[GC]Using Shale Capacity for Predicting Well Performance Variability*

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General Statement

The goal of reservoir characterization work carried out for a shale play is to enhance hydrocarbon production by identifying the favorable drilling targets. The drilling operators have the perception that in organic-rich shale formations, horizontal wells can be drilled anywhere, in any direction, and hydraulic fracturing at regular intervals along the length of the laterals can then lead to better production. Given that this understanding holds true, all fracturing stages are expected to contribute impartially to the production. However, studies have shown that only 50 percent of the fracturing stages contribute to overall production. This suggests that repetitive drilling of wells and their completions without attention to their placement must be avoided, and smart drilling needs to be followed by operators.

Smart drilling consists of optimally placing a horizontal well and thereafter stimulating it in such a way that more uniform production across fracturing stages occurs, which leads to a better overall production. To be able to locate such fertile pockets, an integration of different types of reservoir properties, such as organic richness, fracability, fracture density and porosity, is essential. One way of achieving this is by using cutoff values for the different reservoir properties and generating a shale capacity volume. Thus, the foregoing discussion emphasizes the integration of different reservoir properties for predicting the potential of a shale play. Mathematically, shale capacity (SC) is defined as a function of total organic content (TOC), natural fracture density (FD), brittleness (BRT), and porosity (Ø) as follows:

$$SC = TOC_{net} \times FD_{net} \times BRT_{net} \times Ø_{net} \qquad \text{Equation 1}$$

where $TOC_{net} = 0$ when $TOC < TOC_{\text{cut-off}}$
$FD_{net} = 0$ when $FD < FD_{\text{cut-off}}$
$BRT_{net} = 0$ when $BRT < BRT_{\text{cut-off}}$
and $Ø_{net} = 0$ when $Ø < Ø_{\text{cut-off}}$

From the above equation, it is obvious that an optimal combination of all four parameters could lead to a higher shale capacity, i.e. the shale capacity exists only in case all four parameters are above their cut-off values. In other words, an ideal shale well must be drilled in a high TOC zone, which is brittle enough to be fractured, and a natural fracture system must be intercepted by the induced hydraulic fractures to develop a high porosity system. Therefore, due attention should be devoted to all these parameters for determining the potential of a shale play.

Seismically-Derived Attributes

The availability of core data, well-log curves such as dipole sonic with azimuthal measurements and image logs could probably arm the reservoir engineers or petrophysicists with direct measurements of different reservoir properties (organic richness, fracability, fracture density and porosity) for estimating shale capacity. However, direct measurements of such properties are possible only at well locations. A way out here would be to determine the individual components of shale capacity from seismically-derived properties.

But again, to couple reservoir properties with seismically-derived attributes is complex and not easy to understand. Therefore, different seismic attributes should be analyzed simultaneously to get an individual component of shale capacity volume. For example, organic richness and porosity have a prominent impact on P-impedance, density, VP/VS, and Lambda-rho, and thus these attributes can be treated as their proxies. Furthermore, fracture toughness (see The Importance of Fracture Toughness - And its Azimuthal Variation for Fracability Analysis, Search and Discovery Article #42519), strain energy density, and fracture intensity computed using VVAz (see Integration of AVAz/VVAz and Coherence/Curvature Seismic Attributes, Search and Discovery Article #42355) and fracture toughness can be considered as a proxy for hydraulic fracture-ability and fracture/stress induced anisotropy in addition to curvature attributes.

Principal Component Analysis

Consequently, different kinds of attributes must be considered in the process of defining shale capacity, which is not an easy task to tackle manually. Therefore, an attempt has been made here to perform such an integration with the help of a machine learning technique (see Reservoir Property Prediction from Seismic Inversion Attributes Using MARS, Search and Discovery Article #42202) called “principal component analysis,” or PCA, for a 3-D seismic dataset from central Alberta, Canada, where the Montney and Duvernay formations represent the zone of interest. With all the seismic attributes mentioned above available, they were put through the machine learning PCA computation, to figure out the patterns and relationships in them. Usually the first three principal components carry most of the information contained in the input attributes, with PCA-1 containing a large part of that. Consequently, PCA-1 can be treated as a proxy for the shale capacity volume. Figure 1 shows an arbitrary line passing through different wells from the PCA-1 volume. The display exhibits both the lateral and temporal variations.

To capture the lateral variations in the data, Figure 2 shows a horizon slice averaged over a 30-millisecond window covering the Duvernay Formation. The hot colors on the display represent higher values than the greenish/bluish colors, but as PCA is an unsupervised machine learning technique, it is difficult to conclude as to which color conveys what information. To gain some insight into this dilemma, the nine-month cumulative BOE (barrel of oil equivalent) production data available for those wells are brought in and found to be associated with different colors. Notice the productivity of a well increases in going from the greenish color to hot colors. It may therefore be concluded that hotter colors are preferable for the delineation of sweet spots.

Machine Learning

When it comes to the attributes used in Equation 1 for seismically determining shale capacity, it is difficult to make a manual choice for the cut-off values. To alleviate such a problem, application of machine learning techniques could be useful and thus worth exploring.

There are different categories of machine learning techniques that may be used for our purpose, but we begin our discussion with unsupervised and supervised techniques. While supervised learning techniques are preferred over unsupervised, it is always challenging to collect adequate data for the former and abundance of data are required for training and validation purposes. For example, if we wish to predict shale capacity using one of the supervised machine learning techniques, say, based on neural networks, it is necessary to have enough training data points for SC. On the other hand, unsupervised machine learning techniques do not carry such requirements and hence have immense potential for use in the geophysical domain, where the lack of appropriate data is quite common. Therefore, an attempt has been made here to extract SC information with the help of unsupervised machine learning techniques. The prerequisite to follow any of the unsupervised techniques is that the production data associated with different wells must be available. As the well production data are easily available in the public domain in Canada, a dataset from the Western Canadian Sedimentary Basin is considered for application of machine learning computation for estimating shale capacity volume.

Preferred Properties

An ideal shale well would be drilled in a formation that has the following properties:

- It is organically rich and porous, and thus can produce enough quantity of hydrocarbons.

- It is brittle/ hydraulic fracture-able enough to get fractured easily.

- The induced fractures resulting from hydraulic fracturing intercept the existing natural fracture system in the formation.

- The induced fractures are compatible with the type of fracture network pattern for the development.

Knowing the limitations of seismic data in measuring these properties directly, their proxies are derived from seismic data. For example, porosity variations may give rise to changes in impedance, density, velocity ratio, etc. Similarly, high quartz or carbonate content may impact on Young’s modulus and Poisson’s ratio in addition to other rock properties. Consequently, it should be possible to detect changes in different properties required for shale capacity volume from surface seismic response. However, coupling of reservoir properties with seismically-derived attributes are complex and not easy to understand. Therefore, different seismic attributes should be analyzed simultaneously to derive the individual components of shale capacity volume. For example, organic richness and porosity have prominent impact on P-impedance, density, VP/VS, and Lambda-rho and thus these attributes can be treated as their proxies. Furthermore, strain energy density, and fracture intensity computed using velocity variation of azimuth (VVAz) and fracture toughness (FT) approach can be considered as a proxy for hydraulic fracture-ability and fracture/stress induced anisotropy in addition to curvature attributes. Next, all these attributes should be integrated using machine learning techniques to predict the shale capacity volume as illustrated in the cartoon shown in Figure 3.

In order to determine the input attributes required for shale capacity, simultaneous impedance inversion was performed on 5-D PSTM pre-stack data by following proper data conditioning, robust low frequency models and accurate inversion parameters (discussed in Prestack Impedance Inversion Aids Interpretation, Search and Discovery Article #41664). Such inversion yields P- and S-impedance volumes. Thereafter, other attributes such as Lambda-rho, Mu-rho, E-rho, Poisson's ratio, fracture toughness (see The Importance of Fracture Toughness - And its Azimuthal Variation for Fracability Analysis, Search and Discovery Article #42519), and strain energy density (SED) were computed using impedance volumes. Next, simultaneous inversion was performed on the individual azimuth-sectored gathers to determine FT volumes for different azimuths. Having computed these volumes, the magnitude of seismic anisotropy was estimated from FT azimuthal variation via differential horizontal fracture toughness ratio (DHFTR). The analysis of variation of velocity with azimuth (VVAz) and the variation of amplitude with azimuth (AVAz) were also performed on the dataset used here. Volumetric curvature attributes are valuable in mapping subtle flexures and folds associated with fractures in deformed strata. There are many curvature measures that can be computed, but the principal most-positive and most-negative curvature measures are the most useful in that they tend to be most easily related to geologic structures.

Predicting Shale Capacity Volume Using Unsupervised Machine Learning

These attributes were generated for the dataset under investigation and put through the unsupervised machine learning technique to predict the shale capacity volume. For the sake of simplicity, we began with principal component analysis (PCA), to figure out the patterns and relationships in them. Usually the first three principal components carry almost all the information contained in the input attributes, with PCA-1 containing a large part of that.

Consequently, PCA-1 can be treated as a proxy for the shale capacity volume. The lateral and temporal variation of it has been shown above, where it was noticed that the productivity of a well increases from the greenish color to hot colors. It may therefore be concluded that hotter colors are preferable for the delineation of sweet spots. Consequently, we look for correlation of the variation in production for the different horizontal wells drilled from the same pad with the colours on the display. Figure 4 exhibits a zoom of the four wells seen to the southeast part of the horizon slice in Figure 2, along with their nine-month cumulative BOE production data. The general trend of increased productivity with the intensity of hot colors holds true if wells W1 and W4 are compared. However, it falls short of explaining the higher production associated with W2. In our attempts to find an answer here, PCA-2 and PCA-3 volumes are also examined, in the hope of extracting additional information. It was found that PCA-3 is dominated by the curvature attribute, which as a discontinuity attribute is different from the other input attributes. Although only ranking third in PCA, it is a key component in defining shale capacity volume.

Therefore, the different lineaments in the zone of interest are identified on the curvature attribute and then overlaid on the horizon slice from PCA-1 attribute using the transparency as shown in Figure 5. The well W2 seems to have been drilled into a naturally fractured zone as it is passing through a lineament that could be the possible reason of exhibiting higher production. Similarly, the enhanced production from well

W5 is seen to be associated with a zone exhibiting hot colors and crossing a large lineament that probably exhibits higher permeability. In a similar fashion, the variation of different wells from the northern side can be explained in terms of amplitude on PCA-1 being associated with lineaments interpreted on the curvature attribute. Well W7 seen on the display in Figure 2 is associated with higher production than well W6, though they are both drilled from the same pad and exhibit similar amplitudes in terms of their colors. There are, however, curvature lineaments that well W7 traverses, but not well W6. In a similar vein, well W8 drilled from the same pad but in the southerly direction yields higher production than well W6, even though it is not associated with hot colors, but traverses more lineaments.

Conclusions

Finally, in Figure 6, besides overlaying the curvature lineaments using transparency, the production data has been posted on the horizon slice, with the higher producing wells having bubbles of a bigger radius. Based on the discussion mentioned above, the following are the takeaway points from this analysis:

- Production of a well is seen to increase with the intensity of colors.

- The presence of intersecting lineaments in the hot-colored zones leads to the higher production as noticed for the wells W5 and W9.

- As shown in Figure 6, the location of double-sided magenta arrows could be considered as hot spots for future drilling.

Thus, in conclusion, considering the importance of shale capacity in defining the potential of a shale play, we have attempted to extract this information from seismic data using machine learning techniques. The different input attributes (namely, organic richness, porosity, natural fracture density and hydraulic fracture-ability) for shale capacity determination were derived from seismic data and integrated using principal component analysis. The variability in well performance was addressed by using the PCA-1 along with the curvature attribute (PCA-3). Such an analysis suggests that the combination can be used for identifying future drilling locations.

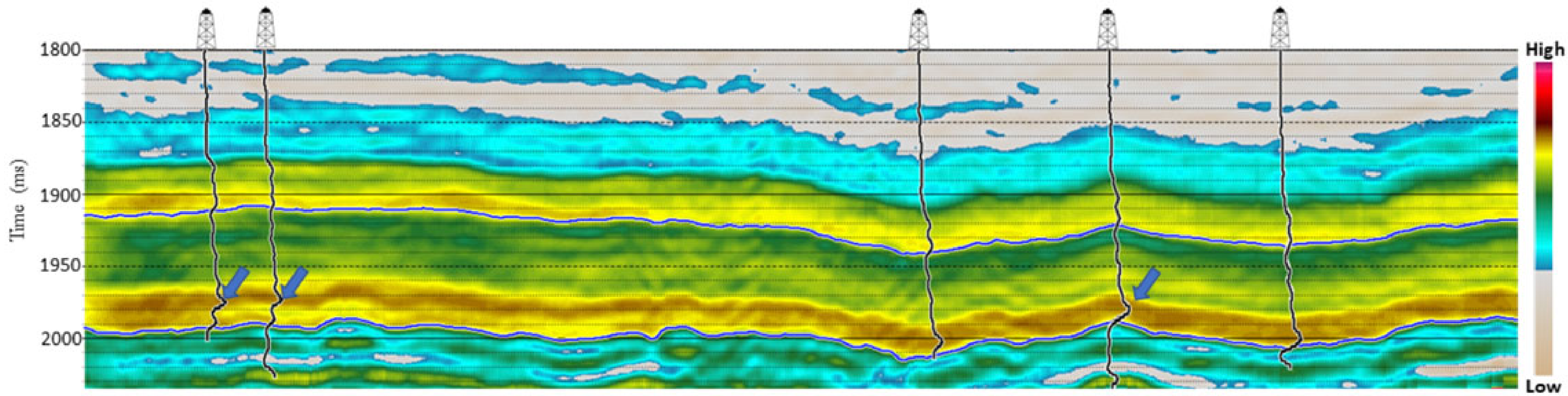

Figure 1. An arbitrary line section passing through different wells from ‘PCA1 (shale capacity)’. Overlaid GR curves show the location of Duvernay Formation as it is associated with high GR response highlighted by blue arrows. Notice a spatial as well as vertical variation of estimated PCA1 attribute that needs to be calibrated with the production data available for different wells. Data courtesy of TGS, Canada.

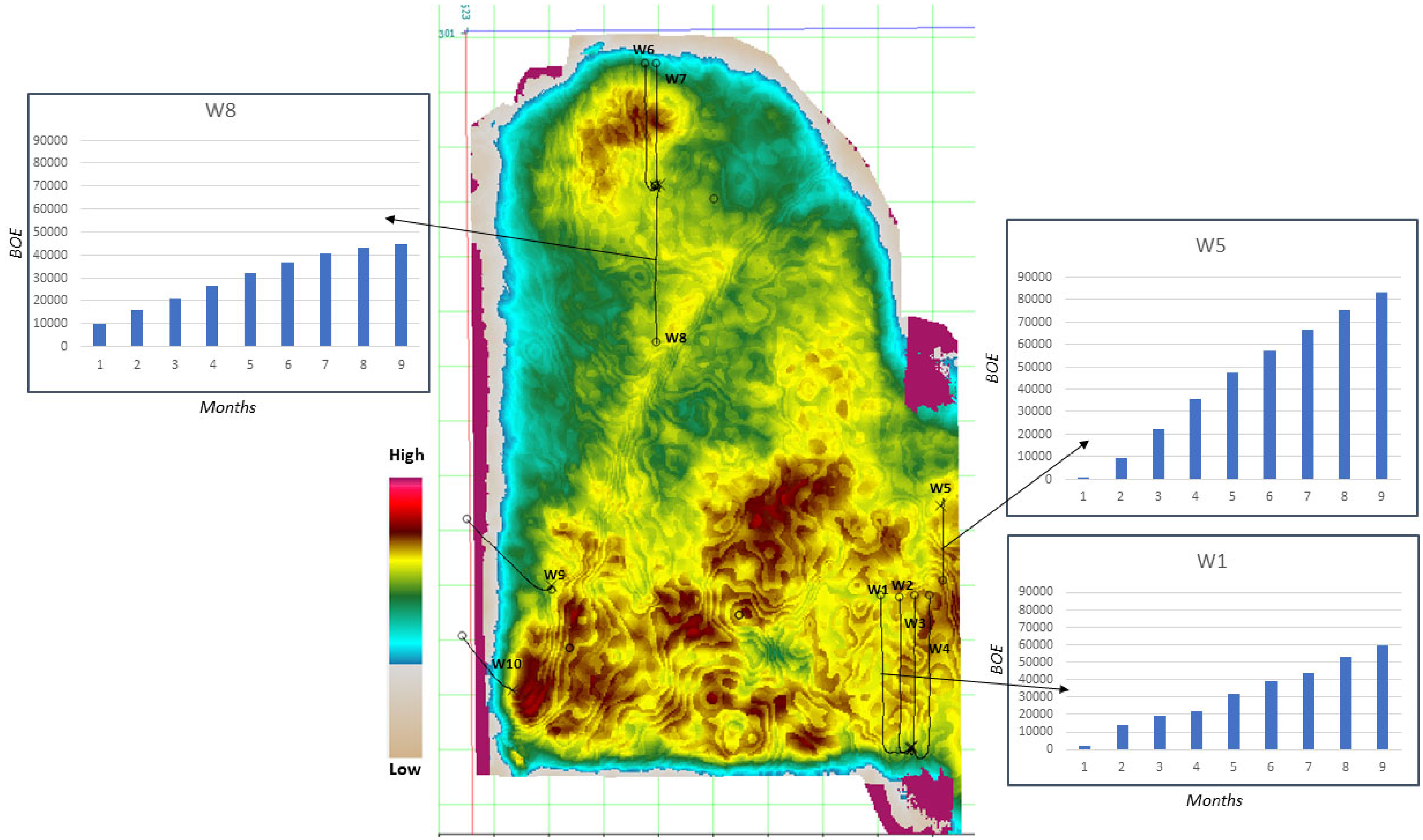

Figure 2. Horizon slice extracted from the PCA1 volume averaged over a 30-millisecond window to map the variability within the Duvernay Formation. As PCA is an unsupervised machine learning technique, the choice of preferable color needs to be decided by calibrating it with other available datasets. Therefore, the production data of three different wells associated with different colors was considered and it suggests that preference should be given to hot colors for delineating the sweet spots as production is increasing with the intensity of colors. Data courtesy of TGS, Canada.

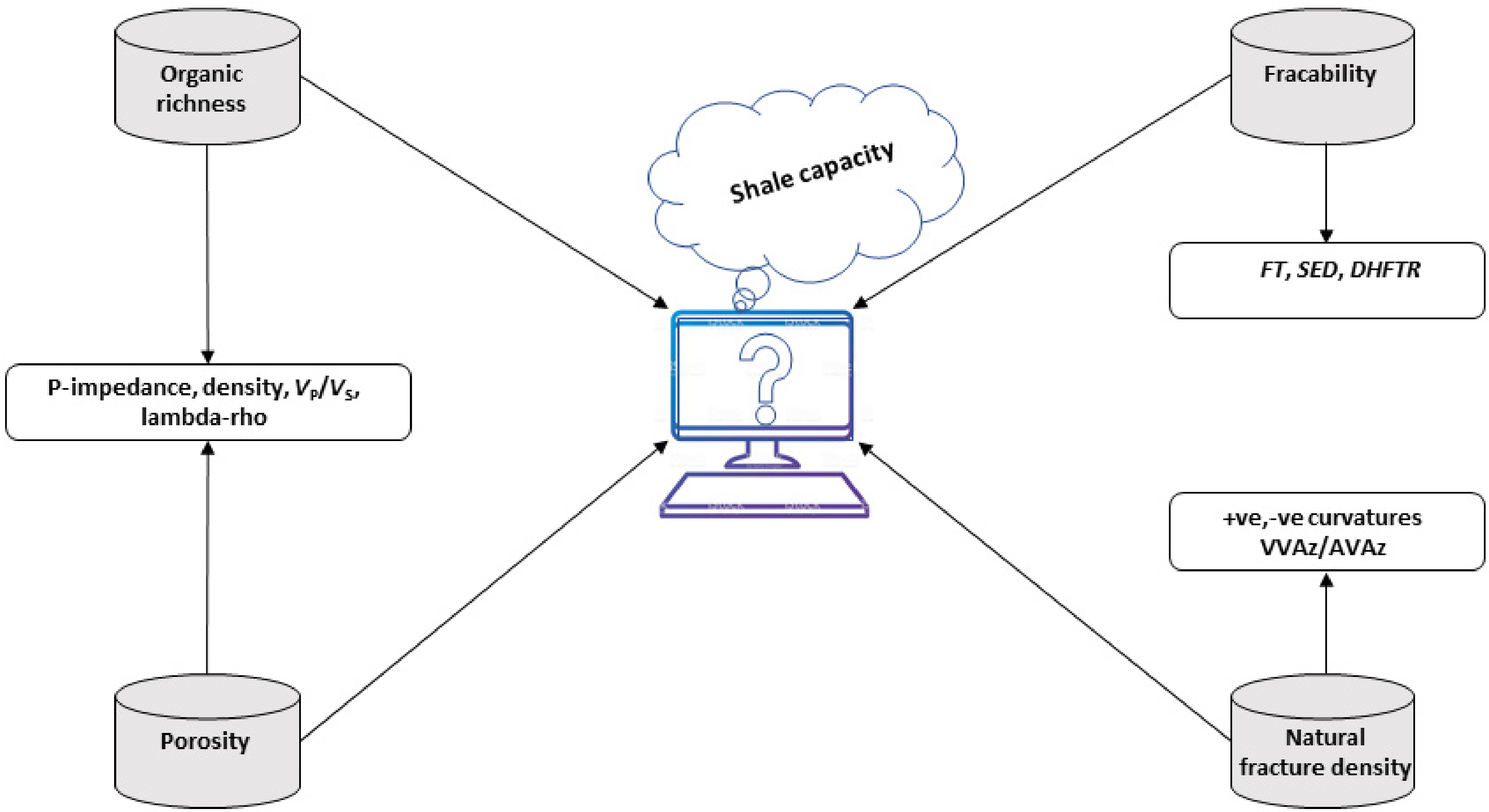

Figure 3. A cartoon illustrating the machine learning approach of predicting shale capacity volume by integrating different required elements. Adapted from Sharma and Chopra (2020).

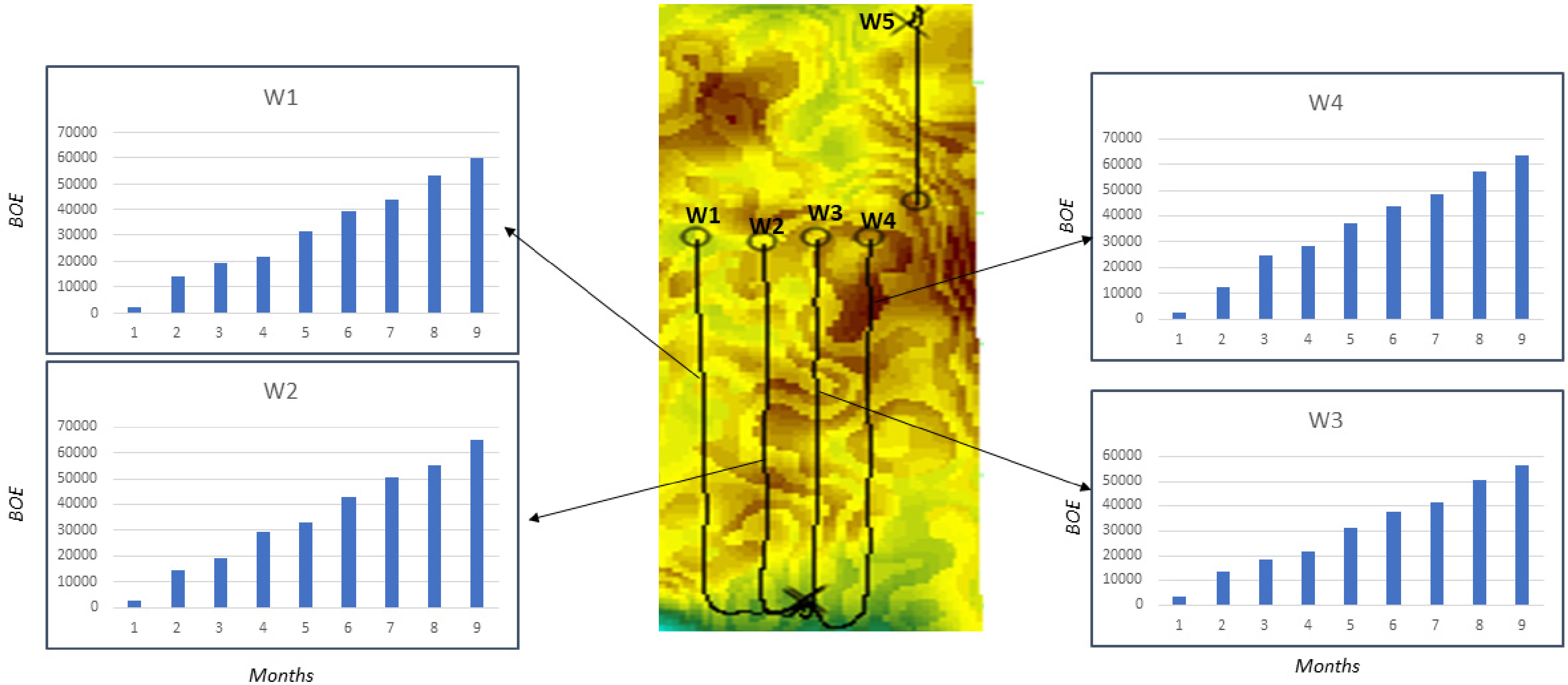

Figure 4. Zoom of southeastern part of horizon slice shown in [Figure 2](#). Sharma and Chopra (2020).

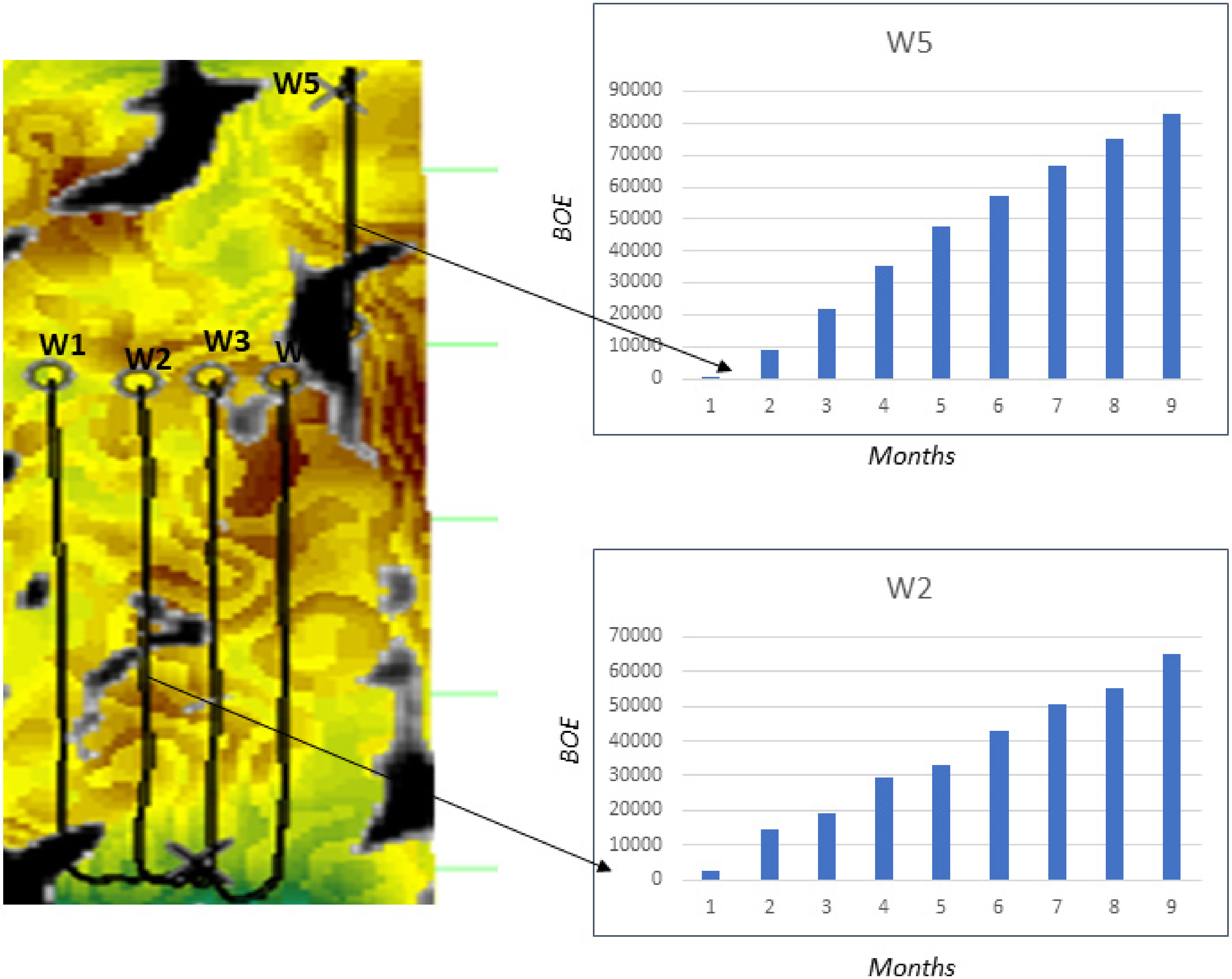

Figure 5. Equivalent display to the one shown in [Figure 2] after overlaying the lineaments interpreted on the curvature attribute using transparency. Sharma and Chopra (2020).

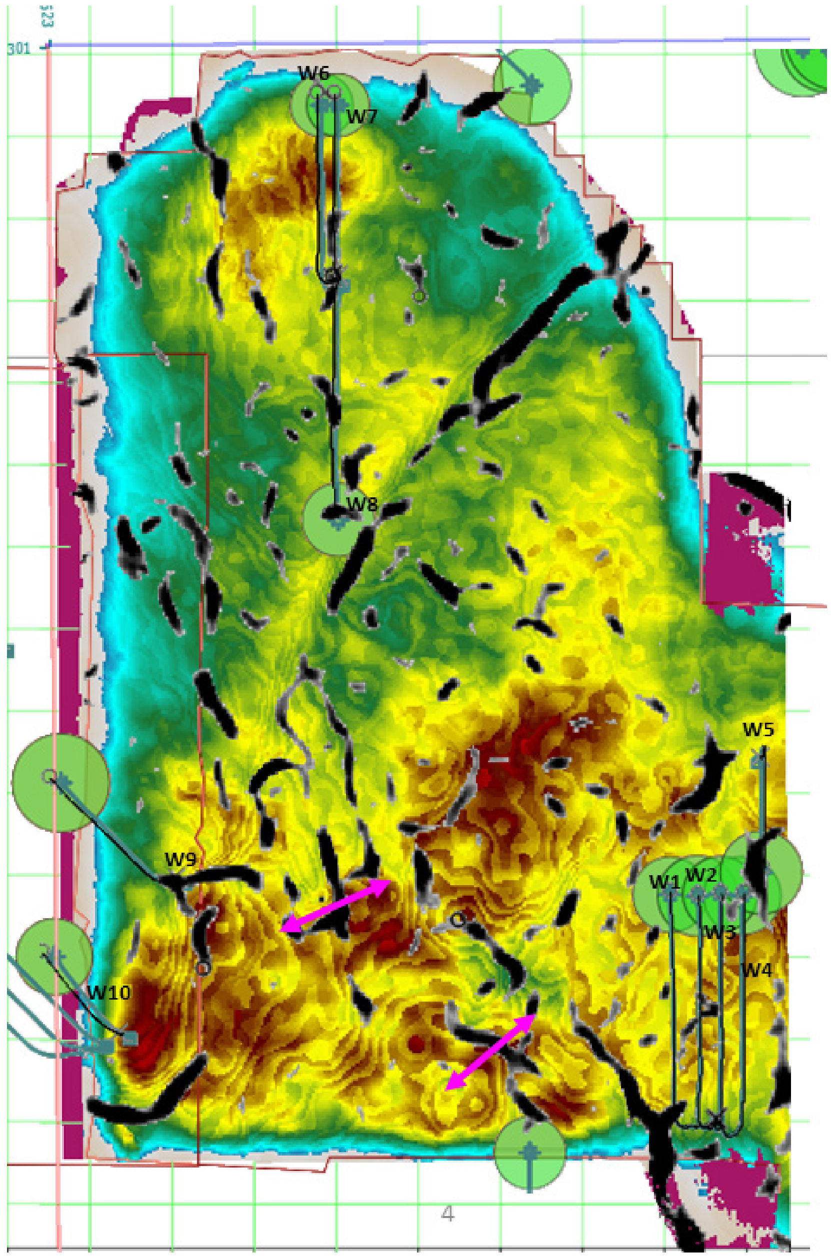

Figure 6. Composite horizon slice display from the PCA-1 volume averaged over a 30-millisecond window covering the Duvernay interval, overlaid with curvature lineaments using transparency and cumulative nine-month BOE production. Sharma and Chopra (2020).