

Seismic Acquisition and Processing as a Coupled System: A Data-Driven Audit from Prestack Noise to Stack Signal

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Summary

This study introduces a data-driven framework for auditing the seismic imaging budget from prestack gathers to the final stacked image. The analysis uses a dense land experiment at the Devine test site in Texas acquired with a 7.5×7.5 m nodal receiver grid. To isolate the role of spatial sampling, the same dataset is evaluated at three receiver densities: the native 7.5×7.5 m grid, a coarser 15×15 m geometry, and an interpolated 3.75×3.75 m configuration. Prestack SNR is estimated as a function of offset using a stack-based, data-driven diagnostic and propagated through the acquisition geometry to predict stack SNR, which is then compared with SNR measured directly in the stacked image. The results reveal systematic gaps between theoretical stacking predictions and realized image quality. The analysis provides a quantitative audit of the seismic imaging system, effectively acting as an X-ray that links acquisition density, prestack signal statistics, processing efficiency, and the final interpretable image.

Introduction

High-density acquisition has often been advocated as the primary driver of seismic image quality (Ourabah et al., 2015). While such studies demonstrated correlations between trace density and various interpretive attributes, they did not directly quantify prestack signal-to-noise ratio (SNR) or track how signal statistics propagate through stacking. Yet SNR fundamentally controls the reliability of both prestack and poststack interpretation tasks, including amplitude fidelity required for AVO analysis (Raban et al., 2024). Consequently, the actual performance gains from increased density, and the degree to which theoretical stacking expectations are realized in practice, remain poorly constrained.

Seismic acquisition design is still largely evaluated using geometric descriptors such as fold, offset distribution, and trace density (Vermeer, 2012; Meunier, 2011). These parameters describe how the wavefield is sampled but provide limited insight into the signal quality recorded in prestack data. As a result, acquisition performance is rarely evaluated directly from the data themselves.

However, trace density alone does not fully determine seismic image quality. Acquisition performance reflects the combined influence of multiple coupled parameters, including source strength, receiver response, array design, and spatial sampling (Meunier et al., 2011). Simple signal-statistics models therefore indicate that improvements in trace density can be offset by degradations in other acquisition variables. For example,

Bakulin and Silvestrov (2023) showed that increases in trace density may be outpaced by reductions in effective source strength, resulting in lower overall image SNR despite denser sampling. These interactions make it difficult to evaluate acquisition performance using geometric descriptors alone. In practice, the industry often relies on qualitative arguments that “more traces are better,” while the cumulative effects of acquisition and processing choices on final signal recovery remain largely unquantified. Without a systematic accounting framework linking prestack signal statistics to the final image, such trade-offs remain hidden.

Recent work introduced data-driven diagnostics such as prestack SNR, enabling signal quality to be estimated directly from seismic data (Bakulin et al., 2022). Such approaches address the long-standing challenge of evaluating very noisy land datasets, although robust estimation at very low SNR is inherently difficult and requires sufficiently large statistical ensembles. Bakulin and Silvestrov (2023) suggested that these diagnostics could help close the loop between acquisition design, processing, and final image quality through a complete seismic assessment framework, yet practical demonstrations linking prestack statistics to stack performance remain limited. The conceptual workflow of this data-driven seismic imaging audit is illustrated in Figure 1b.

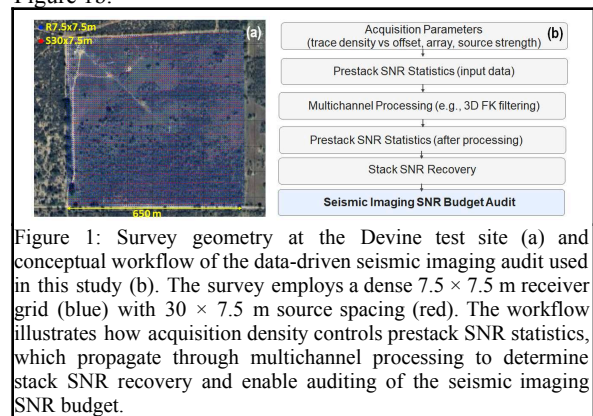


Figure 1: Survey geometry at the Devine test site (a) and conceptual workflow of the data-driven seismic imaging audit used in this study (b). The survey employs a dense 7.5×7.5 m receiver grid (blue) with 30×7.5 m source spacing (red). The workflow illustrates how acquisition density controls prestack SNR statistics, which propagate through multichannel processing to determine stack SNR recovery and enable auditing of the seismic imaging SNR budget.

Here we examine how prestack SNR statistics propagate to stack performance using datasets with different spatial sampling densities. Offset-dependent prestack SNR is first estimated to quantify how acquisition density influences multichannel noise suppression. These statistics are then propagated through the acquisition geometry to predict the expected stack uplift and compared with the observed stack

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results. This analysis effectively audits the seismic SNR budget from prestack data to the final stack. While the relative ranking of acquisition densities broadly follows prestack SNR behavior, the realized stack recovery is systematically lower than predicted by classical stacking assumptions, revealing hidden coherence losses in the acquisition and processing chain.

Data and Method

The analysis uses data from a dense land seismic experiment conducted at the Devine test site in Texas. The survey employs a 7.5×7.5 m receiver grid of single-sensor nodes with 30×7.5 m source spacing, providing unusually dense sampling of the wavefield (Figure 1a).

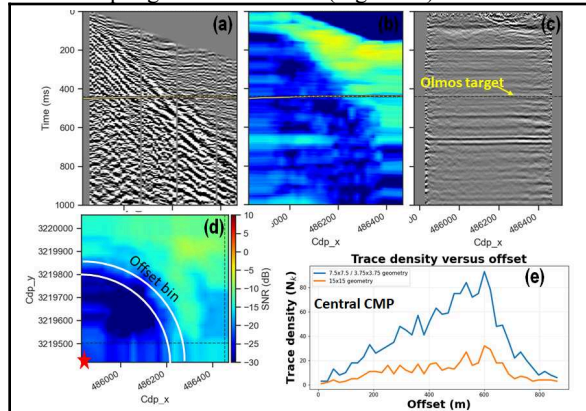


Figure 2: Workflow used for prestack SNR estimation and offset statistics. (a) Representative common-shot gather used for SNR evaluation. (b) Corresponding SNR cross-section derived from the prestack data. (c) Stacked section showing the Olmos target horizon used for the analysis. The reflector occurs at approximately 500 m depth and is relatively weak but was selected because it represents the planned hydrogen injection interval at the Devine test site (Bakulin et al., 2025). (d) Map view of SNR along the target horizon after NMO, showing low SNR inside the near-offset noise cone and higher SNR toward larger offsets. The red star marks the shot location. SNR–offset curves shown in Figure 3 are obtained by condensing this SNR map through averaging along offset, conceptually illustrated by the white arc. (e) Trace-density histogram versus offset for the central CMP used in the imaging-budget analysis.

To evaluate the impact of spatial sampling on imaging performance, three acquisition-density scenarios were analyzed. The native 7.5×7.5 m receiver grid was used as the reference case. Two additional datasets were constructed through controlled resampling: interpolation to 3.75×3.75 m and decimation to 15×15 m. This approach allows direct comparison of acquisition-density effects while preserving the same underlying wavefield. The analysis follows the data-driven imaging audit workflow illustrated in Figure 1b, linking acquisition density, prestack signal statistics, multichannel processing, and final stack performance.

Prestack SNR was estimated using a stack-based, data-driven diagnostic applied to 3D common-shot gathers (Bakulin et al., 2022), producing 3D SNR volumes with the same dimensions as the input shot gathers. These volumes were sampled along the target reflection horizon and condensed into SNR–offset statistics by binning traces by offset and averaging over azimuth, thereby focusing on the offset dependence of SNR. Each dataset was subjected to a simplified but consistent processing sequence designed to isolate the role of spatial sampling in multichannel noise suppression. In particular, 3D F–K filtering was applied to suppress linear noise and enhance reflection energy.

Prestack SNR statistics were propagated through the acquisition geometry to predict stack uplift and compared with stack SNR measured directly from the stacked data, providing a fully data-driven audit of the seismic SNR budget from prestack gathers to the final image.

Prestack SNR results

Prestack SNR statistics were estimated from four corner 3D common-shot gathers representing typical survey conditions. The workflow is shown in Figure 2. Shot gathers (Figure 2a) were used to compute 3D prestack SNR volumes (Figure 2b), from which SNR slices were extracted along the Olmos target horizon after NMO correction (Figure 2d). Offset-dependent SNR statistics were then obtained by averaging along offset and across the four shots. Figure 3 shows the resulting SNR–offset relationships for the five acquisition and processing scenarios. Several consistent patterns emerge. First, prestack SNR shows a clear imprint of the near-offset noise cone, where values drop to about -35 dB. SNR increases toward larger offsets as reflection coherence improves.

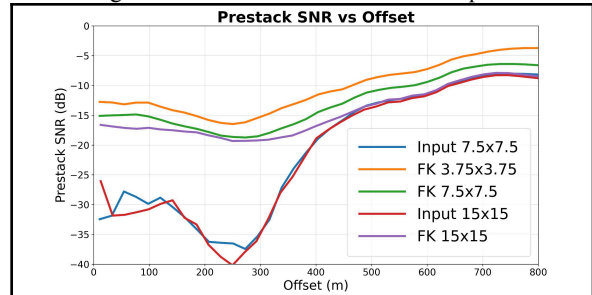


Figure 3: Prestack SNR as a function of offset estimated for the central CMP. Curves correspond to different acquisition densities and processing stages, including input data and FK-processed results. The curves illustrate how prestack SNR varies with offset and how spatial densification and FK processing modify the offset-dependent signal quality used for the stack-SNR prediction.

Second, multichannel processing improves prestack SNR, with 3D F–K filtering suppressing coherent and incoherent noise and enhancing reflection energy. After multichannel processing, overall SNR rises but the near–far contrast remains roughly 10 dB.

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Third, acquisition density controls the effectiveness of multichannel processing. Higher spatial sampling consistently produces higher SNR across offsets. The coarsest geometry (15×15 m) exhibits the lowest SNR, while the densified 3.75×3.75 m configuration yields the highest values. The native 7.5×7.5 m sampling lies between these extremes.

However, the processing gain remains modest, reaching at most about 10–20 dB even for the highest sampling density. For more regular reflectors with stable phase behavior and predominantly linear noise, multichannel filtering can produce much larger improvements, approaching 40 dB. The limited uplift observed here therefore reflects the weak, speckled character of the target reflector and the complexity of the recorded waveform. This behavior suggests that residual scattering, phase variability, and partially coherent noise limit the effectiveness of multichannel suppression. These prestack statistics therefore provide an additional diagnostic of reflector stability and processing effectiveness, forming the basis for evaluating how signal quality propagates through stacking and ultimately determines final image quality.

Poststack Results and Imaging Budget

Stacked sections were generated for the five acquisition–processing scenarios to evaluate how prestack statistics propagate to the final image. Poststack SNR was estimated along the Olmos horizon using the similar data-driven, stack-based SNR diagnostic as in the prestack analysis.

The resulting SNR distributions are shown in Figure 4. The 15×15 m configuration produces the lowest stack SNR, while the interpolated 3.75×3.75 m case yields the highest, with the native 7.5×7.5 m geometry between them. This ordering mirrors the prestack behavior, confirming that acquisition density remains a primary control on image quality. To quantify imaging performance, SNR values were extracted at the central CMP in Figure 4 to demonstrate the end-to-end imaging audit workflow (Figure 1b) linking prestack statistics to the final stacked trace. The measurements are summarized in Table 1. Because the same SNR diagnostic is applied before and after stacking, this comparison provides a fully data-driven audit linking prestack signal statistics to the final stacked image.

Stack SNR prediction from prestack statistics

To close the loop between prestack statistics and stack performance, the expected stack SNR was predicted from the prestack SNR–offset relationship and the acquisition geometry. The prediction uses the trace-density distribution versus offset for the central CMP shown in Figure 2e, which defines the number of traces contributing within each offset interval. The corresponding prestack SNR as a

function of offset is taken from the curves in Figure 3a. Assuming identical signal contributions across traces and uncorrelated noise within each offset bin, the expected stack SNR can be estimated by propagating the offset-dependent prestack SNR through the acquisition geometry:

$$SNR_{stack}^{dB} = 10 \log_{10} \left(\frac{\left(\sum_k N_k \right)^2}{\sum_k (N_k / r_k)} \right),$$

where the summation is performed over offset bins k , N_k is the trace density in offset bin k from the trace-density distribution in Figure 2e, and $r_k = 10^{SNR_k^{dB}/10}$ is the prestack SNR in linear units derived from the offset-dependent SNR curves in Figure 3a.

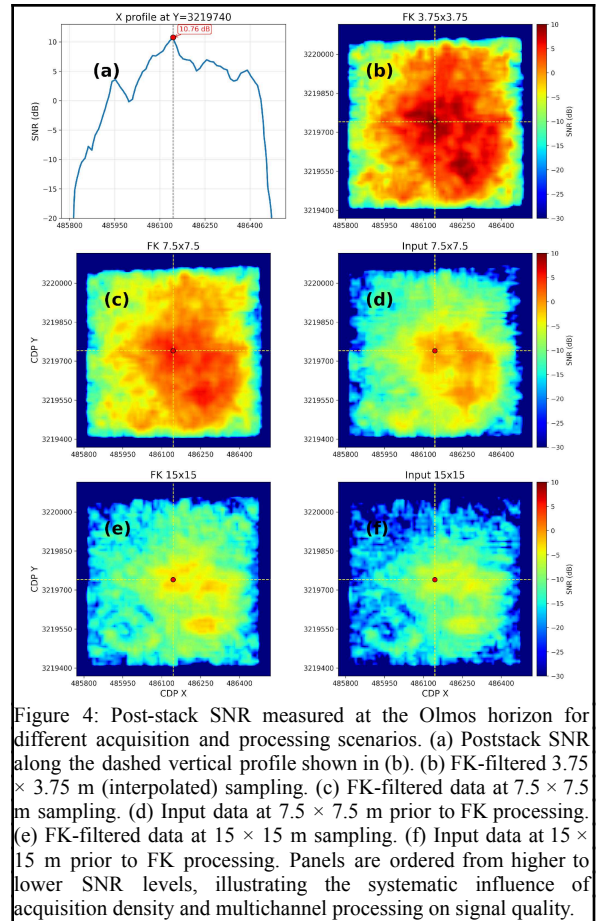


Figure 4: Post-stack SNR measured at the Olmos horizon for different acquisition and processing scenarios. (a) Poststack SNR along the dashed vertical profile shown in (b). (b) FK-filtered 3.75×3.75 m (interpolated) sampling. (c) FK-filtered data at 7.5×7.5 m sampling. (d) Input data at 7.5×7.5 m prior to FK processing. (e) FK-filtered data at 15×15 m sampling. (f) Input data at 15×15 m prior to FK processing. Panels are ordered from higher to lower SNR levels, illustrating the systematic influence of acquisition density and multichannel processing on signal quality.

Discussion

Comparison of predicted and observed stack SNR (Table 1) reveals several consistent patterns. The relative ranking of acquisition scenarios remains stable from prestack statistics

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to the final stack: denser geometries systematically produce higher SNR, with the interpolated 3.75×3.75 m case performing best and the 15×15 m geometry worst. This confirms that acquisition density remains a primary control on image quality.

Scenario	Observed (dB)	Predicted (dB)	Obs – Pred (dB)
FK 3.75×3.75	10.2	20.3	–10.1
FK 7.5×7.5	5.9	17.8	–11.9
Input 7.5×7.5	0.2	3.3	–3.1
FK 15×15	–2.9	11.0	–13.9
Input 15×15	–6.4	–4.2	–2.2

Table 1. Observed and predicted stack SNR for the five acquisition–processing scenarios evaluated at the central CMP along the Olmos horizon (Figure 4a). Observed SNR is measured directly from the stacked trace using the data-driven diagnostic. Predicted SNR is derived from prestack SNR statistics assuming ideal stacking of uncorrelated noise. The difference between observed and predicted values quantifies the loss of stacking efficiency relative to the theoretical $\sqrt{N}$ gain and reflects the combined influence of acquisition geometry, near-surface noise, geological conditions, and processing performance.

However, the realized stack uplift is systematically lower than predicted by ideal stacking theory. For the central CMP with roughly 1500 traces contributing in the dense geometries, perfectly uncorrelated noise would theoretically yield about 31 dB of stacking gain. The observed gains fall well below this limit, revealing reduced stacking efficiency captured by the imaging audit.

At the same time, for the input datasets, stacking behavior remains close to theoretical expectations. The difference in observed stack SNR between the native 7.5×7.5 m geometry and the coarser 15×15 m case is 6.6 dB, which closely matches the 7.5 dB difference predicted from prestack SNR statistics and trace-density variations. The corresponding Obs–Pred residuals are small (–3.1 and –2.2 dB), indicating that stacking efficiency is largely preserved when applied directly to the input data.

In contrast, the FK-processed datasets show much larger discrepancies between predicted and observed stack SNR. Although 3D F–K filtering improves prestack SNR, the realized stack values remain roughly 10–14 dB below theoretical predictions. This behavior indicates that the wavefield departs from the assumptions underlying ideal stacking. The Olmos reflector is weak and speckled, while the dominant noise is irregular, partially scattered, and only loosely linear. Under these non-ideal conditions, FK filtering struggles to cleanly separate signal and noise. The resulting wavefield therefore contains remnants of coherent noise and partially degraded signal that stack inefficiently, reducing stacking efficiency relative to theoretical expectations.

Together, these results reveal a measurable gap between theoretical stacking performance and realized image

quality. Quantifying this gap provides a practical audit of stacking efficiency and exposes how acquisition geometry, prestack signal statistics, and wavefield complexity jointly control the final seismic image.

Conclusions

This study demonstrates a practical framework for auditing the seismic imaging budget from prestack data to the final stacked image. Using data-driven SNR diagnostics, prestack signal statistics can be propagated through the acquisition geometry to predict the expected stack response and compared directly with the observed image quality. This provides a quantitative accounting system linking prestack gathers, acquisition density, processing efficiency, and the final interpretable image.

The results show that stacking performance is controlled jointly by acquisition geometry, prestack signal statistics, and the effectiveness of multichannel processing. In particular, the analysis reveals systematic gaps between theoretical stacking predictions and the SNR realized in the final image. Quantifying this gap provides a direct measure of imaging efficiency and exposes the mechanisms that limit signal recovery.

In many ways, this framework resembles financial accounting in a large organization. If expenditures are tracked carefully, inefficiencies can be identified and corrected. Without such accounting, losses remain hidden. Seismic imaging currently lacks this type of end-to-end tracking: acquisition design is often evaluated through geometric attributes such as fold and trace density, while processing success is judged primarily by the appearance of the final image. The connection between these stages is rarely quantified.

By tracing signal-to-noise ratio through the entire imaging chain, the proposed framework makes this connection explicit. It becomes possible to determine where signal is gained, where it is lost, and which parts of the acquisition and processing workflow contribute most strongly to the final image.

More broadly, this accounting perspective enables a more engineering-driven approach to seismic acquisition and processing. Survey design and processing strategies can be evaluated in terms of their measurable contribution to the final imaging objective. Because interpretation ultimately depends on recoverable signal-to-noise ratio, acquisition and processing decisions can be guided directly by their impact on the interpretable image. What can be measured can be engineered. By tracking signal recovery through the full seismic workflow, the imaging system can be optimized as a unified process rather than a sequence of loosely connected steps.

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