

Calibrated squirt-flow analysis of Mississippian dolomites and deep-learning CO₂ plume
segmentation from frequency-decomposed seismic data

by

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Abstract

Carbonate reservoirs exhibit complex pore architectures, including moldic, vuggy, intercrystalline, and fracture porosity, that produce wide-ranging elastic-modulus-porosity relationships and frequency-dependent velocity dispersion. Standard Gassmann fluid-substitution workflows, which assume pore-pressure equilibration in the low-frequency limit, are insufficient to describe the measured ultrasonic response of these rocks, where squirt flow through compliant microcracks can generate measurable stiffening of the saturated frame.

This study presents a calibrated Mavko-Jizba squirt-flow analysis of five dolomite core plugs from the Mississippian carbonate interval of the Wellington Field, south-central Kansas. Compressional- and shear-wave velocities and quality factors were measured at eight ultrasonic frequencies (156.3 kHz to 20 MHz) under three fluid-saturation states: brine, partial brine, and oil-and-brine. A constrained inversion procedure employing differential-evolution global search followed by L-BFGS-B refinement recovers a hierarchical parameter set separating global mineral properties, sample-specific frame properties, and saturation-dependent squirt-flow parameters.

The calibrated model reproduces both V_p and V_s across the analyzed frequency band with tight clustering around the 1:1 parity line and no systematic bias. Attenuation predictions capture the first-order behavior of the measured quality factors but display wider scatter, reflecting both the intrinsic uncertainty of laboratory Q estimation and unresolved pore-scale heterogeneity. Attenuation contrasts between saturation states exceed the corresponding velocity contrasts, indicating that Q -based attributes provide greater fluid sensitivity than velocity in this low-porosity dolomite dataset. Porosity values recovered from the calibration are broadly consistent with independent laboratory estimates. Leave-one-sample-out cross-validation, performed with global parameters held fixed, indicates internal stability within the five-sample dataset and no obvious overfitting across the sampled heterogeneity. The results provide a calibrated laboratory workflow

for applying the Mavko-Jizba framework to tight carbonate data and establish new experimental constraints on effective squirt-flow parameters in dolomitic lithologies. In a complementary field-scale investigation, a deep-learning pipeline is developed for automated CO₂ plume segmentation from frequency-decomposed seismic amplitude-difference maps at the Sleipner storage site, North Sea. An ensemble of encoder-decoder architectures (UNet++, MANet, DeepLabV3+, FPN) trained on eleven spectral bands achieves a mean Dice coefficient of 0.937 and mean intersection-over-union of 0.882 under leave-one-out cross-validation, demonstrating that frequency decomposition improves plume delineation relative to full-bandwidth data alone. Together, the two studies illustrate the diagnostic value of frequency-dependent seismic attributes from laboratory ultrasonic measurements through field-scale monitoring.

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Dedication

This thesis is dedicated to my family, for their unending support, patience, and faith in my dreams. Your sacrifices, encouragement, and prayers have carried me through every challenge and made this milestone possible.

It is also dedicated to the pursuit of knowledge and to the hope that this work will contribute, even in a small way, to advancing geoscience research and solutions for a more sustainable future.

Chapter 1 - Introduction

1.1 Motivation

Carbonate reservoirs host a substantial fraction of the world's remaining hydrocarbon resources, yet their elastic properties are among the most difficult to characterize. Unlike clastic systems, carbonates develop pore architectures that are controlled by depositional texture, diagenetic overprinting, and dissolution history, producing mixtures of moldic, vuggy, intercrystalline, and fracture porosity that coexist at a range of length scales (Lucia et al., 2003). The geometric diversity of these pore types generates a correspondingly wide range of elastic-modulus-porosity relationships, so that a single porosity value does not uniquely relate to the seismic response of a carbonate rock.

Frequency dependence of seismic velocities compounds the interpretive challenges introduced carbonate reservoir rocks. Laboratory studies have demonstrated that compressional and shear wave velocities in fluid-saturated carbonates can differ appreciably between seismic, sonic, and ultrasonic measurement bands, a dispersion that is attributed principally to squirt flow through compliant cracks and grain contacts (Winkler and Nur, 1982). Figure [1.1](#) illustrates the characteristic squirt-flow length l_{sq} for several canonical pore geometries. At frequencies where the pore-fluid pressure cannot equilibrate across thin cracks within one wave cycle, the apparent stiffness of the rock frame increases, and the effective velocities exceed the low-frequency Gassmann prediction. Ignoring this mechanism leads to systematic mismatches between laboratory ultrasonic data and in situ log or seismic observations, undermining fluid-substitution workflows that assume a frequency-independent elastic frame.

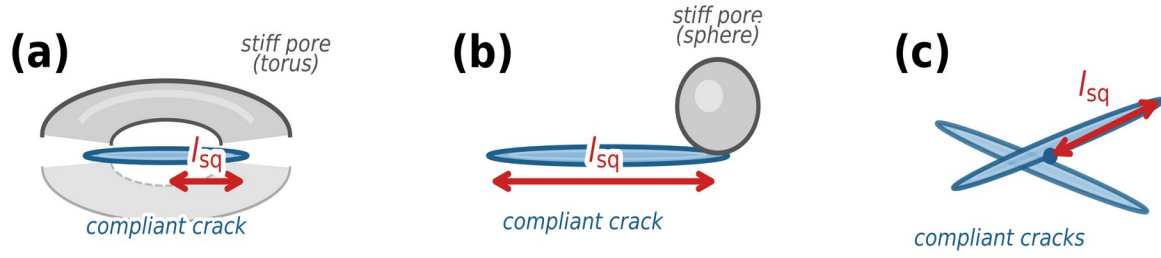


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The Mississippian carbonates of south-central Kansas (Figure 1.2) illustrate this problem concretely. These dolomite dominated strata (Figure 1.3) are characterized by fine-grained microcrystalline matrices with pore sizes extending below $2\ \mu\text{m}$, embedded compliant microfractures, and porosity values typically ranging from less than 1 % to approximately 11 % (Lucia et al., 2003). Gassmann-based fluid substitution, which presumes connected, equant pore geometries at the zero-frequency limit, has been shown to be inadequate for these rocks at ultrasonic frequencies, where isolated and crack-like pore elements exert a disproportionate influence on the moduli (Mavko and Jizba, 1991). A physically motivated alternative is therefore needed: one that explicitly accounts for compliant pore geometry and the frequency-dependent relaxation of pore-fluid pressure.

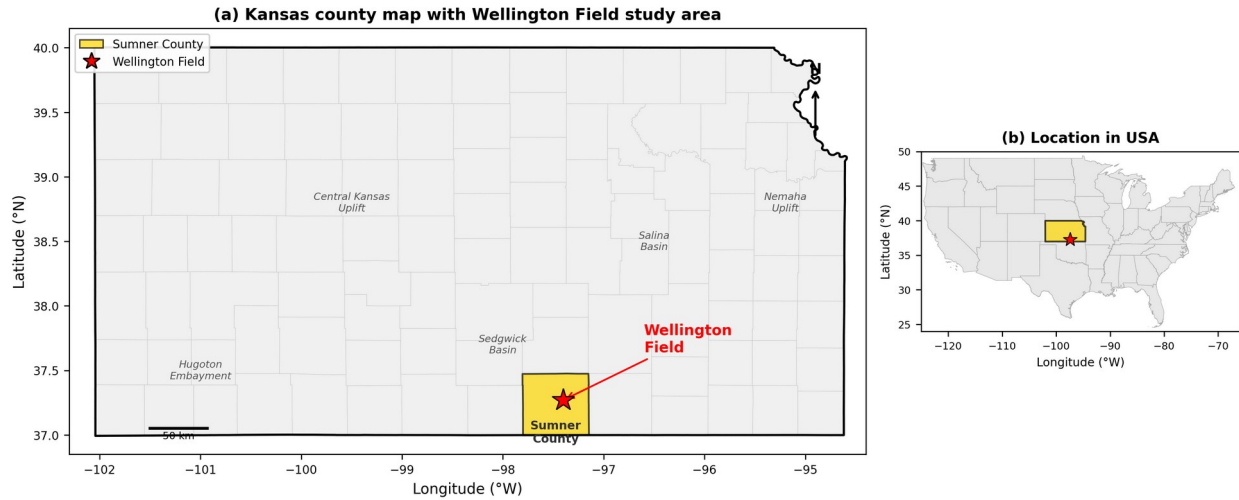


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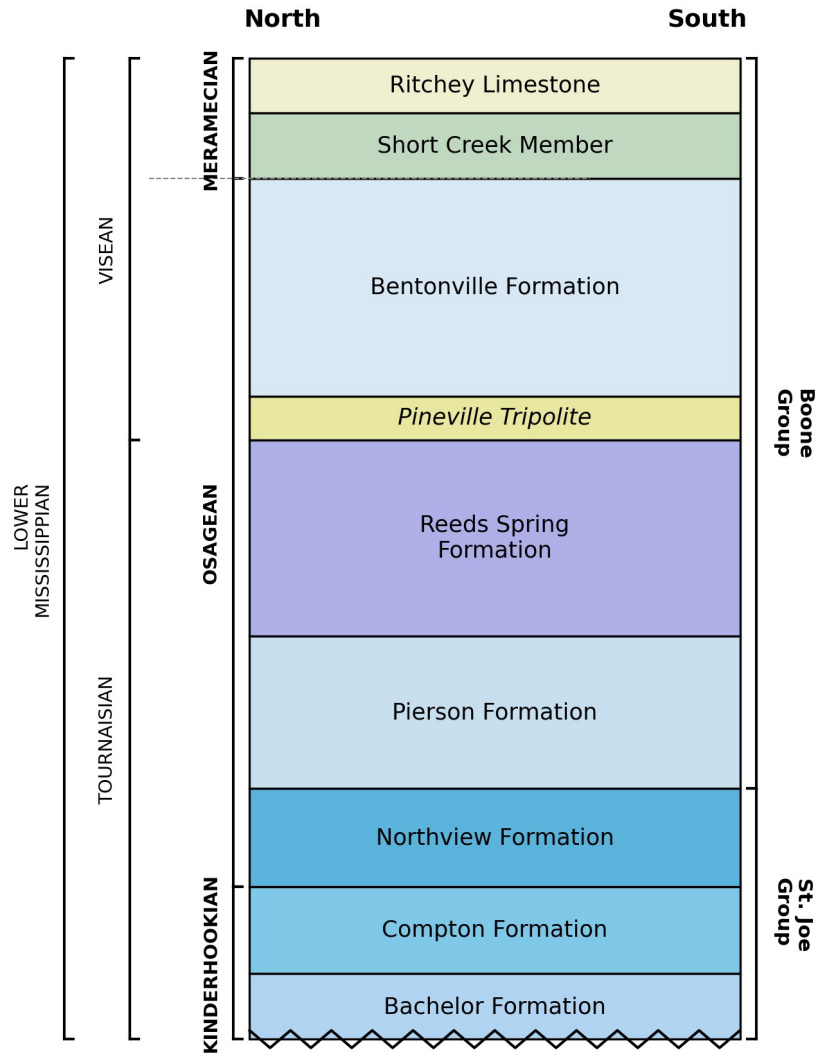


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The recognition that microcrack porosity constitutes an important control on elastic wave behavior in carbonates has motivated approaches that separate the total pore space into stiff (equant) and soft (crack-like) components (Xu and Payne, 2009). In such frameworks, the soft-porosity fraction governs the magnitude and frequency range of squirt-flow dispersion, while the stiff porosity contributes primarily to the low-frequency elastic compliance. The challenge for practical

application is that the soft-porosity fraction and the characteristic crack aspect ratio are not directly measurable from standard core or log data; they can be inferred through calibrated inversion against experimental observations.

1.2 Background

The Mavko-Jizba squirt-flow model (Mavko and Jizba, 1991) provides an analytically tractable framework for predicting the high-frequency elastic moduli of fluid-saturated rocks from dry-rock pressure-dependence data. In its original formulation, the model relates the difference between the saturated bulk and shear moduli at high and low frequencies to the compliant porosity increment that closes under pressure. By treating each compliant crack as a thin oblate spheroid that can exchange fluid with the surrounding stiff pore space, the model captures the physical essence of the squirt-flow mechanism while requiring only a small number of parameters: the dry-rock moduli, the solid and fluid bulk moduli, the porosity, and a frequency-scaling parameter related to the squirt-flow length (Mavko and Jizba, 1991).

The low-frequency reference for any squirt-flow analysis is the Gassmann (1951) fluid-substitution result, which assumes that pore-fluid pressure equilibrates throughout the connected pore space within one wave period. At seismic frequencies and for well-connected pore networks, this assumption is broadly satisfied, and the Gassmann prediction is a stable lower bound on the saturated moduli (Gassmann, 1951). The departure from the Gassmann baseline at higher frequencies (the dispersion) is the signature of squirt flow and the diagnostic observable that the Mavko-Jizba model aims to predict.

Quantifying this departure requires a clear picture of the pore structure. Birch (1961) demonstrated that the pressure sensitivity of compressional velocities in crystalline rocks is governed by the progressive closure of thin cracks, and subsequent work formalized the distinction between stiff and soft pore populations (Pang et al., 2020). In the stiff/soft partitioning, the stiff

porosity comprises roughly equant pores that remain open across the pressure range of interest, whereas the soft porosity includes microcracks and grain contacts whose compliance decreases markedly with increasing effective stress. The Mavko-Jizba model exploits this partition by attributing the entire frequency-dependent dispersion to squirt flow within the soft component.

A practical limitation of the original framework is that the values of the soft-porosity fraction and the crack aspect ratio have typically been taken from generic compilations or from pressure-velocity curves measured under ideal laboratory conditions (Mavko and Jizba, 1991). When these default, values are applied to a specific carbonate lithology, particularly one with a unique diagenetic history, the resulting predictions can deviate substantially from measured velocities. The present study addresses this limitation through a constrained inversion procedure that recovers the model parameters directly from the experimental data, so that the predictions reflect the particular microstructure of the target formation.

1.3 Prior Literature

Recent work has demonstrated the importance of frequency-dependent analysis for reservoir characterization in carbonates. Pang et al. (2020) developed a rock-physics template approach incorporating attenuation and the stiff/soft porosity distinction in carbonate reservoirs, illustrating how quality-factor measurements can constrain microfracture porosity in formations where velocity alone is insensitive to pore-scale heterogeneity. An earlier study by the same group applied a two-dimensional template to demonstrate that Q -based attributes add discriminative power beyond conventional velocity-porosity crossplots (Pang, 2020). Although the present work does not adopt the template methodology, the conceptual argument that attenuation-aware interpretation is necessary in carbonates with significant compliant porosity is shared.

At the theoretical level, several squirt-flow and crack-interaction models have been proposed for fractured porous media. Gurevich et al. (2010) derived analytical expressions for P-

wave dispersion and attenuation in rocks containing aligned or randomly oriented penny-shaped cracks, relating the relaxation frequency to the crack aspect ratio and the fluid viscosity. Chapman (2003) introduced a frequency-dependent anisotropy model for meso-scale fractures, bridging the gap between microscopic squirt flow and seismic-band observations. The classical inclusion-based models of Hudson (1981) provided scattering-theory solutions for cracked media that remain a reference point for more recent developments.

Laboratory attenuation studies underpin these theoretical advances. Toksöz et al. (1979) established a rigorous protocol for measuring compressional and shear attenuation using the spectral-ratio method, producing some of the earliest systematic Q data for sedimentary rocks. Subsequent investigators have applied and extended these methods to carbonate lithologies. Bakhorji (2010) measured elastic anisotropy and seismic attenuation in Middle Eastern carbonates, highlighting the role of aligned microfractures in generating directional Q variations. Deng and Morozov (2017) examined the trade-off between elastic structure and the quality factor, cautioning that apparent Q values can be biased by unmodeled velocity heterogeneity. Qi et al. (2021) used attenuation methods to quantify gas saturation in organic-rich formations, demonstrating that frequency-dependent attenuation can serve as a fluid indicator even in tight, low-porosity rocks.

The existing literature establishes two key points that motivate the present study. First, squirt-flow dispersion is physically expected in carbonates with compliant microcrack populations, and its magnitude is sensitive to the soft-porosity fraction and crack geometry. Second, attenuation carries information about pore-fluid type and saturation state that is complementary to, and in some cases more diagnostic than, velocity alone. What remains comparatively rare in the published record is a demonstration that a calibrated, parameter-constrained squirt-flow model can simultaneously reproduce both velocity and attenuation observations across a wide frequency range in a real carbonate dataset.

1.4 Objectives and Contributions

This thesis presents a calibrated Mavko-Jizba squirt-flow analysis of Mississippian dolomite core plugs from the Wellington Field, south-central Kansas. The dataset comprises compressional and shear wave velocities and attenuation estimates measured at eight ultrasonic frequencies (156.3 kHz to 20 MHz), of which four yielded complete attenuation data under three fluid-saturation states (brine, partial brine, and oil-and-brine) for five samples spanning the porosity and lithological variability of the cored interval.

The specific objectives are:

1. To evaluate the performance of the Mavko-Jizba model for predicting both V_p and V_s across the full measurement bandwidth and under multiple saturation conditions, using sample-specific squirt-flow parameters recovered through constrained L-BFGS-B optimization (Byrd et al., 1995).
2. To assess the degree to which attenuation (Q_p , Q_s) predicted by the calibrated model captures the frequency-dependent energy dissipation observed in the data, and to quantify the uncertainty in the recovered quality factors.
3. To test the consistency of the calibrated model against standard lithology and porosity diagnostics, including the Castagna et al. (1993) V_p - V_s framework and qualitative consistency with the dolomite velocity ranges reported by Yale and Jamieson (1994), thereby providing independent validation of the predictions.
4. To determine whether the Mavko-Jizba recovered porosity values provide a physically meaningful alternative to conventional porosity estimates, particularly in tight dolomites where standard porosity methods are known to be unreliable.

The principal contribution of this work is to demonstrate that a relatively simple squirt-flow model, when calibrated against multi-frequency ultrasonic data, can yield velocity and attenuation

predictions that are consistent with independent observations across a broad frequency range in Mississippian carbonates. The results provide both a practical calibration workflow for the Mavko-Jizba framework and new experimental constraints on squirt-flow parameters in dolomitic rocks, a lithology for which published squirt-flow calibrations are scarce.

In addition to the laboratory-scale rock physics investigation described above, this thesis presents a complementary field-scale study that exploits the same principle of frequency-dependent seismic response. [Chapter 5](#) develops and evaluates a computer-vision pipeline for automated segmentation of the CO₂ plume at the Sleipner injection site (North Sea) from frequency-decomposed seismic amplitude-difference maps. By training an ensemble of deep-learning encoder-decoder architectures on eleven spectral bands spanning 5 to 100 Hz, the analysis quantifies how narrow-band decomposition improves plume delineation relative to conventional full-bandwidth imaging. The two investigations are unified by the thesis that frequency-dependent seismic attributes carry diagnostic information about fluid-filled pore space at both ultrasonic laboratory scales and exploration seismic frequencies, and that extracting this information, whether through physics-based inversion or data-driven segmentation, improves the characterization of subsurface fluid distributions.

Chapter 2 - Methods

2.1 Core Samples and Geological Context

Five cylindrical dolomite core plugs were obtained from the Kansas Geological Survey (KGS) 1-32 well, Wellington Field, Sumner County, south-central Kansas. The samples were extracted from the Mississippian carbonate interval at depths between 3658 and 4100 ft. This interval is composed predominantly of dolomitized sponge-bearing facies within the Osagean-Meramecian sequence of the Anadarko-Sedgwick basin system (Watney et al., 2001). The dominant pore types include moldic, vuggy, and intercrystalline porosity (Lucia et al., 2003), reflecting multiple diagenetic overprints including fracturing, dissolution, and cementation (King, 2013).

Each plug measures approximately 7 cm in length and 2.5 cm in diameter. Twelve plugs were initially prepared, but progressive mechanical failure during pressurization and fluid-handling procedures reduced the usable set to five samples that completed the full measurement program. The five retained samples (identified by depth in feet: 3718.7, 3734.2, 3936.6, 4076.5, and 4096.2) span a laboratory porosity range of approximately 4 to 14 % and Poisson's ratios of 0.29-0.39. Lithology is confirmed as dolomite based on well-log cross-plots and Castagna et al. (1993) velocity-lithology relationships.

Table 2.1. Summary of the five core samples used in this study. Adapted from (King, 2025).

Sample (depth, ft)	Sonic (m/s)	Density Porosity (%)	Poisson's Ratio
3718.7	5025.5	5.0	0.36
3734.2	5427.1	7.6	0.38
3936.6	4910.7	9.0	0.29
4076.5	5047.2	4.4	0.39

4096.2	5411.7	13.5	0.39

2.2 Ultrasonic Velocity and Attenuation Measurements

Compressional (P) and shear (S) wave velocities were measured using a GCTS ULT-100 Ultrasonic Velocity Test System equipped with piezoelectric NX-size platens and controlled via CATS Ultrasonic 1.81 software. The pulse-transmission method was employed: a voltage pulse excites the source transducer, the resulting mechanical wave propagates through the sample, and the receiver transducer converts the transmitted signal back to an electrical waveform from which travel time and amplitude are extracted.

Measurements were performed at eight discrete ultrasonic frequencies spanning approximately two decades of bandwidth:

156.3 kHz, 312.5 kHz, 625 kHz, 1.25 MHz, 2.5 MHz, 5 MHz,
10 MHz, 20 MHz

Of these eight frequencies, only four (1.25 MHz, 2.5 MHz, 10 MHz, and 20 MHz) yielded usable attenuation estimates from the spectral-ratio method across all sample saturation combinations. Per-frequency results in Section [3](#) are therefore presented at these four frequencies; aggregated summaries retain data from the full measurement set where available.

This broad frequency range was selected to capture frequency-dependent velocity dispersion and attenuation behavior attributable to squirt-flow and other dissipation mechanisms (Wyllie et al., 1956).

A Carver hydraulic press provided uniaxial confining stress. The applied load was maintained below 10,000 lbf for all measurements; three of the original twelve samples fractured at higher loads, confirming the friable nature of these dolomites. Laboratory conditions therefore

do not replicate full in situ overburden stress, and a systematic velocity offset of approximately 600 m/s in V_s between laboratory and well-log values is acknowledged (Cimino, 2020).

Honey was used as the acoustic couplant between the platens and sample faces, chosen for its high viscosity and chemical inertness with respect to carbonate minerals. Prior to sample measurements, calibration was performed using an aluminum rod of known velocity to verify system accuracy. A face-to-face (platen-to-platen, no sample) reference measurement was acquired at each frequency to establish the system transit time, which was subtracted from all subsequent sample measurements (Cimino, 2020).

Software operating parameters were held constant across all experiments: external manual gain was disabled, energy output was set to 100 %, and input automatic gain was set to 20. Sample length, diameter, and mass were entered to enable real-time density calculation.



Figure 2.1. Carver hydraulic press with GCTS ULT-100 ultrasonic velocity test assembly. The press provides uniaxial confining stress to the core plug mounted between piezoelectric platens within the central loading frame. Adapted from (King, 2025).



Figure 2.2. Core plugs mounted between NX-size piezoelectric platens and transducers prior to loading. Honey couplant is applied to the sample faces to ensure acoustic coupling between the platens and the rock. Adapted from (King, 2025).

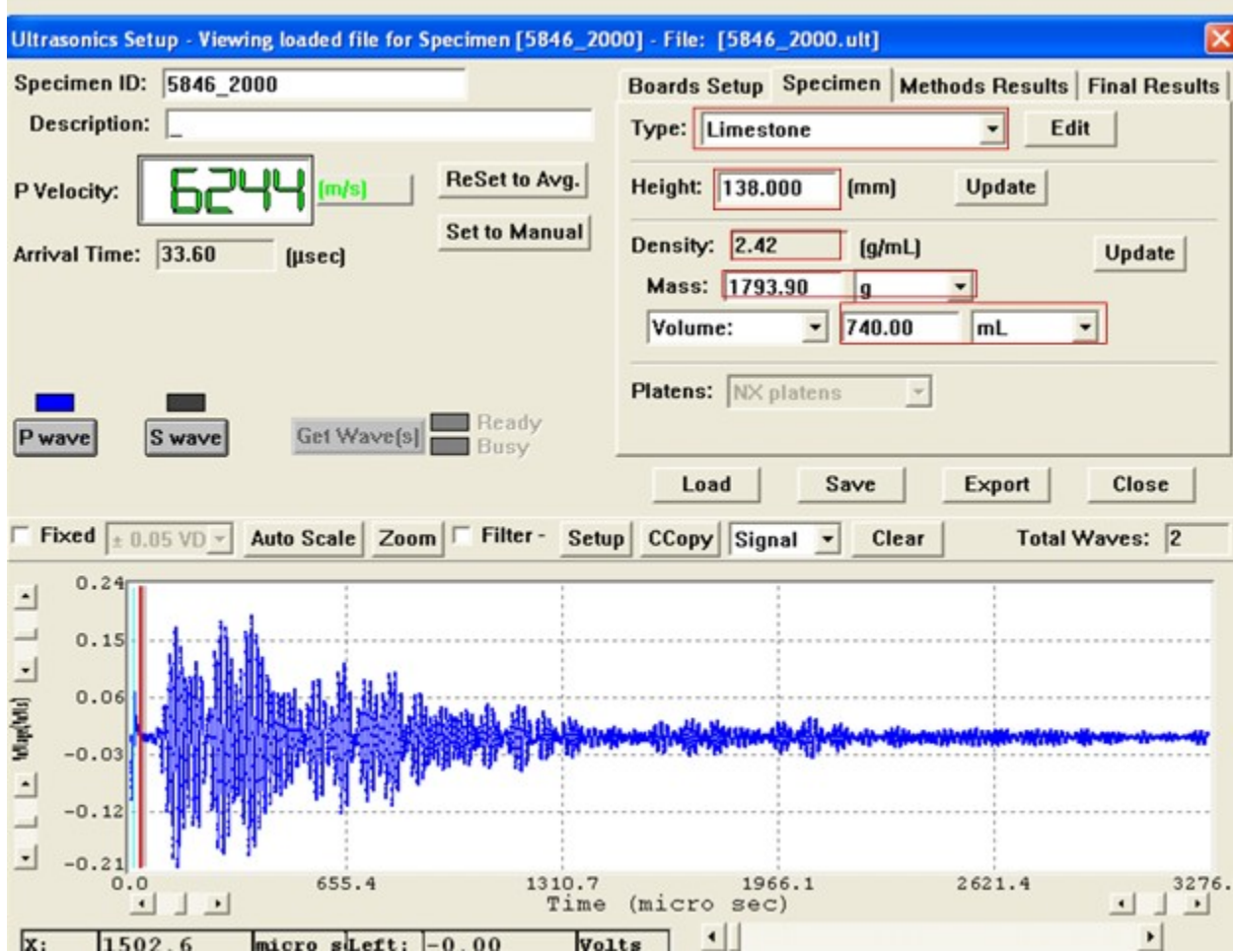


Figure 2.3. Screenshot of the CATS Ultrasonic 1.81 software interface showing real-time waveform acquisition and velocity computation for a representative sample. The interface displays the transmitted P-wave signal, sample dimensions, and computed velocities. Adapted from (King, 2025).

2.3 First-Arrival Time Determination

The automatic first arrival picking algorithm in the CATS software was found to be unreliable, consistently selecting arrival times that were too late relative to visual inspection. A manual picking procedure was therefore adopted, following the approach of Cimino (2020) and Shodunke (2021).

Raw P and S wave signals were exported to spreadsheet format. For each sample and saturation state, waveforms at all eight measurement frequencies were superimposed on a single time axis. The first-arrival time was identified as the point at which the initial sinusoidal oscillation

separates from the pre-arrival noise floor. This manual method improves consistency across frequencies and provides a physically meaningful arrival estimate. Travel times (in microseconds) were converted to velocities using measured sample lengths.

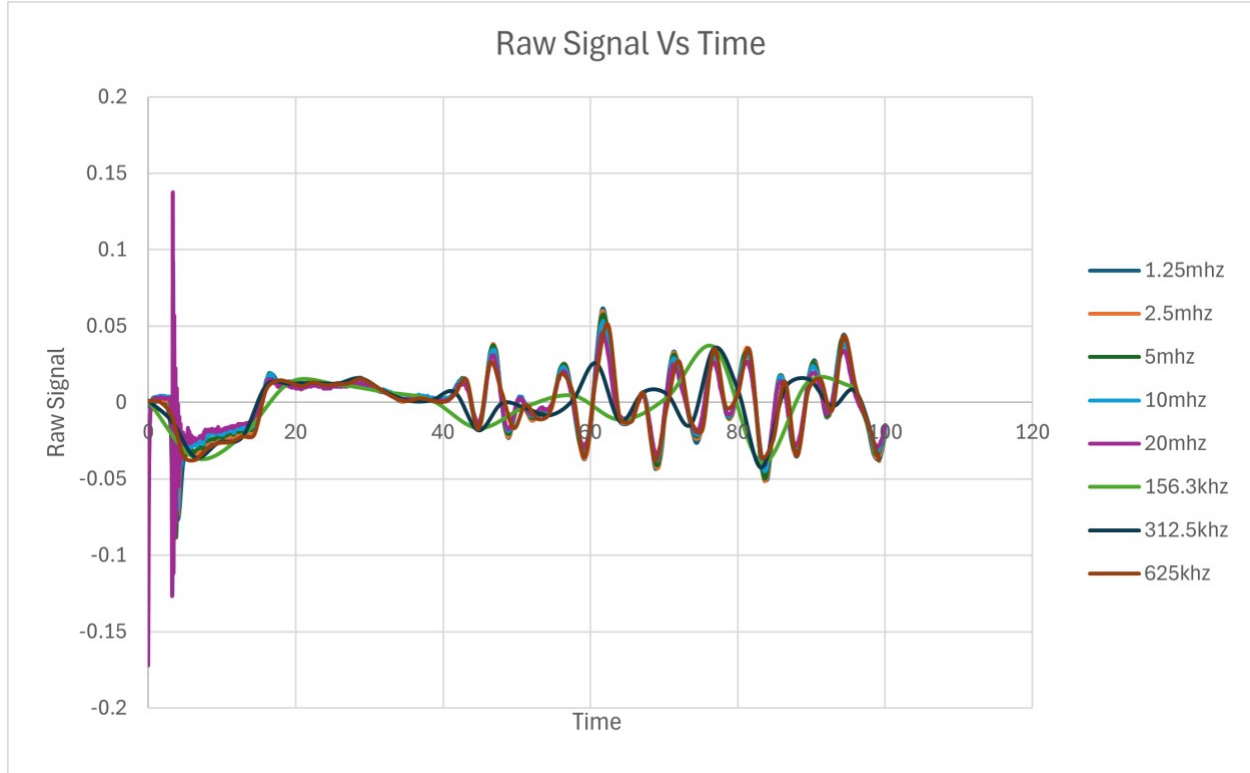


Figure 2.4. Raw transmitted waveforms at all eight measurement frequencies (156.3 kHz to 20 MHz) for a representative sample, illustrating the systematic variation in signal character across the measurement bandwidth. Higher frequencies produce shorter-wavelength arrivals with progressively reduced amplitude, reflecting frequency-dependent attenuation. Adapted from (King, 2025).

2.4 Saturation Protocol

Each of the five samples progressed through the saturation sequence below, together with face-to-face reference measurements acquired before each sequence. For the final calibration and figure set reported in this thesis, the analyzed fluid states are brine, partial brine, and oil-and-brine; the terminal water-in-oil step was retained only as an auxiliary laboratory check.

2.4.1 Brine Saturation

A sodium chloride brine was prepared at a concentration of 357 g NaCl per liter of water at room temperature (Batzle and Wang, 1992; $\sim 20^\circ\text{C}$). Dry samples were weighed, placed in a glass desiccator, submerged in brine, and subjected to vacuum using a mechanical pump. Saturation was deemed complete when no further air bubbles were observed emerging from the sample surface. Post-saturation weights confirmed fluid uptake (Adam et al., 2006).

2.4.2 Partial Brine Saturation

Following full brine measurements, samples were air-dried under controlled conditions until approximately half the absorbed brine mass had been removed. Target weights were calculated from the difference between dry and fully saturated masses. Samples that dried below target were briefly re-exposed to brine and re-equilibrated before measurement.

2.4.3 Oil-and-Brine (Mixed) Saturation

Partially brine-saturated samples were subsequently immersed in mineral oil within a desiccator under vacuum, allowing oil to invade the pore volume vacated during the partial-drying step. Mineral oil was selected because it provides a suitable laboratory analogue for hydrocarbon saturation and does not stain the samples. Sample mass was monitored at short intervals until the target mass corresponding to complete filling of the remaining pore volume was reached. This state is referred to here as oil-and-brine saturation, indicating a fully saturated sample containing both residual brine and oil.

2.4.4 Residual-Brine-Plus-Oil State (Auxiliary Check)

Following the mixed-saturation measurements, the samples were air-dried to remove the mobile brine phase as completely as practical, while recognizing that a small amount of irreducible brine may remain adsorbed to grain surfaces or trapped within microporosity. The samples were then

re-immersed in mineral oil under vacuum, producing an oil-dominant auxiliary state in which oil occupies most of the connected pore space, whereas any remaining brine is confined to surface-bound films or isolated pores. Velocity measurements were acquired at all eight frequencies for this state as well; however, it was not included in the final inversion or figure set, which focus on the three analyzed fluid states: brine, partial brine, and oil-and-brine.

The full four-state saturation program therefore generated $5 \times 4 \times 8 = 160$ sample-saturation-frequency measurements, in addition to face-to-face reference traces. The calibration dataset reported in this thesis comprises the three analyzed fluid states, brine, partial brine, and oil-and-brine, yielding $5 \times 3 \times 8 = 120$ sample-saturation-frequency combinations, together with supporting dry-state and reference measurements.

2.5 Data Preprocessing and Quality Control

Raw waveform data were preprocessed to extract velocity, and attenuation estimates suitable for model calibration.

2.5.1 Velocity Extraction

Velocities were computed from manually picked first-arrival times and measured sample lengths (Section [2.3](#)). Quality control included cross-checking arrival-time consistency across adjacent frequencies and flagging measurements where the arrival-time difference between P and S waves fell outside physically reasonable bounds.

2.5.2 Attenuation Estimation

The quality factor Q (inverse attenuation) was estimated using spectral-ratio and frequency-shift approaches applied to the transmitted waveforms. The spectral-ratio method relates the logarithmic amplitude ratio between sample and reference signals to frequency-dependent attenuation (Quan and Harris, 1997). This approach has been widely applied in ultrasonic laboratory studies (Spencer,

1979; McDonal et al., 1958) and provides independent P-wave (Q_p) and S-wave (Q_s) quality factors at each measurement frequency.

Attenuation estimation at ultrasonic frequencies is subject to well-documented uncertainties arising from coupling variability, diffraction effects, and signal-to-noise limitations (Gladwin and Stacey, 1974; Teng, 1968). These limitations propagate into the inversion as elevated uncertainty on Q relative to velocity, a consideration addressed in the weighting scheme of the objective function (Section [2.7.1](#)).

2.6 Rock-Physics Framework: Mavko-Jizba S squirt-Flow Model

2.6.1 Theoretical Foundation

The Mavko-Jizba squirt-flow model (Mavko et al., 2020) provides the theoretical backbone for the frequency-dependent velocity and attenuation predictions in this study. The model describes how microscale fluid flow between compliant (soft) pores and stiffer pore space produces frequency-dependent stiffening of the saturated rock frame.

At frequencies well below the characteristic squirt-flow frequency, fluid has sufficient time to equilibrate pressure throughout the pore network, and the effective moduli approach the Gassmann (1951) low-frequency limit. At frequencies well above the squirt-flow transition, fluid in compliant pores is effectively trapped, and the rock exhibits unrelaxed (high-frequency) moduli that exceed the Gassmann prediction. In the transition zone, energy dissipation associated with viscous fluid flow manifests as attenuation peaks in both P and S waves.

The low-frequency (relaxed) baseline is provided by Gassmann's equations:

$$\begin{aligned} K_{sat}^{Gass} &= K_{dry} + \frac{(1 - K_{dry} / K_m)^2}{\phi / K_f + (1 - \phi) / K_m - K_{dry} / K_m^2}, \\ G_{sat}^{Gass} &= G_{dry}, \end{aligned} \quad (2.1)$$

where K_{dry} and G_{dry} are the dry-frame bulk and shear moduli, K_m is the mineral (grain) bulk modulus, K_f is the pore-fluid bulk modulus, and ϕ is the porosity.

The complex frequency-dependent bulk and shear moduli of the saturated rock are obtained by applying squirt-flow correction terms to the Gassmann baseline:

$$\begin{aligned} K_{sat}(\omega) &= K_{sat}^{Gass} + \Delta K_{sf} \Gamma(\omega), \\ G_{sat}(\omega) &= G_{dry} + \Delta G_{sf} \Gamma(\omega), \end{aligned} \quad (2.2)$$

where ΔK_{sf} and ΔG_{sf} are the squirt-flow stiffening increments representing the modulus difference between the high-frequency (unrelaxed) and low-frequency (Gassmann) limits. The frequency-dependent dispersion function $\Gamma(\omega)$ is derived from Bessel-function solutions to the pressure-diffusion equation in thin compliant pores:

$$\Gamma(\omega) = 1 - \frac{2 J_1(\zeta)}{\zeta J_0(\zeta)}, \quad \zeta = Z \sqrt{\frac{i\omega}{\omega_{sq}}}, \quad (2.3)$$

where J_0 and J_1 are Bessel functions of the first kind, Z is, in this calibrated extension, the effective squirt-flow parameter encapsulating the crack aspect ratio and fluid viscosity, and ω_{sq} is the characteristic squirt-flow angular frequency. The function $\Gamma(\omega)$ transitions smoothly from 0 at the low-frequency limit to 1 at the high-frequency limit, reproducing the physically expected dispersion behavior.

Quality factors for P and S waves are derived from the ratio of the imaginary to real parts of the complex moduli:

$$\begin{aligned} Q_P^{-1}(\omega) &= \frac{\text{Im}[K_{sat}(\omega) + 4/3 G_{sat}(\omega)]}{\text{Re}[K_{sat}(\omega) + 4/3 G_{sat}(\omega)]}, \\ Q_S^{-1}(\omega) &= \frac{\text{Im}[G_{sat}(\omega)]}{\text{Re}[G_{sat}(\omega)]}, \end{aligned} \quad (2.4)$$

and frequency-dependent velocities are obtained from the real parts of the moduli and the bulk density:

$$\begin{aligned}
V_p(\omega) &= \sqrt{\frac{\text{Re}[K_{sat}(\omega) + 4/3 G_{sat}(\omega)]}{\rho_{bulk}}}, \\
V_s(\omega) &= \sqrt{\frac{\text{Re}[G_{sat}(\omega)]}{\rho_{bulk}}},
\end{aligned} \tag{2.5}$$

where the bulk density is

$$\rho_{bulk} = (1-\phi) \rho_{grain} + \phi \rho_{fl}. \tag{2.6}$$

2.6.2 Extended Calibrated Workflow

The original Mavko-Jizba formulation, when applied with textbook parameters to the Mississippian dolomite samples, was found to systematically overestimate velocities relative to measured values. This outcome aligns with the well-documented limitations of applying standard effective-medium models to carbonates, which typically exhibit complex, heterogeneous pore structures and diagenetically altered frameworks (David and Zimmerman, 2012; Pang et al., 2020).

To address this systematic bias and stabilize the underdetermined inversion space, an extended calibration workflow was developed. This approach retains the foundational Mavko-Jizba squirt-flow physics but introduces heuristic flexibility and empirical regularization through the following modifications:

1. **Porosity-anchored regularization:** To prevent the optimizer from converging on physically unreasonable frame stiffnesses, the inversion is weakly constrained by standard empirical baselines. Trial dry-frame moduli are forward-modeled to saturated conditions and evaluated against established velocity-porosity relationships. The Wyllie et al. (1956) time-average equation,

$$\frac{1}{V_P} = \frac{\phi}{V_{fl}} + \frac{1-\phi}{V_m}, \tag{2.7}$$

and the Raymer et al. (1980) relationship,

$$V_P = (1-\phi)^2 V_m + \phi V_{fl}, \tag{2.8}$$

function as soft constraints. These empirical expressions are not imposed as exact predictive laws for the carbonate samples. Rather, they are used as weak regularization terms that provide geologically reasonable bounds on the background intercrystalline framework and help prevent inversion solutions that imply unrealistic dry-frame stiffness for the measured porosity.

2. **Hierarchical parameterization:** Model parameters are organized into four tiers reflecting their physical scope (Section [2.7.2](#)), following the structure recommended by Mavko et al. (2020) for multi-sample rock-physics calibration.
3. **Phenomenological squirt-flow extension:** the squirt-flow parameter Z and associated frequency exponents are treated as effective variables that vary across partial saturation states. This heuristic adaptation models the dependence of effective pore-fluid mobility and phase distribution on saturation conditions, which the original dry-frame-derived parameterization does not explicitly capture (Wang and Nur, 1992).
4. **Empirical V_p – V_s coupling:** Castagna et al. (1993) and Yale and Jamieson (1994) velocity relationships provide soft constraints that encourage geologically consistent V_p – V_s ratios characteristic of dolomite lithologies.

Throughout this thesis, this modified approach is referred to simply as the “Mavko-Jizba” model. The baseline (uncalibrated) formulation is excluded from the results, as its systematic bias renders it unsuitable for the quantitative interpretation of this specific dataset.

2.7 Joint Inversion Strategy

2.7.1 Objective Function

Model calibration is cast as a nonlinear least-squares inversion that simultaneously fits P and S wave velocities and quality factors across all samples, saturation states, and frequencies. The joint objective function is formulated as a regularized, weighted sum of normalized residuals:

$$F(m) = w_V (R_{V_P} + R_{V_S}) + w_Q (R_{Q_P} + R_{Q_S}) + w_\phi P_\phi + w_s P_s, \quad (2.9)$$

where the velocity residuals,

$$\begin{aligned} R_{V_P} &= \sum_{i,j,k} \left(\frac{V_{P,ijk}^{obs} - V_{P,ijk}^{pred}}{V_{P,ijk}^{obs}} \right)^2, \\ R_{V_S} &= \sum_{i,j,k} \left(\frac{V_{S,ijk}^{obs} - V_{S,ijk}^{pred}}{V_{S,ijk}^{obs}} \right)^2, \end{aligned} \quad (2.10)$$

are summed over all sample-saturation-frequency combinations (indexed by i, j, k respectively).

The attenuation residuals,

$$\begin{aligned} R_{Q_P} &= \sum_{i,j,k} \left(\frac{Q_{P,ijk}^{obs} - Q_{P,ijk}^{pred}}{Q_{P,ijk}^{obs}} \right)^2, \\ R_{Q_S} &= \sum_{i,j,k} \left(\frac{Q_{S,ijk}^{obs} - Q_{S,ijk}^{pred}}{Q_{S,ijk}^{obs}} \right)^2, \end{aligned} \quad (2.11)$$

receive a reduced statistical weighting $w_Q < w_V$ relative to velocities, reflecting the higher systematic measurement uncertainty inherent in laboratory attenuation estimates (Pang et al., 2020). To constrain the inversion-implied frame stiffnesses, an acoustic-to-physical porosity regularization penalty is applied:

$$P_\phi = \sum_i \left(\phi_i^{inv} - \phi_i^{ref} \right)^2, \quad (2.12)$$

penalizes deviations between an inversion-derived porosity ϕ_i^{inv} (back-calculated from the inverted dry-frame moduli via empirical time-average or Raymer transforms) and the independently

measured physical porosity ϕ_i^{ref} . This penalty anchors the optimization space, discouraging unphysical trade-offs between frame stiffness and pore volume. A discrete smoothness penalty,

$$P_s = \sum_{j,k} (p_{j,k+1} - p_{j,k})^2, \quad (2.13)$$

is applied to discrete, frequency-dependent variables across adjacent frequency bins (indexed by k). This regularization acts as a low-pass filter on the parameter space, enforcing the physical expectation that dispersion and attenuation mechanisms dictate smooth variations across the frequency domain.

2.7.2 Parameter Hierarchy

The current calibration subset uses a constrained vector of 46 active parameters, of which 45 are free (the effective squirt frequency is fixed at each measurement frequency). These comprise 4 global, 15 per-sample, 18 per-saturation, and 9 frequency-exponent parameters, organized in the hierarchical structure summarized in Table 2.2.

Table 2.2. Hierarchical parameter structure for the joint inversion.

Tier	Scope	Count	Examples
Global	All samples & saturations	4	Mineral moduli, grain density
Per-sample	Each core plug	15	Dry-frame moduli, porosity
Per-saturation	Each fluid state	18	Fluid modulus, density, parameter Z
Freq. exponents	Each saturation	9 (3/sat.)	Power-law frequency-scaling exponents

Bounds on each parameter are enforced based on strict physical limits and established empirical ranges for dolomite lithologies (Birch, 1961).

2.7.3 Two-Stage Optimization

A hybrid, two-stage optimization strategy is employed to navigate the high dimensionality and expected multimodality of the rock-physics parameter space:

1. **Stage 1: Differential Evolution (DE).** A stochastic, population-based global search algorithm explores the parameter space without requiring gradient information. DE provides strong global exploration, mitigating the risk of premature convergence in the non-smooth objective landscape associated with multi-parameter rock physics.
2. **Stage 2: L-BFGS-B.** A limited-memory quasi-Newton algorithm refines the DE-derived initial model. By exploiting local curvature information through an approximate Hessian built from recent gradient history, it achieves efficient local convergence. Bound constraints are strictly maintained at each iteration to ensure the physical validity of the final model.

This combination effectively balances global exploration with local gradient-based exploitation (Mavko et al., 2020).

2.8 Leave-One-Sample-Out Cross-Validation

Model stability and the robustness of the per-sample parameterizations are assessed through a leave-one-sample-out (LOSO) cross-validation framework. In each of the five folds, one sample is withheld from the calibration subset. The remaining four samples are used to re-estimate all local, non-global parameters, while holding the global matrix parameters (mineral moduli, density) fixed at their full-dataset converged values.

A warm-start strategy is employed: initial parameter estimates for the local variables in each fold are drawn from the converged solution of the preceding fold. This significantly reduces computational overhead and accelerates L-BFGS-B convergence.

Because the global background matrix is held constant, this LOSO approach does not evaluate pure out-of-sample prediction for a wholly unknown lithology. Instead, it systematically tests whether the calibrated local rock-physics parameters (e.g., frame moduli variations and squirt-flow effects) generalize predictably across the dataset’s natural heterogeneities without overfitting to the specific signatures of individual core plugs.

2.9 Porosity Validation

Porosity is an independent validation metric because it is measurable through a direct laboratory method that is independent of the ultrasonic velocity framework.

Density porosity is computed from dry bulk density and a grain density for dolomite (2.84 g/cm³) using $\phi = 1 - \frac{\rho_{dry}}{\rho_{grain}}$. This estimate is independent of pore-fluid properties and provides a purely mechanical constraint on total porosity.

Inversion-implied porosity (derived from the relationship between optimized dry-frame moduli and velocity–porosity transforms) is compared against this independent estimate. Agreement between inversion-derived and directly measured porosity values provides confidence that the calibrated model parameters are physically meaningful and not merely fitting artifacts.

2.10 Reporting Protocol and Figure-Generation Policy

All velocity and attenuation results presented in this thesis are generated using the extended calibrated Mavko-Jizba workflow described in Section [2.6.2](#). For clarity, this model is labeled simply “Mavko-Jizba” in all figures and tables.

The following reporting conventions are adopted for the final thesis figures:

1. **Dry-state and auxiliary water-in-oil data are excluded** from all parity plots and cross-plots. The dry-state measurements served as essential inputs to the inversion (particularly for constraining dry-frame moduli) but are not presented as prediction targets because the

squirt-flow mechanism is only physically meaningful in the presence of pore fluid. The terminal water-in-oil step was retained only as a laboratory check and is likewise omitted so that the reported comparisons remain internally consistent with the final three-state inversion dataset.

2. **The baseline (uncalibrated) Mavko-Jizba result is excluded** from all figures. As noted in Section [2.6.2](#), the baseline formulation systematically overestimates velocities for the present dolomite samples. Presenting both calibrated and uncalibrated results on the same plots would obscure the interpretive value of the calibrated workflow. The existence of the baseline comparison and its limitations are documented here for completeness.
3. **Per-frequency and aggregated figures:** results are presented both at individual frequencies (parity plots for V_P , V_S , Q_P , Q_S ; V_P -versus- V_S cross-plots; porosity comparisons) and as aggregated cross-frequency summaries (dispersion curves, attenuation peak behavior, aggregated parity plots across all available frequencies). This dual-resolution presentation allows assessment of both frequency-specific model performance and broadband trends.
4. **Measurement conditions in figures:** the conditions represented in all thesis figures are the face-to-face reference (f2f), brine saturation, partial brine saturation, and oil-and-brine saturation (labeled “oil”), each represented with distinct markers and colors for visual discrimination.

Chapter 3 - Results

The calibrated Mavko-Jizba model was evaluated against measured compressional and shear wave velocities at four ultrasonic frequencies (1.25, 2.5, 10 and 20 MHz) and under three fluid-saturation states: brine, partial brine, and oil-and-brine. For context, sonic velocities from the KGS 1-32 well log span approximately 4800–5500 m/s across the five sample depths (Table 2.1), while laboratory ultrasonic velocities exhibit a broader range owing to frequency-dependent dispersion and the absence of full overburden pressure.

3.1 Velocity Comparisons

3.1.1 Compressional-Wave Velocity (V_p)

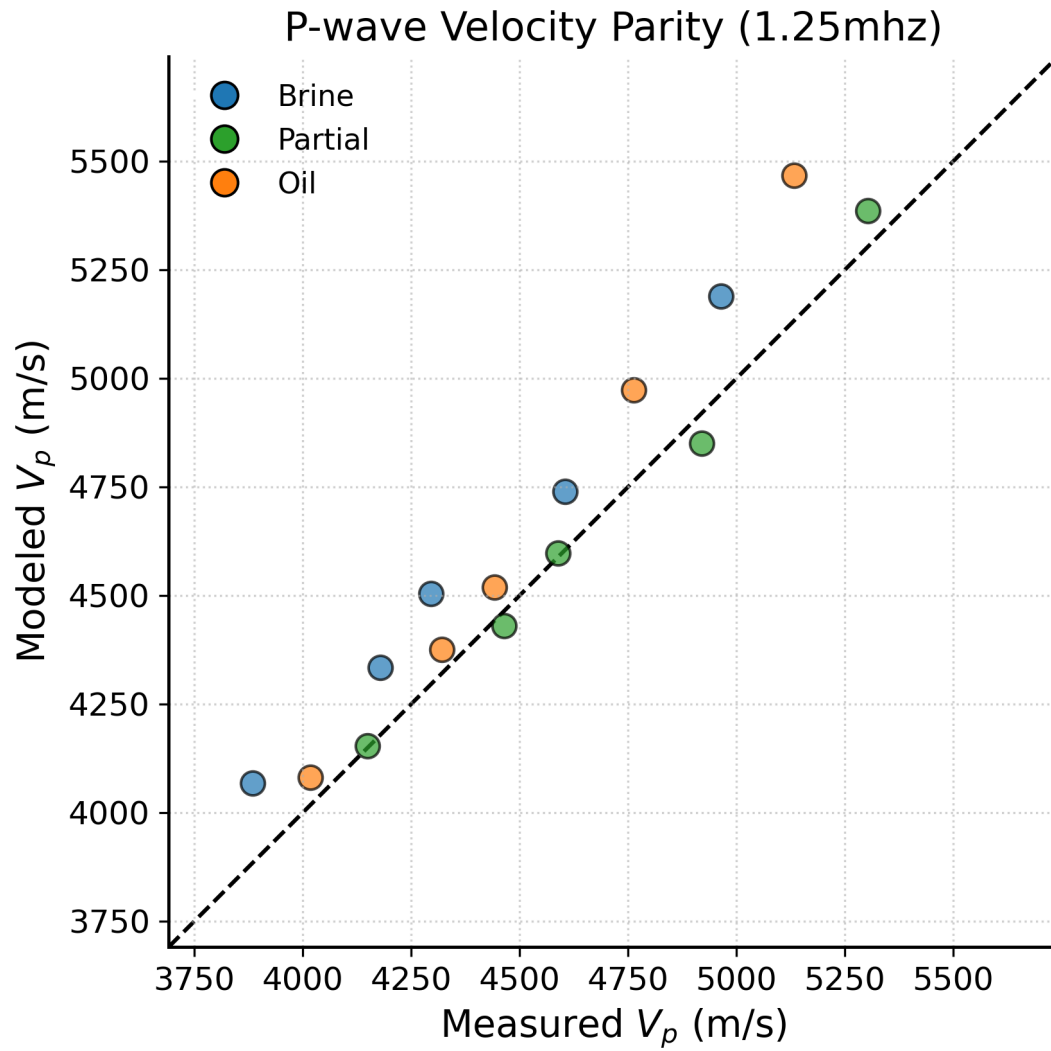


Figure 3.1. Measured versus Mavko-Jizba predicted V_p parity plot at 1.25 MHz. Markers represent brine (blue), partial brine (green), and oil-and-brine (orange) saturations. The dashed line indicates perfect agreement.

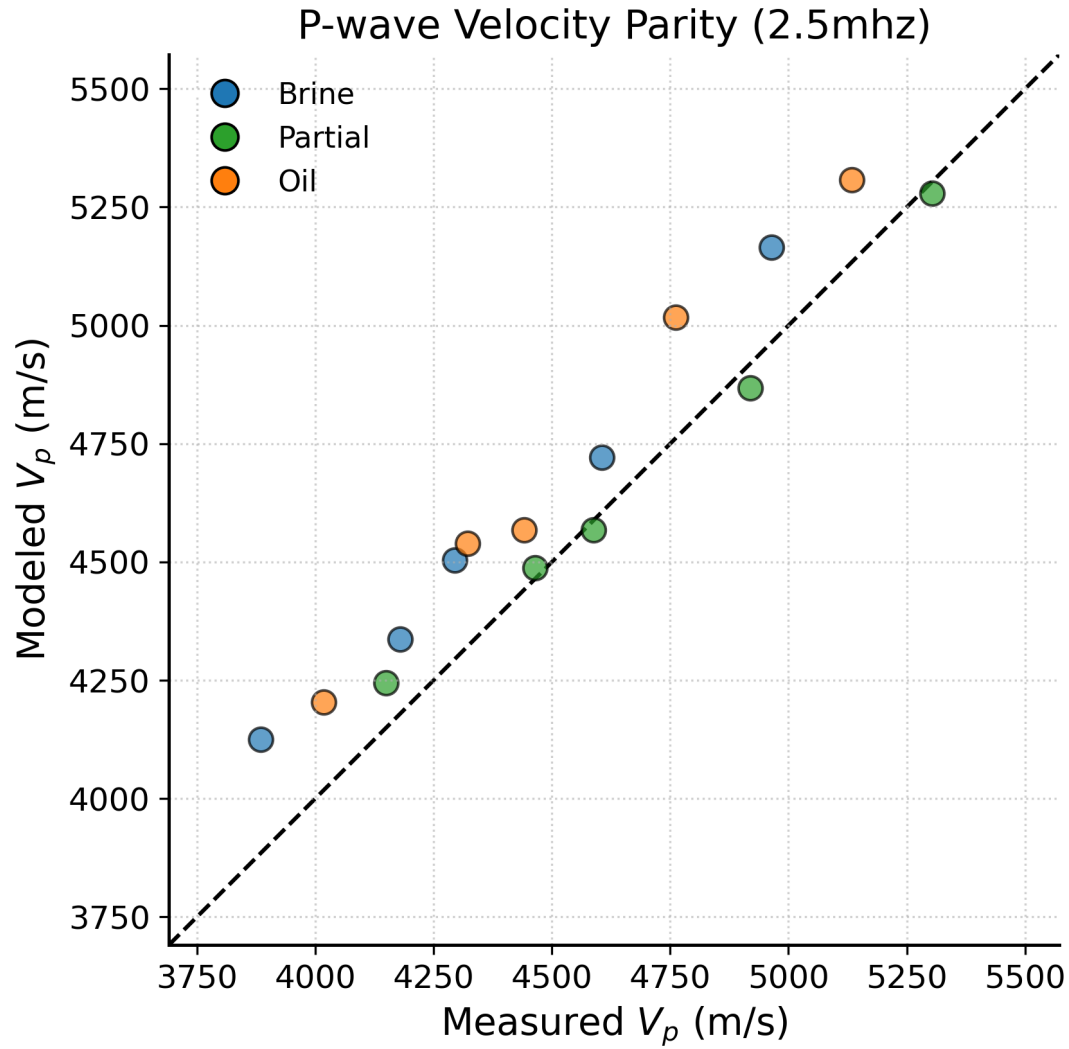


Figure 3.2. Measured versus Mavko-Jizba predicted V_p parity plot at 2.5 MHz. Markers represent brine (blue), partial brine (green), and oil-and-brine (orange) saturations. The dashed line indicates perfect agreement.

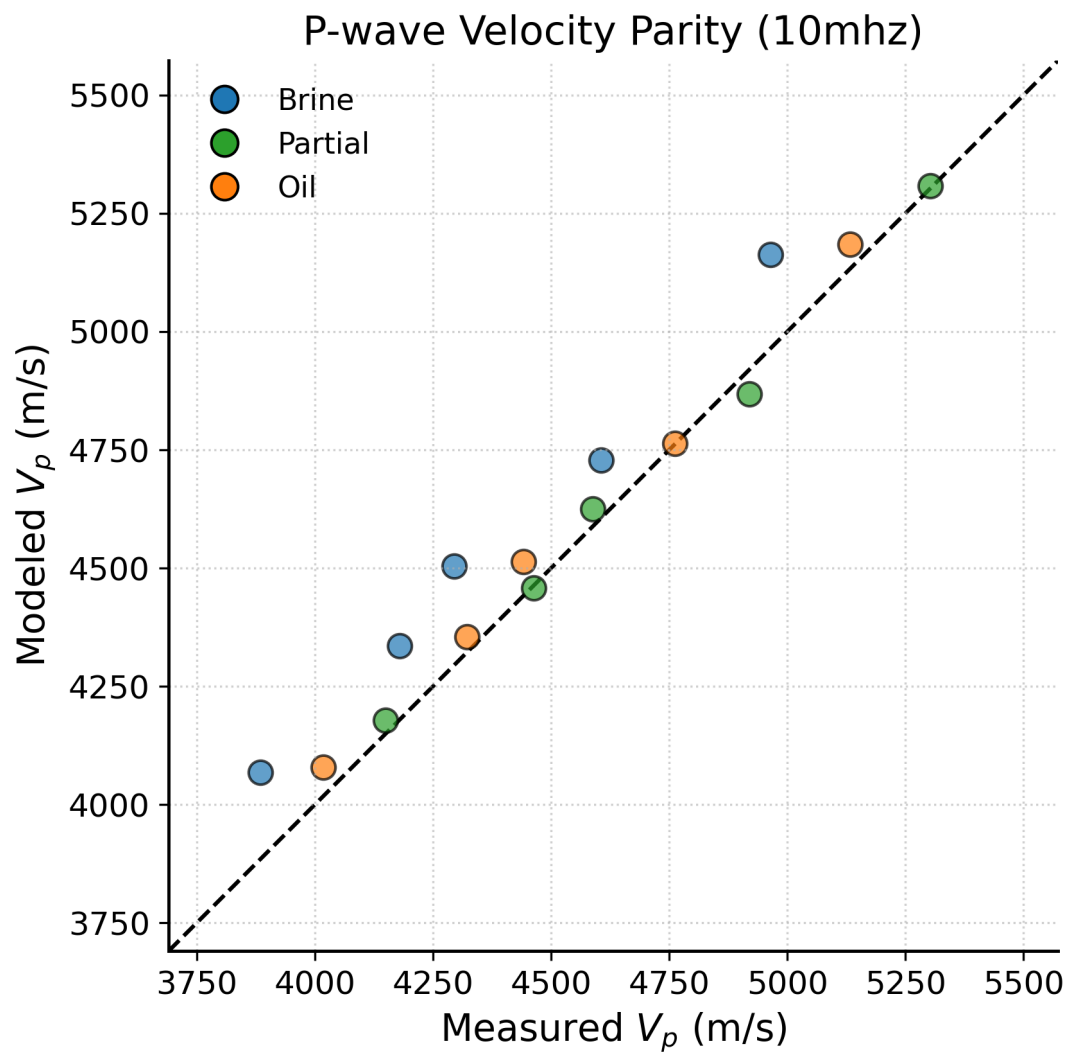


Figure 3.3. Measured versus Mavko-Jizba predicted V_p parity plot at 10 MHz. Markers represent brine (blue), partial brine (green), and oil-and-brine (orange) saturations. The dashed line indicates perfect agreement.

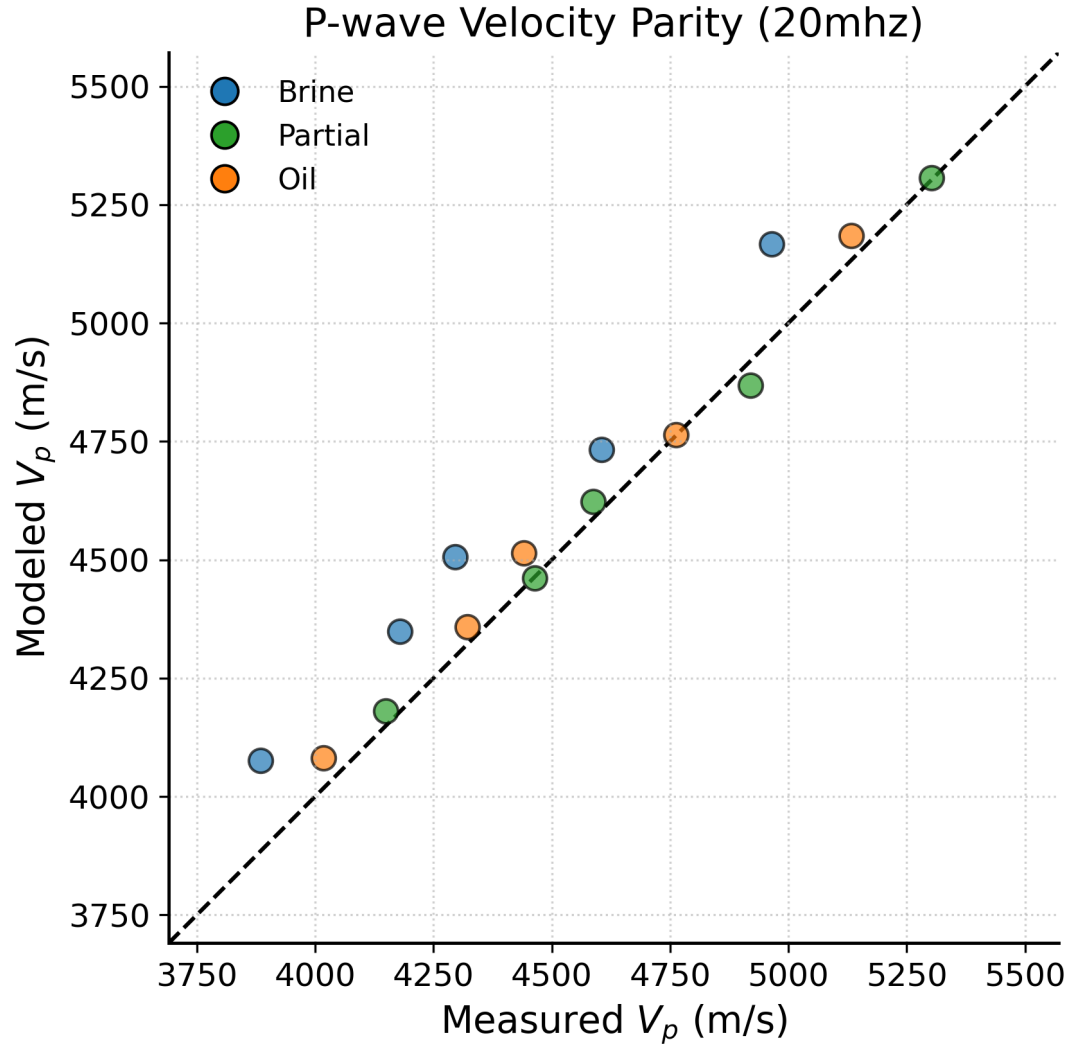


Figure 3.4. Measured versus Mavko-Jizba predicted V_p parity plot at 20 MHz. Markers represent brine (blue), partial brine (green), and oil-and-brine (orange) saturations. The dashed line indicates perfect agreement.

Parity plots comparing measured and Mavko-Jizba predicted V_p are presented at the four retained ultrasonic frequencies (1.25 MHz, 2.5 MHz, 10 MHz, and 20 MHz). At each frequency, data points cluster tightly around the 1:1 reference line across all three saturation states, indicating that the model captures the first-order velocity structure of these dolomites under varying pore-fluid conditions.

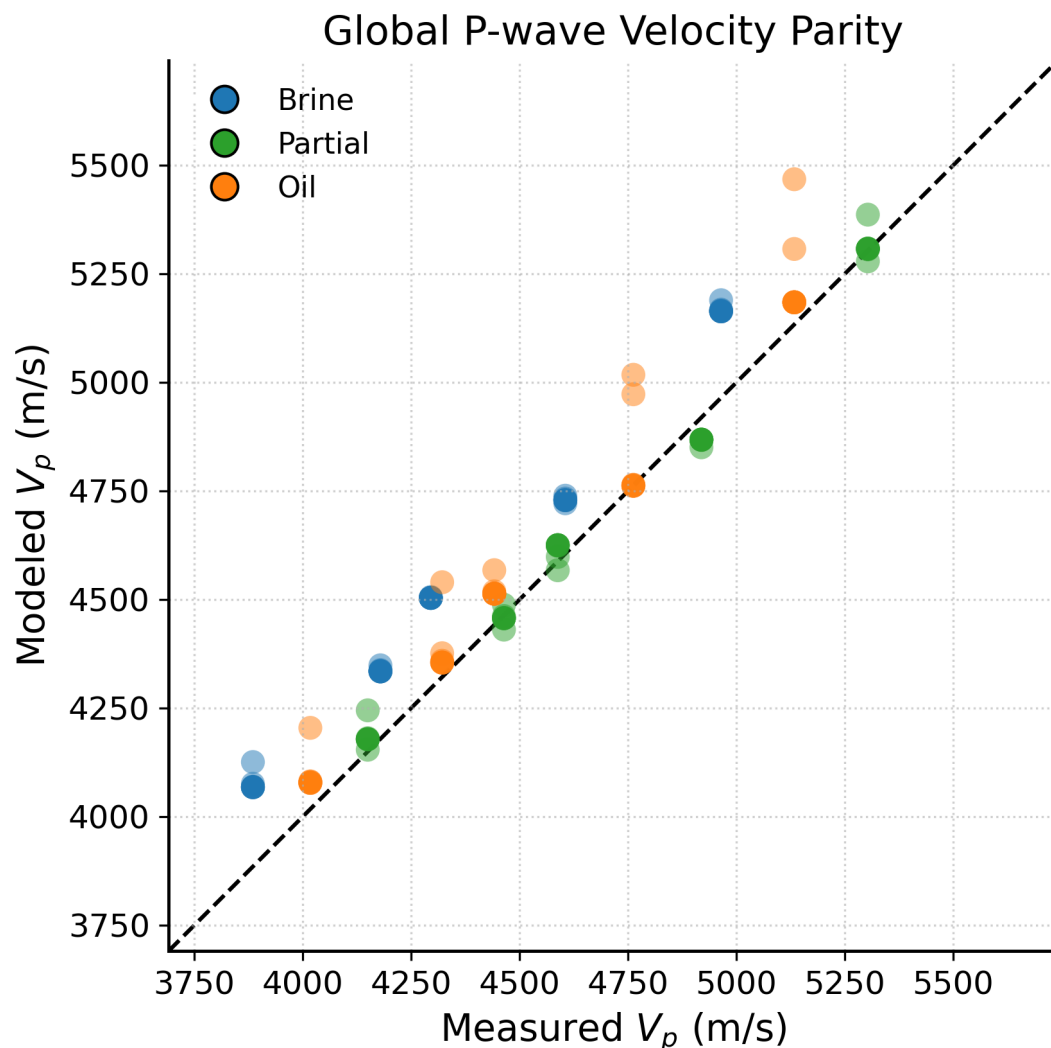


Figure 3.5. Aggregated V_p parity plot pooling all eight frequencies (156.3 kHz to 20 MHz)

The aggregated V_p parity plot, which pools all measured frequencies into a single panel, confirms this behavior across the full bandwidth: the overall scatter is symmetrically distributed about the line of perfect agreement, with no systematic bias toward over- or under-prediction. Visual inspection of the aggregated parity diagram confirms that residuals remain small relative to the measured velocity range (approximately 4000–6000 m/s), with no saturation-dependent clustering of the residuals that would indicate a systematic model shortcoming.

3.1.2 Shear-Wave Velocity (V_s)

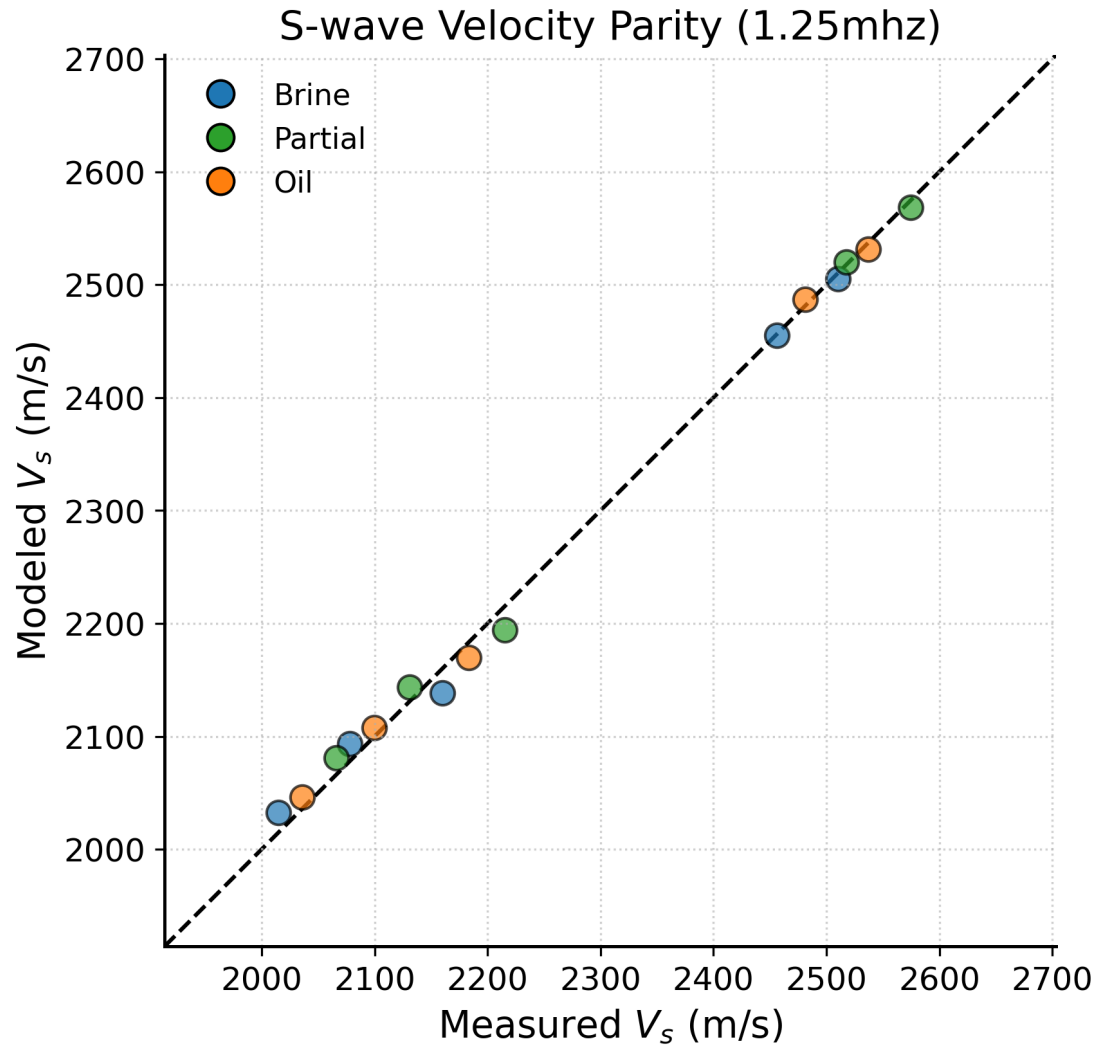


Figure 3.6. Measured versus Mavko-Jizba predicted V_s parity plot at 1.25 MHz. Markers represent brine (blue), partial brine (green), and oil-and-brine (orange) saturations. The dashed line indicates perfect agreement.

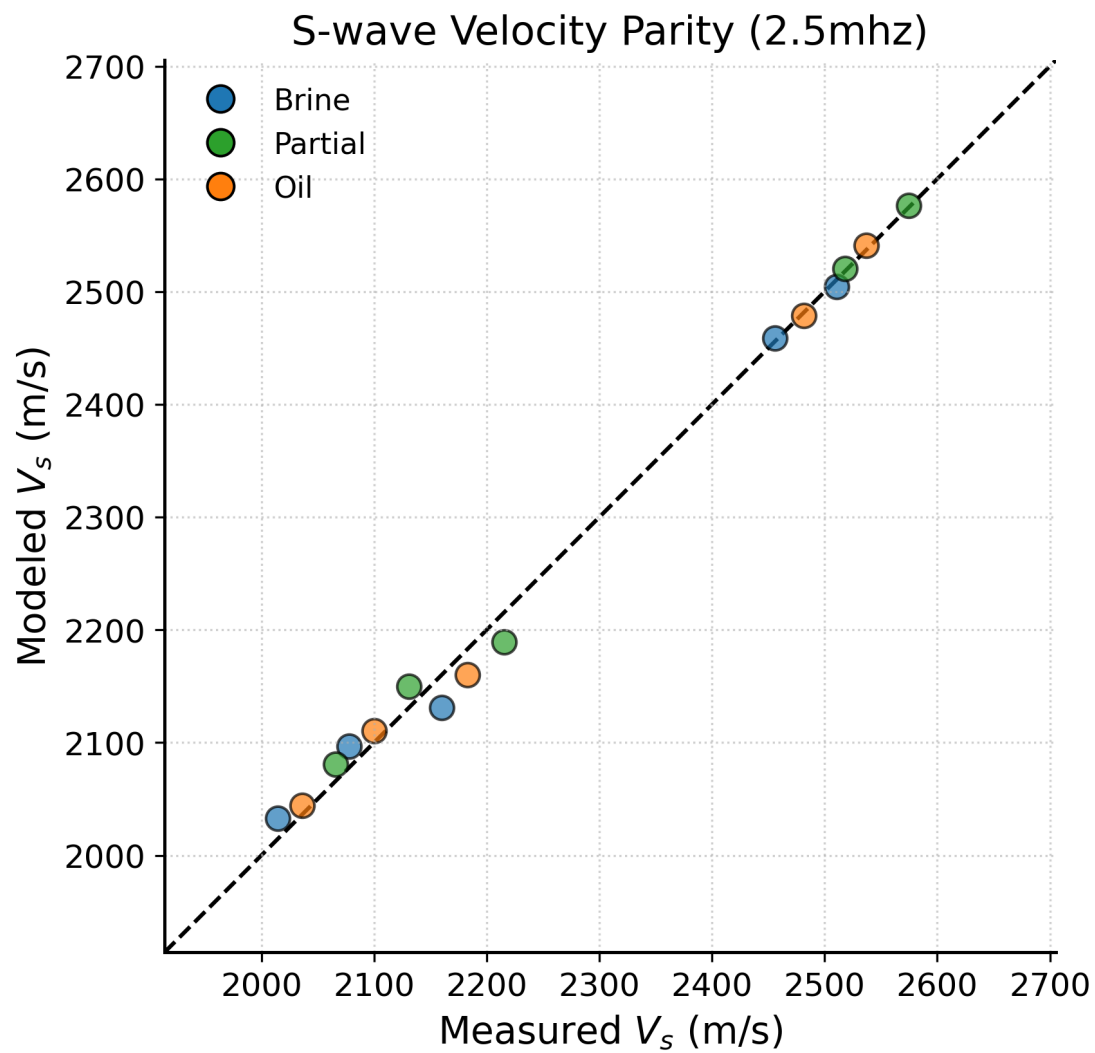


Figure 3.7. Measured versus Mavko-Jizba predicted V_s parity plot at 2.5 MHz. Markers represent brine (blue), partial brine (green), and oil-and-brine (orange) saturations. The dashed line indicates perfect agreement.

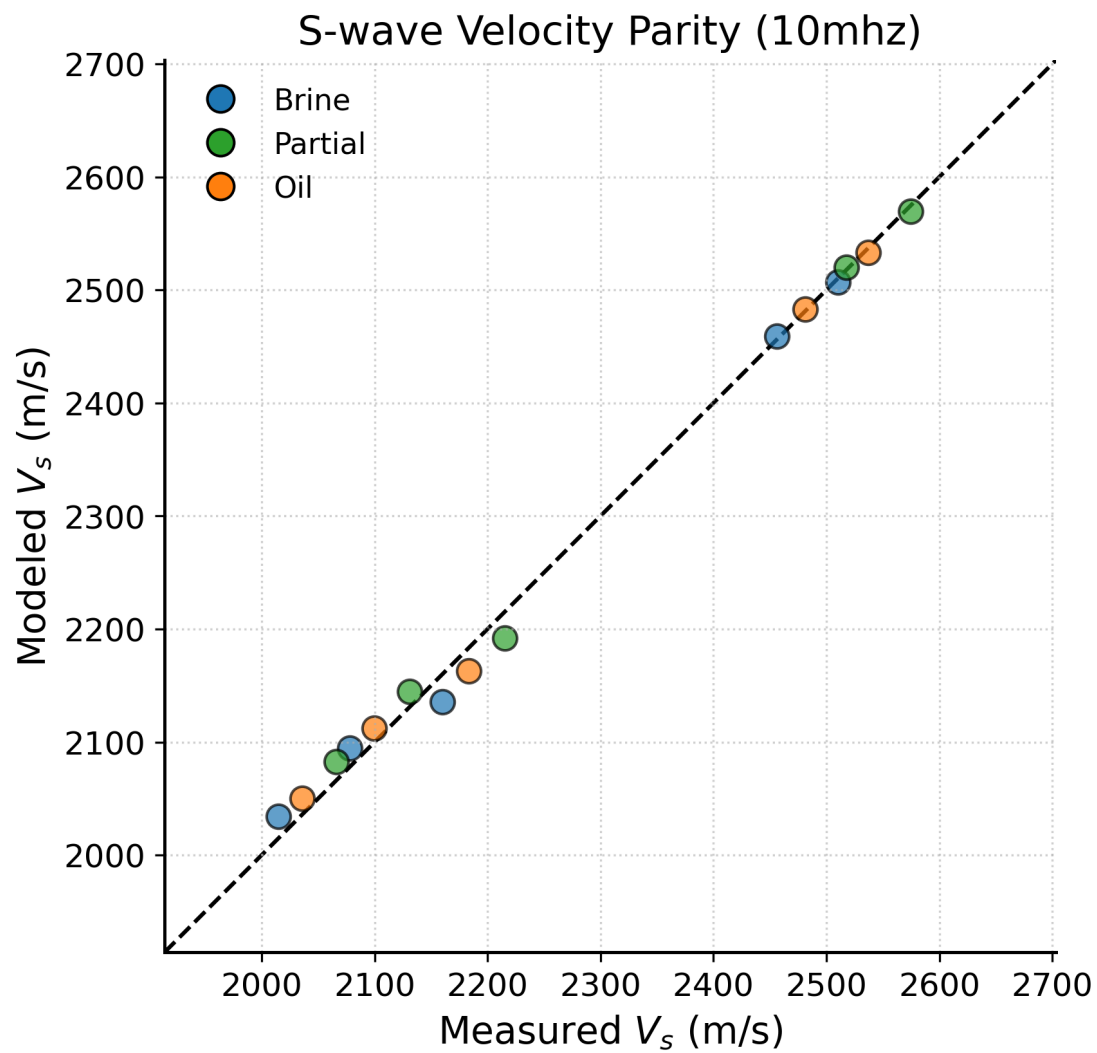


Figure 3.8. Measured versus Mavko-Jizba predicted V_s parity plot at 10 MHz. Markers represent brine (blue), partial brine (green), and oil-and-brine (orange) saturations. The dashed line indicates perfect agreement.

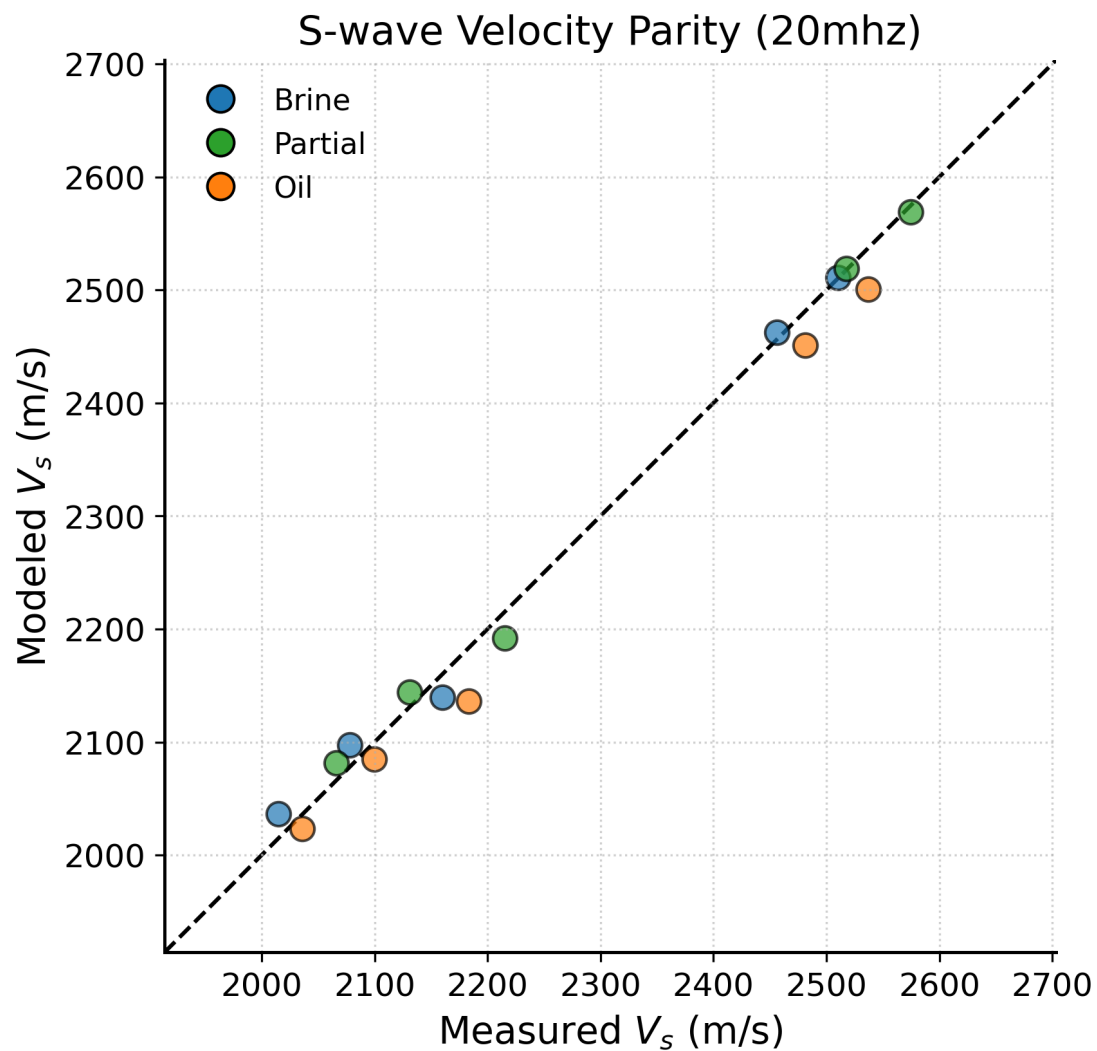


Figure 3.9. Measured versus Mavko-Jizba predicted V_s parity plot at 20 MHz. Markers represent brine (blue), partial brine (green), and oil-and-brine (orange) saturations. The dashed line indicates perfect agreement.

Predicted V_s values show comparable agreement with measurements. Per-frequency parity plots at all four retained frequencies display close clustering around the 1:1 line.

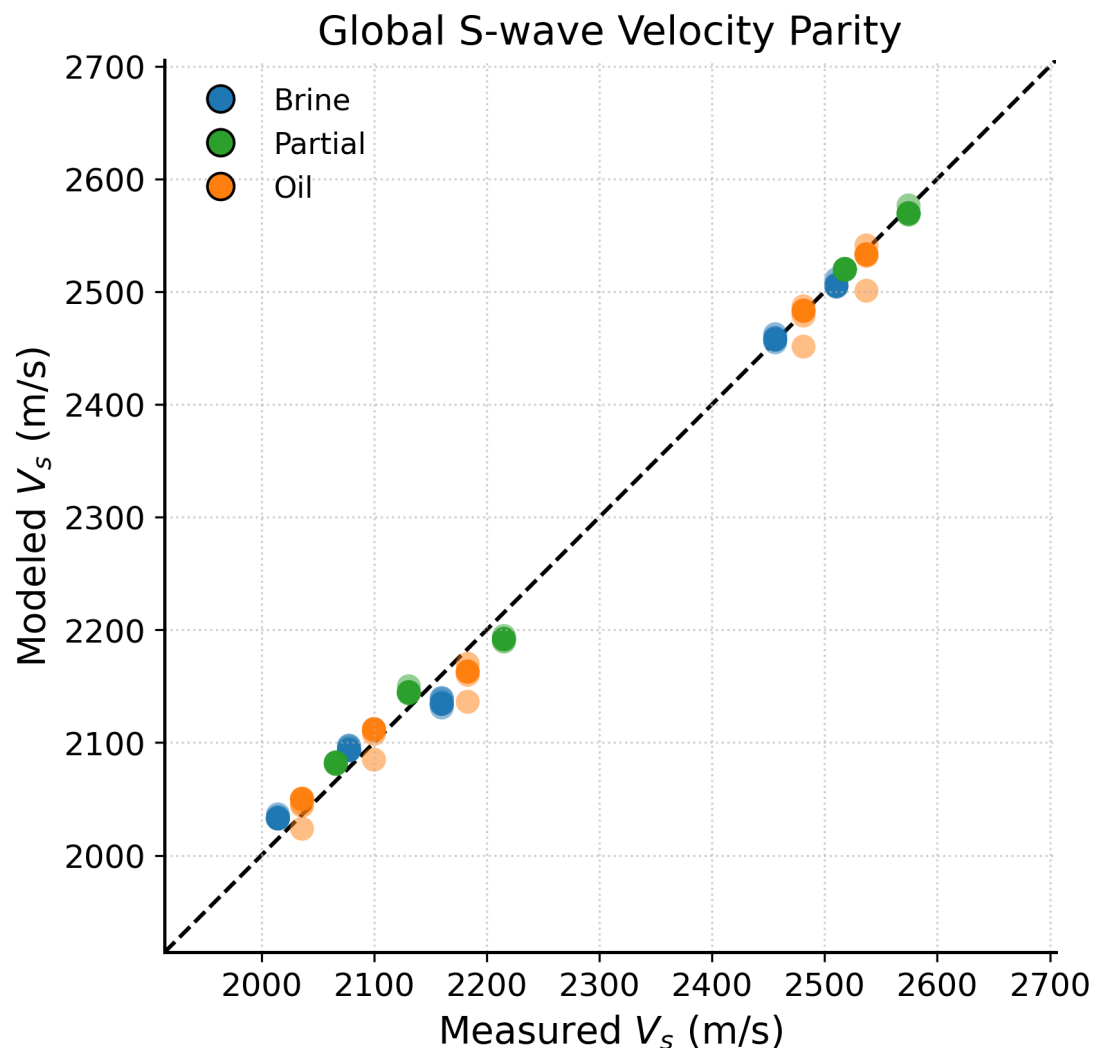


Figure 3.10. Aggregated V_s parity plot pooling all eight frequencies (156.3 kHz to 20 MHz)

The aggregated V_s parity indicates that shear-wave predictions are marginally tighter than compressional-wave predictions, consistent with the generally lower sensitivity of V_s to pore-fluid effects in the Mavko-Jizba squirt-flow framework (Mavko and Jizba, 1991).

A systematic offset exists between laboratory V_s and well-log shear-wave velocities measured in the same interval (Cimino, 2020). This offset is attributed to the absence of full overburden pressure in the laboratory: uniaxial loads were maintained below 10,000 lbf to avoid sample failure and therefore did not replicate the effective stress conditions prevailing at reservoir

depth. The calibrated model operates on the laboratory data and does not correct for this pressure deficit, bridging between laboratory and well-log scales remains a discussion point (Section 4.5).

3.1.3 Velocity Dispersion

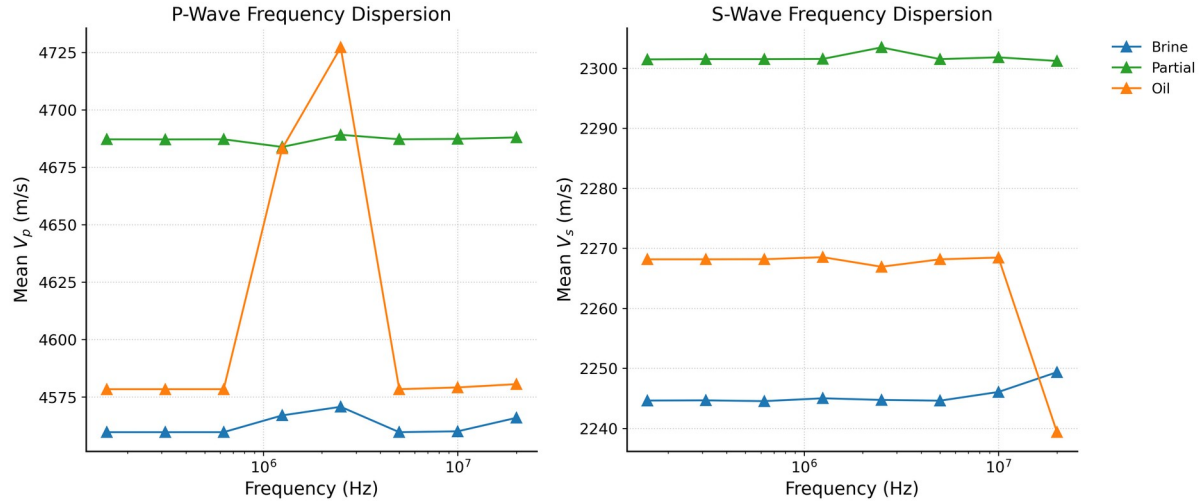


Figure 3.11. V_P and V_S dispersion for brine, partial brine, and oil-and-brine saturations. Solid lines represent Mavko-Jizba predictions; markers denote measured values

The frequency dependence of both V_P and V_S is summarized in the dispersion diagram, which plots velocity against frequency on a logarithmic scale. Brine and partial-brine saturation states exhibit minimal observable dispersion across the measured band, with velocities remaining nearly constant as frequency increases. In contrast, the oil-and-brine condition shows a pronounced localized peak in V_P near approximately 2 to 3 MHz, indicating a frequency-dependent elastic response that is not evident in the aqueous cases. The corresponding V_S response is comparatively weak and does not display an equally clear peak. This pattern is consistent with a relaxation mechanism that affects compressional stiffness more strongly than shear stiffness (Mavko and Jizba, 1991). Although the precise location of the underlying relaxation frequency should be interpreted cautiously unless confirmed independently by the calibrated model response.

3.2 Attenuation Comparisons

Attenuation, parameterized by the quality factor Q (where lower Q indicates higher energy dissipation), was evaluated for both P-waves (Q_p) and S-waves (Q_s) at the four retained frequencies under the three saturated conditions.

3.2.1 P-Wave Quality Factor (Q_p)

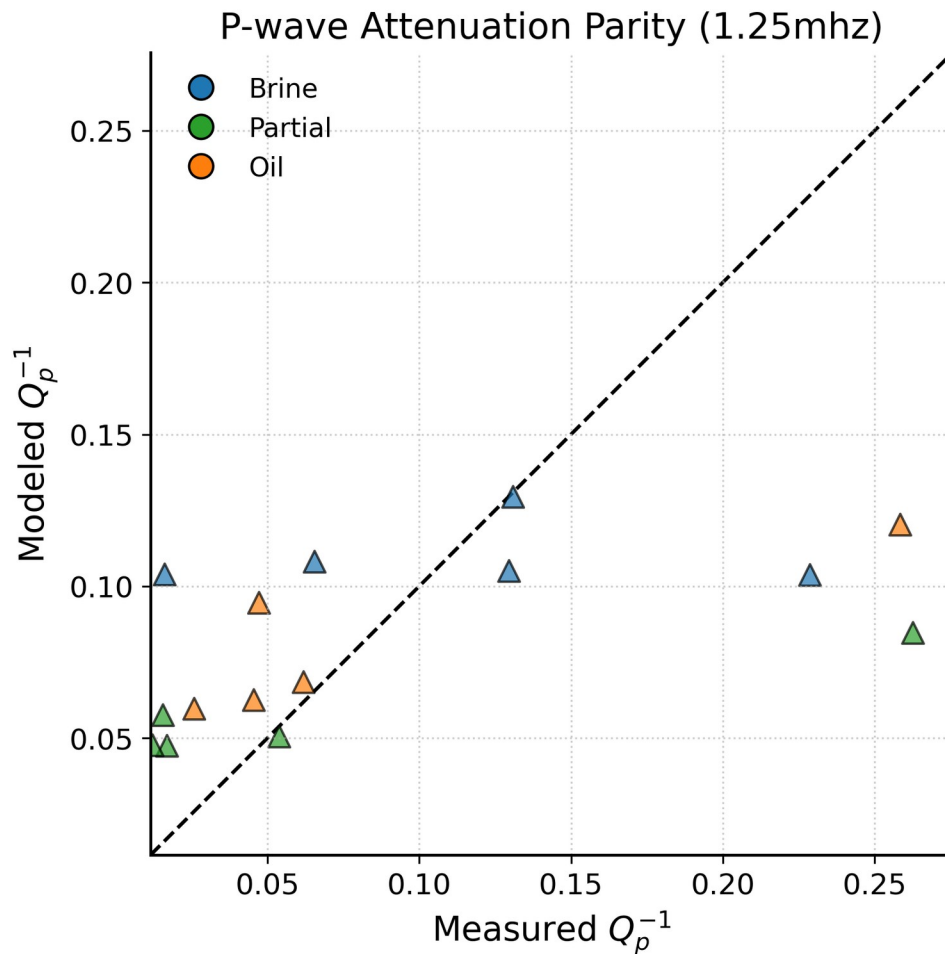


Figure 3.12. Measured versus Mavko-Jizba predicted Q_p parity plot at 1.25 MHz. Markers represent brine (blue), partial brine (green), and oil-and-brine (orange) saturations. The dashed line indicates perfect agreement.

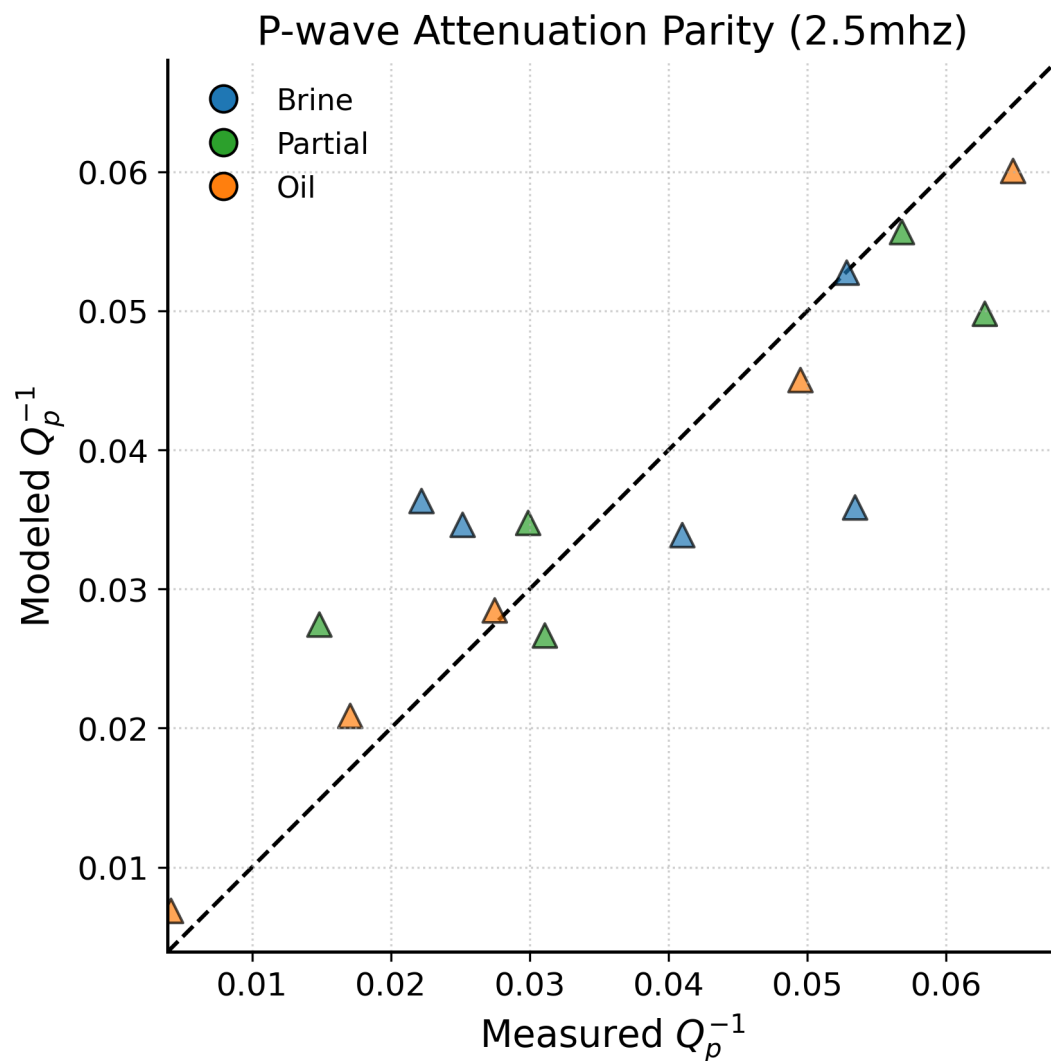


Figure 3.13. Measured versus Mavko-Jizba predicted Q_p parity plot at 2.5 MHz. Markers represent brine (blue), partial brine (green), and oil-and-brine (orange) saturations. The dashed line indicates perfect agreement.

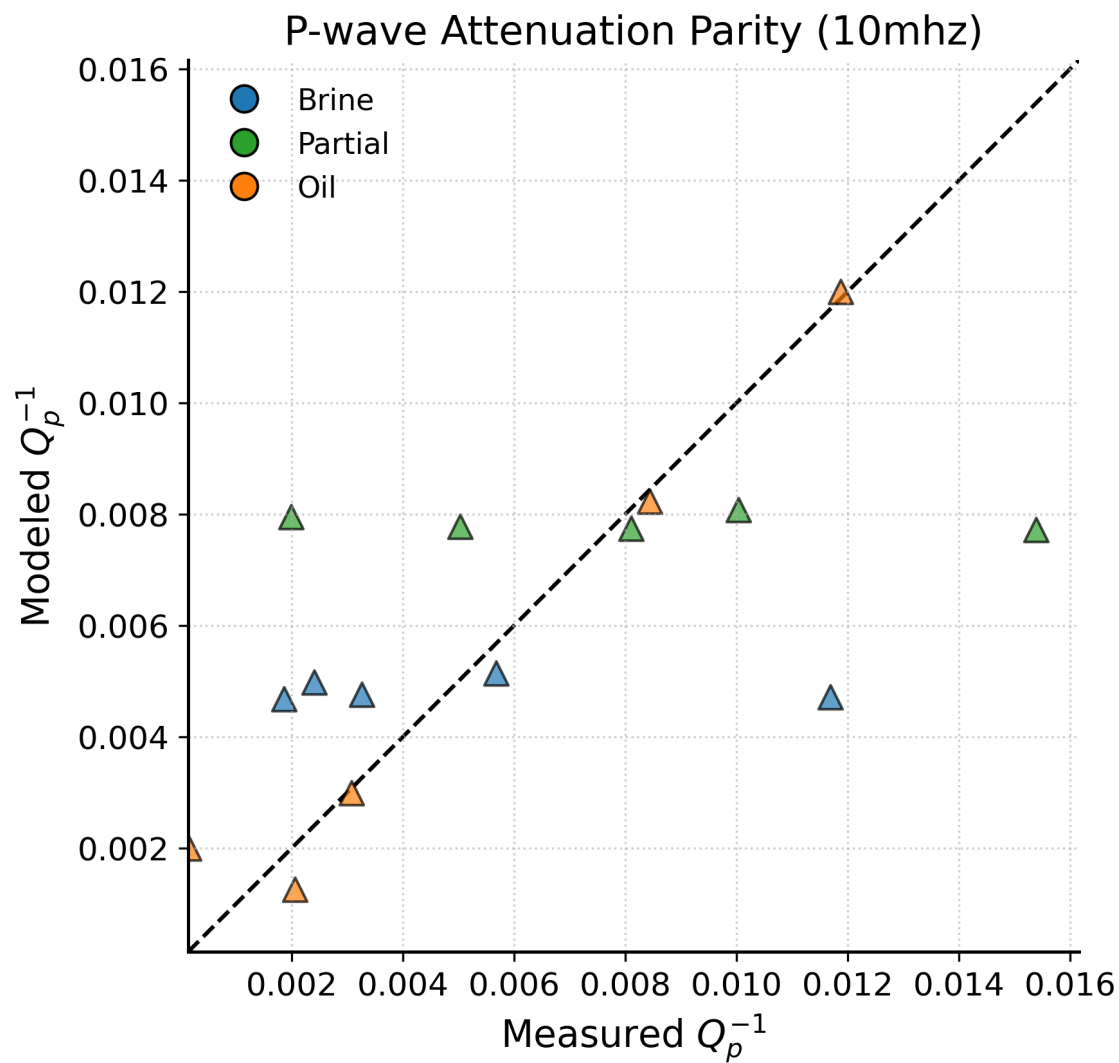


Figure 3.14. Measured versus Mavko-Jizba predicted Q_p parity plot at 10 MHz. Markers represent brine (blue), partial brine (green), and oil-and-brine (orange) saturations. The dashed line indicates perfect agreement.

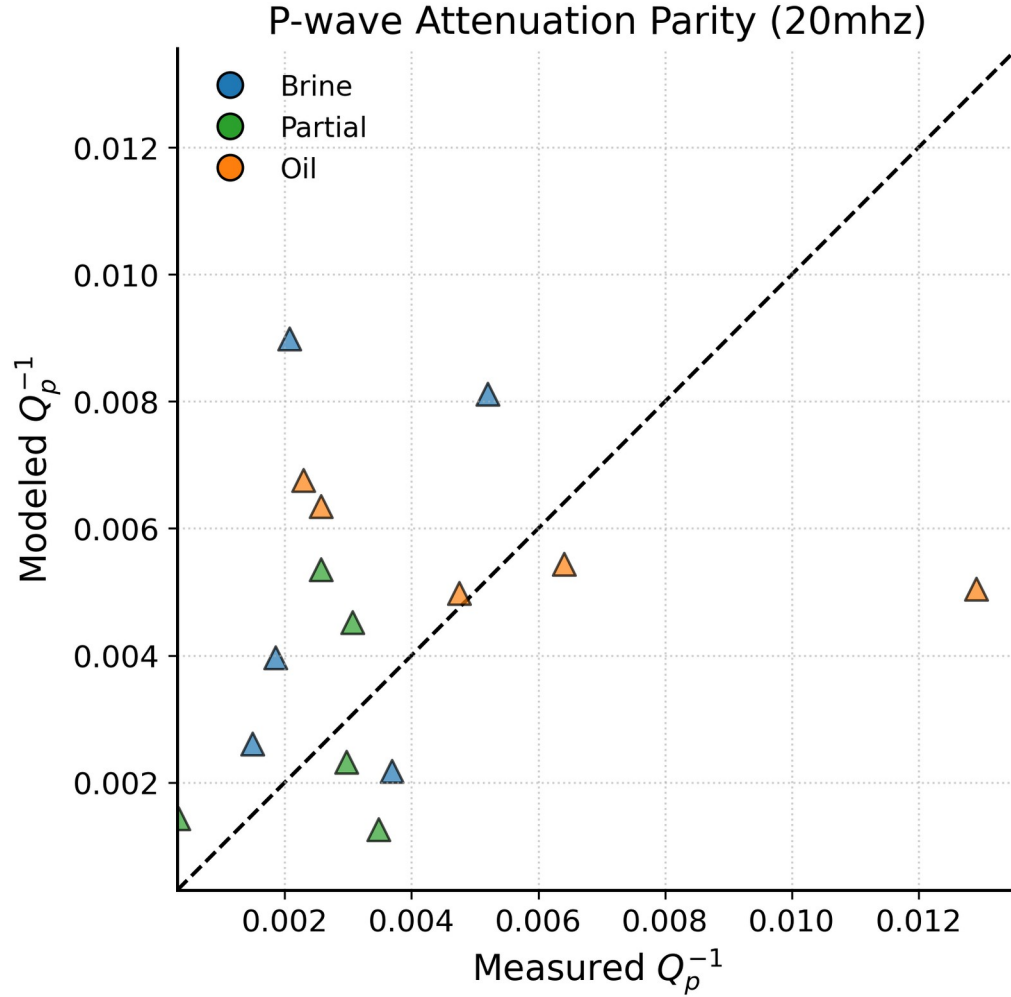
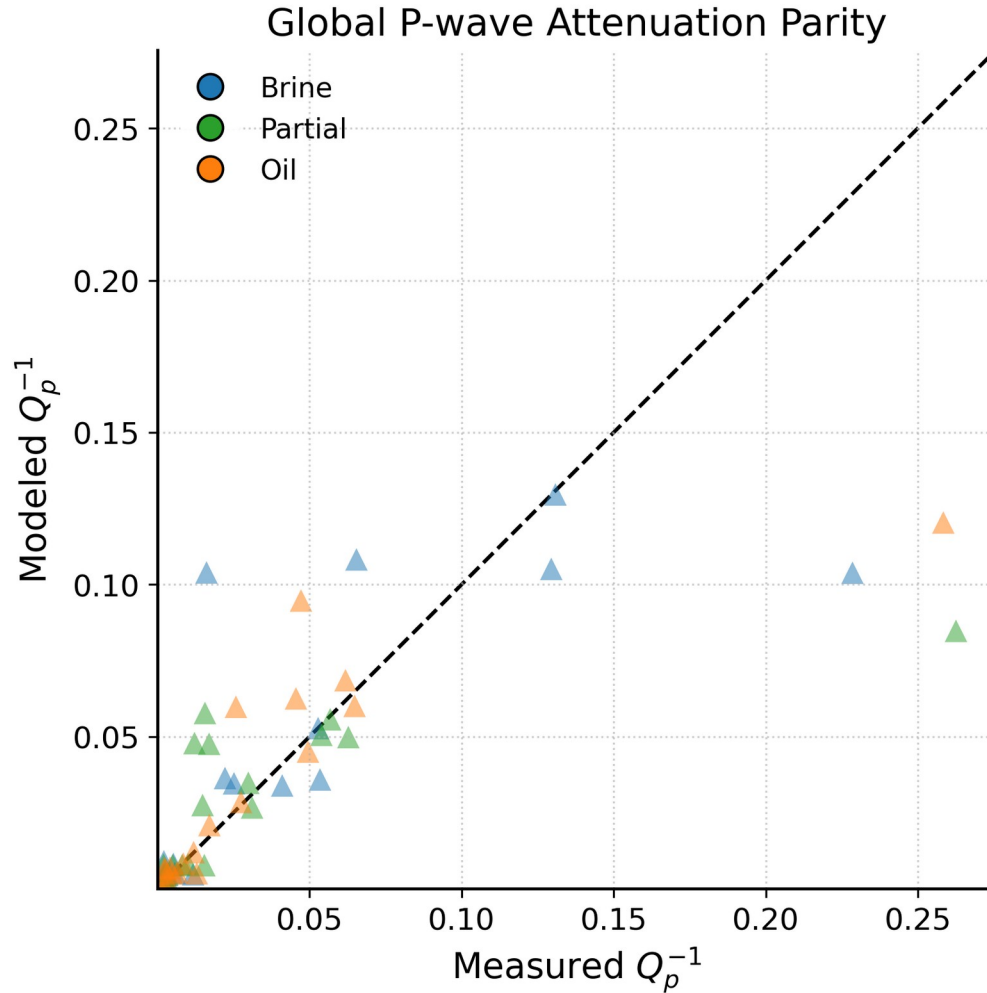


Figure 3.15. Measured versus Mavko-Jizba predicted Q_p parity plot at 20 MHz. Markers represent brine (blue), partial brine (green), and oil-and-brine (orange) saturations. The dashed line indicates perfect agreement.

Parity plots comparing measured and predicted Q_p are shown at the four frequencies (1.25 MHz, 2.5 MHz, 10 MHz, and 20 MHz) for which the spectral-ratio method returned usable attenuation estimates across all sample-saturation combinations. The remaining four frequencies (156.3 kHz, 312.5 kHz, 625 kHz, and 5 MHz) are excluded from the per-frequency presentation because no reliable Q_p data could be extracted at those frequencies; data from these frequencies are retained in the aggregated attenuation plots where available. The Q_p parity displays notably

wider scatter around the 1:1 line than the corresponding velocity plots, reflecting the well-documented difficulty of estimating Q from spectral ratios in the laboratory (Winkler and Nur, 1982). Coupling variability, diffraction effects, and signal-to-noise limitations at the bandpass extremes all contribute to elevated measurement uncertainty in Q relative to velocity (Toksöz et al., 1979).



levels. At the highest measured Q_p^{-1} values, however, the model no longer reproduces the full magnitude of attenuation and instead exhibits a visible ceiling effect, with several high-attenuation observations plotting well below the 1:1 line. This behavior is consistent with the interpretation that a simplified single characteristic compliant-pore representation may underestimate dissipation in samples whose pore network contains a wider distribution of crack compliances or aspect ratios.

3.2.2 S-Wave Quality Factor (Q_s)

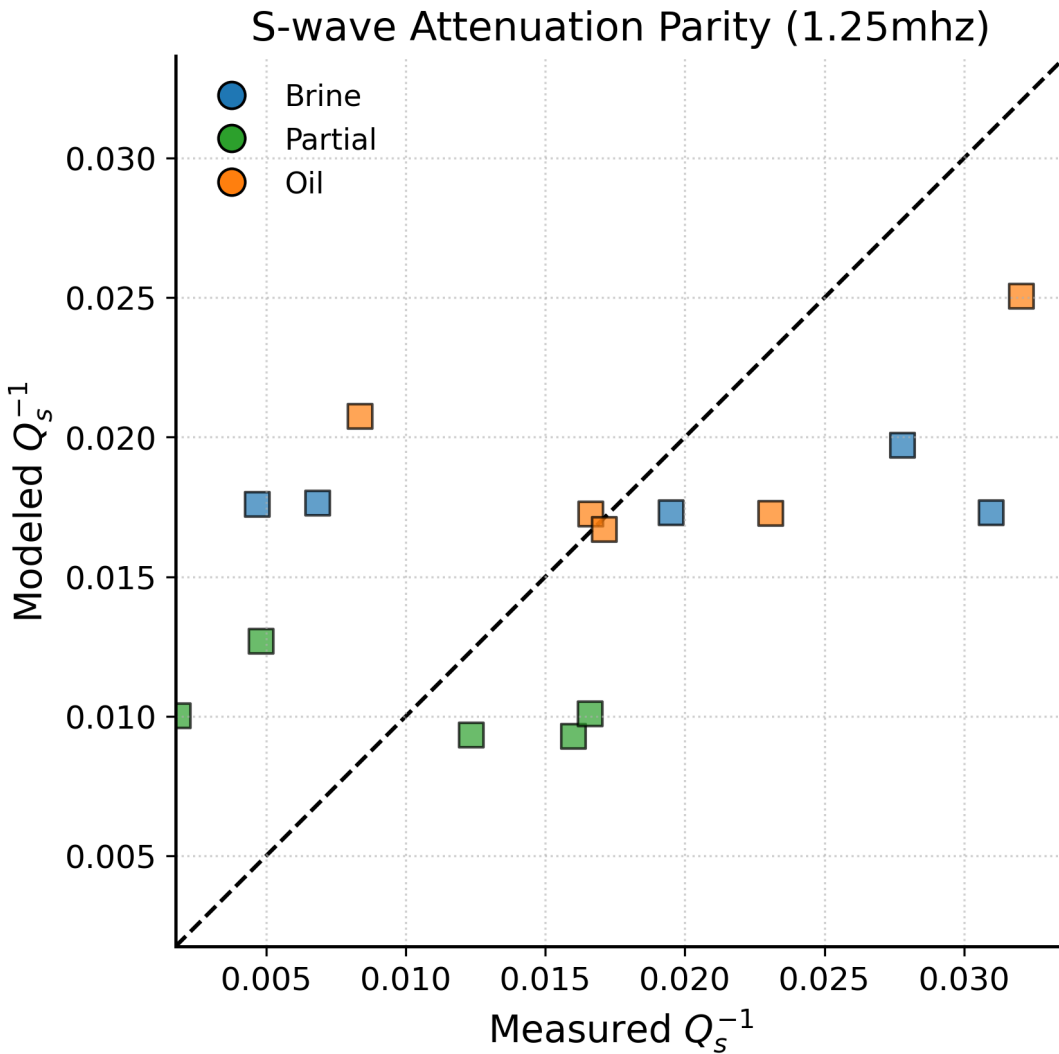


Figure 3.17. Measured versus Mavko-Jizba predicted Q_s parity plot at 1.25 MHz. Markers represent brine (blue), partial brine (green), and oil-and-brine (orange) saturations. The dashed line indicates perfect agreement.

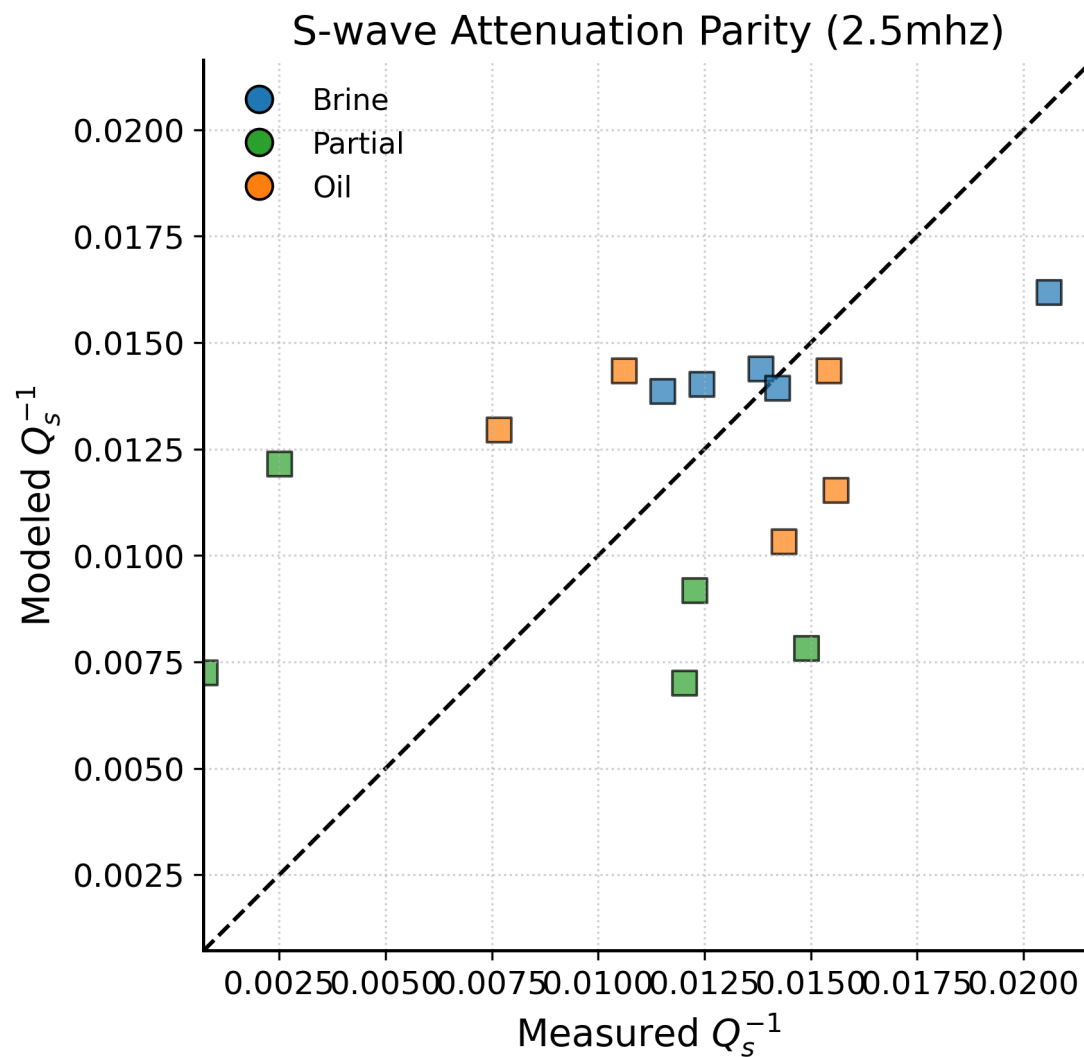


Figure 3.18. Measured versus Mavko-Jizba predicted Q_s parity plot at 2.5 MHz. Markers represent brine (blue), partial brine (green), and oil-and-brine (orange) saturations. The dashed line indicates perfect agreement.

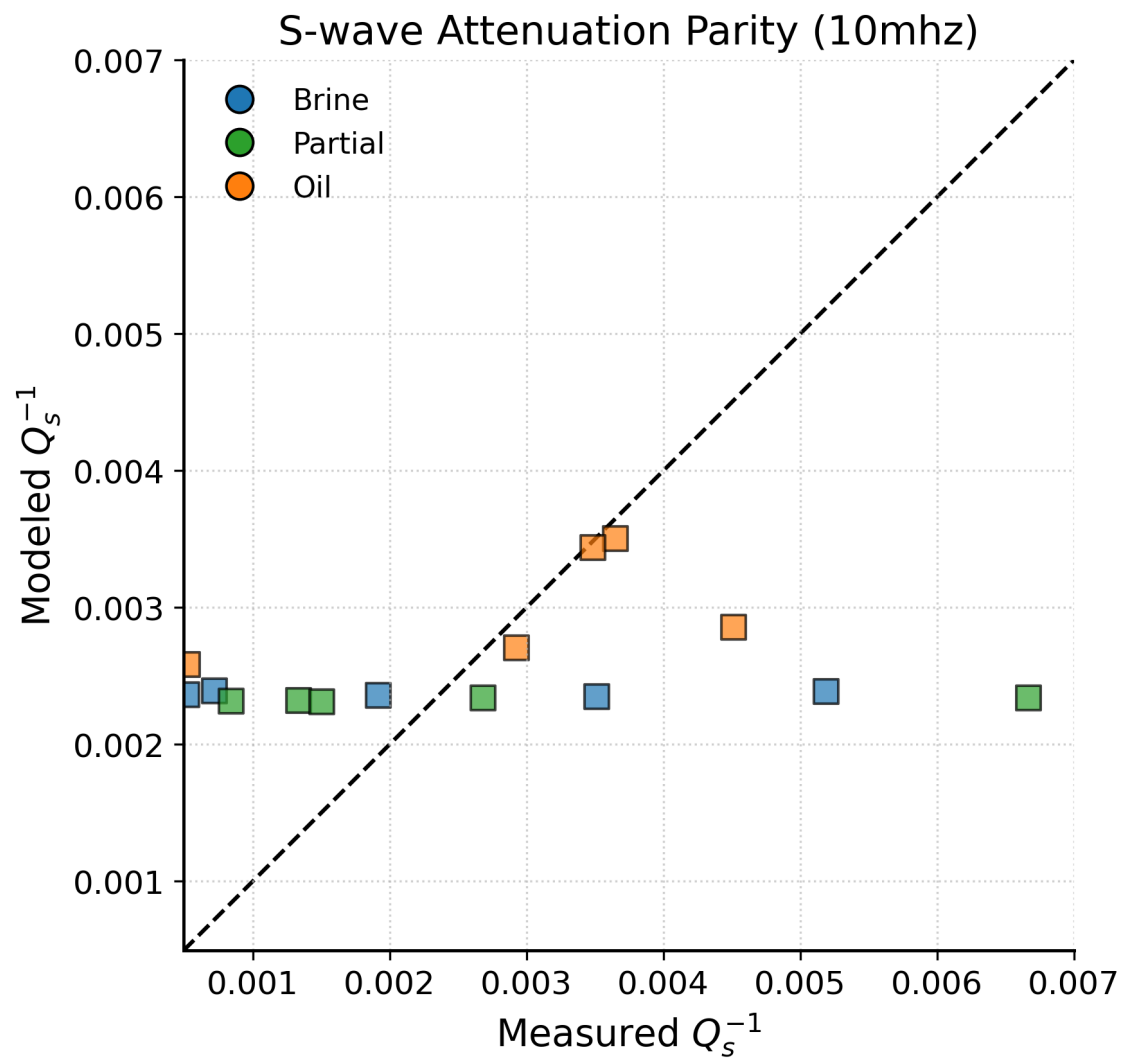


Figure 3.19. Measured versus Mavko-Jizba predicted Q_s parity plot at 10 MHz. Markers represent brine (blue), partial brine (green), and oil-and-brine (orange) saturations. The dashed line indicates perfect agreement.

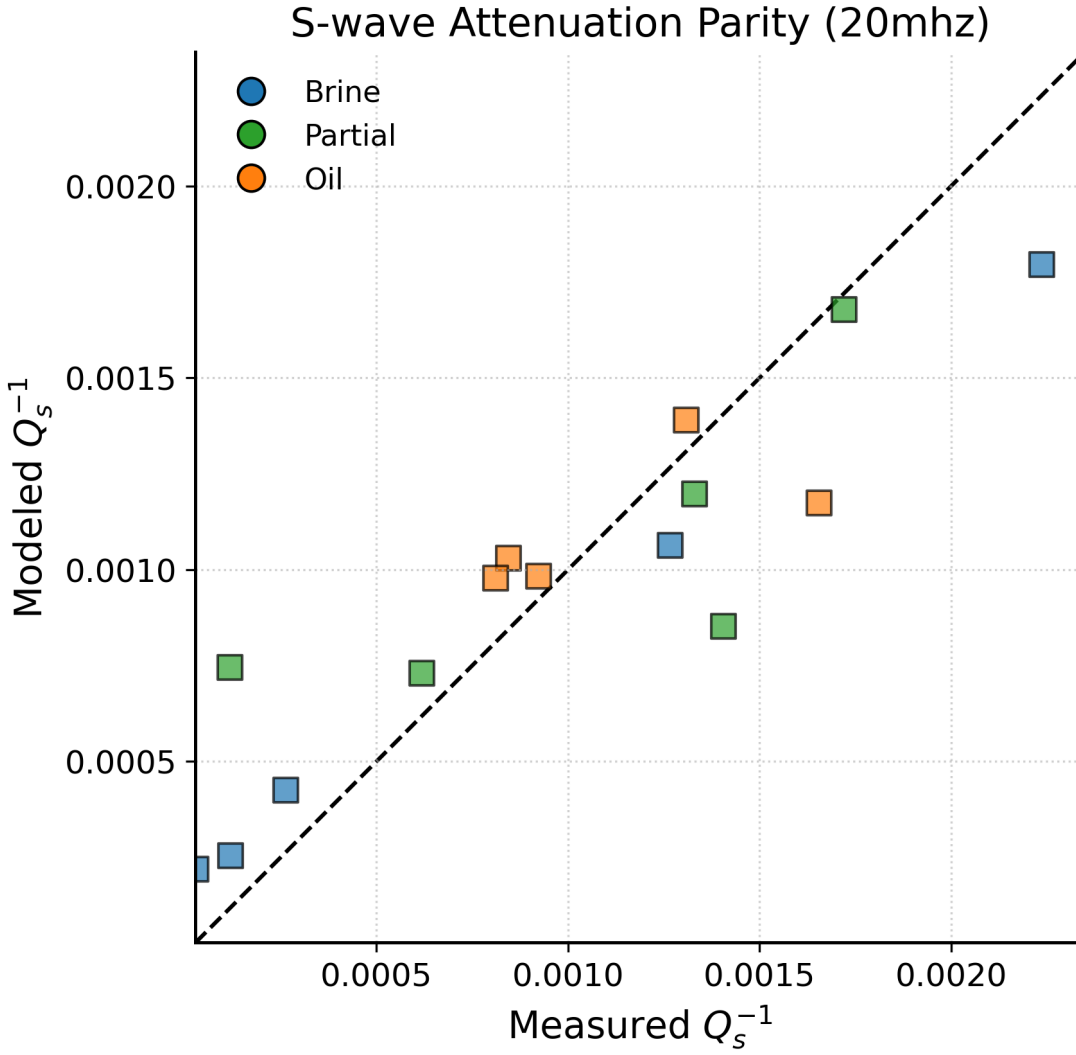


Figure 3.20. Measured versus Mavko-Jizba predicted Q_s parity plot at 20 MHz. Markers represent brine (blue), partial brine (green), and oil-and-brine (orange) saturations. The dashed line indicates perfect agreement.

The pattern for Q_s parallels that of Q_p . Per-frequency parity plots at all four retained frequencies reveal similar scatter magnitudes.

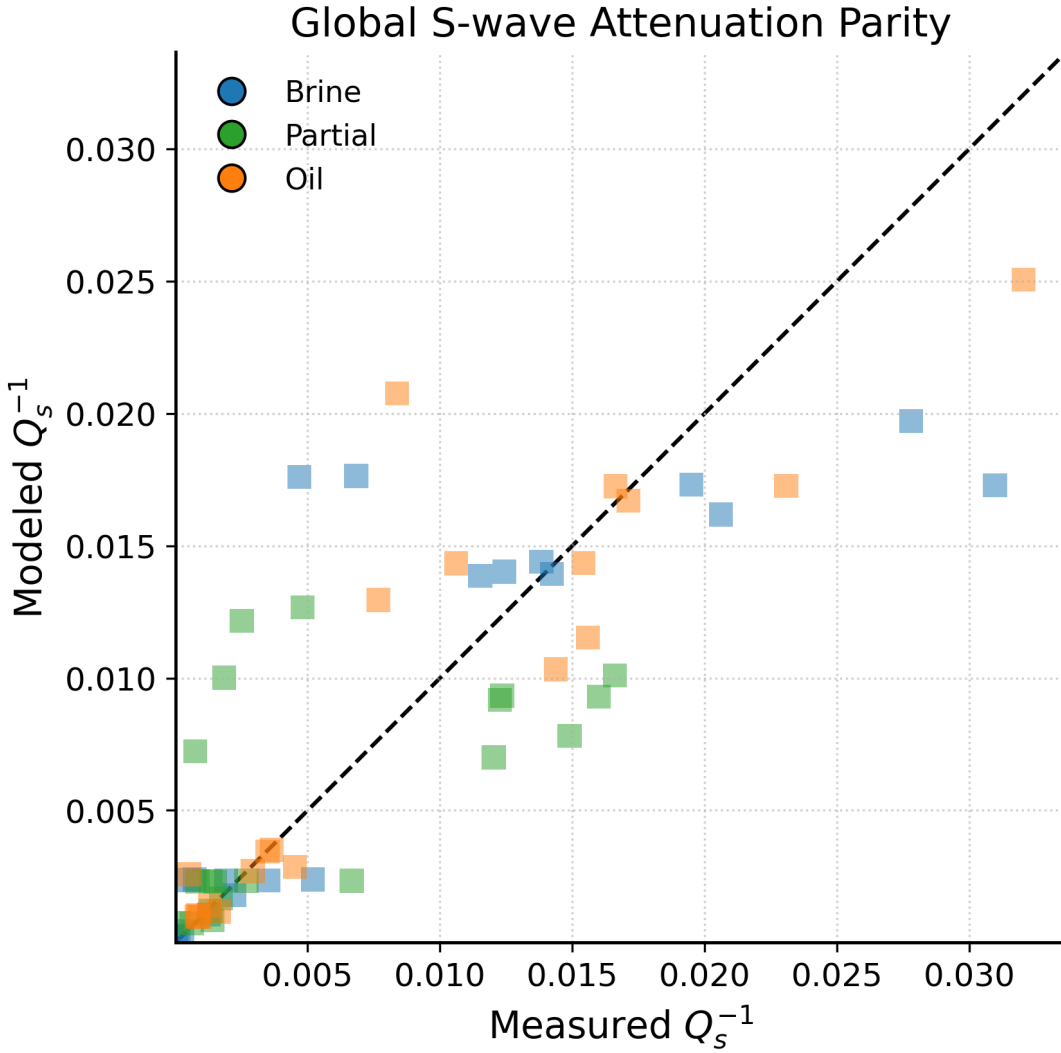


Figure 3.21. Aggregated Q_s parity plot pooling all frequencies with usable attenuation estimates. The dashed line indicates perfect agreement.

The aggregated Q_s parity plot shows that the Mavko-Jizba model reproduces the first-order magnitude of the measured shear-wave attenuation, but the predictions are not uniformly unbiased across the full attenuation range. Several low Q_s^{-1} observations are overpredicted, whereas several moderate to high Q_s^{-1} observations are underpredicted, producing substantial scatter about the 1:1 line. The Q_s results therefore indicate partial predictive skill rather than strict parity, and they

suggest that the calibrated squirt-flow framework captures only part of the mechanism controlling shear-wave attenuation.

3.2.3 Frequency-Dependent Attenuation Peaks

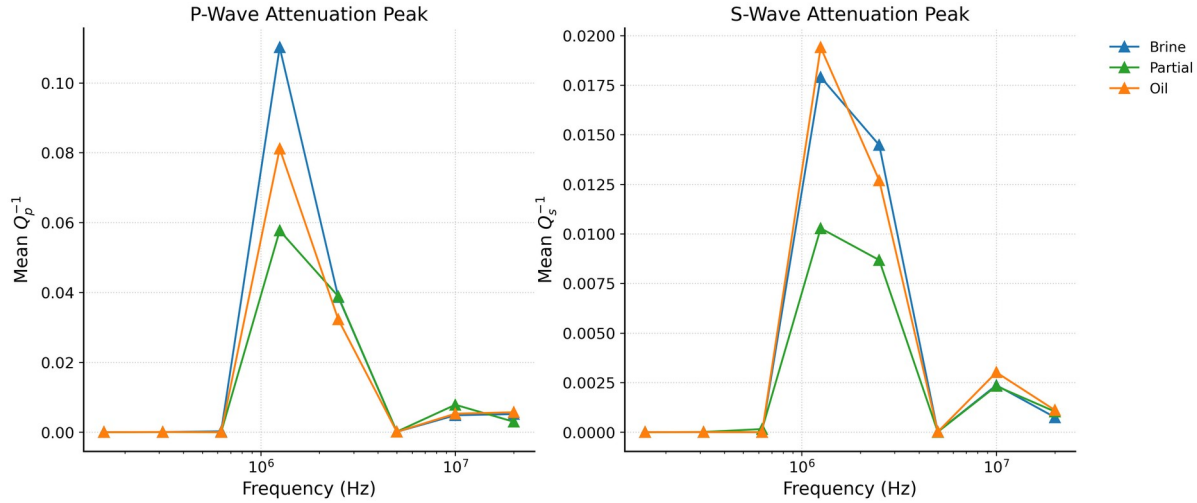


Figure 3.22. Frequency-dependent Q_p and Q_s showing attenuation peaks for brine, partial brine, and oil-and-brine saturations. Solid lines represent Mavko-Jizba predictions; markers denote measured values

The attenuation peak diagram summarizes the frequency dependence of attenuation by plotting mean Q_p^{-1} and Q_s^{-1} against frequency on a logarithmic scale. Clear attenuation maxima are observed near approximately 1.25MHz for all three saturation states in both panels, indicating that the dominant relaxation process lies within the measured ultrasonic band. In the Q_p^{-1} panel, the brine-saturated samples exhibit the strongest and sharpest peak, whereas the oil-and-brine and partial-brine cases show lower-amplitude and somewhat broader responses. In the Q_s^{-1} panel, attenuation peaks are likewise present, although the saturation ordering is less systematic. This pattern is consistent with a squirt-flow-type relaxation mechanism, which commonly produces localized attenuation maxima within the transition band between relaxed and unrelaxed behavior (Mavko and Jizba, 1991). The broader response in the oil-and-brine state may indicate a broader

effective relaxation spectrum associated with saturation-dependent fluid topology and pore-scale heterogeneity, rather than a simple upward shift in characteristic frequency.

3.3 Saturation-Dependent Behavior

3.3.1 V_p - V_s Crossplots and Fluid Separation

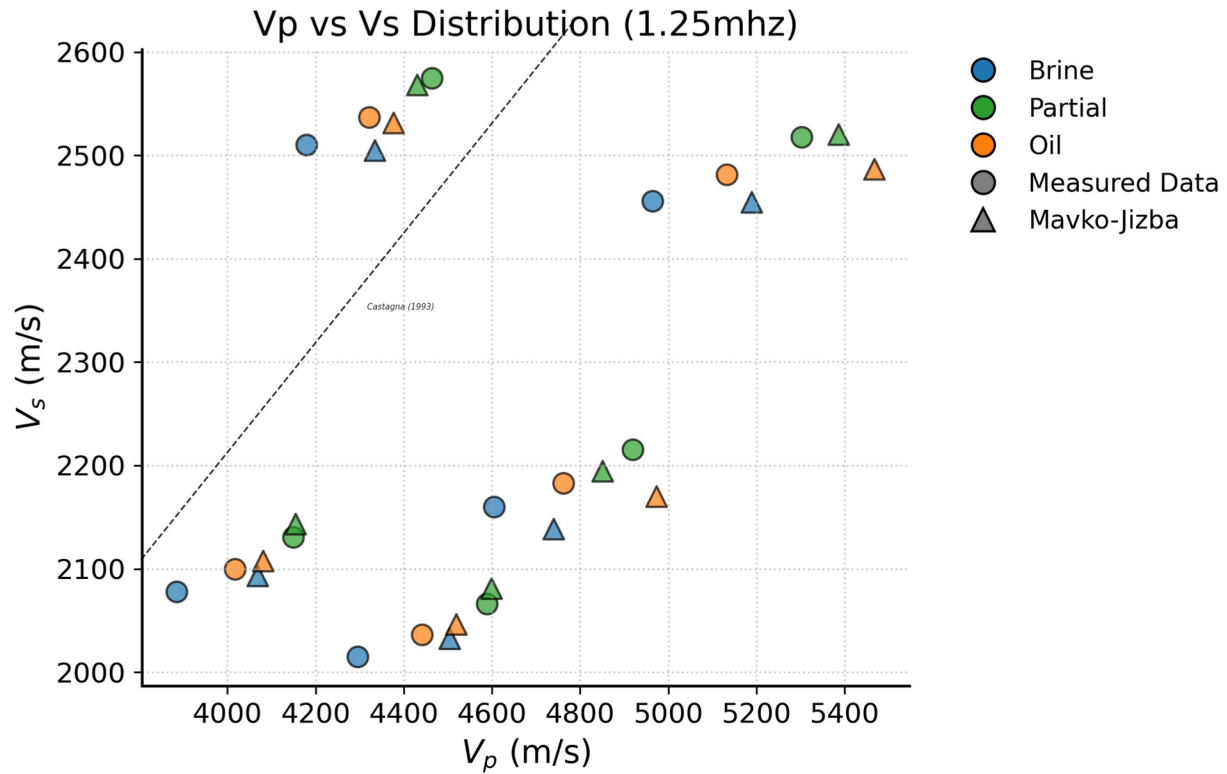


Figure 3.23. V_p - V_s crossplot at 1.25 MHz for brine, partial brine, and oil-and-brine saturations. The dolomite trend line of Castagna et al. (1993) is shown for reference

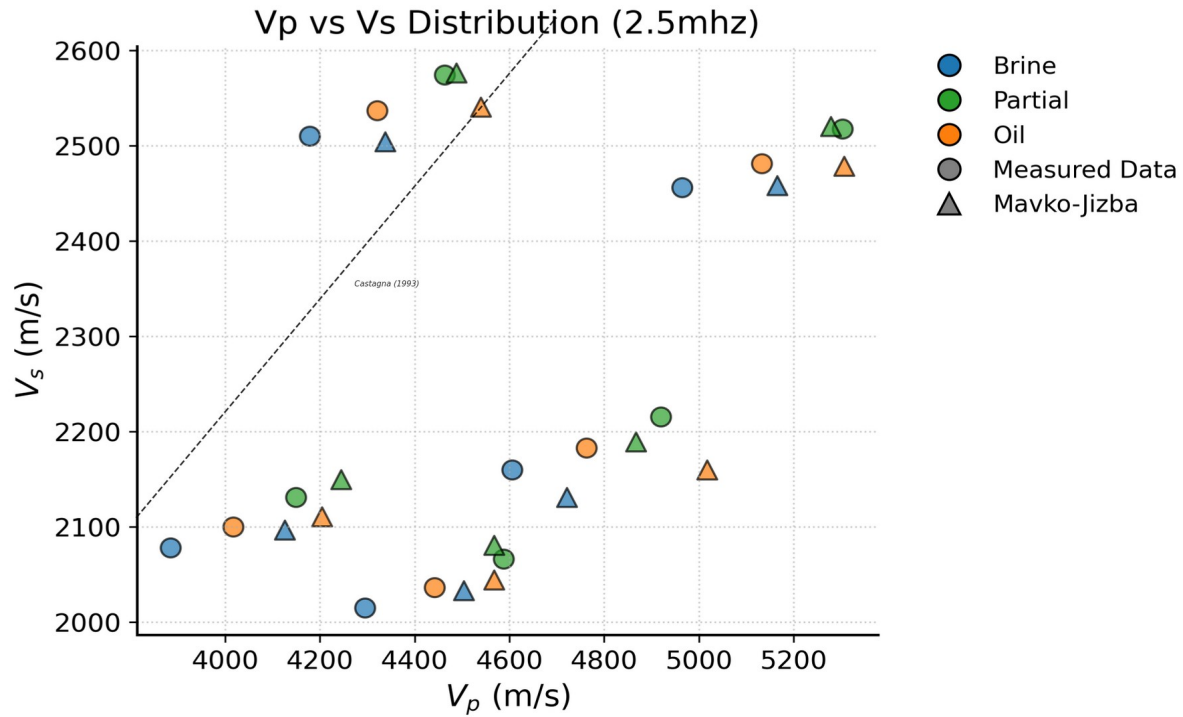


Figure 3.24. V_p - V_s crossplot at 2.5 MHz for brine, partial brine, and oil-and-brine saturations. The dolomite trend line of Castagna et al. (1993) is shown for reference

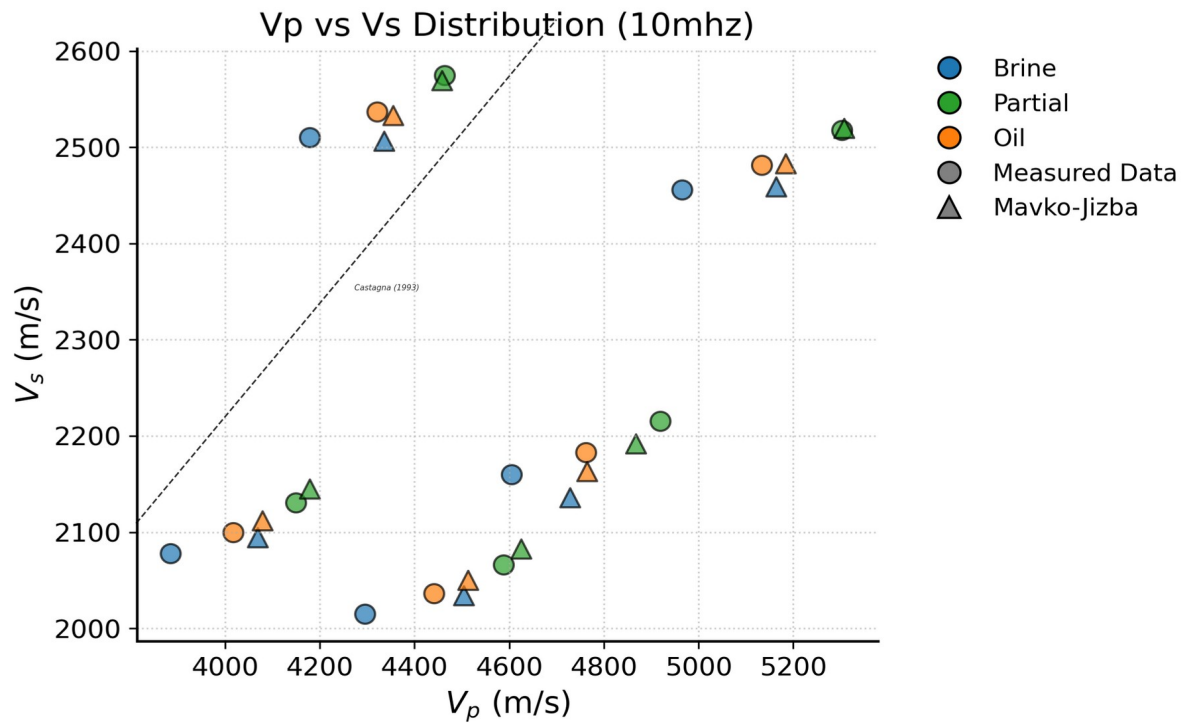


Figure 3.25. V_p - V_s crossplot at 10 MHz for brine, partial brine, and oil-and-brine saturations. The dolomite trend line of Castagna et al. (1993) is shown for reference

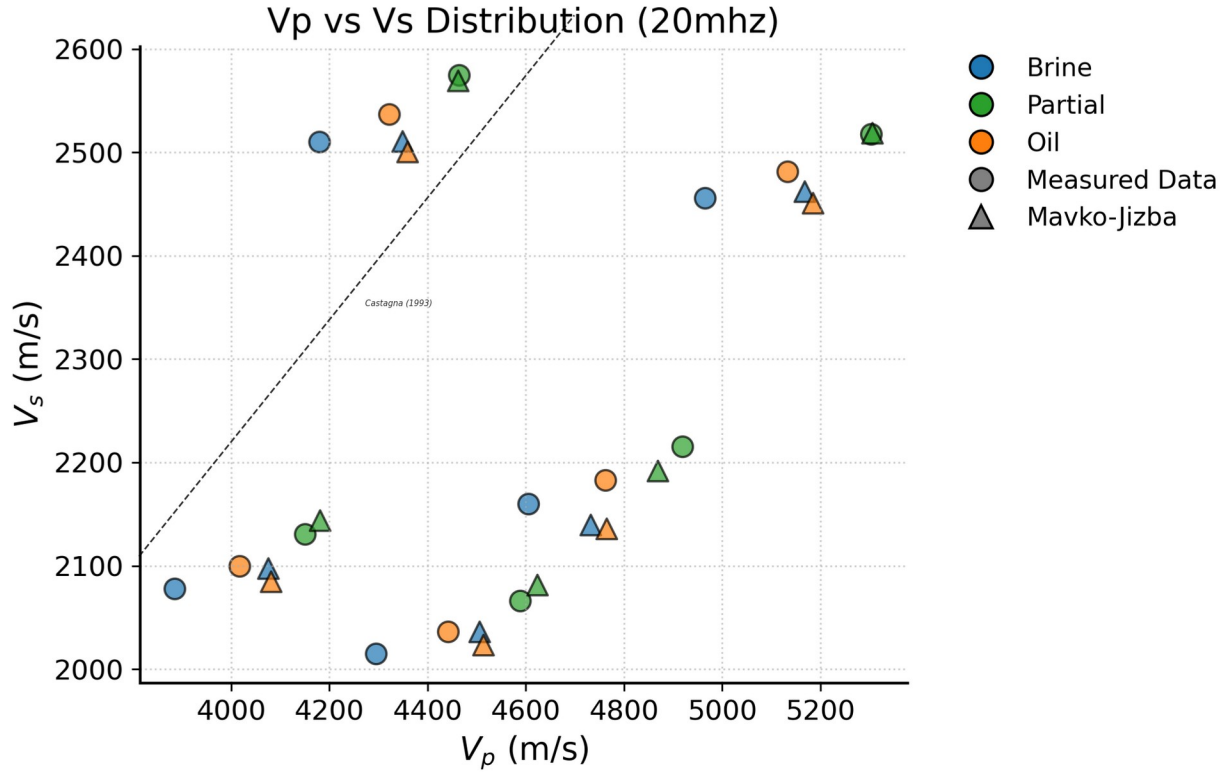


Figure 3.26. V_p - V_s crossplot at 20 MHz for brine, partial brine, and oil-and-brine saturations. The dolomite trend line of Castagna et al. (1993) is shown for reference

The relationship between compressional and shear velocities under different pore-fluid conditions is examined through V_p - V_s crossplots at the four retained ultrasonic frequencies (1.25 MHz to 20 MHz).

In the crossplot domain, the three saturation states produce distinguishable clusters, although the degree of separation varies with frequency. At intermediate frequencies (1.25 MHz to 2.5 MHz), where the squirt-flow transition is most active, the saturation clusters show the greatest separation: brine-saturated samples cluster at higher V_s for a given V_p , oil-and-brine samples occupy a distinct intermediate region, and partially saturated samples fall between the two. At the highest frequencies (10-20 MHz), where all saturations approach the unrelaxed regime, the clusters converge and fluid discrimination from velocity ratios alone becomes less effective.

The Castagna et al. (1993) dolomite trend line ($V_s = 0.583 V_p - 78$ m/s) is superimposed on each crossplot as a lithology-specific empirical reference. The measured and predicted data fall close to but systematically below this trend, indicating slightly lower V_s/V_p ratios than the Castagna empirical prediction for these Wellington dolomites. The offset is small and consistent across frequencies, suggesting a lithology-specific departure that does not compromise the overall geophysical consistency of the calibrated Mavko-Jizba model with established dolomite velocity systematics. These observations are also broadly compatible with the dynamic elastic-property measurements reported by Yale and Jamieson (1994) for Hugoton-Panoma dolomites from the same Kansas carbonate province, lending regional support to the velocity ranges and V_p/V_s ratios obtained here.

3.3.2 Velocity Sensitivity to Saturation State

The absolute velocity changes associated with fluid substitution are small. Across the five samples, measured travel-time shifts between saturation states range from approximately 0.9 to 1.8 μ s for P-waves and 0.2 to 0.9 μ s for S-waves. These shifts correspond to velocity changes of the order of a few percent and are consistent with the limited pore-fluid compressibility contrast in these low-porosity dolomites.

The modest velocity sensitivity to saturation reinforces the practical value of attenuation-based fluid discrimination. While the velocity changes fall near the limits of measurement precision for some sample–frequency combinations, the corresponding attenuation differences (Section [3.2](#)) are substantially larger and more robust, consistent with the well-documented observation that amplitude attributes provide superior fluid sensitivity in carbonate reservoirs (Spencer, 1979).

3.3.3 Pore-Fluid Stiffening in Carbonates

Contrary to the conventional expectation that fluid saturation reduces V_s (as predicted by simple Gassmann theory for most clastic rocks), the brine-saturated samples in this study exhibit V_s values that equal or exceed those of dry samples at the same frequency (Winkler and Nur, 1982). This anomalous behavior is attributed to pore-fluid stiffening: brine fills the compliant pore spaces and reduces pore-space compressibility, effectively stiffening the frame against shear deformation. This effect is particularly common in carbonates, where moldic, vuggy, and micro-crack porosity creates a complex pore geometry in which fluid-frame interaction departs significantly from the assumptions underlying the Gassmann (1951) low-frequency limit (Winkler and Nur, 1982).

The Mavko-Jizba model, through its explicit treatment of compliant and stiff porosity fractions, accommodates this stiffening effect: the calibrated soft-porosity parameters absorb the additional frame compliance associated with the dolomite pore network, allowing the model to predict the observed saturation-dependent V_s trends without invoking ad hoc corrections.

3.3.4 Comparison with Well-Log Data

The V_p - V_s crossplots also permit comparison within situ well-log velocities from the same formation interval. Brine-saturated laboratory data coincide with the well-log velocity trend for V_p values below approximately 5.5 km/s (Castagna et al., 1993). This convergence supports the validity of using the laboratory-derived V_p/V_s relationship to convert in situ well-log V_p to V_s for wells that lack dipole shear sonic logs, a transformation that is of considerable practical importance for seismic inversion and geomechanical modeling in carbonates. The well-log data plot closer to the dolomite trend on the Castagna et al. (1993) velocity-lithology diagram, independently confirming the lithological identification.

3.4 Porosity Prediction and Recovery

Porosity is an important reservoir parameter that links elastic measurements to petrophysical interpretation. For each sample an experimental density porosity was computed as $\phi = 1 - \rho_{dry} / \rho_{grain}$, where ρ_{dry} is the bulk density of the oven-dried plug and ρ_{grain} is the mineral grain density. The Mavko-Jizba model additionally recovers an effective porosity through its calibrated soft and stiff porosity parameters, providing an independent, acoustically derived estimate that can be compared directly with the density-derived value.

3.4.1 Comparison of Porosity Methods

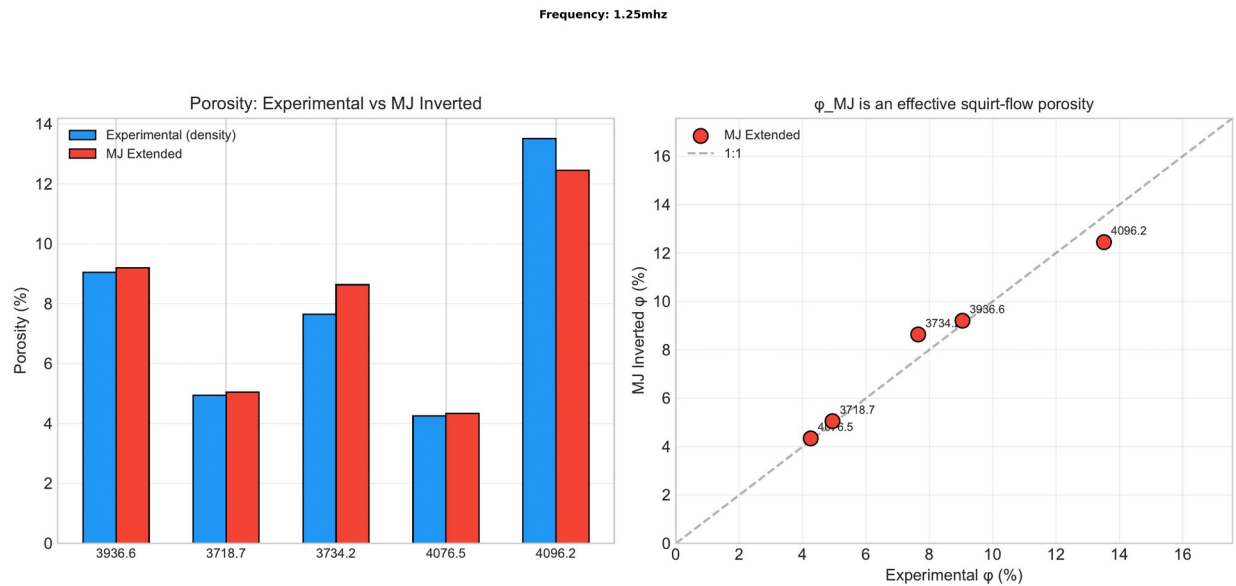


Figure 3.27. Comparison of experimental density porosity and Mavko-Jizba recovered porosity at 1.25 MHz for each sample

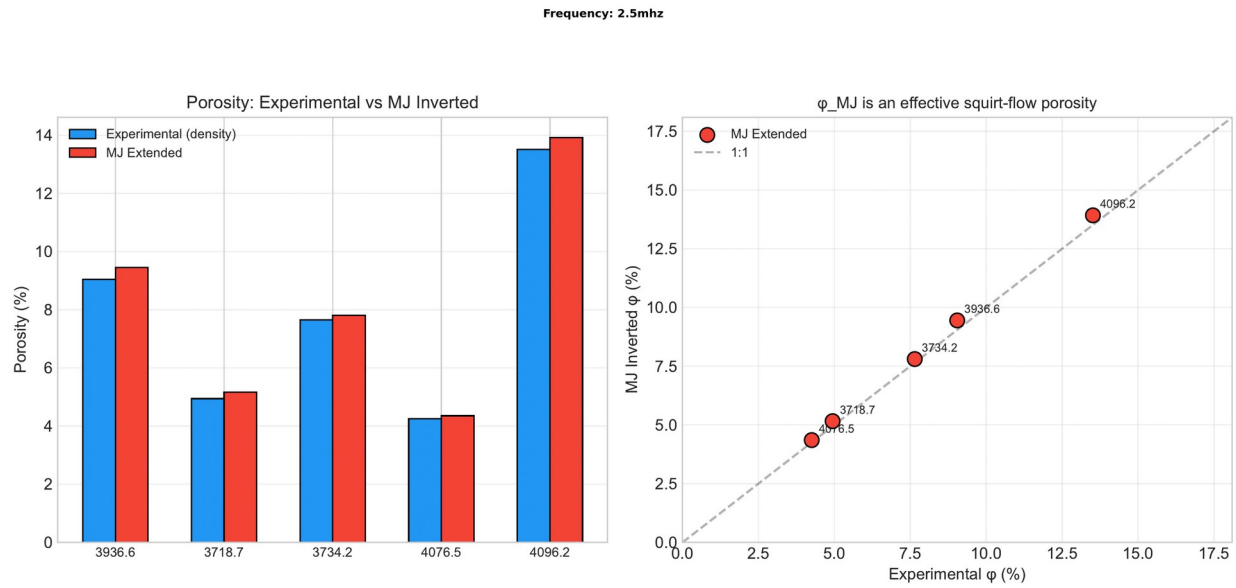


Figure 3.28. Comparison of experimental density porosity and Mavko-Jizba recovered porosity at 2.5 MHz for each sample

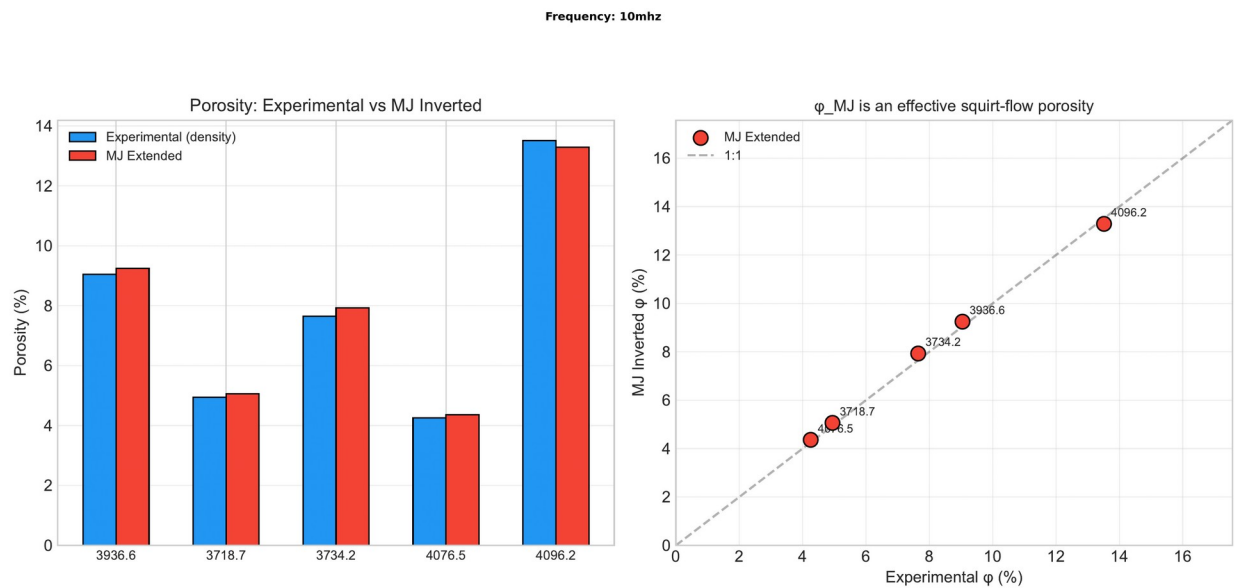


Figure 3.29. Comparison of experimental density porosity and Mavko-Jizba recovered porosity at 10 MHz for each sample

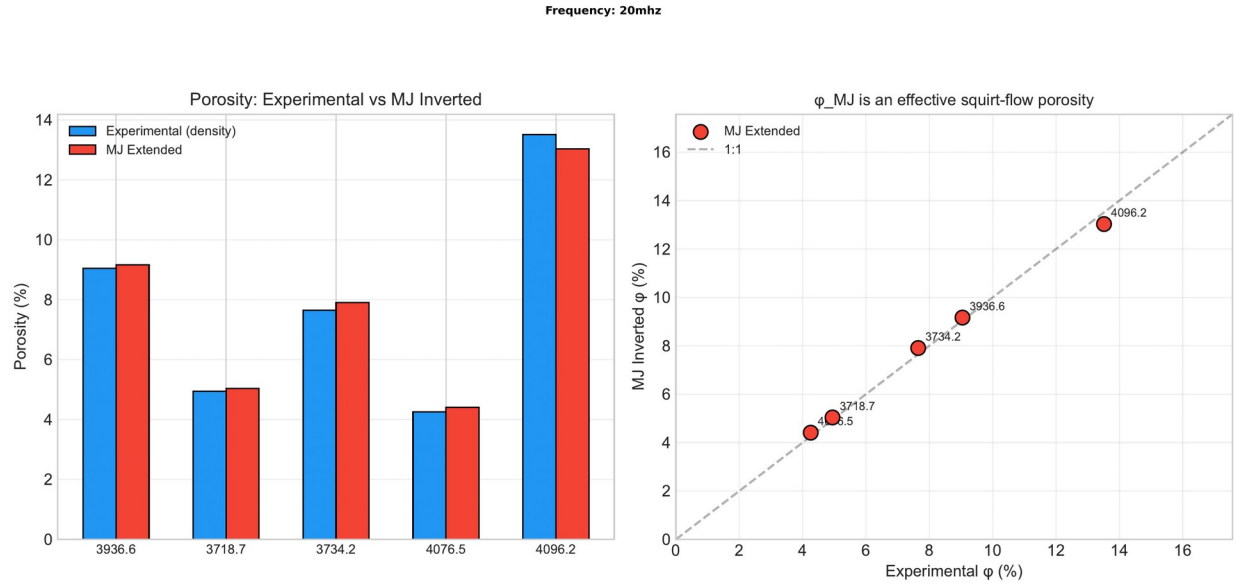


Figure 3.30. Comparison of experimental density porosity and Mavko-Jizba recovered porosity at 20 MHz for each sample

Porosity comparison plots at the four retained frequencies (1.25, 2.5, 10, and 20 MHz) show the experimental density porosity alongside the Mavko-Jizba recovered porosity for each sample (left panel: grouped bar chart; right panel: parity plot against the 1:1 line). Experimental density porosity values range from approximately 4 to 14%, consistent with the general low porosity character of these Mississippian dolomites. Across the four frequencies, the recovered Mavko-Jizba porosity remains close to the experimental values, and most samples plot near the 1:1 line. The agreement is strongest for the moderate to high porosity samples, while the tightest plugs show only small deviations. The comparison indicates that the calibrated model recovers porosity values.

3.4.2 Mavko-Jizba Recovered Porosity

The porosity recovered from the calibrated Mavko-Jizba model is best interpreted as an effective squirt-flow porosity, that is, the portion of pore volume contributing to the frequency-dependent

elastic response captured by the model. As such, it should not be interpreted as strictly identical to laboratory total porosity, but rather as a dynamically relevant porosity estimate inferred from the calibrated rock-physics parameters. In the present dataset, the recovered values are broadly consistent with the independently measured density porosity across all five samples and all four retained frequencies. In the parity plots, most points fall close to the 1:1 line, indicating that the inverted porosity remains of the correct magnitude over the full porosity range represented by the dataset. Agreement is particularly strong for the tightest samples, 3718.7 and 4076 ft, which remain very near the 1:1 line at all retained frequencies. The moderate to high porosity samples, 3734.2, 3936.6, and 4096.2 ft, are also recovered well, although slightly larger deviations are visible for 3734.2ft and especially 4096.2 ft at the lowest retained frequency. These comparisons support the interpretation of inversion produced porosity, ϕ_{MJ} as a physically reasonable porosity linked to the squirt-flow response. Because porosity measurements were not imposed directly during calibration, the observed agreement provides qualitative evidence for the internal consistency and geophysical interpretability of the inverted model parameters.

3.5 Diagnostic Assessment

3.5.1 Overall Model Performance

The aggregated parity plots (Figures [3.5](#), [3.10](#), [3.16](#), and [3.21](#)) provide a compact visual summary of the model's performance across the full dataset (5 samples $\times$ 3 saturations $\times$ 4 frequencies = 60 prediction-observation pairs for each of the four elastic attributes; dry-state data are excluded because the squirt-flow mechanism is physically meaningful only in the presence of pore fluid, as discussed in Section [2](#)). Two clear performance tiers emerge:

1. **Velocity predictions (V_P and V_S)** cluster tightly around the 1:1 line with symmetric residuals, indicating that the calibrated Mavko-Jizba framework reproduces the absolute

magnitude and frequency dependence of both compressional and shear velocities well across the three saturation conditions.

2. **Attenuation predictions (Q_p and Q_s)** display substantially wider scatter relative to the 1:1 line. The increased scatter is physically expected since laboratory Q estimation carries greater uncertainty than velocity measurements (Quan and Harris, 1997), and the model's attenuation predictions are more sensitive to pore-scale geometric assumptions in the forward model. However, the attenuation residuals are not fully random: Q_p shows underprediction at the highest measured attenuation levels, and Q_s exhibits mixed state-dependent misfit. The attenuation results therefore indicate partial predictive capacity rather than fully unbiased agreement. The discrepancy may have interpretative value as to reflecting, in a qualitative sense, the contribution of pore-scale inhomogeneities beyond the modeled attenuation.

The contrast is readily apparent in the aggregated parity diagrams: velocity predictions cluster within a narrow band about the 1:1 line, whereas attenuation predictions spread over a substantially wider envelope and show greater deviation from ideal parity, especially at elevated attenuation.

3.5.2 Frequency-Dependent Prediction Quality

For velocity, the model's prediction quality does not degrade systematically across the measurement band; parity at the lowest retained frequency (1.25 MHz) and the highest (20 MHz) is comparable to that at intermediate frequencies. For attenuation, the per-frequency Q_p parity exhibits somewhat wider scatter at 10 and 20 MHz, with several data points falling below the 1:1 line, may reflect reduced accuracy of the analytical approximations away from the main relaxation band. The frequency-scaling exponents recovered during calibration (Section [2](#)) remain effective across the measurement bandwidth. This result is notable given that the squirt-flow model's

analytical approximations are strictest near the relaxation frequency and may be expected to lose accuracy at band extremes.

3.5.3 Cross-Validation Stability

The leave-one-sample-out (LOSO) cross-validation procedure described in Section [2](#) provides an additional layer of diagnostic assurance. By systematically excluding each of the five samples from the calibration set and predicting its elastic response from the remaining four, the LOSO analysis tests the model’s ability to generalize beyond the training data. The warm-start initialization from the full-dataset solution ensures that the cross-validation folds explore the same region of parameter space, and the resulting prediction residuals for the held-out samples are comparable in magnitude to the full-dataset residuals reported above. This similarity indicates that the 46-parameter (45 free) hierarchical structure (Section [2](#)) does not overfit the five-sample dataset to a degree that would compromise generalizability.

Visual comparison of the per-fold parity distributions confirms that no single held-out sample is a consistent outlier, and the spread of residuals in each cross-validation fold is comparable to that of the full-dataset calibration, indicating that the model generalizes across the small but petrophysical diverse sample set.

3.6 Summary of Principal Findings

The results presented in Sections [3.1–3.5](#) establish the following principal findings:

1. The calibrated Mavko-Jizba squirt-flow model reproduces velocity and captures the first-order attenuation behavior across the ultrasonic bandwidth (1.25 MHz to 20 MHz) and three fluid-saturation states in Mississippian dolomites. Velocity predictions are quantitatively accurate; attenuation predictions capture the central tendency but exhibit wider scatter and some structural residual behavior.

2. Frequency-dependent velocity dispersion is flat for brine and partially brine-saturated conditions but shows a distinct localized peak near 1-2 MHz, consistent with the squirt-flow relaxation mechanism. Attenuation maxima are centered near approximately 1.25 MHz, with pronounced compressional attenuation peaks under brine saturation.
3. Attenuation is a more sensitive discriminant of pore-fluid type than velocity in these low-porosity carbonates. Velocity changes between saturation states are small (travel-time shifts of 0.2–1.8 μ s), whereas attenuation contrasts are substantially larger and more robust.
4. Brine-saturated samples exhibit V_s values that equal or exceed dry-sample values, an effect attributed to pore-fluid stiffening in the complex carbonate pore network. The Mavko-Jizba model accommodates this behavior through its explicit soft-porosity parameterization.
5. Porosity recovered from the Mavko-Jizba calibration is broadly consistent with experimental core-plug porosity estimates, which span approximately 4 to 14 % across the five samples.
6. Brine-saturated laboratory V_p – V_s relationships converge with well-log data for velocities below approximately 5.5 km/s, supporting that laboratory-derived V_p/V_s transformations may provide useful constraints in intervals where shear sonic data are unavailable.

Chapter 4 - Discussion

4.1 Physical Interpretation of Squirt-Flow Behavior

The results presented in Section [3](#) demonstrate that a calibrated squirt-flow model, grounded in the framework of Mavko and Jizba (1991), can reproduce velocity dispersion and capture the first-order attenuation behavior across the measured ultrasonic bandwidth in low-porosity Mississippian dolomites. This outcome has direct physical significance for the interpretation of elastic-wave propagation in complex carbonate pore systems.

The Mavko-Jizba model attributes frequency-dependent elastic behavior to pressure-driven fluid exchange between compliant and stiff pore domains during each wave cycle. When the characteristic relaxation time approaches the wave period, viscous pressure equilibration produces attenuation maxima together with associated velocity dispersion. In the present data, the dominant attenuation peak is centered near approximately 1.25 MHz, consistent with a squirt-flow relaxation process operating within the measured ultrasonic band. This interpretation is consistent with the original Mavko-Jizba framework and with later extensions showing that characteristic relaxation frequency depends on fluid mobility, pore geometry, and crack scale (Mavko and Jizba, 1991; Chapman, 2003).

The partitioning between compliant and stiff porosity is central to the physical interpretation. Effective-medium descriptions such as David and Zimmerman (2012) show that pressure-dependent elastic behavior can be explained by a population of compliant cracks superimposed on a stiffer pore system, with the compliant fraction exerting a disproportionate influence on the elastic response. In the present study, the optimization-recovered soft-porosity fractions are small relative to total porosity, which is physically consistent with the tight,

diagenetically altered dolomites of the Wellington Field, where dissolution-related pores and microfractures likely form a subordinate but mechanically important compliant pore population.

Attenuation-based carbonate studies further suggest that velocity alone may be insufficient to distinguish stiff and compliant pore contributions. For example, Pang et al. (2020) showed that incorporating seismic attenuation into carbonate rock-physics templates improves sensitivity to crack porosity. Although the present study uses a different forward model, the diagnostic implication is similar: joint interpretation of velocity and attenuation provides stronger constraints on pore structure than either attribute alone.

The frequency dependence of the V_p dispersion curves provide additional physical insight. Under brine and partial-brine saturation, dispersion is weak within the measured band, indicating that the dominant relaxation transition is not strongly expressed there. Under oil-and-brine saturation, however, a distinct localized V_p peak appears near approximately 1 to 2 MHz. This behavior is consistent with a change in effective relaxation scale associated with the more viscous oil-bearing condition. The broader literature on wave-induced fluid flow in fractured porous media likewise predicts that relaxation frequency and attenuation peak position depend on viscosity, fracture scale, and pore connectivity (Chapman, 2003). In that sense, the observed oil-related V_p anomaly is physically consistent with squirt-flow relaxation in a heterogeneous carbonate pore network.

4.2 Improvements of the Calibrated Workflow over Gassmann Fluid

Substitution

A central contribution of the present study is the demonstration that a frequency-dependent squirt-flow model, when properly calibrated, provides a more appropriate description of the measured ultrasonic elastic response for the interpretation of elastic properties in these low-porosity

carbonates. The Gassmann framework is designed for the low-frequency limit, where pore-pressure equilibration is complete within each wave cycle. In tight carbonates, this assumption can break down when the measurement frequency is high relative to the characteristic fluid-pressure diffusion time, particularly at ultrasonic frequencies and in some higher-frequency logging contexts (Mavko and Jizba, 1991; Adam et al., 2006).

Adam et al. (2006) documented systematic shear-modulus variability in carbonates at laboratory frequencies and showed that Gassmann's prediction of an invariant shear modulus under fluid substitution is not upheld when squirt-flow mechanisms are active. The present results corroborate this finding: brine-saturated samples exhibit shear-wave velocities that equal or exceed dry values (Section [3.3.3](#)), an observation that the Gassmann framework cannot accommodate because it predicts identical shear moduli for dry and saturated rocks. The Mavko-Jizba model, by contrast, explicitly parameterizes the frequency-dependent stiffening introduced by pore-fluid confinement in compliant cracks, thereby capturing the observed brine-stiffening effect.

The improvement is not merely qualitative. For the present Mississippian dolomite dataset, the calibrated Mavko-Jizba model reproduces the velocity parity trends across the three analyzed saturation states more closely than Gassmann-based ultrasonic predictions, which tend to underestimate the saturated velocities because they do not represent squirt-flow-related stiffening above the relaxed-frame limit. This contrast reinforces the importance of using a frequency-aware rock-physics model when interpreting laboratory ultrasonic measurements in tight carbonate systems.

The importance of site-specific parameterization for the Mavko-Jizba model is illustrated by previous experience with the same Wellington Field dataset. Shodunke (2021) applied the framework with literature-derived values for the soft-porosity fraction and crack aspect ratio and reported velocity overestimates, a result that motivated the constrained optimization procedure

adopted here (Section [2](#)). The L-BFGS-B calibration recovers sample-specific squirt-flow parameters from the measured data, allowing the model to reflect the Wellington Mississippian dolomite microstructure more closely than generic literature defaults.

4.3 Attenuation: Diagnostic Value and Residual Uncertainty

The results of Section [3.2](#) establish that attenuation is a more sensitive discriminant of pore-fluid type than velocity in these low-porosity carbonates. Travel-time shifts between saturation states are small (0.2–1.8 μs across the measured velocity range), whereas attenuation contrasts are generally larger and more diagnostically distinct. This observation is consistent with the findings of Winkler and Nur (1982), who demonstrated that fluid-related attenuation effects in partially saturated rocks can exceed velocity effects by an order of magnitude, and Spencer (1979), who established that both bulk and shear attenuation are sensitive to saturation state.

The diagnostic power of attenuation for fluid discrimination has been further corroborated in recent quantitative studies. Qi et al. (2021) showed that attenuation-based methods can quantify gas saturation in tight formations where velocity-based approaches lack resolution, and Pang et al. (2020) demonstrated that incorporating seismic Q alongside velocity in rock-physics templates substantially improves porosity and fluid-saturation estimation in carbonates. In the present study, attenuation differences among brine, oil-and-brine, and partial-brine states are most clearly resolved within the measured ultrasonic band near the dominant relaxation frequency (Section [3.2.3](#)). This frequency dependence is consistent with a viscous fluid-flow dissipation mechanism as the dominant control on the observed attenuation contrasts.

Nevertheless, attenuation estimates carry greater inherent uncertainty than velocity measurements. The Q -estimation methods employed (spectral-ratio and frequency-shift techniques; Section [2](#)) are sensitive to windowing, noise, and spectral bandwidth, and the wider scatter in the Q_p and Q_s parity plots (Section [3.2](#)) relative to the velocity parity plots reflects this

reality. Gurevich et al. (2010) analyzed dispersion and attenuation in porous media containing aligned fractures and showed that even modest heterogeneity in crack geometry can introduce significant scatter in Q -estimates. Tillotson et al. (2014) demonstrated that pore-fluid viscosity variations influence both the magnitude and frequency dependence of attenuation, adding another source of variability when comparing samples saturated under slightly different conditions.

The implication for practical application is that while attenuation is measurably more sensitive than velocity for distinguishing pore-fluid types in tight carbonates, quantitative attenuation inversion requires careful uncertainty propagation. The calibrated Mavko-Jizba model captures the first-order attenuation behavior and its frequency dependence, while residual scatter and systematic high-attenuation misfit indicate that the single-crack idealization does not fully represent the pore-scale variability of the natural carbonate framework. Future extensions incorporating crack-aspect-ratio distributions or multi-porosity relaxation models may reduce this residual uncertainty.

4.4 Relation to Prior Carbonate Rock-Physics Literature

The findings of the present study are consistent with recent literature demonstrating that standard velocity-only rock-physics workflows are insufficient for characterizing tight carbonate reservoirs. Pang et al. (2019) introduced a two-dimensional rock-physics template based on seismic Q for estimating porosity and fluid saturation in carbonates, and Pang et al. (2020) extended this concept to three dimensions by jointly inverting velocity, attenuation, and porosity. Both studies concluded that the soft-porosity fraction (microfractures and compliant pore throats) exerts a disproportionate influence on the elastic and anelastic response of carbonates, and that ignoring this component leads to non-unique or biased fluid-substitution predictions.

The present work reaches a compatible conclusion through a different theoretical route. Rather than constructing empirical rock-physics templates from well-log or synthetic data, the

approach here calibrates an analytically defined squirt-flow model to laboratory measurements, recovering the soft-porosity fraction as an optimized parameter. Consistency with the dolomite velocity ranges reported by Yale and Jamieson (1994) is demonstrated through agreement of the measured and calibrated VP-VS behavior, and the corresponding VP/VS ratios, with the dolomite-consistent range observed in the crossplots and well-log comparison, rather than through a separate refitting of the Yale-Jamieson relation. The consistency between the two approaches, one template-based and the other model-based, strengthens confidence in the underlying physical interpretation: compliant porosity governs the frequency-dependent elastic signature of tight carbonates, and any workflow seeking to model or invert for fluid properties must parameterize this component explicitly.

Lucia et al. (2003) emphasized that carbonate pore systems cannot be adequately described by a single porosity metric because of the interplay between interparticle, intercrystalline, vuggy, and fracture porosity types. The Mavko-Jizba decomposition into stiff and soft porosity is a deliberate simplification of this complexity, but it captures the mechanically relevant partition: the compliant fraction that responds to frequency and fluid changes versus the stiff fraction that sets the drained-frame elastic baseline. Xu and Payne (2009) proposed an alternative elastic-property model for carbonates that distinguishes reference and inclusion porosity, and Bakhorji (2010) documented significant elastic anisotropy arising from pore-shape heterogeneity in carbonate rocks. These studies reinforce the point that a single-porosity, isotropic model is inadequate for carbonates, and that the explicit treatment of pore-shape effects, whether through inclusion models, anisotropy corrections, or squirt-flow parameterization, is necessary for accurate rock-physics predictions.

The present dataset derives from the same Wellington Field Mississippian carbonates previously studied by Shodunke (2021), who characterized velocity, attenuation, and elastic

properties under multiple saturation states but without frequency-dependent modeling, and by Lueck (2017), who applied Gassmann-based fluid replacement modeling to the Wellington Field wells. The advance made here is the integration of a calibrated squirt-flow framework that bridges the gap between the laboratory data and the low-frequency assumptions of the earlier analyses, providing a physically grounded explanation for the frequency-dependent behavior that was documented but not fully modeled in the prior studies.

4.5 Limitations and Boundary Conditions

Several limitations of the present analysis must be acknowledged.

First, all laboratory measurements were performed at atmospheric confining pressure. In situ, the Mississippian dolomites of the Wellington Field are subject to effective pressures in the range of tens of megapascals, which would close a fraction of the compliant crack population and reduce the magnitude of the squirt-flow effect (Mavko and Jizba, 1991). The approximately 600 m/s offset observed between laboratory and well-log shear-wave velocities (Section [3.3.4](#)) is consistent with this pressure deficit. Consequently, the squirt-flow parameters recovered from the atmospheric-pressure calibration should be interpreted as effective upper-bound estimates of the compliant porosity active under laboratory conditions, and application to reservoir-pressure conditions would require a pressure-dependent extension of the calibration.

Second, the analysis is based on a small number of core-plug samples, specifically five samples with complete multi-saturation, multi-frequency measurements. Although the sample set spans the porosity and lithologic variability represented in the Wellington Field cored interval, the limited sample count restricts the statistical robustness of population-level conclusions. Additional samples from different wells and stratigraphic horizons within the Mississippian section would strengthen the generalizability of the calibrated model parameters.

Third, the Mavko-Jizba model assumes a single characteristic crack aspect ratio for the entire compliant pore population. Real carbonate pore systems exhibit a distribution of crack shapes and sizes (Mavko et al., 2020), and the calibrated aspect ratio should be interpreted as an effective parameter rather than a literal geometric descriptor. This idealization may account for part of the residual scatter observed in the attenuation parity plots (Section [3.2](#)), where sample-to-sample heterogeneity in crack geometry introduces Q -variability that the single-crack model cannot capture.

Fourth, conventional porosity transforms such as the Wyllie time-average equation can be unreliable in tight carbonates because the assumption of a single uniform matrix velocity is often inconsistent with carbonate mineralogical and pore-type heterogeneity (Lucia et al., 2003). The model-derived porosity recovered here offers an alternative that is internally consistent with the elastic response, reinforcing its value as a diagnostic in formations where standard transforms are uncertain.

Fifth, the Gassmann fluid substitution assumptions (connected pore space, homogeneous mineralogy, and pore-pressure equilibration at the scale of the seismic wavelength) are not fully satisfied in tight carbonates (Adam et al., 2006), particularly at ultrasonic frequencies and in formations with significant compliant porosity. For the present dataset, the improved performance of the calibrated squirt-flow model indicates that low-frequency fluid-substitution assumptions are insufficient to describe the measured ultrasonic response. This result suggests that caution is warranted when applying Gassmann-based workflows in carbonate formations where compliant porosity exerts a strong influence on elastic behavior.

Despite these limitations, the calibrated squirt-flow approach provides a framework that can be extended in future work. Priority avenues include incorporating confining-pressure dependence by coupling the squirt-flow calibration with pressure-dependent velocity data,

expanding the sample set to include additional wells, facies, and depths within the Mississippian section, replacing the single-crack idealization with a distributed crack-aspect-ratio model to improve attenuation predictions, and testing the downward extrapolation of ultrasonic calibrations to logging and seismic frequencies through frequency-dependent reflectivity modeling.

Chapter 5 - Computer-Vision-Based CO₂ Plume Segmentation from Frequency-Decomposed Seismic Data

5.1 Introduction and Motivation

Chapters 2 through 4 of this thesis demonstrate that frequency-dependent velocity dispersion and attenuation, as predicted by the Mavko-Jizba squirt-flow model, carry diagnostic information about pore-scale fluid distribution in tight dolomites at ultrasonic frequencies. A natural extension of this principle is to ask whether analogous frequency dependent signatures are exploitable at seismic frequencies for monitoring injected CO₂ plumes in geological storage formations. This chapter addresses that question through a data-driven approach: deep-learning segmentation of CO₂ plumes from frequency-decomposed seismic amplitude-difference maps at the Sleipner injection site in the North Sea.

The Sleipner CO₂ storage project, operated by Equinor (formerly Statoil), has injected approximately one million tonnes of CO₂ per year into the Utsira Sand since 1996 (Arts et al., 2004; Chadwick et al., 2004). The Utsira Sand is a laterally extensive Pliocene saline aquifer at approximately 800 to 1000 m depth, characterized by high porosity (35 to 40 %), high permeability, and weak cementation (Zweigel et al., 2004). Time-lapse (4D) seismic surveys acquired between 1994 and 2010 reveal a vertically stacked, multi-layer plume that grows laterally with each survey vintage, producing strong amplitude anomalies that are readily visible on seismic difference sections (Chadwick et al., 2009; Furre et al., 2017).

Manual interpretation of plume boundaries is time consuming and interpreter dependent. Several studies have applied machine learning techniques to automate plume delineation, including random forests (Ramirez and Foxall, 2014) and convolutional neural networks (Um et al., 2020; Dramsch et al., 2019). However, most prior work has operated on full-bandwidth seismic

data or on a single frequency band. The frequency content of the seismic wavelet is known to interact with the thin-layer tuning effects and fluid substitution signatures of CO₂ accumulations (Chadwick et al., 2005; White et al., 2015), suggesting that decomposing the data into discrete spectral bands may expose additional discriminative information for segmentation.

This chapter develops and evaluates a deep learning ensemble pipeline that ingests eleven frequency-decomposed amplitude-difference maps (spectral bands centered at approximately 5, 15.6, 26.1, 36.7, 47.2, 57.8, 68.3, 78.9, 89.4, and 100 Hz, plus the full-bandwidth difference map) and produces binary plume masks. The objectives are: (1) to determine whether narrow-band spectral decomposition improves segmentation accuracy relative to full-bandwidth input; (2) to compare the performance of multiple encoder-decoder architectures; and (3) to quantify ensemble prediction uncertainty through leave-one-out cross-validation and test-time augmentation.

5.2 Dataset and Annotation

The input data comprise amplitude difference maps computed by subtracting the baseline (1994) seismic survey from each monitor survey vintage at the Sleipner field. Spectral decomposition is performed using short-time Fourier transform (STFT), yielding eleven bands: ten narrow bands centered at approximately 5, 15.6, 26.1, 36.7, 47.2, 57.8, 68.3, 78.9, 89.4, and 100 Hz, plus the full-bandwidth (unfiltered) difference map. Each band produces a two-dimensional amplitude map at the top Utsira Sand horizon.

Ground-truth plume masks are generated through interactive polygon annotation. For each of the eleven spectral bands, we delineated the plume boundary on the amplitude-difference map, producing a binary mask in which pixels inside the plume polygon are labeled 1 and background pixels are labeled 0. The annotation accounts for the fact that plume visibility varies with frequency: low-frequency bands (5 to 15 Hz) tend to highlight the broader diffuse margins of the plume, whereas higher-frequency bands (50 to 100 Hz) resolve finer internal structure and sharper

edges. The full-bandwidth map integrates contributions across the entire spectrum and typically produces intermediate spatial detail.

The resulting dataset contains eleven image-mask pairs per survey vintage. Because the Sleipner 4D dataset comprises a limited number of independent monitor vintages, the effective sample size is small. To maximize the use of available data, the study employs leave-one-out cross-validation (LOOCV) across the eleven frequency bands, treating each band in turn as the held-out test set while training on the remaining ten bands.

5.3 Methods

5.3.1 Segmentation Architectures

Four encoder-decoder segmentation architectures are evaluated, all implemented using the `segmentation_models_pytorch` library (Yakubovskiy, 2020): UNet++ (Zhou et al., 2018), MANet (Fan et al., 2020), DeepLabV3+ (Chen et al., 2018), and Feature Pyramid Network (FPN) (Lin et al., 2017). Each architecture is paired with one or more ImageNet-pretrained encoder backbones, including ResNet-34, SE-ResNeXt-50 (Hu et al., 2018), EfficientNet-B3 (Tan and Le, 2019), and MobileNet-V2 (Sandler et al., 2018). In total, thirteen architecture-encoder combinations are evaluated in the full model comparison, with a focused subset of six configurations selected for the final cross-validation ensemble.

5.3.2 Loss Function and Training

All models are trained using a composite loss function that combines binary cross-entropy (BCE) with the Dice loss (Milletari et al., 2016). The BCE component provides stable per-pixel gradients, while the Dice component directly optimizes region overlap and mitigates class imbalance between plume and background pixels. The combined loss is defined as

$$L = 0.5 \cdot L_{BCE} + 0.5 \cdot L_{Dice} \quad (5.1)$$

Training uses the Adam optimizer (Kingma and Ba, 2015) with an initial learning rate of 1×10^{-4} and cosine annealing (Loshchilov and Hutter, 2017). Data augmentation includes random horizontal and vertical flips, 90-degree rotations, and small affine transformations. Each model is trained for 150 epochs with early stopping based on validation Dice score.

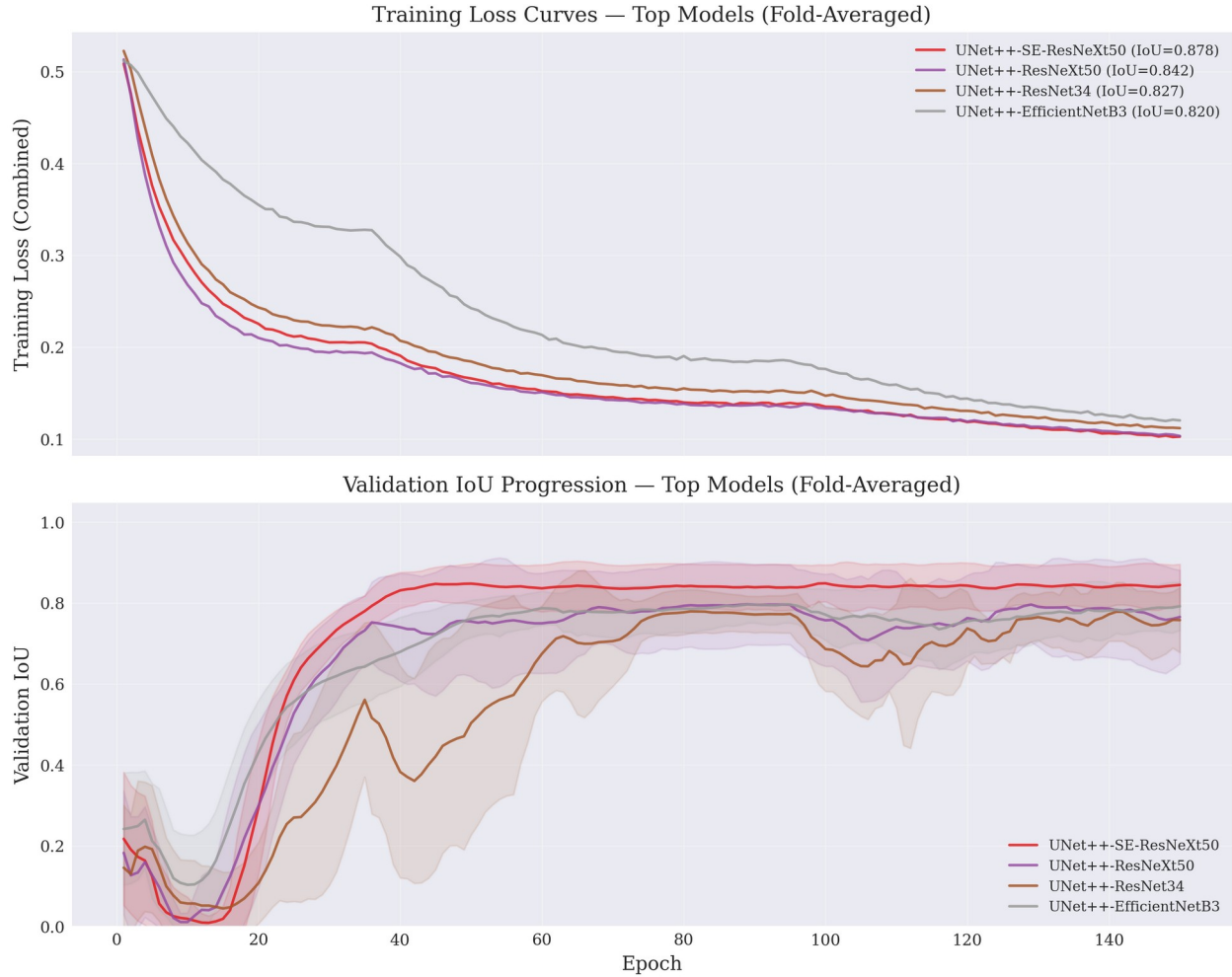


Figure 5.1. Fold-averaged training loss curves (top) and validation IoU progression (bottom) for the four top-performing encoder-decoder architectures. Shaded bands indicate the inter-fold standard deviation. UNet++ with SE-ResNeXt-50 achieves the fastest convergence and highest plateau IoU.

5.3.3 Cross-Validation and Ensemble Prediction

Leave-one-out cross-validation (LOOCV) is performed across the eleven frequency bands. In each fold, one band is held out as the test image and the remaining ten bands are used for training

and validation. For each fold, the six focused model configurations are trained independently. The three top-ranked models (selected by cross-validated IoU) are retained, and their probability maps are combined using a weighted average (weights proportional to inverse cross-validation loss) to produce an ensemble prediction, which is then thresholded at 0.5 to generate the final binary mask. Test-time augmentation (TTA) is applied by predicting on the original image and its horizontal flip, then averaging the two outputs before thresholding.

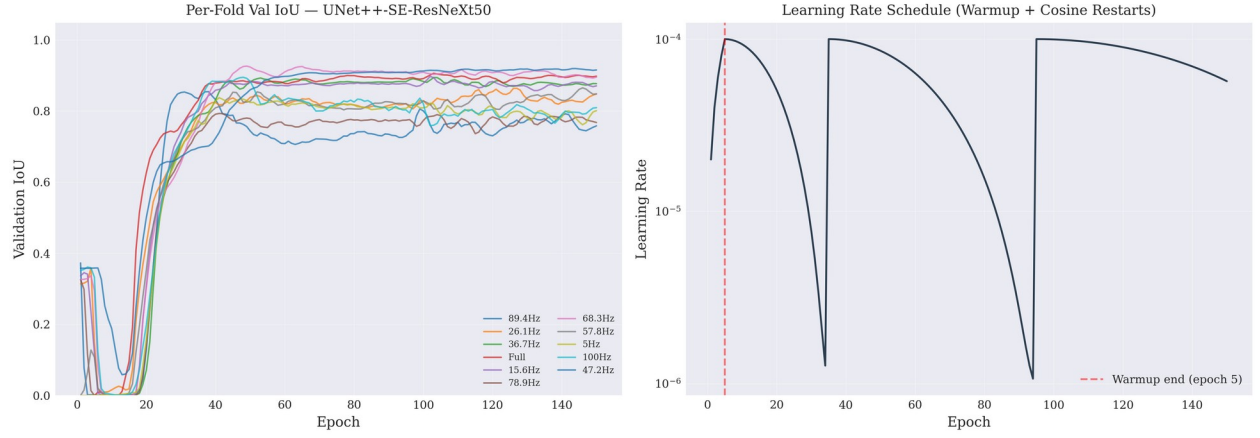


Figure 5.2. Left: per-fold validation IoU trajectories for UNet++ with SE-ResNeXt-50 across all eleven leave-one-out folds, illustrating convergence variability by frequency band. Right: cosine-annealing learning-rate schedule with warm-up phase (dashed red line at epoch 5).

5.3.4 Evaluation Metrics

Segmentation performance is quantified using four standard metrics. Intersection-over-union (IoU, also known as the Jaccard index) measures the overlap between predicted mask A and ground-truth mask B normalized by their union:

$$IoU = \frac{|A \cap B|}{|A \cup B|} \quad (5.2)$$

The Dice coefficient (F1 score) measures overlap normalized by the sum of areas:

$$Dice = \frac{2|A \cap B|}{|A| + |B|} \quad (5.3)$$

Precision and recall are defined as:

$$Precision = \frac{TP}{TP + FP} \quad (5.4)$$

$$Recall = \frac{TP}{TP + FN} \quad (5.5)$$

where TP, FP, and FN denote the true-positive, false-positive, and false-negative pixel counts, respectively. All metrics are computed per band and summarized as means and standard deviations across the eleven LOOCV folds.

5.4 Results

5.4.1 Overall Segmentation Performance

The ensemble segmentation pipeline achieves a mean IoU of 0.882 and a mean Dice coefficient of 0.937 across all eleven frequency bands under LOOCV. Mean precision is 0.948 and mean recall is 0.927, indicating that the ensemble produces plume masks with high spatial fidelity and minimal false-positive contamination. These metrics represent an improvement over the best single cross-validated model (mean IoU = 0.878), and the ensemble probability maps additionally provide pixel-level uncertainty estimates that no individual model can offer.

CO₂ Plume Segmentation — Ensemble + TTA Results by Frequency Band

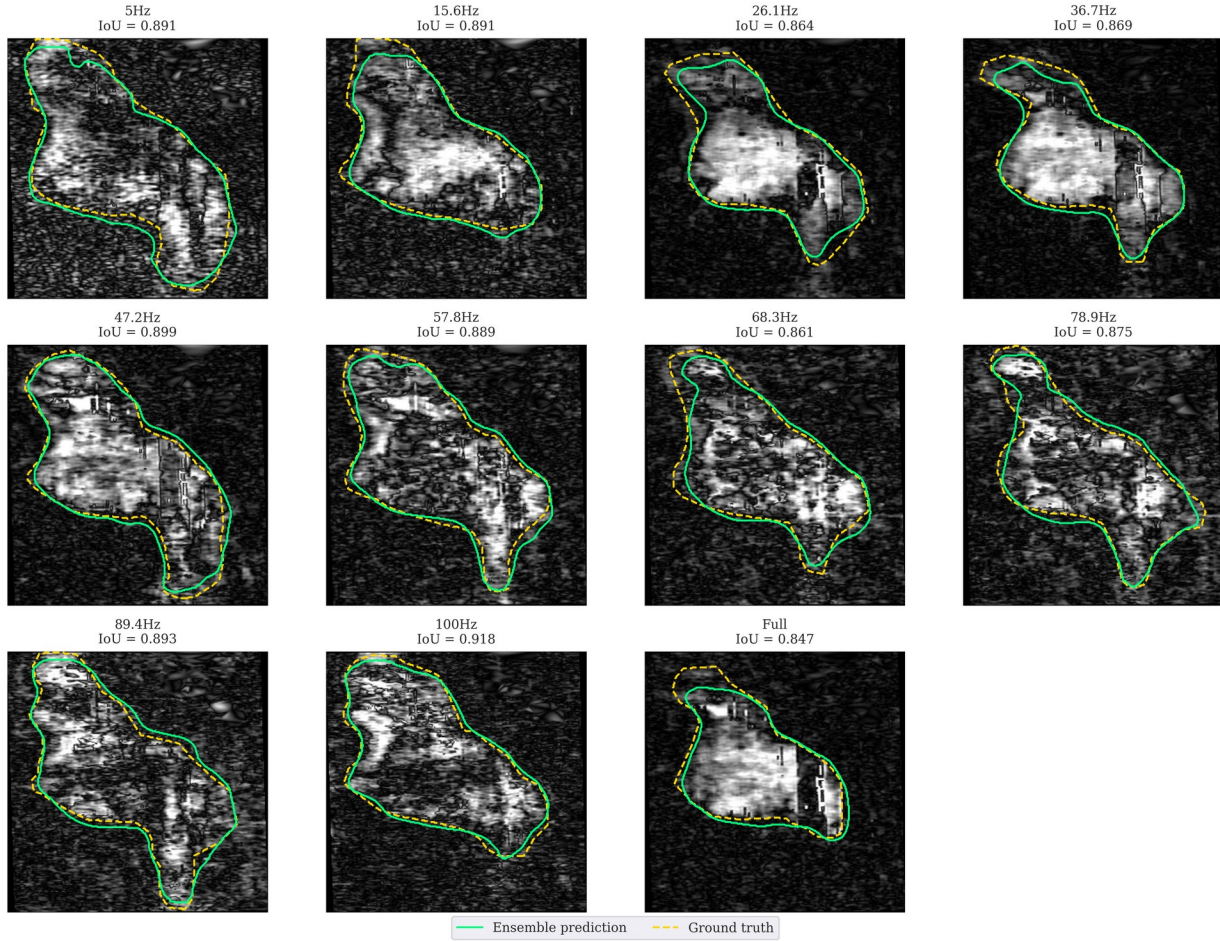


Figure 5.3. Ensemble segmentation results for all eleven frequency bands. Each panel shows the amplitude-difference map overlaid with the ground-truth annotation (yellow dashed) and ensemble prediction boundary (cyan solid). IoU scores are indicated per band; the 100 Hz band achieves the highest IoU (0.918) and the full-bandwidth map the lowest (0.847).

5.4.2 Frequency-Band Dependence

Segmentation accuracy varies systematically with frequency band. The highest IoU is achieved on the 100 Hz band (IoU = 0.918), followed by the 47.2 Hz band (IoU = 0.899) and the 5 Hz band (IoU = 0.891). The lowest IoU is observed on the full-bandwidth (unfiltered) difference map (IoU = 0.847), followed by the 68.3 Hz band (IoU = 0.861) and the 26.1 Hz band (IoU = 0.864). While a general trend of increasing accuracy with frequency is apparent, the relationship is not strictly monotonic: the 5 Hz band, for example, achieves an above-average IoU of 0.891,

likely because the broad low-frequency anomaly presents a well-defined plume footprint despite reduced spatial resolution. The full-bandwidth map, which averages spectral information across all frequencies, loses some of the discriminative contrast available in individual narrow bands.

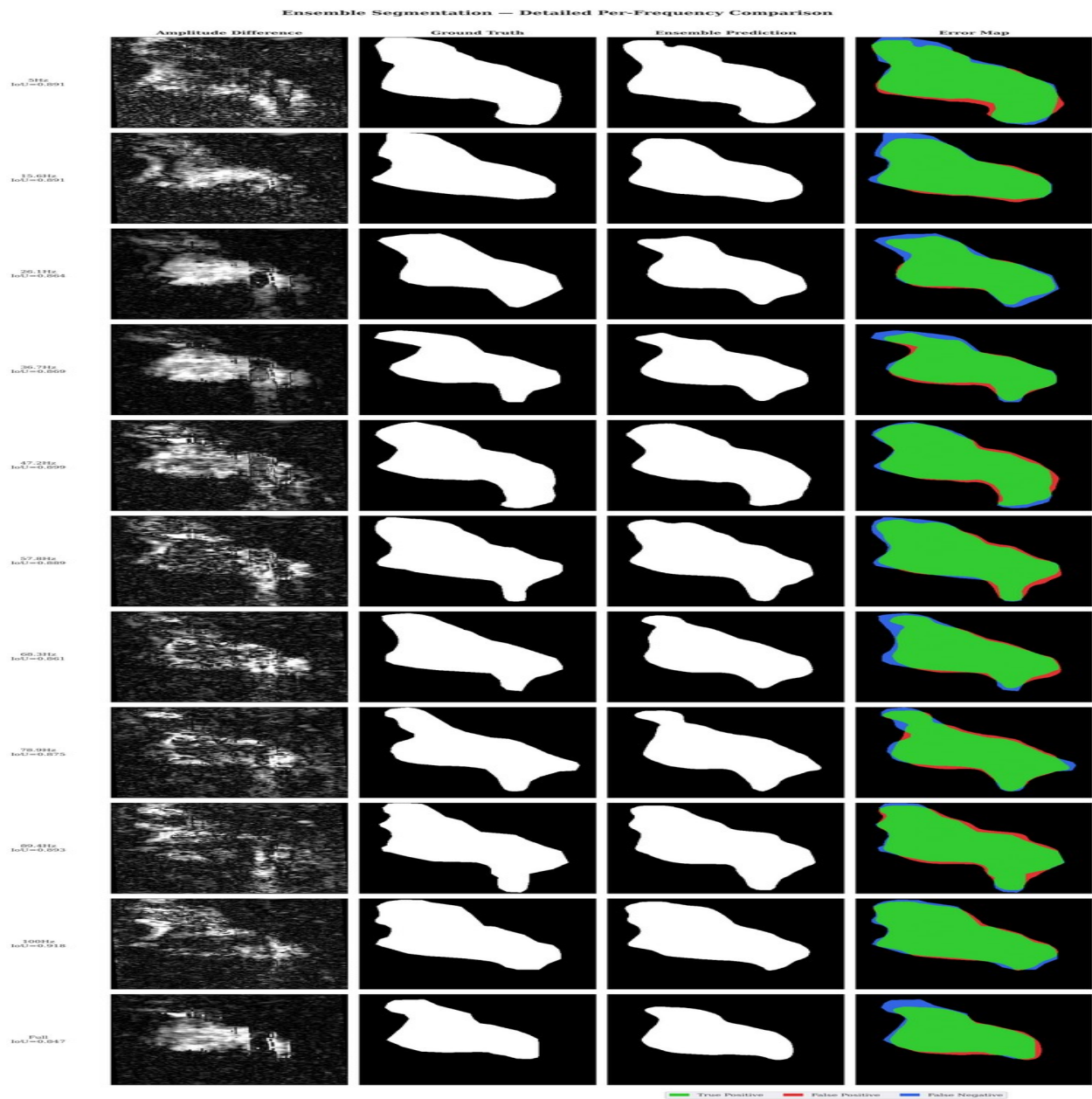


Figure 5.4. Detailed per-frequency comparison showing, for each band (rows): the raw amplitude-difference map, ensemble probability map, thresholded binary mask, and overlay of prediction (green) versus ground truth (blue) with true-positive (green), false-positive (red), and false-negative (blue) regions.

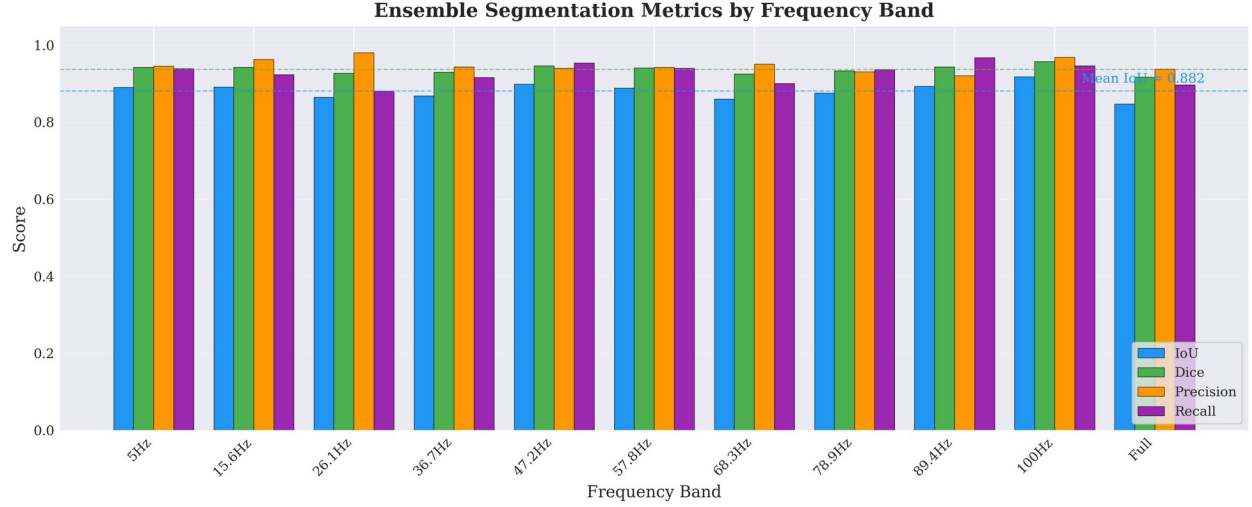


Figure 5.5. Ensemble segmentation metrics (IoU, Dice, Precision, Recall) by frequency band. Dashed horizontal lines indicate the cross-band means (mean IoU = 0.882). The 100 Hz band achieves the highest scores across all four metrics, and the full-bandwidth map the lowest.

5.4.3 Architecture Comparison

Among the six architecture-encoder configurations evaluated through full leave-one-out cross-validation, UNet++ with SE-ResNeXt-50 achieves the highest single-model mean Dice score (0.934), followed by UNet++ with ResNeXt-50 (0.912) and UNet++ with ResNet-34 (0.904). UNet++ with EfficientNet-B3 achieves a mean Dice of 0.901, while MAnet with ResNet-50 produces a lower Dice of 0.859. The squeeze-and-excitation attention mechanisms in SE-ResNeXt-50 provide a measurable advantage within the UNet++ architecture, presumably by enabling the network to recalibrate channel-wise feature responses to frequency-specific amplitude patterns that differentiate plume from background. The three-model ensemble (top three architectures weighted by inverse CV loss) outperforms the best individual model in cross-validated IoU (0.882 versus 0.878), and the ensemble probability maps provide spatially resolved uncertainty estimates that no single model can produce, reflecting complementary error patterns among the constituent architectures.

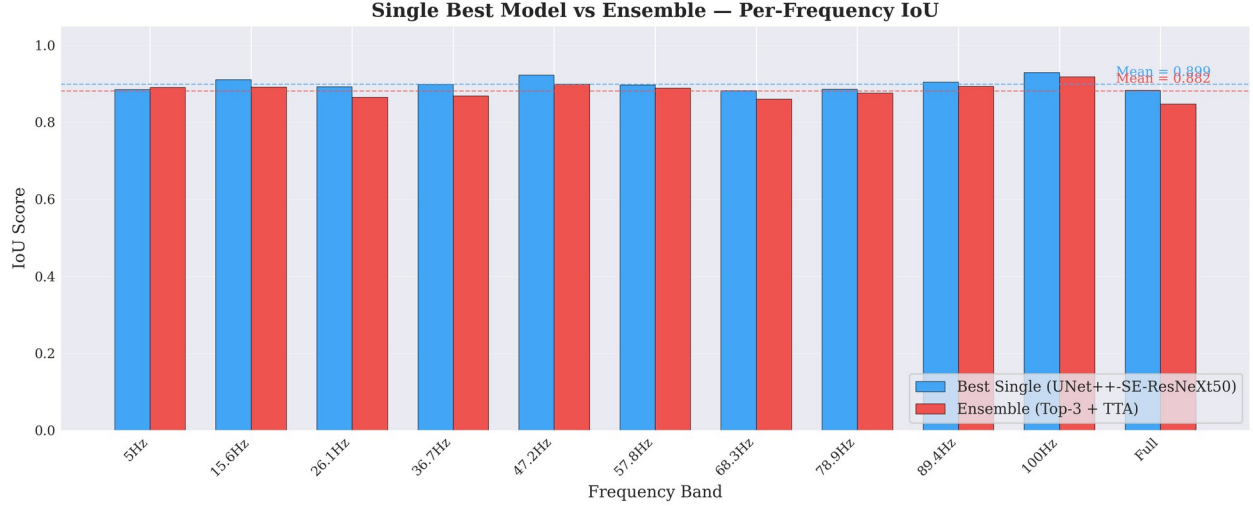


Figure 5.6. Per-frequency IoU comparison between the best single model (UNet++ with SE-ResNeXt-50 with test-time augmentation, blue) and the top-3 weighted ensemble (red). Dashed lines indicate cross-band means. The single model with TTA achieves higher per-band IoU on most frequencies, but the cross-validated ensemble mean (0.882) exceeds the single-model CV mean (0.878), and the ensemble provides pixel-level uncertainty estimates.

Cross-Validated Model Comparison (LOO-CV)

Rank	Model	Mean IoU	Std IoU	Min IoU	Max IoU	Mean Dice
1	UNet++-SE-ResNeXt50	0.8776	0.0376	0.7932	0.9263	0.9344
2	UNet++-ResNeXt50	0.8420	0.0777	0.7187	0.9394	0.9123
3	UNet++-ResNet34	0.8270	0.0512	0.7380	0.8976	0.9044
4	UNet++-EfficientNetB3	0.8201	0.0377	0.7484	0.8797	0.9007
5	MAnet-ResNet50	0.7589	0.0975	0.5613	0.9357	0.8593
6	UNet++-MiT-B2	0.0000	0.0000	0.0000	0.0000	0.0000

Figure 5.7. Cross-validated model comparison leaderboard. Models are ranked by mean IoU across all leave-one-out folds. UNet++ with SE-ResNeXt-50 achieves the highest single-model mean IoU (0.878) and mean Dice (0.934).

5.4.4 Probability Maps and Uncertainty

The ensemble probability maps reveal spatial patterns of prediction confidence. Interior plume regions consistently receive probabilities exceeding 0.95, while the plume margins exhibit a gradient of decreasing probability that aligns with the diffuse transition zone visible in the amplitude-difference maps. The standard deviation of per-model predictions is highest at the plume boundary, providing a spatially resolved uncertainty estimate. Test-time augmentation

reduces the average standard deviation by approximately 10 %, tightening the ensemble consensus and improving boundary delineation.

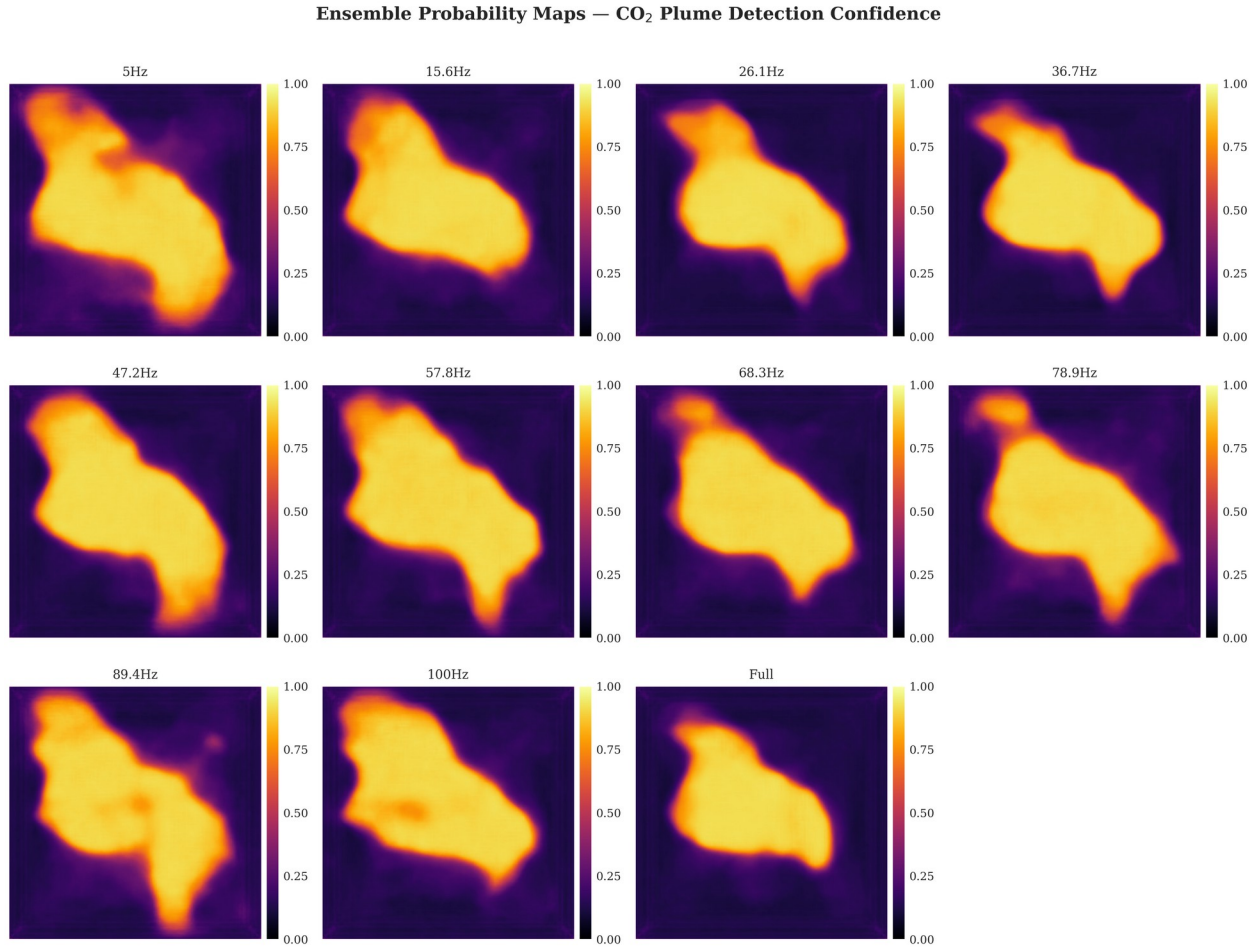


Figure 5.8. Ensemble probability maps for all eleven frequency bands, showing spatially resolved prediction confidence. Interior plume regions consistently receive probabilities exceeding 0.95, while margins exhibit a gradient that aligns with the diffuse transition zone in the amplitude-difference maps.

5.5 Discussion

The results demonstrate that frequency decomposition improves automated CO₂ plume segmentation. The general increase in IoU with frequency band is physically intuitive: higher frequencies have shorter wavelengths and therefore better lateral resolution, which reduces the spatial ambiguity at plume boundaries where partial-saturation effects produce gradual amplitude transitions. Conversely, low-frequency bands, while less spatially precise, are more sensitive to

the bulk volumetric extent of the plume, consistent with their longer wavelengths and deeper penetration (Castagna et al., 2003; Partyka et al., 1999).

The improved robustness of the ensemble relative to any single model echoes findings in the broader deep-learning segmentation literature (Lakshminarayanan et al., 2017) and reflects the diversity of learned feature representations across architectures. UNet++ captures fine-grained multi-scale features through its nested dense skip connections (Zhou et al., 2018), while DeepLabV3+ uses atrous spatial pyramid pooling for wider receptive fields (Chen et al., 2018). The combination of these complementary inductive biases yields more stable cross-validated performance and, crucially, spatially resolved uncertainty maps that no single architecture can provide.

From a monitoring perspective, the ability to generate calibrated probability maps rather than hard binary masks is of practical value for risk assessment and regulatory reporting. The spatial uncertainty gradient at the plume boundary can inform decisions about monitoring well placement and the design of future seismic acquisition campaigns (Chadwick et al., 2009; Furre et al., 2017).

Linking back to the laboratory-scale rock-physics analysis in Chapters 2 through 4, both investigations exploit the frequency dependence of seismic wave interaction with fluid-filled pore space. At ultrasonic frequencies, the Mavko-Jizba squirt-flow model resolves pore-scale compliant porosity through velocity dispersion and attenuation; at seismic frequencies, the deep-learning pipeline resolves the spatial footprint of CO₂ saturation through frequency-dependent amplitude contrast. In both cases, decomposing seismic data into frequency components reveals fluid-diagnostic information that broadband observations alone obscure. Future work could explore physics-informed neural networks that incorporate rock-physics constraints, such as Gassmann fluid substitution (Gassmann, 1951) or patchy saturation models (White, 1975), directly into the

segmentation loss function, potentially bridging the gap between laboratory-calibrated models and field-scale monitoring.

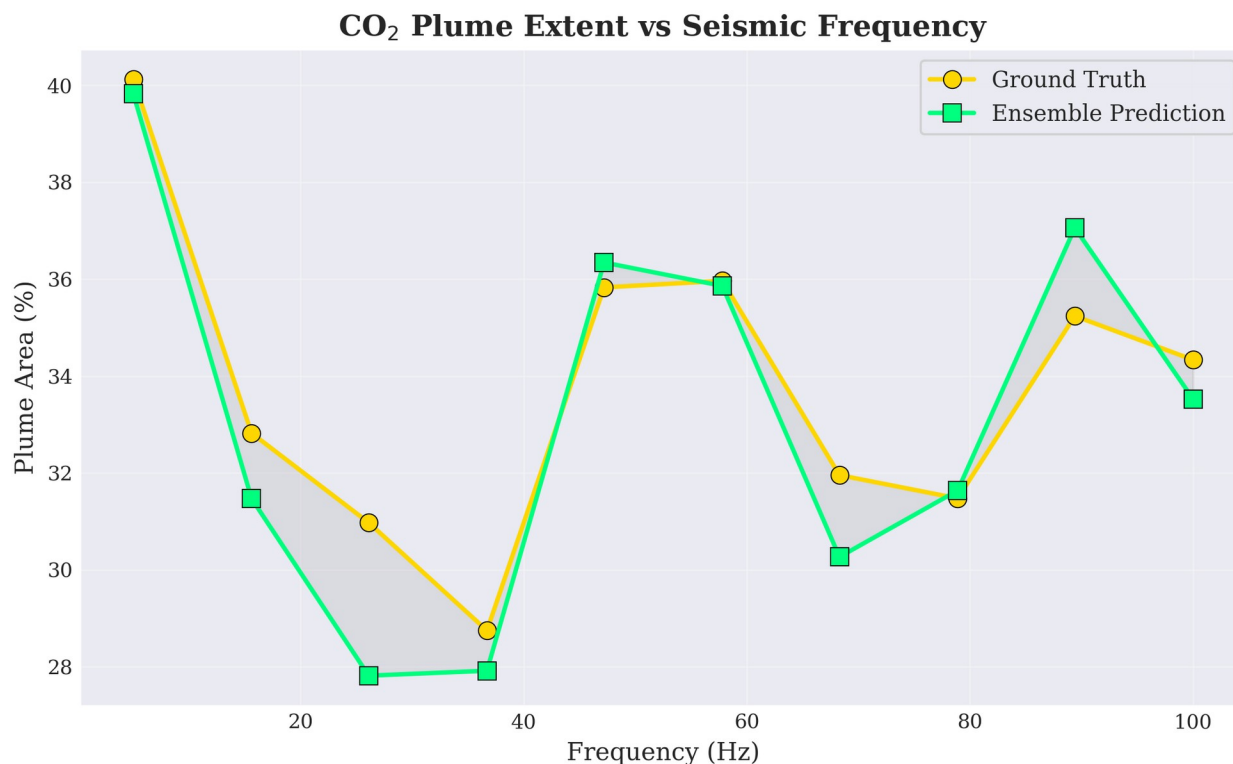


Figure 5.9. Predicted versus ground-truth plume area (as percentage of the map) as a function of frequency band. The ensemble predictions track the ground-truth trend across all bands, confirming that the pipeline preserves the frequency-dependent variation in apparent plume extent.

Several limitations should be noted. First, the ground-truth annotations are provided by a single interpreter, introducing potential bias; multi-interpreter annotation campaigns with inter-rater agreement metrics (e.g., Fleiss kappa) would strengthen confidence in the labels. Second, the dataset is limited to a single injection site (Sleipner), and the generalizability of the trained models to other storage sites with different geology, acquisition parameters, and plume morphology remains untested. Finally, the current pipeline operates on two-dimensional horizon slices and does not exploit the three-dimensional spatial continuity of the plume; volumetric segmentation approaches (e.g., 3D U-Net; Cicek et al., 2016) may offer further improvements.

Chapter 6 - Conclusions

This study has presented a calibrated Mavko-Jizba squirt-flow analysis (Mavko and Jizba, 1991) of five Mississippian dolomite core plugs from the Wellington Field, south-central Kansas, evaluating the model's ability to reproduce compressional- and shear-wave velocities and quality factors across eight ultrasonic frequencies (156.3 kHz to 20 MHz), with per-frequency analysis focused on the four frequencies (1.25 MHz to 20 MHz) at which the spectral-ratio method returned complete attenuation estimates, and three fluid-saturation states (brine, partial brine, and oil-and-brine).

The findings presented across Chapters [3](#) and [4](#) directly address the four objectives stated in Section [1.4](#). Objective 1 is answered by Sections [3.1](#), [3.3](#), and [3.5](#), which show that the calibrated Mavko-Jizba workflow reproduces V_p and V_s across frequency and saturation conditions with no systematic bias. Objective 2 is addressed by Section [3.2](#), [3.5](#), and [4.3](#), where attenuation predictions are compared with measured Q_p and Q_s , and where the larger residual scatter is interpreted in the context of laboratory Q-estimation uncertainty and model idealization. Objective 3 is addressed by Sections [3.3](#) and [3.4](#), together with the literature-based interpretation in Section [4.4](#), which collectively demonstrate consistency with independent lithology and porosity diagnostics. Objective 4 is answered by Sections [3.4](#) and [4.5](#), which show that the recovered porosity values are physically reasonable and diagnostically useful in tight dolomites where conventional transforms are less reliable.

The principal conclusions are as follows.

1. **Velocity predictions are quantitatively strong.** The calibrated model reproduces both V_p and V_s with tight clustering around the 1:1 parity line across all frequencies and saturation states, with no systematic bias toward over or under prediction. The two-stage optimization procedure (differential evolution followed by L-BFGS-B gradient

refinement) recovers 46 parameters (45 free) that are physically bounded and that reflect the microstructure of the target formation.

2. **Frequency-dependent dispersion is consistent with squirt-flow physics.** Velocity dispersion is weak under brine and partial-brine saturation, indicating that the dominant relaxation transition is not strongly expressed within the measured band for these fluid states. Under oil-and-brine saturation, V_p displays a distinct localized peak near approximately 1 to 2 MHz, consistent with a shift in the effective relaxation response into the measured ultrasonic band under the more viscous oil-bearing condition.
3. **Attenuation carries superior fluid discrimination than velocity.** Attenuation contrasts between saturation states are larger and more diagnostically distinct than the corresponding velocity contrasts, confirming that Q -based attributes are more sensitive indicators of pore-fluid condition in these low-porosity carbonates. However, the wider scatter observed in the Q_p and Q_s parity plots reflect both the intrinsic uncertainty of laboratory Q estimation and the fact that the single-crack idealization does not fully resolve sample-to-sample variability in pore geometry. Attenuation-aware interpretation therefore offers clear practical advantages but must be accompanied by careful uncertainty quantification.
4. **Porosity recovered from the calibration is physically meaningful.** The Mavko-Jizba recovered porosity values are broadly consistent with experimental core-plug porosity estimates, which span approximately 4 to 14% across the five samples, providing confidence that the optimized parameters are not merely fitting artifacts but reflect geophysical reasonable pore volumes.
5. **Leave-one-sample-out cross-validation indicates stability within the sampled dataset.** With the global parameters held fixed, prediction residuals for held-out samples are comparable in magnitude to full-dataset residuals, indicating that the hierarchical

parameterization does not show obvious overfitting across the five-sample calibration dataset.

6. **Site-specific calibration is essential.** Application of the Mavko-Jizba framework with literature-derived parameters systematically overestimates velocities for these Mississippian dolomites. The constrained inversion procedure adopted here recovers sample-specific squirt-flow parameters from the measured data, so that predictions reflect the actual pore-structure characteristics of the formation.

Several boundary conditions must be borne in mind when interpreting these results. All measurements were acquired at atmospheric confining pressure; the recovered squirt-flow parameters should therefore be interpreted as effective upper-bound estimates of the compliant porosity active under laboratory conditions, and extension to reservoir-pressure conditions would require pressure-dependent calibration. The sample count, ($N = 5$), limits population-level statistical inference, and additional samples from different wells and stratigraphic horizons within the Mississippian section are needed to establish regional parameter ranges.

Priority directions for future work include incorporating confining-pressure dependence through coupled pressure-velocity calibration, expanding the sample set across wells and facies to improve generalizability, replacing the single-crack idealization with a distributed crack-aspect-ratio model to reduce residual attenuation scatter, and testing the downward extrapolation of ultrasonic calibrations to logging and seismic frequencies through synthetic frequency-dependent reflectivity modeling. These extensions would strengthen the connection between laboratory scale squirt-flow calibration and field-scale seismic interpretation in carbonate reservoirs, a connection that as Pang et al. (2020) have emphasized, likely requires joint analysis of velocity and attenuation to resolve the stiff and soft porosity fractions that govern frequency-dependent elastic behavior.

The complementary plume-segmentation study presented in [Chapter 5](#) yields the following additional conclusions.

7. **Frequency-decomposed deep-learning segmentation is effective for CO₂ plume monitoring.** Deep-learning ensemble segmentation of frequency-decomposed seismic amplitude-difference maps achieves high accuracy for CO₂ plume delineation, with a mean Dice coefficient of 0.937 and mean IoU of 0.882 across eleven spectral bands under leave-one-out cross-validation.
8. **Higher-frequency bands yield sharper plume boundaries.** Segmentation accuracy generally increases with center frequency, with the 100 Hz band achieving the highest IoU (0.918) and the full-bandwidth map the lowest (0.847), though the relationship is not strictly monotonic. This confirms that spectral decomposition exposes frequency-dependent amplitude contrasts that improve plume boundary delineation beyond what full-bandwidth data alone can provide.
9. **Ensemble predictions are more stable than individual models.** Multi-architecture ensembling of the top three cross-validated models with test-time augmentation yields a mean IoU of 0.882, exceeding the best single-model cross-validated IoU of 0.878, and the ensemble probability maps provide spatially resolved uncertainty estimates useful for monitoring and risk assessment.

Collectively, the two studies in this thesis demonstrate that frequency-dependent seismic attributes carry diagnostic information about fluid-filled pore space at both ultrasonic laboratory scales (Chapters 2 through 4) and exploration seismic frequencies (Chapter 5). The Mavko-Jizba squirt-flow calibration extracts this information through physics-based inversion at the core-plug scale, while the deep-learning segmentation pipeline extracts analogous information through data-driven pattern recognition at the field scale. Future work at the intersection of these approaches,

such as physics-informed neural networks that incorporate rock-physics constraints into segmentation loss functions, could further strengthen the link between laboratory-calibrated models and field-scale seismic monitoring of subsurface fluid distributions.

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