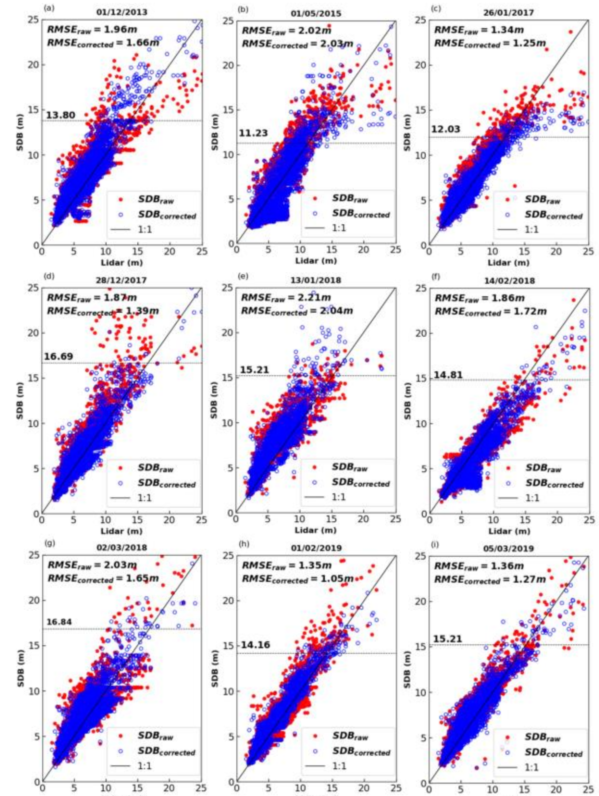
Factors affecting SBB (UAV or satellite) - Solution

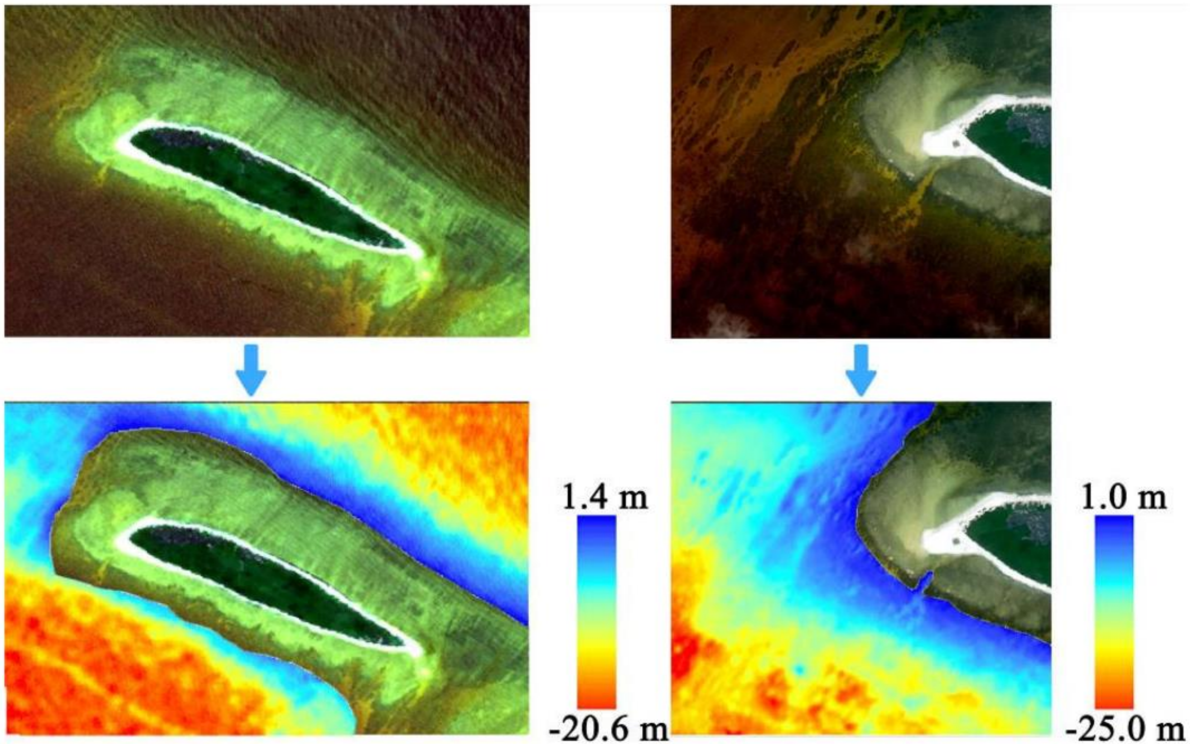
Multi-scene processing to improve the accuracy





Figures: Ilori and Knudby, 2020

Deep Learning for SBB



A modified ResNet

Ai, Bo, et al. "Convolutional neural network to retrieve water depth in marine shallow water area from remote sensing images." *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 13 (2020): 2888-2898.

Fine tuning SBB ML/DL models with LiDAR data

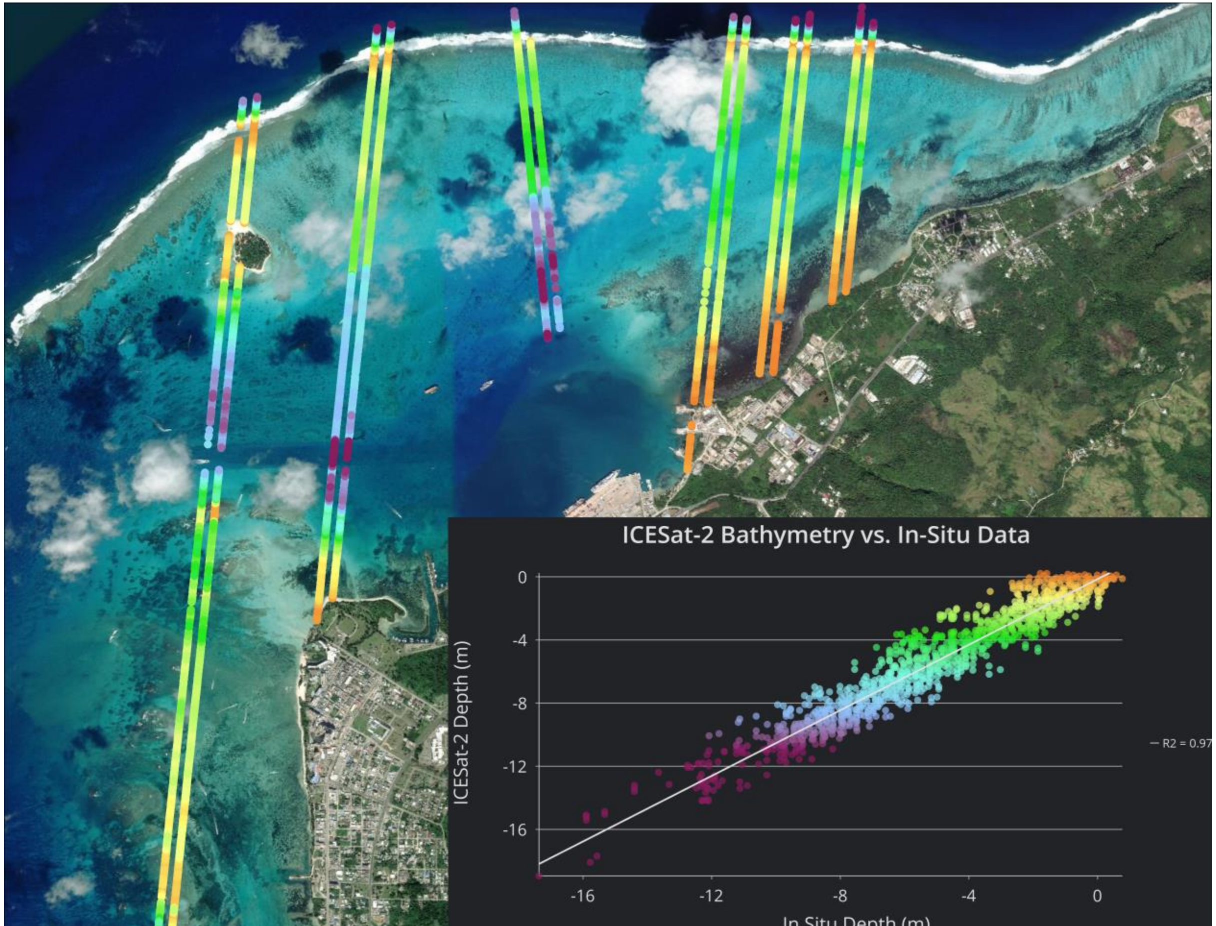
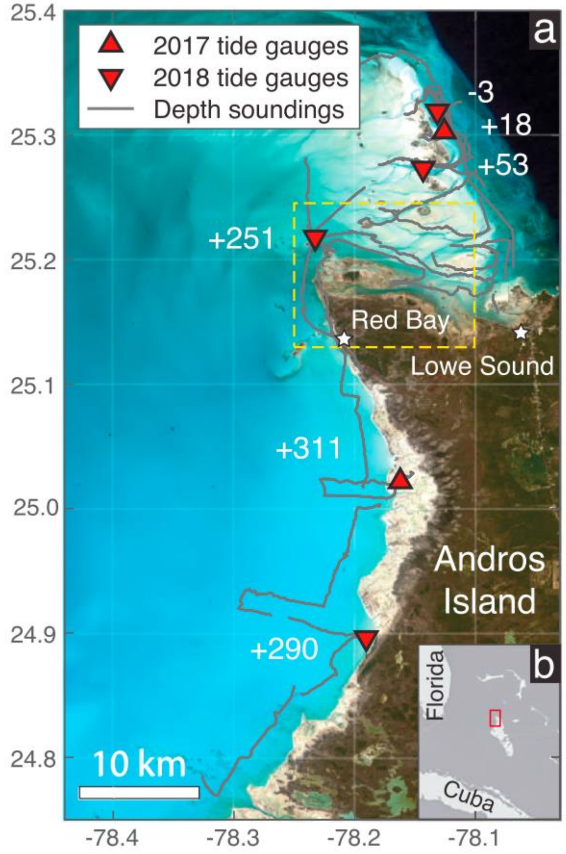
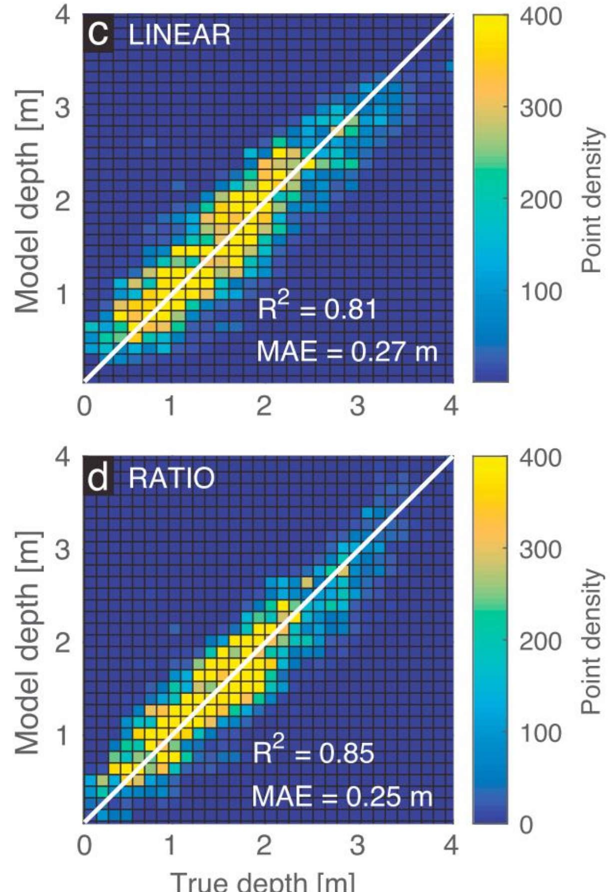
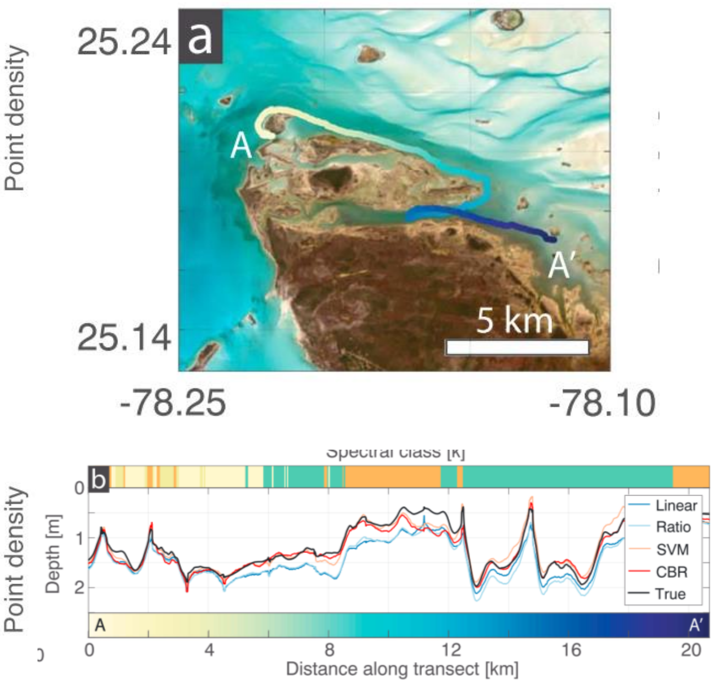


Figure: TCARTA, https://www.tcarta.com/events/geospatial-intelligence-month-april-2020

Examples-SBB – Satellite-borne



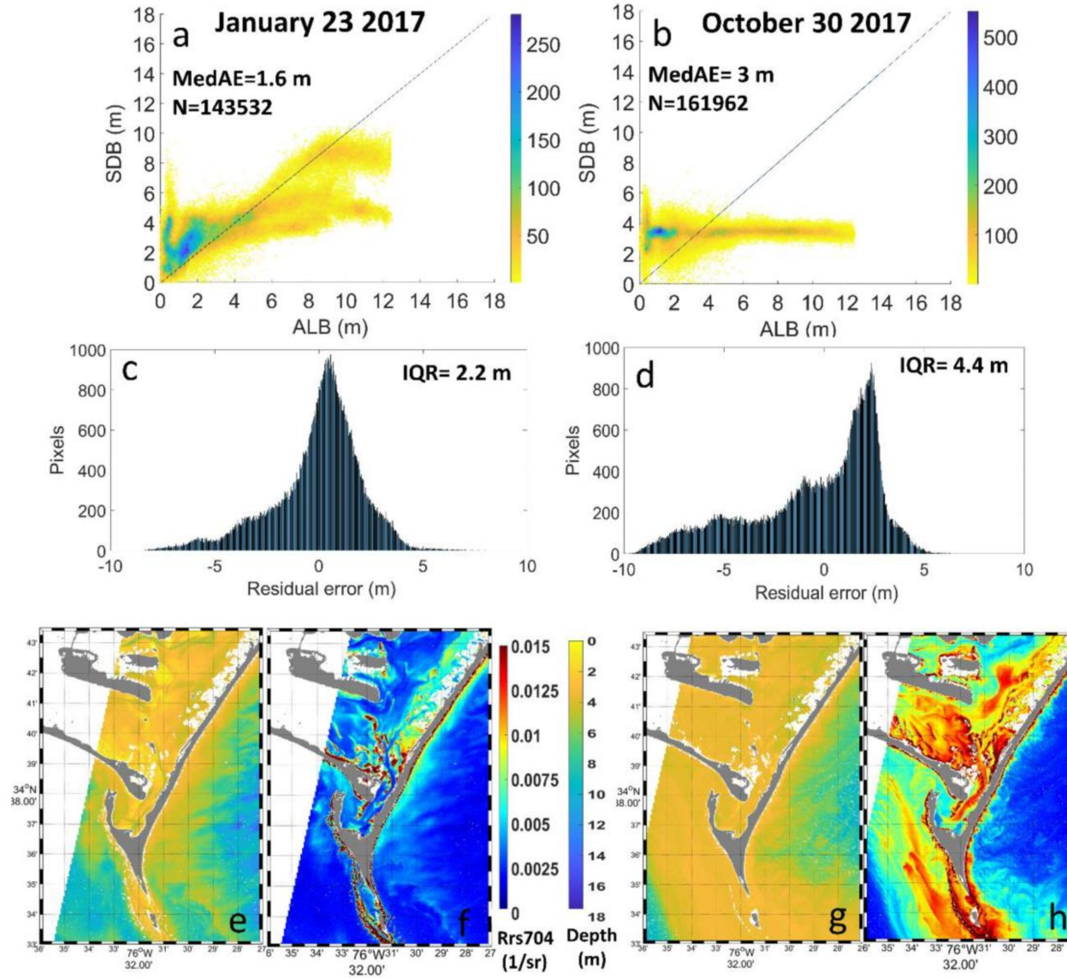




Figures: Geyman and Maloof, 2019

Examples-SBB – Satellite-borne – Variation of depths through time

Figures: Caballero and Stumpf, 2020



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Wrap up

Geometric Methods (Multi-media SfM-MVS) - <u>refraction correction is necessary!</u>

- Passive method
- Geometric
- Requires texture to perform SfM-MVS
- Measured depth through triangulation & Delivers colour information
- <u>Delivers high point density in shallow water areas</u>
- Max depth ~ 1 Secchi

Spectrally based methods

- <u>No sophisticated geometry processing necessary</u>
- Requires visibility of bottom features (similar to SfM-MVS, but not texture is required here)
- Can handle certain differences in substrate type and water clarity
- Requires ground-truth for calibrating coefficients
- <u>Covers large areas (satellite)</u>
- Max depth ~ 1 Secchi

- Lack generalization potential due to the daily/seasonal etc . variability of spectral values

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