Obtaining local proportions from coarse-scale soft attributes through a unique multi-attribute, multi-scale (MA-MS) calibration

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SPODDS

Stanford Project on Deep-Water Depositional Systems

Introduction:

Revisiting the use of seismic attributes as soft data

Geostatistical modeling originated within the mining industry to estimate average minable ore grade from large support volumes given samples measured on small volume support. In petroleum geostatistics, the goal is more equivocal due to several different scales of support of input data, which are often incongruent with the desired prediction scale. Techniques for bringing together disparate data types into one model have been extensively addressed in the everyday application of petroleum geostatistics. Due to the indirect relationship between facies and seismic attributes, seismic attribute data are converted to a probability defining the presence or absence of a facies. Many different methods are used to generate these probabilities, from simple well-to-seismic calibration, to more detailed approaches such as principal component analysis (PCA), statistical rock physics, and neural network classification, to name a few. However, in light of these advances, the original strength of geostatistical modeling in addressing issues of scale or volume support has become secondary.

The fundamental omission with these approaches is the **lack of an explicit model of scale**. That is, the vertical resampling of both the well logs and the seismic attributes presupposes a different volume support than is actually prescribed by the data itself. The distribution and the spatial structure of the data are inherently linked to the scale at which they were measured. Furthermore, a set of seismic attributes, of low resolution and band-limited frequency, do not inform simply the presence or absence of a category, rather they inform the combination of a specific pattern of sub-resolution categories that generate the resulting seismic response.

This poster addresses the issues of modeling sub-seismic scale facies with seismic attributes while **explicitly incorporating the information content of each datum at the correct support at which it informs the model scale**. First, the scales of interest are introduced. Then a data-driven, multi-attribute, multi-scale (MA-MS) well-to-seismic calibration is shown along with the application of the calibration to unsampled regions. The issue of undersampling is addressed with statistical rock properties and forward modeling. Finally, the general workflow is demonstrated on synthetic outcrop datasets and the results linked to geostatistical and pattern-based facies modeling.

Problem:

Model Scale <> Data Scale(s)

The common practice for reconciling these disparate scales is to upscale log data and resample the seismic attributes to the model grid. The model grid is defined by depth-converted surfaces interpreted from seismic reflectivity profile and internal stratigraphic layers of a specified thickness between the surfaces. The layer thicknesses in the model grid are generally finer than the vertical seismic resolution, whereas the x-y cell size is usually the same as the binning of the seismic traces (Fig. 1). For facies modeling, the simplest (not necessarily the best) upscaling of log facies uses a most of selection, also known as majority rule.

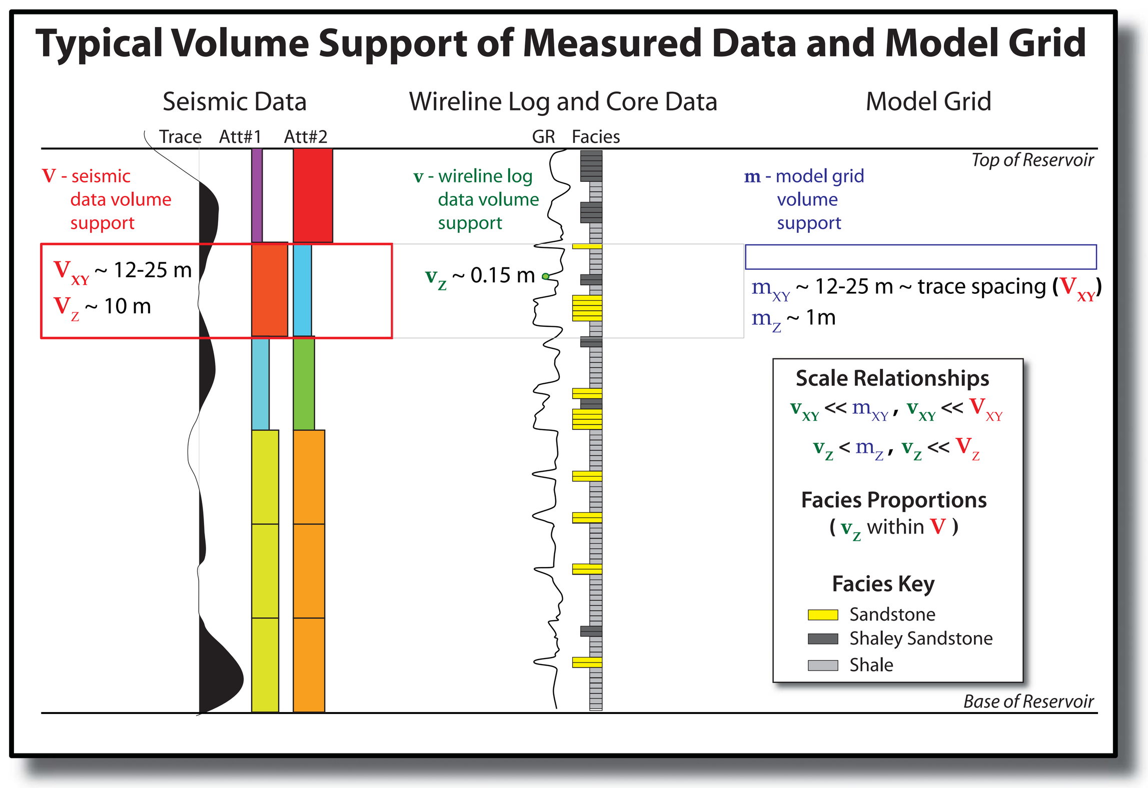
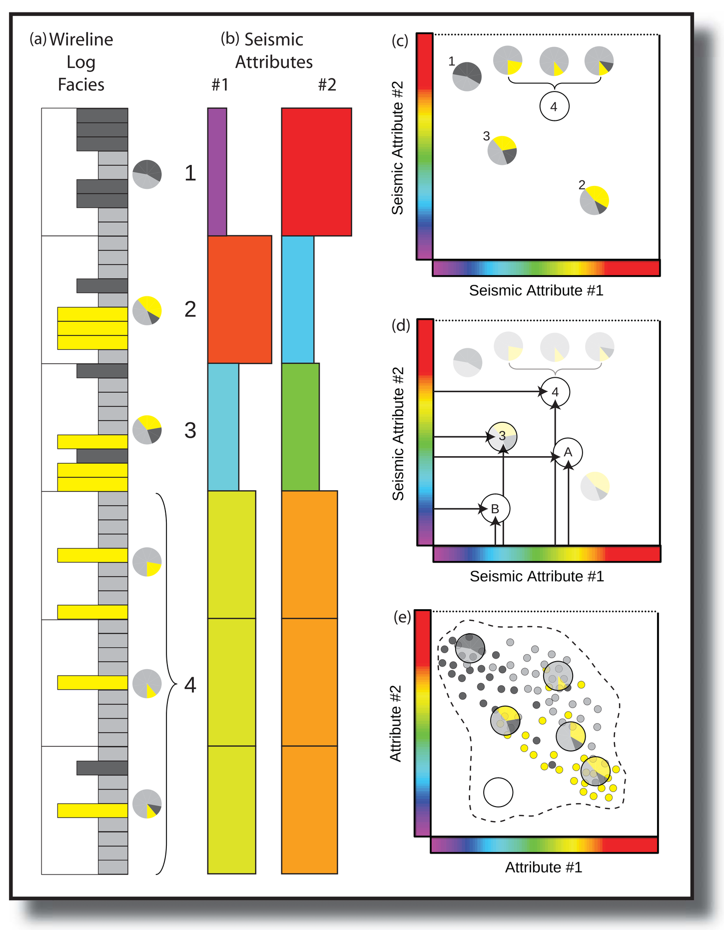


Figure 1. Conceptual depiction of the input scales of data (seismic data, V, and well log data, v) that contribute information for geostatistical modeling to property prediction at the model scale (m). Collocated log and seismic traces provide calibration information for using lower resolution, exhaustively sampled seismic attributes as soft information for facies proportion prediction.

MA-MS Calibration:

Probabilities vs. Proportions

The proportion, Pp (|V|), should not be confused with a probability, Pr{I(|V|)=1}, which refers to an event occurring at the larger support |V|. For example, assume that location |V| has a value 30% for sandstone facies. Consider the two following interpretations for the 30%: (a) 30% is a proportion Pp(|V|) = 30% and (b) 30% is a probability Pr{I(|V|)=1} = 30%, where I(|V|) is an indicator of the presence (1) or absence (0) of the sandstone facies. The latter probabilistic interpretation refers to the likelihood of a specific event I(|V|) = 1 to occur. That is, the coarse pixel |V| is sandstone and all sub-pixels |v| are also sandstone. On the other hand, considering 30% as a proportion automatically refers to a smaller support where the events occur, say |v| < |V |, and that 30% of the sub-pixels are sandstone.



A novel approach is proposed for calibrating high resolution small-support well data to large-support seismic attributes by considering the fine scale constituents that compose the coarse scale effective seismic response. Facies proportions are calculated from well log and/or core data for each collocated coarse scale block. These proportions are cross-plot as pie charts as a function of the seismic attributes from the collocated seismic attribute traces in the seismic data volumes .

Either a unique combination of facies or, conceivably, different organizations of bed thicknesses and facies proportions for a unique set of seismic attributes may be observed. Non-unique facies force a decision must be made as to whether each of these set of proportions is equally probable or whether, based on adjacent proportion/seismic attribute combinations, one is more likely than the other. A probabilistic model of proportions can then be created from this data-driven approach.

Figure 2. Conceptual illustration of the **multi-attribute, multi-scale (MA-MS) calibration method**. Fine-scale facies (left log, a) collocated with a set of seismic attributes which might be, for example, P-Impedance and Vp/Vs (right logs, b) are shown in three cross-plots: (c) MA-MS cross plot, and (d) proportion look-up when applying the calibration, and (e) raw log data (points) and the extent of all of the seismic samples in the volume (dashed line). Refer to Figure 1 for facies legend.

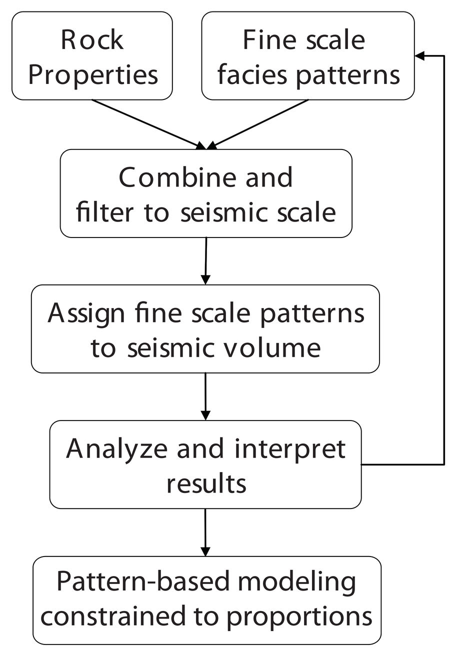


Figure 3. **General modeling workflow** for predicting sub-seismic scale proportions from a data-driven pattern-based model. Note the more general use of the term patterns. Proportions are just one of the attributes that can be derived directly from patterns.

Implementation- Case Study:

Late Oligocene Puchkirchen Field, Molasse Basin, Upper Austria

Challenges: 1) A change in reservoir quality from west to east is not expressed in amplitude nor impedance contrasts, 2) Known producing thin-bedded gas sandstone do not have an amplitude character, nor an impedance contrast.

Goals: Analyze proportions predicted from the MA-MS calibration to discern whether 1) this detailed multi-scale rock property correlation could **differentiate gas sandstone from soft shale**, and 2) whether proportions can **delineate thin gas sandstone** in the zone below the major gas producing layer.

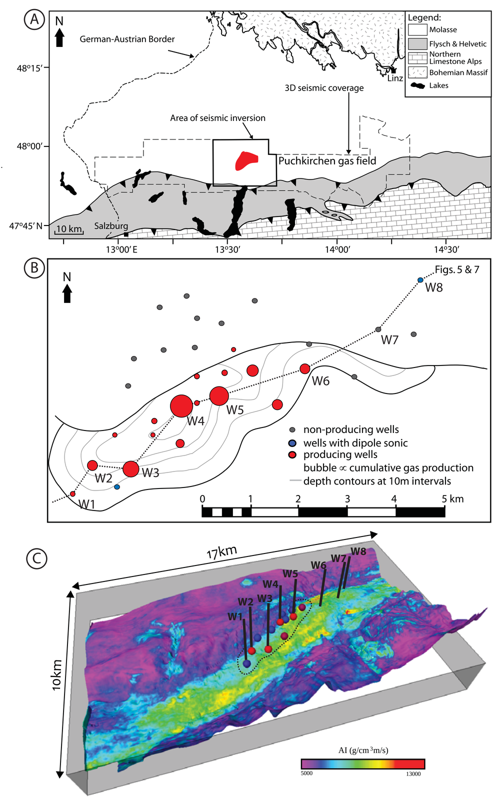


Figure c1. Basemap of the Austrian Molasse Basin and **location of study area**. (A) The Puchkirchen gas field location. (B) Well and cross section locations with gas production bubbles. (C) Acoustic impedance attribute shown on a stratigraphic surface. Well locations show the location of the Puchkirchen gas field (outlined), which was drilled on a structural high. Each sphere near well shows the amount of cumulative gas production, from red (high) to blue (low).

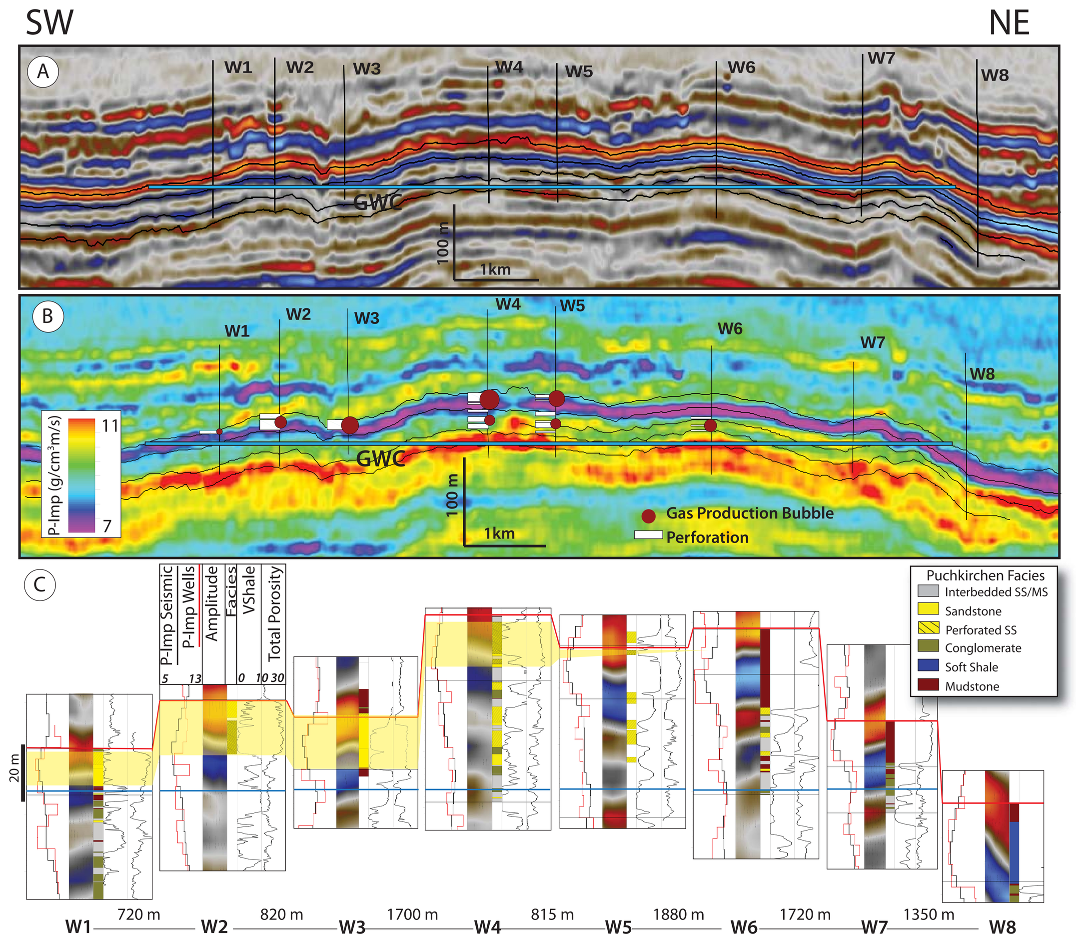
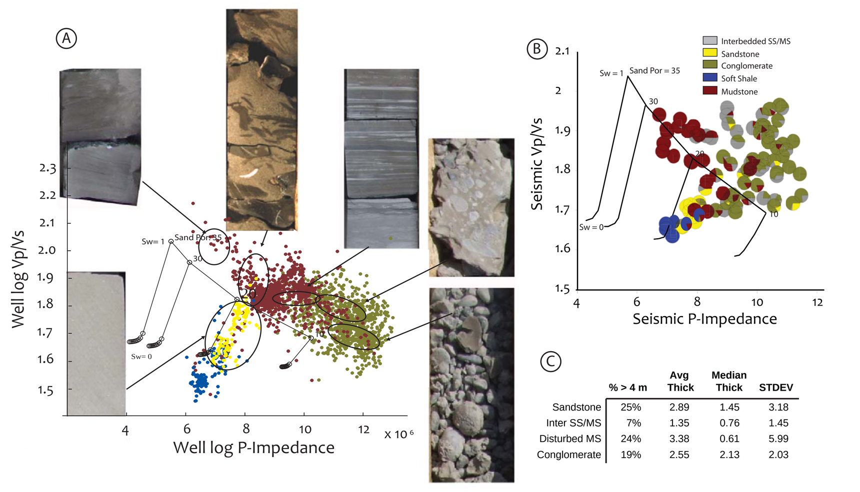


Figure c2. **Input data.** (A) Cross-section showing the amplitude variations, (B) P-impedance volumes, and (C) facies interpretations from the seismic data and the wells in the channel belt. The gas reservoir is a low impedance zone at the top of the section. The well data shows the reservoir sandstone (yellow) thinning basin-ward (southwest to northeast), while the seismic amplitudes and impedances reveal limited changes. Finally, perforated and produced zones are shown overlain on the impedance cross-section (white = perforations, red circles = gas production bubbles) and on the well section (cross-hatched yellow = perforated sandstones).



	% > 4 m	Avg Thick	Median Thick	STDEV
Sandstone	25%	2.89	1.45	3.18
Inter SS/MS	7%	1.35	0.76	1.45
Disturbed MS	24%	3.38	0.61	5.99
Conglomerate	19%	2.55	2.13	2.03

Figure c3. (A) Plot of Vp/Vs ratio vs. P-impedance cross-plot with core samples overlain to validate facies category definitions. Rock physics template is overlain. (B) **MA-MS calibration** where each pie chart shows the fine-scale facies proportions within a seismic sample. (C) Bed thickness statistics. Soft shale is omitted because there is only one bed that is 22 m thick.

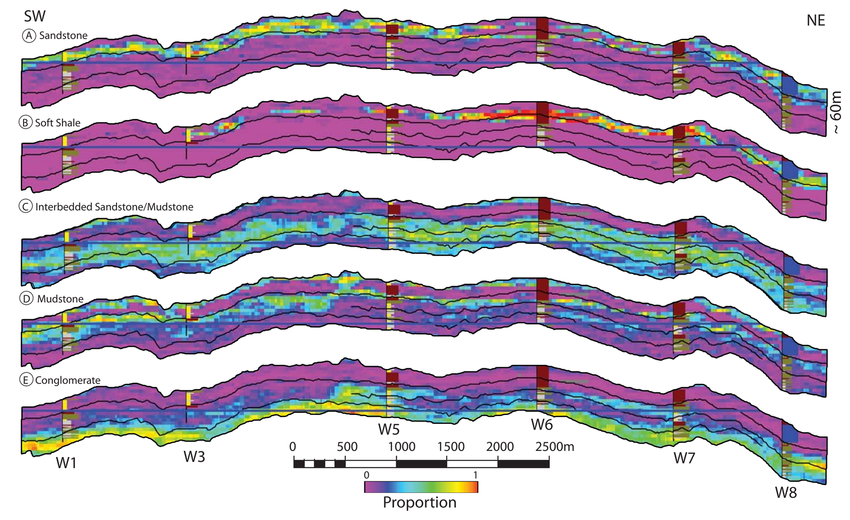


Figure c4. Cross-section of **proportion models** for each facies. The GWC is plotted at a constant height for reference.

Results:

- Reservoir SS is differentiated from soft shale in upper zone.
- Disturbed mudstone is predicted as soft shale because either the mudstone contains soft shale, or gas.
- Low proportions of thinly interbedded SS/MS are predicted above the GWC where the known producing zones exists.
- Disturbed mudstone, which is hypothesized to control the depositional morphology of SS, is predicted in high proportions in and around upper SS zone.

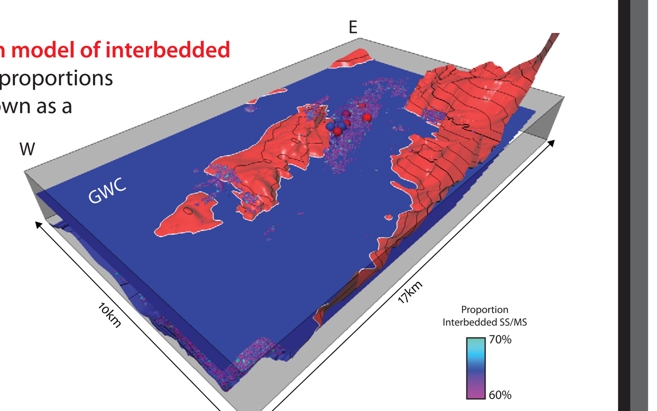


Figure c5. 3-D view of **proportion model of interbedded sandstone/mudstone** filtered to proportions higher than 60%. The GWC is shown as a constant, flat surface. This sub-seismic scale reservoir sandstone is predicted where the observed production (spheres: red high cumulative production, blue-low cumulative production)

Conclusion

Data-driven MA-MS predicts local proportions based on rock properties

Prior to using seismic attributes in modeling, this paper has shown that it is important to first question the volume support of the input data as it relates to the desired prediction volume support. Secondly, simply using probabilities, which are conceptual constructions and non-physical measurements, to account for the approximate relationship between facies descriptions and seismic attributes may camouflage issues between the rock properties assumptions in the wells and their expression in the seismic data. Proportions, as presented herein, are data-driven observations of sub-seismic scale features that directly relate to seismic scale attributes. Proportions, therefore, lend themselves more easily to direct calibration and analysis, and hopefully, better numerical models.

The proportions at |V| can directly be used as inputs to modeling at |m| either through covariance-based methods or multiple-point or pattern based methods. In covariance-based methods, indicator variograms and block indicator cokriging are used to approximate the probability that a pixel |m| belongs to a particular facies, given the proportions at |V|, while honoring facies descriptions at hard data locations in the wells, |v|. With a training image (TI) based method, proportions of fine scale patterns in the TI are upscaled and calculated at |V| thereby making a direct link between proportions and their associated patterns.

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