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Maximum likelihood estimation for hyperspectral remote sensing of coastal environments: a pixelwise approach

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⁶ CS Systèmes d'Information

⁷ DGA/DS/MRIS

Ocean Optics XXIII

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Introduction

□ Characterization of marine environments from optical remote sensing

✓ Open ocean :

- Characterization of water turbidity (phytoplankton pigments, colored dissolved organic matter and suspended matter).
- Ok with multispectral imagery using a few well-positioned spectral bands in the VIS, e.g., *O'Reilly et al. 1998; Lee et al. 2002; Werdell et al., 2013...*

✓ Coastal areas :

- Characterization of water turbidity + depth + bottom cover,
- Decoupling these effects more accurate with hyperspectral imagery, i.e., using more (a few dozen) and narrower spectral bands in the VIS (*Hochberg & Atkinson, 2003; Kutser et al, 2003; Hedley et al., 2012; Botha et al., 2013*),

□ Hyperspectral remote sensing of shallow waters mostly done using :

- ✓ A semi-analytical (SA) model of subsurface remote-sensing reflectance (*Lee et al, 1998, 1999; Albert & Mobley, 2003*): $\tilde{r}_{rs} = \tilde{r}_{rs}(\Theta)$ where Θ = targeted parameters,
- ✓ An inversion method that solves

$$\hat{\Theta} = \underset{\Theta}{\operatorname{argmin}} f(\mathbf{r}_{rs}, \tilde{r}_{rs}(\Theta))$$

Cost function Measured reflectance SA Model (or exact RTM simulations)

Iterative optimization, e.g., *Lee et al. (1999, 2001); Brando et al. (2009); Dekker et al. (2011); Giardino et al. (2012); Garcia et al (2014); Mc Kinna et al. (2015); Jay & Guillaume (2016)...*

Look-Up Tables (LUT), e.g., *Mobley et al., (2005); Hedley et al., (2009, 2012)...*

Introduction

□ About the cost function...

- ✓ Mostly the Least-Square (LS) criterion (or Euclidean distance):

$$f(\mathbf{r}_{rs}, \tilde{\mathbf{r}}_{rs}(\Theta)) = \sqrt{(\mathbf{r}_{rs} - \tilde{\mathbf{r}}_{rs}(\Theta))^t (\mathbf{r}_{rs} - \tilde{\mathbf{r}}_{rs}(\Theta))} = \sqrt{\sum_{\lambda} (r_{rs}(\lambda) - \tilde{r}_{rs}(\lambda; \Theta))^2}$$

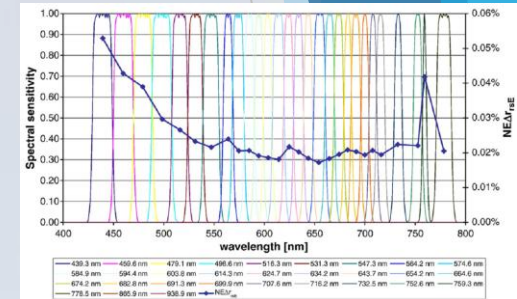
- ✓ But, LS optimal if...

- Noise variance (e.g., $NE\Delta r_E^2$) = wavelength-independent

- ➔ Some solutions :

- (1) remove the noisiest bands, e.g., *Mobley et al (2005)*, or
- (2) weight each waveband by the inverse of $NE\Delta r_E^2$ (*Brando et al., 2009; Botha et al., 2013*).

(Brando et al, 2009)



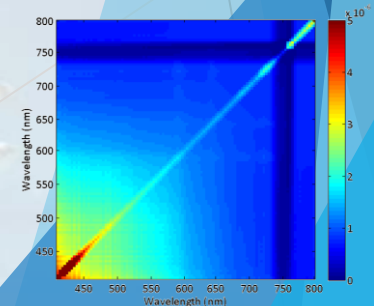
- Wavebands uncorrelated

« As homogeneous as possible »
optically-deep water

- ✓ Accounting for the full spectral covariance matrix Γ ?



Spectral covariance matrix =
spectrally-correlated version of $NE\Delta r_E^2$



Introduction

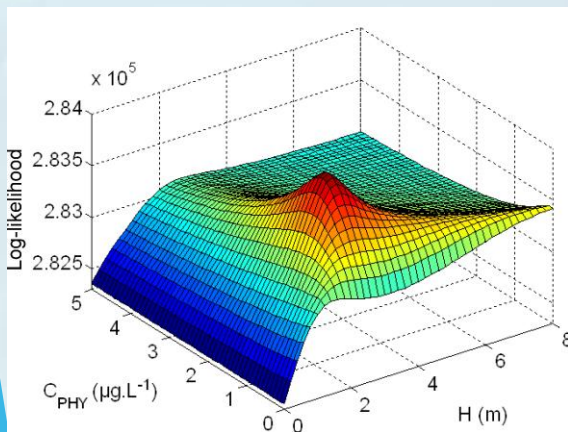
Maximum likelihood (ML) estimation, some first attempts...

- ✓ $\mathbf{r}_{rs} \sim \mathcal{N}(\boldsymbol{\mu}(\boldsymbol{\Theta}); \boldsymbol{\Gamma}(\boldsymbol{\Theta}))$ where (1) $\boldsymbol{\mu}(\boldsymbol{\Theta}) = \tilde{\mathbf{r}}_{rs}(\boldsymbol{\Theta}) = \text{SA model}$
(2) $\boldsymbol{\Gamma}(\boldsymbol{\Theta})$ estimated on a local neighborhood, within which $\boldsymbol{\Theta}$ is assumed to be constant (Jay et Guillaume., 2012) or to vary linearly (Jay & Guillaume, 2014).

- ✓ $\hat{\boldsymbol{\Theta}}_{ML} = \underset{\boldsymbol{\Theta}}{\operatorname{argmax}} \prod_i \frac{1}{\sqrt{(2\pi)^L |\boldsymbol{\Gamma}|}} e^{-0,5(\mathbf{r}_{rs,i} - \tilde{\mathbf{r}}_{rs}(\boldsymbol{\Theta}))^t \boldsymbol{\Gamma}^{-1}(\mathbf{r}_{rs,i} - \tilde{\mathbf{r}}_{rs}(\boldsymbol{\Theta}))}$

- ✓ ++ (1) Account for spectral and spatial correlations, (2) Accuracy \nearrow if assumptions are fully met
- ✓ -- (1) Loss in spatial resolution, (2) Accuracy \searrow if assumptions are not fully met...

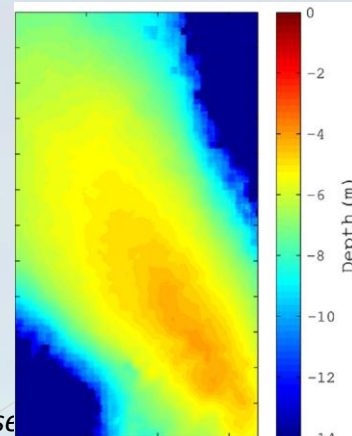
A pixelwise ML method ?



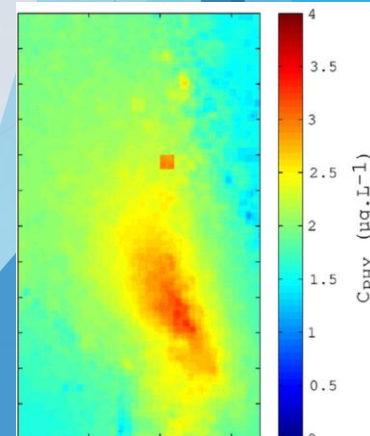
estimation f



note se



ents



Outlines

- Methods
 - ✓ Proposed ML methods,
 - ✓ Comparison methods,
 - ✓ Implementation,
- Data
- Results

Proposed ML methods

- Assumption: $\mathbf{r}_{rs} \sim \mathcal{N}(\boldsymbol{\mu}(\boldsymbol{\Theta}); \boldsymbol{\Gamma}(\boldsymbol{\Theta})) \Leftrightarrow \mathbf{r}_{rs} = \boldsymbol{\mu}(\boldsymbol{\Theta}) + \mathbf{n}$ where $\mathbf{n} \sim \mathcal{N}(\mathbf{0}; \boldsymbol{\Gamma}(\boldsymbol{\Theta}))$
- Goal: parameterize $\boldsymbol{\mu}(\boldsymbol{\Theta})$ and $\boldsymbol{\Gamma}(\boldsymbol{\Theta})$ as a function of water column parameters
- Mean vector parameterized by a SA model (Lee et al, 1998; 1999)
 - ✓ $\mu(\lambda; \boldsymbol{\Theta}) = \tilde{r}_{rs}(\lambda; \boldsymbol{\Theta}) = r_{rs, \infty}(\lambda)(1 - e^{-(k_a(\lambda) + k_u^c(\lambda))H}) + (1/\pi)[B_1 \rho_{b,1}(\lambda) + B_2 \rho_{b,2}(\lambda)]e^{-(k_a(\lambda) + k_u^b(\lambda))H}$
 - ✓ Or in matrix notation $\boldsymbol{\mu}(\boldsymbol{\Theta}) = \tilde{\mathbf{r}}_{rs}(\boldsymbol{\Theta}) = (\mathbf{I} - \mathbf{K}_c)\mathbf{r}_{rs, \infty} + (1/\pi)\mathbf{K}_b(B_1 \boldsymbol{\rho}_{b,1} + B_2 \boldsymbol{\rho}_{b,2})$
 - ✓ $\boldsymbol{\Theta} = (H, P, G, X, B_1, B_2)$
 - ✓ Importantly, two options for bottom parameterization:
 - $\sum_i B_i = 1$ (Klonowski et al, 2007; Goodman & Ustin, 2007; Brando et al, 2009; Hedley et al, 2009; 2012)
 - ➔ ++ : only one parameter $B = B_1 = 1 - B_2$ (= fractional cover of substratum 1)
 - ➔ -- : bottom within-class variability is poorly accounted for.
 - $\sum_i B_i \neq 1$ (Fearnas et al, 2011; Garcia et al, 2014)
 - ➔ ++ : the bottom within-class variability is accounted for through a brightness factor.
 - ➔ -- : two parameters B_1 and B_2 (= fractional cover + within-class variability)

Proposed ML methods

□ Parameterization of covariance matrix

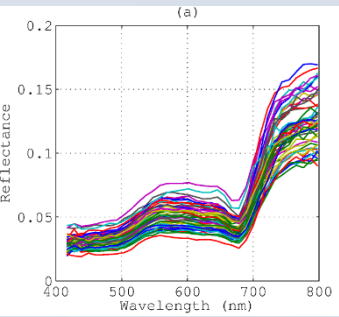
- ✓ Case 1: No bottom within-class variability (if sum-to-one) / bottom within-class variabilities perfectly described by brightness factors (if no sum-to-one)

$$\text{> } \mathbf{r}_{rs} = \underbrace{(\mathbf{I} - \mathbf{K}_c)\mathbf{r}_{rs,\infty} + (1/\pi)\mathbf{K}_b(B_1\boldsymbol{\rho}_{b,1} + B_2\boldsymbol{\rho}_{b,2})}_{\text{deterministic}} + \underbrace{\mathbf{n}_s}_{\text{random}}$$

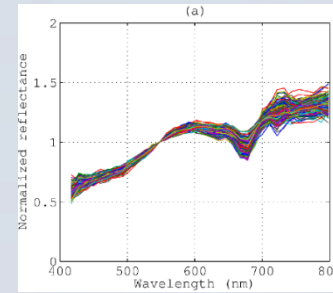
- text> $\mathbf{n} = \mathbf{n}_s \sim \mathcal{N}(\mathbf{0}; \boldsymbol{\Gamma}_s)$, where $\boldsymbol{\Gamma}_s$ is a spectrally-correlated version of the environmental noise $NE\Delta r_E^2$ and is estimated over an « as homogeneous as possible » area of optically-deep water.
- text> \mathbf{n}_s describes the sensor noise and scene-specific above-water variabilities (residuals from imperfect ATM, air-water interface and sun glint corrections, effects related to the rough water surface, etc) (Brando & Dekker, 2003; Wettle et al, 2004)

used ML methods

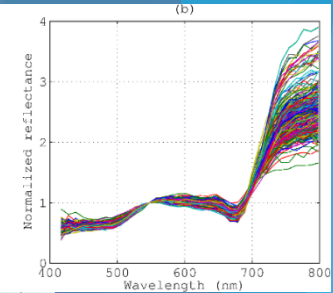
Actual seagrass spectra



Sand spectra normalized at 550 nm

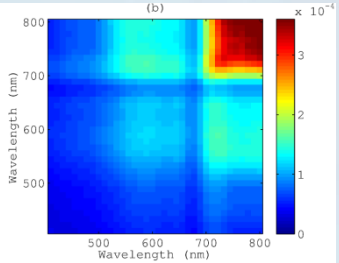


Seagrass spectra normalized at 550 nm



Parameterization of covariance matrix

Seagrass covariance matrix



Case 2: bottom within-class variabilities not perfectly represented using brightness factors

- Two Gaussian distributions with covariances $\Gamma_{b,1}$ and $\Gamma_{b,2}$ are used to describe within-class variabilities,
- A single factor B is used to describe the fractional cover of substratum 1 ($B \leq 1$)

$$\mathbf{r}_{RS} = (\mathbf{I} - \mathbf{K}_c)\mathbf{r}_{RS,\infty} + \mathbf{K}_b(1/\pi)[B(\boldsymbol{\rho}_{b,1} + \mathbf{n}_{b,1}) + (1 - B)(\boldsymbol{\rho}_{b,2} + \mathbf{n}_{b,2})] + \mathbf{n}_s$$

$$\mathbf{r}_{RS} = \underbrace{\mathbf{r}_{RS,\infty}(\mathbf{I} - \mathbf{K}_c) + (1/\pi)(B\boldsymbol{\rho}_{b,1} + (1 - B)\boldsymbol{\rho}_{b,2})\mathbf{K}_b}_{\text{deterministic}} + \underbrace{\mathbf{K}_b(B\mathbf{n}_{b,1} + (1 - B)\mathbf{n}_{b,2}) + \mathbf{n}_s}_{\text{random}}$$

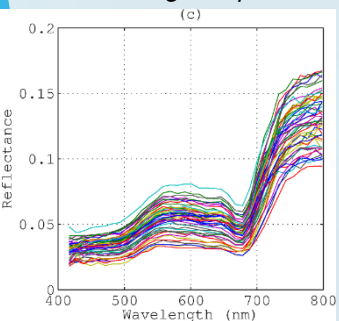
- In this case, it can be shown that

$$\Gamma = \underbrace{\mathbf{K}_b[B^2\Gamma_{b,1} + (1 - B)^2\Gamma_{b,2}]\mathbf{K}_b}_{\text{bottom variability} = f(\Theta)} + \underbrace{\Gamma_s}_{\text{above-water variability} \neq f(\Theta)}$$

- Decoupling of the influences of within-class variabilities and fractional covers !

- ✓ Only one parameter to estimate for bottom parameterization (= fractional cover), AND
- ✓ Bottom within-class variability is accounted for (but not estimated).

Simulated seagrass spectra



Proposed ML methods / Comparison methods

- ML 1: $\mu(\Theta) = \tilde{r}_{rs}(\Theta)$, $\Gamma = \Gamma_s$ and $\Theta = (H, P, G, X, B_1, B_2)$

$$\checkmark \hat{\Theta}_{ML1} = \underset{\Theta}{\operatorname{argmax}} \frac{1}{\sqrt{(2\pi)^L |\Gamma_s|}} e^{-0,5(\mathbf{r}_{rs} - \tilde{r}_{rs}(\Theta))^t \Gamma_s^{-1} (\mathbf{r}_{rs} - \tilde{r}_{rs}(\Theta))} = \underset{\Theta}{\operatorname{argmin}} (\mathbf{r}_{rs} - \tilde{r}_{rs}(\Theta))^t \Gamma_s^{-1} (\mathbf{r}_{rs} - \tilde{r}_{rs}(\Theta))$$

- ML 2: $\mu(\Theta) = \tilde{r}_{rs}(\Theta)$, $\Gamma = \Gamma_s + \mathbf{K}_b [B^2 \Gamma_{b,1} + (1 - B)^2 \Gamma_{b,2}] \mathbf{K}_b$ and $\Theta = (H, P, G, X, B)$

$$\checkmark \hat{\Theta}_{ML2} = \underset{\Theta}{\operatorname{argmax}} \frac{1}{\sqrt{(2\pi)^L |\Gamma|}} e^{-0,5(\mathbf{r}_{rs} - \tilde{r}_{rs}(\Theta))^t \Gamma^{-1} (\mathbf{r}_{rs} - \tilde{r}_{rs}(\Theta))}$$

- LS \approx $\mu(\Theta) = \tilde{r}_{rs}(\Theta)$, $\Gamma = \sigma^2 \mathbf{I}$ and $\Theta = (H, P, G, X, B)$ or $\Theta = (H, P, G, X, B_1, B_2)$

$$\checkmark \hat{\Theta}_{LS} = \underset{\Theta}{\operatorname{argmin}} (\mathbf{r}_{rs} - \tilde{r}_{rs}(\Theta))^t (\mathbf{r}_{rs} - \tilde{r}_{rs}(\Theta)) = \underset{\Theta}{\operatorname{argmin}} \sum_{\lambda} (r_{rs}(\lambda) - \tilde{r}_{rs}(\lambda; \Theta))^2$$

Implementation

- ❑ Model inversion using iterative optimization (trust-region reflective algorithm, Matlab®),
- ❑ Pairwise estimation of the two bottom types,
- ❑ Initialization
 - ✓ Initial guesses derived from reflectance values (*Lee et al, 1999*), OR
 - ✓ Latin Hypercube Sampling (*Garcia et al, 2014*)
 - ➔ Generation of LUTs of 100,000 spectra/parameters.
 - ➔ Initial guesses corresponding to the closest spectrum in the LUT.

Data



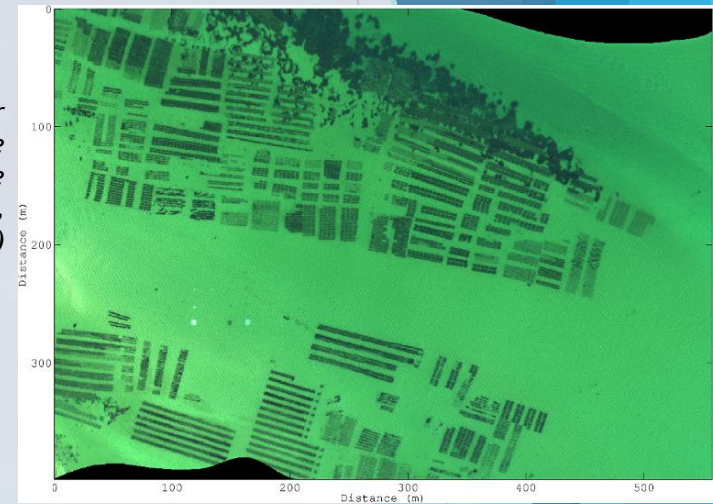
□ Real data set

- ✓ Airborne Hypsux image collected over the Quiberon Peninsula, France (Actimar, HypLitt 2012),
- ✓ Spatial resolution = 0.50 m,
- ✓ 36 spectral bands between 400 et 800 nm (spectral sampling interval ≈ 11 nm),
- ✓ $1 \text{ m} < H < 5 \text{ m}$,
- ✓ Four bottom types: sand, oyster bags, seagrass, brown algae,

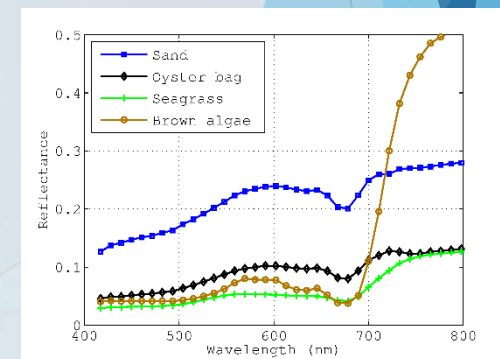
- Estimation of bottom reflectance spectra and covariance matrices from spectral data.

- + 14 additional Hypsux images of other areas of the Peninsula to validate bathymetry retrieval ($0.44 \text{ m} < H < 12 \text{ m}$)

True color composite image (deglinted, subsurface)



Bottom reflectance spectra



Data

□ Simulations

✓ Statistical modeling #1

$$\text{> } \mathbf{r}_{rs} = \underbrace{(\mathbf{I} - \mathbf{K}_c)\mathbf{r}_{rs,\infty} + (1/\pi)\mathbf{K}_b(B_1\rho_{b,1} + B_2\rho_{b,2})}_{\text{deterministic}} + \underbrace{\mathbf{n}_s}_{\text{random}}$$

✓ Statistical modeling #2

$$\text{> } \mathbf{r}_{rs} = \underbrace{\mathbf{r}_{rs,\infty}(\mathbf{I} - \mathbf{K}_c) + (1/\pi)(B\rho_{b,1} + (1 - B)\rho_{b,2})\mathbf{K}_b}_{\text{deterministic}} + \underbrace{\mathbf{K}_b(B\mathbf{n}_{b,1} + (1 - B)\mathbf{n}_{b,2}) + \mathbf{n}_s}_{\text{random}}$$

✓ H = 1; 5; 10; 15 m

✓ Intermediate water turbidity (*Garcia et al, 2015*) : P = 0.05 m⁻¹; G = 0.1 m⁻¹; X = 0.01 m⁻¹

✓ 4 pure bottom spectra + 6 mixtures of two bottom spectra (50%-50%) → 10 bottom spectra in total

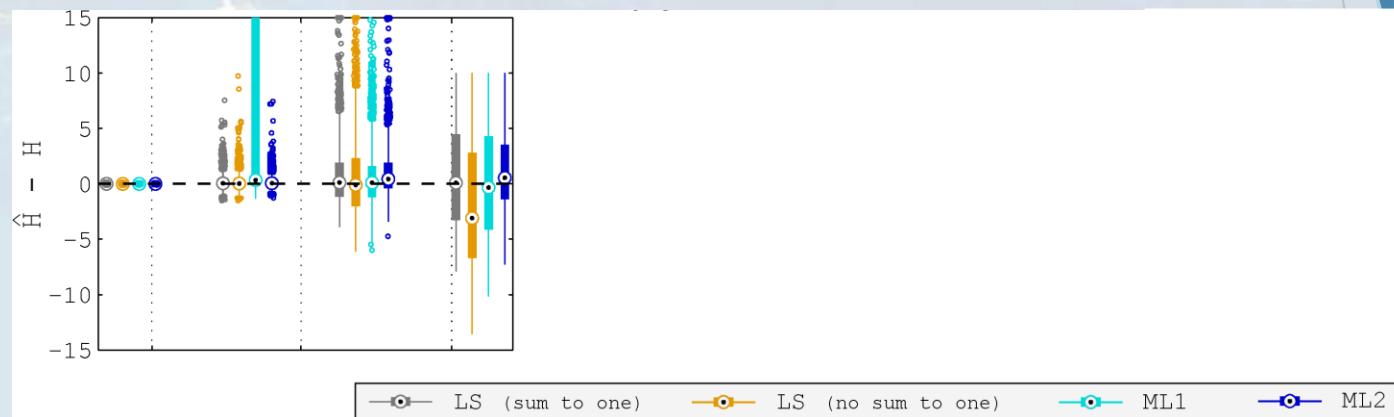
✓ For each statistical modeling, 2,000 simulations for each depth.

Results - Simulations - Statistical modeling #1

Bias of H estimation

Bias of P estimation

Bias of X estimation



Reflectance-derived initialization

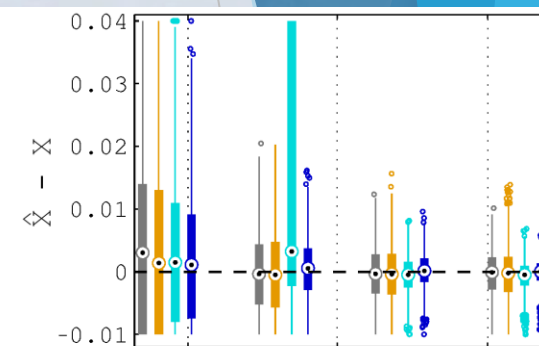
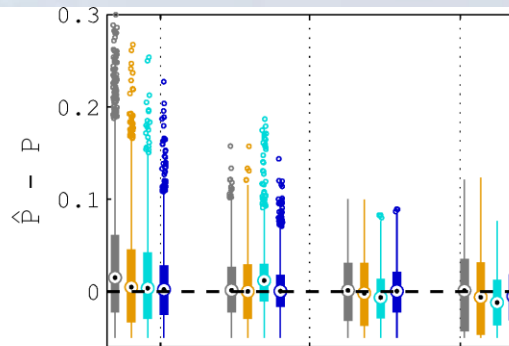
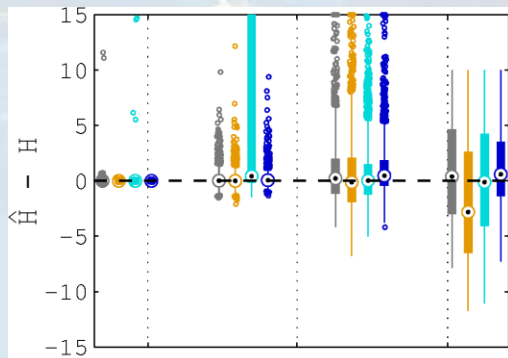
LHS sampling based initialization

Results - Simulations - Statistical modeling #2

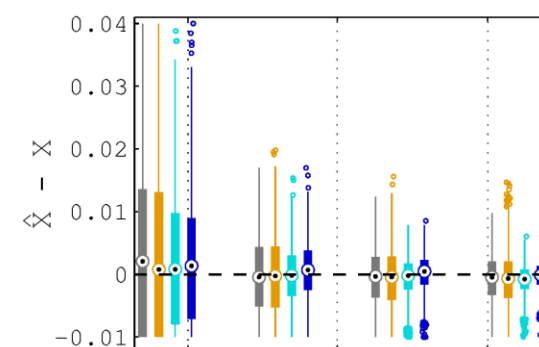
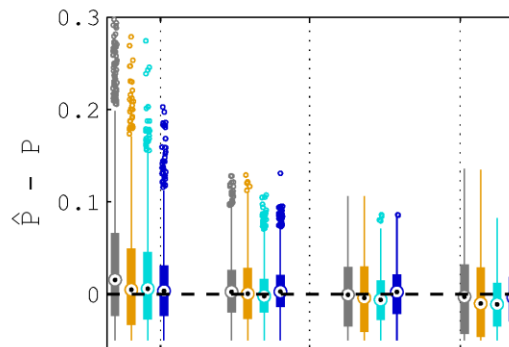
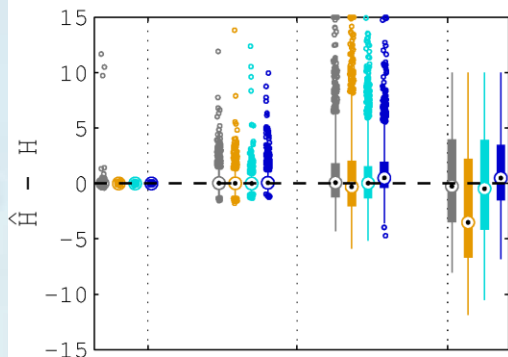
Bias of H estimation

Bias of P estimation

Bias of X estimation

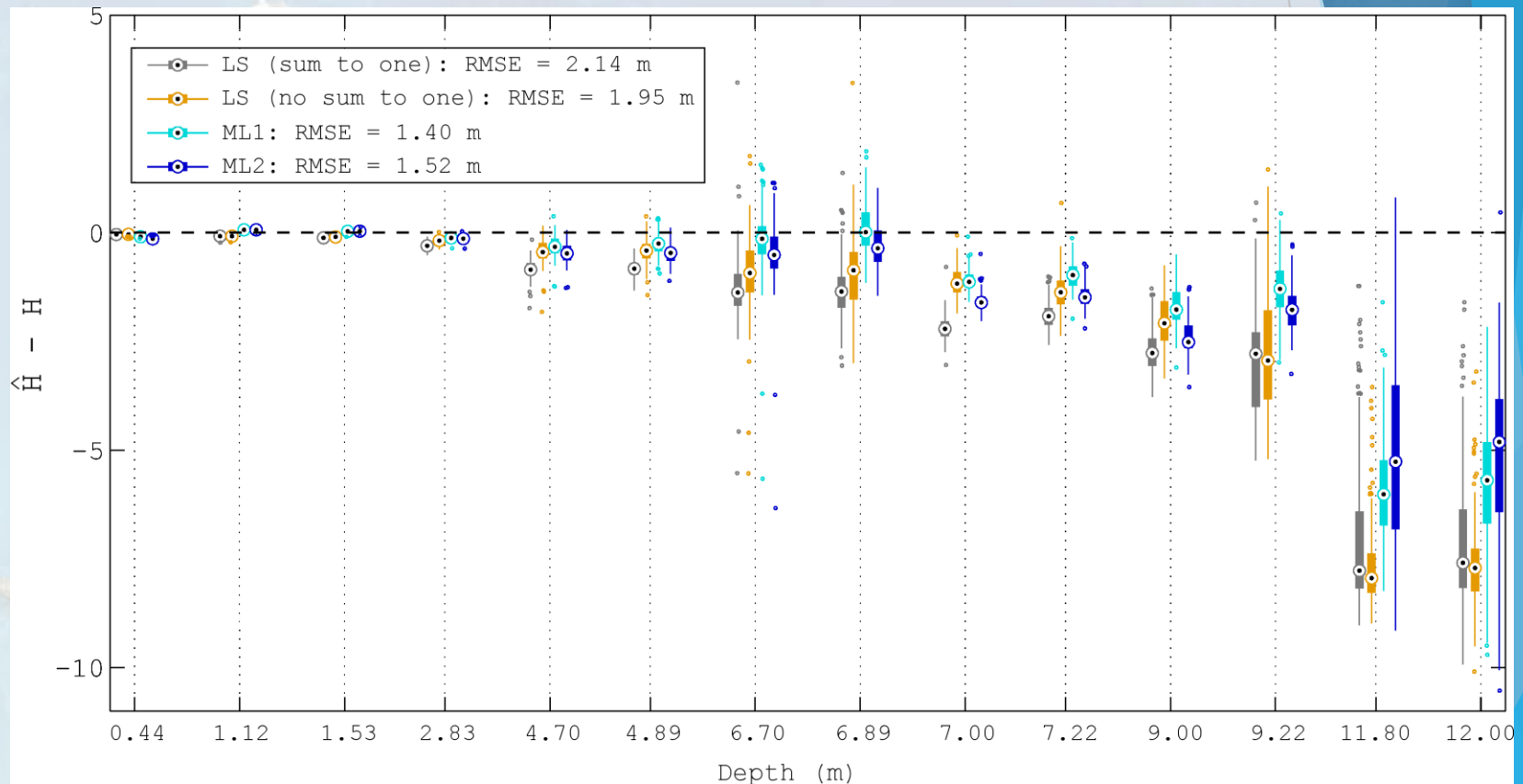


Reflectance-derived
initialization

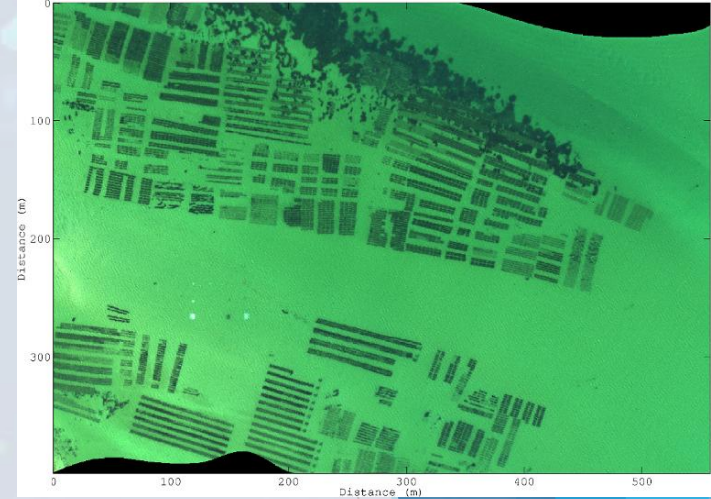


LHS sampling based
initialization

Results - Real data - Bathymetry estimation



Results - Real data - Bathymetry estimation

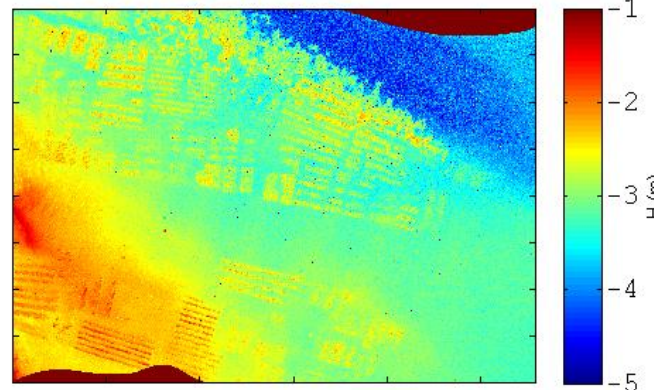
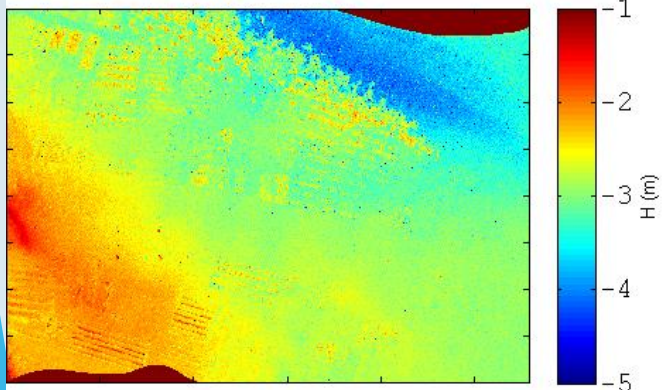


Sum-to-one

No sum-to-one

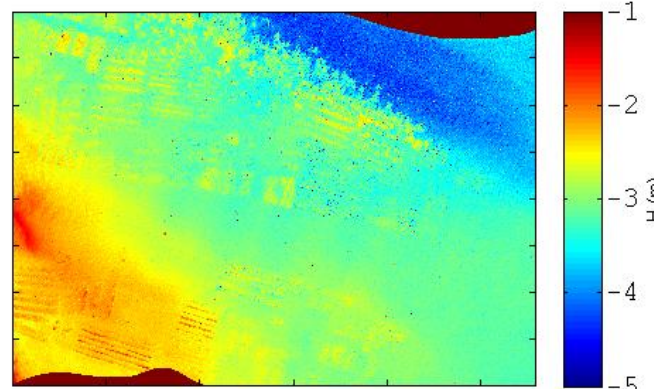
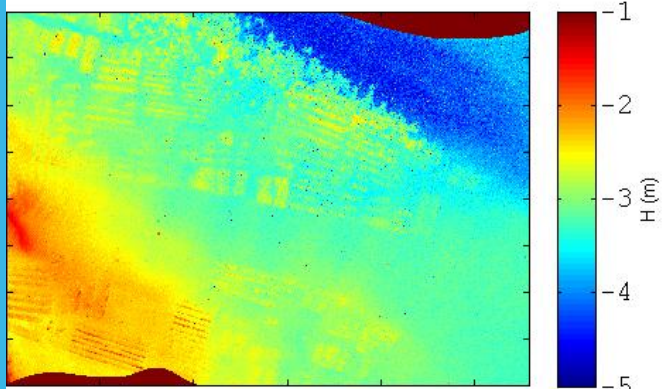
LS (sum to one)

LS (no sum to one)



ML 1

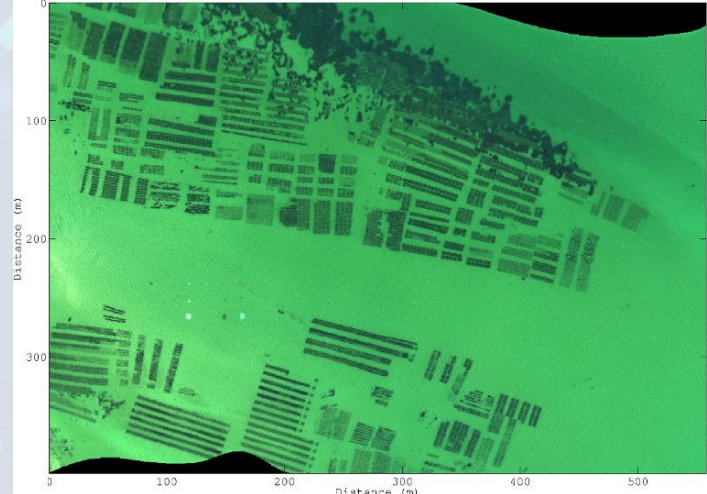
ML 2



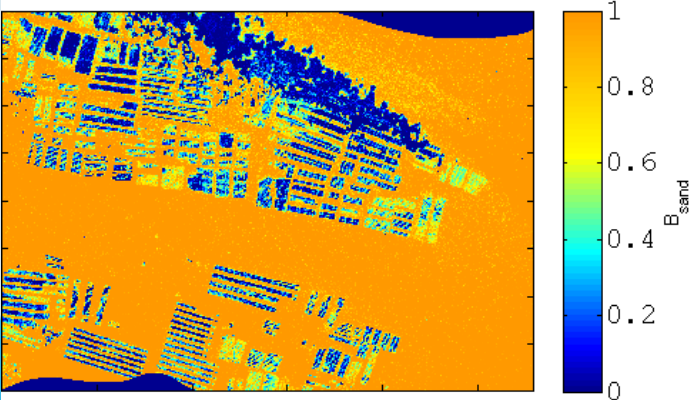
Results - Real data - Bottom cover estimation

Sum-to-one

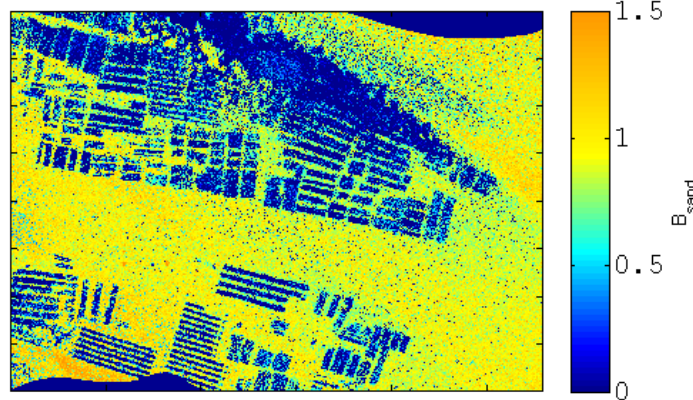
No sum-to-one



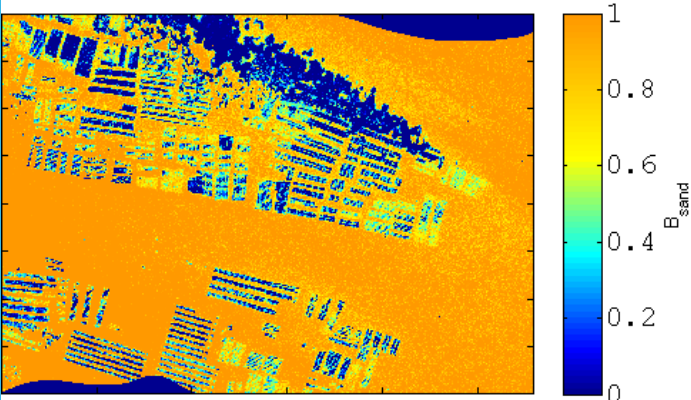
LS (sum to one)



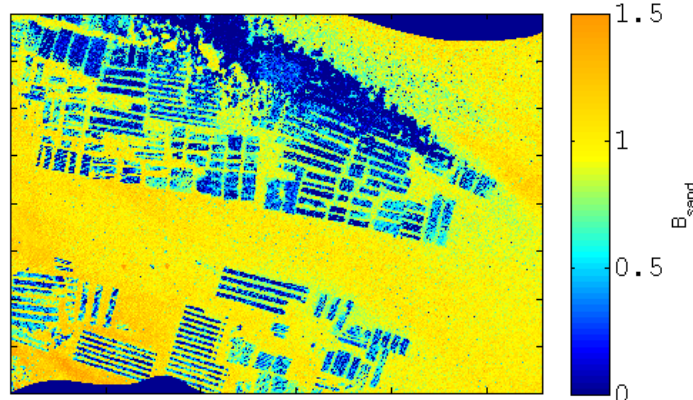
LS (no sum to one)



ML 2

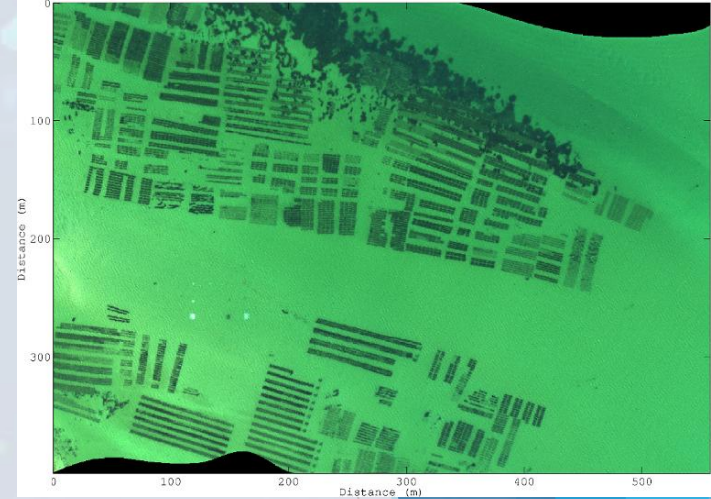


ML 1



SAND

Results - Real data - Bottom cover estimation

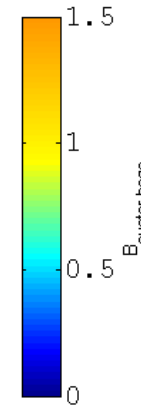
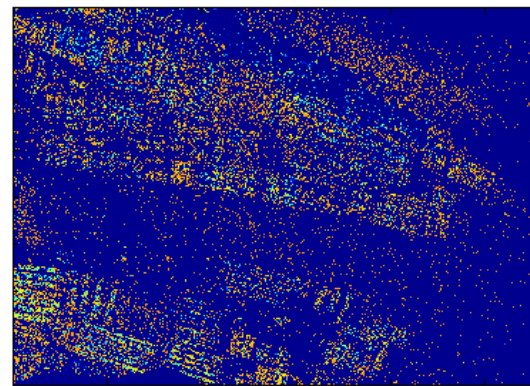
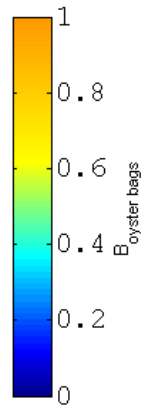
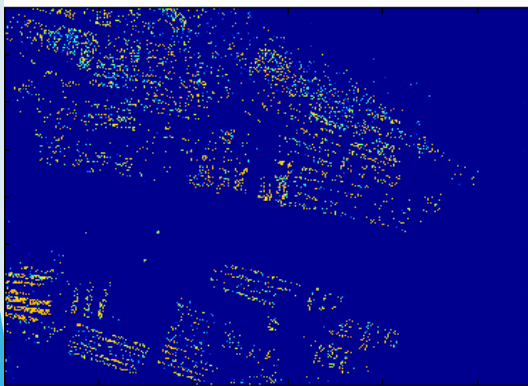


Sum-to-one

No sum-to-one

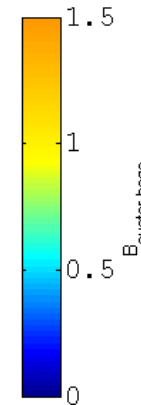
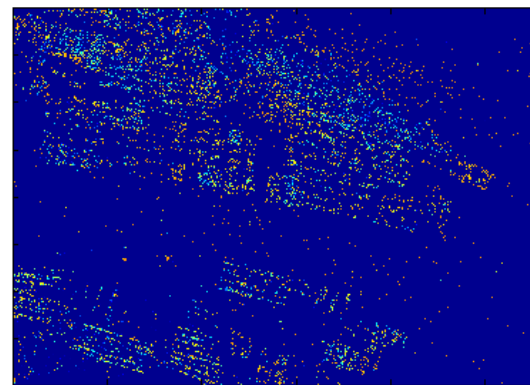
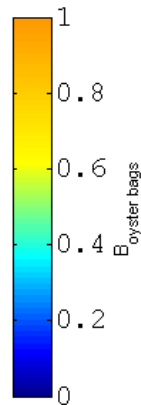
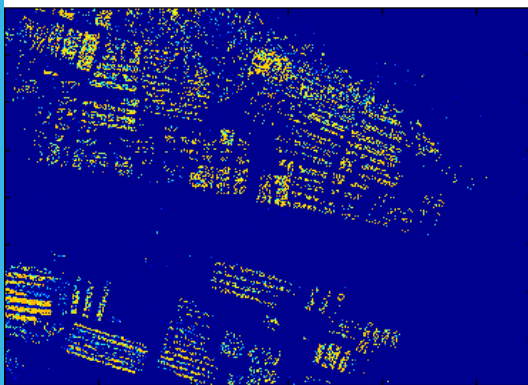
LS (sum to one)

LS (no sum to one)



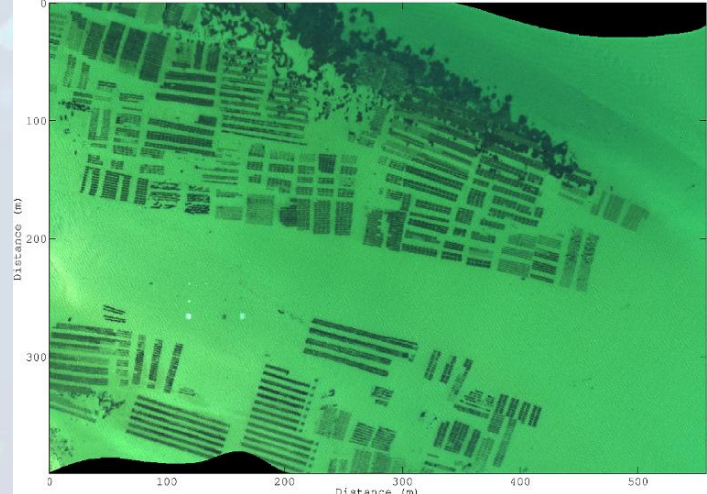
ML 2

ML 1



**OYSTER
BAGS**

Results - Real data - Bottom cover estimation

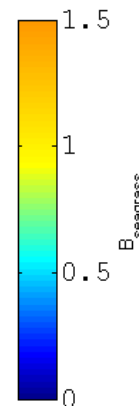
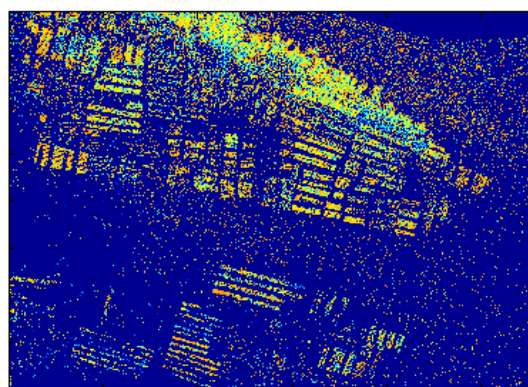
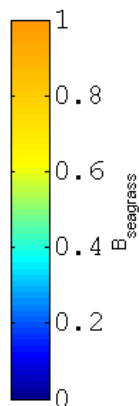
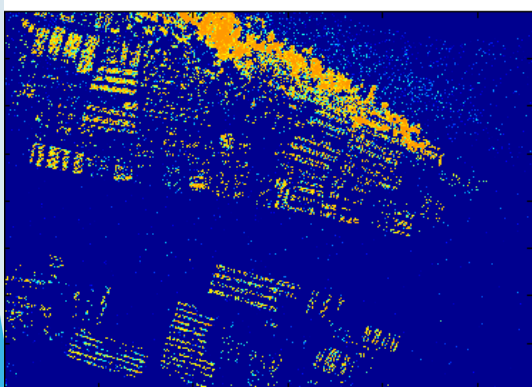


Sum-to-one

No sum-to-one

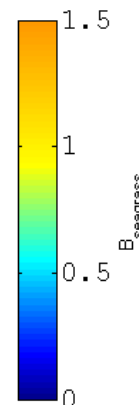
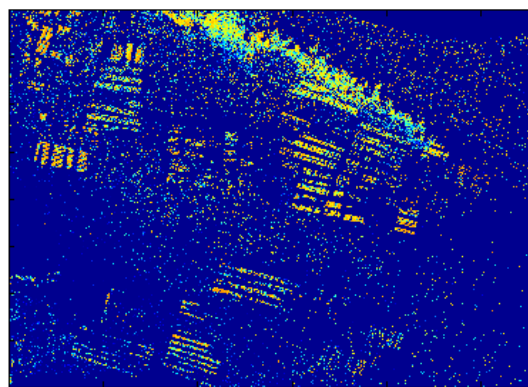
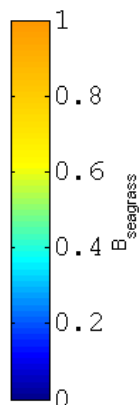
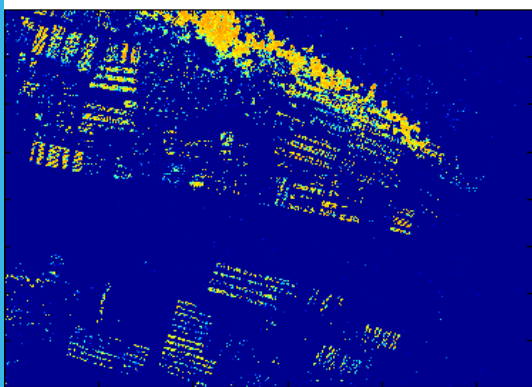
LS (sum to one)

LS (no sum to one)



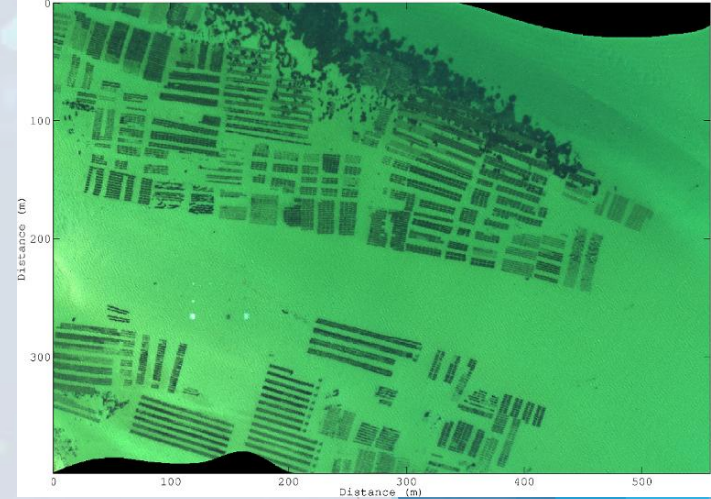
ML 2

ML 1



SEAGRASS

Results - Real data - Bottom cover estimation

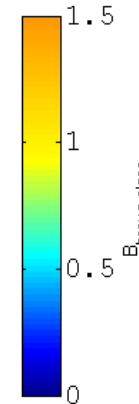
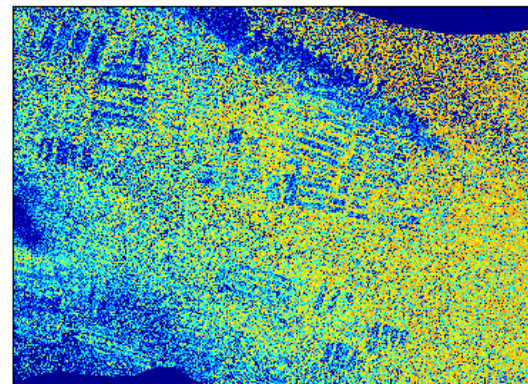
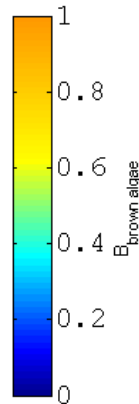
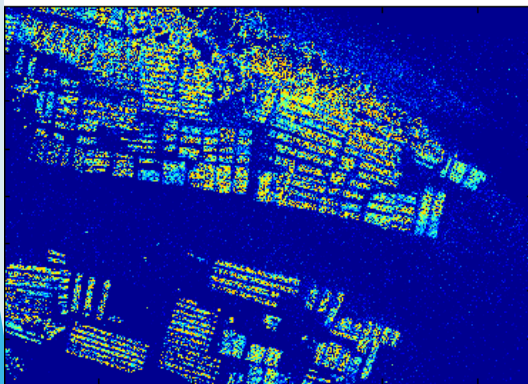


Sum-to-one

No sum-to-one

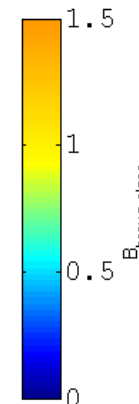
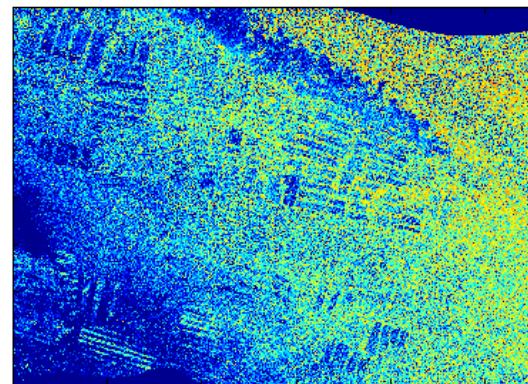
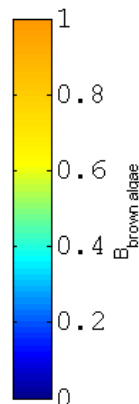
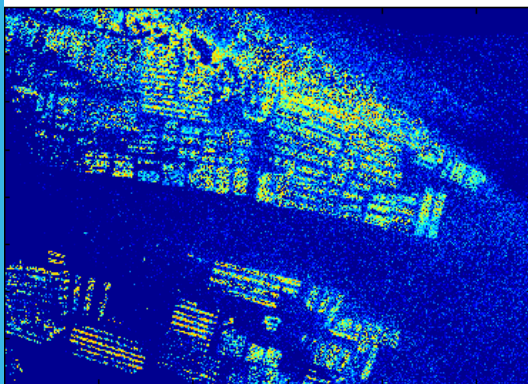
LS (sum to one)

LS (no sum to one)



ML 2

ML 1



**BROWN
ALGAE**

Conclusions & Future works...

- ❑ Most inversion methods do not account for spectral covariance,
- ❑ We propose two alternative methods (ML1 and ML2) based on Maximum Likelihood estimation to invert a SA model,
- ❑ Importance of initialization, especially for ML1,
- ❑ ML2 allows accounting for (potentially complex) bottom within-class variability while limiting the ill-posedness of the inversion problem,
- ❑ Estimation accuracy generally increases compared with LS methods,
- ❑ ML2 requires estimating bottom covariance matrices beforehand (ground-based measurements ?),

- ❑ Future works include
 - ✓ Investigating how accurate the estimation of bottom covariance matrices should be ?
Is it possible to use standard matrices ?
 - ✓ Testing LUT-based inversion to avoid local minima ?
 - ✓ ...

Thanks for your attention !!



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