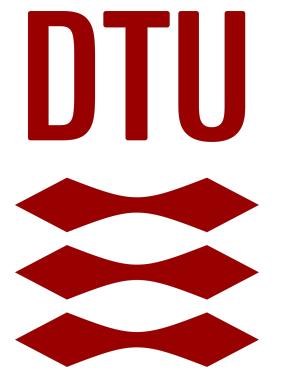


# Inferring Functions with Uncertain Regularity

SIAM UQ23 - Trieste

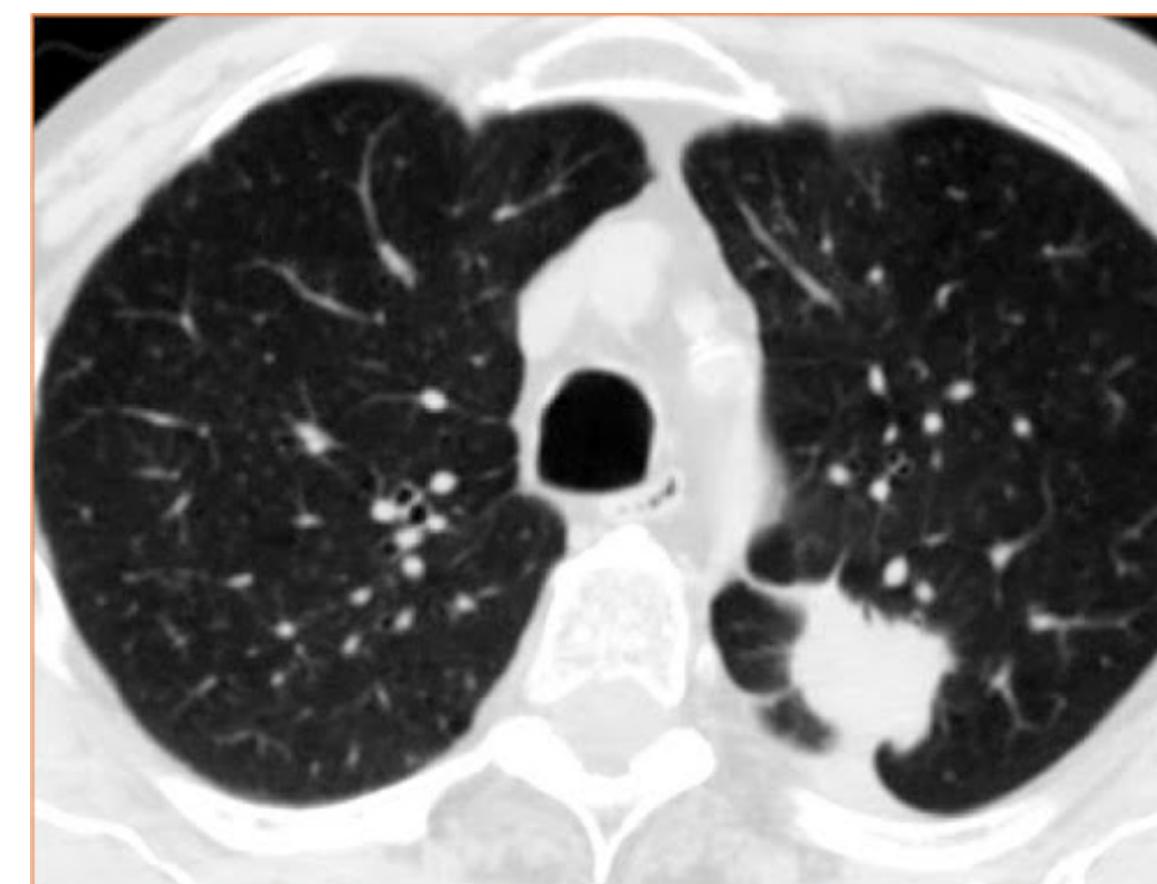
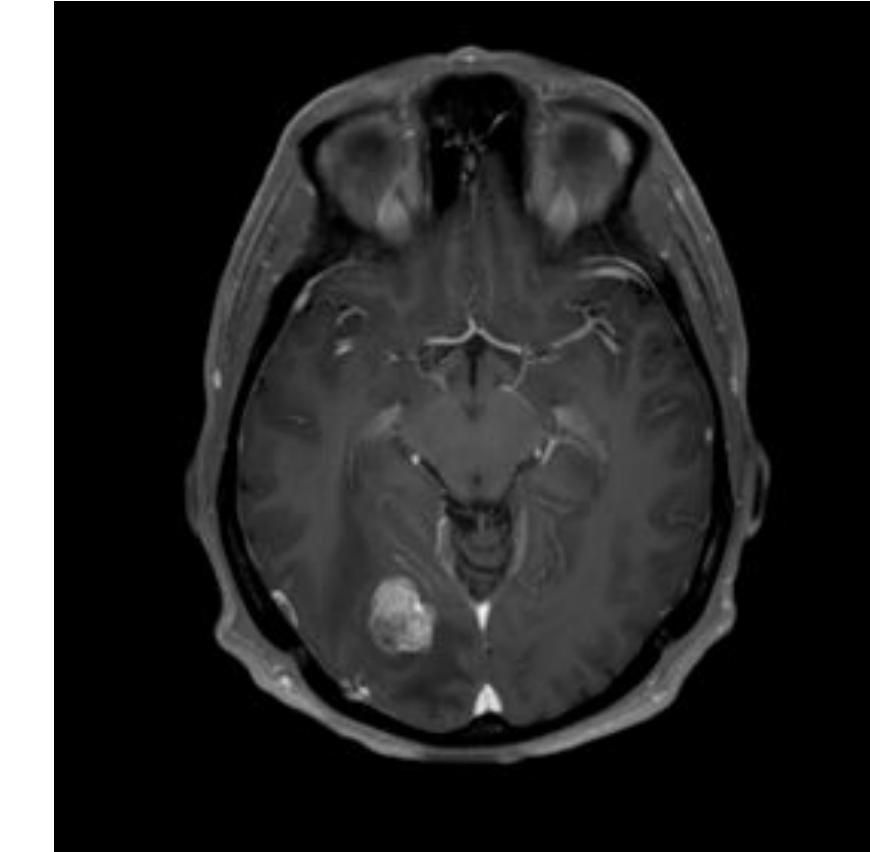
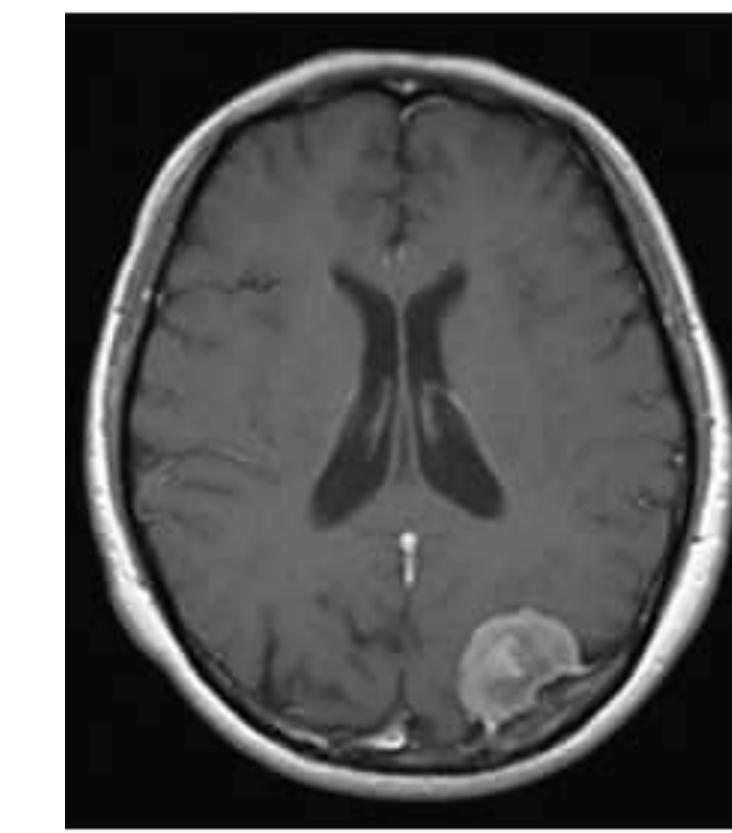
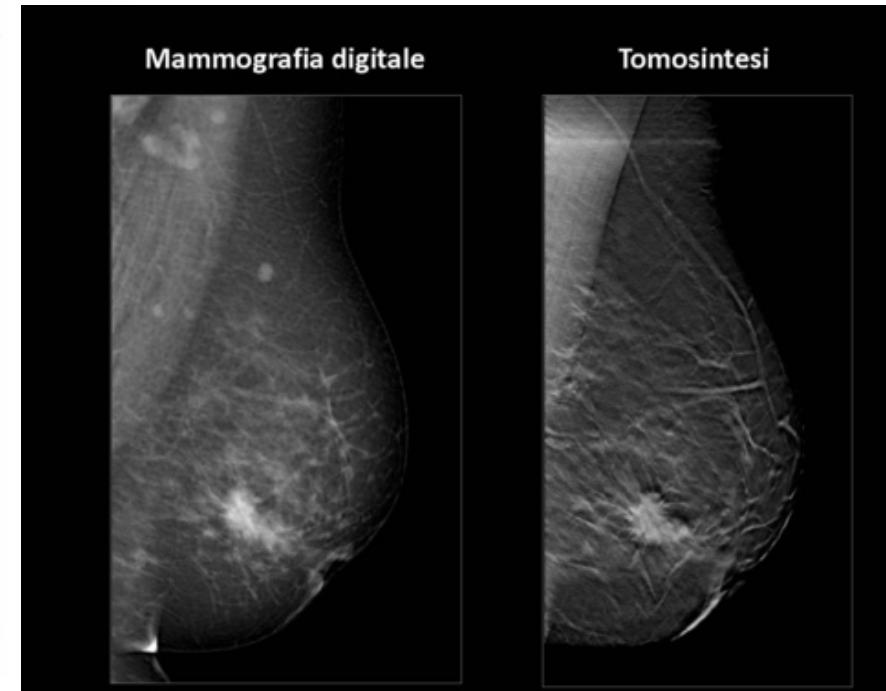
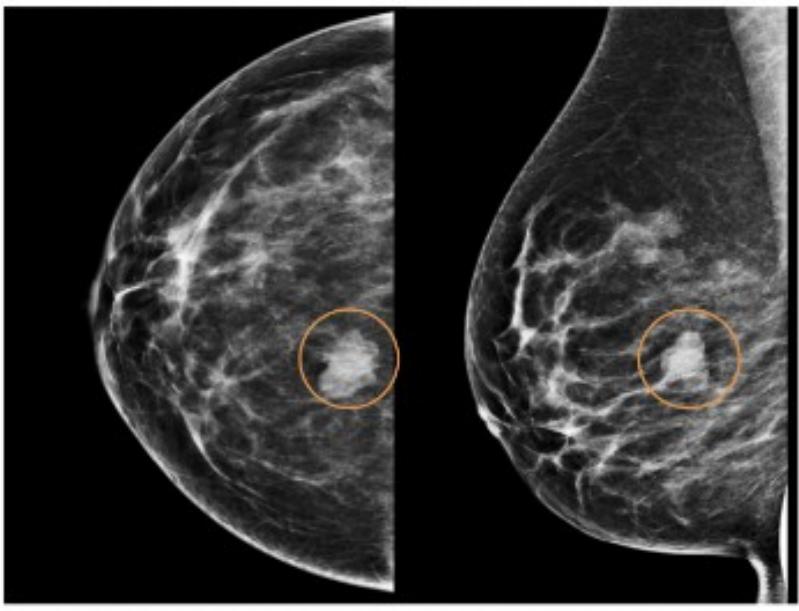


**B. M. Afkham, N. A. Riis, Y. Dong, P C. Hansen (DTU), A. Carpio (UCM)**



# Importance of Regularity In X-ray CT

MAMMOGRAFIA: NODULI BENIGNI

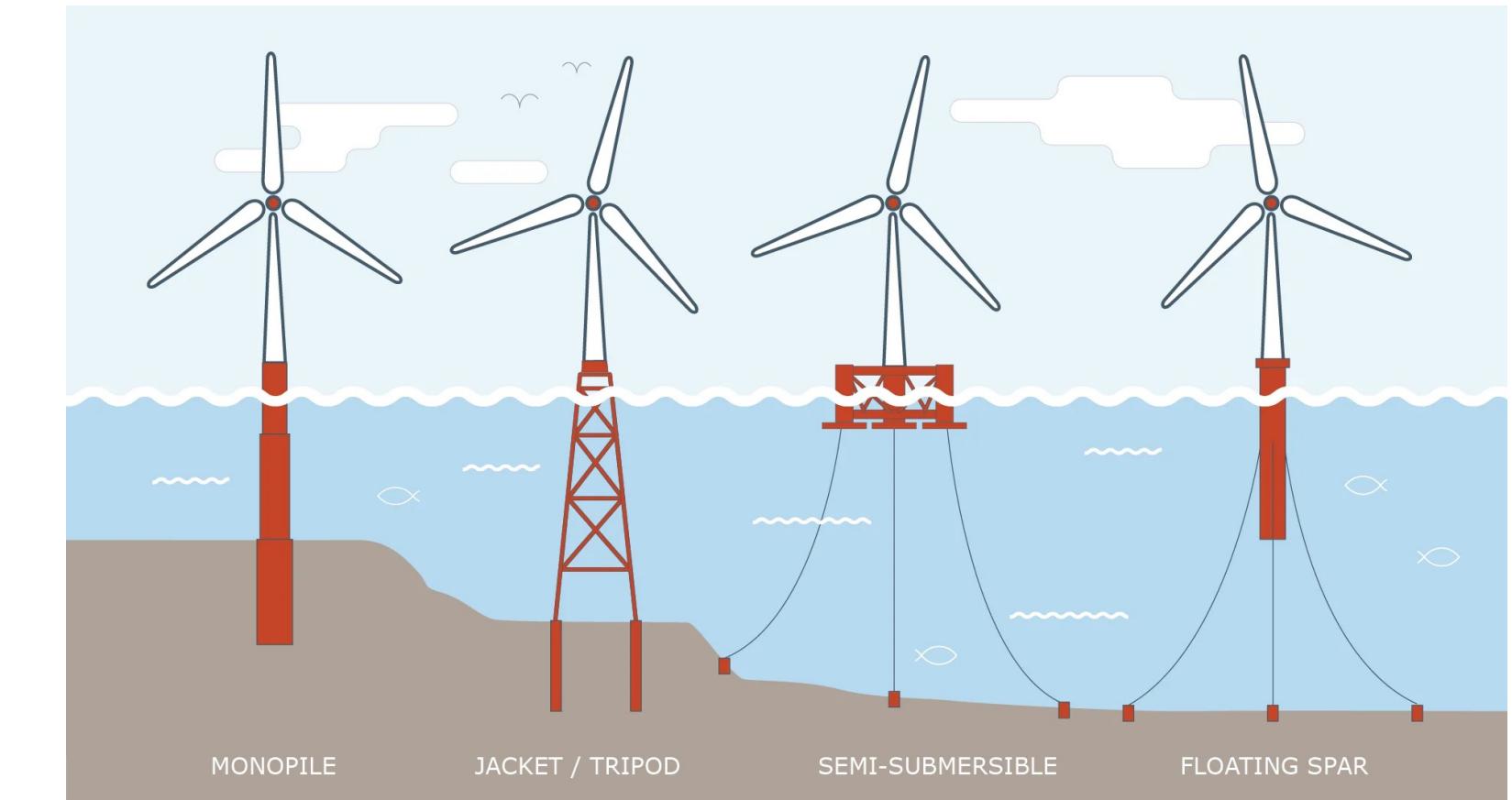
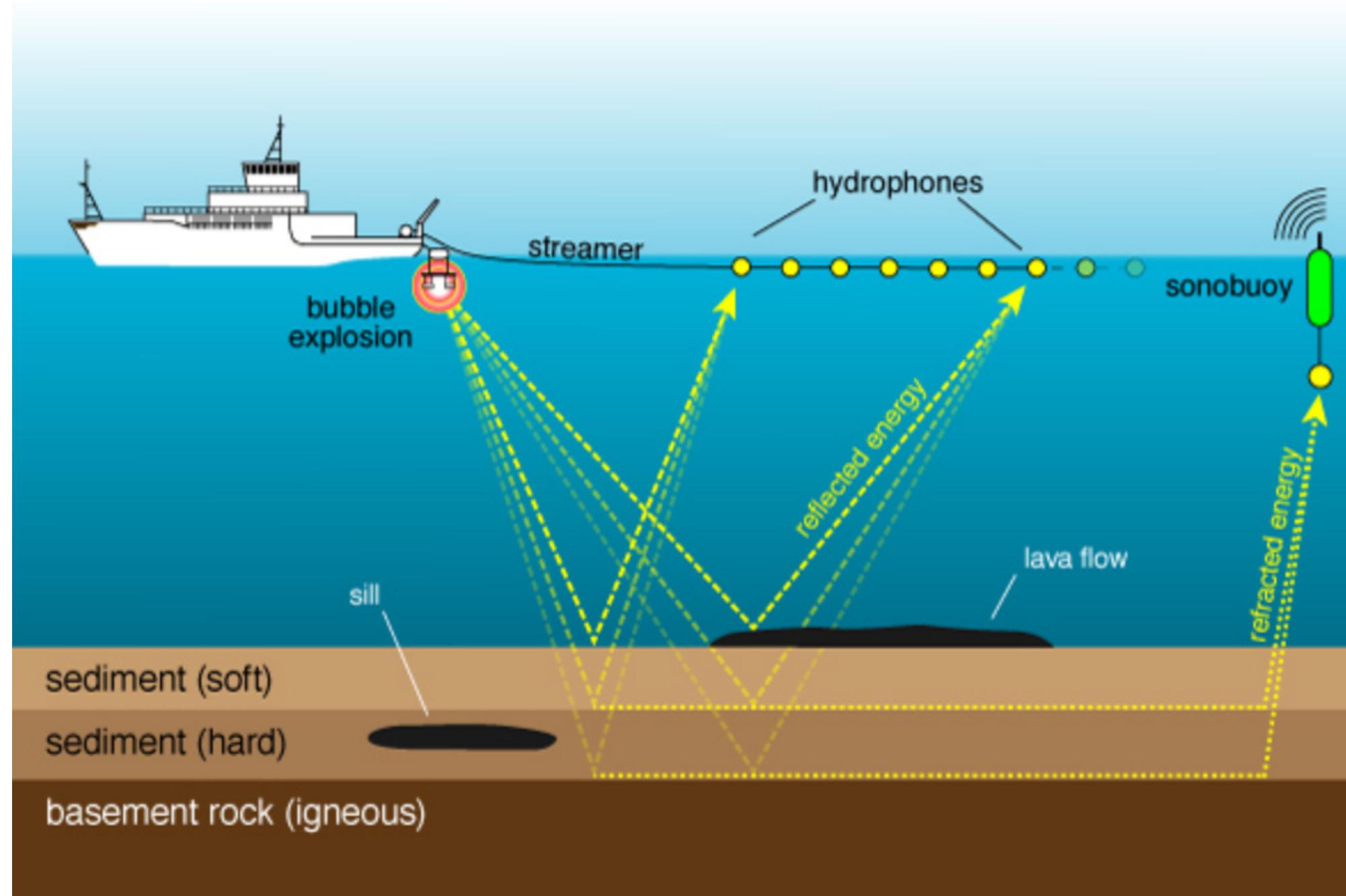


images: publicly available on Google  
info: Dr. Riccardo R. Colciago

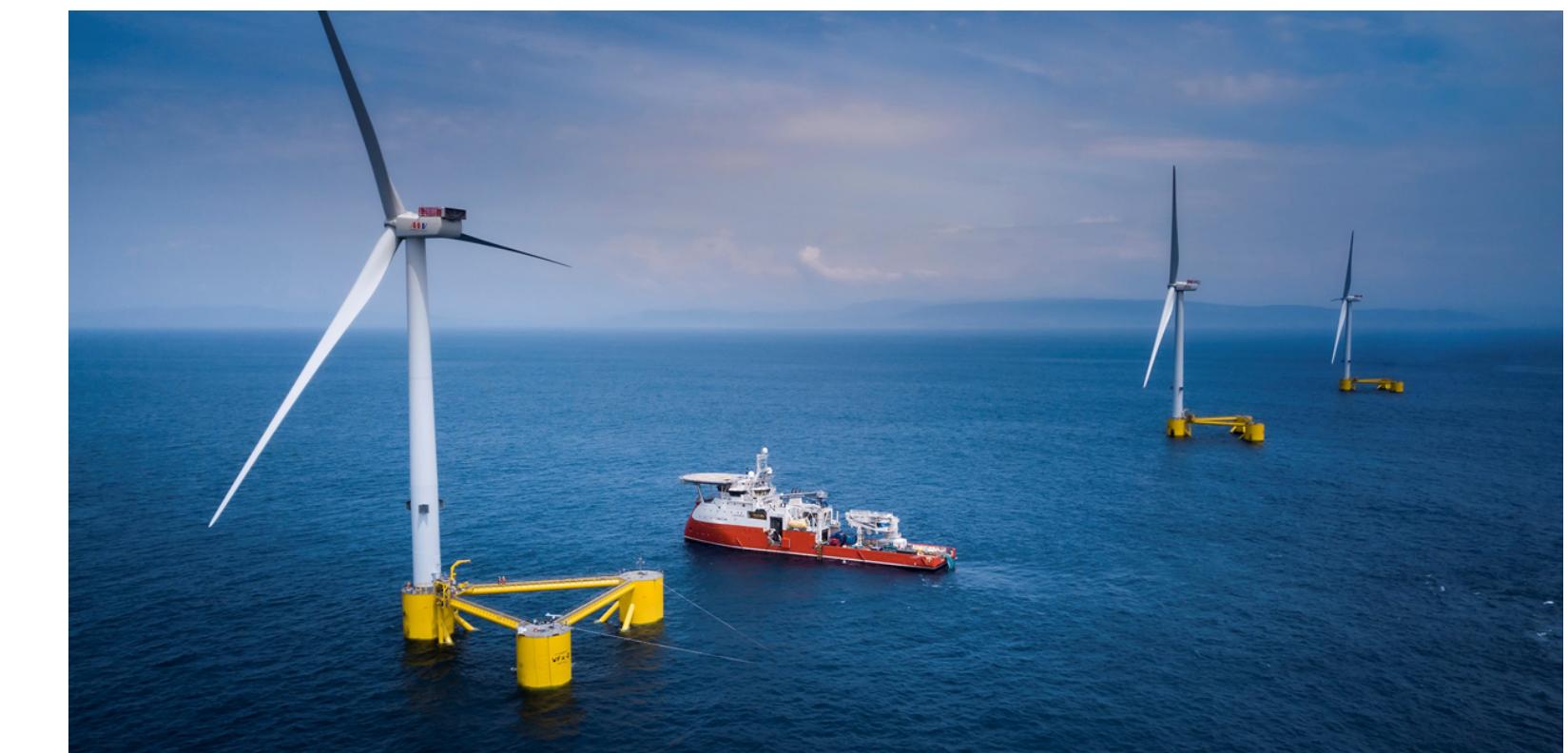
# Importance of Regularity

In seabed tomography

Joint work with Ana Carpio (UCM)



Source: [cowi.com](http://cowi.com)

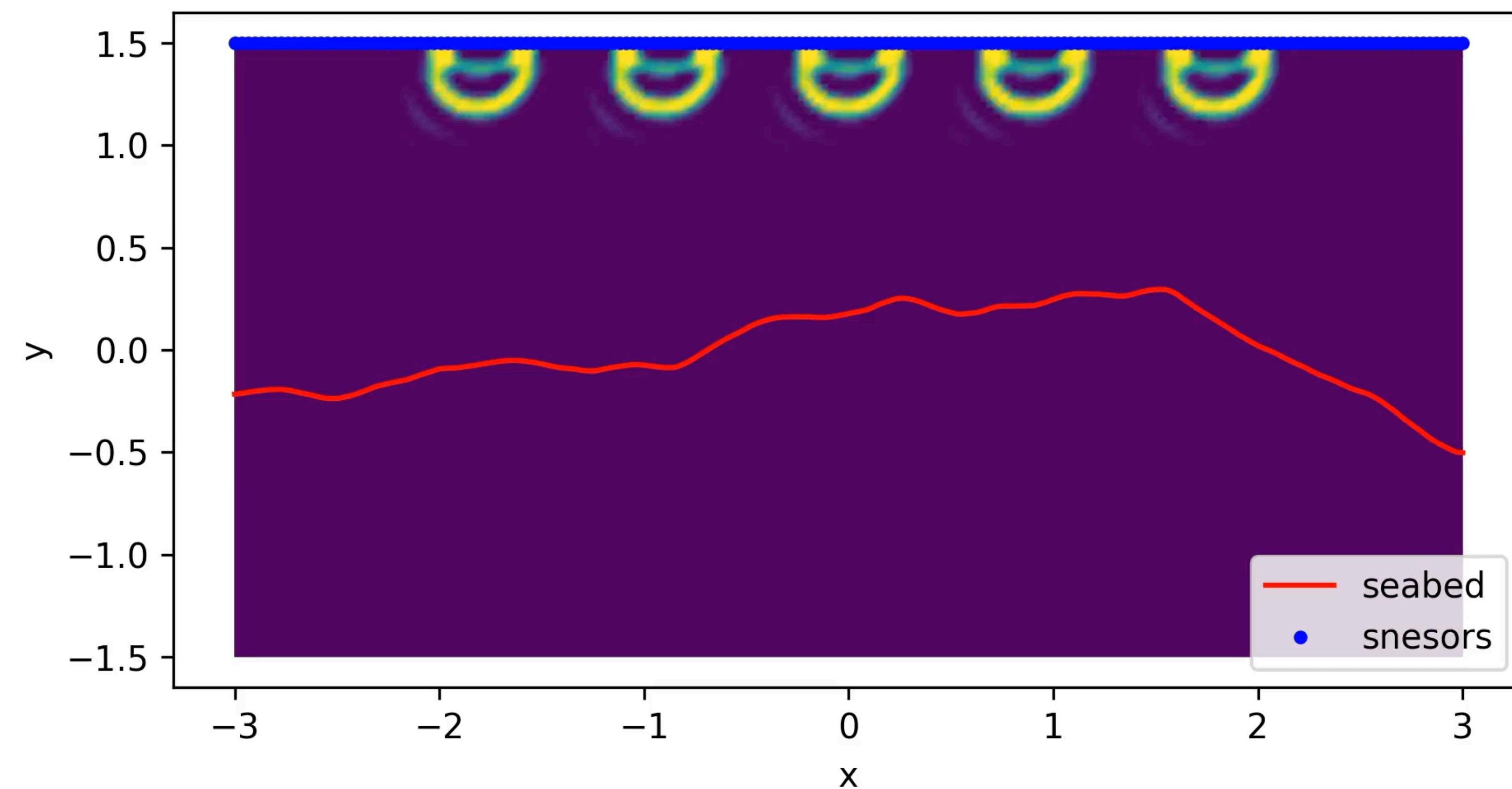


Source: [agcs.allianz.com](http://agcs.allianz.com)

# Importance of Regularity

In seabed tomography

Joint work with Ana Carpio (UCM)



# Forward Model

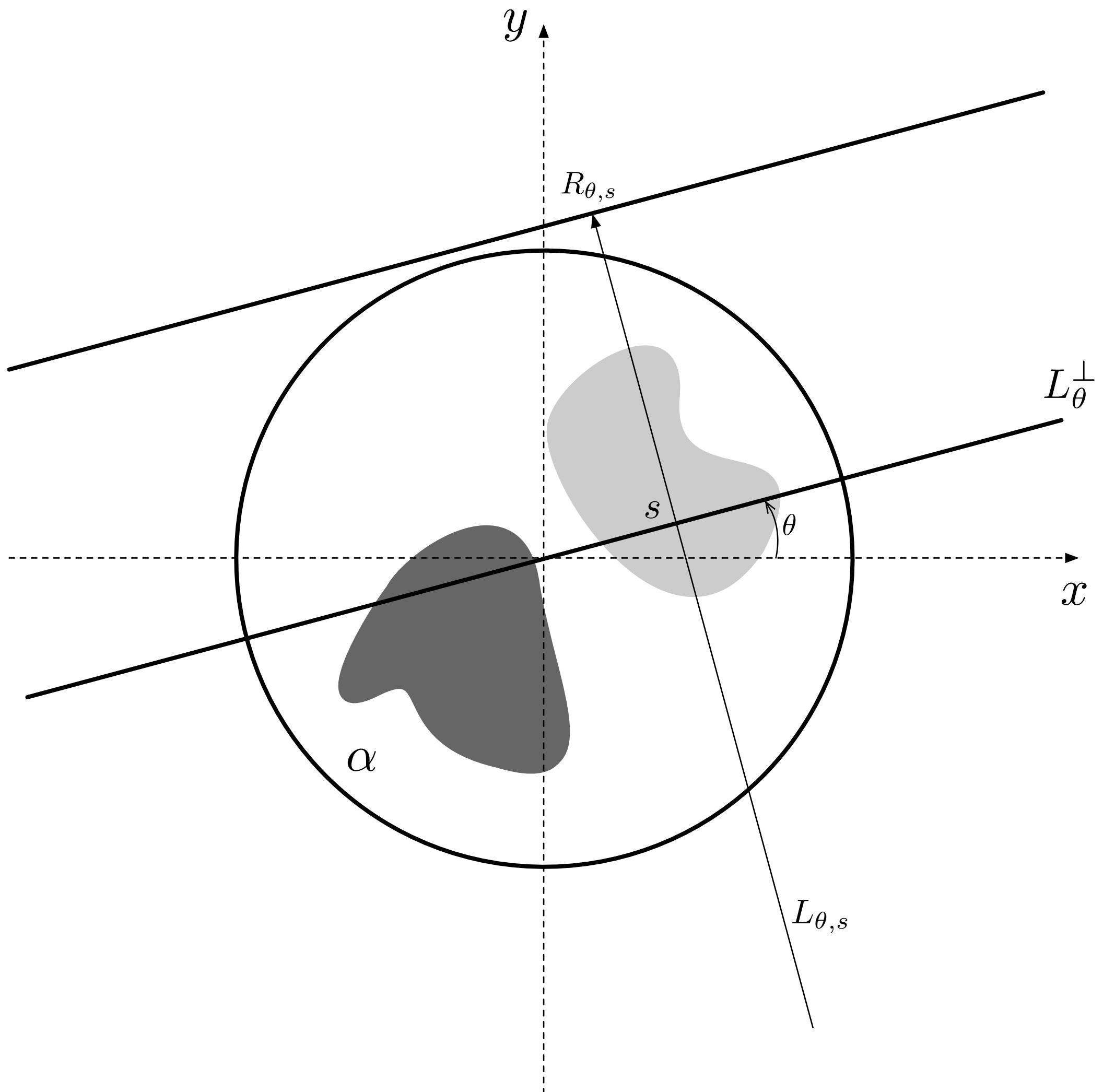
## Radon transform

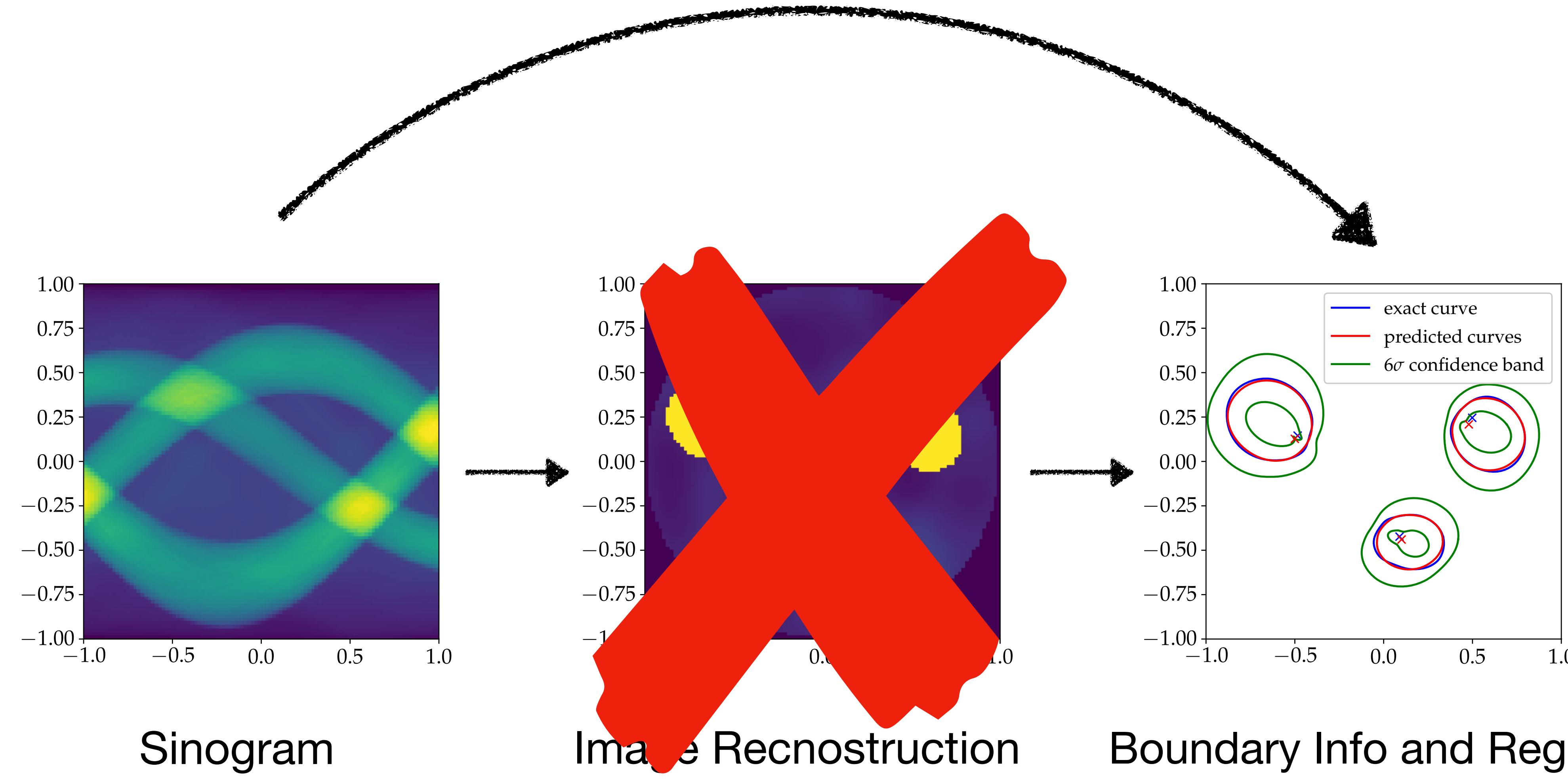
- Modelling X-ray interaction with line integrals:

$$R_{\theta,s}[\alpha] := \int_{L_{\theta,s}} \alpha(x, y) \, dl$$

- Collect in vector form:

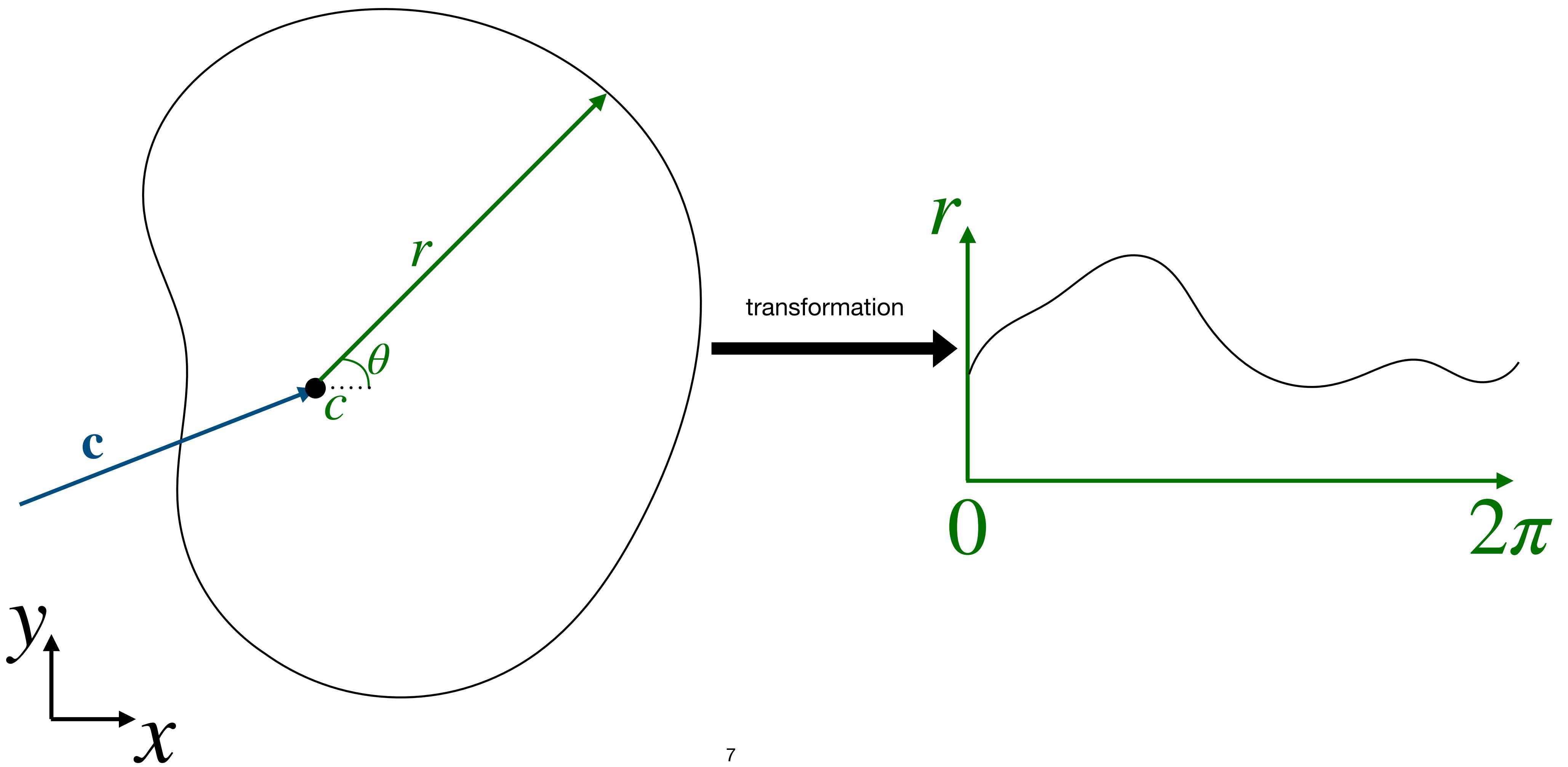
$$y(\alpha) = G(\alpha) + \varepsilon$$





# Prior Modelling

## Star-shaped boundary



# Notion of Regularity

## Fractional differentiability

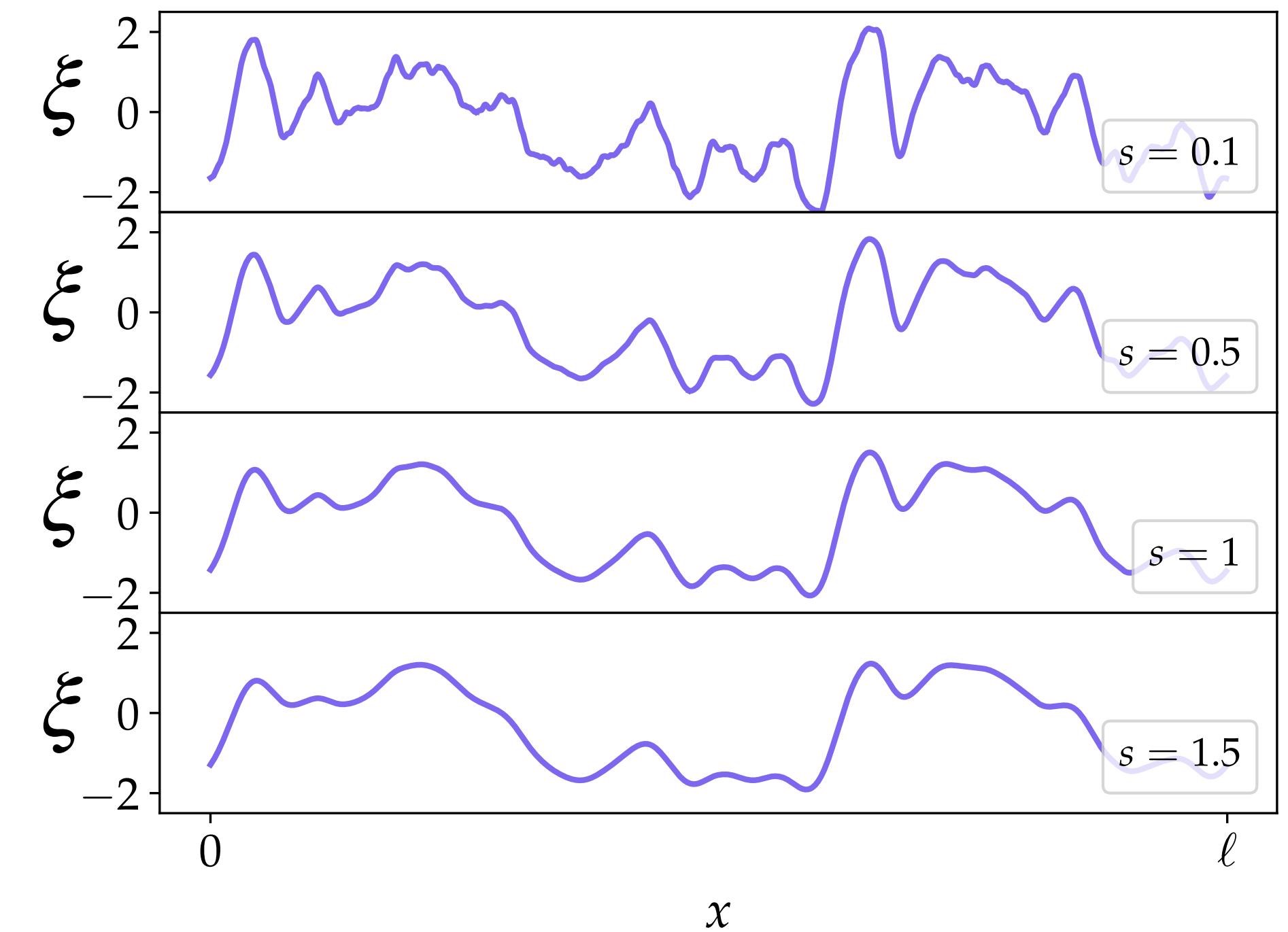
- Choose a basis (Fourier Basis)  $\{\mathbf{e}_i\}$  and define

$$\xi = \sum_{i=1}^{\infty} x_i \mathbf{e}_i$$

- To make sense of the infinite series

$$\xi = \sum_{i=1}^{\infty} x_i \lambda_i^{s+\frac{1}{2}} \mathbf{e}_i, \quad \lambda_i \asymp \frac{1}{i^2}$$

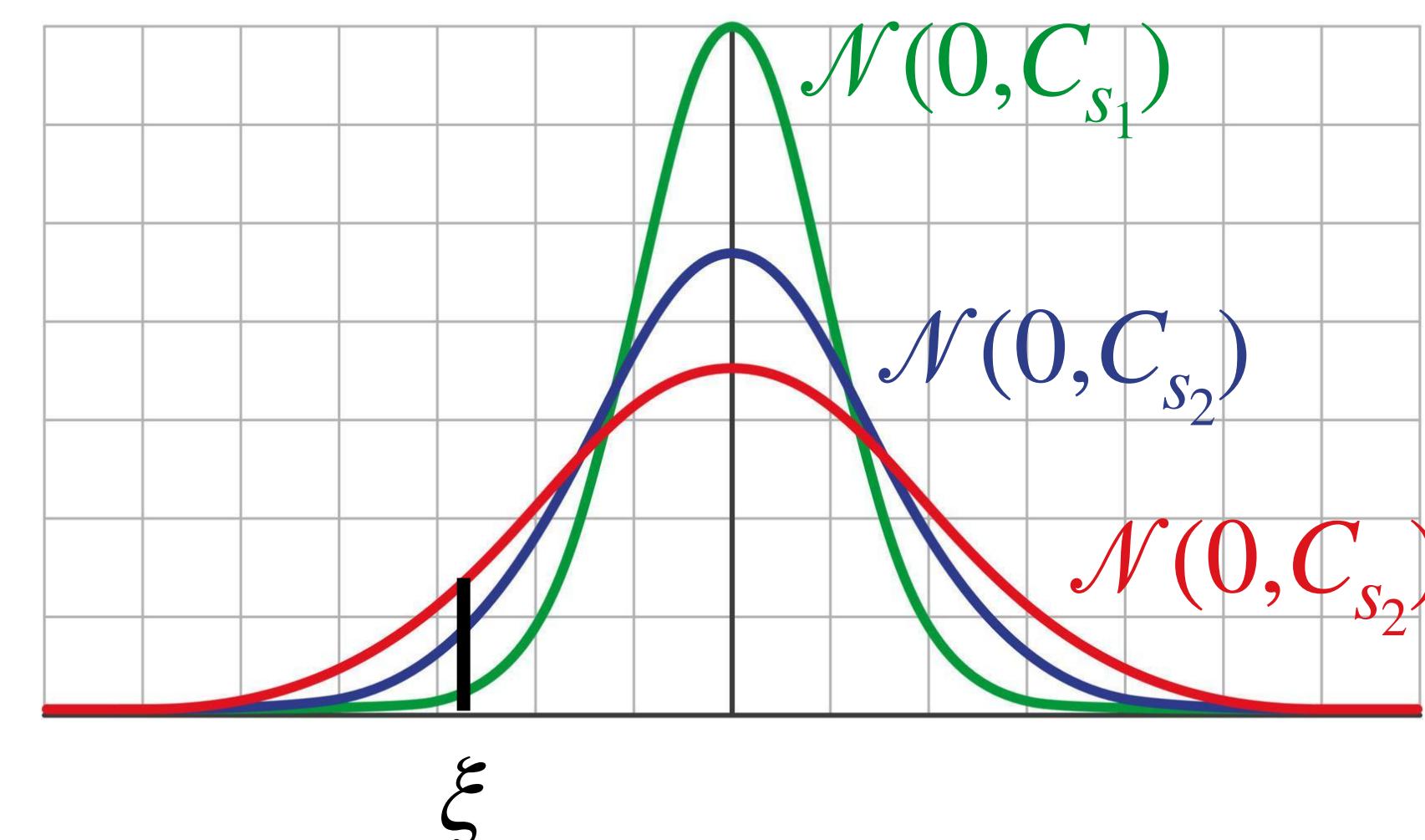
- $\xi \in H^{2t+1/2}$  for all  $t < s$  [Dunlop et al. 2017]



# What can we say about the uncertainty in $s$ ? Family of Gaussians

- We can construct a covariance as:

$$C_s = \sum_{i=1}^{\infty} \lambda_i^{s+1/2} \langle e_i, \cdot \rangle e_i$$



# Goal Oriented Forward Map

## boundary to image

- Recall:

$$y(\alpha) = G(\alpha) + \varepsilon$$

- We define the forward-map to be:

$$\mathcal{G} = G \circ F.$$

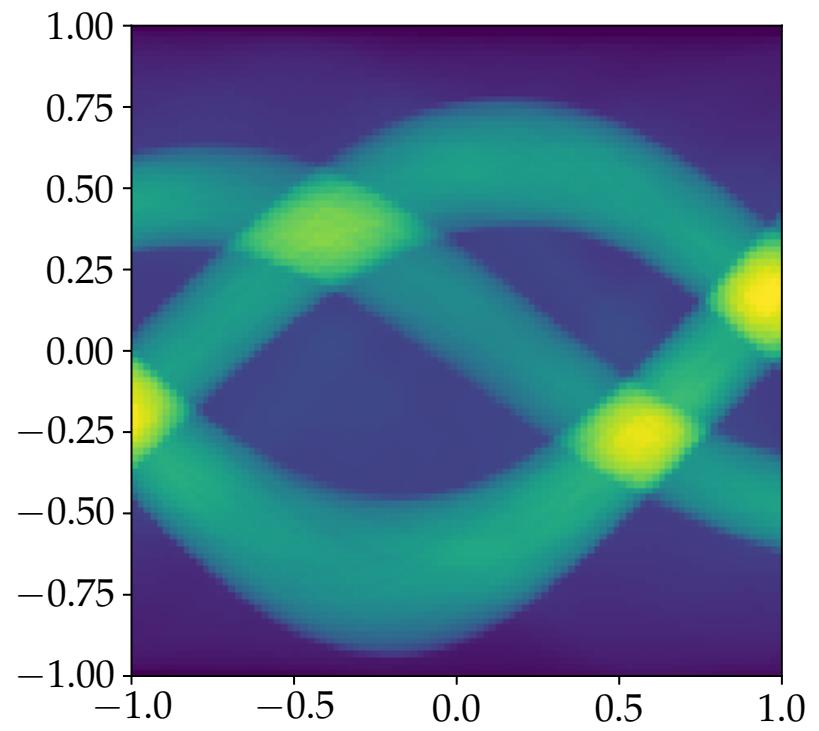
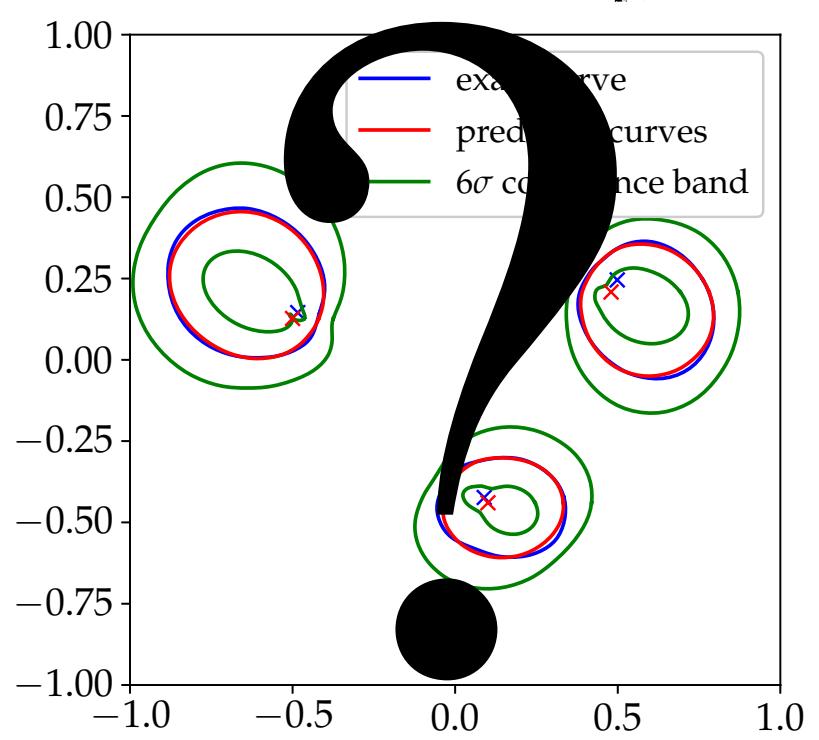
- New forward map:

$$y = \mathcal{G}(\mathbf{x}, s) + \varepsilon$$

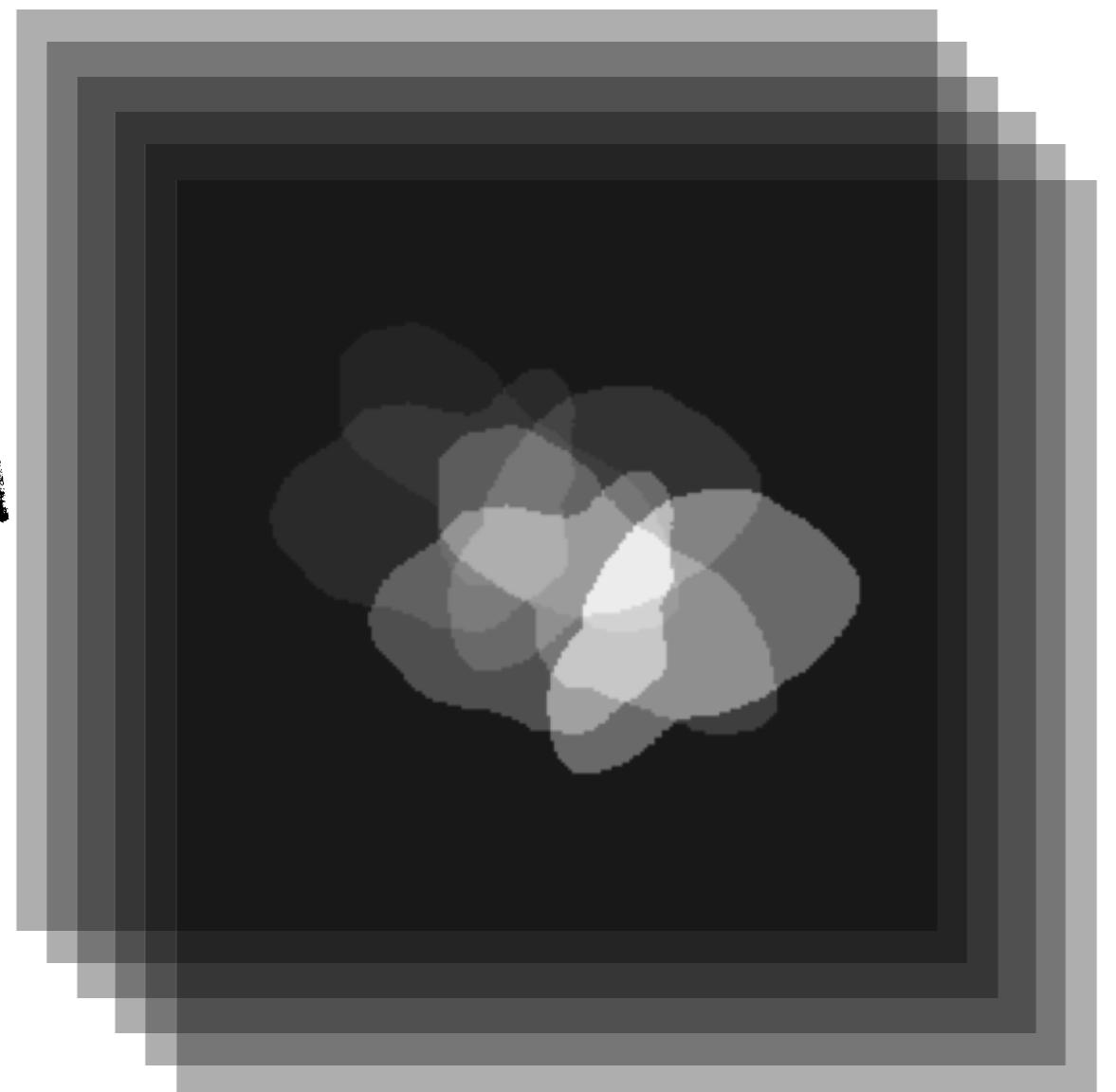
# Bayesian Formulation for the CT problem

- Applying the Bayes' theorem:

$$\pi_{\text{post}}((\mathbf{x}, s) | y) \propto \pi_{\text{like}}(y | (\mathbf{x}, s)) \pi_0(\xi | s) \pi_0(s)$$



$$y = \mathcal{G}(\mathbf{x}, s) + \varepsilon$$



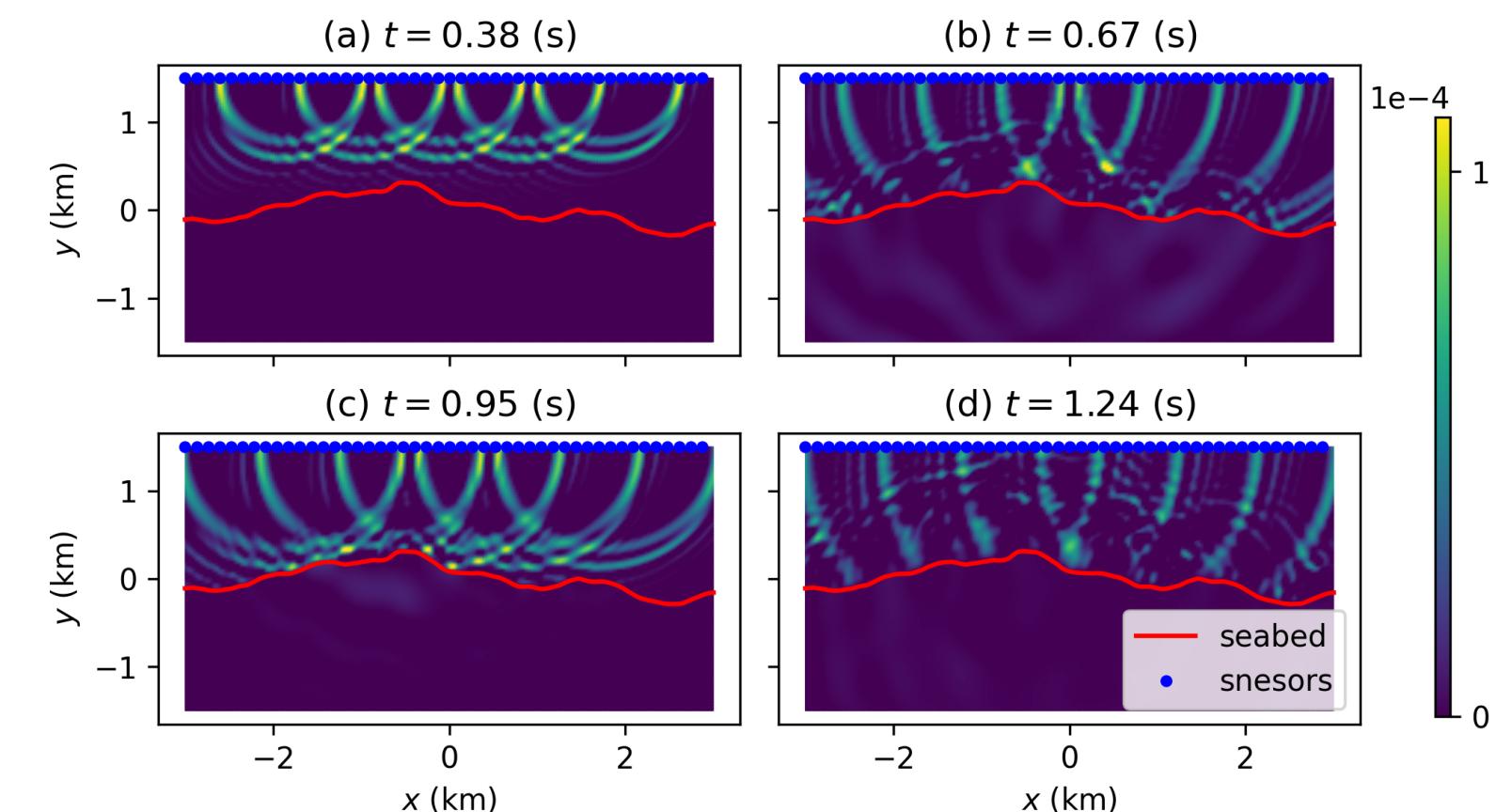
# Posterior and The Gibbs Sampler

- We can form the posterior:

$$\pi_{\text{post}}((\mathbf{x}, s) | y) \propto \pi_{\text{like}}(y | (\mathbf{x}, s)) \pi_0(\mathbf{x} | s) \pi_0(s)$$

- Gibbs sampler:

- Sample from  $\pi(\mathbf{x} | s, y)$
- Maximum likelihood estimation for  $s$

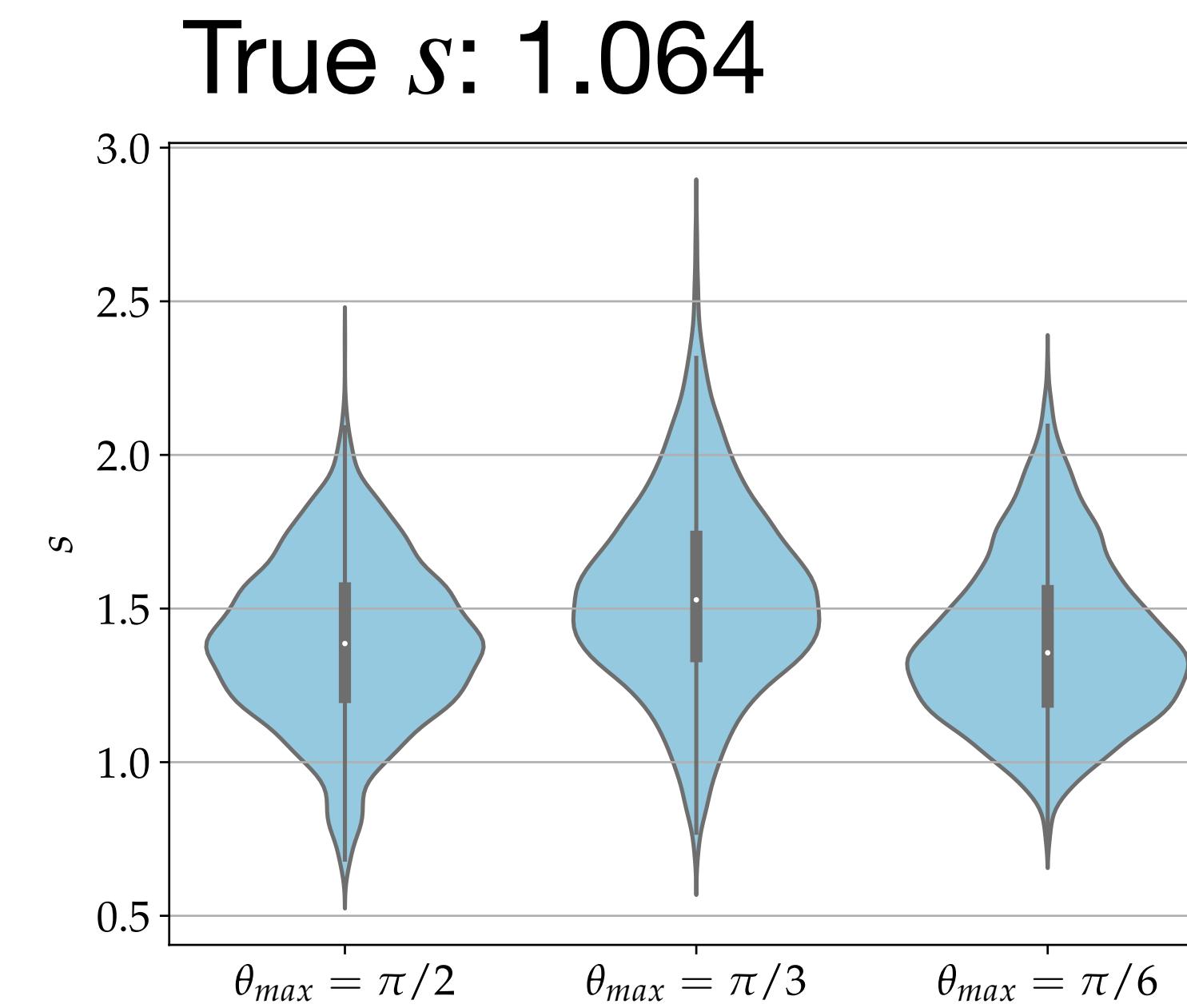
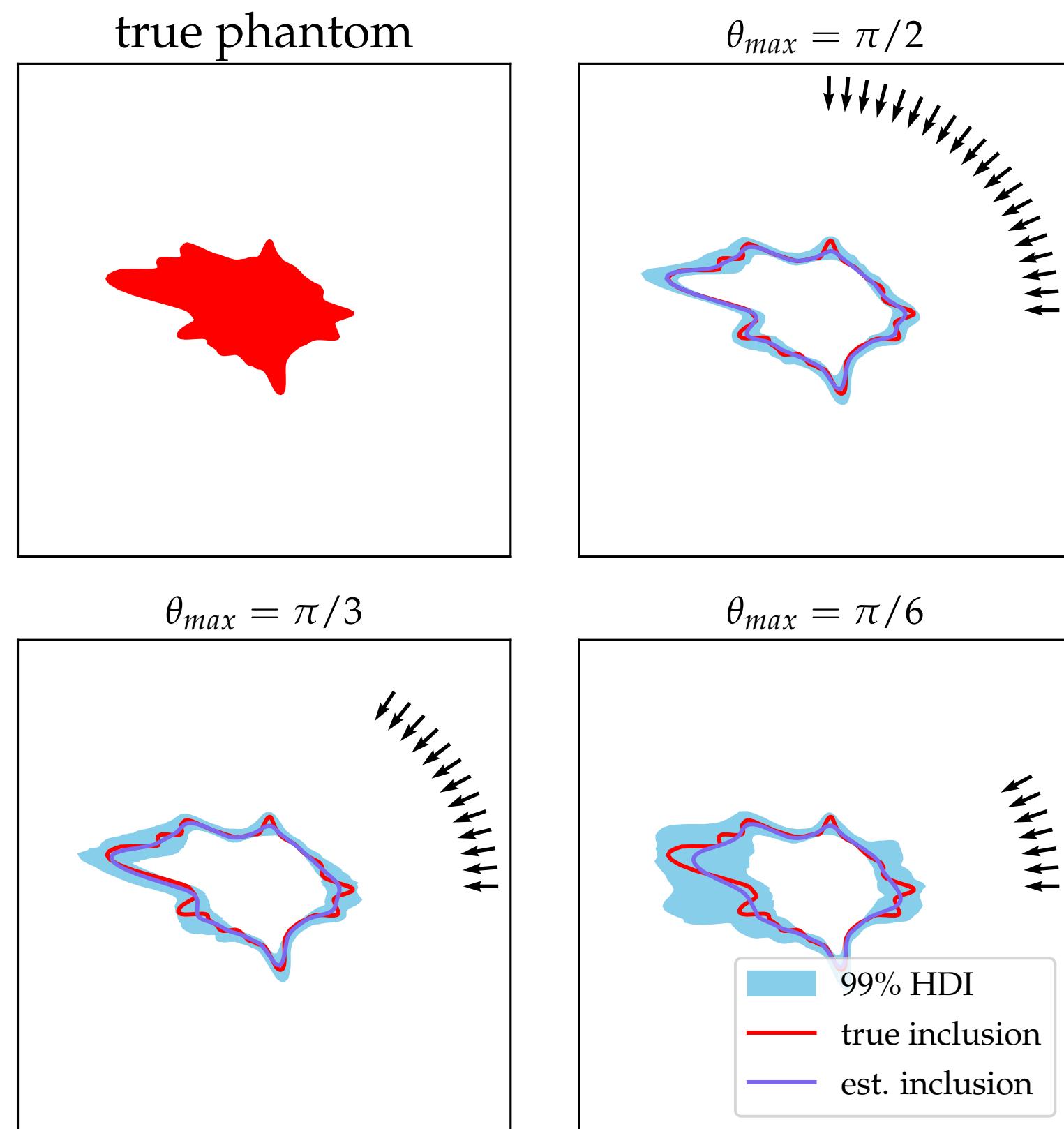


SIAM IS24

Atlanta

# Performance

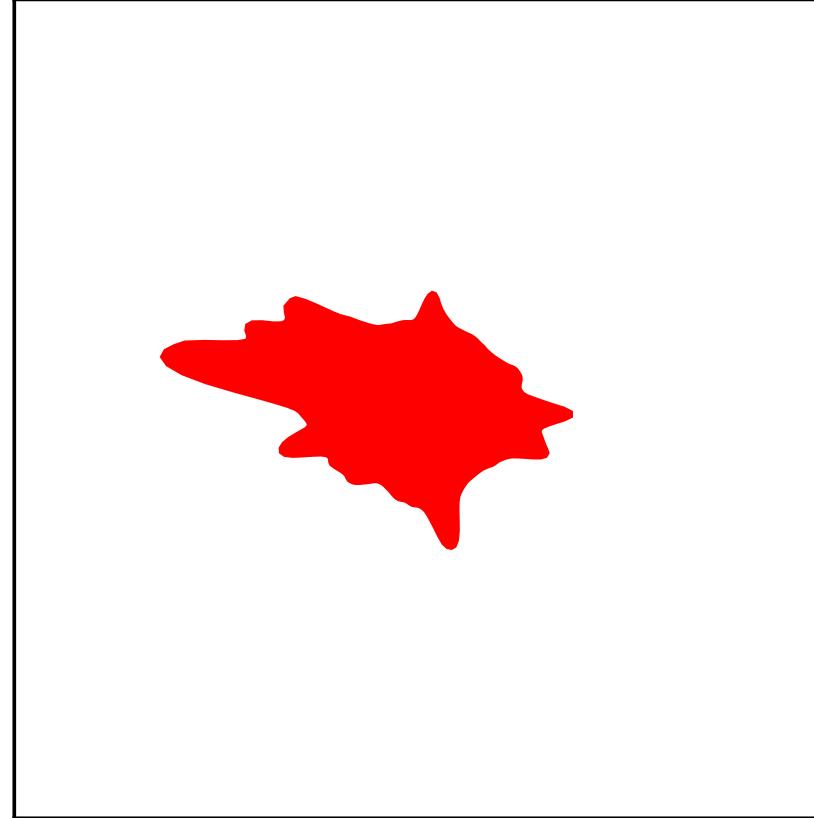
## Limited-angle X-ray CT (partial data)



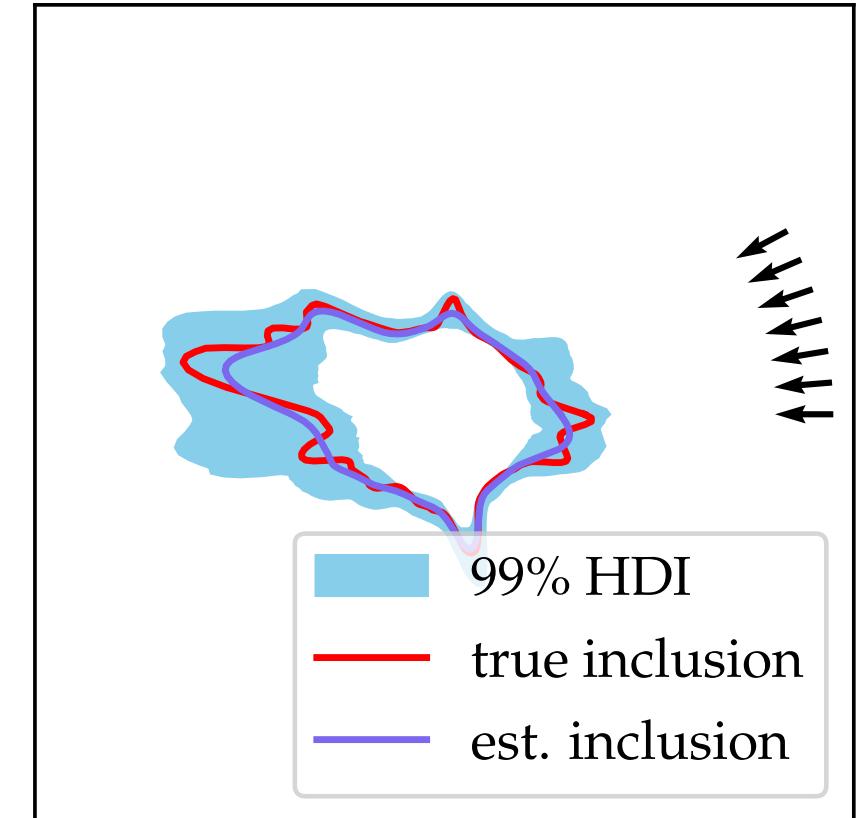
# Performance Comparison with the state-of-the-art

## Hierarchical Bayesian

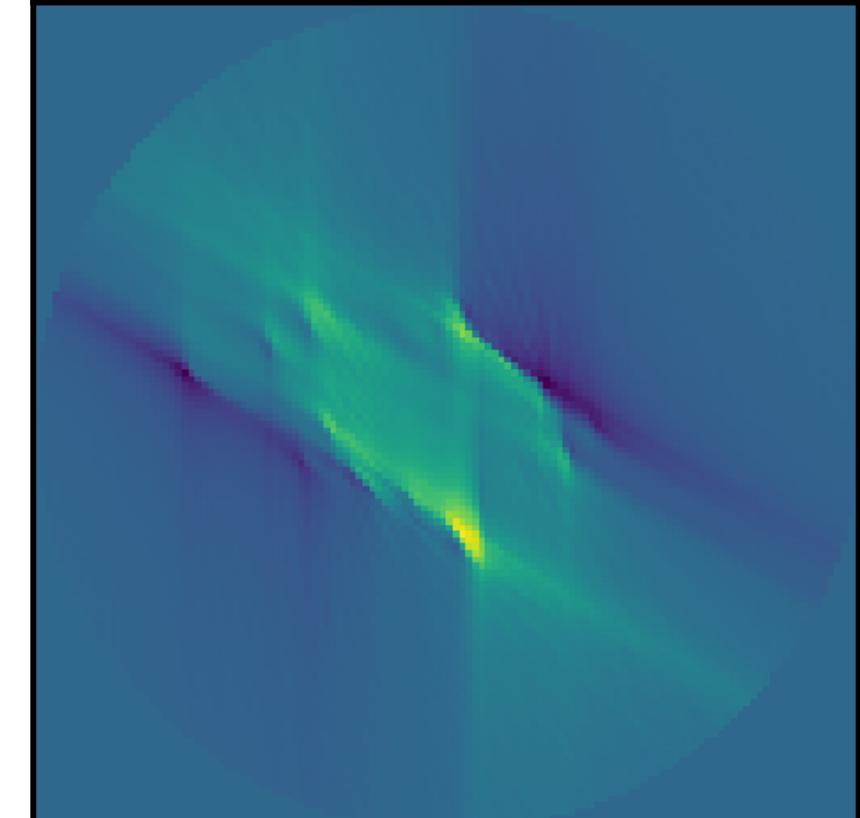
true phantom



$\theta_{max} = \pi/6$



(a) reconstruction

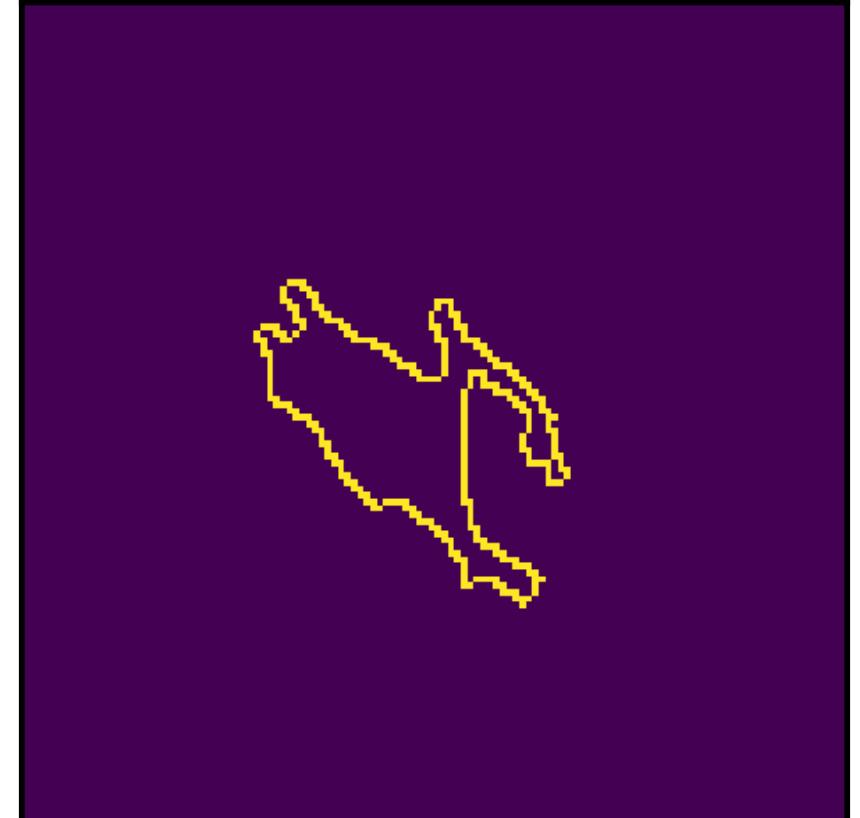


## FBP

(b) segmented



(c) boundary

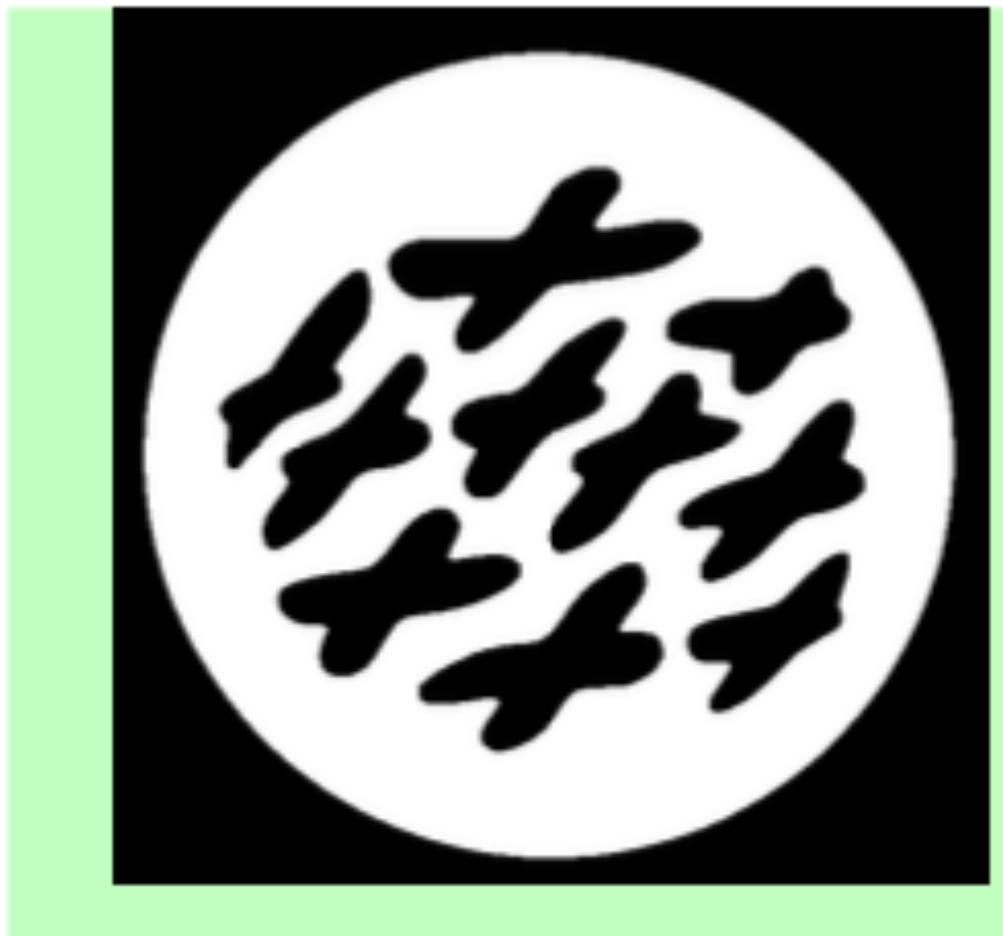


# Performance

## Comparison with the state-of-the-art

Helsinki tomography challenge 2022 (FIPS): 30° limited angle CT

ground truth



$15_A$



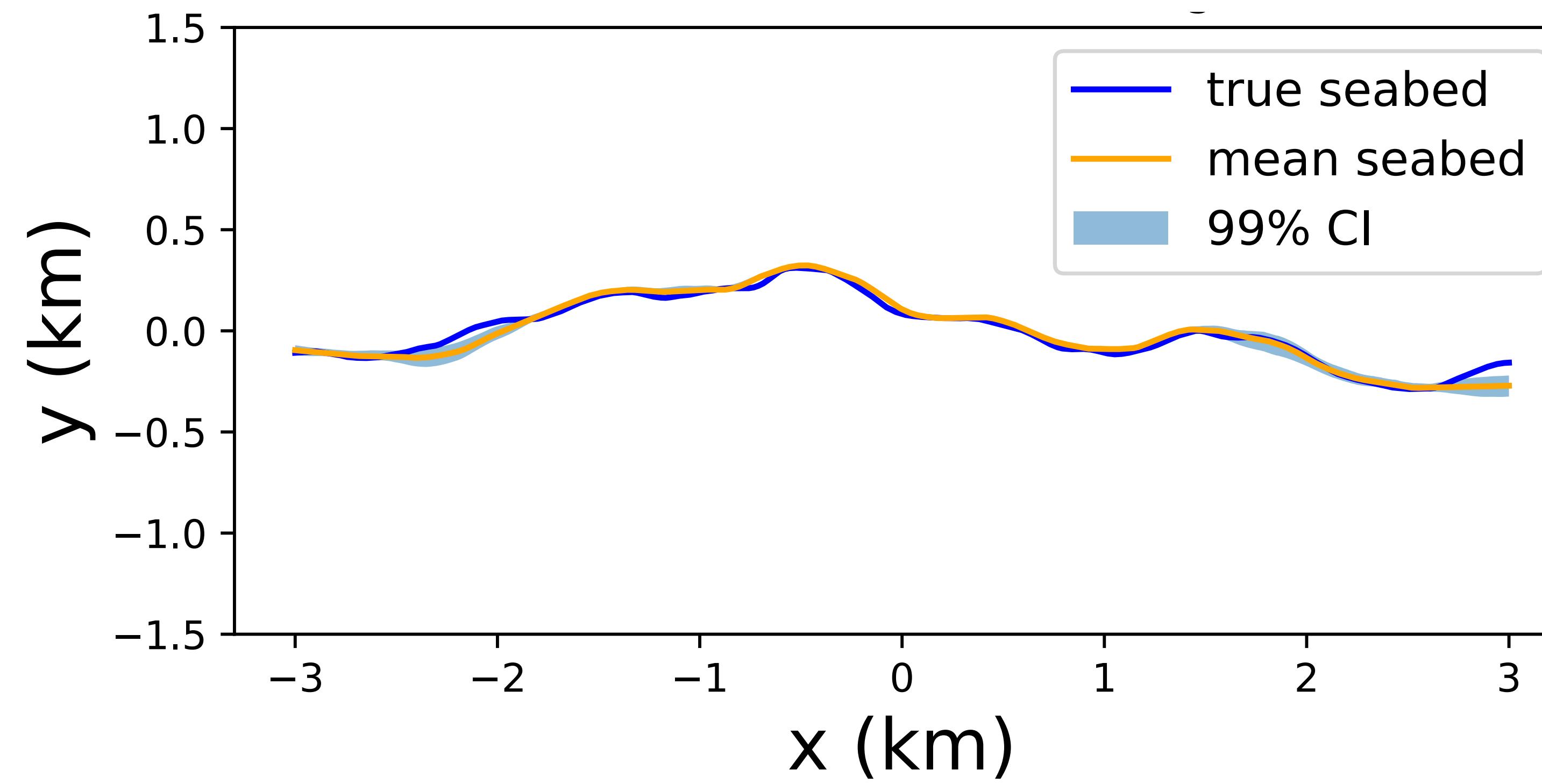
$16_B$



$24_B$



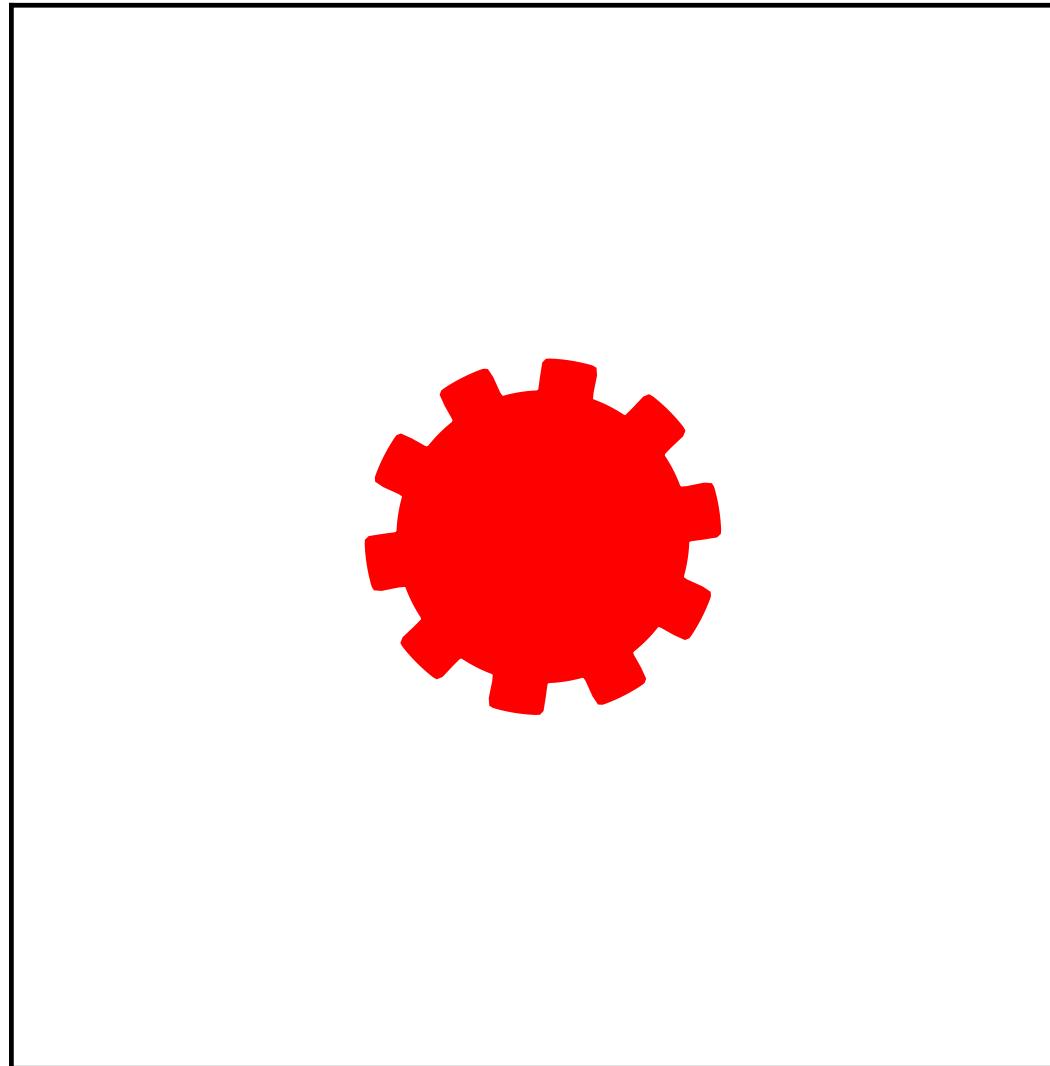
# Performance Seabed Tomography with Acoustic Waves



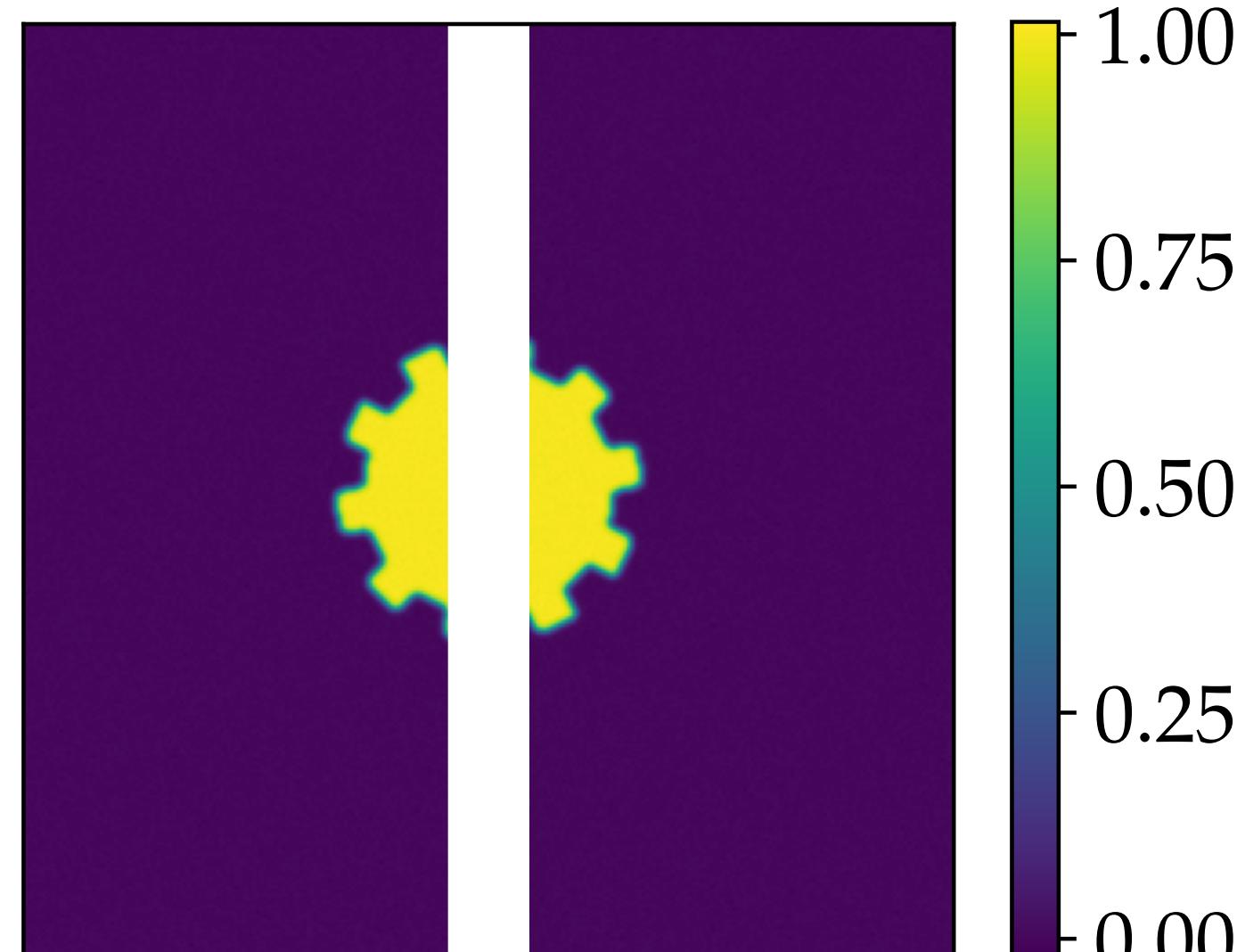
# Performance

## Image in-painting (Gaussian noise)

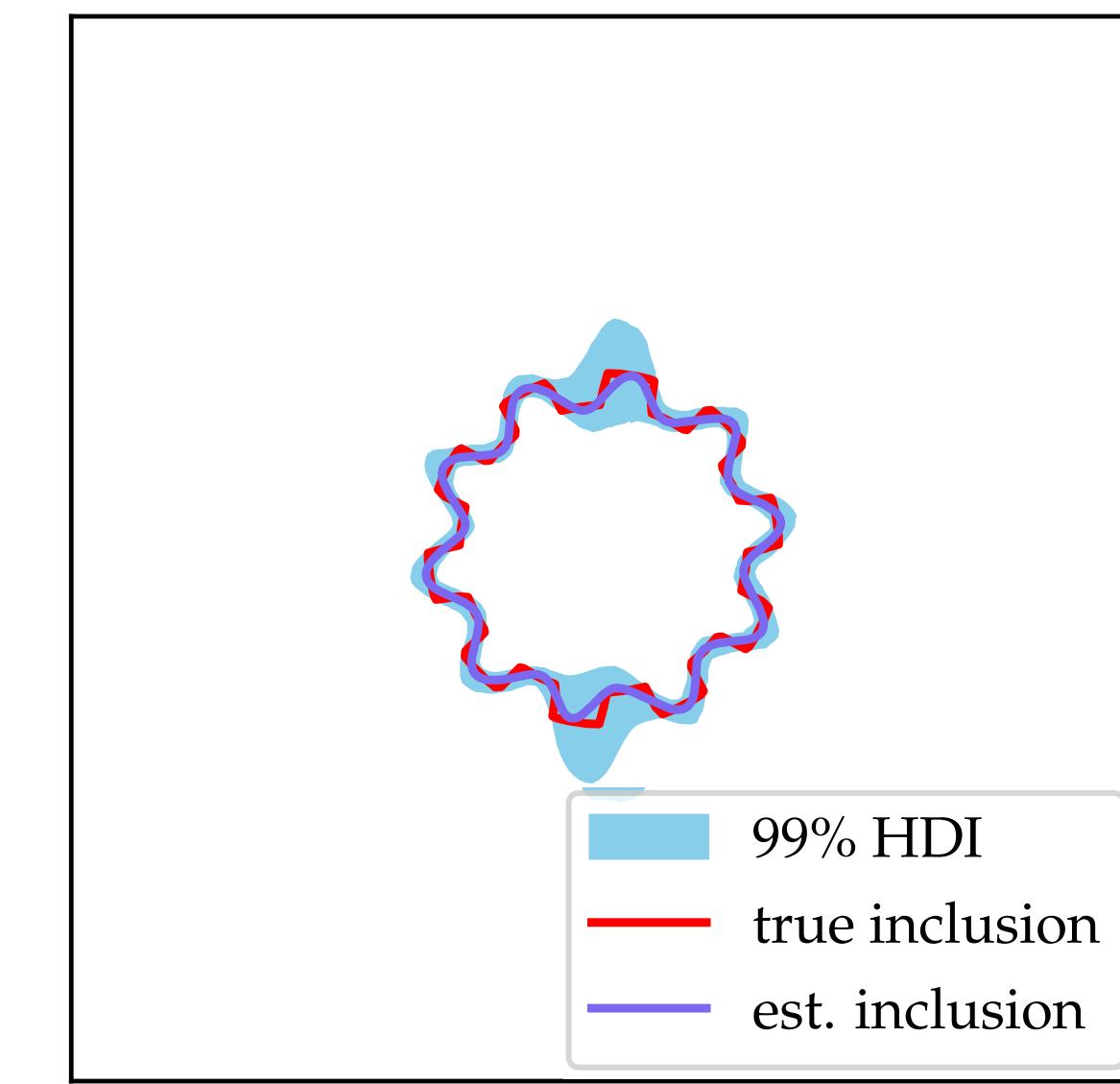
true phantom



Data with 2% noise



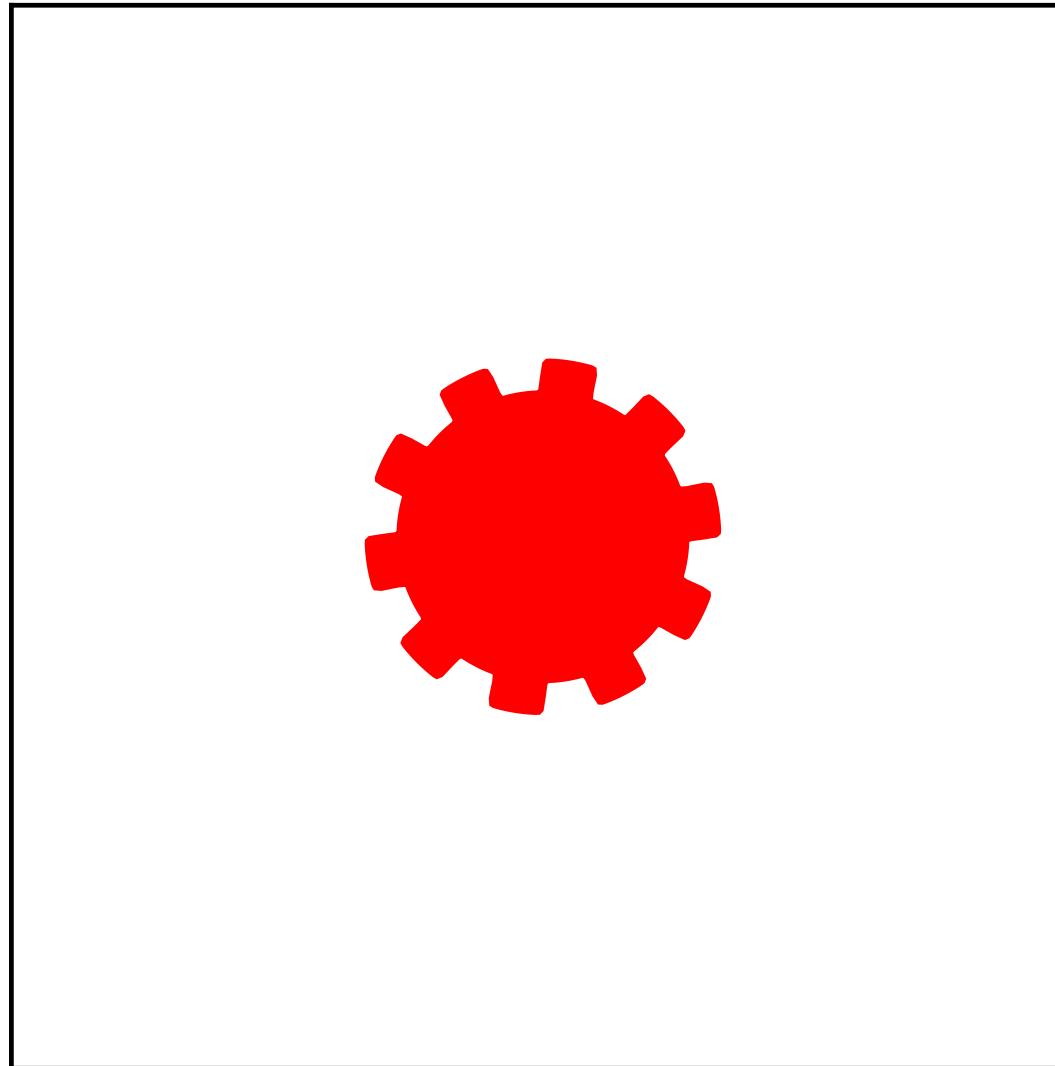
Estimate of the boundary



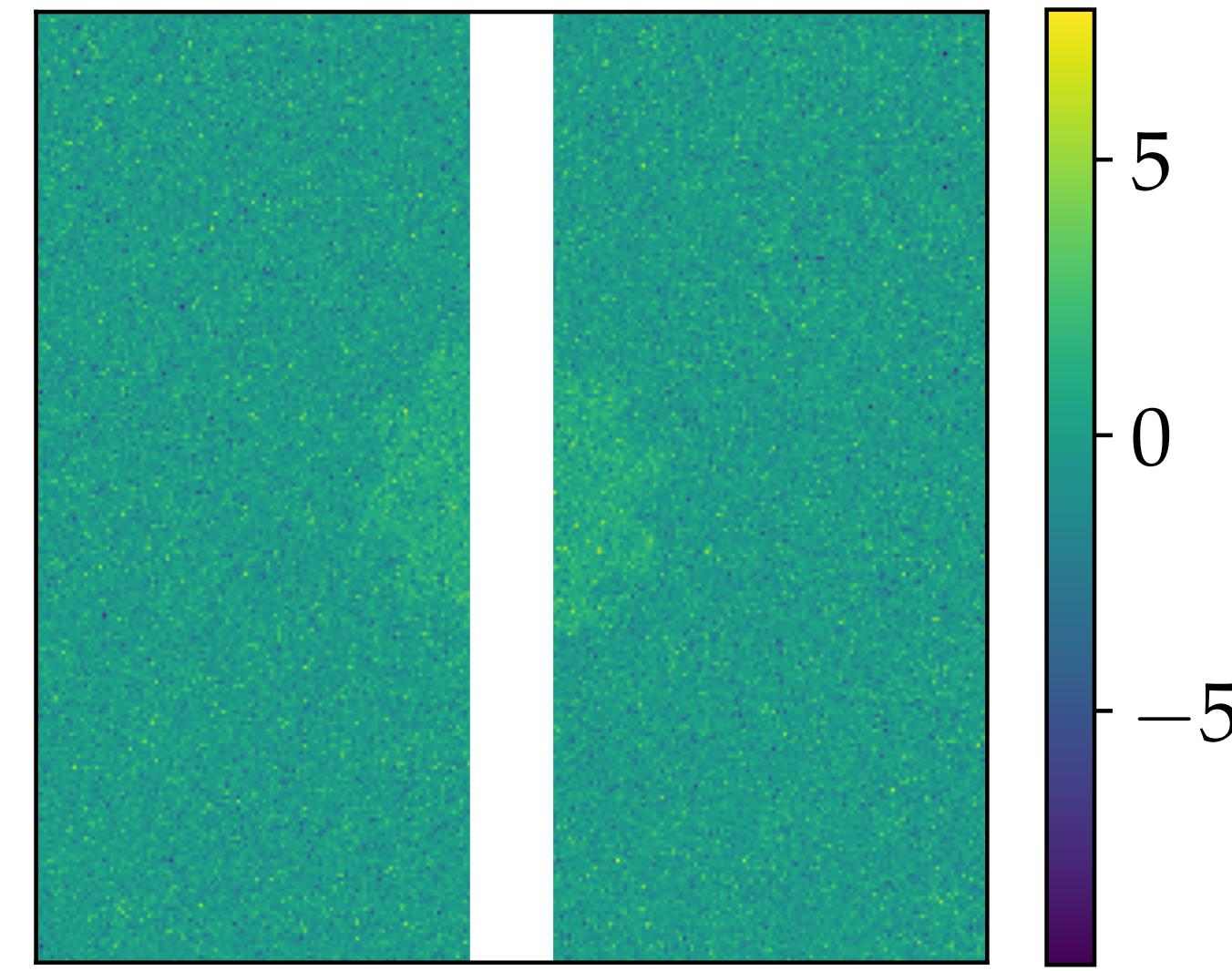
# Performance

## Image in-painting (Laplace noise)

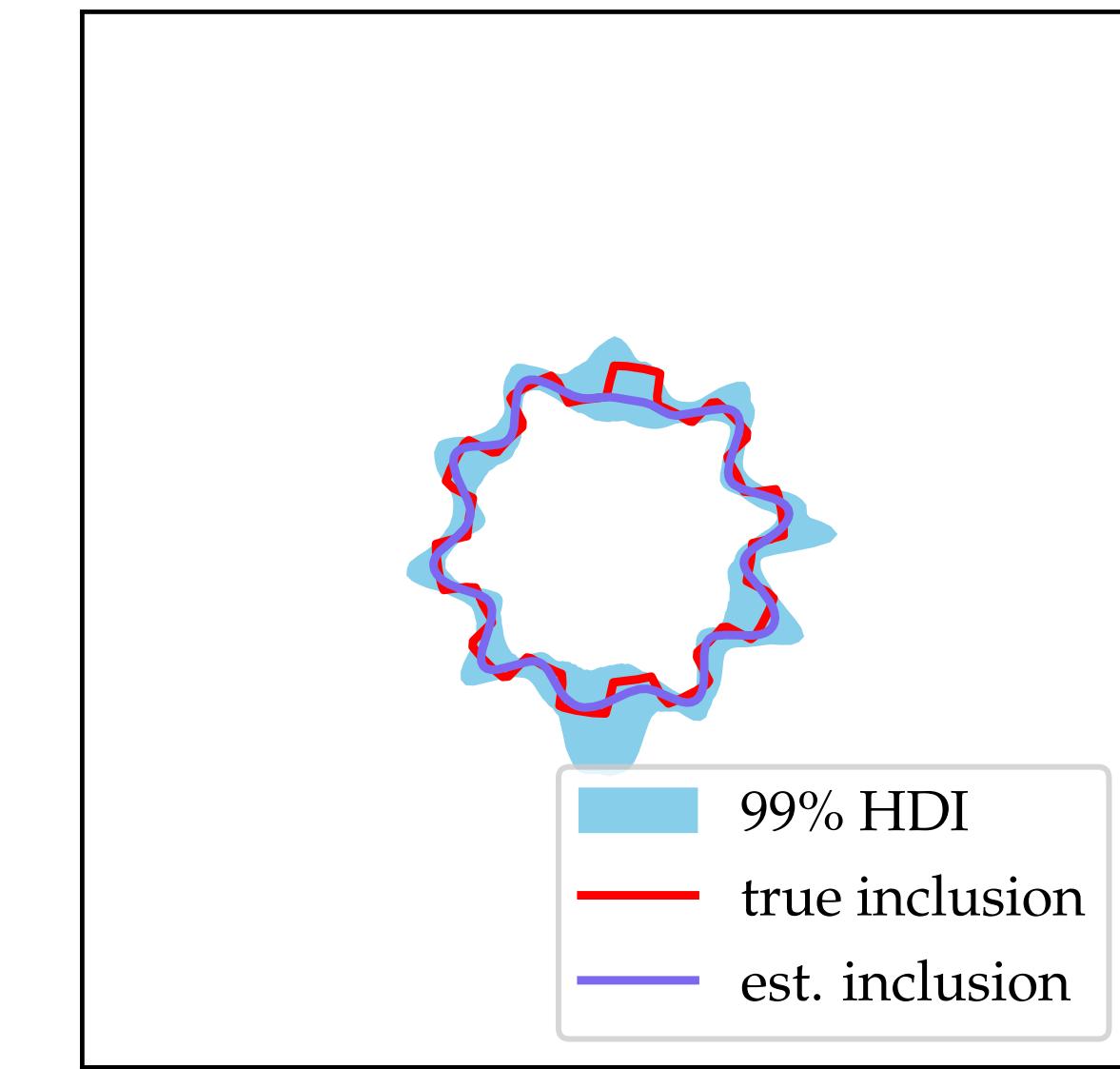
true phantom



Data with 2% noise



Estimate of the boundary



# References

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- **Inferring Object Boundaries and their Roughness with Uncertainty Quantification**  
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- **Simultaneous Estimation of Seabed and Its Roughness with Acoustic Waves**  
B.M. Afkham. A. Carpio (preprint soon available)
- **Hierarchical Bayesian Level Set Inversion**,  
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- **MCMC methods for functions: modifying old algorithms to make them faster**,  
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