Predicting Well Performances Using the Shale Capacity Concept – Application to the Haynesville*

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Abstract

Increasing production from shales may be accomplished through better modeling of the key reservoir properties. To achieve consistent, high production from a shale well, it is important to consider more than the length of the wellbore and the number of frac stages. Shale drivers, which have an impact on well performance, have both vertical and lateral variability. This needs to be modeled in order to identify the most productive zones. In this Haynesville case study, geologic models of gamma ray, a proxy for Total Organic Content (TOC), porosity, brittleness, and conductivity, a proxy for natural fracture density, were generated using multiple post-stack seismic attributes derived from a narrow azimuth survey. These shale drivers were integrated into a Shale Capacity model which was able to explain the differences observed in existing well performances. With a strong correlation between the shale capacity model and production results, this model could be used to plan successful future wells.

Introduction

The current focus in shale development is the reduction of uneconomical wells and frac stages. This effort is mostly focused on trying to identify the single or multiple shale properties which drive well performance. Many attempts are currently made to statistically correlate the various shale drivers (TOC, porosity, brittleness, fracture density, etc.) to some kind of well performance.

These attempts are also made in the Upper Jurassic Haynesville Shale, and varying results have been reported in the literature. In some cases, no apparent driver seems to control the large variability observed in the production. Figure 1 shows 9-month gas production as a function of frac stages in the Haynesville (Modeland et al., 2011). The first observation is that for a given frac stage number, e.g., 10 frac stages, this production could vary by one order of magnitude, between 100 to 3,000 MMCF. Moreover, the intuitive idea that more frac stages will ensure higher production (Figure 1) does not seem to hold in the Haynesville, thus confirming the important role played by the reservoir properties, their impact on the success of the frac stages, and their contribution to the overall production of the well.

Among the shale drivers investigated in the Haynesville, TOC seems to play a major role (Younes et al., 2011). Lateral variations in the stratigraphy of the Haynesville and surrounding formations, which significantly affected the distribution of natural fractures, have also been found to be another production driver (Rhodes, 2010). Metzner and Smith (2013) recognized the importance of going beyond the brittleness, but they did not estimate additional shale drivers. They relied mostly on 17 seismic attributes, extracting from them a single average value per horizontal well, which was correlated with EUR. Out of these 17 seismic average values per well, the Mu-Rho and Young Modulus seemed to correlate well with the EUR. The area studied by Metzner and Smith (2013) was located within a sweet-spot with perceived minor geologic variations. This is not the case in many other areas of the Haynesville Shale.

Solely within the Haynesville itself, significant variation can be found in the gamma ray, (a good proxy for TOC), porosity, and brittleness measured in well logs, as shown in Figure 2 histograms. These shale drivers are interdependent, as shown in Figure 3. The brittleness is reduced as the porosity increases, and the GR increases for the specific well shown in Figure 3.

To account for all the possible shale drivers, the models of gamma ray (a proxy for TOC), porosity, brittleness, and conductivity (a proxy for natural fracture density), which relate to the well performance, were integrated into a single model. This shall be referred to as the Shale Capacity model, from which the Relative Intercepted Shale Capacity (RISC) may be calculated (Ouenes, 2013). RISC refers to the percentage of the well intersecting a positive Shale Capacity region.

In this case study, the process of generating a 3D shale capacity model is described. By modeling these properties in 3D, and integrating them into a shale capacity model, a strong correlation between the model and the production data may be found. The entire modeling effort was undertaken in the CRYSTAL software.

Shale Drivers and Their Estimation in 3D

The data for this project includes a narrow azimuth post-stack seismic survey, horizon and fault interpretations, three pilot wells with sonic, shear sonic, density, gamma ray, porosity, resistivity, and brittleness logs, corresponding horizontal wells, and production data. The post-stack seismic data was used to generate multiple attributes derived from volumetric curvature, spectral imaging, deterministic and stochastic inversions. This data was integrated in order to generate and validate geologic models of the Haynesville.

Multiple frequency-dependent and statistical spectral attribute volumes were calculated from the post-stack seismic data. A horizon slice of the statistical attribute, called total energy, is shown in Figure 4.

Volumetric curvatures were calculated, which may identify potential areas of deformation, faulting, and fracturing. It is common to see the volumetric curvature computed along the inline and crossline directions whereas the main structural features are present in a diagonal direction. To circumvent this problem, the Euler curvature is computed along any specific azimuth (Figure 5), thus capturing the key structural features present in that specific direction.

The last seismic attributes are the impedances derived from post-stack deterministic and stochastic inversions. Prior to these inversions, well ties were performed on the three pilot wells. The interpreted 3D faults and horizons were used to build a water-tight, faulted framework model (Figure 6). The framework was used in the generation of all inversions and background models, such that the complex stratigraphy was honored, and geologic features were preserved, even near faults.

With well ties and a framework built, the impedance logs from the three pilot wells were used to generate a background model and absolute impedance models, using colored and stochastic inversions. A horizon slide of the impedance derived from the stochastic inversion is shown in Figure 7. Notice the large lateral variability of the impedance, which could be a good proxy for rock brittleness.

To use all these seismic attributes, a 3D geologic grid, in the time domain, was built over the extent of the Haynesville interval, honoring the constraints of the framework model (Figure 8). All seismic attributes were resampled to this time 3D geocellular grid so they could be used in the geologic modeling effort. The geologic modeling is done in the depth domain; so the 3D geocellular grid in time was converted into the depth domain.

With all the seismic attributes now in the depth grid, they were integrated with well log data to create geologic models of the Haynesville reservoir. This was done with use of a neural network. The attributes were first ranked, based on their correlation to the well log being modeled, and a few of the higher-ranked attributes were chosen to generate a 3D reservoir model of the well log property.

Although most spectral attributes do not have a direct relationship to rock properties, the neural network may find quantitative relationships between the attribute and the log data. By using several attributes which represent different aspects of that property, the 3D modeling of that property may be done effectively.

Once the neural network generated several models, the models were reviewed using several methods, including blind wells. This process led to the estimation of multiple shale drivers, including gamma ray, porosity, brittleness, and resistivity. These multiple shale drivers could be integrated in the shale capacity model.

The Shale Capacity model is a combination of multiple shale drivers. The models used to calculate the Shale Capacity for this case study were gamma ray, porosity, brittleness, and resistivity. Gamma ray was used as a proxy for TOC, and resistivity, inverted for conductivity, was used as a proxy for fracture density. The resulting shale capacity model was used to compute the Relative Intercepted Shale Capacity (RISC), which could be correlated to the well performance.

Relative Intercepted Shale Capacity (RISC) and Well Performance

The Relative Intercepted Shale Capacity (RISC) is calculated by dividing the length of the deviated section of the well intersecting the positive Shale Capacity model by the total length of the deviated section. This represents the percentage of the well which will contribute to production. The RISC is generally expected to be high for wells with good production and low for wells with bad production.

Based on the production results (Figure 9), it is expected that Well 3 would have a higher RISC than Well 1 and Well 2. Well 3 had an average production of 80.2 MMCF/month while Well 2 had an average production almost three times less (30.9 MMCF/month).

Figures 10 and 11 display models of the four shale drivers for wells 2 and 3, respectively. Figure 12 shows the Shale Capacity for these two wells, calculated from the four shale drivers. Well 3 shows intersection with many more cells than Well 2, and the cells it intersects are generally of a higher Shale Capacity than Well 2. This shows a good correlation between the Shale Capacity model and the production data. Further validation of the quality of this model could be tested with additional wells.

The Well 3 lateral has a length of 4670 feet, and 3440 feet of this length intersects non-zero cells of the Shale Capacity model. This translates to a RISC of about 74% for Well 3 which has an average monthly production of 80.2 MMCF/month. The Well 2 lateral has a length of 3800 feet, and 1320 feet of this length intersects non-zero cells of the Shale Capacity model. This translates to a RISC of about 35% for Well 2 which has a monthly average production of 30.9 MMCF/month. The calculated RISC for these two wells correctly predicts that Well 3 should have a higher production than Well 2, which is confirmed by the average monthly production and their decline curves (Figure 9).

Conclusions

Due to heterogeneities in the Haynesville Shale, both vertically and laterally, geologic models of the subsurface may provide important information to optimally drill and frac wells, and ultimately drill consistent high production wells which are fraced in the appropriate zones. Many geologic factors can affect well production, including TOC, porosity, brittleness, and natural fractures. The Shale Capacity model integrates all of these geologic factors into a single model and allows the prediction of areas of high production vs. low production, throughout the reservoir area. The Relative Intercepted Shale Capacity (RISC), the percentage of the well intersecting with acceptable values of Shale Capacity, could be used to predict the relative well performance of any future wells.

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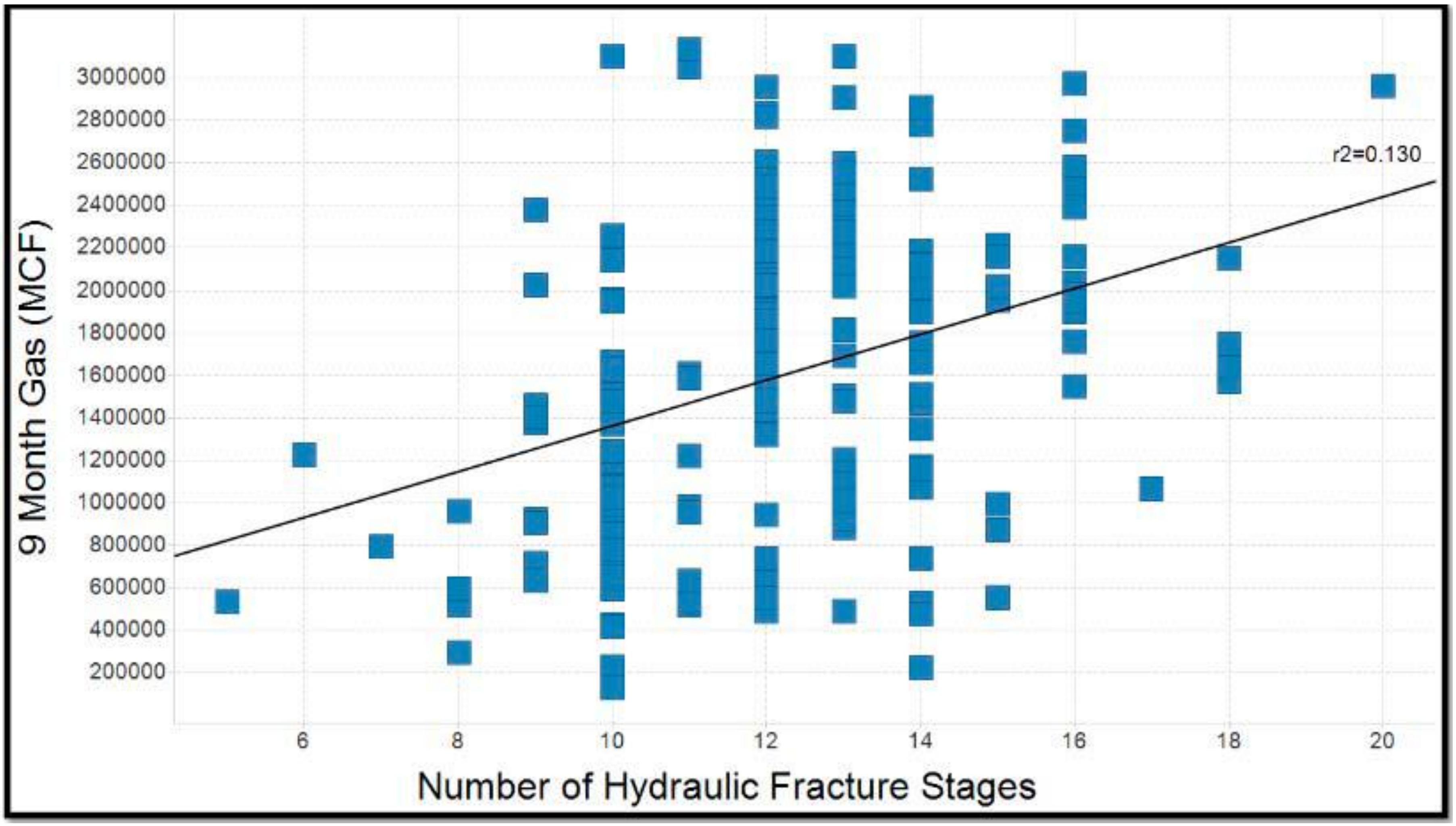

Figure 1. Haynesville production shows a very large variability for a given frac stage. Many wells with 10 or 11 frac stages out-perform wells with 14 to 18 frac stages, thus confirming the importance of the reservoir properties, their impact on the success of the frac stages, and their contribution to the overall production of the well. (From Modeland et al., 2011.)

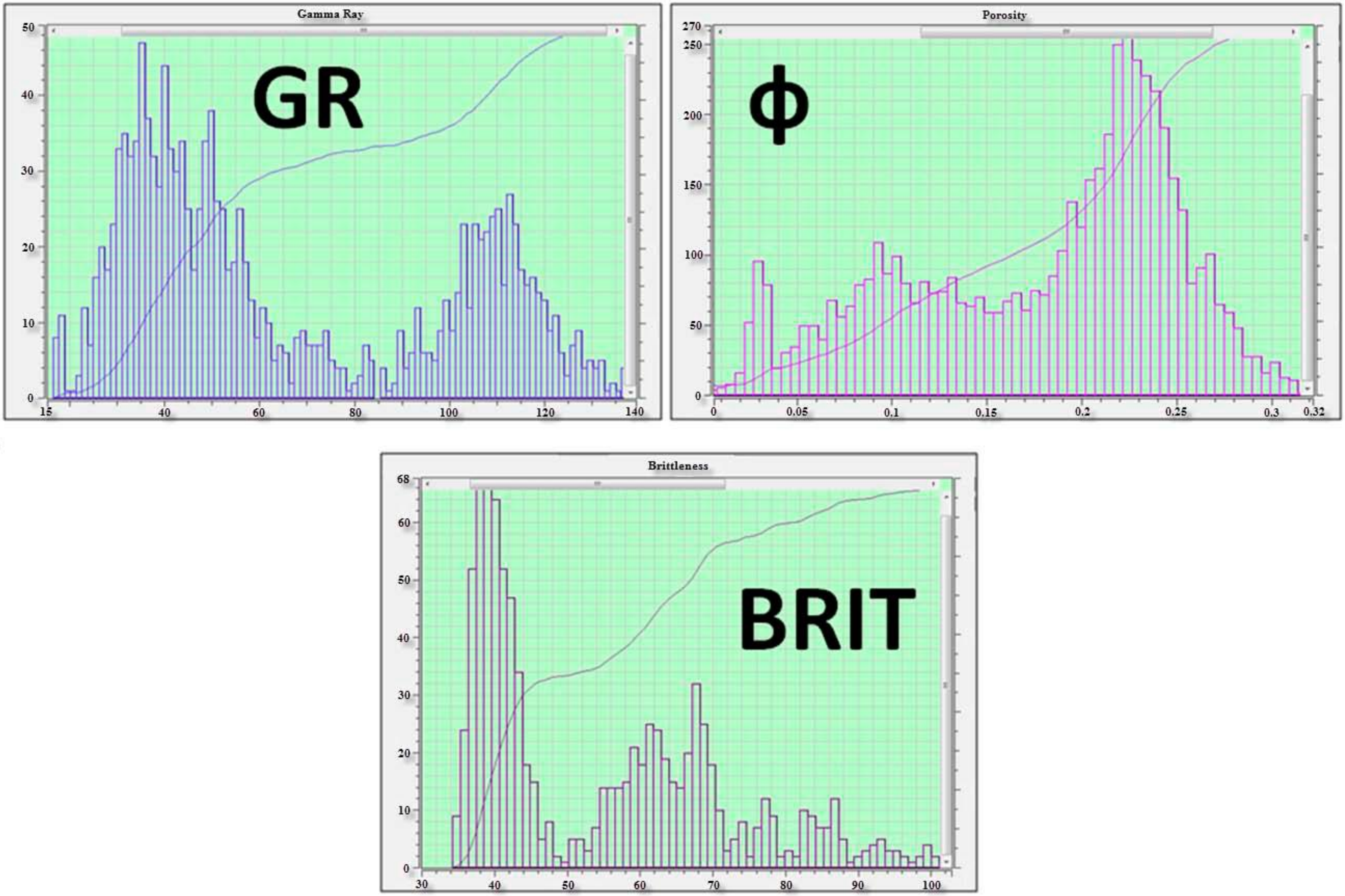

Figure 2. Histograms showing the distribution from well logs of Gamma Ray (GR), Porosity (ϕ), and Brittleness (BRIT). Notice the large variations in the values of the Haynesville key rock properties and their bimodal nature.

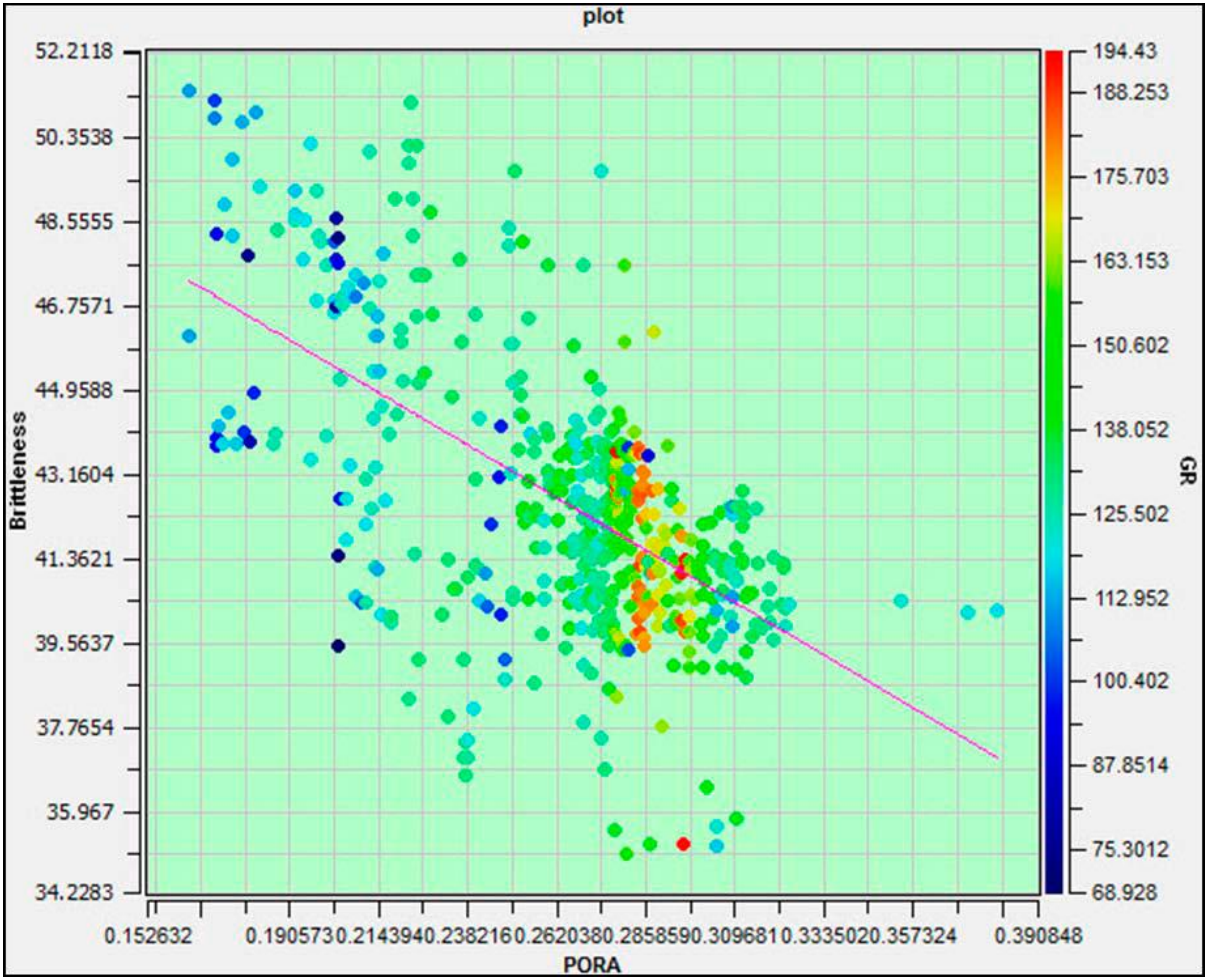

Figure 3: Interdependence of the brittleness, porosity, and gamma ray at a specific well. This trend is also found in other wells.

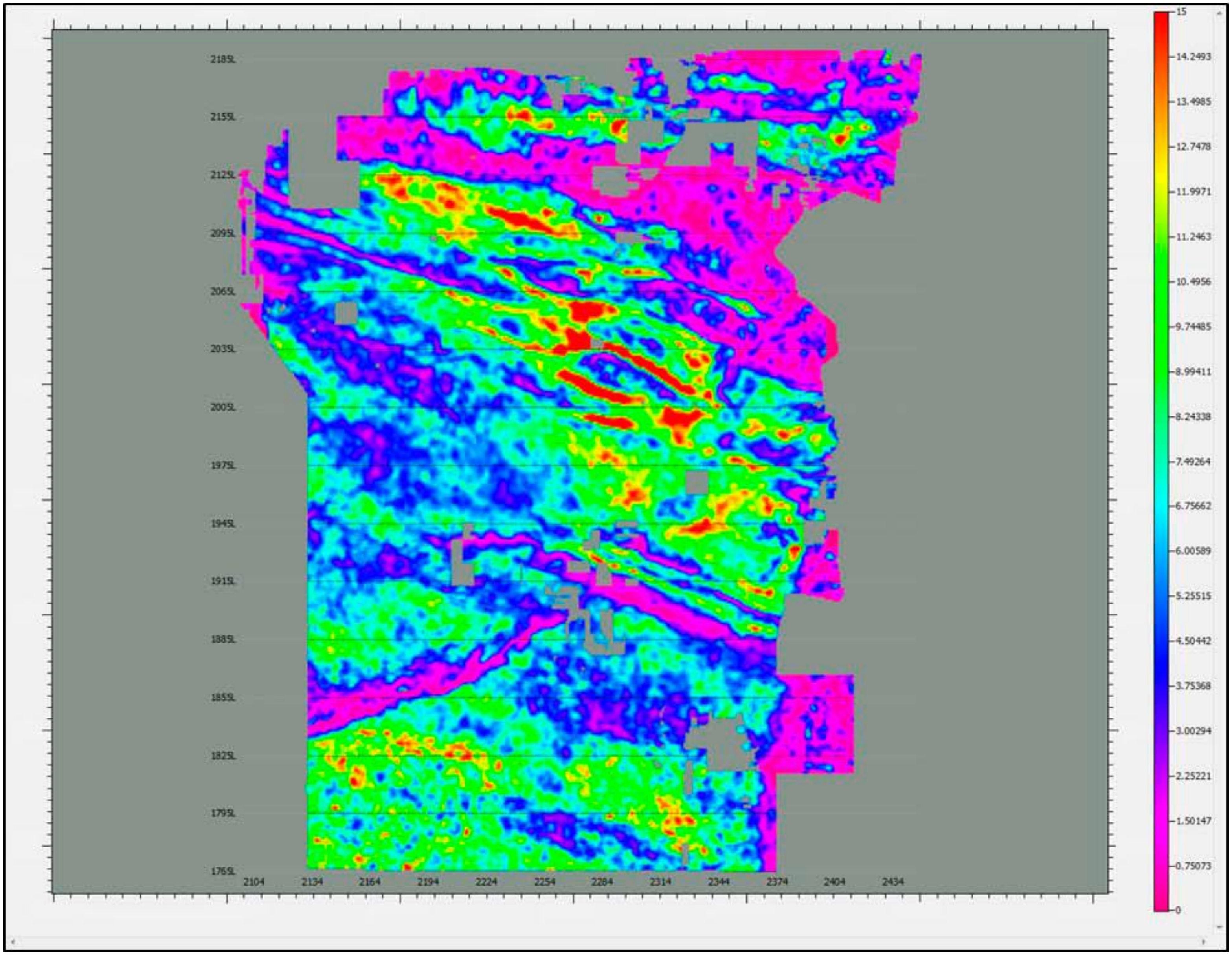

Figure 4. A horizon slice taken at baseof Haynesville, showing a statistical spectral attribute called total energy. Notice the geologic features along the faults captured by this attribute.

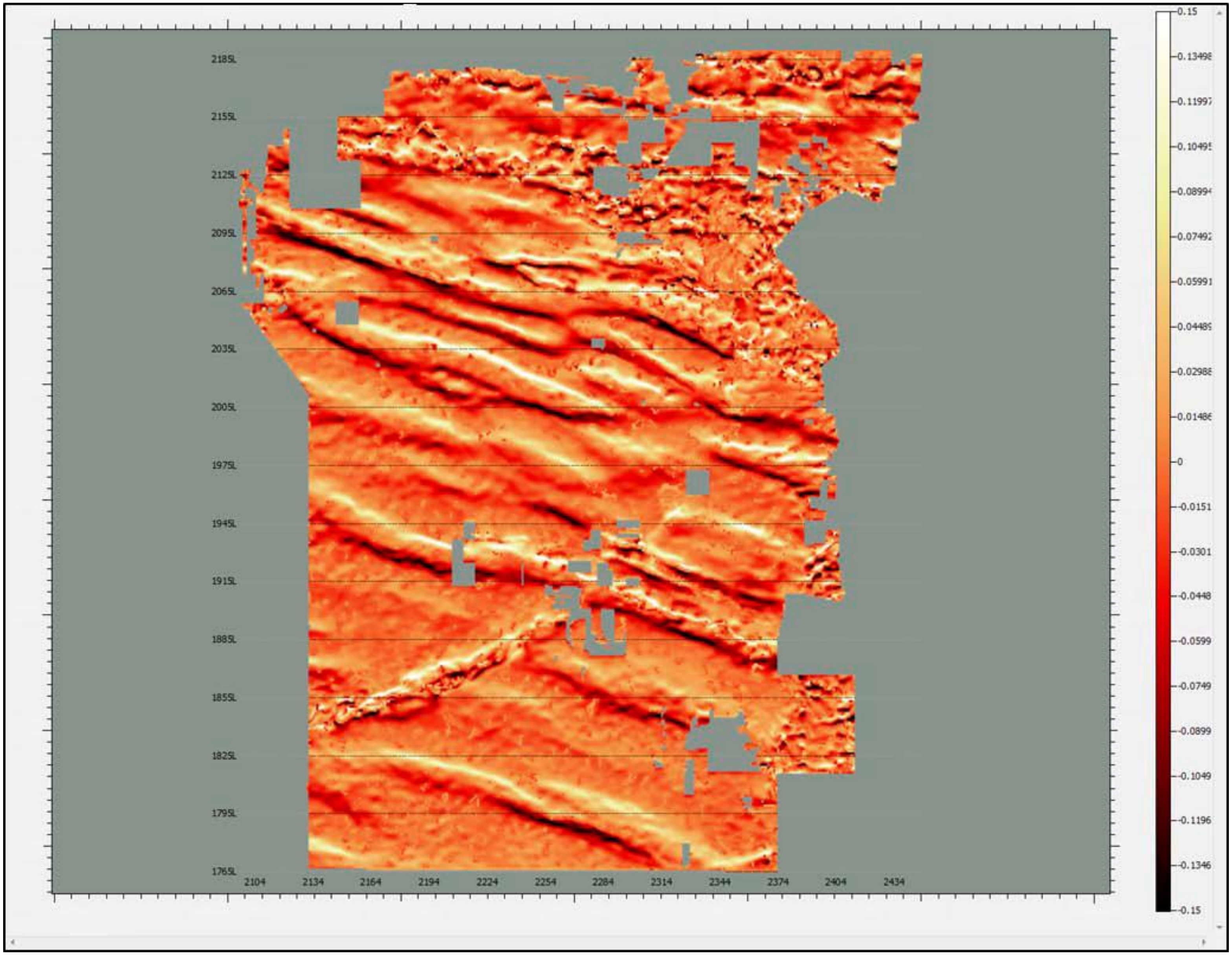

Figure 5. Horizon slice at the base of the Haynesville, showing the Euler curvature computed along the azimuth in which the key structural features are present.

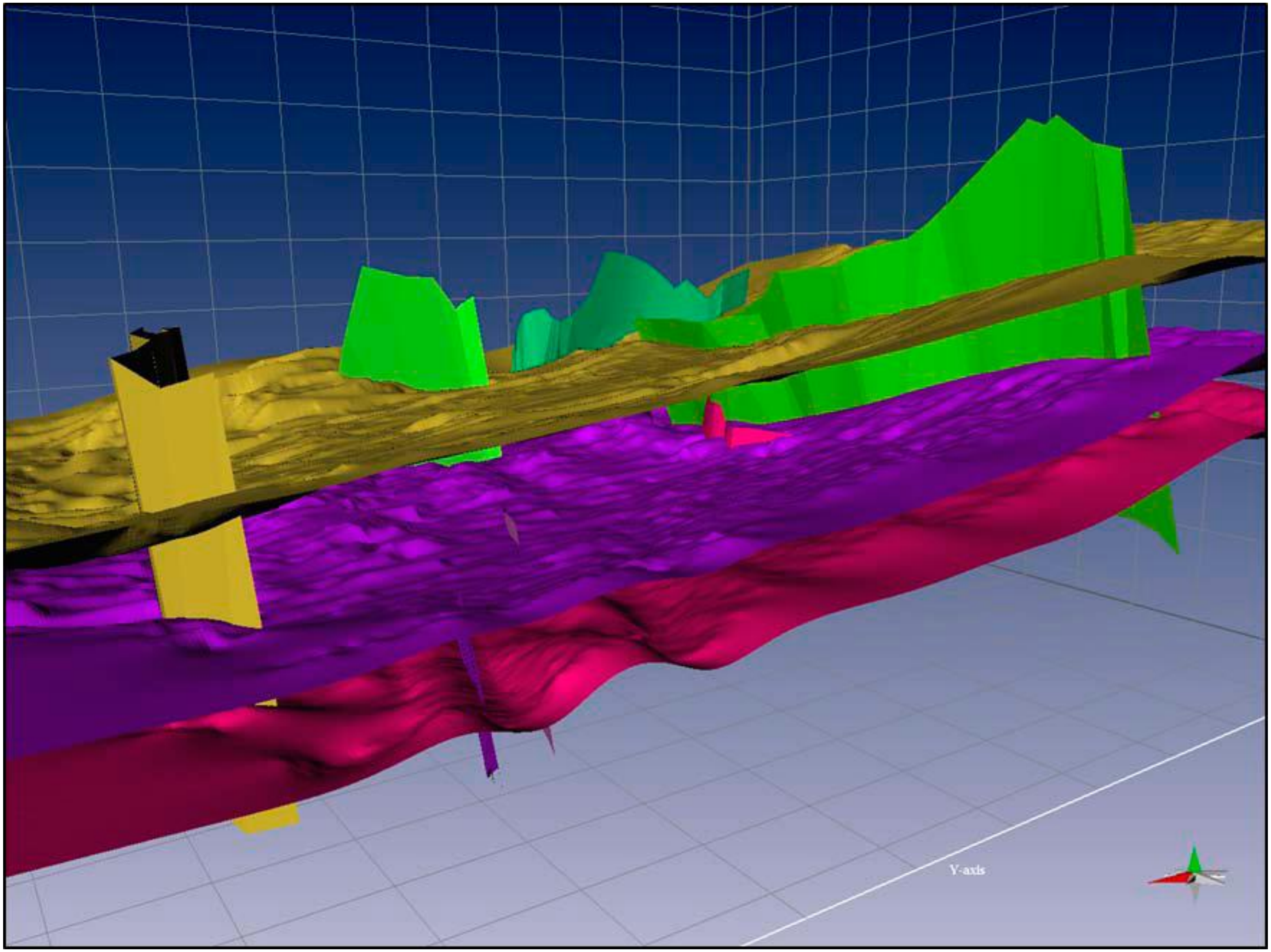

Figure 6. Horizons and faults used to build a water-tight, structural framework model.

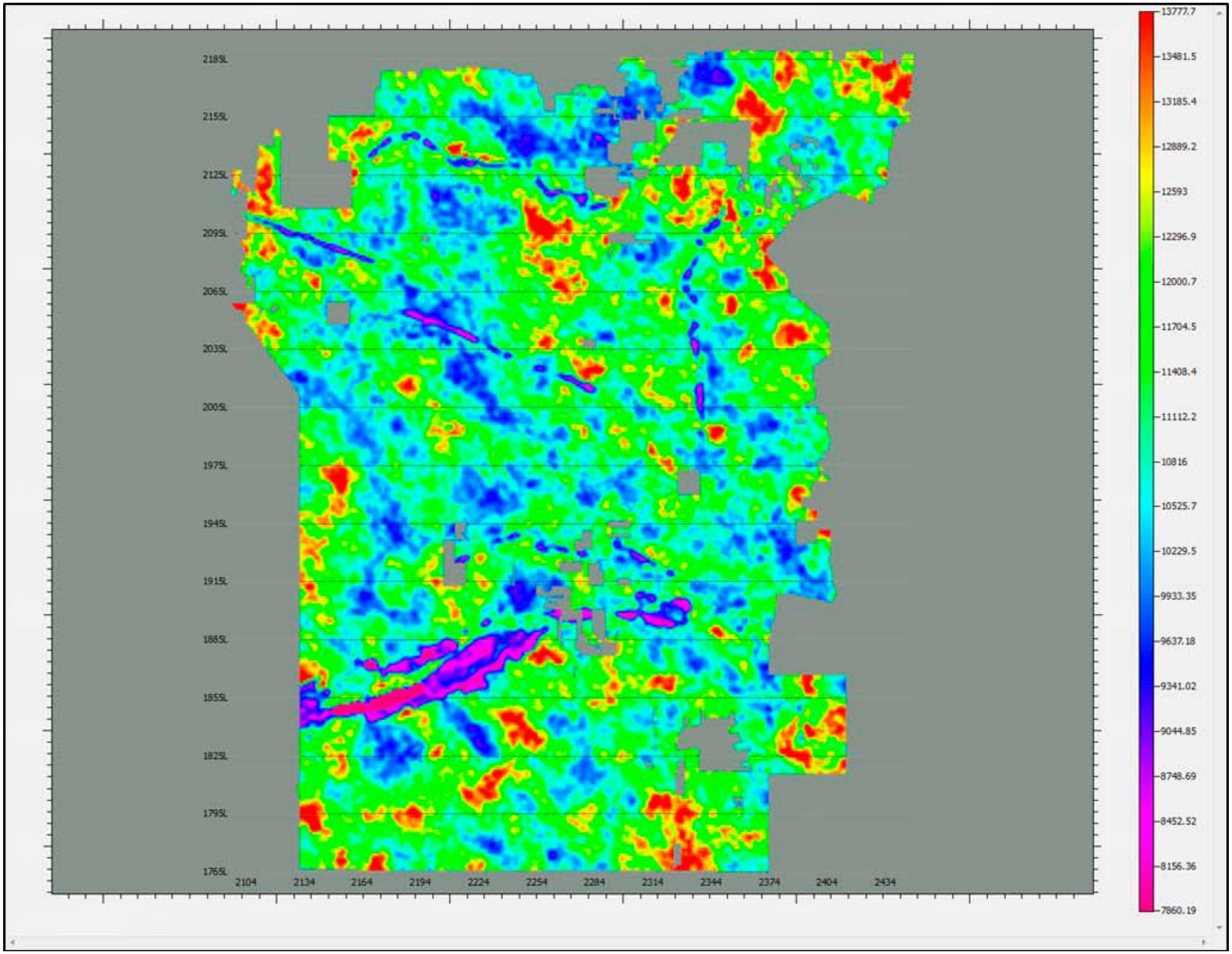

Figure 7. Horizon slice at the base of the Haynesville showing the impedance derived from the Stochastic inversion.

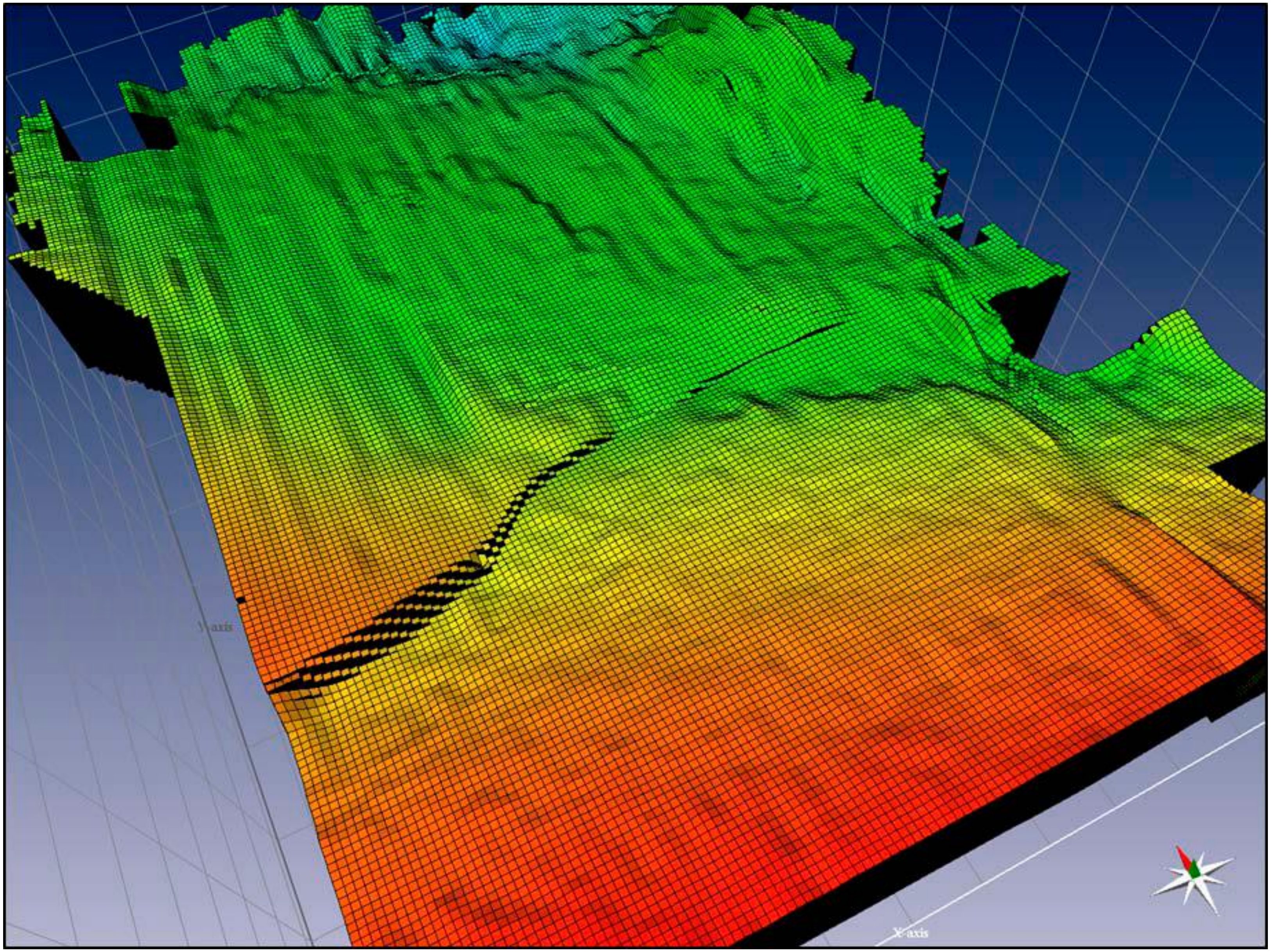

Figure 8. 3D geologic grid in time domain.

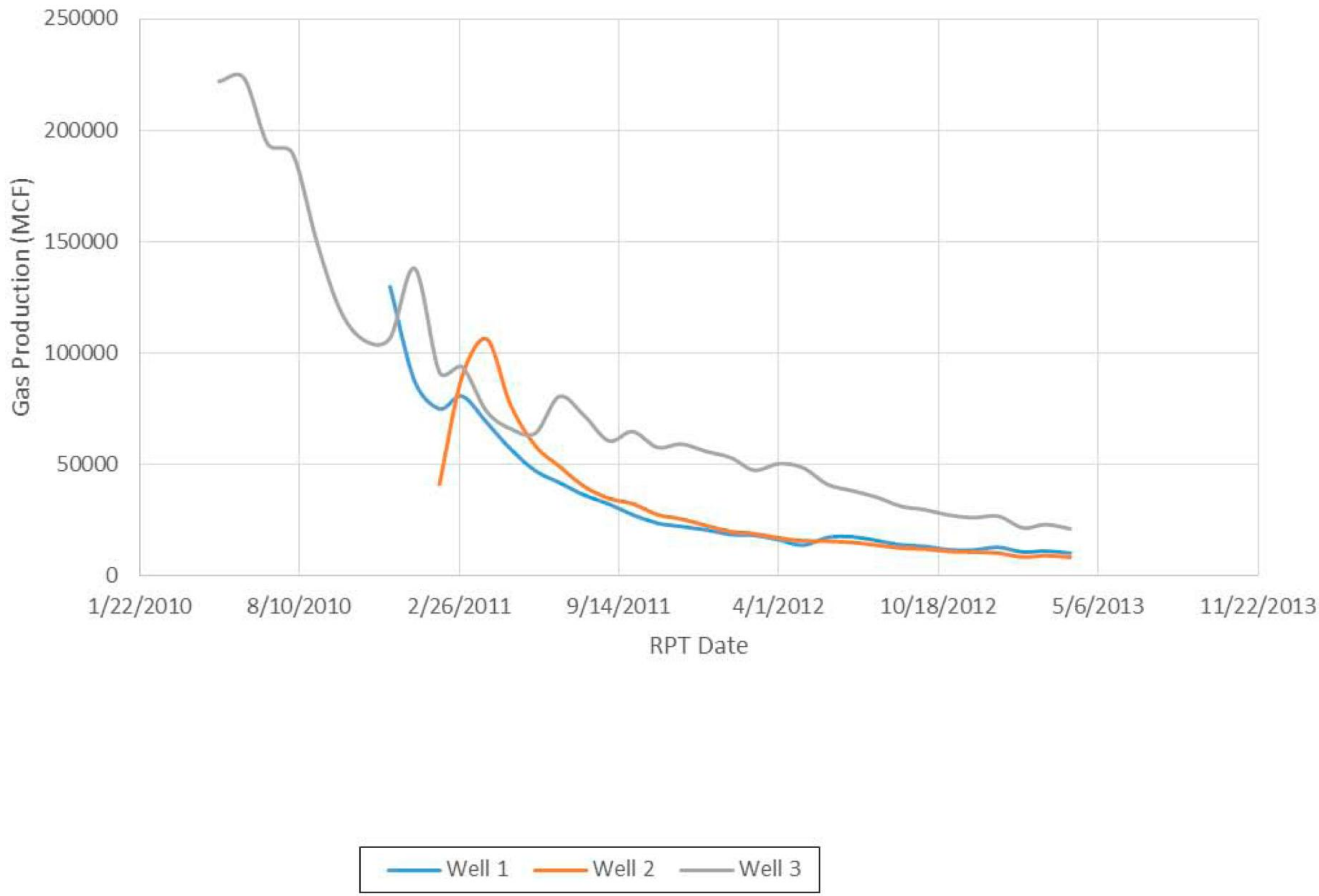

Figure 9. Production data for three deviated wells. Well 2 has an average monthly production of 30.9 MMCF/month while Well 3 has an average monthly production of 80.2 MMCF/month

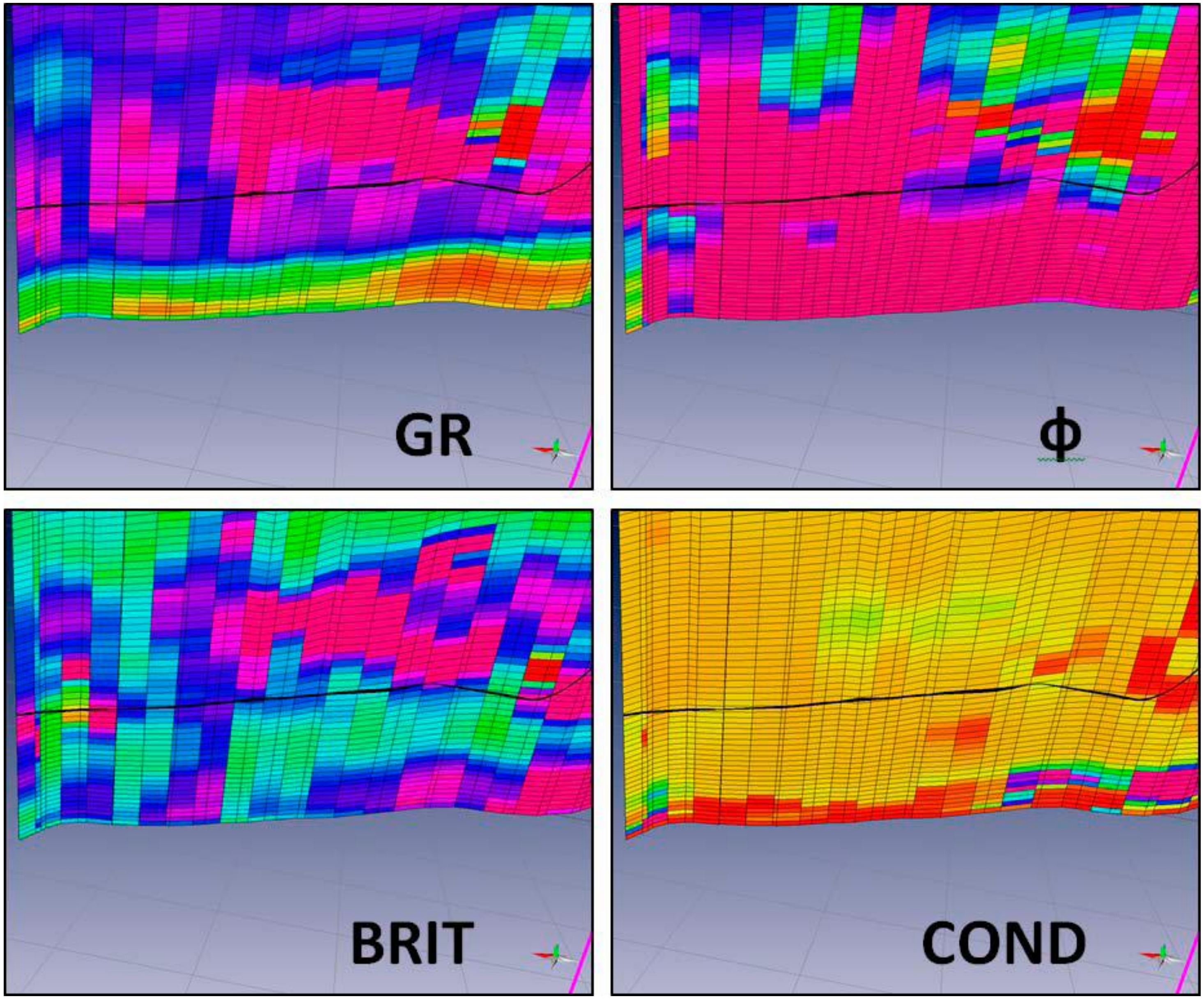

Figure 10. Cross section along Well 2, displayed by black line; this well has worse production than Well 3. The four drivers used to calculate Shale Capacity are displayed: Gamma ray (GR), Porosity (ϕ), Brittleness (BRIT), and Conductivity (COND). Red cells are high values; blue and purple cells are low values; magenta cells are zero values, which were below the cutoff values of the specified driver.

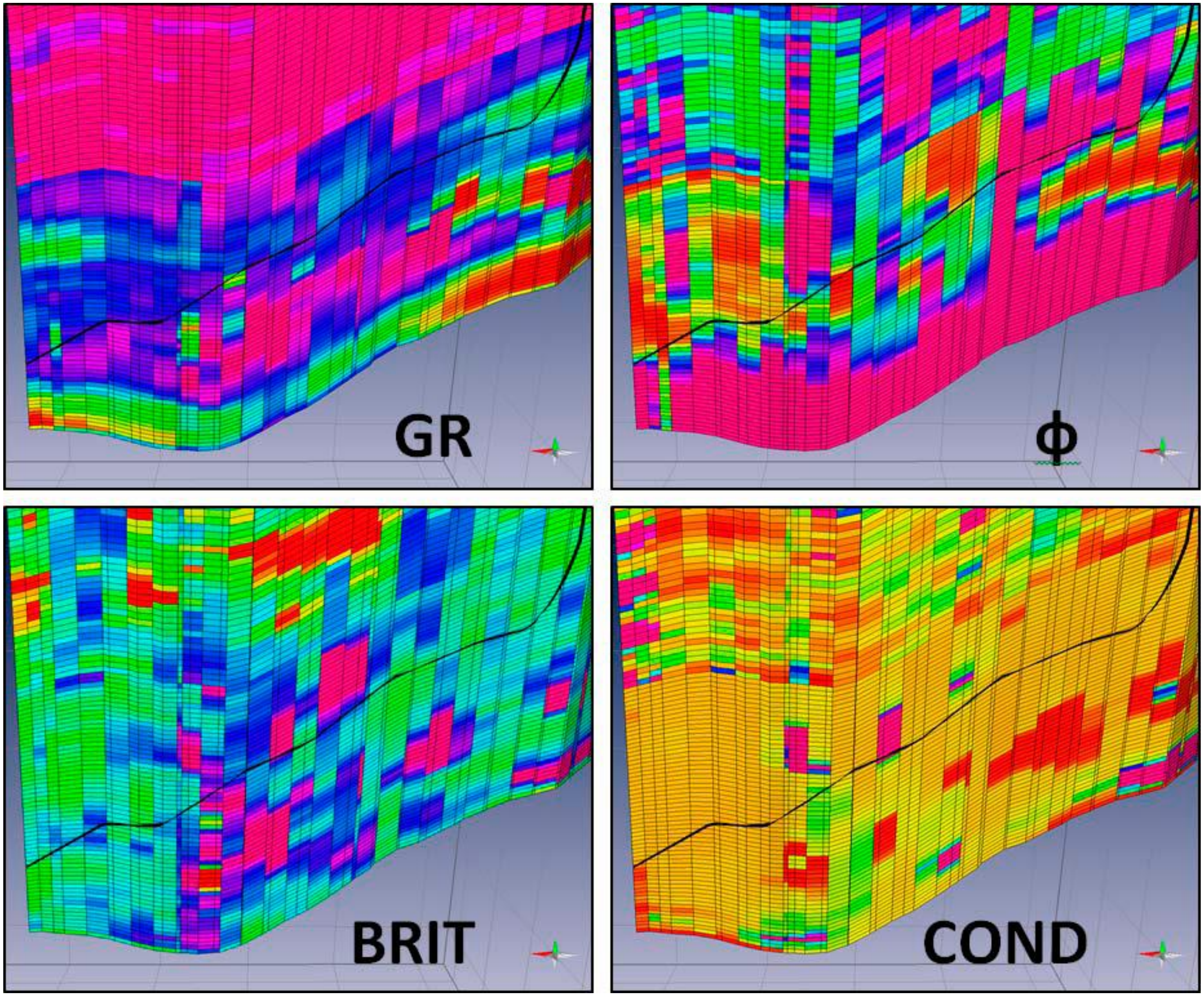

Figure 11. Cross section along Well 3, displayed in black; this well has better production than Well 2. The four drivers used to calculate Shale Capacity are displayed: Gamma ray (GR), Porosity (ϕ), Brittleness (BRIT), and Conductivity (COND). Red cells are high values; blue and purple cells are low values; magenta cells are zero values, which were below the cutoff values of the specified driver.

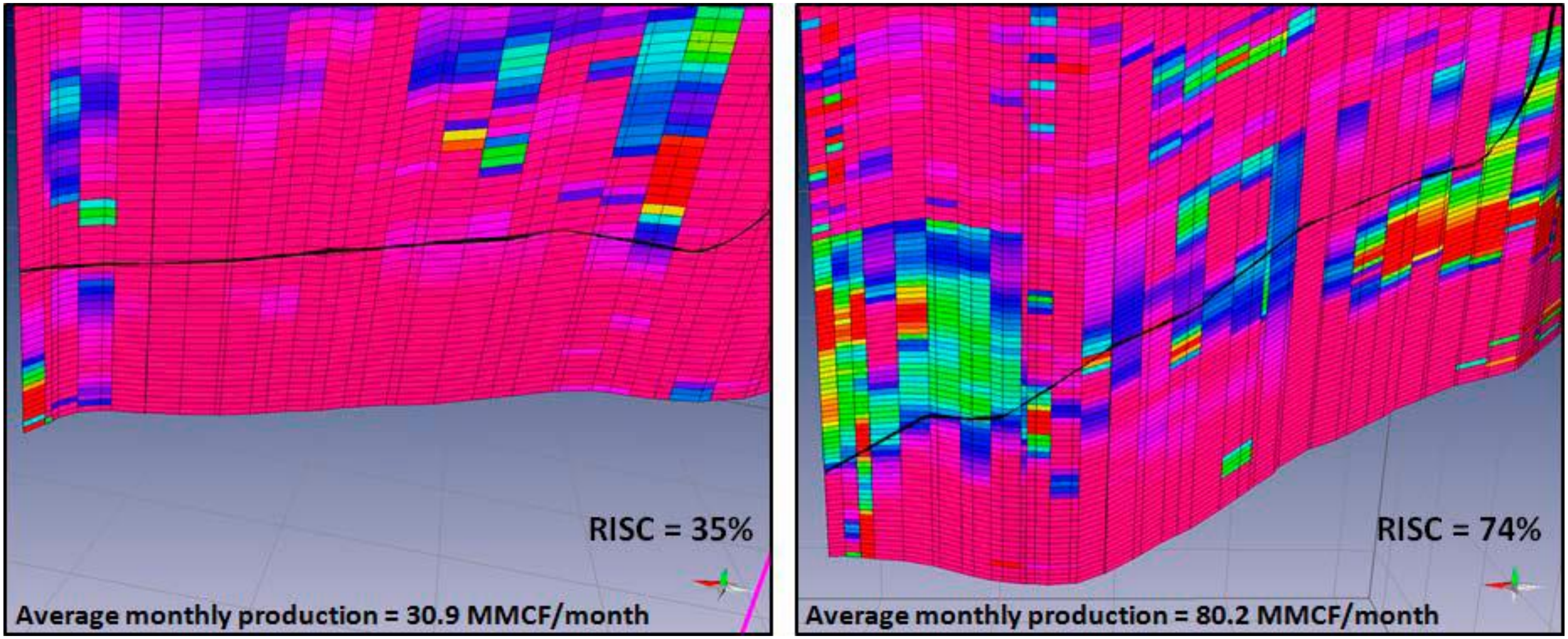

Figure 12. Shale Capacity (SC) model for Well 2 (left) and Well 3 (right). Well 3 shows intersection with more, higher value cells. Well 2 intersects with a small number of smaller value cells. Well 3 has a RISC of 74%, while Well 2 has a RISC of 35%.