To optimize drilling decisions and well planning in overpressured areas, it is essential to carry out pore-pressure predictions before drilling. Knowledge of pore pressure implies knowledge of the effective stress, which is a key input for several geomechanics applications, such as fault slip and fault seal analysis and reservoir compaction studies. It is also a required input for 3D and 4D seismic reservoir characterization. Because the seismic response of shales and sand depends on their compaction history, the effective stress will govern the sedimentary seismic response. This is in contrast to normally pressured regimes, where the depth below mudline (or overburden stress) is typically used to characterize the compaction effect.

This paper presents a consistent workflow to show how high-resolution seismic velocities (Banik et al., 2003) were used to predict pore pressure and effective stress in a deepwater environment where overpressured sediments are known to exist. Effective stress allows mapping nonstationary sedimentary compaction in space and is used as an additional attribute in the Bayesian lithofacies classification (Bachrach et al., 2004; Mukerji et al., 2001). The other attributes in the process are elastic parameters such as acoustic and shear impedances obtained from the multi-attribute seismic inversion (Roberts et al., 2005). To allow for consistency between well and seismic data and stratigraphic layers, geostatistical mapping (trend-kriging) techniques were applied using several key horizons. The final trend-kriged model is constrained by the structural framework and the geology of the basin.

The case for a joint geomechanics-seismic inversion workflow. Figure 1 shows the well-log data from two adjacent wells in the area. The P-wave impedance \( I_P \), S-wave impedance \( I_S \), and density data are plotted as a function of depth below mudline and color-coded by volume of clay. Sands are blue points. All data have been fluid-substituted to 100% brine. Note that while, in general, \( I_P \), \( I_S \), and density are increasing with depth, there is a zone of several hundred feet where \( I_P \), \( I_S \), and density decrease with increasing depth. This behavior can be observed in well A and well B at different depths, although the wells are close to each other—in well A at 10 000–12 000 ft and in well B at 10 000–14 000 ft.

Figure 2 shows the same wells and data as Figure 1 but in the effective-stress attribute domain. The vertical effective stress is calculated using the overburden stress and pore pressure derived from high-resolution seismic velocity and a rock model as discussed in the following sections. It is evident from Figures 1 and 2 that the compaction trends for shale and sand show a more consistent increase in the vertical effective-stress domain than in the depth domain. Thus, the vertical effective stress is a more appropriate attribute to describe lithofacies than depth. The ability to predict effective stress in three dimensions overcomes the shortcoming of using just depth as the attribute governing sediment compaction.

Figure 1. Data from two adjacent wells in the study area as a function of depth below mudline. The color bar represents volume of clay. In both wells \( I_P \), \( I_S \), and density are left to right, respectively.

Figure 2. Data from two adjacent wells in the study area as a function of depth below mudline. The color bar represents volume of clay. In both wells \( I_P \), \( I_S \), and density are left to right, respectively.
paction behavior of the sediments. The available data do not indicate major second-order effects associated with different stress paths (e.g., loading and unloading) that may affect the pore-pressure prediction. The pore-pressure prediction described here assumes an isotropic medium.

**Methodology.** The four components that comprise the joint workflow are a high-resolution velocity analysis, a pore-pressure and effective-stress prediction, a multi-attribute seismic inversion, and a Bayesian lithofacies classification using $I_p$, $I_s$, and effective stress.

*High-resolution velocity analysis (step 1).* The interval velocities in the present study were obtained using a method that maximizes the stacking power of spatially continuous events in prestack gathers (Mao et al., 2000). The initial interval velocity model was built using a velocity model builder that inverts stacking velocity functions for interval velocity profiles using a singular value decomposition method. Because the inversion of interval velocity is nonunique, the initial velocity model is regularized using a semblance-based interactive velocity analysis system. This fit-for-purpose velocity analysis method was successfully used previously for pore-pressure and effective-stress prediction (e.g., Banik et al., 2003).

The velocity model, thus obtained, went through geostatistical mapping (trend-kriging) using the upscaled well-log velocities within several key stratigraphic layers. Kriging techniques can be used for interpolating a single variable in two or three dimensions. Trend-kriging uses the extra information provided by another variable to guide the interpolation. In this study, the seismic velocity is used as the spatially varying mean when using kriging to spatially interpolate the well-log velocity data into stratigraphic 3D layers, which honor the geologic structure (see Goovaerts, 1997, for more details). In the vicinity of the well, the well-log velocity data will carry more weight, while away from the wells, the velocity field will go to its mean, which is the seismic velocity. The input needed for this analysis is a 3D variogram model, consisting of a single spherical structure with a given vertical correlation length and an isotropic lateral correlation length (parallel to bedding), horizons, well data, and seismic velocities. The kriging is done within a stratigraphic framework, to ensure consistency between the interpreted horizons and geology. Figure 3 shows the structural framework associated with the geostatistical mapping. Figures 4a and b show the velocity model before (Figure 4a) and after trend-kriging (Figure 4b). Note that near the wells (within the correlation length) the resolution approaches the well-log resolution and the data are influenced more by the well-log data.

*Pore-pressure and effective-stress prediction (step 2).* Most methods for pore-pressure prediction are based on Terzaghi’s effective stress principle (1943), which implies that elastic-wave velocities are a function of the effective stress tensor, which is defined as the difference between the total stress tensor and the pore pressure $p$. In the study presented here, it is assumed that the elastic-wave velocity is a function only of the vertical effective stress $\sigma_{\text{eff}}$. Then Terzaghi’s relationship can be written as

$$\sigma_{\text{eff}} = S - p$$

The vertical component $S$ of the total stress is assumed to be the weight of the rock matrix and the fluids in the pore space overlying the interval of interest. $S$ is calculated by integrating the bulk density from the surface to the specific depth:

$$S = g \int_0^z \rho(z) \, dz$$

where $\rho(z)$ is the density at depth $z$ below the surface and $g$ is the acceleration due to gravity.

Effective-stress methods used to predict pore pressures
include the methods of Bowers (1995) and Eaton (1975). Eaton's method estimates the effective stress from the devi-
ation of velocity in normally pressured sediments (normal
velocity). For this study, Eaton's approach was used fol-
lowing the inversion methodology of Sayers et al.
(GEOPHYSICS, 2002). The velocity-to-pore-pressure transform
duced from data from wells in the area of interest or
offset wells. The formation pore pressure is assumed to be
represented by the mud weights used for drilling these
wells, because during drilling operations mud weights are
increased to prevent fluid and gas influxes from the for-
mation into the wellbore; therefore these relevant mud
weights can provide a reasonably close estimate of forma-
tion pressure. By inverting to the available pore-pressure data in these nearby wells in order to calibrate the velocity-
to-pore-pressure transform, the normal velocity can be accu-
rately defined, allowing identification of possible shallow
overpressures. This method contrasts with current methods
that fit a trend line to velocity data as a function of depth
below mudline. This trend is often referred to as a “normal
trend” which captures the expected velocity variation with
depth when the pore pressure is hydrostatic.

The calibration of the transform is based on evaluating
the misfit between the predicted pore pressure and the mea-
sured pore pressure and is quantified by the root mean
square (rms) of the residuals (Sayers et al., 2002). An esti-
mate of the inherent uncertainty is given by minimizing and
mapping the rms with respect to the parameters that define
the pore-pressure transform.

Pore-pressure data used for calibration were obtained
from an analysis of mud weights and formation pressure
test data. The overburden stress $S$ is calculated from Equation
2. To estimate overburden stress at the depth of interest, an
analytical form for $\rho(z)$ was used. This was used to com-
pute density over the depth range for which density data
were not available.

Figure 5 shows the up-scaled sonic log velocities for the
offset wells versus the effective vertical
stress. The dots represent effective stress (the difference between over-
burden and pore pressure) for relevant mud weights. Based on drilling
reports, these mud weights provide an estimate of formation pore pres-
sure. The different colors and signs indicate different wells. The blue
line represents the normal velocity derived by inversion (vertical and
horizontal scales not included for reasons of confidentiality).

Figure 6. Pore-pressure estimate using up-scaled sonic velocities at a
calibration well location. (a) Upscaled sonic (magenta) and normal
velocity (blue), which is estimated by inverting to the pressure data, as
explained in the text. (b) Pore-pressure gradient, estimated as equiva-
lent mud weights with calibration data: mud weights (blue dots) and
LOT data (red dots). The black curve represents the overburden gradi-
ent (vertical scale not included for reasons of confidentiality).
used for drilling these wells, assuming that the occurrence of gas and fluid influxes during drilling and the associated mud weights allow a close estimate of the formation pore pressure. The curve in Figure 5 is based on an Eaton-type normal velocity plotted versus effective stress and shows a good fit to the well data. The deviations from the curve represent possible variations in porosity and clay content.

The normal velocity derived by inversion and shown in Figures 5 and 6 was then used in an Eaton approach to calculate effective stress and to determine pore pressure. Figure 6 shows an example for a calibrated well. Mud weights are considered to be the upper bound for pore pressure while leak-off test (LOT) data are considered to be close to the vertical effective stress. In the calibrated model, both pore-pressure and overburden stress predictions are consistent with these calibration data.

The calibrated velocity-to-effective-stress transform was then applied to the trend-kriged velocities. To apply the pore-pressure transform, it is necessary to determine density at all locations so that a 3D volume of total vertical stress can be calculated. To do this, a density cube was built by geostatistically mapping the available well-log data in the area, constrained by depth horizons and a 3D trend. The geostatistical mapping (trend-kriging) of the upscaled density log data is guided by a 3D density-trend volume, which was built by applying a locally calibrated Gardner relationship (Gardner et al., 1965) to the seismic velocity cube. This density-trend cube was resampled into 3D curvilinear stratigraphic grids representing stratigraphic layers for use as a 3D trend (local mean). The upscaled density log data were then kriged in each layer assuming a geostatistical model consisting of a single spherical structure with a given vertical correlation length and an isotropic lateral correlation length (parallel to bedding). Integration of the density cube using Equation 2 thus allows the total vertical stress to be determined anywhere in the model.

Note that the velocity model went through geostatistical mapping (trend-kriging) using the upscaled well-log velocities within several key stratigraphic layers, similar to the method applied in creating the density model. The use of horizons helped to maintain consistency of the well data and the geologic structure. The velocity-to-pore-pressure transform, which is established from nearby well data, is then applied to this trend-kriged velocity volume. The final volumes of pore pressure and effective stress are shown in Figures 7a and b.

Multi-attribute seismic inversion (step 3). The multi-attribute seismic inversion process has been presented previously (McWhorter et al., 2005). The workflow is schematically shown in Figure 8. The processes enclosed in the light blue rectangles describe the needed modification in the workflow for incorporation of the effective stress. The background models for $IP$ and $IS$ were derived from the trend-kriged velocity and density volumes. This step is important, because all attributes used in the model must have a common background model and follow a consistent set of assumptions. Figure 9 shows absolute $IP$ and $IS$ along an inline, derived from multi-attribute seismic inversion after low-frequency compensation (see Roberts et al., 2005, for more details).

Lithofacies classification using effective stress, $IP$, and $IS$ (step 4). The key to using effective stress as an attribute for reservoir characterization is to understand the underlying behavior of the elastic parameters ($IP$ and $IS$) with respect to lithology and effective stress. Figure 10a shows a schematic relationship between $IP$ versus effective stress for shale and brine-filled sand representing sediment compaction in clastic basins. In general, $IP$ will increase with effective stress for shales (black line) and brine sands (green line). It is clear that the presence of hydrocarbons in the pore space will reduce $IP$, as both $VP$ and density will be lower than in the brine-filled case. This is schematically represented by the dotted line in Figure 10a. To statistically quantify the depen-
Differences between elastic parameters, effective stress and lithology units $I_P$ and $I_S$ are calculated from well-log data and plotted with respect to the effective stress attribute. The data are color-coded by lithology. The scatter of shale and brine sands around the compaction trend is used to derive a probability density function (pdf). Figure 10b shows the scatter of $I_P$, $I_S$, and effective stress for four lithology units: brine sand, shale, gas sand, and oil sand. It is clear from Figure 10b that discriminating between oil and gas in this system is very difficult due to the scatter of the data. Therefore, the oil sands and gas sands are included in a single “hydrocarbon” class.

The scatterplot in Figure 10b allows the discrimination of three lithofacies classes that were used for inversion in the basin: shale, brine sand, and hydrocarbon sand. In Figure 11, the derived 4D pdf $P(I_P, I_S, \sigma_{eff} \mid \text{Lithoclass})$ is plotted at different effective stress intervals. Note that the ability to discriminate shale, brine sand, and hydrocarbon sand changes as a function of the effective stress according to the compaction model. Furthermore, the effective stress is spatially varying, as seen clearly in Figure 7. Thus, to correctly classify a lithofacies type, knowledge of $I_P$ and $I_S$ is necessary, and the spatially varying effective stress is needed as shown in Figure 11. This allows defining the position with respect to the compaction curve (Figure 10a).

The class probability values were obtained for each set of $I_P$, $I_S$, and effective stress for each seismic data sample and effective stress value by deriving the posterior pdf $P(\text{Lithoclass} \mid I_P, I_S, \sigma_{eff})$ (as shown in Bachrach et al., 2004). From Figure 11 it is clear that the ability to correctly identify the pay zone is related also to the vertical effective stress, and not only to the seismic attributes.

Figure 12 shows the computed hydrocarbon sand probability values along an inline using the method described above. A control well shows good agreement between a saturation log and high hydrocarbon probability. Figure 13 shows another inline, which allows comparison of the hydrocarbon probability and effective stress at the same location.

In Figure 14, hydrocarbon sand probability values are posted on a horizon with and without effective stress as an attribute. As is evident from Figure 11, without effective stress the results are not as clear as when effective stress is used, because the probability functions are “smeared.” Furthermore, if effective stress is not taken into account, only the shallower events are identified as potential hydrocarbon sands. This can be seen in the left of Figure 14, where potential hydrocarbons are visible only in the structurally
shallower part of the horizon. If effective stress is included as an attribute (right of Figure 14), however, the hydrocarbon probabilities in the deeper, more compacted areas, can be mapped as well. The good match between the well and seismic (shown in Figure 12) is possible because the effective stress “riding” on \( I_P \) and \( I_S \) efficiently captures the spatial variation in the rock model (both vertically and laterally) for lithofacies class discrimination.

**Conclusion.** The effective stress used in this case study (along with \( I_P \) and \( I_S \) as attributes in the lithofacies classification based on Bayesian statistics) was derived from high-resolution seismic velocity analysis. \( I_P \) and \( I_S \) were established from multi-attribute seismic inversion. Pore-pressure and effective stress prediction based on trend-kriging incorporates the multitude of available data. The application of trend-kriging, a statistical mapping process, allows a spatially varying mean, the incorporation of offset well data, as well as honoring the geologic structure. The results were used successfully in low-frequency background model building for multi-attribute seismic inversion and for a high-quality lithofacies prediction using effective stress as an attribute.

The use of effective stress efficiently discriminates various lithofacies classes in an overpressured basin with a high degree of spatial variability in sediment compaction and associated disequilibria. By identifying the stress, velocity and density dependencies, a set of probability distribution functions was derived, such that, given a set of \( I_P \), \( I_S \), and effective stress values, a lithofacies class probability value can be predicted. The method has been successfully applied to a deepwater basin known to have varying pore pressure. Because lithofacies classification and hydrocarbon prediction takes into account both the fluid effects (through Gassmann’s equation) and the separation in \( I_P \) and \( I_S \) associated with the sand and the shale compaction curves, effective stress, and not the depth below mudline, is the appropriate attribute to use for seismic-inversion-based reservoir characterization.

In this study the vertical effective stress is used, and it is assumed that compaction disequilibrium is the governing pore-pressure mechanism. These assumptions are valid for the zone of interest, and within the scope of this study they provide estimates for a larger area during the exploration phase. However, these assumptions may be violated in structurally complex areas, such as proximity to salt. In these cases one may need to solve for the full stress tensor and re-examine the derivation of effective stress. However, the incorporation of effective stress should help in the lithofacies classification.

The keys to success are to have a fit-for-purpose velocity field, calibrated pore-pressure model, multi-attribute seismic inversion, and a consistent background model for all seismic attributes. An effective-stress-based method efficiently captures the spatially varying rock properties in overpressured basins, providing a high-quality solution for reservoir characterization.


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