

RESEARCH ARTICLE OPEN ACCESS

Synthetic Seismic Data Generation for Deep Learning Segmentation of Clinoforms: Integrating Process-Based Forward Stratigraphic Modelling and Ray-Based Seismic Modelling

Waleed AlGharbi¹  | Rebecca E. Bell¹ | Cédric John^{1,2}

¹Department of Earth Science and Engineering, Imperial College London, London, UK | ²Digital Environment Research Institute, Queen Mary University of London, London, UK

Correspondence: Waleed AlGharbi (w.algharbi21@imperial.ac.uk)

Received: 24 June 2025 | **Revised:** 17 March 2026 | **Accepted:** 25 June 2026

Keywords: clinoforms | deep learning | forward stratigraphic modelling | point spread function | segmentation | synthetic seismic

ABSTRACT

Clinoform identification plays a major role in sequence stratigraphy and applied geosciences, offering key insights into sediment fluxes, basin evolution, and natural resource exploration. However, manual interpretation of clinoform geometries in seismic data is time-consuming and labour-intensive. This study proposes a deep learning framework to automate clinoform detection and segmentation. One of the greatest challenges of seismic interpretation with deep learning is the scarcity of labelled training data. To address this, we generated 20,000 synthetic seismic images using process-based forward stratigraphic modelling followed by ray-based seismic modelling, ensuring both geological realism and variability of data. The generated synthetic seismic images were split into training (70%), validation (15%), and testing (15%) sets. The clinoform binary masks were labelled using the top and base layers from the forward stratigraphic models. Then, a YOLOv8m model was trained on this dataset, achieving 86% precision, 82% recall, and 83% Dice coefficient on segmenting clinoforms in the synthetic testing dataset. Qualitative validation on real seismic images confirmed accurate bounding box detection and segmentation of clinoform bodies. These results highlight the potential of deep learning to accelerate seismic interpretation, particularly during early scanning phases, where rapid clinoform analysis supports stratigraphic assessment and reservoir characterisation. The proposed workflow bridges the synthetic-to-real domain gap in seismic data, offering a scalable approach to train algorithms for advancing subsurface analysis.

1 | Introduction

Clinoforms were first defined by Rich (1951) as inclined stratal surfaces referring only to the sloping segment of depositional profiles. However, modern usage expanded the term to encompass the entire sigmoidal geometry from coastal plain to deep water (Patruno et al. 2015; Pellegrini et al. 2020; Steel and Olsen 2002) (Figure 1). Clinoforms represent basinward dipping architectural elements that can be observed across a spectrum of temporal and spatial scales (Patruno et al. 2015; Pellegrini et al. 2020). As the main record of slope regressive-to-transgressive

successions, clinoforms portray the transition from shallow water to deep water environments (Pellegrini et al. 2020). Their stratal architecture is a useful tool in reconstructing depositional histories and quantifying basin fill dynamics in both siliciclastic and carbonate systems (Bhattacharya 2006; Mitchum et al. 1977; Pirmez et al. 1998).

Due to their critical role in advancing the understanding of sedimentary processes and basin evolution, clinoforms have been studied extensively since the mid-1900s (Rich 1951). Identifying clinoforms is fundamental to both classical

This is an open access article under the terms of the [Creative Commons Attribution](https://creativecommons.org/licenses/by/4.0/) License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

© 2026 The Author(s). *Basin Research* published by International Association of Sedimentologists and European Association of Geoscientists and Engineers and John Wiley & Sons Ltd.

Highlights

- Identifying clinoforms in seismic data is fundamental to both sequence stratigraphy and applied geosciences.
- Forward stratigraphic modelling is a viable way of producing realistic geometries for synthetic seismic data.
- Using publicly available reference models ensures geologically constrained models that simulate real scenarios.
- Point spread function captures the expected illumination artefacts from inclined reflections in real seismic data.
- YOLOv8m demonstrates robust performance in clinoform detection and segmentation.

sequence stratigraphy and applied geosciences. In sequence stratigraphy, clinoforms and their bounded sedimentary units (clinothem) serve as key chronostratigraphic markers that help in identifying system tracts and depositional sequences (Neal and Abreu 2009; Patruno and Helland-Hansen 2018; Steel and Olsen 2002). Their stacking patterns reflect the interplay between sea-level fluctuations, tectonics (uplift and subsidence), sediment supply, and climate variation (Helland-Hansen and Hampson 2009; Mitchum et al. 1977; Neal and Abreu 2009; Pellegrini et al. 2020; Steel and Olsen 2002). The high sedimentation rates over the subsidence rate associated with clinoforms capture detailed records of climate change, oceanographic conditions, and terrestrial sediment flux, making them invaluable for studying and reconstructing base-level changes (Patruno et al. 2015; Petter et al. 2013). In applied geosciences, clinoform analysis aids natural resource exploration by predicting reservoir distribution and seal potential. Reefal and/or sand-prone porous clinothem often form major reservoirs, while muddy tight units within the clinothem succession can act as seals. Additionally, these clinothem reservoirs can be potential CO₂ sequestration sites, particularly in tectonically stable basins (Cummings and Arnott 2005; Graham et al. 2015; Holgate et al. 2014; Jackson et al. 2009; Sydow et al. 2013).

Seismic data has revolutionised the study of clinoforms, providing unparalleled insights into the architecture and evolution of sedimentary basins. Clinoform analysis relies heavily on seismic imaging to resolve their geometry, scale, and spatial relationships (Catuneanu 2019; Helland-Hansen and Hampson 2009;

Houseknecht et al. 2009; Mitchum et al. 1977). While outcrops and well logs allow for high-resolution facies analysis, seismic imaging contextualises these observations by revealing basin-scale clinoform sets and their stacking patterns (Steckler et al. 1999; Vail et al. 1977).

In the last decade, machine learning has emerged as a transformative tool in seismic interpretation, enabling the automation of geological feature detection and segmentation such as faults and salt bodies (Di et al. 2018; Shi et al. 2019; Wrona et al. 2021; Wu et al. 2019), horizon picking (Kvalvaer et al. 2020; Tschannen et al. 2020; Wrona et al. 2021; Wu and Zhang 2018), and seismic facies classification (Chopra and Marfurt 2019; Coléou et al. 2003; de Matos et al. 2007; Kaur et al. 2023; Liu et al. 2020; Wrona et al. 2018). While the number of studies focusing on machine learning applications in geosciences has increased rapidly (Zhang et al. 2022), clinoform detection and segmentation remain understudied despite their stratigraphic significance. Early efforts, such as Kvalvaer et al. (2020), focused on horizon tracking within clinoform systems using Convolutional Neural Networks (CNN). Wu et al. (2019), on the other hand, introduced ClinoformNet-1.0, a modified encoder-decoder network for delineating clinoform geometries. However, the latter requires the manual cropping of interpreted clinoform regions to then segment the details of internal clinoform geometry. Thus, it does not identify clinoform packages directly from seismic sections.

In this study, we present the first deep learning method for end-to-end clinoform detection and segmentation. A persistent challenge, common to many machine learning applications in seismic interpretation, is the scarcity of labelled training data. To overcome this challenge, we built realistic and diverse synthetic seismic data using process-based forward stratigraphic modelling as input for ray-based seismic modelling. This workflow effectively generated synthetic seismic data that is complex, diverse, and closely replicating real seismic data while leveraging stratigraphic models as ground truth labels. We trained a YOLOv8m on synthetic seismic data, produced using process-based forward stratigraphic modelling and ray-based seismic modelling, to detect and segment clinoforms in real seismic data. You Only Look Once (YOLO), first introduced by Redmon et al. (2016), is a deep learning object detection algorithm that uses a single-shot approach to identifying and classifying objects (Redmon et al. 2016). Unlike traditional methods that rely on multi-stage pipelines, YOLO employs a single convolutional neural network (CNN) to predict bounding boxes and class probabilities in one pass, using the entire image as input. It eliminates the need for region

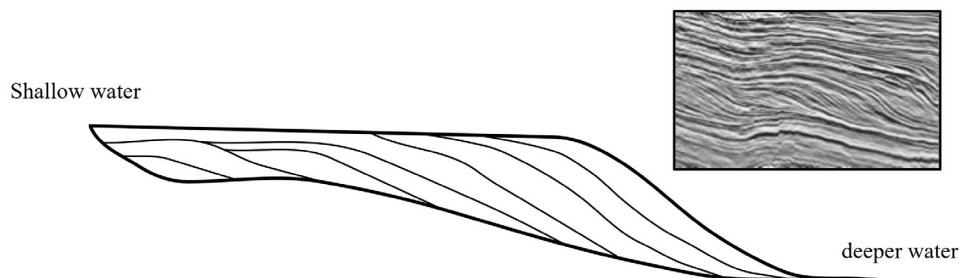


FIGURE 1 | Diagram showing a clinoform two-dimensional profile (after Vail et al. 1977) with a clinoform example from real seismic data in the top-right corner (Demeter 3D survey, NW Australia).

proposals or patch-based analysis, which are common in traditional methods like Faster R-CNN (Diwan et al. 2023). This streamlined approach allows the network to reason globally about the image and all objects within it. YOLOv8m fits the presented application by enhancing the contextual understanding of the geology in seismic sections, thus reducing false positives. Testing the model on an unseen dataset yielded promising results both qualitatively and quantitatively, which represent a significant advancement in automating the process of clinoforms identification.

2 | Methodology

2.1 | Process-Based Forward Stratigraphic Modelling

Due to the complex nature of clinoforms, a process-based approach was needed to synthesise clinoform geometries. Unlike geometric or purely conceptual models, process-based forward stratigraphic modelling (FSM) is a numerical method that discretises space and time to emulate the entrainment, transport, and deposition of sediments over geological timescales. It is governed by key parameters such as subsidence, uplift, sediment supply, erosion, and eustatic sea-level changes (Burgess et al. 2012). FSM simulations are typically initiated from an initial bathymetry and processed through selected time steps. During each time step, stratigraphic processes such as accommodation creation or removal, sediment supply, and transport are quantified (Paola 2000; Seard et al. 2013; Watney et al. 1999).

We used DionisosFlow, a commercial process-based FSM software developed by Beicip-Franlab and part of the OpenFlow package. DionisosFlow incorporates user-defined inputs such as subsidence or uplift maps and eustatic sea-level curves to control accommodation dynamics. It accounts for sediment fluxes and in situ carbonate production while applying diffusion equations to model sediment transport and deposition. The mathematical principles of DionisosFlow were first described by Granjeon (1996). The two main diffusion equations governing the sediment transport and distribution in the simulations are the slope-driven diffusion (Equation 1) and the wave-driven diffusion (Equation 2):

$$Q = K_{\text{slope}} \times S \quad (1)$$

$$Q = K_{\text{wave}} \times E_{\text{wave}} \times S \quad (2)$$

where Q is transported sediment, K_{slope} is estimated diffusion coefficient for slope, K_{wave} is estimated wave diffusion coefficient, E_{wave} is wave energy, and S is slope. By integrating these processes within a deterministic framework, DionisosFlow enables the reproduction of stratigraphic architectures that reflect the interaction between tectonic activity, sediment supply variations, and depositional environments (Granjeon and Joseph 1999; Granjeon 2014; Hawie et al. 2017; Seard et al. 2013).

We generated our geometries from two distinct and publicly available reference FSM models: a published carbonate-dominated system (Cretaceous of Oman, Al-Salmi et al. 2018) and an unpublished, but available within DionisosFlow, mixed

siliciclastic-carbonate system. This ensures geologically constrained models that simulate real scenarios. For the carbonate systems, Al-Salmi et al. (2018) ran a series of simulations to model the Lower Cretaceous (149–113 Ma) carbonates of Northern Oman. The models' domain size is 300 km × 300 km with a 2 km × 2 km grid resolution, and it is modelled with 0.2 Ma time steps. Three sediment types were included: coarse carbonate (0.5 mm), medium carbonate (0.1 mm), and carbonate muds (0.004 mm). Sediment transport was governed by wave-driven (0–0.9 km²/Ka) and gravity-driven (0.1–0.95 km²/Ka) diffusion coefficients. The wave direction was NE–SW with a 20 to 25 m wave base. Carbonate production was set at a constant rate of 325 m/Ma, with maximum production occurring in the upper 20 m of the water column and tapering to zero production at 80 m. Al-Salmi et al. (2018) tested the influence of eustasy on clinoform geometries using three eustatic curves: Miller et al. (2005), Haq and Boersma (1998), and Haq (2014).

The mixed siliciclastic-carbonate system, based on a Paleogene (70–24 Ma) case study, is confidential but available as a sanitised reference template within the DionisosFlow software package (Granjeon and Joseph 1999). This reference study features an 84 × 50 km domain with 2 × 2 km grid resolution and a 0.5 Ma time step. Five sediment classes were modelled in this simulation: sand (0.2 mm), silt (0.03 mm), carbonate (1 mm), reef (0.2 mm), and marine organic matter (0.004 mm). While wave- and gravity-driven diffusion parameters range from 0.001 to 0.7 km²/Ka, the water-driven transport reaches up to 6.0 km²/Ka. Carbonate production was set to a constant rate (24 m/Ma) with two phases of siliciclastic supply from the south. Sediment compaction was not considered, and the wave direction was set to NE–SW with a 20 m wave base. In this mixed model, sea-level influence came mainly from the short-term eustatic curve (Haq 2014). All the parameters used in our study are derived from the reference models and summarised in Table 1.

By combining the Al-Salmi et al. (2018) carbonate framework with the DionisosFlow's mixed-system template, our methodology captures clinoform geometries under varying depositional environments. This dual approach enables comparative analysis of carbonate platform sensitivity to eustasy versus mixed-system responses to coupled sediment fluxes, providing a spectrum of stratigraphic architectures. We leveraged these reference parameters to construct 11 complex and diverse, yet realistic 3D geological models, with a particular focus on clinoform geometries. From each model, we extracted 10 dip-oriented 2D cross-sections, parallel to the depositional dip to capture maximum clinoform expression.

Recognising the need for robust training data capable of simulating varying stratigraphic thickness, we implemented multiple sampling strategies during profile extraction. Each cross-section was extracted at four different stratigraphic intervals: full model resolution (every layer) and subsampled configurations retaining every third, fifth, or tenth layer (Figure 2). This approach ensures compatibility with stratigraphic models differing in thickness.

To further augment the models and prepare more subsurface imaging scenarios, we applied post-processing transformations to the 2D profiles. Vertical exaggeration factors of 1/2 and 1/4 were implemented through axis scaling modifications, introducing

smaller scale clinoforms to the training dataset (Figure 3B–D). By incorporating varying levels of exaggeration into the generated dataset, we improve geometric accuracy and realism, expose the deep learning model to diverse geological scenarios, and enhance its generalisation potential. Additionally, clinoform geobodies were translated vertically and horizontally in the 2D profiles to simulate changes in position and mimic natural variability in depositional architectures (Figure 3C,D). This methodological framework incorporates controlled geological

TABLE 1 | Forward stratigraphic models input parameters summary.

	Carbonate-dominated models	Mixed siliciclastic-carbonate model
Domain size (km)	300×300	84×50
Cell size (km)	2×2	2×2
Period (Ma)	149–113	70–24
Time steps (Ma)	0.2	0.5
Gravity-driven diffusion	0.1–0.95	0.001–0.7
Wave-driven diffusion	0–0.9	0.001–0.2
Water-driven diffusion	—	0.001–6.0
Production rate (m/Ma)	325	24
Wave base (m)	20–25	20

scenarios and scale dependencies, enabling the development of synthetic data that emulate real-world geological scenarios.

Finally, we simulated filling the basin with sediment by adding additional layers at the upper and lower boundaries of the modelled clinoforms (Figure 3). To do this, additional layers were generated based on the existing clinoform geometry. First, the top layer of the clinoform package was identified. A strata-slicing technique (Zeng 2010) was then applied to extend this layer upward to the top of the window while preserving its original thickness and geometrical characteristics. Similarly, the basal layer of the clinoform package was identified and extended downward to the base of the window using the same strata-slicing approach. This step helped to emulate the appearance of clinoforms in real seismic data and prevented having the clinoforms’ tops sitting at the surface.

Using the top and base layers of each clinoform as markers, we create a binary mask that comprises the entire clinoform, and thus serves as our label during training (Figure 4B). The dataset was further optimised by incorporating examples of conformable geological models (i.e., no clinoforms), varying in thickness. A script was used to generate these conformable geological models with evenly spaced horizontal layers following AlGharbi et al. (2025). The number of layers was defined as 10, 25, or 50 with a uniform vertical spacing of one unit between them, simulating sequences of thick, medium, and thin beds. Using a loop, each layer was drawn as a horizontal band by filling the space between two vertical coordinates on a 2D plot (Figure 4C).

2.2 | Ray-Based Seismic Modelling

To prepare the geological models for automatic acoustic impedance value assignment, we populated the interlayer spaces with

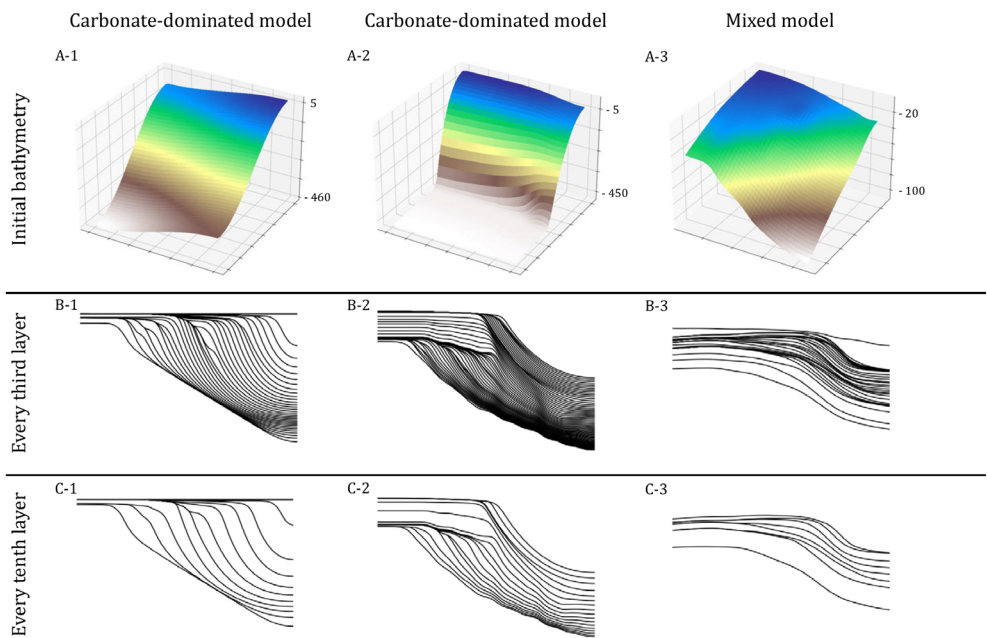


FIGURE 2 | Three examples from the generated geological models. Column (1) is a carbonate dominated model with small gradient initial bathymetry (Model-A in Al-Salmi et al. 2018). Column (2) is a carbonate dominated model with high gradient initial bathymetry (Model-B in Al-Salmi et al. 2018). Column (3) is a mixed siliciclastic-carbonate model. Row (B) are 2D profiles from the models with every third layer plotted. Row (C) are 2D profiles from the same models with every tenth layer plotted.

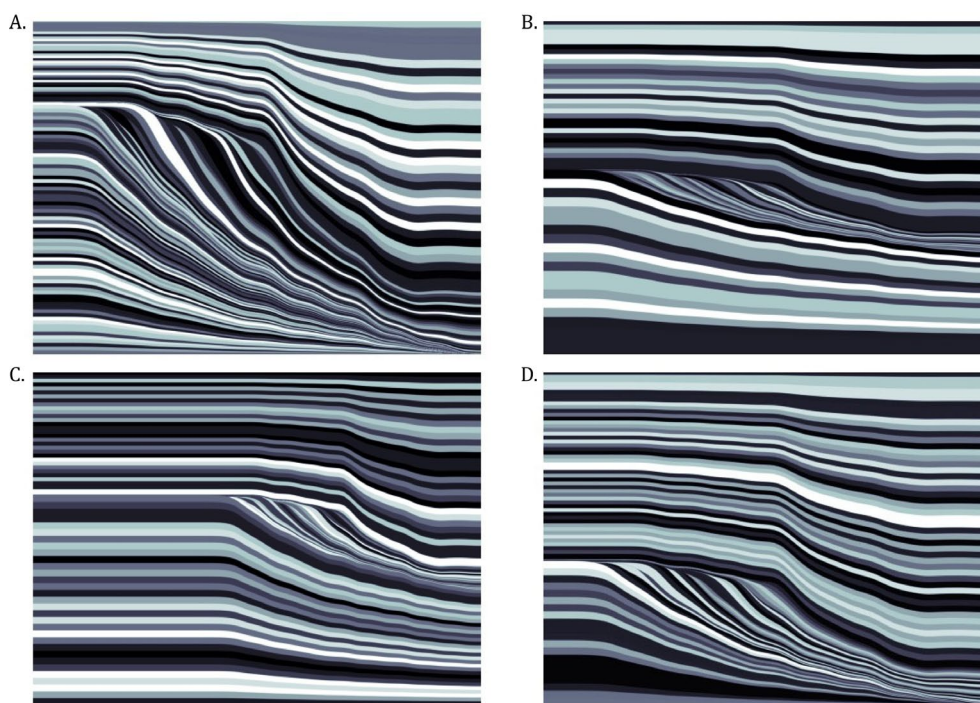


FIGURE 3 | A 2D profile with different geometrical augmentation: (A) The original size and position from the simulated model. (B) Half size centred clinoform. (C) Half size shifted to the right. (D) The clinoform moved downward.

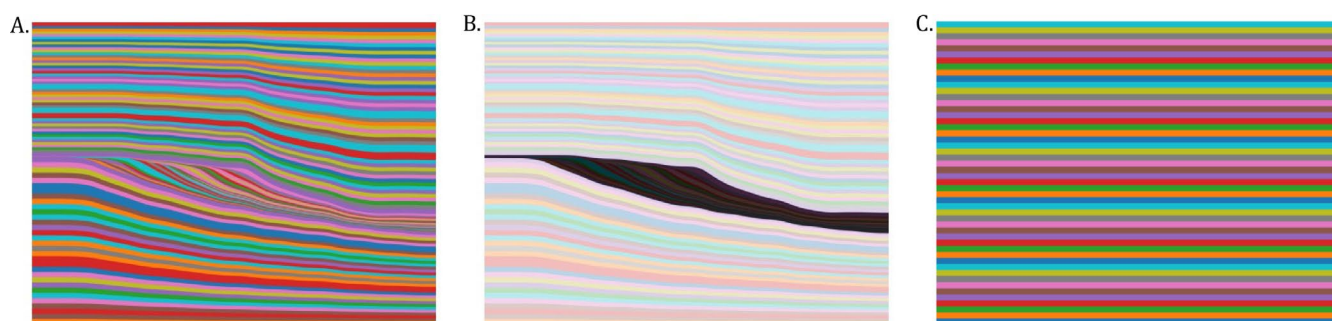


FIGURE 4 | Examples from the generated geological models with colour fill. (A) A clinoform in the middle of the section with top and base layers. (B) The same model with clinoform mask overlaying the model. (C) An example of a conformable 'thin beds' model without clinoforms.

random colours (Figure 4). Then, we used DBSCAN to identify colours and assign a random acoustic impedance value to each one.

DBSCAN (Density-Based Spatial Clustering of Applications with Noise) (Ester et al. 1996) is a widely used unsupervised machine learning method that is part of the scikit-learn (Pedregosa et al. 2011) clustering toolkit. It identifies the core points in high-density regions and expands the clusters from these points (Schubert et al. 2017). The main two parameters for this method are (1) *eps*, the maximum distance between two points for one to be considered within the neighbourhood of the other and (2) *min_samples*, the minimum number of samples (including the point itself) required in a neighbourhood for a point to be classified as a core point. In our implementation, we empirically determined values of 0.5 for *eps* and 10 for *min_samples*. This parametric configuration allowed DBSCAN to effectively capture the spatial heterogeneity of the geological models. While DBSCAN was employed to assign acoustic impedances to the

layers, we acknowledge that alternative, potentially simpler methods may yield comparable results.

The second step was to generate seismic Point Spread Functions (PSF). Adapted from microscopy principles where PSF represents a blurred rendering of point-like objects (Cole et al. 2011), geophysical PSF characterises the Earth's impulse response to wave propagation (Lecomte and Kaschwich 2008). To generate seismic PSFs, a synthetic point scatterer in a reflectivity model undergoes de-migration and subsequent least-squares migration. The resulting blurred scatterer image encapsulates resolution limits, illumination gaps, and overburden-induced distortions specific to the survey configuration (Lecomte et al. 2015) (Figure 5IV).

In this study, we used a 2D convolution approach, where a PSF as the convolution kernel is used to generate 2D seismic images from 2D reflectivity models. The seismic forward modelling

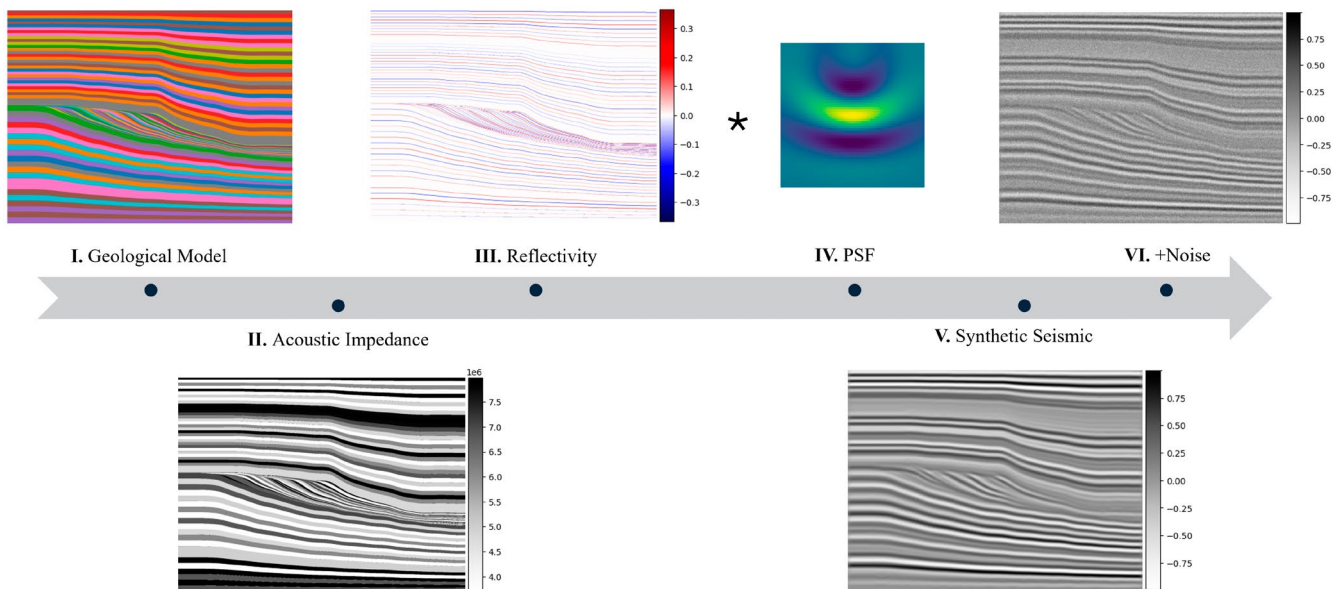


FIGURE 5 | Seismic forward modelling workflow. After assigning an acoustic impedance value to each layer in the geological model, the reflection coefficient model is calculated and convolved with a PSF. The result is a synthetic seismic image that captures a desired configuration.

workflow starts with three fundamental parameter sets: (1) initial average velocity models ranging from 1000 m/s to 5000 m/s to encompass the likely range of velocities encountered in clastic and carbonate settings, (2) zero-phase Ricker wavelets (Ricker 1953) with a range of dominant frequencies 1–20 Hz to generate a realistic synthetic seismic data given the thickness of the units in the geological models, and (3) acoustic impedance contrasts between 1 and $8 \times 10^6 \text{ kg/m}^2 \times \text{s}^{-1}$ to generate physically realistic reflection coefficients. Key implementation stages progress as follows: First, a 2D reflectivity model incorporating source-receiver configurations is constructed, followed by analytical PSF derivation through least-squares migration operator. Second, reflection coefficient models were calculated using the acoustic impedance models by mathematically dividing the difference in acoustic impedance of overlying layers by the sum of acoustic impedance of the same layers at the interface. Third, convolve reflection coefficient with the built PSF. Fourth, adding two levels of Gaussian white noise (low and high) to the generated synthetic seismic data mimicking different seismic acquisition and processing scenarios. Finally, the generated synthetic seismic images were resized to 640×640 pixels to be compatible with the input requirements of YOLOv8m.

In total, we generated 20,000 synthetic seismic images, of which 4220 do not contain clinoforms. The dataset was split into 70% training, 15% validation, and 15% testing sets (Géron 2022). This yields 14,000 training instances, 3000 validation instances, and 3000 testing instances, with the proportion of images without clinoforms maintained across each subset. These synthetic seismic images are represented in pixels, making them suitable for training models for both time- and depth-domain seismic interpretation.

2.3 | YOLO Architecture and Hyperparameters

Our approach is data-centric, and thus we used off-the-shelf API model for segmentation. YOLOv8m, the medium-scale

variant of the eighth generation ‘You Only Look Once’ architecture, represents a significant advancement in object detection through optimised architectural modularity and enhanced multi-scale feature aggregation (Vijayakumar and Vairavasundaram 2024). Its architecture consists of a backbone, neck, and head. The backbone extracts hierarchical features across low, medium, and high spatial resolutions using a custom CSPDarknet53. The neck fuses multi-scale features to improve detection accuracy for objects in cluttered environments. In the YOLOv8 segmentation framework, each predicted segmentation mask is automatically associated with a bounding box that encloses the segmentation polygon, meaning that object detection is obtained as a direct by-product of the segmentation output. This architecture eliminates predefined anchor boxes through its anchor-free head, directly predicting bounding box coordinates and class segmentation via decoupled prediction heads.

For the segmentation tasks presented in this paper, we trained YOLOv8m on 640×640 pixel images over 500 epochs, with early stopping triggered after 20 epochs of no improvement on validation loss. Throughout training, we used a batch size of 32 with initial learning rate at 0.001 and a 0.1 learning rate factor at the last epoch, yielding 0.0001 final learning rate. The first 22 layers of the neural network were frozen to minimise the risk of overfitting while preserving generalisable feature extraction capabilities. To simulate different viewpoints without distorting critical spatial relationships, four types of geometrical augmentation integrated within YOLOv8m were used: 0.2 rad rotation, 0.1 fractional translation/shear, and 0.5 probability horizontal flipping.

2.4 | Performance Evaluation Metrics

Evaluating model performance requires careful selection of metrics that account for class imbalance and ensures the

relevance of detection and segmentation errors for the study. Traditional accuracy, defined as the ratio of correctly predicted pixels to total pixels (Equation 3), proves inadequate in the context of this study due to the possible imbalance between clinoform pixels and background. A model naively predicting all pixels as background could achieve high accuracy in most of the instances while failing to detect clinoforms entirely.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

where TP is true positives, TN is true negatives, FP is false positives, and FN is false negatives. Alternatively, precision (Equation 4) and recall (Equation 5) provide more reliable insights. Precision quantifies the confidence in detected clinoforms by measuring the proportion of true positives among all predicted positives, effectively penalising false alarms in areas like seismic noise or stratigraphic artefacts. Recall, conversely, evaluates predictions proportion by quantifying the fraction of actual clinoforms captured. It is a crucial metric for getting a model with a lower number of missed clinoforms. Dice coefficient (or F1-score) and Intersection over Union (IOU) are similarity metrics that penalise false positives. Dice is the harmonic mean of precision and recall, giving more weight to the intersected part between predicted and labelled segmentations. It can be mathematically stated for two pixel sets: label (A) and prediction (B) in Equation (6). On the other hand, IOU is the intersection between labelled pixels and predicted pixels over their union (Equation 7). It can be inferred from their equations that IoU penalises errors more than the dice coefficient.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (4)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (5)$$

$$\text{Dice}(A, B) = \frac{2 |A \cap B|}{|A| + |B|} \quad (6)$$

$$\text{IoU}(A, B) = \frac{|A \cap B|}{|A \cup B|} \quad (7)$$

2.5 | Testing the Trained Model on Real Seismic

After evaluating the model performance on the synthetic testing dataset, a final performance evaluation was performed on real seismic data. Two 3D seismic surveys and multiple 2D seismic lines were used to evaluate the model predictions on data from different acquisition configurations with various qualities and resolutions. The first 3D seismic survey is the open-source 3D seismic Demeter survey from the Northern Carnarvon basin in northwestern Australia. This dataset was selected due to its high signal-to-noise ratio and the presence of well-defined clinoforms. Covering an area of 3590 km² with a nominal fold number of 133, the Demeter survey was acquired in 2004, processed, and made available for interpretation in 2005 (Bennett and Bussell 2006). The second 3D seismic survey is the F3 survey, also an open-source 3D seismic survey from the North Sea Dutch sector. It is an old and noisy survey, acquired and

processed in 1987. It covers 386 km² with 12 nominal fold number (TerraNubis 2020). The 2D seismic lines are reprocessed data located northwest of the Demeter, acquired in 2013 and reprocessed in 2017 (National Offshore Petroleum Information Management System, Geoscience Australia).

3 | Results and Discussion

3.1 | Analysis of the Geological Models' Geometries

The data used for training our model is available on Zenodo (AlGharbi 2026). In the carbonate-dominated models (derived after augmentation from the models in Al-Salmi et al. 2018), initial bathymetry emerges as a critical variable for slope gradient. Here, we use an identical terminology to refer to specific model as in Al-Salmi et al. 2018 (i.e., models A-L). Readers can refer to the original publication for more details. While both Model-A and Model-B exhibit the same overall bathymetric change (0–450 m), the rate at which this change occurs differs (cf. Figure 2A1,A2). Model-A bathymetry has a gentle slope (2 m/km) that develops gradually toward the basin, whereas Model-B bathymetry has a steeper slope (10 m/km) that flattens at the basin. This produces a gradual increase of the clinothem thickness in Model-A and abrupt slope breaks with thinner basinal units in Model-B (Figure 6A,B). Using the same parameters with only increasing the wave base depth by 5 m, the slope in Model-C becomes gentler (Figure 6C).

The eustatic influence can be seen in Model-G (Figure 6D). While the Haq (2014) short-term eustatic curve was used as the eustatic curve in all the previous models, employing the long-term Haq and Boersma (1998) in this model produced an almost flat shelf-edge trajectory throughout nearly all the simulation steps.

In Model-I (Figure 6E), two different subsidence maps were used at different ages. As a result, we have a stratal geometry of forced regression with larger lateral variation in thickness. The mixed model demonstrates a totally distinct geometric signature (Figure 6F), where carbonate production dominates during transgressive phases with multiple build-ups and clastic fluxes preferentially accumulated during sea-level falls. This interplay generates pronounced 3D heterogeneity with noticeable geometric variability between the extracted 2D profiles (cf. Figure 7A,B). The observed heterogeneity contrasts with carbonate-dominated systems, where uniform depositional processes often yield architecturally consistent 2D profiles (cf. Figure 7C,D).

Real-world geological systems are incredibly complex, with numerous interacting processes. Process-based models, by their nature, may not fully capture all of this complexity, which can result in a simplified and potentially uniform representation of the stratigraphy (Al-Salmi et al. 2018; Wu et al. 2019). This uniformity is model-dependent and governed by the input parameters. Profiles extracted from the models' edge versus the centre show clear geometric contrasts in some cases (differing clinoforms' shape, orientation, and/or thickness trends), while remaining nearly identical in others (Figure 7).

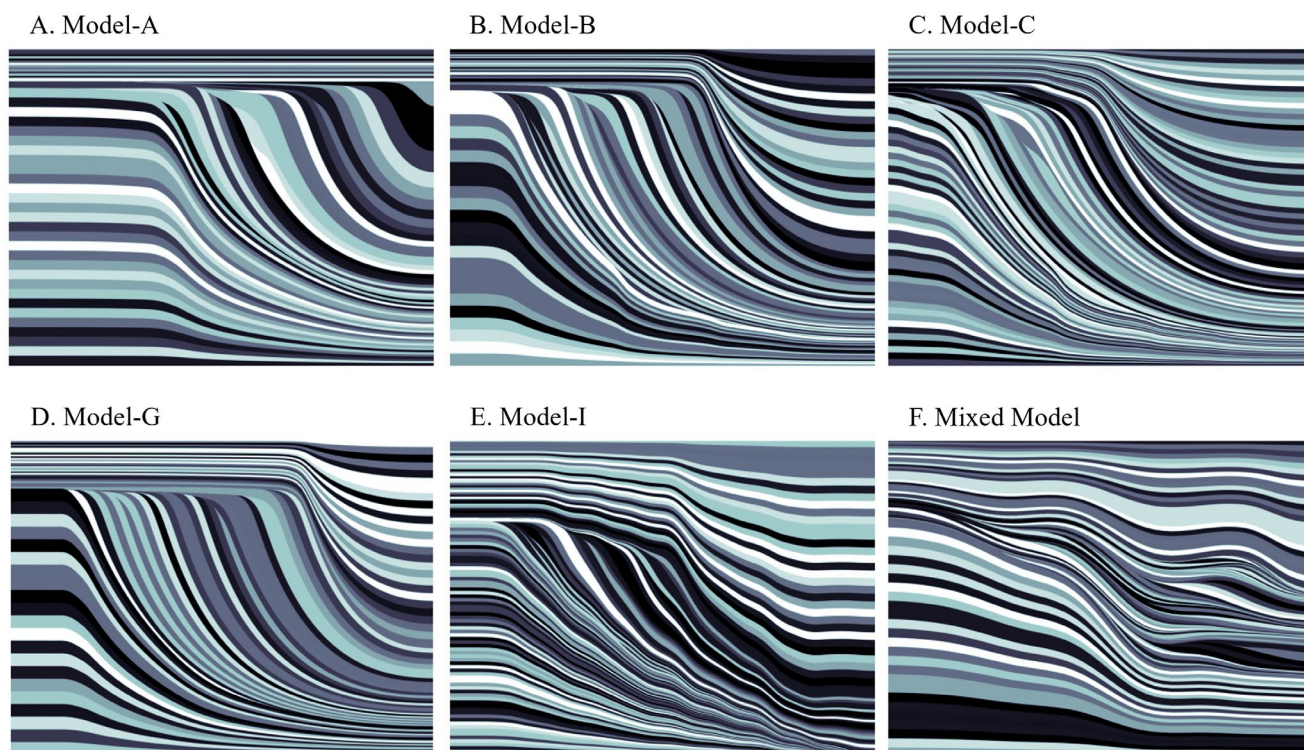


FIGURE 6 | 2D profiles from different 3D SFMs. The size and geometry of the clinoforms differ based on the input parameters.

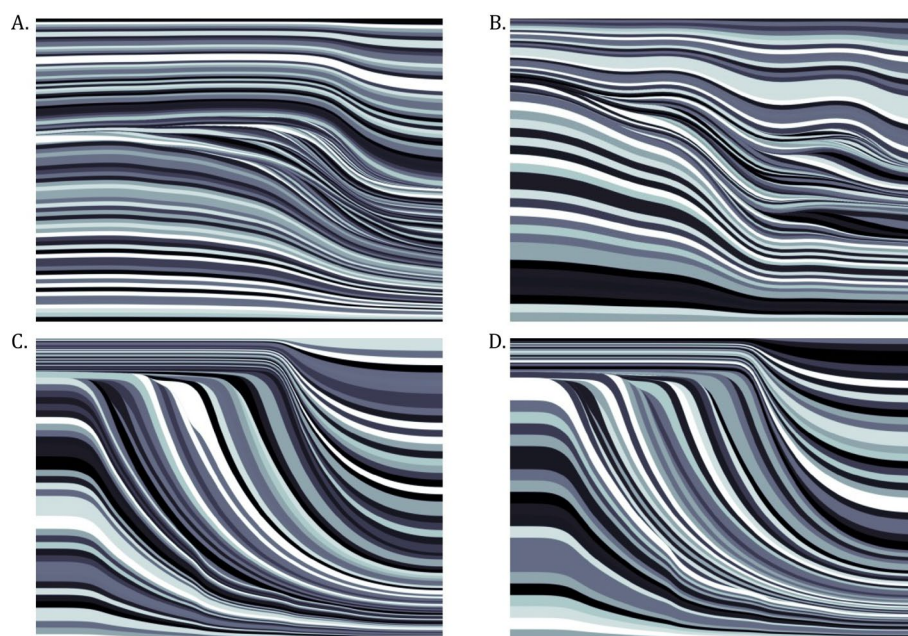


FIGURE 7 | 2D profiles demonstrate the difference in heterogeneity of the simulated 3D models. A (from the edge of the model) and B (from the centre) are two sections from the mixed model, showing the model's geometrical heterogeneity. On the other hand, C and D are two sections from the carbonate-dominated Model-B. They are almost identical in structure, which gives us an indication that this 3D model is practically uniform.

However, the geophysical part of the workflow (seismic modelling) can help with this challenge and introduce another layer of diversity to geometrically identical profiles. Subtle variations in acoustic impedance generate divergent seismic responses between adjacent/similar profiles. This step reduces the limitations of relying solely on the stratigraphy to create large and diverse synthetic data.

3.2 | Synthetic Seismic Images

Frequency of the source wavelet and initial model velocity are the two main parameters that govern the resolution of the generated synthetic seismic data using PSF. Ranges of dominant frequencies and initial velocities were used to

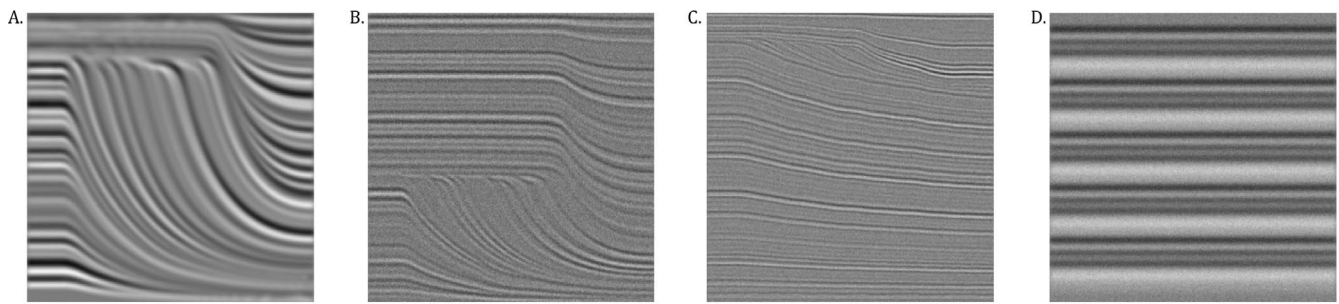


FIGURE 8 | Four different samples from the generated synthetic seismic data. (A) A synthetic seismic image with high clinoform relief, low frequency, and high signal-to-noise ratio. (B) A noisy lower relief clinoform with higher frequency. (C) Smaller clinoform with the highest frequency and lowest relief in the presented examples. (D) A synthetic seismic section without clinoform.

increase the diversity of the data and systematically evaluate their impact on the resolution of different geological scenarios. By incorporating low (1–4 Hz), mid (4–10 Hz), and high (10–20 Hz) frequency ranges into the synthetic dataset, we were able to assess how seismic resolution varies with different frequencies. Although the overall range (1–20 Hz) is at the lower end of conventional seismic bandwidths, it effectively produced realistic-looking synthetic seismic images given the stratigraphic thicknesses used in the models. Low-frequency models show lower vertical resolution due to longer wavelengths, which results in prominent tuning effects that obscured small-scale stratigraphic features (Figure 8A). Mid-frequency scenarios improved resolvable details, with reflection spacing aligning more closely with actual layer thicknesses (Figure 8B). High-frequency models achieved optimal resolution, resolving clinoform geometries and terminations with minimal tuning artefacts (Figure 8C). Destructive interferences that attenuate amplitudes are expected at clinoforms offlap boundaries especially at low frequency (Kallweit and Wood 1982) (Figure 8A). The generated synthetic seismic data demonstrate that frequency selection critically controls the resolvability of stratigraphic architectures in seismic datasets. Initial velocities have the inverse effect on seismic resolution, producing lower resolution with higher initial velocities. By incorporating these different ranges of frequencies and initial velocity, we added an extra layer of complexity and diversity to the generated synthetic seismic images.

Compared to conventional 1D convolution, which is widely used in generating synthetic seismic data due to its computational efficiency, the ray-based (PSF) method better preserves illumination effects caused by steeply dipping layers (Figure 8A,B). While 1D convolution fails to account for lateral resolution limitations in complex structures such as dipping layers in clinoforms, the PSF approach maintains the amplitude attenuation from steeper reflectors, emulating real seismic data.

3.3 | YOLOv8m Model Predictions

3.3.1 | Model Training and Predictions on Synthetic Seismic

The training weights of the best YOLO model are available for download on Zenodo (AlGharbi 2026). While the maximum training epochs was set at 500, the training halted at 400 epochs

once validation loss stopped improving for 20 epochs (early stopping). The YOLOv8 model is trained using a combined loss function composed of bounding box loss, objectness loss, and segmentation loss. The bounding box loss measures the error between predicted and ground-truth bounding box geometries, while the objectness loss evaluates the confidence that an object is present within a predicted box. The segmentation loss quantifies the difference between the predicted segmentation and the ground-truth segmentation masks. The overall loss is computed as a weighted sum of these components during training. Notably, the validation loss curves for both detection and segmentation remain consistently lower than the training losses (Figure 9A,B). This behaviour can occur when the training dataset is made more challenging through augmentation and regularisation. During training, the loss is computed on mini batches that include geometrically augmented samples (e.g., rotation, translation, and flipping), which increases the difficulty of the learning task and may lead to higher instantaneous training losses. In contrast, the validation loss is evaluated after each epoch using the finalised model on the un-augmented validation dataset, which is generally easier to predict. Consequently, the validation loss may remain lower than the training loss even as both curves stabilise toward the end of training. Precision plateaued near 90% for both detection and segmentation (Figure 9C). On the other hand, recall showed a 5% performance gap between the two tasks, highlighting segmentation's high sensitivity to boundary ambiguities at clinoform edges (Figure 9D). Detection outperformed segmentation overall, with 2%–5% higher precision and recall, reflecting the added complexity of pixel-level classification versus bounding-box localisation. This divergence suggests semantic segmentation is challenged with subtle geometric variations in clinoform boundaries, where minor misalignments between predicted and ground truth labels propagate errors more than detection tasks. However, the YOLOv8m model demonstrated robust performance in clinoform detection and segmentation, achieving a validation precision of 92% and recall of 90% for bounding box localisation, with segmentation metrics slightly lower at 90% precision and 85% recall.

To get a better sense of the model performance, we measured the precision, recall, dice, and IoU on an unseen synthetic testing dataset. The results are 86%, 82%, 83%, and 73%, respectively. These metrics collectively address the challenges of imbalanced segmentation by focusing on clinoform-specific performance rather than global pixel counts. Their combined

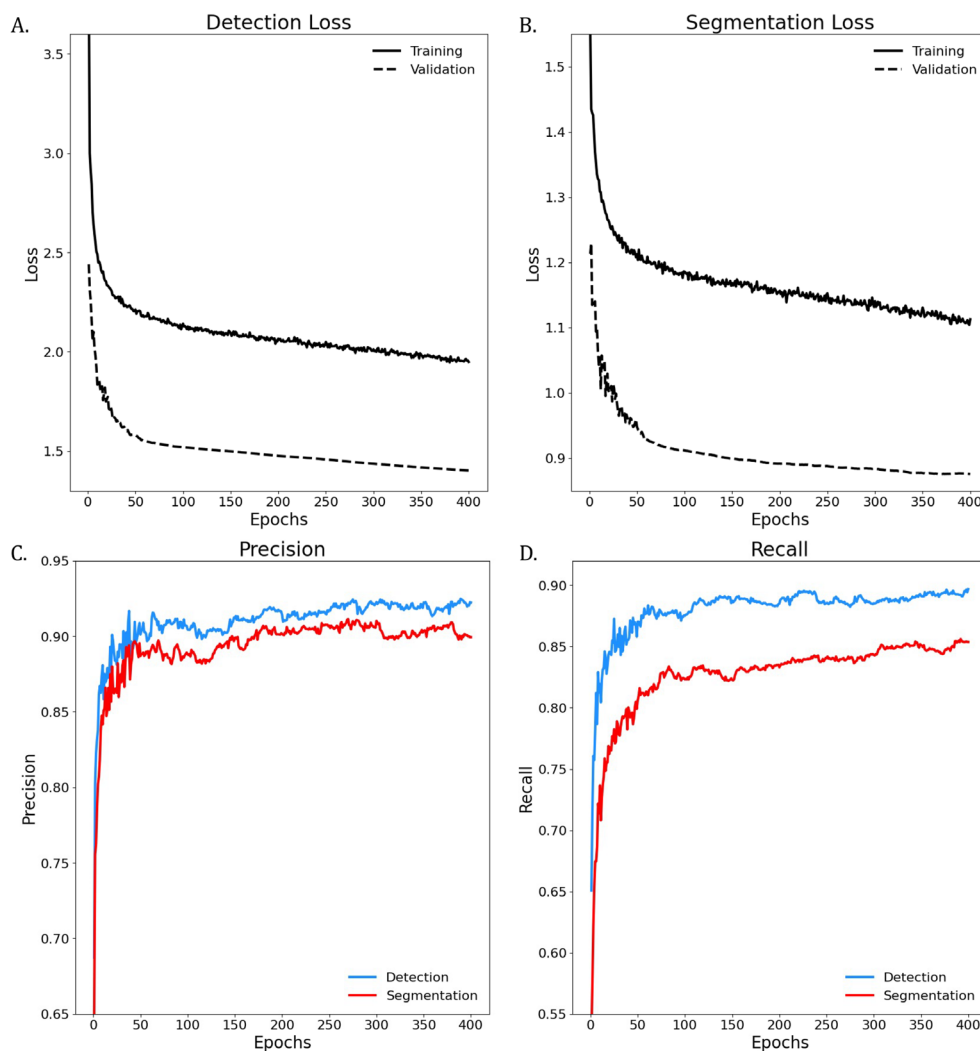


FIGURE 9 | The loss and performance curves. (A) Training and validation loss curves for the detection exercise. (B) Training and validation loss curves for the segmentation exercise. (C) Precision curves plateauing around 0.9 for both detection and segmentation exercises. (D) Recall curve for detection plateaus at a high value compared to segmentation.

use enables robust evaluation of a model's ability to delineate clinoforms while minimising both false positives and false negatives.

Visual evaluation of YOLOv8m predictions on the synthetic seismic images (Figure 10) confirmed its capacity to delineate clinoforms across diverse geometries, generating both bounding boxes and segmentation masks.

3.3.2 | Predictions on Real Seismic

Integrating semantic segmentation and object detection in clinoform delineation exhibit complementary strengths. While semantic segmentation captures detailed morphological features of clinoform geometries, detection bounding boxes enclose the full size of the clinoforms. This dual approach proves particularly valuable where segmentation struggles, specifically at the tapered margins of clinoforms (Figure 11). When testing 2D real seismic images, the bounding box successfully encapsulated the entire clinoform structure, whereas the semantic segmentation delineated the clinoform geobody but missed some parts in

the shallow-water, thinner stratigraphic sections (Figure 11A). Similarly, the model detected and highlighted the clinoforms in the Demeter seismic images (Figure 11B). Demeter is a relatively modern seismic survey with a high signal-to-noise ratio, which we suggest contributed to the model's improved performance. In contrast, the F3 survey is an older seismic volume with a low signal-to-noise ratio, which made segmenting the full clinoform body more challenging. The prediction on the F3 seismic image (Figure 11C) indicates that both the detection bounding box and semantic segmentation failed to capture the lower extent of the clinoform toward the deeper-water region. This challenge in the terminal zone is likely due to a low acoustic impedance contrast or a destructive interference resulting from bed thinning below the vertical resolution limit. For reliable seismic imaging, clinoforms must satisfy three criteria: (1) relief exceeding vertical seismic resolution, (2) lateral spacing wider than tuning thickness, and (3) acoustic impedance contrasts sufficient to generate reflective interfaces either through lithology (e.g., sandstone-shale boundaries) or diagenesis (e.g., carbonate-cemented layers) (Holgate et al. 2014). The model was also evaluated on a larger seismic section, where a clinoform body occupies the lower right corner, to assess its performance on full 2D seismic profiles

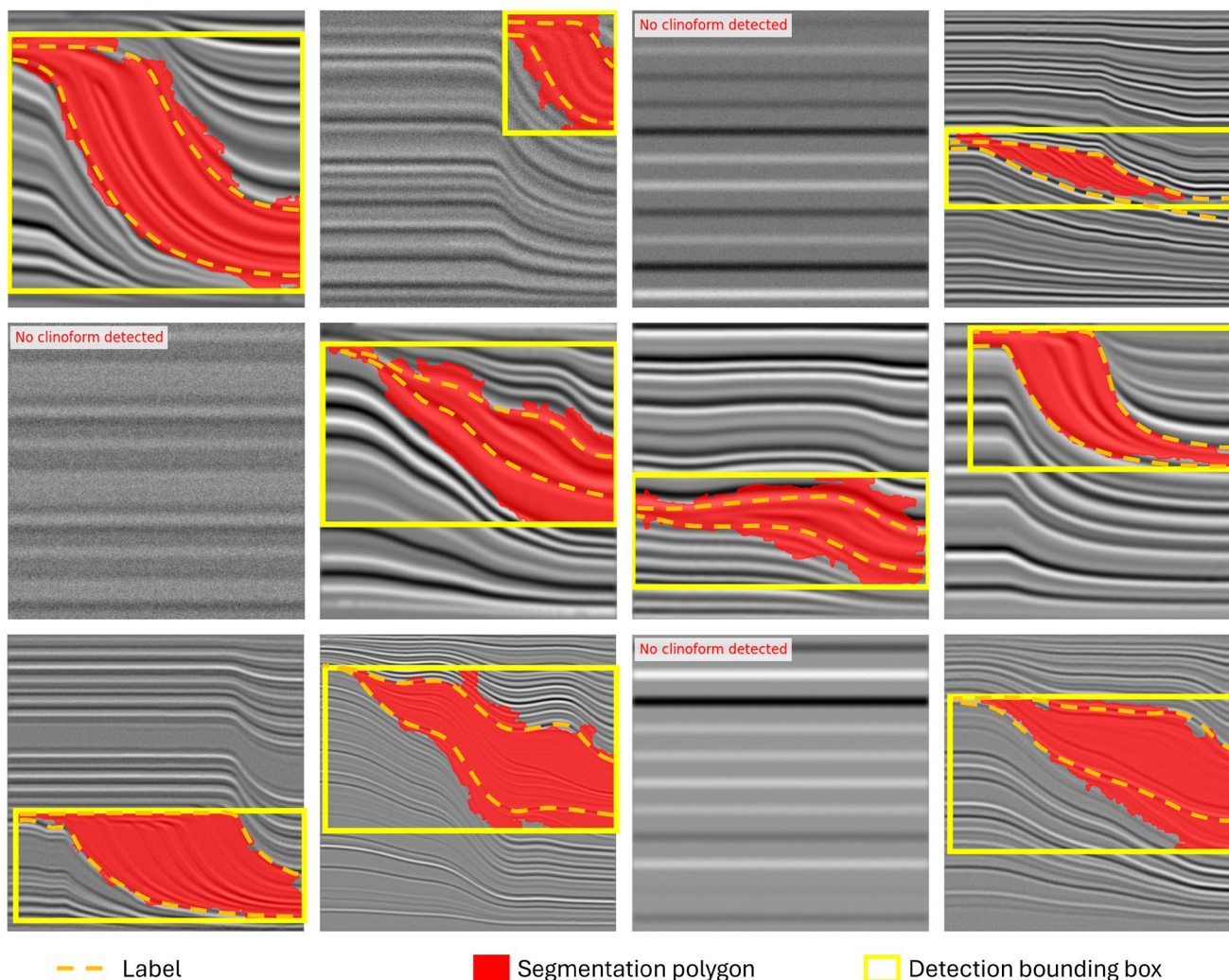


FIGURE 10 | Clinoform detection and segmentation on synthetic seismic images with different clinoform sizes and geometries.

containing multiple geological features. The detection bounding box successfully enclosed the entire body of the clinoform succession, while the segmentation captured most of its geometry (Figure 11D).

YOLOv8m model demonstrated robust generalisation capabilities, effectively delineating clinoforms in real seismic images from different acquisition configurations with varying qualities and resolutions. The model exhibited reliable performance in producing both bounding boxes and segmentation outputs, highlighting its adaptability to complex and heterogeneous subsurface imaging conditions. We believe integrating this deep learning framework into the seismic interpretation workflow can significantly streamline the process, delivering rapid and reproducible results. This operational efficiency will enable geoscientists to reallocate effort from labour-intensive manual delineation to higher-order analytical and interpretive tasks, thereby enhancing both the productivity and scientific value of seismic stratigraphic analysis.

Real seismic data presents substantial challenges for automated clinoform detection compared to synthetic datasets. A primary difficulty arises from elevated noise levels, including both random seismic noise and coherent interference caused

by overlapping geological features. These structural complexities include faults that disrupt stratal continuity and post-depositional tectonic processes (e.g., uplift and rotation) that distort the original clinoform geometries. These distortions are clear in the 2D seismic images (Figure 11A), where the clinoform body is tilted at a high angle due to post deposition tectonics. The inherent variability of field data necessitates robust synthetic data generation and augmentation, essential for achieving reliable model performance across diverse geological settings. Geometric augmentations including translation, flipping, and rotation during training helped the model to generalise across tilted or rotated clinoform configurations observed in real seismic. Additionally, adding noise as well as amplitude normalisation and standardisation prove critical for bridging the domain gap between synthetic training data and field datasets like the noisy F3 seismic volume. Real seismic noise can degrade model performance unless synthetic training data incorporate noise in the creation process.

While these techniques enhance model adaptability, fundamental limitations remain, particularly with noisy data or when tectonic overprints significantly alter depositional geometries. In addition, limitations in seismic resolution present further challenges for clinoform analysis, as vertical resolution constraints

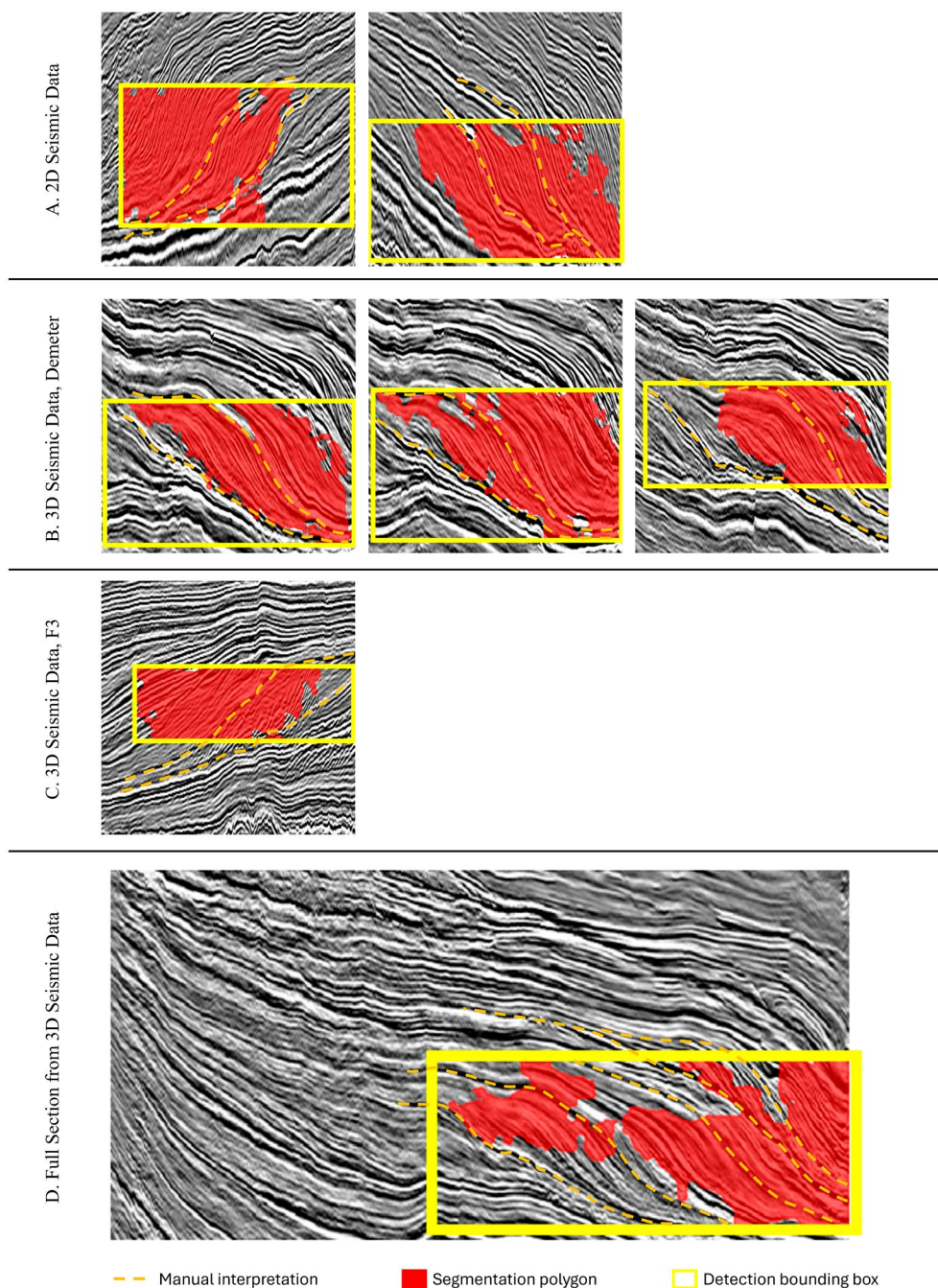


FIGURE 11 | Model detection and segmentation on images from real seismic data. The manual interpretations show examples from stacked clinoforms. (A) Clinoform prediction on 640×640 2D seismic image. (B) Clinoform prediction on 640×640 3D seismic image from the Demeter Survey. (C) Clinoform prediction on 640×640 3D seismic image from the F3 Survey. (D) Clinoform prediction on a 4650×2310 3D seismic image.

often obscure small-scale clinoforms, and tuning effects can artificially amalgamate genetically distinct depositional units.

4 | Conclusions

This study demonstrates that deep learning, when trained on geologically realistic synthetic seismic data, can effectively automate clinoform detection and segmentation with minimal human intervention. By integrating process-based forward stratigraphic modelling with ray-based seismic modelling, we

were able to replicate the complexity of clinoforms across different depositional systems. This data-centric approach addresses two key challenges: the scarcity of labelled field data and the domain gap between synthetic and real seismic datasets.

The YOLOv8m architecture achieved robust performance, with 86% precision and 82% recall in segmenting clinoforms of varying geometries, including carbonate and mixed siliciclastic-carbonate systems. Notably, the model generalised well to real seismic data, successfully delineating clinoform boundaries despite elevated noise levels and overlapping geological features.

Three key insights emerge from this study:

1. Process-based Forward Stratigraphic Modelling (FSM) enables the generation of stratigraphically plausible clinoform geometries by simulating depositional processes, avoiding the oversimplifications of geometric and conceptual models.
2. Ray-based Point Spread Function (PSF) seismic modelling, incorporating frequency and velocity variations, introduces geophysical diversity as well as improves the model resilience and generalisation.
3. The proposed workflow highlights clinoform quickly with high accuracy, allowing geoscientists to focus on high-value interpretative tasks rather than manual picking.

While the model excels in early-stage screening, challenges remain in highly noisy or structurally complex settings. Future work could expand the synthetic training dataset to include additional depositional environments and structural configurations. Nevertheless, the proposed framework presents a step forward in automating and accelerating subsurface interpretation while reducing subjective bias.

Acknowledgements

The results presented here are part of Waleed M. AlGharbi's PhD research at Imperial College London, funded by Saudi Aramco. We thank Geoscience Australia and dGB Earth Sciences for the publicly available seismic data. We would also like to thank the John Lab research group at Queen Mary University of London and the Landscapes and Basins Research Group at Imperial College London for their valuable contributions and insightful discussions during the various stages of preparing this work.

Funding

The authors have nothing to report.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Name of the code/library: ClinoSeg.

Hardware requirements: The operating system used was Ubuntu Linux release 22.04 on an Intel Xeon processor, 128 GB (4 × 32GB) RAM, and NVIDIA Quadro RTX 8000 GPU.

Program language: Python.

Software required: The data generation, training, testing, and evaluation were done using Python (version 3.10.6) (Van Rossum and Drake 1995). A number of external dependencies (Python libraries) were used: TensorFlow (2.9.1) (Abadi et al. 2016), TensorFlow-keras (2.9.0) (Chollet 2015), NumPy (1.21.5) (Harris et al. 2020), Pandas (McKinney 2010), YOLO (Jocher et al. 2023), bruges (0.5.4) (Hall and Scientific 2015), SEG-Y-SAK (0.3.4) (Hallam 2020), SciPy (1.8.0) (Virtanen et al. 2020), Scikit-learn (0.23.2) (Pedregosa et al. 2011), Matplotlib (3.5.1) (Hunter 2007), and seaborn (0.12.0) (Waskom 2021).

Program size: 52.3 MB.

The source code is available on GitHub (<https://github.com/wa314/ClinoSeg>) as well as a Zenodo Archive (AlGharbi 2026).

References

- Abadi, M., P. Barham, J. Chen, et al. 2016. "{TensorFlow}: A System for {Large-Scale} Machine Learning." In *12th USENIX Symposium on Operating Systems Design and Implementation (OSDI 16)*, 265–283.
- AlGharbi, W. M. 2026. "wa314/ClinoSeg: Paper." Zenodo. <https://doi.org/10.5281/zenodo.18977525>.
- AlGharbi, W. M., R. E. Bell, and C. M. John. 2025. "SRT-Ai: Identifying Seismic Reflection Terminations Using Deep Learning." *Applied Computing and Geosciences* 27: 100271.
- Al-Salmi, M., C. M. John, and N. Hawie. 2018. "Quantitative Controls on the Regional Geometries and Heterogeneities of the Rayda to Shu'aiba Formations (Northern Oman) Using Forward Stratigraphic Modelling." *Marine and Petroleum Geology* 99: 45–60.
- Bennett, K. J., and M. R. Bussell. 2006. "Demeter High Resolution 3D Seismic Survey—Revitalised Development and Exploration on the North West Shelf, Australia." *APPEA Journal* 46, no. 1: 101–126.
- Bhattacharya, J. P. 2006. "Deltas." In *Facies Models Revisited*, edited by R. G. Walker and H. Posamentier, vol. 84, 237–292. SEPM (Society for Sedimentary Geology) Special Publications.
- Burgess, P. M., D. Roberts, and A. Bally. 2012. "A Brief Review of Developments in Stratigraphic Forward Modelling, 2000–2009." In *Regional Geology and Tectonics: Principles of Geologic Analysis*, vol. 1, 379–404. Elsevier.
- Catuneanu, O. 2019. "Model-Independent Sequence Stratigraphy." *Earth-Science Reviews* 188: 312–388.
- Chollet, F. 2015. "Keras." GitHub. Available at: <https://github.com/fchollet/keras>. [Accessed 7 October 2024].
- Chopra, S., and K. J. Marfurt. 2019. "Unsupervised Machine Learning Applications for Seismic Facies Classification." In *Unconventional Resources Technology Conference, Denver, Colorado, 22–24 July*, 3135–3142. Unconventional Resources Technology Conference (URTEC); Society of Exploration Geophysicists.
- Cole, R. W., T. Jinadasa, and C. M. Brown. 2011. "Measuring and Interpreting Point Spread Functions to Determine Confocal Microscope Resolution and Ensure Quality Control." *Nature Protocols* 6, no. 12: 1929–1941.
- Coléou, T., M. Poupon, and K. Azbel. 2003. "Unsupervised Seismic Facies Classification: A Review and Comparison of Techniques and Implementation." *Leading Edge* 22, no. 10: 942–953.
- Cummings, D. I., and R. W. C. Arnott. 2005. "Growth-Faulted Shelf-Margin Deltas: A New (But Old) Play Type, Offshore Nova Scotia." *Bulletin of Canadian Petroleum Geology* 53, no. 3: 211–236.
- de Matos, M. C., P. L. Osorio, and P. R. Johann. 2007. "Unsupervised Seismic Facies Analysis Using Wavelet Transform and Self-Organizing Maps." *Geophysics* 72, no. 1: P9–P21.
- Di, H., M. Shafiq, and G. AlRegib. 2018. "Patch-Level MLP Classification for Improved Fault Detection." In *SEG Technical Program Expanded Abstracts 2018*, 2211–2215. Society of Exploration Geophysicists.
- Diwan, T., G. Anirudh, and J. V. Tembhurne. 2023. "Object Detection Using YOLO: Challenges, Architectural Successors, Datasets and Applications." *Multimedia Tools and Applications* 82, no. 6: 9243–9275.
- Ester, M., H. P. Kriegel, J. Sander, and X. Xu. 1996. "A Density-Based Algorithm for Discovering Clusters in Large Spatial Databases With Noise." In *Proceedings of the Second International Conference on Knowledge Discovery and Data Mining*, vol. 96, 226–231. AAAI Press.
- Géron, A. 2022. *Hands-On Machine Learning With Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems*. O'Reilly Media, Inc.
- Graham, G. H., M. D. Jackson, and G. J. Hampson. 2015. "Three-Dimensional Modeling of Clinoforms in Shallow-Marine Reservoirs:

- Part 2. Impact on Fluid Flow and Hydrocarbon Recovery in Fluvial-Dominated Deltaic Reservoirs." *AAPG Bulletin* 99, no. 6: 1049–1080.
- Granjeon, D. 1996. "Modelisation Stratigraphique Deterministe – Conception et Applications d'un Modele Diffusif 3D multilithologique." PhD Dissertation, Memoires Geosciences Rennes.
- Granjeon, D. 2014. "3D Forward Modelling of the Impact of Sediment Transport and Base Level Cycles on Continental Margins and Incised Valleys." In *From Depositional Systems to Sedimentary Successions on the Norwegian Continental Margin*, 453–472. Wiley.
- Granjeon, D., and P. Joseph. 1999. "Concepts and Applications of a 3-D Multiple Lithology, Diffusive Model in Stratigraphic Modeling."
- Hall, M., and A. Scientific. 2015. *Bruges: A Python Library for Geophysics*. GitHub. Available at: <https://github.com/agilescientific/bruges>. Accessed: 11 November 2024.
- Hallam, T. R. 2020. *SEG-Y SAK: A Python Library for Reading, Writing, and Processing SEG-Y Seismic Data*. GitHub Available at: <https://github.com/trhallam/segysak>. [Accessed: 11 November 2024].
- Haq, B. U. 2014. "Cretaceous Eustasy Revisited." *Global and Planetary Change* 113: 44–58.
- Haq, B. U., and A. Boersma, eds. 1998. *Introduction to Marine Micropaleontology*. Elsevier.
- Harris, C. R., K. J. Millman, S. J. Van Der Walt, et al. 2020. "Array Programming With NumPy." *Nature* 585, no. 7825: 357–362.
- Hawie, N., R. Deschamps, D. Granjeon, et al. 2017. "Multi-Scale Constraints of Sediment Source to Sink Systems in Frontier Basins: A Forward Stratigraphic Modelling Case Study of the Levant Region." *Basin Research* 29: 418–445.
- Helland-Hansen, W., and G. J. Hampson. 2009. "Trajectory Analysis: Concepts and Applications." *Basin Research* 21, no. 5: 454–483.
- Holgate, N. E., G. J. Hampson, C. A. L. Jackson, and S. A. Petersen. 2014. "Constraining Uncertainty in Interpretation of Seismically Imaged Clinoforms in Deltaic Reservoirs, Troll Field, Norwegian North Sea: Insights From Forward Seismic Models of Outcrop Analogs." *AAPG Bulletin* 98, no. 12: 2629–2663.
- Houseknecht, D. W., K. J. Bird, and C. J. Schenk. 2009. "Seismic Analysis of Clinoform Depositional Sequences and Shelf-Margin Trajectories in Lower Cretaceous (Albian) Strata, Alaska North Slope." *Basin Research* 21, no. 5: 644–654.
- Hunter, J. D. 2007. "Matplotlib: A 2D Graphics Environment." *Computing in Science & Engineering* 9, no. 3: 90–95.
- Jackson, M. D., G. J. Hampson, and R. P. Sech. 2009. "Three-Dimensional Modeling of a Shoreface-Shelf Parasequence Reservoir Analog: Part 2. Geologic Controls on Fluid Flow and Hydrocarbon Recovery." *AAPG Bulletin* 93, no. 9: 1183–1208.
- Jocher, G., J. Qiu, and A. Chaurasia. 2023. "Ultralytics YOLO (Version 8.0.0) [Computer Software]." <https://github.com/ultralytics/ultralytics>.
- Kallweit, R. S., and L. C. Wood. 1982. "The Limits of Resolution of Zero-Phase Wavelets." *Geophysics* 47, no. 7: 1035–1046.
- Kaur, H., N. Pham, S. Fomel, et al. 2023. "A Deep Learning Framework for Seismic Facies Classification." *Interpretation* 11, no. 1: T107–T116.
- Kvalvaer, M., C. Kelley, A. R. Rahbi, J. Stammeijer, and N. Balushi. 2020. "Clinoform Interpretation for Stratigraphic Features Utilizing Machine Learning Methodology." In *SEG International Exposition and Annual Meeting*, D031S055R002. SEG.
- Lecomte, I., and T. Kaschwich. 2008. "Closer to Real Earth in Reservoir Characterization: A 3D Isotropic/Anisotropic PSDM Simulator." In *SEG Technical Program Expanded Abstracts 2008*, 1570–1574. Society of Exploration Geophysicists.
- Lecomte, I., P. L. Lavadera, I. Anell, S. J. Buckley, D. W. Schmid, and M. Heeremans. 2015. "Ray-Based Seismic Modeling of Geologic Models: Understanding and Analyzing Seismic Images Efficiently." *Interpretation* 3, no. 4: SAC71–SAC89.
- Liu, M., M. Jervis, W. Li, and P. Nivlet. 2020. "Seismic Facies Classification Using Supervised Convolutional Neural Networks and Semisupervised Generative Adversarial Networks." *Geophysics* 85, no. 4: O47–O58.
- McKinney, W. 2010. "Data Structures for Statistical Computing in Python." *SciPy* 445, no. 1: 51–56.
- Miller, K. G., M. A. Kominz, J. V. Browning, et al. 2005. "The Phanerozoic Record of Global Sea-Level Change." *Science* 310, no. 5752: 1293–1298.
- Mitchum, R. M., P. R. Vail, and S. I. I. Thompson. 1977. "Seismic Stratigraphy and Global Changes of Sea Level, Part 2: The Depositional Sequence as a Basic Unit for Stratigraphic Analysis."
- Neal, J., and V. Abreu. 2009. "Sequence Stratigraphy Hierarchy and the Accommodation Succession Method." *Geology* 37, no. 9: 779–782.
- Paola, C. 2000. "Quantitative Models of Sedimentary Basin Filling." *Sedimentology* 47: 121–178.
- Patruno, S., G. J. Hampson, and C. A. Jackson. 2015. "Quantitative Characterisation of Deltaic and Subaqueous Clinoforms." *Earth-Science Reviews* 142: 79–119.
- Patruno, S., and W. Helland-Hansen. 2018. "Clinoforms and Clinoform Systems: Review and Dynamic Classification Scheme for Shorelines, Subaqueous Deltas, Shelf Edges and Continental Margins." *Earth-Science Reviews* 185: 202–233.
- Pedregosa, F., G. Varoquaux, A. Gramfort, et al. 2011. "Scikit-Learn: Machine Learning in Python." *Journal of Machine Learning Research* 12: 2825–2830.
- Pellegrini, C., S. Patruno, W. Helland-Hansen, R. J. Steel, and F. Trincardi. 2020. "Clinoforms and Clinoforms: Fundamental Elements of Basin Infill." *Basin Research* 32: 187–205.
- Petter, A. L., R. J. Steel, D. Mohrig, W. Kim, and C. Carvajal. 2013. "Estimation of the Paleoflux of Terrestrial-Derived Solids Across Ancient Basin Margins Using the Stratigraphic Record." *Bulletin* 125, no. 3–4: 578–593.
- Pirmez, C., L. F. Pratson, and M. S. Steckler. 1998. "Clinoform Development by Advection-Diffusion of Suspended Sediment: Modeling and Comparison to Natural Systems." *Journal of Geophysical Research: Solid Earth* 103, no. B10: 24141–24157.
- Redmon, J., S. Divvala, R. Girshick, and A. Farhadi. 2016. "You Only Look Once: Unified, Real-Time Object Detection." In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 779–788. IEEE.
- Rich, J. L. 1951. "Three Critical Environments of Deposition, and Criteria for Recognition of Rocks Deposited in Each of Them." *Geological Society of America Bulletin* 62, no. 1: 1–20.
- Ricker, N. 1953. "The Form and Laws of Propagation of Seismic Wavelets." *Geophysics* 18, no. 1: 10–40.
- Schubert, E., J. Sander, M. Ester, H. P. Kriegel, and X. Xu. 2017. "DBSCAN Revisited, Revisited: Why and How You Should (Still) Use DBSCAN." *ACM Transactions on Database Systems* 42, no. 3: 1–21.
- Seard, C., J. Borgomano, D. Granjeon, and G. Camoin. 2013. "Impact of Environmental Parameters on Coral Reef Development and Drowning: Forward Modelling of the Last Deglacial Reefs From Tahiti (French Polynesia; IODP Expedition# 310)." *Sedimentology* 60, no. 6: 1357–1388.
- Shi, Y., X. Wu, and S. Fomel. 2019. "SaltSeg: Automatic 3D Salt Segmentation Using a Deep Convolutional Neural Network." *Interpretation* 7, no. 3: SE113–SE122.
- Steckler, M. S., G. S. Mountain, K. G. Miller, and N. Christie-Blick. 1999. "Reconstruction of Tertiary Progradation and Clinoform Development

on the New Jersey Passive Margin by 2-D Backstripping." *Marine Geology* 154, no. 1–4: 399–420.

Steel, R., and T. Olsen. 2002. "Clinoforms, Clinoform Trajectories and Deepwater Sands." In *Sequence Stratigraphic Models for Exploration and Production: Evolving Methodology, Emerging Models and Application Histories*, edited by J. M. Armentrout and N. C. Rosen, 367–381. Proceeding of the 22nd Annual Bob F. Perkins Research Conference. Gulf Coast Section, Society of Economic Paleontologists and Mineralogists (GCS-SEPM).

Sydow, J. C., J. Finneran, and A. P. Bowman. 2013. "Stacked shelf-edge delta reservoirs of the Columbus Basin, Trinidad, West Indies."

TerraNubis. 2020. "Project F3 Demo 2020." <https://terranubis.com/datainfo/F3-Demo-2020>.

Tschannen, V., M. Delescluse, N. Ettrich, and J. Keuper. 2020. "Extracting Horizon Surfaces From 3D Seismic Data Using Deep Learning." *Geophysics* 85, no. 3: N17–N26.

Vail, P. R., R. M. Mitchum, and S. I. I. I. Thompson. 1977. "Seismic Stratigraphy and Global Changes of Sea Level, Part 3: Relative Changes of Sea Level From Coastal Onlap."

Van Rossum, G., and F. L. Drake Jr. 1995. *Python Tutorial*. Vol. 620. Centrum voor Wiskunde en Informatica.

Vijayakumar, A., and S. Vairavasundaram. 2024. "Yolo-Based Object Detection Models: A Review and Its Applications." *Multimedia Tools and Applications* 83, no. 35: 83535–83574.

Virtanen, P., R. Gommers, T. E. Oliphant, et al. 2020. "SciPy 1.0: Fundamental Algorithms for Scientific Computing in Python." *Nature Methods* 17, no. 3: 261–272.

Waskom, M. L. 2021. "Seaborn: Statistical Data Visualization." *Journal of Open Source Software* 6, no. 60: 3021.

Watney, W. L., E. C. Rankey, and J. Harbaugh. 1999. "Perspectives on Stratigraphic Simulation Models: Current Approaches and Future Opportunities."

Wrona, T., I. Pan, R. E. Bell, R. L. Gawthorpe, H. Fossen, and S. Brune. 2021. "3D Seismic Interpretation With Deep Learning: A Brief Introduction." *Leading Edge* 40, no. 7: 524–532.

Wrona, T., I. Pan, R. L. Gawthorpe, and H. Fossen. 2018. "Seismic Facies Analysis Using Machine Learning." *Geophysics* 83, no. 5: O83–O95.

Wu, H., and B. Zhang. 2018. "A Deep Convolutional Encoder-Decoder Neural Network in Assisting Seismic Horizon Tracking." arXiv Preprint. arXiv:1804.06814.

Wu, X., L. Liang, Y. Shi, and S. Fomel. 2019. "FaultSeg3D: Using Synthetic Data Sets to Train an End-To-End Convolutional Neural Network for 3D Seismic Fault Segmentation." *Geophysics* 84, no. 3: IM35–IM45.

Zeng, H. 2010. "Stratal Slicing: Benefits and Challenges." *Leading Edge* 29, no. 9: 1040–1047.

Zhang, W., X. Gu, L. Tang, Y. Yin, D. Liu, and Y. Zhang. 2022. "Application of Machine Learning, Deep Learning and Optimization Algorithms in Geoengineering and Geoscience: Comprehensive Review and Future Challenge." *Gondwana Research* 109: 1–17.