Subsurface

Insights

April 2021

Advantaged Hydrocarbons: A Head Start in the Race to Project Sanction

The Evolution of Assisted Fault Interpretation — Part 2

Python™: How to Free a Geoscientist

HALLIBURTON

Landmark

Subsurface insights

APRIL 2021

CONTENTS

Dear Reader,

Welcome to the April edition of the Subsurface Insights magazine. This is an exciting edition for me, as it is my first as the new editor. I replace Rebecca Head, who is moving to a new position within the company, having served as editor for four years. Best of luck Rebecca!

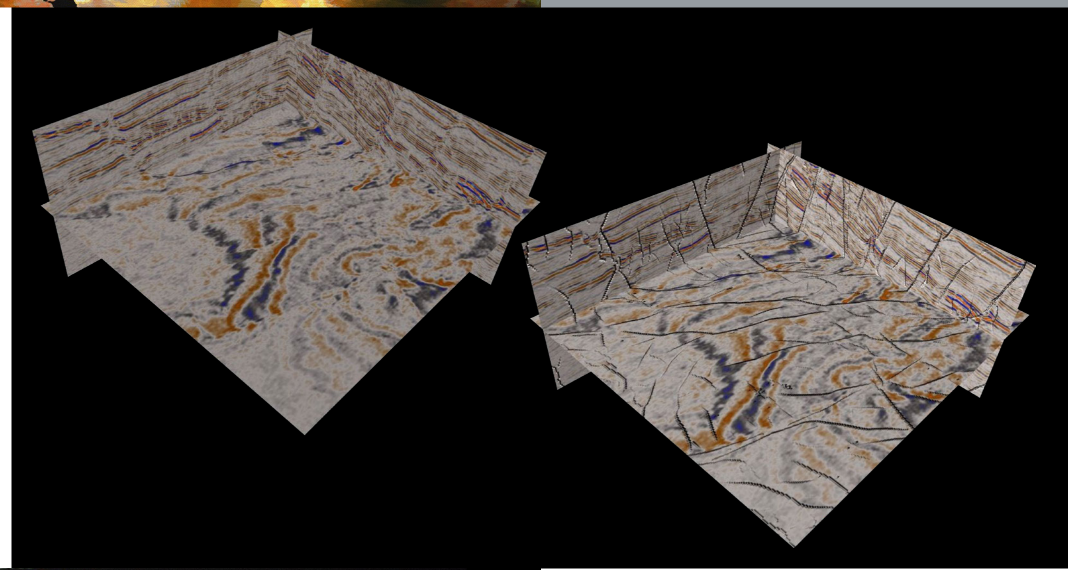
Over the years, the readership and reach of this magazine has grown, and we have also widened the scope of the subject matter. I am committed to continuing that trend. The ambition of the magazine has been to provide substantive, state-of-the-art pieces on a wide range of subjects that appeal to customers and non-customers, alike. Forthcoming articles will be no different.

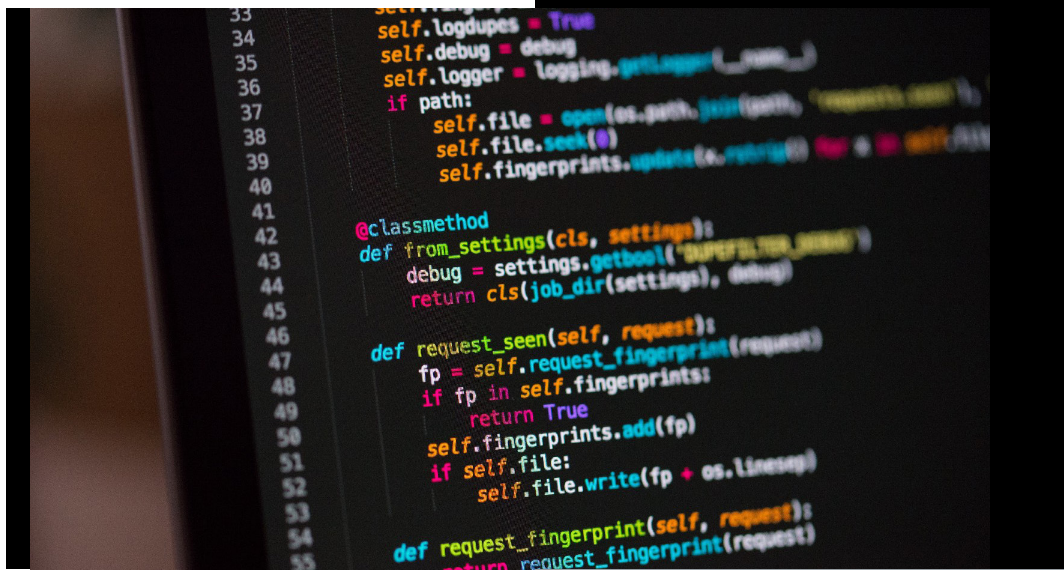
This is certainly an interesting moment for me to be taking the reins, with so many changes occurring in the industry. Recent events are forcing oil and gas companies to re-focus on value generation, higher value assets, closer-to-market targets, and geological knowledge adjacencies. In response to such challenges, our lead article this month discusses 'advantaged hydrocarbons,' which is becoming a key concept as companies assess their portfolios and future exploration plans with the energy transition in mind.

As part of our aim to broaden the magazine's view, this edition includes the second installment of a two-part feature on Landmark innovations, highlighting the use of machine learning in seismic analysis. Finally, we have an insightful piece on our continued drive to increase the efficiency of Neftex® geoscience workflows; in this case, by using Python™ software to solve complex geometrical and paleogeographical mapping problems.

I hope you enjoy this special edition. Your interest is very much appreciated, and your feedback is always welcome — please do not hesitate to contact us.

Joss Smith
EDITOR,
SUBSURFACE INSIGHTS





Editor
Joss Smith
Editorial Advisor
Mike Simmons
Artwork
Rachel Hopper
Design
Rachel Hopper
Marketing
Amy Taylor & Rachel Round
Circulation
Stefanie Clayton

On the cover: Image by natureworks from Pixabay

Enjoying the *Subsurface Insights* magazine?

This magazine is published by Halliburton Landmark.
For comments and suggestions contact:
ExplorationEnquiries@Halliburton.com.

The Search for Advantaged Hydrocarbons: A Key Consideration in the 21st Century Energy Transition

by: Andrew Davies, Mike Simmons, and Alex Bromhead

MEETING DEMAND, RESPONSIBLY

Together, oil and gas currently provide around 55 percent of the global energy supply (BP, 2020). Simmons et al. (2020) and Davies and Simmons (2020) have highlighted how challenging it is to quickly replace hydrocarbons with low-carbon energy sources. Consequently, oil and gas form a significant part of the energy mix in future energy demand scenarios, even those focused on meeting the goals of the Paris Agreement on Climate Change. An analysis of recently published rapid energy transition scenarios suggests around 950 billion barrels of oil (BBBL) and 4,750 trillion cubic feet (Tcf) of gas will be required in the next three decades, with around 280 BBBL of oil and 2,200 Tcf of gas needing to be found to complement existing recoverable reserves (Figure 1) (Davies and Simmons, in press). To place this in context, that is an oil demand equivalent to approximately 62 percent of all the oil we have so far consumed, and approximately 108 percent of all the gas we have consumed to date. A key consideration for the oil and gas industry will be the emphasis placed on '*advantaged hydrocarbons*' — those with a relatively low carbon/energy intensity to discover and produce. In combination with significant carbon sequestration activity, this will help ensure that demand for hydrocarbons is met in the most environmentally responsible manner.

In this article, we review the concept of 'advantaged hydrocarbons', with a focus on how the nature of the subsurface, and the hydrocarbon fluids to be extracted, impact the carbon/energy intensity of exploration and production operations.

RECOGNIZING 'ADVANTAGE' IN THE SUBSURFACE

The term 'advantaged hydrocarbons' is beginning to resonate within the oil and gas industry, although it has lacked a precise definition. The term has been related to low-risk, large volumes of oil or gas, with a relatively low cost of exploitation (e.g. because of proximity to established infrastructure). 'Super basins' (Fryklund and Stark, 2020) are an example of this concept. However, it can be expanded to capture the notion that hydrocarbons need to be found and produced while keeping greenhouse gas (GHG) production to a minimum during operations. Indeed, low-cost, low-risk, large volumes and minimal GHG emissions often go hand in hand. In determining which plays and prospects to explore, and which assets to exploit, consideration of the relative degree of advantage will form part of the screening and decision-making process, leading to project sanction. Such a concept is compatible with the increased focus on sustainability within the industry (IPIECA, 2020; OGCI, 2020).

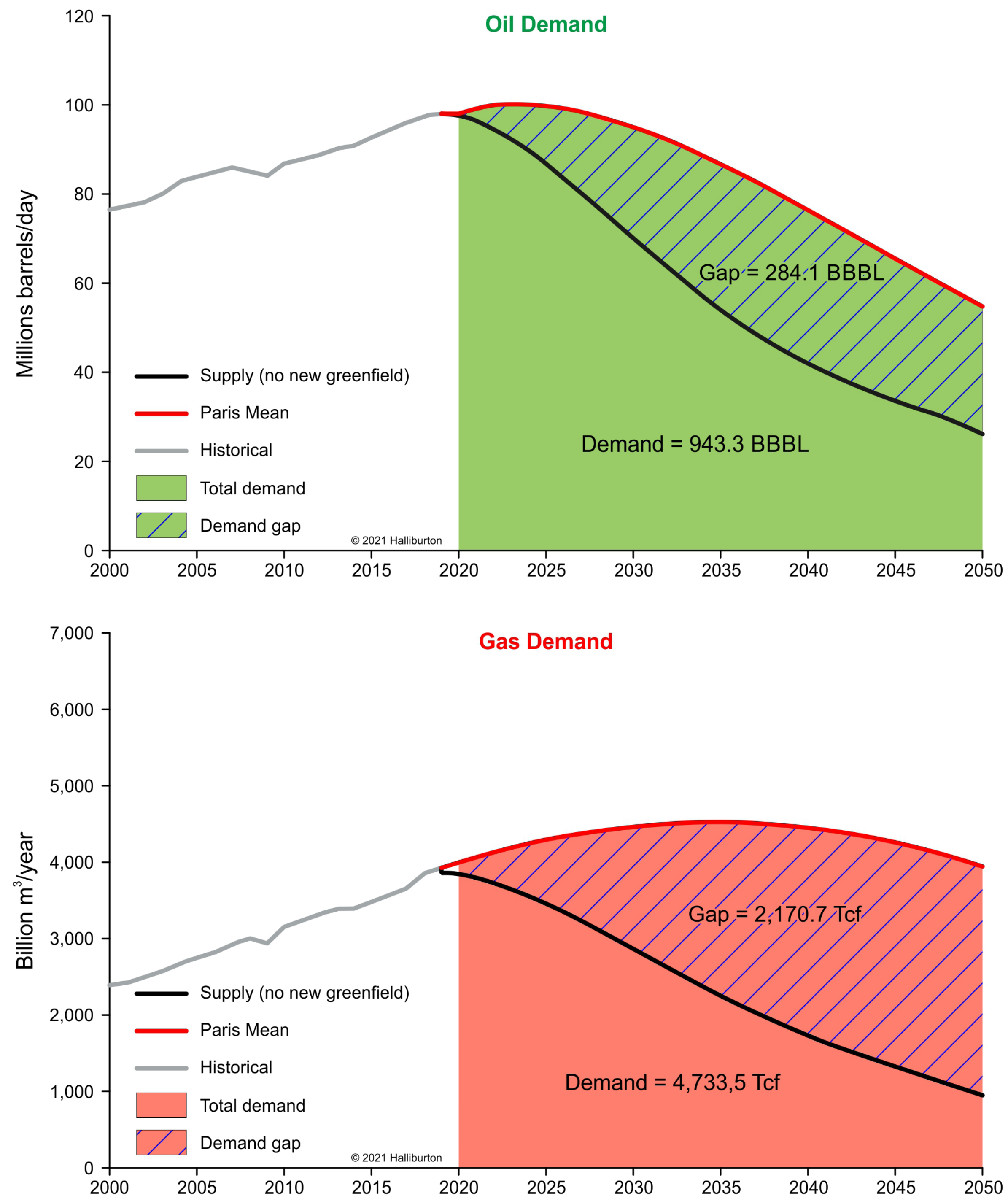


Figure 1 > Future oil and gas demand as determined from an analysis of multiple rapid energy transition scenarios. The red Paris Mean curve is a mean value calculated from nine future energy demand scenarios, all in keeping with best efforts to meet the goals of the Paris Agreement on Climate Change. Scenarios analyzed are: Barclays (Dynamism), BP (Rapid Transition), Equinor (Rebalance), IEA (Sustainable Development), McKinsey (Accelerated Transition), Rystad Energy (Governmental Targets), Shell (Sky), Total (Rupture), and World Energy Council (Unfinished Symphony). Modified after Davies & Simmons (in press).

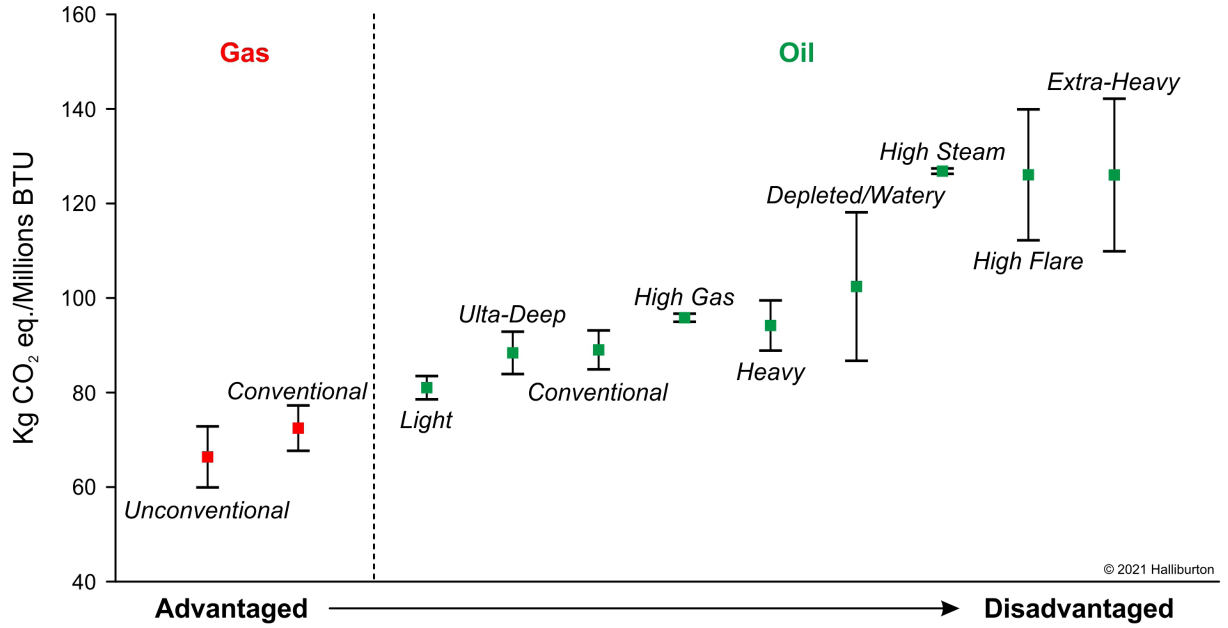


Figure 2 > Total lifecycle GHG emissions associated with different types of hydrocarbons. Data for oil come from Gordon et al. (2015) and Jiang et al. (2011), and Burnham et al. (2012) for gas. Modified after Davies & Simmons (in press).

We, therefore, favor the following definition for advantaged hydrocarbons:

Economically prioritized hydrocarbons that can be discovered, exploited, and decommissioned in a long-term, low-oil-price context in a sustainable and environmentally sensitive way, with minimal carbon intensity.

Advantage will not be the only factor that determines the sanctioning of an exploration or production project, but it does give an indication of the head start a project may have in the race to be sanctioned.

Key characteristics of advantaged hydrocarbons include:

» Low risk of exploration failure or poor production characteristics per well
Note: Dry wells or high water-cut production wells are wasted energy and can create unnecessary GHG emissions.

» Relatively simple to drill

» Minimal need for subsurface interventions once in production, leading to limited topside environmental footprint with predictable and stable long-term production

Herein, we are particularly concerned with emissions associated with upstream activities, although ultimately, the emissions associated with the full lifecycle of the product are important (Jing et al., 2020). Gordon et al. (2015) created the Oil-Climate Index (OCI) to quantify the total lifecycle GHG emissions of individual oils. They noted a range of GHG emissions corresponding to a range of oil types classified by their density, depth, and extraction method (Figure 2). Extra-heavy oils have typical GHG emissions 60 percent greater than light oils. Similar calculations have been conducted for total lifecycle GHG emissions for gas (Jiang et al., 2011; Burnham et al., 2012).

The Oil Production Greenhouse Gas Emissions Estimator (OPGEE) (El-Houjeiri et al., 2013, 2017) takes the concept of OGI one step further. OPGEE considers a comprehensive set of factors that contribute to GHG emissions during the complete lifecycle of oilfield development and enables calculation of GHG emissions and carbon intensity. Upstream factors include seismic data gathering, exploratory drilling, development drilling, lifting, injection, fluid separation, and storage.

Using OPGEE, Masnadi et al. (2018) reviewed the average Carbon Intensity (CI) index (g CO_2 eq. MJ^{-1}) of oil and gas operations in a large number

of countries. Results ranged from a low of 3.3 (within a range of 3–7) for Denmark to a high of 20.3 for Algeria and Venezuela (within a range of 15–30+). This wide spectrum reflects production ranging from pure methane or light oil in geologically simple, relatively shallow reservoirs, to the exploitation of heavy, biodegraded oil in complex reservoirs. The CI index, therefore, reflects both subsurface geology and engineering practices, although the two are intimately linked.

With favorable geology, drilling and subsurface engineering becomes easier and less energy intensive, leading to lower GHG emissions.

Benchmarking studies are required to fully assess and quantify the impact of all the possible variations of subsurface geology on advantage; but, nonetheless, some broad observations on geological criteria and their impact on advantage can be made (Table 1).

Category	Geological Risk	Impact on Carbon Intensity
Drilling	Depth to reservoir	Greater depths require more energy
	Overburden stratigraphy	Difficult to penetrate lithologies; require greater energy to drill through
	Subsurface drilling hazards	These (e.g. shallow gas, borehole instability, pressure anomalies) can extend drilling time and energy use. Shallow gas may need disposal.
Hydrocarbon Type	Fluid type	Pure light crude or methane will be the least energy intensive to produce and process.
	Fluid impurities	Undesirable impurities require greater energy for mitigation activity and processing. Examples include: • CO_2, which requires capture and disposal (although can be reinjected to enhance recovery) • H_2S
	Gas:Oil Ratio (GOR)	Production is less energy intensive if only one hydrocarbon fluid phase is present. Gas presence in oil fields requires separation and possibly highly undesirable flaring.
Reservoir	Reservoir quality	High porosity/permeability reservoirs are easier to produce and require less energy intensive stimulation.
	Vertical and horizontal reservoir heterogeneity	Complex heterogeneities (e.g. baffles and barriers) result in low recovery factor and complex production drilling. Laterally continuous reservoirs can be exploited by a relatively low number of long-reach lateral wells.
	Reservoir pressure	Optimal subsurface pressure allows hydrocarbons to flow to surface with minimal artificial lift/waterflood (at least initially).

Table 1 > Example of geological risks to be considered in screening for advantaged hydrocarbons. Modified after Davies and Simmons (in press).

The geological risks listed in Table 1 can be screened at the play, prospect, or asset scale to determine relative advantage, or disadvantage, to assess their impact on the carbon/energy intensity of operations. Benchmarking and sensitivity analysis are required to quantify the impact of each risk and the interplay between them, but qualitative analysis allows for relative ranking.

Methane emission reduction is a key industry target in reducing the GHG footprint of oil and gas operations (OGCI, 2020). Upstream gas management strategies could potentially mitigate approximately 18 Gt of CO_2 equivalent emissions in the 21st century (Masnadi et al., 2018).

In addition to these geological factors, there are other criteria that serve to reduce the energy intensity and potential GHG emissions of exploration and production operations. Examples include:

- Proximity to existing infrastructure, including availability of gas processing to exclude flaring
- Operations taking place outside of environmental extremes
- Use of geothermal energy from produced waters, or tethered wind energy facilities
- Reinjection of produced CO_2 both into associated saline aquifers (as at Sleipner in the Norwegian North Sea) and to facilitate enhanced oil recovery (EOR)
- Maximize use of existing data to understand the subsurface geology for both exploration and production

EXAMPLES OF ADVANTAGE

A good example of advantaged hydrocarbons can be found in the oil fields offshore Guyana and Suriname (e.g. Liza). It is anticipated that eight production wells will be required in a field such as Liza, with each well capable of producing 56 million BBL during its lifetime (Presley, 2019). The oil is a low-sulphur, light, sweet crude with the reservoir formed of thick, low-heterogeneity, highly porous and permeable sandstones. The reservoir has a relatively high pressure, reducing the need for artificial lift, at least in the early stages of the field's life. These discoveries are at the lower end of the exploration and production cost spectrum (USD 35 break-even).

Other examples of advantaged hydrocarbons include the recent gas discoveries in the Eastern Mediterranean (e.g. Zohr) and the Black Sea (e.g. Domino, Tuna/Sakarya). In a more mature province, new discoveries near the ETAP (Eastern Trough Area Project) cluster of fields in the Central North Sea can be integrated into an existing, GHG-efficient infrastructure.

Gas as an energy source contributes to significantly reduced GHG emissions (Tanaka et al., 2019). The partial replacement of coal for electricity generation by gas derived from shale gas plays has contributed to significant reductions of GHG emissions in North America (Schivley et al., 2019). While the paradigm of advantaged hydrocarbons is focused on the energy expenditure and GHG emissions associated with exploration and production, gas should be considered 'advantaged' in an overriding, general sense.

LOOKING AHEAD

The concept of advantage will change the landscape for oil and gas explorers. Plays, prospects, and assets once considered viable for exploration based on prospective return on investment may no longer be sanctioned if they fail to be classified as advantaged. Moreover, fields in the late stages of their life move from advantaged to disadvantaged as energy-intensive EOR techniques are required to sweep remaining hydrocarbons from a reservoir (Masnadi and Brandt, 2017). Hence, while there are large volumes of discovered oil and gas to meet demand for many years to come, is it the best resource? Most of the world's undeveloped barrels have stayed in the ground because they are high cost and need higher prices to bring to market. This indicates that they are geologically complex and, therefore, will be energy-intensive to produce. Discovery of new, advantaged hydrocarbon resources may be preferable.

Geoscience and engineering ingenuity have enabled oil and gas to be found and exploited in diverse environments and subsurface settings. That same ingenuity can be used to turn disadvantage into advantage. An example of shifting to technologies that have a reduced carbon footprint include the use of reformulated (non-Portland) cements. Ocean bottom sensor nodes are also creating an energy efficient revolution is seismic imaging (Walker, 2020). Most importantly, ever-improving modeling and characterization of the subsurface will drive more effective and efficient exploration for, and exploitation of, hydrocarbons, leading to associated reductions in carbon/energy intensity.

Looking ahead, exploration in a low-carbon world will be more targeted, focusing on the best rocks and fluids, especially gas. In the last two years, aggregate upstream carbon intensity has fallen by 7 percent to reach 21.1 kg CO_2e BOE^{-1} (OGCI, 2020). The Oil & Gas Climate Initiative (OGCI) has set a goal of 20 kg CO_2e BOE^{-1} for 2025. If the focus on advantaged hydrocarbons continues, Brandt et al. (2018) calculate that emissions equivalent to 10–50 Gt of CO_2 could be mitigated by 2050. Such mitigation measures can be supported by substantial efforts regarding carbon capture, utilization, and storage (February 2021 issue of Subsurface Insights Magazine).

CONCLUSIONS

Advantaged hydrocarbons can be in part characterized by their geological attributes, as this in turn governs the energy intensity of their exploration and production (Davies and Simmons, in press). Better subsurface understanding leads to lower exploration risk and the drilling of fewer dry wells, with minimization of associated wasted energy and, hence, GHG production. Similarly, better reservoir models can lead to optimal well placement and efficient recovery of hydrocarbons, thereby, reducing energy expenditure per barrel recovered and, therefore, reducing GHG emissions.

Examples of favorable geological attributes include the occurrence of only a single phase of hydrocarbon fluids with minimal impurities and extensive, thick, homogeneous reservoirs with excellent reservoir quality. Benchmarking and sensitivity analysis are needed to quantify the advantage-disadvantage spectrum associated with different hydrocarbon exploration and production opportunities, as that spectrum relates to subsurface geology (a primary controlling factor) and associated engineering. Nonetheless, a qualitative screening for relative advantage based on geological criteria is possible.

ACKNOWLEDGEMENTS

We wish to thank Owen Sutcliffe, Michael Treloar, Helen Smyth, Karen Heyburn, and James Etienne for discussions and comments that assisted us. We have also benefitted from numerous discussions with colleagues in the oil and gas industry at large.

REFERENCES

BP, 2020. Statistical Review of World Energy [Online]. Available: https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html.

Brandt, A.R. Masnadi, M.S., Englander, J.G., Koomey, J. and Gordon, D. 2018. Climate-wise choices in a world of oil abundance. Environmental Research Letters, 13, 4, 044027.

Burnham, A., Han, J., Clark, C.E., Wang, M., Dunn, J.B. and Palou-Rivera, I. 2012. Life-Cycle Greenhouse Gas Emissions of Shale Gas, Natural Gas, Coal, and Petroleum. Environmental Science and Technology, 46, 2, 619–627.

Davies, A. and Simmons, M. 2020 Who needs Stratigraphers, Sedimentologists & Paleontologists? Evolving roles through the Energy Transition. The Sedimentary Record, 18, 4, 12-15.

Davies, A. and Simmons, M.D. in press. Demand for 'advantaged' hydrocarbons during the 21st century energy transition. Energy Reports.

El-Houjeiri, H.M., Brandt, A.R., and Duffy, J.E. 2013. Open-Source LCA Tool for Estimating Greenhouse Gas Emissions from Crude Oil Production Using Field Characteristics Environmental Science and Technology, 47, 11, 5998–6006.

El-Houjeiri, H.M., Masnadi, M.S., Vafi, K., Duffy, J.E. and Brandt, A.R. 2017. Oil Production Greenhouse Gas Emissions Estimator OPGEE v2.0. [Online]. Available: http://pangea.stanford.edu/departments/ere/dropbox/EAO/OPGEE/OPGEE_documentation_v2.0.pdf.

Fryklund, B. and Stark, P. 2020. Super basins—New paradigm for oil and gas supply. AAPG Bulletin, 104, 12, 2507–2519.

Gordon, D. Brandt, A.R., Bergerson, J.A. and Koomey, J. 2015. Know Your Oil: Creating a Global Oil-Climate Index. Carnegie Endowment for International Peace, https://carnegieendowment.org/2015/03/11/know-your-oil-creating-global-oil-climate-index-pub-59285.

IPIECA, 2020. Sustainability reporting guidance for the oil and gas industry. IPIECA, IOGP Report 437 [Online]. Available: https://www.ipieca.org/media/5115/ipieca_sustainability-guide-2020.pdf.

Jiang, M., Griffin, W.M., Hendrickson, C., Jaramillo, P., VanBriesen, J. and Venkatesh, A. 2011. Life cycle greenhouse gas emissions of Marcellus shale gas. Environmental Research Letters, 6, 3, 034014.

Jing, L. et al. 2020. Carbon intensity of global crude oil refining and mitigation potential. Nature Climate Change, 10, 6, Article 6.

Masnadi, M.S. and Brandt, A.R. 2017. Climate impacts of oil extraction increase significantly with oilfield age. Nature Climate Change, 7, 8, Article 8.

Masnadi, M.S. et al. 2018. Global carbon intensity of crude oil production. Science, 361, 6405, 851–853.

OGCI, 2020. Delivering on a Low carbon Future: A Progress Report from the Oil and Gas Climate Initiative. OGCI [Online]. Available: https://oilandgasclimateinitiative.com/.

Presley, J. 2019. Back to Deep Water. E&P Magazine, Hart Energy.

Schivley, G., Azevedo, I. and Samaras, C. 2018. Assessing the evolution of power sector carbon intensity in the United States. Environmental Research Letters, 13, 6, 064018.

Simmons, M., Davies, A., Hill, A.W., Stephenson, M. 2020. Who needs geoscientists? GeoExpro, 17, 4, 15-18.

Tanaka, K., Cavalett, O., Collins, W.J. and Cherubini, F. 2019. Asserting the climate benefits of the coal-to-gas shift across temporal and spatial scales. Nature Climate Change, 9, 5, Article 5.

Walker, C., 2020. Ocean Bottom Node Technology-What Next? Conference Proceedings, Second EAGE Marine Acquisition Workshop, Aug 2020, 1-3.

AUTHORS

Dr Andrew Davies, Chief Geoscience Advisor, Halliburton Landmark

Andrews main role is to help develop the next generation of geoscience tools for use in the oil and gas industry. Previously, he held various positions at Neftex, including Senior Research and Development Geoscientist and Head of Innovation acting as part of the Neftex leadership team. Andrew also holds the position of visiting Senior Research Fellow at the University of Leeds, UK.

Prof. Mike Simmons, Technology Fellow for Geosciences, Halliburton

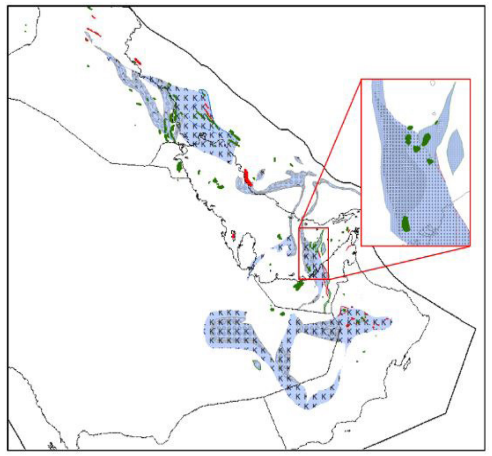
Mike is responsible for the investigation into innovation in geoscience related to hydrocarbon exploration and production. Previously, he was Earth Model Director at Neftex and before that worked for BP, Aberdeen University, and CASP at Cambridge University. His main interests are applied stratigraphy and the geology of the Tethyan region. Mike teaches at a number of universities, where he promotes the value of sequence stratigraphy in the exploration process.

Alex Bromhead, Principal Geoscientist — Core Regional Geoscience, Halliburton Landmark

Alex started his career with Neftex Petroleum Consultants in 2013. He worked across a diverse range of teams and geological provinces before focusing on unconventionals, leading projects concerned with the screening and resource assessment of unconventional plays. Within the Core Regional Geoscience Team, he is involved in both exploration and thought leadership projects. Alex holds an MSci degree in Geology from the University of Southampton, UK.

DISCLAIMER

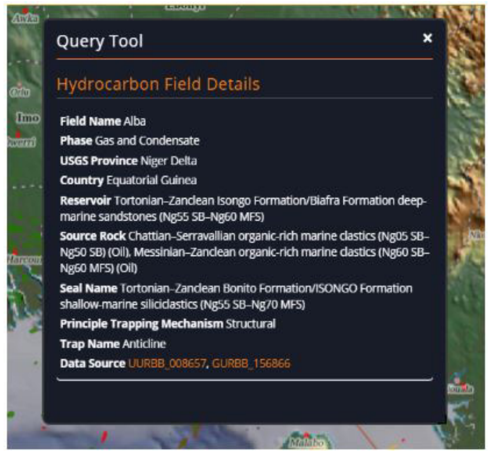
WHAT'S NEW IN NEFTEX® PREDICTIONS



CHARACTERIZING THE PROLIFIC MIDDLE CRETACEOUS PETROLEUM SYSTEMS OF THE ARABIAN PLATE

Exploration for stratigraphic plays can be geologically challenging as it requires a detailed understanding of depositional facies change. Neftex® demonstrate how this can be achieved for the Middle Cretaceous of the Arabian Plate by characterizing paleogeography within a sequence stratigraphic framework.

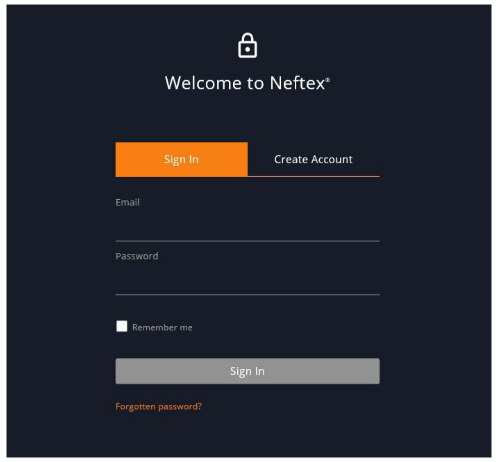
Learn more...



DELVE DEEPER INTO HYDROCARBON FIELDS THROUGH THE WEBMAPPER

We have made improvements to our Petroleum Occurrence layer that significantly enhance the usability of the data provided as part of Neftex® Predictions for researching and analyzing hydrocarbon fields globally.

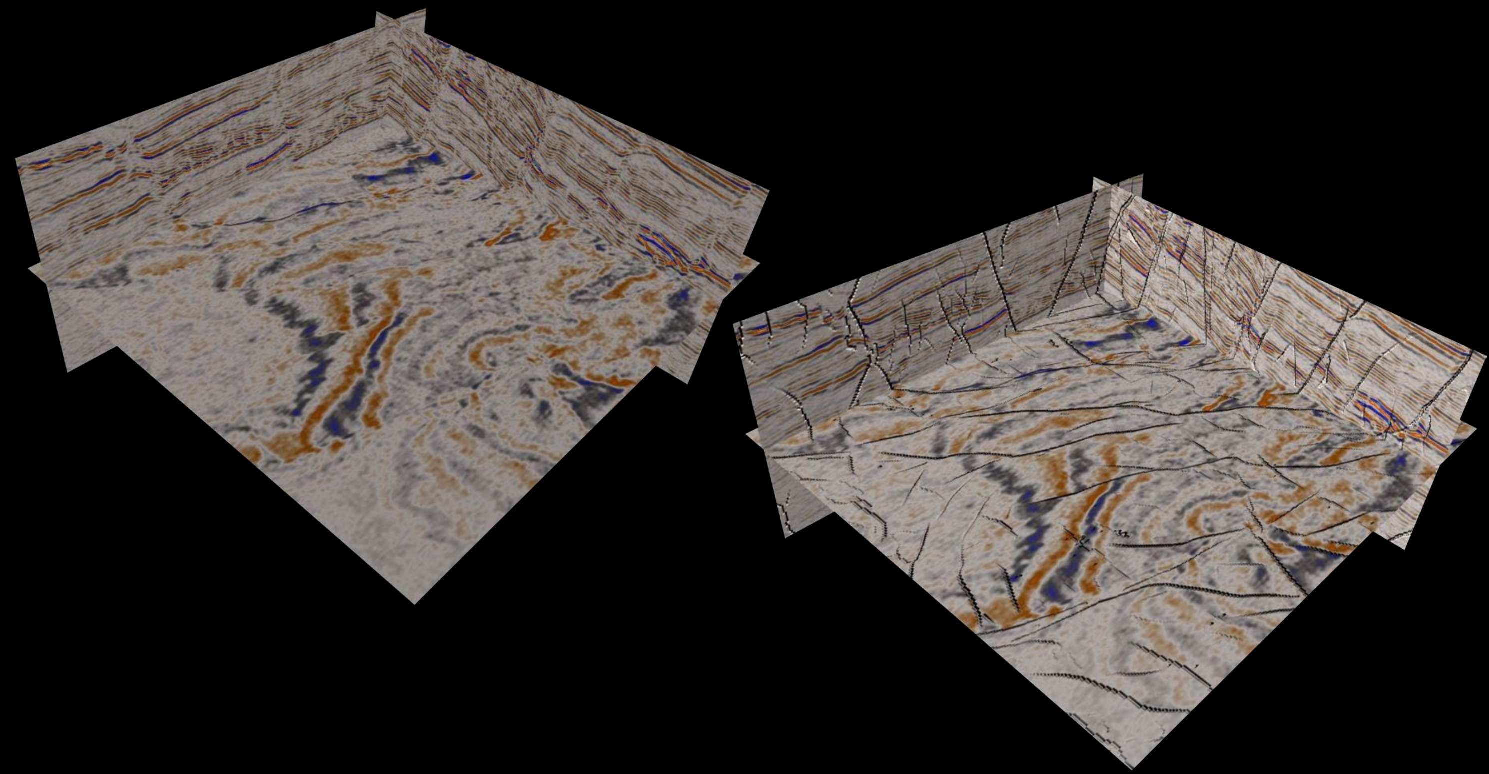
Learn more...



YOUR NEFTEX ACCOUNT IS CHANGING

To protect your Neftex account we are moving to the Landmark standard Okta secure identity platform. Moving to Okta will improve our security protocols to protect your details and access to the Neftex website.

Learn more...



The Evolution of Assisted Fault Interpretation — Part 2

by: Philip Norlund and Fan Jiang

Example of a machine learning fault prediction. The first image is the original input seismic. The second image shows the predicted faults merged with the original data. Data courtesy of Geoscience Australia.

The interpretation of faults in 3D seismic data is an important component of hydrocarbon exploration and development workflows. However, the traditional methods of interpreting faults (typically, the manual interpretation of faults sticks) can be labor-intensive and expensive. To address this, a wave of innovative, technological improvements has led to the creation of tools for assisting, or automating, fault interpretation. The first article of this series (Norlund and Angelovich, 2021) discussed traditional, physics-based approaches and how software advances, such as Halliburton Landmark's Seismic Engine, a DecisionSpace® 365 cloud application, have revolutionized the industry's ability to generate accurate fault-imaging attributes and provide new insights into interpretation uncertainties. This follow-up article discusses how emerging machine learning (ML) technologies are being leveraged today, and how they help change our approach to assisted fault interpretation.

With traditional, physics-based fault imaging approaches, even advanced attributes, such as fault likelihood, can have their limitations. For example, they often misidentify features in seismic data that are not faults, but other geological discontinuities or defects in the seismic data. Additionally, these attributes typically require a clean break in the seismic data to identify a fault; however, many faults are not clearly imaged due to seismic processing limitations (e.g. fault shadows). Thus, these approaches can have trouble with noisy data.

During manual interpretation, an experienced geoscientist can often overcome such limitations by successfully differentiating between real geologic faults and seismic data quality defects. They can also often correctly identify faults even in poorly imaged seismic.

That is where ML can help by incorporating elements of the interpreter's learned knowledge into automated workflows. This article discusses three ML approaches — convolutional neural network (CNN), random forest, and generative adversarial network — and shows how they are being used within Landmark software to assist the geoscientist and significantly reduce the interpretation life cycle.

USING MACHINE LEARNING TO IMAGE FAULTS

We can think of identifying faults in seismic as an image classification problem. In a seismic section, the goal is to classify (label) all the samples as either 'fault' or 'not-fault', something that is done via Seismic Engine. CNNs have shown to be effective tools for solving these types of issues in other industries, such as biomedicine (e.g. Ronneberger et al., 2015). A CNN is a deep learning algorithm, which can take an input image, assign importance to various aspects in the image, and then differentiate one aspect from another. It does this through a series of layers, each more sophisticated at identifying details in an image. In a U-Net CNN architecture, which is essentially two mirrored CNNs, an output image is generated the same size as the input, but with specific features predicted. This is precisely the problem needing to be solved, as shown in Figure 1.

CNNs have been applied to the challenge of detecting faults with good results (e.g. Huang et al., 2017; Jiang and Norlund, 2020). In these examples, the process is the same; train a model based on a subset of data with known answers

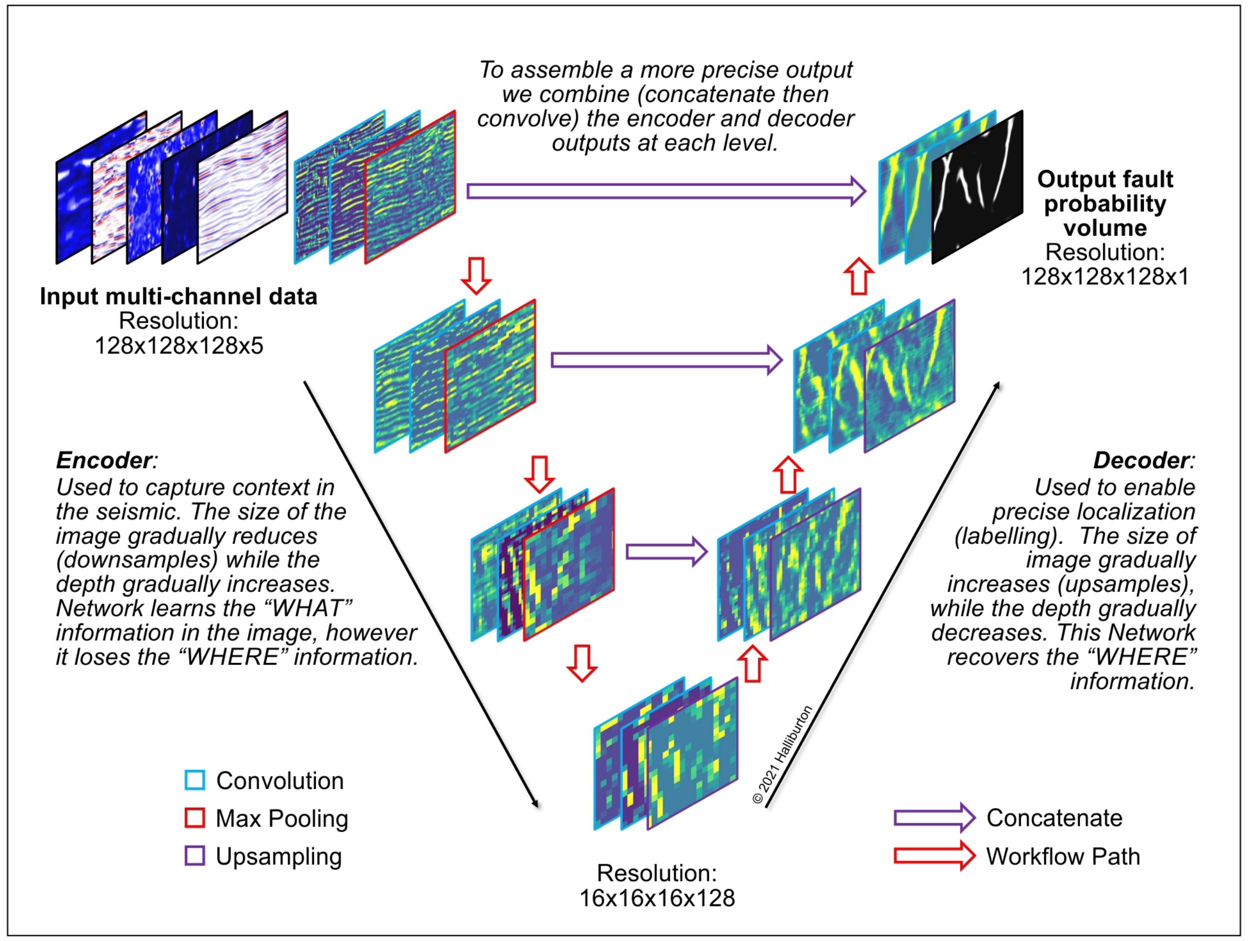


Figure 1 > A simplified diagram showing how a U-Net Convolutional Neural Network takes an input seismic volume and classifies it into distinct features (fault & not-fault). Resolution = IL, XL, Z, Channels.

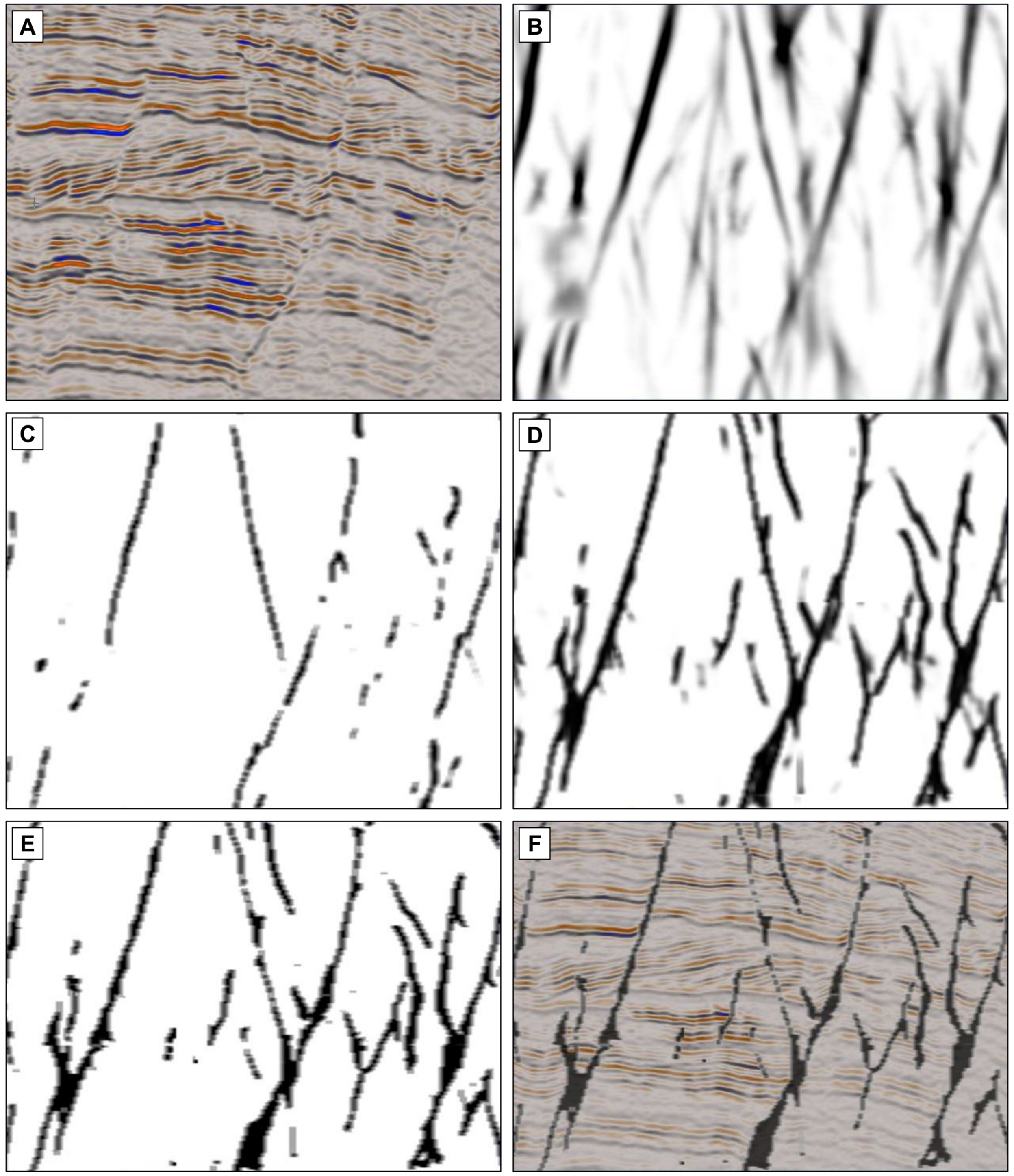


Figure 2 > Examples of attributes discussed, imaged in the same seismic section. (A) Original amplitude seismic, (B) raw fault likelihood, (C) ML fault probability from amplitude data, (D) ML fault probability from multiple seismic attributes, (E) ML fault probability from multiple seismic attributes with GAN applied, and (F) volume 'e' overlain in original seismic 'a'. Data courtesy of Geoscience Australia.

(input seismic + fault labels), and then run that model on the full dataset to generate a fault probability volume. Typically, synthetic data are used to train the model, which is then applied to real field data to generate the output. The input fault labels represent the interpreter's knowledge that is required to build the predictive model.

Figure 2 compares a traditional, physics-based attribute (2B) with a CNN-derived prediction (2C). The ML result compares favorably to the physics-based approach, but lacks a lot of detail. It is also clear, however, that the physics-based attribute has identified many features that are most likely not faults.

LEVERAGING SEISMIC ATTRIBUTES TO IMPROVE FAULT PREDICTION

Results from a CNN approach can be improved in several ways. First, more synthetic data (more interpreter knowledge) could be generated to train a better model. Another way is not just to provide more of the same data, but to provide better data.

A seismic image has more information than a traditional photograph. It is made up of complex traces from which multiple properties (attributes) can be calculated. These attributes give further insight into a dataset, since different attributes can reveal very specific subsurface features (e.g. variations in frequency volumes give insight into the expected fluid or gas content of a reservoir). Different attributes can also vary in how well they image faults throughout a volume. This additional information can be incorporated into the training and prediction process. Additional attributes are added as new channels into an extended U-Net architecture (Jiang and Norlund, 2020) (Figure 3a).

There are two potential challenges with this approach. Firstly, having to generate additional seismic attributes at multiple steps of an ML fault-identification workflow could be prohibitively expensive, from a computational point of view. To overcome this, technologies such as cloud computing and Halliburton Landmark's Seismic Engine can be used to parallelize and distribute any process, allowing thousands of computations to be run at the same time. Additionally, the elasticity of the cloud can be used to scale-up and make available the resources needed to efficiently run the entire workflow. Once the intensive computations are complete, Seismic Engine can automatically scale back down, so expense is not wasted on resources that are no longer required.

The second challenge is, which attributes should be used? Rather than manually testing every combination of seismic attributes to see which ones give the best results, an ML technique called random forest (RF) architecture is adopted. RF methods can efficiently decipher which seismic attributes are optimal for predicting faults. Once identified, these attributes are input as additional channels into a multi-channel U-Net. Figure 2 shows the results from Seismic Engine using multiple attributes (2D) versus the single amplitude volume (2B). It can be seen that much greater detail has been gained and fault prediction improved, while avoiding many of the false predictions inherent in the traditional approach.

While the addition of further attributes predicts more faults, with better continuity, there are areas where fault predictions extend beyond actual fault-plane locations, and the imaging is not as clear as an interpreter would hope for. Further improvement is, thus, desirable.

BRINGING FAULT PREDICTIONS INTO FOCUS

The third ML technique is a post-processing step that helps to fine-tune the fault probability images generated by the previous methods. Generative adversarial networks (GANs) are algorithmic architectures that pit two neural networks against each other as 'adversaries'. One network (the generator) creates new images, while the other network (the discriminator) tries to classify examples as real or fake. The two models are trained together until the discriminator outwits the generator. GANs have been applied to many different geophysical problems, such as reducing noise in seismic processing workflows and assisting in the identification of features such as salt bodies and facies (Liu et al 2019). Here again, synthetic data are used to train the adversarial model, which is then applied to real data. Figure 2 shows that the fault images reconstructed with GANs (2E & F) display clearer, thinner, and more continuous segments.

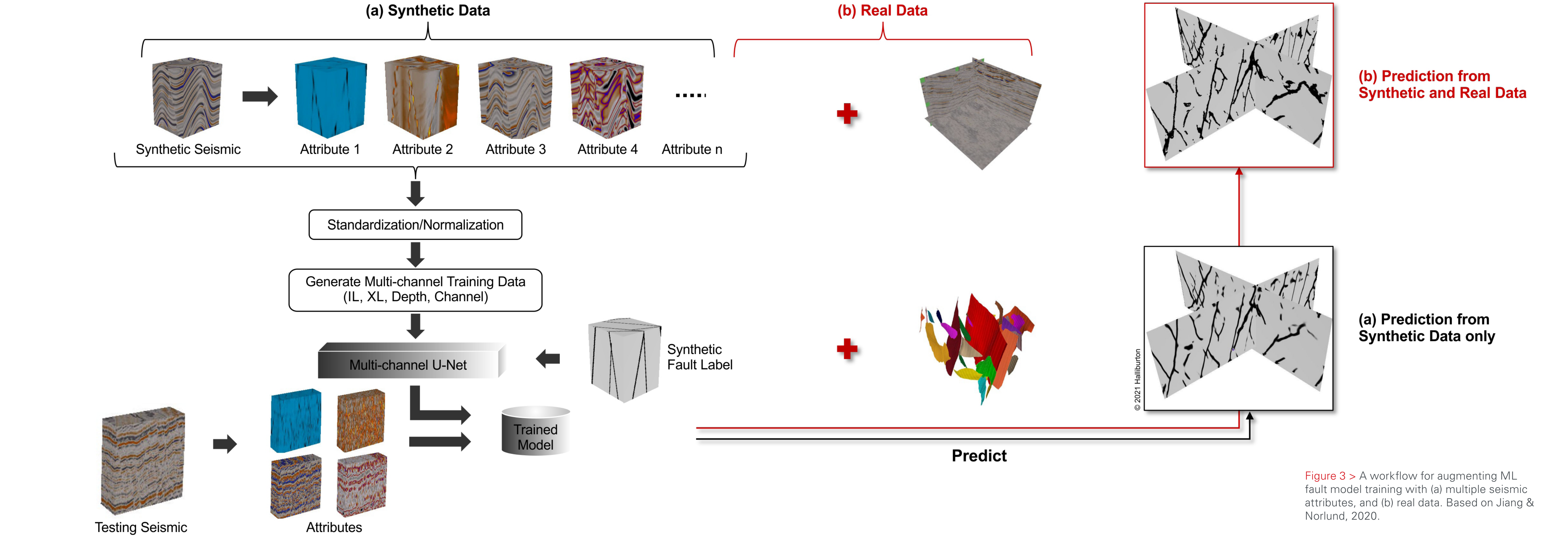


Figure 3 > A workflow for augmenting ML fault model training with (a) multiple seismic attributes, and (b) real data. Based on Jiang & Norlund, 2020.

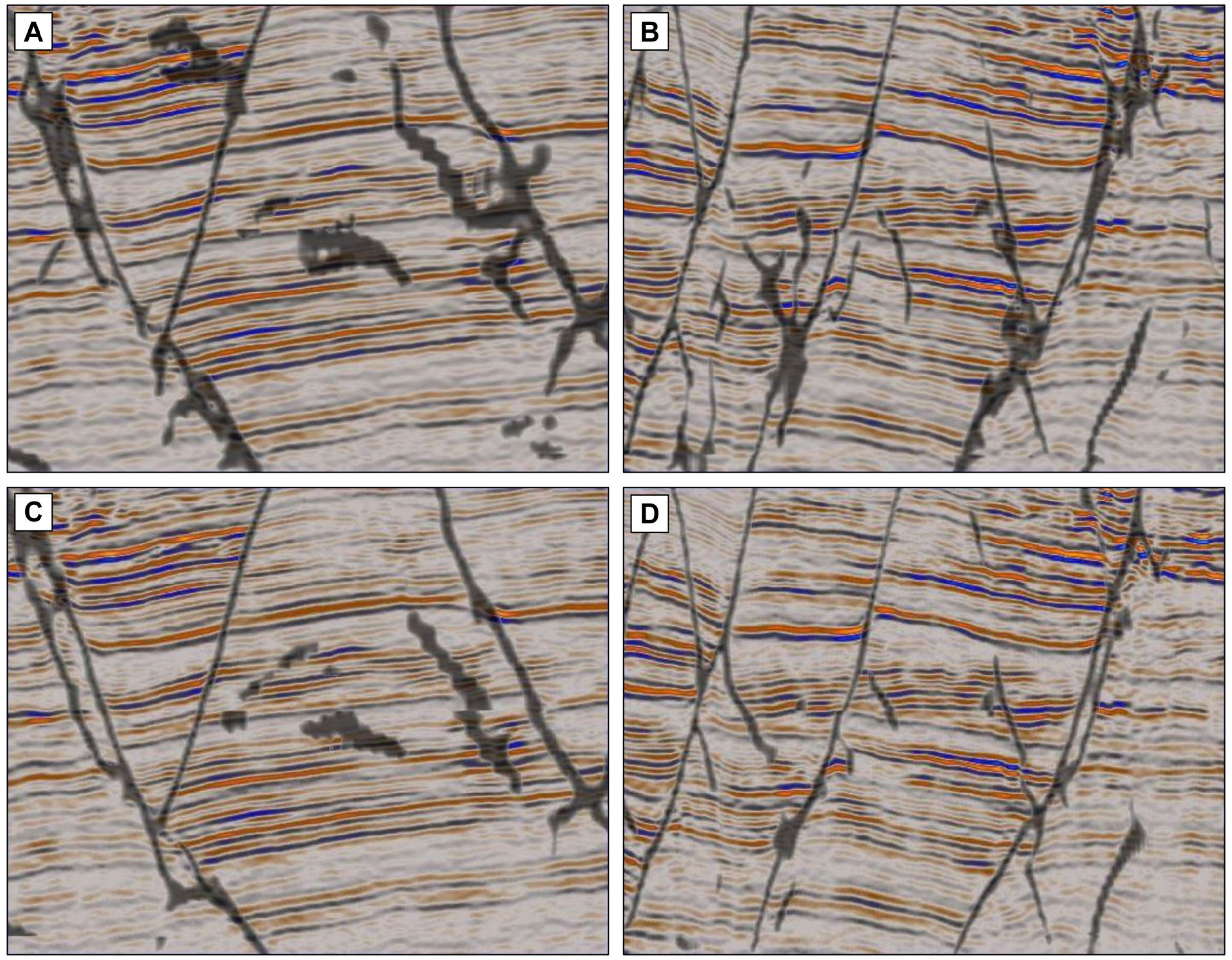


Figure 4 > Examples of an ML fault prediction volume created using synthetic data only (A, B) compared to a volume created using a model augmented with real data (C, D). Data courtesy of Geoscience Australia.

ADDING REAL WORLD DATA TO OUR MODELS

In all the ML approaches discussed so far, the examples exclusively use synthetic data to train the models. Why not use real data and its manual interpretation? The reason for using synthetic data is that examples can be created where there is only one possible correct interpretation. Thus, the model is always being trained with the correct answer. Real, field-acquired seismic data and its manual (human) interpretation, however, are not so simple. It has been shown by a number of experiments (e.g. Alcade et al., 2017) that even experienced interpreters can come up with different interpretations of the same seismic. This shows that interpretation, by its very nature, is a non-deterministic challenge with multiple answers available for every seismic section analyzed. There is not one correct answer to train a model. As such, examples from real datasets need to be selected with caution and instances favored where the potential variation in answers is minimal. Luckily, only a small amount of real data is needed to make a noticeable improvement in prediction accuracy.

Figure 4 shows the impact of augmenting synthetic models by incorporating real data into the CNN training process. In this example, a dataset from offshore NW Australia is used. Figures 4A and 4B show the results from generating an ML probability volume using only synthetic data and labels. Figures 4C and 4D show the results when the model is re-trained, augmenting it with a small subset of real data and its associated manual fault interpretations (Figure 3b). Despite the small amount of real data used (the manually interpreted data covered only approximately one percent of the full volume), a significant improvement is achieved using the augmented model. Faults are more clearly imaged, especially where the geology is complex.

As good as these ML results are, it is important to understand the limitations of the approach. Firstly, any uncertainties, biases, or errors in the manual interpretations are incorporated into the model and will be propagated throughout the output fault probability volume. Secondly, it is unlikely that every fault in the real seismic subset had been interpreted, as there is often neither the time, nor need, to interpret every fault present. In such situations, the model is trained not to recognize valid faults, which further compromises the results. While these challenges do not invalidate the use of real data in training models for seismic interpretation, it good to appreciate the limitations of this approach in order to extract the full value from the ML predictions.

SUMMARY

We are now in the Age of Machine Learning, and one can clearly see how many of these technologies can be leveraged to assist the seismic interpreter. Convolutional neural networks are well suited to identifying faults in seismic, random forest approaches can indicate which data to use as an input for training, and generative adversarial networks can clean and optimize fault image volumes. By incorporating experienced geoscientists' knowledge into the workflow automation process, ML improves upon traditional methods by better identifying faults in noisy data and helping to differentiate between real faults and other discontinuities. However, as with any new technology we must be careful not to replace one approaches limitations with a new set.

ML also requires caution not to incorporate the imperfections of human interpretation into the new models, and remember that there are still many areas where traditional physics-based approaches give superior results. So, for now, both physics- and ML-based approaches should both be leveraged to assist in fault identification.

Cloud technologies, like Halliburton Landmark's Seismic Engine, are helping efficiently deliver these new tools to users, while allowing integration with more traditional workflows. With Seismic Engine, physics- and ML-based approaches can be combined to produce optimal results for any dataset. This is especially important as datasets continue to grow in size, and the need for assisted seismic interpretation becomes more important.

REFERENCES

Alcalde, J., Bond, C. E., Johnson, G., Ellis, J. F. and Butler, R. W. (2017). Impact of seismic image quality on fault interpretation uncertainty, GSA TODAY 27.

Huang, L., Dong, X., Clee, E., 2017. A scalable deep learning platform for identifying geologic features from seismic attributes. SEG The Leading Edge, March 2017.

Jiang, F., and Norlund, P., 2020. Improving Resolution of a Fault Probability Map by a Deep Learning Generative Adversarial Network, AAPG 2020 Annual meeting, Expanded Abstracts.

Jiang, F., and Norlund, P., 2020. Seismic attribute-guided automatic fault prediction by deep learning, EAGE 2020 Annual meeting, Expanded Abstracts.

Jiang, F., and Norlund, P., 2020. Super Resolution of Fault Plane Prediction by a Generative Adversarial Network, EAGE Digital 2020, Expanded Abstracts.

Liu, M., Li., W., Jervis, M., and Nivlet, P., 2019. 3D Seismic Facies Classification using Convolutional Neural Network and Semi-supervised Generative Adversarial Network. SEG Technical Program Expanded Abstracts 2019.

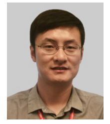
Norlund, P., and Angelovich, S., 2021. The Evolution of Assisted Faut Interpretation Part 1. Subsurface Insights Magazine, March 2021.

Ronneberger, O., P. Fischer, and T. Brox, 2015, U-net: Convolutional networks for biomedical image segmentation: International Conference on Medical image computing and computer-assisted intervention, Springer, 234–241.

AUTHORS

Philip Norlund, Domain Manager, Geophysics — Halliburton Landmark

Philip is responsible for setting research and development strategy around all aspects of geophysics. He has been at Landmark for 25 years and was previously the Product Manager for GeoProbe®, DecisionSpace® Seismic Interpretation, and Drilling Analytics. Philip has a bachelor's degree in Physics and Geology from Manchester University, UK, and a master's degree in Geology from the University of Houston, US.



Fan Jiang, Research Geophysicist — Halliburton Landmark

Fan is responsible for research and development in machine learning/deep learning applications for geophysical interpretation, including seismic feature extraction, salt body delineation, assisted fault prediction, and seismic multi-facies classification. He has over 10 years' experience in seismic processing, imaging, and interpretation development. He has been granted multiple US patents, and has published over 20 peer-reviewed technical papers. Fan has a PhD in Geophysics from Texas Tech University.

DISCLAIMER

How to Free a Geoscientist: Using Python™ to Automate the Mundane

by: James Scotchman

Python programming language. Image courtesy of 1840151sudarshan, CC BY-SA 4.0, via Wikimedia Commons.

INTRODUCTION

Creating palinspastic gross-depositional environment (pGDE) maps is a time-consuming task. Not only does a geoscientist need to understand the regional geological context, but also the effects of plate movement through geological time. With such a complex 4-dimensional challenge, anything that could be automated is worth investigating, as this will enable geoscientists to bring their skills to bear on the other pieces of the puzzle — without being distracted by mundane tasks, such as data manipulation. This article demonstrates how Python™ programming language can be leveraged to automate time-consuming geospatial operations, thereby, enabling the geoscientist to spend more time and creative energy on the higher value tasks of understanding and predicting the geology.

THE VALUE OF PGDE MAPS

Neftex® Predictions pGDE maps are an important part of our holistic Earth Systems approach to understanding and depicting the evolution of the planet. The rigorous and integrated nature of our global models provides regional context and a robust framework of geological understanding within which to better predict the occurrence, extent, and quality of key petroleum elements. pGDE maps show potential reservoir, source, and seal intervals in the context of the paleo geographies in which they were deposited. This allows for a greater appreciation of the factors involved in their deposition, particularly when considering progressively older stratigraphy. Details on pGDE map creation and utility are outlined within a previous Neftex Exploration Insights magazine article (Saunders et al. 2019).

WHAT'S TAKING SO LONG?

Creation of a global pGDE map for a single time slice takes many weeks. The process involves a team of geoscientists, who require time to collate and assimilate available data, reconstruct the data to its palinspastic position, become familiar with the regional geological setting, and finally begin drawing pGDE facies onto the map. This process takes not only time, but also requires geological brainpower. On top of this, the geoscientist is presented with an initial map of reconstructed geometries, created through the application of our geodynamic model (Figure 1). These "shattered glass" maps are full of overlapping polygons, empty space, and minute fragments of polygons. Tectonically complex areas are particularly prone to this problem. Such errors are the result of the splitting and rotation of polygons that overlap plate boundaries during reconstruction to palinspastic space. The manual resolution of these errors consumes a significant amount of time that would be better spent focussing on the geoscience. So, what can be done to remove this time sink?

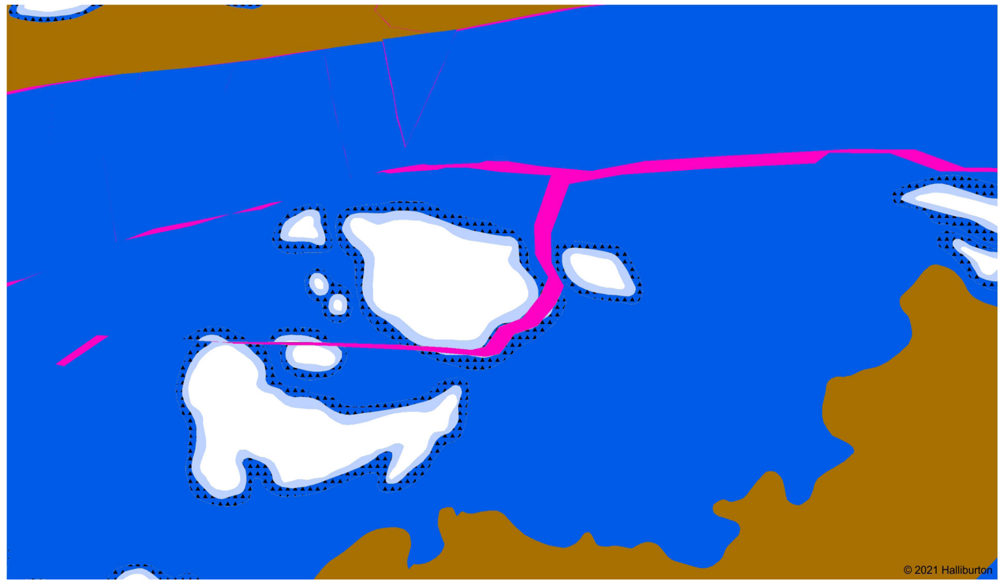


Figure 1 > Example of GDE polygons from present day reconstructed into palinspastic space. Pink areas represent gaps created as a result of reconstruction.

PYTHON TO THE RESCUE

Over recent years, Python has become an important, if not vital, tool in geoscience. It is a high-level, object-orientated programming language that is easy-to-use and, therefore, an ideal choice for a beginner's introduction to programming. Python is delivered with a large standard library that supports the majority of basic tasks. Functionality can be easily expanded using numerous open source libraries that are readily available.

An important first step in any automation task is to fully understand the problem being addressed. Here, the problem is represented by the gaps created during reconstruction of present day GDE polygons to palinspastic space (Figure 1). Two differing techniques were used to infill the gaps,

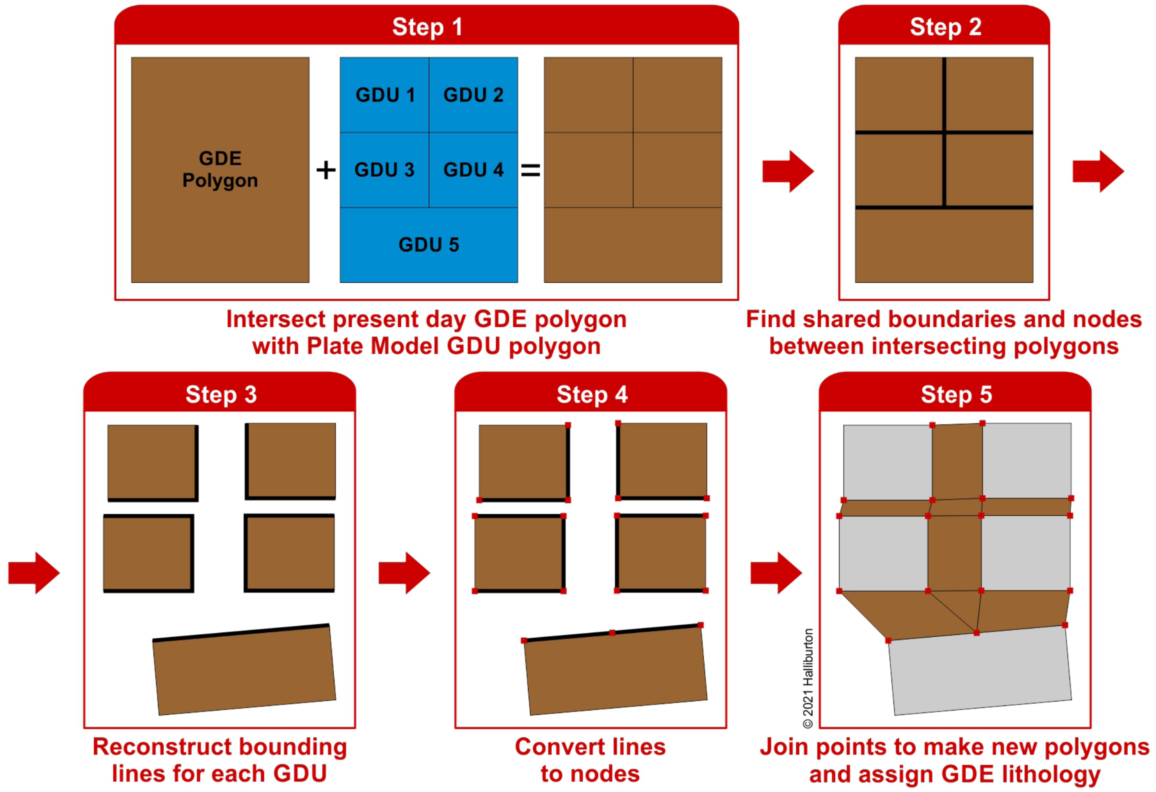


Figure 2 > Method 2: Using the Neftex® Predictions Plate Model to create and fill the gap polygons. Inputs being the Neftex Predictions Plate Model Geodynamic Units (GDUs) and present-day GDE map polygons. Output being a series of polygons filling the gaps created once present-day polygons are reconstructed back to palinspastic space.

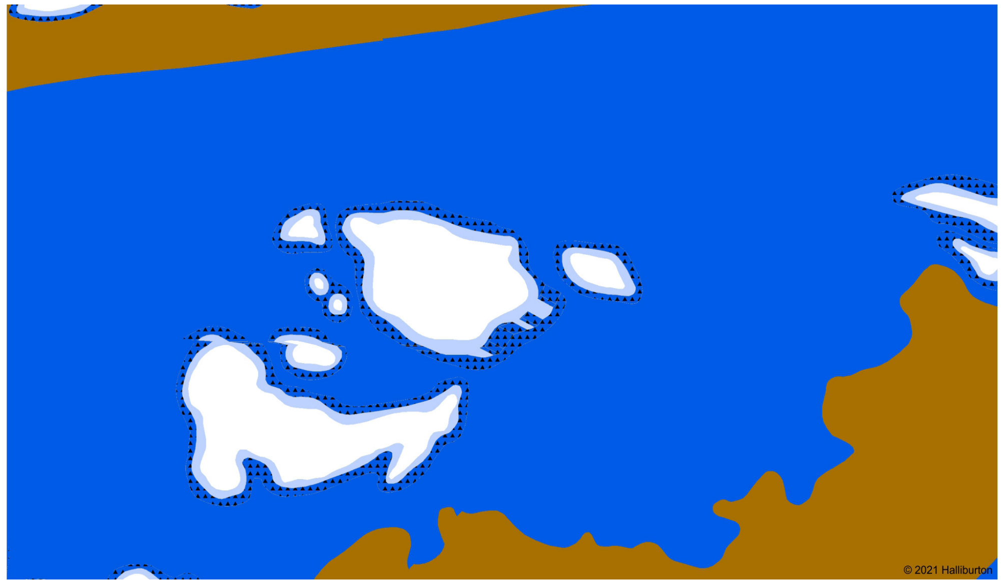


Figure 3 > Addition of the newly created polygons resulted in the infilling of gaps created as a result of reconstruction.

with varying levels of success. Method 1 involved firstly, identifying the gaps created within the pGDE once it had been placed in palinspastic space; and secondly, using these gaps to select its bounding lithology polygons. The adjacent polygons were used to assign a lithology to the gap polygon.

After unsatisfactory results from Method 1, the plate reconstruction process that creates the gaps within the pGDE maps was itself investigated. It was realized that it was more effective to create the gap polygons from reconstructing the vertices of the present-day GDE polygons using the Neftex® Predictions Plate Model. This also made assigning the lithology much simpler. The approach is outlined in Figure 2.

Application of the script to our most recent pGDE map resulted in the successful infilling of the gaps (example within Figure 3). As a result, the geoscientists completing the pGDE map were able to minimize time spent on finding and filling gaps between reconstructed polygons and, thus, allocate more time to enhance the geological resolution of the product.

This single example demonstrates how the use of Python can result in increased productivity and provide the geoscientist more time to focus on the things that matter — the geoscience — rather than fixing gaps between polygons. Such automated processes are essential steps in working toward an evergreen, subsurface geological model where client data can be seamlessly incorporated into the Neftex Predictions product suite.

Embracing the use of programming languages, such as Python, within the Neftex Predictions product suite allows for the automation of processes, such as data collection and interpretation. This automation is vital to enable us to efficiently maintain and update such a large suite of products, while retaining our geoscientific rigor. Once achieved, it is possible to generate a dynamically updatable, subsurface geological model with the option to incorporate client proprietary data for bespoke model delivery.

REFERENCES

Saunders, L., C. Willcox, J. Smith, C. Gravestock and B. Greselle 2019. A Holistic Earth Systems Approach to Cretaceous Palinspastic Mapping as a Tool for Exploration. Exploration Insights Magazine. Exploration Insights Magazine no. May, p. 11-16. (XURBB_641254).

AUTHOR

Dr. James Scotchman, Principal Technologist, Neftex Predictions

James works across the Neftex® Predictions product suite, creating new derived products and improving workflow efficiency via automation and/or utilizing machine learning techniques. Prior to joining Neftex in 2012, he obtained his doctorate from University College London.

DISCLAIMER

Halliburton
97 Jubilee Avenue
Milton Park
Abingdon
Oxfordshire
OX14 4RW
United Kingdom
landmark.solutions/Neftex
ExplorationEnquiries@halliburton.com
Tel: +44 (0)1235 442699

HALLIBURTON | Landmark