GEOSTATS 2024 ● 12th International Geostatistical Congress ● Azores ● 2-6 September 2024

Uncertainty in AI Based Reservoir Modelling Workflows

V. Demyanov, Q. Corlay, A. Nathanail, C. Sun, G. Shishaev, D. Arnold[1]
Institute of GeoEnergy Engineering, Heriot-Watt University, Edinburgh
geodatascience.hw.ac.uk, v.demyanov@hw.ac.uk

Abstract. Reservoir modelling workflows are subject to large uncertainties on every step starting from interpretation of exploration data, coming up with a reservoir modelling concept, describing reservoir characteristics and property distribution, integration of dynamic data and model calibration and update as new data become available.
Modern development of AI tech opens outstanding opportunities to handle the above generic tasks with the methods designed to handle diverse and noisy data. AI can discover patterns in data, describe complex geological patterns with dependencies learned from data, adapt models to data and search for a range of possible optimal development options subject to uncertainty. Effective AI application to reservoir modelling workflows relies on the ability to ensure interpretability of the machine learning model outcomes. This can be achieved by embedding the domain context into the AI model structure, so the data are no longer treated as merely digital values but the variables with physical meaning and interpretation in the subsurface context.
In this overview demonstrates a few examples of how AI tech can help elicit and describe uncertainty in a geologically consistent way to ensure realism of geological interpretations and geomodel outcomes. AI applications will cover several steps of reservoir modelling workflow including:
1) AI seismic segmentation and geobody interpretation with unsupervised learning [1].
2) Constrain geological conceptual modelling with learning from outcrops [2].
3) Populate facies in meandering fluvial reservoir models based on learning from depositional process modelling with generative adversarial networks (GANs) [3].
4) Dynamic and static data integration with variational autoencoders and uncertainty representation via latent space to predict reservoir dynamics [4].
The work will demonstrate how to gain better understanding and representation of associated geological uncertainty when geological domain knowledge is embedded into the AI algorithms' structure.

Keywords: machine learning, unsupervised, computer vision, generative learning, seismic interpretation, sedimentological structures, facies modelling, history matching, uncertainty.

1 Introduction

Uncertainty quantification remains an integral component of subsurface studies and accurate uncertainty identification, description, prediction and management become a key to the successful resource development. Subsurface uncertainty is associated with many geological aspects and physical characteristics of flow in porous media.

Predictive modelling always relies on the incomplete data and understanding of the subsurface reservoir systems. Accurate characterization, propagation and inference of these uncertainties is the key for reliable prediction of subsurface system performance under development.

Geostatistics has been seen a powerful tool to handle uncertainty in describing spatial distribution of properties in geological systems. However, it is limited to describe certain types of uncertainty better than others. For instance, interpretational and conceptual uncertainty is significantly difficult to quantify, due to its subjective nature [5]. Geostatistics is capable of handling inherent uncertainty due to subscale heterogeneity to a certain extent, and uncertainty associated with geostatistical model parameters, e.g. multi-scale spatial correlation and distribution. A wide family of geostatistical algorithms allows to account for model uncertainty only to a certain extent and is still limited to hand model inadequacy and missing unknowns. Geological data is subject to inherent measurement and interpretational uncertainty (e.g. petrophysics), and geostatistics offers little help to account for input data uncertainty. Moreover, most of geostatistical algorithms treat point data as hard data, which is seen as a large stretch in the model conditioning assuming a steep upscaling step.

AI have found its way into geostatistical context a few decades ago and proved its efficiency as a complimentary and even alternative modelling technology to conventional geostatistics [6,7]. Machine learning offers several important advantages: (i) it is not tied to fixed model assumptions (e.g., stationarity, Gaussianity); (ii) inherently adapts to data without enforcing “hard” conditioning (e.g., kriging); (iii) offers certain flexibility to control the model complexity and predictive power in a data driven way. Machine learning is used nowadays in a wide range of subsurface modelling applications: seismic processing, interpretation and inversion; petrophysics, spatial geological property distribution and flow modelling, data mining of many reservoir attributes, etc. One of the common drawbacks of purely data driven approaches remain the lack of interpretability. It remains at the forefront of active research and many ideas have been developed to empower AI with interpretable physics driven/hybrid element.

Generic subsurface modelling tasks can be represented by four consequent steps:

(i) Discover patterns in geological and reservoir data subject to uncertainty;
(ii) Describe variability and heterogeneity in subsurface models;
(iii) Predict dynamic outcomes of subsurface resources development;
(iv) Decide on resource development with confidence under uncertainty.

AI is capable of tackling each of the above steps and, therefore, extends the capability of geostatistics.

This work presents a selective overview of subsurface modelling workflows associated with some of the above tasks and feature a common focus on gaining interpretability of AI applications in subsurface modelling. This overview will briefly describe the following geological modelling workflows developed in a number of recent PhD theses [1-4] at Heriot-Watt University:

1) AI seismic interpretation with detection of geobodies by unsupervised segmentation [1] – (i) discover patterns in data;

2) Gaining conceptual model understanding through learning from outcrop pattern recognition [2] – (i) discover patterns in data;
3) 3D reconstruction of facies spatial distribution with generative learning [3] – (ii) describe spatial variability;
4) Match geological model to dynamic data to predict reservoir response with Graph Variational Auto-encoders [4] – (iii) Predict reservoir dynamics.

2 AI seismic interpretation

Fast screening of target geobodies from seismic is essential to identify the range of plausible geological interpretations, which is usually very expert time consuming and subjective. A proposed seismic interpretation workflow is aimed to segment geobodies through density based clustering of the point cloud seismic, which decodes seismic information based on extrema extracted from seismic traces [1]. Point cloud representation reduces the seismic cube with a factor of two. Further segmentation with Density-Based Spatial Clustering of Applications with Noise (DBSCAN) identifies connected segments and leads to the further reduction in the model description to the finite set of objects (10^3) [8]. The second stage of the workflow (see IV in Fig. 1) aims to characterise the discovered objects as particular geological shape according to the target concept (e.g. a fan, or a channel, or an intrusive sill). Given a small number of manually interpreted labelled data (identified geobodies) conventional supervised learning approaches are not feasible. Therefore, the search for the closest similar shapes among the found segments is conducted in a feature space using binary hashing approximate nearest neighbour method. The high dimensional feature space is constructed using geometric features extracted from the segmented shapes: seismic amplitude metric (Zeboudj's disparity), aspect ratio, contour ratio.

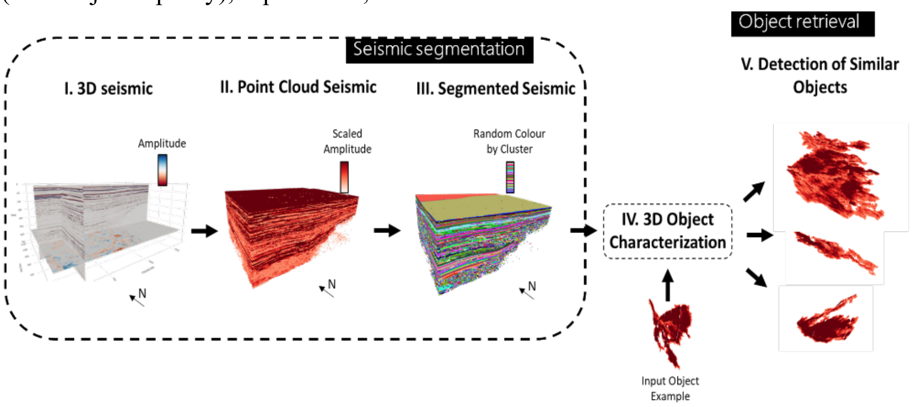
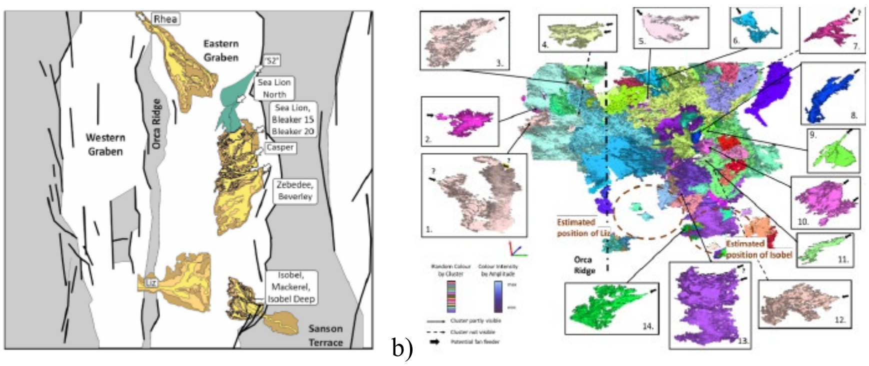


Fig. 1. AI seismic interpretation workflow for geobody segmentation and object characterization according to seismic amplitude and shape feature similarity.

Uncertainty in seismic segmentation is handled by the tuneable DBSCAN parameters (*epsilon*-neighbourhood and the minimum number of points in a cluster). The variability between the obtained segmentations is indexed with a clustering noise metric ratio to achieve the balance between over- and under-segmentation.

Figure 2 demonstrates the output of the interpreted turbidite fans in North Falkland Basin and compares with those interpreted manually by the BGS (Dodd, 2023). Ten potential fans are located in the Eastern Graben, with sediment inputs mainly coming from the eastern margin (objects 5 to 14, Fig. 2b)), and four potential fans are located in the North of the Western Graben (objects 1 to 4), with sediment inputs either from the east (intragraben high - Orca Ridge) or the western margin. By comparing these potential fans with the fan map drawn up by Dodd et al. [9] (Fig. 2a), we can identify with varying degrees of confidence five of the seven interpreted fans: Rhea (object 5 in figure 5.8(a)), Sea Lion North (object 9), Sea Lion (object 10), Casper (object 11) and Zebedee and Beverley (northern part of object 13).



a) b)

Fig. 2. Position of the main fans interpreted in the North Falkland Basin used as ground-truth detection (from [9]) (a); Results of the 100 closest objects to the Sea Lion fan analysis of the potential fans observed (b).

Seismic segmentation through clustering is performed in time domain, hence all the object sizes and shapes are not in measured metric distance. Time-depth conversion can be performed with conventional seismic inversion (SI) workflows. Segmented seismic objects can inform SI workflows as an additional conditioning constraints and help propagated interpretational uncertainty into SI.

3 Learning from outcrop pattern recognition

Conceptual uncertainty is one of the most difficult to describe and quantify due its subjective nature. Conceptual depositional interpretation is usually based on sparce fragmental evidence collated with the geological knowledge and understanding based on past experience elicited from analogues. Outcrop information is the key source of evidence of plausible combination of depositional features that constitute combined evidence to justify one or another geological interpretation. Therefore, there is an opportunity to use AI pattern recognition for rapid screening of large banks of available outcrops to solicit geological evidence and attribute them to sparce *in situ* data from the target case. Interpretation based on the relevant outcrop information can help to come up with multiple conceptual modelling scenarios to better capture conceptual uncertainty.

Pattern recognition with supervised deep learning is able to detect depositional structures and segment facies sequence from an outcrop [2]. The conceptual understanding of the facies sequences and the associated depositional structures is then attributed to associate with the sparce data from the target case to come up with multiple conceptual modelling scenarios (Fig. 3).

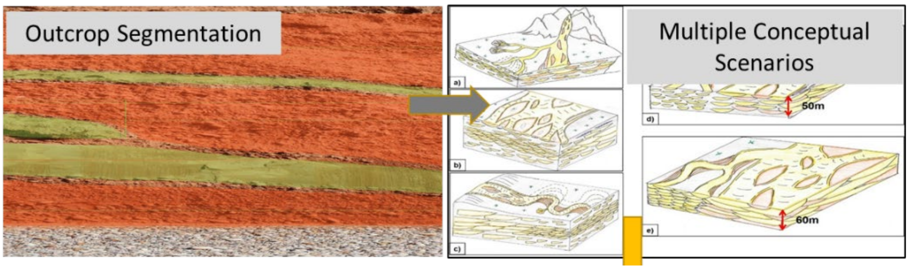


Fig. 3. A figure caption is always placed below the illustration. Short captions are centered, while long ones are justified. The macro button chooses the correct format automatically.

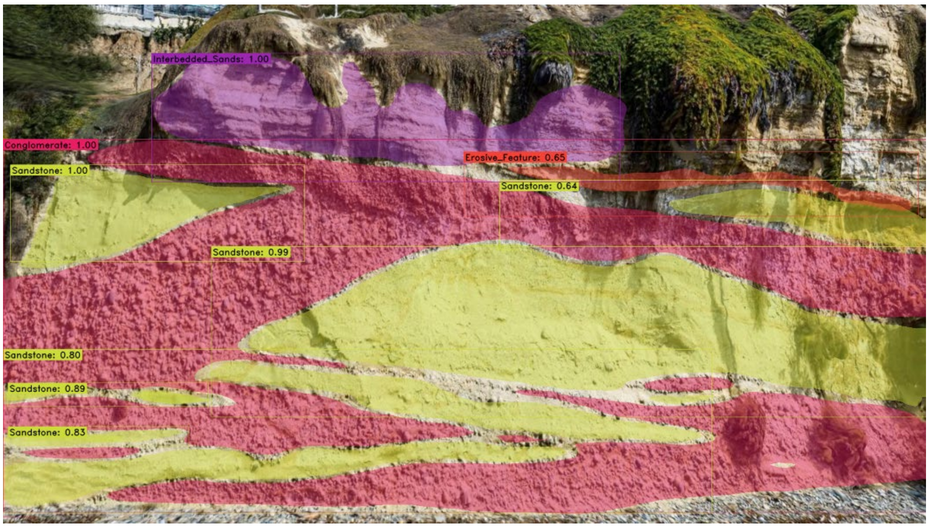


Fig. 4. Instance Segmentation predictions of sedimentary structures (sandstone, interbedded sands, conglomerates), including a mask, bounding box, label, and the associated probability of the prediction on a Deep Marine depositional environment.

Deep convolution neural networks were used to detect sedimentary structures You only look once (YOLO) [16] and segment sedimentary structures You Only Look At

Coefficients (YOLACT) [17]. Presence of a certain sedimentary structure is detected within a bounding box in the outcrop image in the first instance. Then, the detected sedimentary instance is being segmented with contour shape and the associated probability. Figure 4 illustrates deep marine sedimentary structures segmented in the unseen part of an outcrop after training on the other part of the same outcrop.

Subjectivity of depositional interpretation remains an issue in conventional expert modelling workflows as it relies on the expert experience and exposure to data [18]. Quantification of uncertainty of manual interpretation is challenging and often has to be done in Bayesian inverse way. AI is capable to learn form a much wider and more abundant amount of outcrop evidence. Correctly trained neural network provides an unbiased solution because it balances bias and complexity. The source of bias may still remain with the training data set if it is unbalanced or lacks certain types of examples. Therefore, it is essential to make sure the training/testing/validation data set are representative of the relevant variation of depositional cases to avoid bias in AI interpretation. The annotations of the outcrop features for labelled data was done manually by multiple geologists to avoid bias and mistakes. There is still room to enhance pattern recognition training with conceptual information to de-bias the training and make inference more objective. An example can be found in the work that blends outcrop images with sketch-based interpretation to improve prediction quality [19]. Sketches constitute unconditional expert interpretations and represent domain expert knowledge fused into CNN learning.

Further mitigation of unrealistic pattern recognition outcomes can be addressed with referring to domain knowledge encapsulated in geological literature. Natural Languate Processing was used to scan heritage geologic records and existing publications for realistic combinations of the individual features lined to plausible depositional interpretations [2]. Then, a neural network was trained with the individual features (extracted from the outcrops) and their plausible combinations from the literature to produce the list of plausible conceptual interpretations that match the outcrop evidence.

4 3D facies reconstruction with generative learning (GAN)

Modelling spatial distribution of facies is one of the key steps in geological modelling workflow. Facies distribution is subject to important uncertainties associated with facies interpretation, aspects of the depositional concept, facies shapes, proportions and connectivity. All the above can make a significant impact on further subsurface resource development.

Geostatistics offers various algorithms to populate facies properties based on 2-point spatial correlation, training images or predefined object shapes [10]. These approaches vary in the level of geological realism and natural variability of the deposited facies patterns they can provide and the ability to honor the conditioning data. Geostatistical models may still lack geological realism vs the level that can be achieved by physics-based process models.

Generative deep learning is seen as a viable approach to model complex, non-stationary facies patterns. Deep learning is capable to learn and reproduce complex spatial patterns and can be trained on the geologically realistic patterns from physics-based process models. This opens an opportunity to account for geological uncertainty associated with the variation in the depositional process, e.g. avulsion, and also tackle the challenge of conditioning process models to point and soft data. Generative modelling can be also computationally less expensive than process modelling at field scale, especially for uncertainty quantification studies with ensembles of generated models.

Generative Adversarial Networks (GANs) were used to learn complex 3D fluvial facies distributions from an ensemble of process model realization across variable avulsion low NTG scenarios. Low NTG cases are particularly challenging due to their impact on connectivity. Variability in channel avulsion conditions (*Nav*) provide a range of channel shapes from sheet like (low avulsion) to ribbon-like (high avulsion) that feature different connectivity. An open-access training data set (GAN River I) with a variable avulsion settings was generated using FLUMY process model [11].

Trained GAN was able to realistically reproduce complex fluvial patterns, facies shapes, sequences and connectivity. The bespoke newly developed FluvialGAN avoids many artifacts related to unrealistic geological features and abnormal facies transition [12].

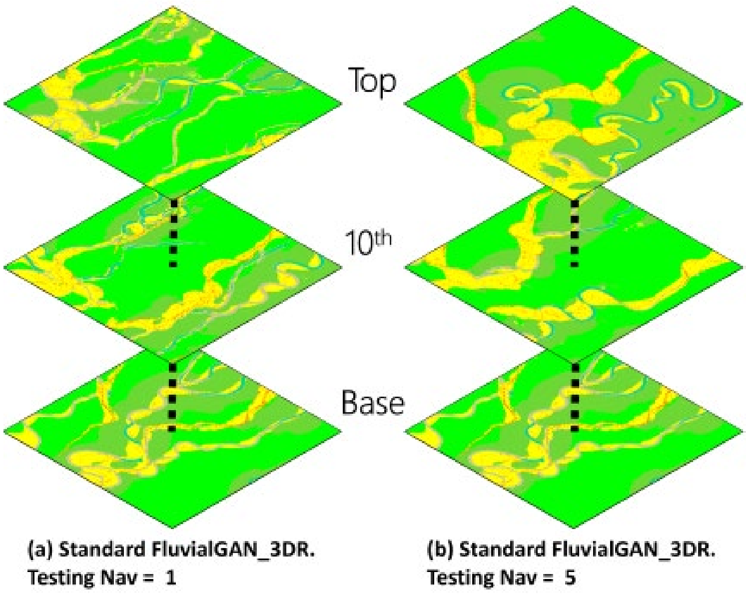
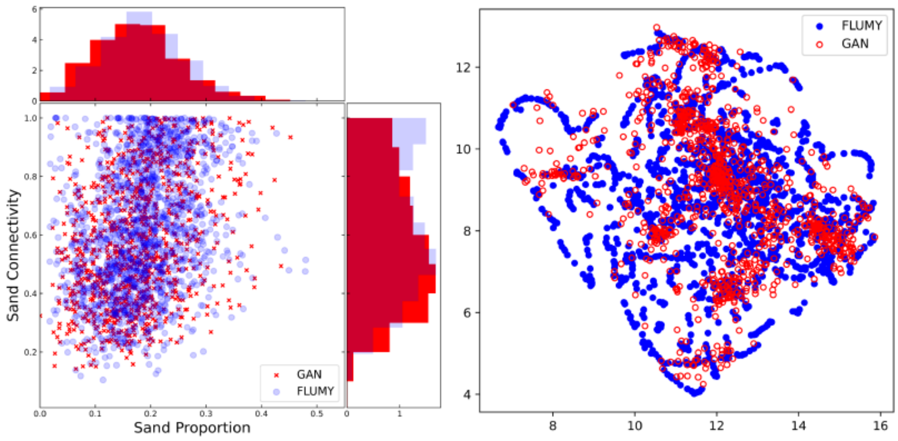


Fig. 5. Comparison of meandering patterns when changing channel avulsion rate Nav from 1 to 5 in the standard FluvialGAN_3DR reconstruction process: with high avulsion rate Nav = 1 during reconstruction, with low avulsion Nav =5 (b).

FluvialGAN_3DR trains on a sequence of 2D facies patterns and then reconstructs a 3D depositional sequence from bottom to top mimicking a natural depositional process [13]. This is also computationally more efficient than training on 3D patterns. FluvialGAN_3DR trained on 2D can then reconstruct fluvial formations of arbitrary thickness not constrained by the 3D training data thickness. Figure 5 illustrates two 3D facies successions generated by the FluvialGAN_3DR for high and low avulsion scenarios. The results confirm that the depositional process can follow the given depositional regime throughout the formation sequence thickness.

Figure 6a illustrates the comparison of S connectivity curves as functions of the channel sand proportion between GAN reconstruction ensemble and the corresponding process model realizations (FLUMY) [3]. The S-curve percolation threshold around 20% of the sand proportion suggests a comparable connectivity level, while the cascade zone around the threshold covers a similar spread of variability across the ensembles. Comparable connectivity spreads in the UMAP projection (Fig. 6b) also illustrate a good agreement between GAN modelling and the process modelling outcomes.

The proposed GAN approach for facies distribution modelling can be compared to geostatistical MPS approach. Though both are able to produce similar types of solutions their algorithmic nature is quite different. MPS is does not generate patterns in as a result of learning from data, it is rather a pattern completion algorithm based on probabilistic sampling from a conditional distribution based on a single training image. This brings pros and cons. MPS works very well with not very complex multi-facie/multivariate patters and is straightforward to condition to hard and soft data. However, MPS often suffers from artifacts, especially locally, and may struggle to represent complex non-linear depositional trends and uncertainty in non-stationary behaviour. Fluvial GAN is a fully generative algorithms that learns from data and generates new patters *not seen* in the data. It has demonstrated how to avoid geologically inconsistent artifacts and embed implicit conditioning to complex non-linear trends learned from depositional process modelling. GAN RIVER I data set [11] offers a challenging benchmark case of highly realistic multi-facie example to compare different modelling algorithms.



(a) The sand connectivity VS NTG plot **(b) Visualisation in the UMAP space**

Fig. 6. The sand connectivity against proportion plot (a) and UMAP visualisation (b) of FLUMY realisations against Fluvial GANs' realisations. Blue points are FLUMY realisations. Red points are Fluvial GANs' realisations.

5 History matching with Graph Variational Autoencoders

Calibration of static geological models to the dynamic data is an integral part of the reservoir prediction uncertainty quantification workflows. This is essentially an inverse problem that implies multiple solutions and usually requires a comprehensive computationally intensive iterative optimisation algorithm to achieve the solution. Dynamic data conditioning implies iterative static model property update, which may result in geologically unrealistic solution if the updates are not constrained with geological consistency. This proved to be difficult to achieve with geostatistical modelling.

Generative learning is one of the AI approaches recently been applied to solve inverse problems in reservoir model update and history matching [14]. This particular work demonstrates a novel flavour of variational autoencoders – Graph Wasserstein Auto-encoder (GWAE) adapted for automated history matching workflow [4]. Graph autoencoders are not restricted to lattice grids and are able to better capture structural discontinuities of geological models, which has been always a limitation of geostatistical model representation. Another advantage of GWAE is that it is inherently multivariate, i.e. represents non-linear relations between corelated properties such as porosity and permeability.

GWAE is trained directly on the continuous property data by skipping the explicit facies modelling step, unlike conventional geostatistical modelling workflows. Training of the encoder decoder pair commences on the ensemble of reservoir model grids populated with continuous porous properties (porosity and permeability) using geostatistical modelling workflow. Designing the training ensemble is essential to ensure its diversity to cover plausible geological model uncertainty range that is represented by a low dimensional latent space. GWAE training implies control of geological realism via interpretative hidden space, which forms a low dimensional representation of the geologically plausible model configurations. Dynamic flow response and production data are not used in training and therefore no prior CPU-costly reservoir flow simulations are required. However, the optimisation loop is run over the designed latent space in the search for the models that that would match production history. This inverse loop requires computing flow simulation model response. Navigation on the GWAE latent space between the encoder and decoder provides efficient model update by generating model realisations that better agree with the dynamic data via optimisation iterations. Finally, GWAE model is conditioned to both static and dynamic data in the same loop, which is gains computational efficiency, balance the model fit to static and dynamic, without assuming the hard point data and 100% certain, which they are not.

GWAE was applied to history matching of the benchmark Brugge field [15]. Figure 7 illustrates the top fluvial layer porosity distribution generated by GWAE compared with the reference object/SGS model. They show good agreement and a normal distribution of their differences. Further agreement between the two models is illustrate with the variogram comparison in Figure 8a and the reproduction of the petrophysical dependency in Figure 8b.

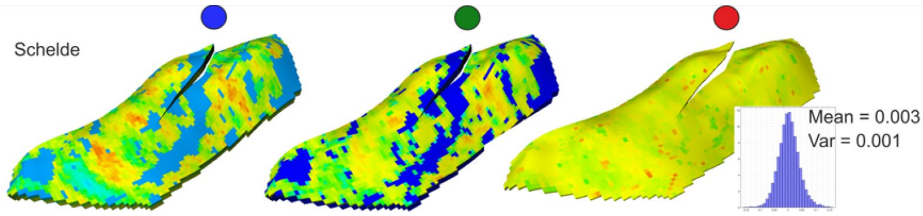
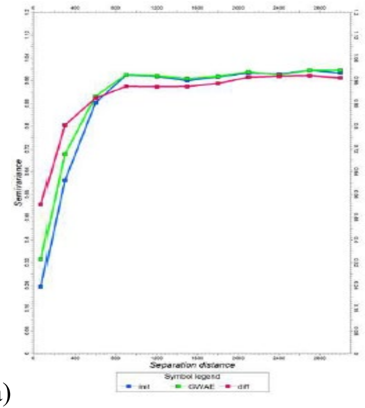
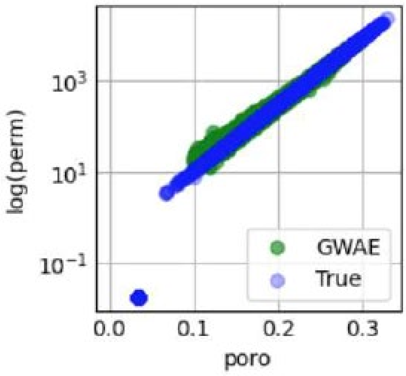


Fig. 7. GWAE reconstruction of the porosity field (●) for the fluvial layer of Brugge model compared with the refence object model (●) and the corresponding difference (●) and its statistics.



a)



b)

Fig. 8. Comparison of the variograms for the GWAE porosity model and the reference for the fluvial layer of Brugge field from Fig 7 vs the variogram of difference (a). Reproduction of porosity-permeability correlation by GWAE model vs the reference (b).

Figure 9 illustrates the obtained individual well history matches vs the initial prior ensemble of models. Static well data are also in good agreement though not hard 100% conditioned but allow some deviation to account for point data uncertainty at the wells.

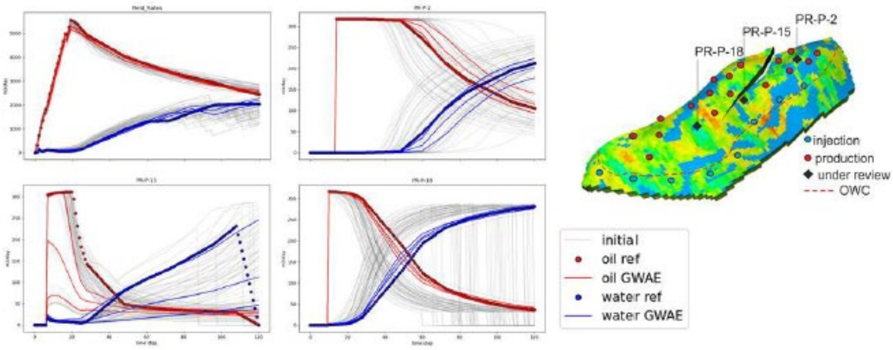


Fig. 9. GWAE AHM results for the selected individual wells vs the observed production.

6 Conclusions

This work provides a selective overview of how various AI methods can help tackle difficult problems across the entire subsurface modelling workflow. Learning from data and their associated uncertainties enables to account for a more diverse range of unknowns than geostatistics in a less rigid way. AI offer a great selection of algorithms that can learn realistic natural dependencies from data in a supervised or unsupervised way to gain geological realism and interpretability.

This overview follows key conventional steps of subsurface modelling and demonstrates how geological uncertainty can be handled in a data driven way at each step: seismic interpretation, conceptual modelling, facies modelling and dynamic. The overview includes examples of: (i) how AI for seismic interpretation learns interpretable seismic features in an unsupervised way; (ii) how supervised deep learning learns and collates depositional contextual information from outcrop data to inform conceptual models and account for interpretational uncertainty; (iii) GANs are capable to learn complex facies spatial distribution pattern from physics based simulations and generate realistic 3D sequences with respect to natural depositional uncertainty factors (channel avulsion); (iv) Graph variational auto-encoder framework for inverse modelling successfully solved history matching problems through reliable model update via the constructed hidden space between encoder and decoder. GWAE navigates the hidden space to generate model updates ensuring geological realism and accurately balances between static and dynamic data match.

AI application requires tailoring standard techniques to account for the geological domain context specifics. This requires a deep understanding of geological context and domain knowledge to be able to embed it into the structure of machine learning algorithms. Success in AI applications in subsurface reservoir modelling is achieved by gaining interpretability of the machine learning outcomes and control in how well their performance is justified by reproducible geologically realistic aspects.

Acknowledgments. This work is based on a series PhD theses completed in 2023/24 from GeoDataScience and UQ group supervised by Prof V. Demyanov and Dr. D. Arnold at Heriot-Watt University that were supported by Natural Environment Research Council (NERC) Centre for Doctoral Training (CDT) in Oil & Gas [grant number NEM00578X/1], NERC National Productivity Investment Fund (NPIF) s and Heriot-Watt University via its James Watt Scholarship scheme. V. Demyanov acknowledges the support from Rock Flow Dynamics to be able to present this work at Geostats 2024. The authors appreciate PhD theses examiners for thorough review work and valuable comments to help improve the work: Prof. A. ElSheikh, Prof. G. Caumon, Prof. M. Kanevski, Prof. U. Nicholson, Prof. G. Rongier, Prof. D. Stow, Prof D. Voskov; and the reviewers of the manuscript submitted to Geostat 2024.

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

References

1. Corlay, Q.: Fast Detection of Geobodies in 3D Seismic with Unsupervised Segmentation PhD thesis, Heriot-Watt University (2023)
2. Nathanail, A.: Capturing interpretational uncertainty of depositional environments with Artificial Intelligence, PhD thesis, Heriot-Watt University (2023)
3. Sun, C.: Use of Generative Learning to Improve Realism in Fluvial Facies Modelling, PhD thesis, Heriot-Watt University (2023)
4. Sishaev, G.: History Matching and Uncertainty Quantification of Reservoir Performance with Generative Deep Learning and Graph Convolutions, PhD thesis, Heriot-Watt University (2024)
5. Bond, C. E., Gibbs, A. D., Shipton, Z. K., and Jones, S.: What do you think this is? "Conceptual uncertainty" In geoscience interpretation. GSA Today, **17**(11):4–10, 2007.
6. Kanevski M., Michel Maignan, M.: Analysis and Modelling of Spatial Environmental Data, EPFL Press/Taylor & Francis, (2004)
7. Kanevski, M., Timonin, V., Pozdnukhov, A.: Machine Learning for Spatial Environmental Data - Theory, Applications, and Software, EPFL Press/Taylor & Francis, (2009)
8. Corlay, Q., Demyanov, V., McCarthy, D., Arnold, D.: Turbidite Fan Interpretation in 3D Seismic Data by Point Cloud Segmentation Using Machine Learning, EAGE 2020 Annual Conference & Exhibition Online, 2020 (1), 1-5.
9. Dodd. T.J.H., McCarthy, D.J., Richards, P.C.: A depositional model for deep-lacustrine, partially confined, turbidite fans: Early Cretaceous, North Falkland Basin, Sedimentology **66** (1), 53-80, (2019)
10. Pyrcz, M., Deutsch, C.: Geostatistical Reservoir Modeling, Oxford University Press, 2nd Edition, (2004)
11. Sun C., Demyanov V., Arnold D.: GAN River-I: A process-based low NTG meandering reservoir model dataset for machine learning studies, Data in Brief **46**, 108785, (2023)
12. Sun, C., V Demyanov, V., Arnold, D.: Geological realism in Fluvial facies modelling with GAN under variable depositional conditions, Computational Geosciences **27** (2), 203-221, (2023)
13. Sun, C., V Demyanov, V., Arnold, D.: A conditional GAN-based approach to build 3D facies models sequentially upwards, Computers & Geosciences **181**, 105460, (2023)
14. Mosser, L., Dubrule, O., Blunt, K., J., DeepFlow: History Matching in the Space of Deep Generative Models, arXiv:1905.05749, (2019)
15. Shishaev G., Demyanov, V., Arnold D., Vygon, R.: Application of Graph Variational Autoencoders for History Matching Problem of Brugge Field, 5th EAGE Conference on Petroleum Geostatistics, Porto, (2023)
16. Redmon J., Divvala S., Girshick R ., Farhadi A.: You Only Look Once: Unified, Real-Time Object Detection, *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Las Vegas, NV, USA, 2016, pp. 779-788, doi: 10.1109/CVPR.2016.91, (2016)
17. Bolya D., Zhou C., Xiao F., Lee YJ.: YOLACT: Real-time Instance Segmentation, arXiv:1904.02689, (2019)
18. Bond C.E., Gibbs A.D., Shipton Z.K., Jones S.: What do you think this is? “Conceptual uncertainty in geoscience interpretation”, GSA today 17 (11), 4, (2007)
19. Nathanail A., Demyanov V., Arnold D. and Gardiner A.: The Importance of Blending Different Data Types to Train Machine Learning Classifiers for Sedimentary Structure Detection, 82nd EAGE Annual Conference & Exhibition, (2021)