Automated geoacoustic inversion and uncertainty: Meso-scale seabed variability in shallow water environments

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LONG-TERM GOALS

Propagation and reverberation of acoustic fields in shallow water depend strongly on the spatial variability of seabed geoacoustic parameters, and lack of knowledge of seabed variability is often a limiting factor in acoustic modeling applications. However, direct sampling (e.g., coring) of vertical and lateral variability is expensive and laborious, and long-range inversion methods can fail to provide sufficient resolution. For proper quantitative examination of variability, parameter uncertainty must be quantified first which can be particularly challenging for large data sets, and in range-dependent and/or dispersive seabed environments. A long-term goal of this work is to substantially advance Bayesian inversion methodology to allow automated analysis of large and complex data sets. These advances will allow mesoscale spatial variability of seabed sediments to be quantified in two and three dimensions.

In addition, more detailed understanding of acoustic propagation in porous sediments is desirable. For example, understanding acoustic dispersion in seabed sediments is of significant interest to the acoustical oceanography community. Inferring such complex quantities from acoustic measurements also requires a higher level of sophistication in modeling the seabed, for example by accounting for shear and scattering in arbitrarily layered seabeds. Obtaining meaningful inferences on low-frequency dispersion is a challenging inverse problem since estimates can strongly depend on the spatial structure (layering) of the sediment and multiple competing physical theories exist that can predict similar dispersion regimes. Further, direct sampling (e.g., laboratory measurements of core properties) is currently not possible for low frequencies (hundreds of hertz). Recent advances in Bayesian inversion (Dettmer et al. 2010, 2012a; Dettmer and Dosso 2013; Holland and Dettmer 2012) allow inferences on complex environments (arbitrary and unknown layering) and advanced physical theories (acoustics of dispersive media and spherical reflection coefficients). A long-term goal is to further understanding of such complex systems and develop a quantitative methodology for understanding and discrimination of physical dispersion theories.

OBJECTIVES

The objective of this research proposal is to carry out geoacoustic inversions with advanced sediment models for complex environments with spatial variability in geoacoustic parameters. In particular, highly-informative data which reduce/eliminate oceanographic effects are considered. The resulting geoacoustic models represent benchmarks for meso-scale variability and uncertainty estimation, and also allow the study of compressional- and shear-wave dispersion and attenuation-frequency dependence. Bayesian hierarchical models and trans-dimensional (trans-D) inversions allow for increasingly automated data analysis in challenging shallow-water environments. The problems are studied with existing data from a Mediterranean Sea test bed. Studies will then be extended to new data from upcoming shallow-water experiments, when available. Particular focus for new shallow-water data will be on rigorous variability and uncertainty estimation, attenuation-frequency dependence, sound-velocity dispersion, and shear-wave velocity structure of the seabed.

APPROACH

Quantifying parameter uncertainty in geoacoustic inversion is achieved here with probabilistic sampling methods (MacKay 2003). Probabilistic uncertainty estimation requires assigning a model which is defined here to include the physical theory describing signal-system interaction, an appropriate parametrization, and a statistical representation of residual errors (the difference between predictions and observations). This model specification constitutes prior information that fundamentally impacts uncertainty estimates. In particular, choosing a model parametrization that is consistent with the resolving power of the data and specifying a statistical description of residual errors are important inter-dependent components which are considered here.

Parametrization and discretization choices strongly influence how well predictions fit observations which can strongly impact uncertainty estimates. Hence, objective model selection is required to obtain meaningful uncertainty estimates. Here, trans-D inference is used to relax model specification from a single parametrization to groups of reasonable parametrizations. Such hierarchical Bayesian models require much less subjective input/choice and can be used for uncertainty estimation with advanced trans-D sampling algorithms (Dettmer et al. 2010; Dosso et al. 2014).

We recently generalized the trans-D algorithm to better address geoacoustic models with large numbers of parameters that model complex physics (Fig. 1). The seabed is parametrized by a 1D irregular (position unknown) grid of *layer nodes* that can be populated by a variable number of active parameter types. The layer nodes always give a natural partitioning for each parameter type with the layer node defining the partition below until the next active parameter of the same type is encountered. This type of parametrization allows a trans-D algorithm to estimate environmental structure for various parameter types individually while avoiding over parametrization due to additional parameters for node positions. The approach also allows the inclusion of parameters in a trans-D model that may not be partitioned as a function of space but rather properties of, e.g., an interface.

A significant challenge in trans-D inversion is addressing dependence in residual errors that often arise

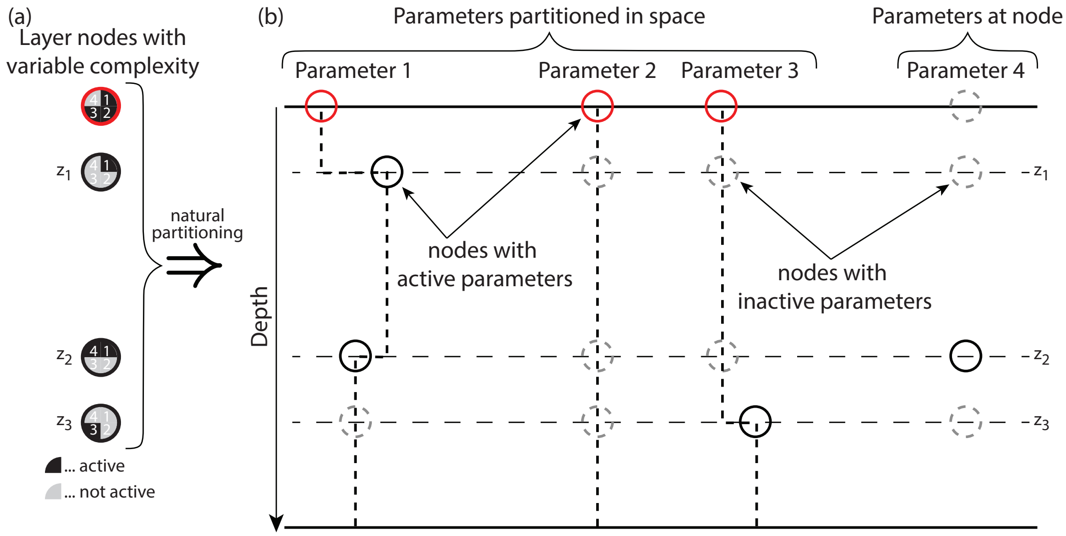

***Figure** 1: Concept of layer nodes and node complexity for generalized trans-D geoacoustic models: (a) Layer nodes are characterized by a position parameter (depth) and are populated with a variable number of active parameter types. (b) The layer nodes always result in a natural partitioning for each parameter type. Red nodes are always populated and give the half-space value when the number of populated nodes is one. Solid horizontal lines mark the limit of the partition and horizontal dashed lines indicate interfaces between layers.*

due to intrinsically correlated noise and the limited ability of the model to capture the full extent of environment complexity for data with high information content. Bayesian inference requires that a statistical distribution form is assumed for residuals (e.g., Gaussian, although any distribution can be applied). However, the parameters of the distribution (variances and covariances) can be estimated as part of a hierarchical model (Dettmer et al. 2012) which is particularly useful for trans-D algorithms. Hierarchical estimation of these parameters impacts uncertainties and can influence model selection when dependence is significant (Dettmer and Dosso 2012). In particular, covariance parameters can be estimated efficiently by modeling residual-error distributions as autoregressive processes which in turn can be considered as trans-D which requires less user input and avoids over parametrization of the error model (Steininger et al. 2013).

Many trans-D algorithms are based on reversible jump Markov-chain Monte Carlo (rjMCMC) sampling (Green 1995), where jumps between sub-spaces are implemented using steps that create or delete structure (e.g., sediment layers). Designing efficient proposals for jump steps is extremely challenging, which results in rare acceptance (causing prohibitively-long convergence times). Parallel tempering methods are shown to improve convergence rates for highly challenging non-linear problems with many posterior modes and strongly correlated parameters (Liu 2001; Dettmer et al. 2012; Dosso et al. 2012; Sambridge 2014), and have also been applied in rjMCMC resulting in much higher acceptance of jumps and improved chain mixing within dimensions (Jasra et al. 2007; Dettmer and Dosso 2012). In addition, parallel tempering is ideally suited for difficult optimization problems (Sambridge 2014) and has substantially reduced burn-in times for the problems considered here. Parallel tempering was developed and applied for geoacoustic inverse problems in this project, providing the ability to carry out uncertainty estimation for highly complex geoacoustic inversions.

WORK COMPLETED

Initial work has focused on advancing trans-D sampling algorithms to study complex geoacoustic inference problems, and in particular dispersive sediments (Holland and Dettmer 2013; Dettmer et al. 2012). The new algorithms have been applied to successfully study acoustic dispersion and attenuation-frequency dependence at three experiment sites on the Malta Plateau. To improve computational efficiency, plane- and spherical-wave reflection-coefficient models were implemented on graphics processing units (GPU) using the compute unified device architecture in Fortran. The GPU implementation resulted in $\sim$2 orders of magnitude speed up for the plane-wave and spherical-wave models. More recently, the GPU spherical-wave reflection coefficient model was generalized to account for shear in arbitrarily layered media. This advancement gives the capability to infer acoustic dispersion in the presence of shear waves in the sediment. In collaboration with Dr. Jorge Quijano we adopted an efficient integration technique (Levin 1996) to substantially reduce the computational time and memory requirements for solving the Sommerfeld integral in the computation of the spherical reflection coefficient. The increased efficiency improves our ability to consider larger data sets (more frequencies) and more complex models (e.g., increased depth windows). The rjMCMC algorithm was implemented for matched-field inversion (Dettmer and Dosso 2012).

Our 170 core high performance compute cluster has been extensively used to support this research. The cluster is jointly funded by ONR and the Natural Sciences and Engineering Research Council (NSERC) of Canada. Several of the inversion algorithms for this project have been developed to take full advantage of the massively parallel architecture of the cluster. In addition, 4 low-cost GPU nodes were added to the compute abilities that, together with new GPU algorithms, result in a substantial increase of computational power.

RESULTS

Results presented in this section focus on some of the research carried out this year to develop a new approach to studying acoustic dispersion in seabed sediments and a new approach to matched-field inversion. A complete account is presented in Holland and Dettmer (2013), Dettmer et al. (2012), and Dettmer and Dosso (2012).

Trans-D inversion is applied to data from *in-situ* sediments on the Malta Plateau (Site 2, see Fig. 2) to study dispersion and attenuation-frequency dependence. Reflection measurements were carried out during the SCARAB98 experiment in 153 m water depth. The reflection measurements were processed to yield reflection-coefficient data as a function of frequency and angle for the uppermost 4 m of sediment. Reflection-coefficient predictions were carried out using Buckingham's viscous grain shearing (VGS) theory (Buckingham 2007), which obeys causality and predicts velocity-dispersion and attenuation-frequency curves.

Figure 3 shows marginal profile distributions of four VGS parameters that were sampled as a function of depth. These marginal distributions are derived from the posterior probability density which constitutes the solution to the probabilistic inverse problem. This section shows several results that are obtained from the posterior by marginalizing in various ways. Several other parameters of VGS theory were fixed at measured *in-situ* values (obtained from a CTD cast) in the inversion. Figure 3 shows that porosity is the most sensitive parameter, while strain hardening is the least sensitive. The time constant τ governs transition between viscous and frictional losses. Viscous losses dominate for small τ values,

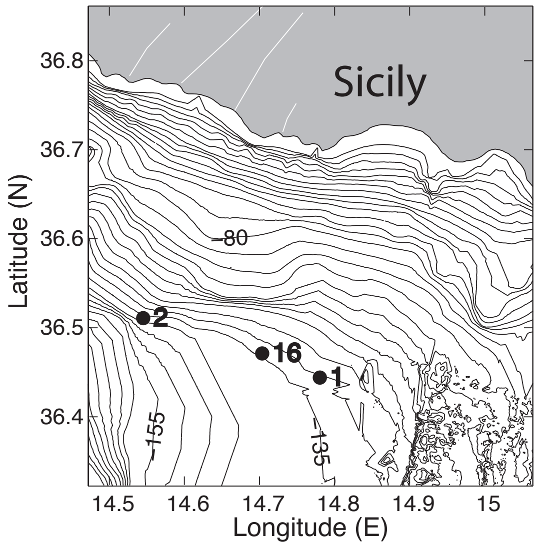

Figure** 2: **Site locations on the Malta Plateau for dispersion studies.

resulting in attenuation-frequency dependence proportional to f^2 at low frequencies and proportional to $f^{1/2}$ at higher frequencies. For large values ($\tau \gtrsim \exp(-5)$) friction dominates and attenuation-frequency dependence for the frequency range considered here is proportional to f^1: The inversion is largely insensitive to τ. Hence, Fig. 3 shows the important result that the inversion is able to discriminate between two dispersion regimes. To 2.7-m depth friction losses dominate, while viscous losses dominate below that depth.

Figure 4 shows the inversion results in terms of geoacoustic parameters which are derived from the VGS parameters. Note that VGS theory provides velocity and attenuation as a function of frequency, and results for 1400 Hz are shown. The inversion results agree very closely with estimates from independent cores taken at the experiment site. Posterior inferences can also be obtained for dispersion curves which are shown for selected depths in Fig. 5.

Inversions were also carried out for two other locations (Sites 1 and 16, see Fig. 2) and the results are shown in Figs. 6 and 7. Note the very close agreement between inversion and core estimates. In addition, velocity-marginal profiles extrapolated to 200 kHz (the frequency of velocity measurements on the core) are shown.

Figure 8 shows inversion results for simulated data where the layering complexity of the true model is different for each parameter: Velocity has 5 homogeneous layers, density 3, and attenuation only 1. The inversion has the ability to adapt to the distinct profile complexity for each parameter in an automated manner while avoiding over-parametrization.

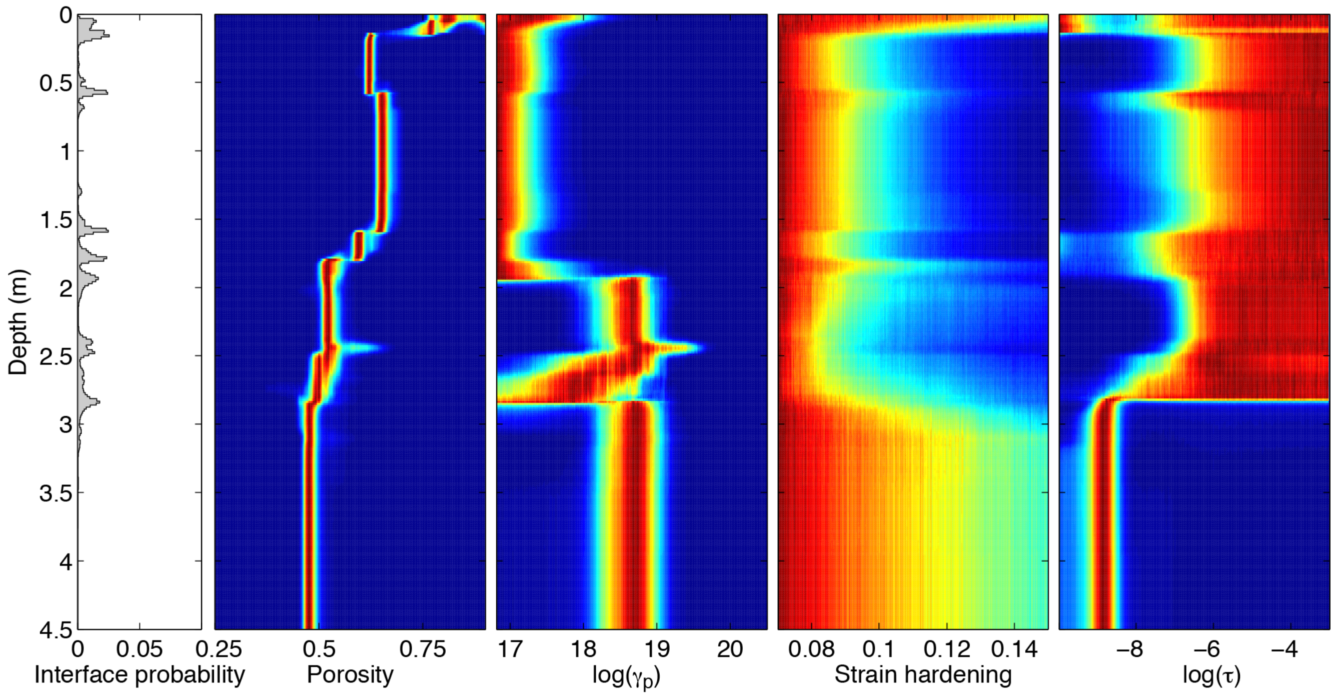

Figure 3: Site 2 marginal profile distributions of VGS parameters and interface probability.

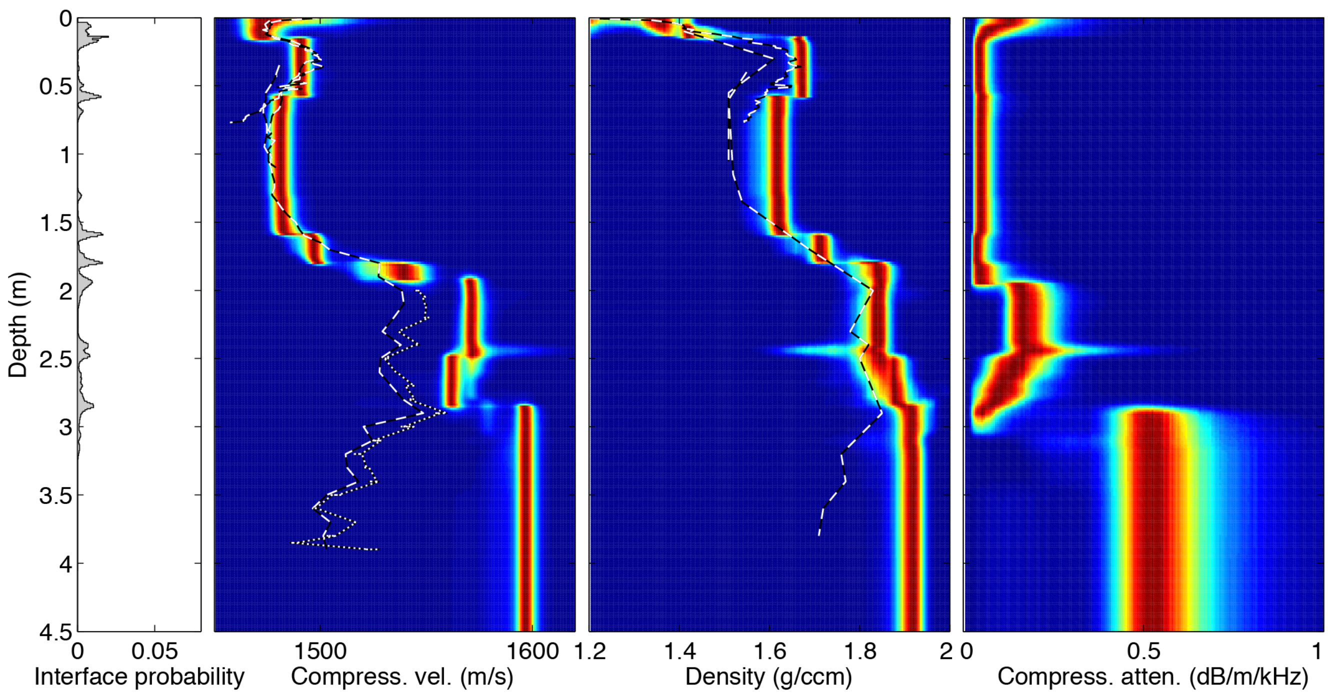

Figure 4: Marginal profile distributions for geoacoustic parameters, derived from the VGS parameters in Fig. 3. Estimates from independent core samples are shown as dashed and dotted lines.

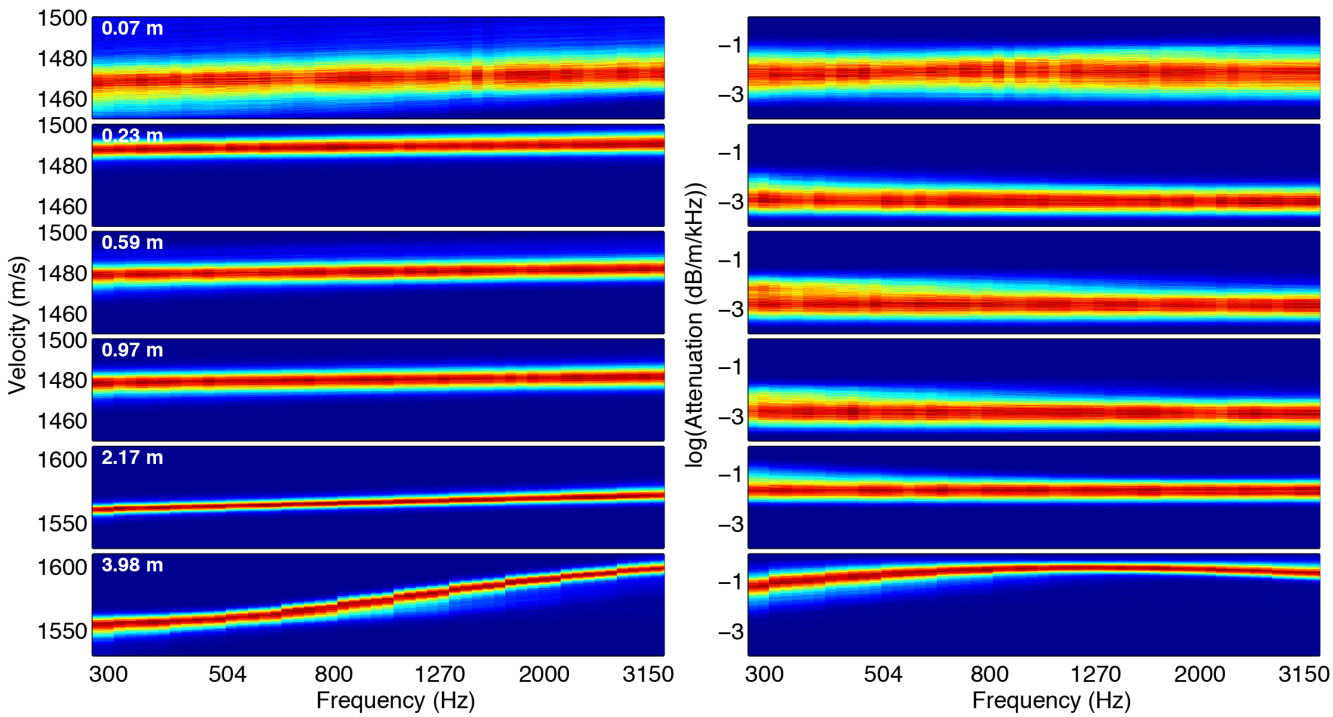

Figure 5: Velocity-dispersion and attenuation-frequency curves for select depths (Site 2).

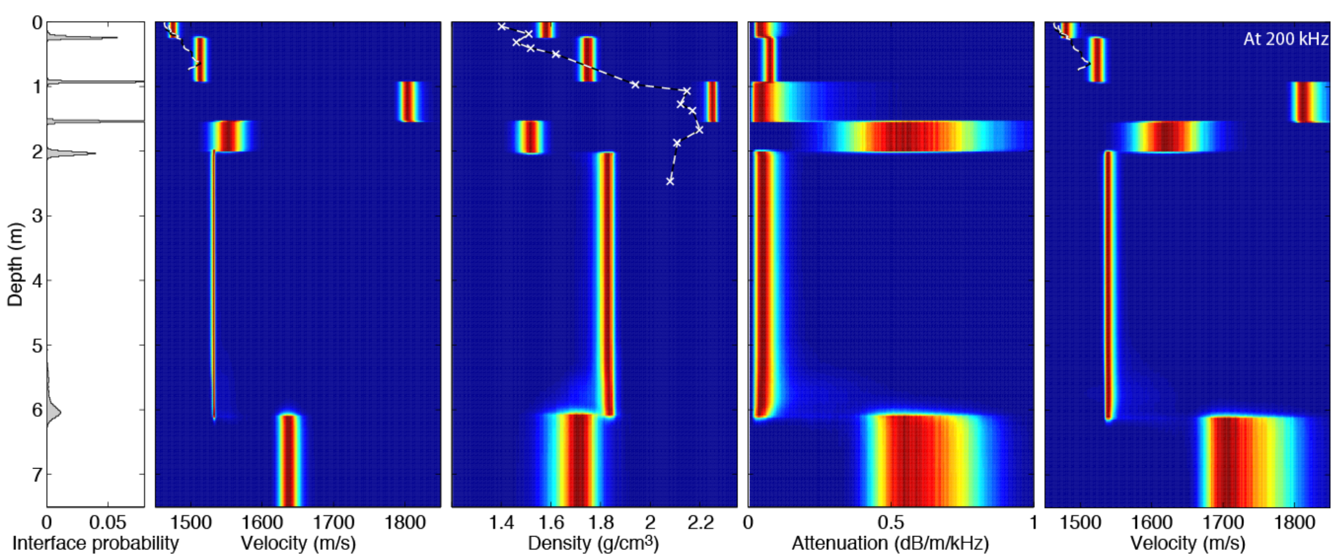

Figure 6: Marginal profile distributions for geoacoustic parameters, derived from VGS parameters (Site 1). Estimates from independent core samples are shown as dashed lines.

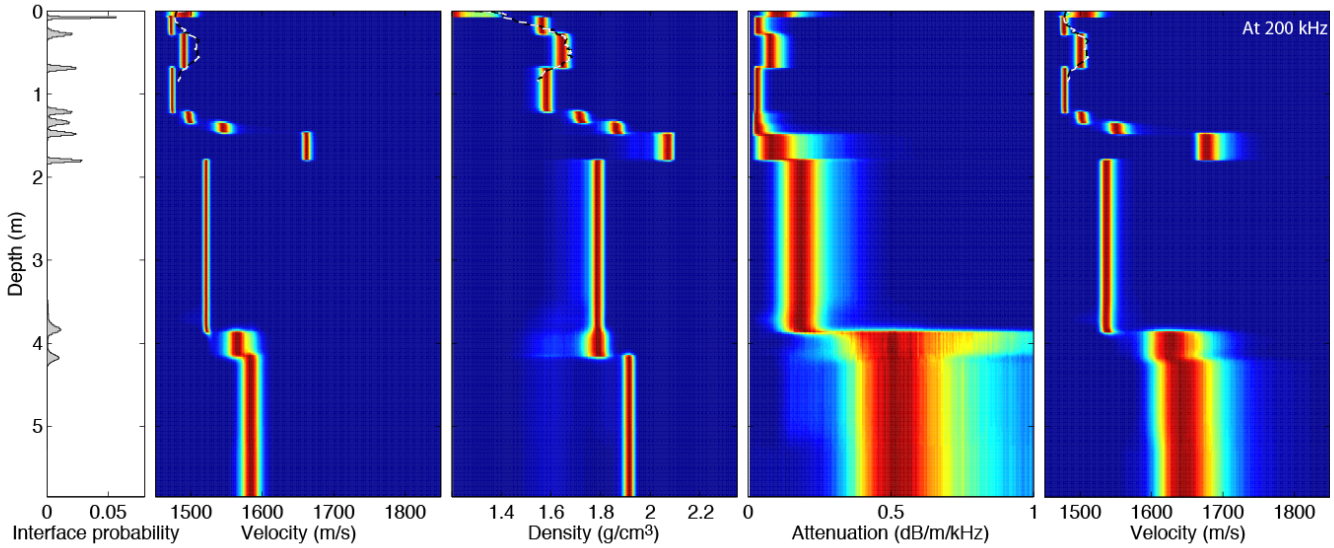

Figure 7: Marginal profile distributions for geoacoustic parameters, derived from VGS parameters (Site 16). Estimates from independent core samples are shown as dashed lines and sample locations for the sparse density core are marked by x.

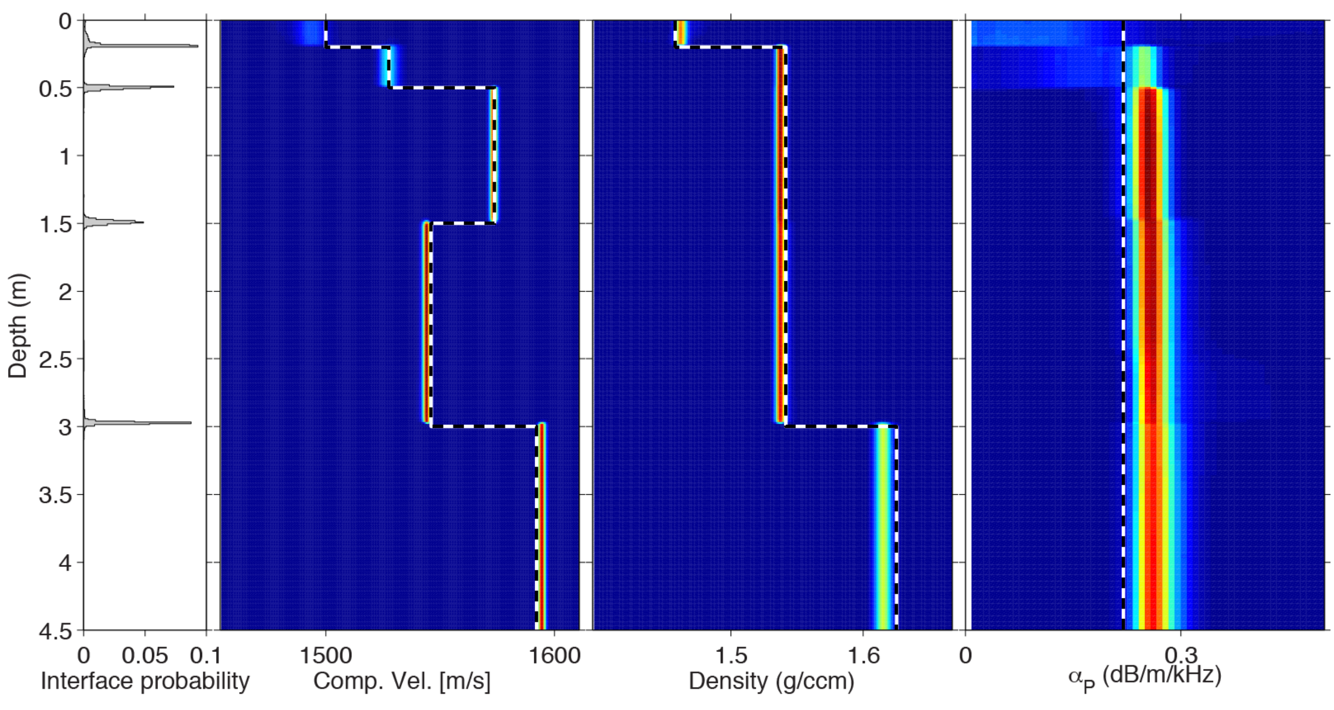

Figure 8: Inversion of simulated data with variable layer-node complexity. The algorithm has the ability to adapt to the various complexities for different parameters. Dashed lines indicate the true model parameter values.

IMPACT/APPLICATIONS

The ability to obtain *in-situ* seabed parameter estimates remotely (i.e., without direct sampling) has important geoscience implications (e.g., understanding sediment processes) and in some cases can be the only feasible way of obtaining such inferences (e.g., low-frequency dispersion). Further, variability estimates for seabed parameters are important for understanding the physics of acoustic-seabed interaction. Since variability can only be estimated if uncertainties are understood, uncertainty estimation is crucial. Important applications also include improved Navy databases (for ASW and MCM), as well as many commercial applications (pipeline or cable laying). A particular strength of this work is rigorous geoacoustic uncertainty estimation. These geoacoustic uncertainty models impact reliability and quality of transmission loss prediction.

RELATED PROJECTS

- Broadband Clutter JRP project (NURC, ARL-PSU, DRDC-A, NRL)
- Dosso's NSERC Discovery Grant "Geoacoustic Inversion" (2009-2014) at the University of Victoria: Dosso and Dettmer work closely together on advancing Bayesian inference applications.
- "Bayesian ambient noise inversion for geoacoustic uncertainty estimation" (2011–2012, Jorge Quijano ONR Postdoctoral Fellowship N000141110214) (Quijano et al. 2012ab): Quijano uses and further develops several algorithms that originated from Dettmer's work.
- "Bayesian inversion of seabed scattering data" (2011–2013, Gavin Steininger ONR PhD Fellowship N00014110213): Steininger uses and furthers several algorithms that originated from Dettmer's work. Dettmer is on Steininger's PhD supervisory committee. Steininger successfully graduated in 2014 with several peer reviewed papers published.
- Dettmer's work at Australian National University in seismology is closely related to some of the methods developed in this program resulting in strong mutual benefits (e.g., Dettmer et al. (2014)).

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