Distribution of Well Performances in Shale Reservoirs and Their Predictions Using the Concept of Shale Capacity*

Ahmed Ouenes[1]

Search and Discovery Article #41139 (2013)**
Posted June 30, 2013

*Manuscript received June 10, 2013; revision received June 20, 2013, accepted June 26, 2013.

[1]SIGMA[3] Integrated Reservoir Solutions, Inc., Englewood, CO (a.ouenes@sigmacubed.com)

Abstract

Various empirical observations have been made regarding the nature of the distribution of shale productivity and the potential existence of three dependent intervals that seem to separate the uneconomical wells from the average and good wells. The areas of good well productivity exhibit a log normal distribution and seem to be controlled mainly by the natural fracture system. These differences in performance seem to be related mostly to the shale capacity defined as the product of four key shale drivers: TOC, porosity, brittleness, and fracture density. When drilling a shale reservoir, it appears that the Relative Intercepted Shale Capacity (RISC) seems to have a strong correlation with the resulting relative well performance. Consequently, well productivity could be predicted in a relative sense with reasonable accuracy if the 3D shale capacity model is available to the operator. Having such a 3D model available, a shale operator can compute the RISC of his future wells and adjust their landing zone, azimuth and length accordingly to reduce drilling and fracing costs, to achieve the best return on investment and accelerate the time to payout.

Background

After more than a decade of successful shale development, many of the pre-conceived initial ideas about these unconventional reservoirs can be revisited now that a wide range of data and experience is available. One of these pre-conceived ideas was that shale reservoirs are uniform and homogeneous and could be "mined" with the proper number of horizontal wells through a "manufacturing process". As expected, the geology of any reservoir is more complex than initially thought, and the reality of shale well performances turned out highly variable. After initial phases of development, often based on "statistical drilling, drilling to secure leases, drilling regular patterns along lease lines or drilling perpendicular to the regional maximum horizontal stress, a few shale operators and their financiers are now questioning the reasons behind the large variations seen in shale well performances. As new shale plays join the shale revolution and add more potential reserves, these questions become more pressing, especially with the reality of low gas prices. The flight to liquids and the focus on liquid shale plays, such as the Niobrara, where variations in well performance are well documented, emphasized once again this issue of large variations in well performances. To illustrate this large variability in well performance, we can examine the extensive data (MIT study) provided from the Barnett Shale (Figure 1). Based on the 2009 well data shown in Figure 1, in the worst case scenario, a Barnett Shale gas well could have an initial IP less than 1000 Mcf/day, or could be an average well between 1000 Mcf/day to 2000 Mcf/day, or result in a very good well that could have an initial IP higher than 5000 Mcf/day. These large variations have drastic consequences on the economics of these shale wells and on a lease overall. For a Barnett gas well, the P50 break-even price requires a 30 day average initial production rate of 1610 Mcf/day and 3500 Mcf/day for a Marcellus gas well (MIT study). Based on these observations, we can conclude that all the Barnett wells with an IP less than 1000 Mcf/day shown in the red box in Figure 1 are uneconomical, those in the yellow box between 1000 and 2000 Mcf are either uneconomical or barely break-even, and the only wells worth drilling are those found in the green box which unfortunately are also those with the lowest probability. The development of these shale reservoirs does not seem to be a straightforward manufacturing process as initially conceived, and a significant amount of ingenuity must be deployed to find the rare wells with the highest IP shown in Figure 1 (green box).

Small U.S. independent operators have shown lots of courage and ingenuity in driving the growth of the shale revolution, and they will continue to exercise that talent to go after the high IP wells. They will achieve that objective by working with multiple "levers" and "knobs" at their disposal.

One major knob that shale players could turn to adjust their well performance is completion and fracing strategy. It is this major knob that allowed in the first place the development of shale plays. It is safe to say now that almost everything has been discovered or tried in the completion and fracing technology. For each shale play, the optimal fracing procedure is known and available to any operator. The catalog for all types of proppant, all types of completion (plug and perf, sliding sleeves, etc.) and all the other components needed to frac a well are almost complete. Fracing service companies have a complete menu to choose from for any basin and budget. This is good news for shale development, and it is amazing that it took the oil industry such a short time to master and adopt these fracing technologies while other technologies, such as horizontal drilling or 3D seismic, had to wait more than 15 years before becoming mainstream. The bad news is that fracing technologies are not able to explain the wide variations in shale well performance. In other words, the maximum increase in well performance when upgrading from a standard fracing technology to an advanced fracing technology is not larger than 20% of the average production. At a time when all the shale operators are trying to reduce fracing costs while increasing well performance, a 20% increase in production is welcome, especially if it comes with a reduction in total proppant and water costs. However, a 20% increase in production is not sufficient to explain the large variability of shale well performance seen in all shale basins and it will not turn a poor well in the red box of Figure 1 into a good well with producing rates seen in the green box of the same figure. In other words, this variability is not due to changes in fracing technologies: the reason is something that is independent of any fracing technology applied to a specific well.

After optimizing the fracing technology knob, the only big knob left is the understanding of the shale reservoir and its complexity. Before examining this complexity and the ways to handle it, let us examine more closely the distribution of shale well performance in other basins and see if conclusions made in the Barnett Shale (Figure 1) can be generalized to all basins.

Distribution of Shale Well Performances

Shale well performance data can be data-mined from various state oil and gas commission databases, SPE publications, and other sources available in the public domain. The focus of this work is on the Barnett, Marcellus, Eagle Ford, Bakken, and Niobrara reservoirs. The data mined for this work is not as rich as the one used for the Barnett (MIT Study), but it could be sufficient to start the dialog and invite other companies and authors to collect more data and expand on this work.

The hypothesis behind this work is that the distribution of shale well productivity in any basin follows a typical distribution that can be seen over any geographical scale, given a sufficient distribution of wells. In other words, the characteristics of this typical distribution remain the same for a 30 sq. mile area, a bigger 100 sq. mile area, or over the entire basin. Of course, the larger the area, the larger the number of wells, and the longer the production times, the better the quantitative distributions of performance can be made for these wells. Furthermore, the hypothesis states that the distribution of well productivity is mainly dependent on the shale reservoir itself, whereas other factors, such as fracing technologies, do not alter dramatically these distributions for the reasons stated in the previous section. The link between the distribution of well productivity and the reservoir is discussed in the next sections, but let us examine now well productivity for five major shale basins.

It appears that the three boxes for poor (Red), average (Yellow), and good (Green) wells seen in the Barnett gas wells (Figure 1) are present in many other shale basins. For example, in the Marcellus, we consider an area of about 50 sq miles which was intensely drilled. From these wells, we extract only 36 wells that have been on production for more than 300 days. The distribution of the IP for these 36 Marcellus gas wells is shown in Figure 2. From the previous section we recall that the P50 break-even price requires a 30 day average initial production rate of 3500 Mcf/day for a Marcellus gas well (MIT study); this puts all the wells in the Red box (2500 < IP < 4000) in the category of uneconomical or barely break-even. The average wells in the yellow box (4000 < IP < 5500) seems to be frequent in the Marcellus. Very high rates (5500 < IP < 8000) have been reported by few Marcellus operators in this study area and other parts of the basin. The well performance distribution in the Marcellus seems to indicate that most of the operators are successful in avoiding uneconomical wells.

For the Eagle Ford Shale, Figure 3 gives the distribution of well performance based on 36 wells over an area of about 60 sq miles. In this case the performance is measured with the sum of the three best months of gas production. The worse wells have an IP less than 10,000 Mcf for 3 months, the average wells have production for the best 3 months between 10,000 < IP < 20,000 Mcf and the best wells have production for the best 3 months that could be as high as 35,000 Mcf.

For the three gas shales examined herein, Barnett (Figure 1), Marcellus (Figure 2), and Eagle Ford (Figure 3), the three intervals for poor (red), average (yellow) and good (green) well productivity seems to follow the same characteristics despite the differences in well numbers and covered area. The reduced number of wells considered for the Marcellus (Figure 2) and Eagle Ford (Figure 3) does affect mainly the distribution of the good wells in the green box. Unlike the Barnett case (Figure 1), where a large number of wells was used, the log normal distribution of the good wells (green box) is not obvious in the Marcellus and Eagle Ford cases. It is very likely that the use of more wells and a larger area would show a green box behavior (log normal distribution) similar to the one seen in the Barnett.

When considering the oil shale plays, two examples are used: the Bakken and the Niobrara. In the Bakken (Figure 4), Pearson et al. (2013) used 870 wells completed since January 2009 to evaluate the performance of the play. The authors compared 18 operators and normalized the 365-day average oil production by acre-feet. In this case, the most noticeable feature is the high probability of good wells in the green box. This is not the case for the Niobrara data (Figure 5), where 19 wells were used including the ten highest IP ever recorded in the last 4 years. In the Niobrara the good wells in the green box are not found easily.

Various observations may be made from these 5 shale plays and the distribution of well productivity:

- The distribution of the good wells in the green box seems to be highly dependent on the importance of the natural fracture system. The natural fracture system affects the well performances in many ways. Sometimes the mineralized and calcite sealed natural fractures will likely have a tendency to reactivate during hydraulic fracture treatments (Gale et al., 2010), thus enhancing the success of the frac job. These observations have been validated with microseismics in the Barnett (Mitchell and Berge, 2009), where the best wells are drilled parallel to the natural fractures as long as they stay away from Ellenberger karsts and both small and large scale faults that provide vertical conduits for water. Avoiding faults is not only a Barnett priority but a good practice for all shale plays. Open and sealed natural fractures are good for the frac jobs but faults, even small ones, are counterproductive. In the Bakken where natural fractures are "abundant," the wells in the green box are highly probable and owe a large part of their performance to the natural fractures. In the Niobrara natural fractures are still eluding many operators who are not aware of the availability of drill-bit tested 3D natural fracture modeling technologies that have been around for two decades. The Barnett green box shows a typical log normal distribution commonly seen in naturally fractured reservoir. The Marcellus and Eagle Ford distributions do not have enough wells to capture the same log normal distribution but it is very likely present if a larger number of wells were used.
- The width of the red, yellow and green boxes in the distributions of well performance seems to follow some given ratios that seem to be consistent from one basin to another.

These observations are purely empirical and have been seen consistently in many data sets from different shale basins, but they need to be confirmed by more data mining and analysis. If confirmed by other authors, they could provide useful information and multiple uses for many shale operators. The most striking observation made from the distribution of shale productivity is their relationship with the shale reservoir as described in the next sections.

Definition of Shale Capacity

One of the pre-conceived ideas in shale well productivity was that a 5000-ft-long horizontal well should produce more hydrocarbons than a 4000-ft long-lateral, based on simple volume of reservoir exposed to fracing. Data from different shale basins showed that this is not the case, and in many instances, shorter laterals have outperform longer ones. Another pre-conceived idea is that bigger fracs and longer perforated lengths would yield higher recovery. This idea was also proven incorrect as documented by Swindell (2012) in the Eagle Ford, and similar observations were made in other basins. In other words, the shale well performance seems to be mainly controlled by the reservoir and its characteristics and not necessarily by the length of the wellbore and the number of perforated intervals. To better understand these shale characteristics and their impact on well productivity, we need to define a new reservoir property, what we call the Shale Capacity.

Shale Capacity is defined as the ability of the shale to produce hydrocarbons when fraced. In conventional reservoirs we simply call this ***reservoir net pay***. In unconventional reservoirs, the fracing process creates the pay, or the so-called Stimulated Reservoir Volume (SRV), which is not limited to the rock properties determined by deposition and diagenesis. This fracing process involves a reservoir property that plays a major role in the shale well performance, ***shale brittleness***. Since this brittleness is a function of the shale properties resulting from the deposition, compaction, and diagenesis, it is highly dependent on the other rock properties described qualitatively by Ouenes (2012) in the shale puzzle. This shale capacity could be defined as the normalized product of four shale drivers defined above a certain cut-off value: Total Organic Content (TOC), Natural Fracture Density (FD), Brittleness (BRT), and Porosity (φ).

- Shale Capacity $SC = TOC_{net} \cdot FD_{net} \cdot BRT_{net} \cdot \varphi_{net}$
- Where $TOC_{net} = 0$ when $TOC < TOC_{cut\text{-}off}$
- Where $FD_{net} = 0$ when $FD < FD_{cut\text{-}off}$
- Where $BRT_{net} = 0$ when $BRT < BRT_{cut\text{-}off}$
- Where $\varphi_{net} = 0$ when $\varphi < \varphi_{cut\text{-}off}$

In other words, the Shale Capacity exists only if all four drivers are above their respective cut-off values. For example, if the shale is too ductile, then the brittleness is too low, and it falls below the cut-off value, thus making the Shale Capacity equal to zero independently of the values of the three other drivers. The four key drivers could be replaced by proxies that represent their behavior. For example, TOC could be replaced by the spectral gamma ray which does mimic reasonably well the behavior of TOC in many shale basins.

In some shale basins, one or more of the four drivers could show reduced variability and could give the impression that it is not an important driver. It is common these days to hear various shale operators stating with lots of confidence that their well productivity depends only on the brittleness or only on the density of the natural fractures. Unfortunately, these perceptions are likely misleading, and it is most probable that all these four drivers are needed in all the shale basins, even if in many cases one of the drivers seems to impose its imprint predominantly on the shale capacity. This leads to the issue of how to estimate these four shale capacity drivers in a 3D reservoir model.

Reservoir properties can be estimated robustly in 3D by using various modeling techniques. The most reliable methods are those that use seismic data to provide the missing information between wells. Some of the seismic processes that provide multiple useful attributes that help with this modeling effort were described in the context of the shale puzzle (Ouenes, 2012). However, the way these seismic attributes are currently used seems to have taken two different diverging paths. On one hand, there is the artificial intelligence route where neural networks are used to correlate the various seismic attributes with rock properties, such as the ones needed to compute the shale capacity. On the other hand there is the route using conventional statistics and associated linear multi-regression analysis tools. The merits of one method over the other could be debated at great length without resolution, and even if the artificial intelligence algorithms are used daily by everybody in their washer machines and their cars, there will be always a large group who will believe that these tools are "black boxes" and therefore cannot be trusted. The reality is that these artificial intelligence algorithms are the only mathematical tools at our disposal to model the complex geology that is characterized by the strong interdependency of these four drivers that create the shale capacity. In other words, the use of linear multivariate regression analysis to correlate some seismic attributes to one of the drivers, the shale capacity or a similar measure describing the shale well performance, violates a geological fact: these four drivers ARE NOT independent. For example, the brittleness of the Marcellus depends mostly on the amount of quartz present in the shale. However, higher quartz content requires that clay content be lower, translating into lower TOC. Thus the interdependency between brittleness and TOC can be explained by the deposition of the Marcellus shale and the unique characteristics it has near the Maximum Flooding Surfaces during transgressive-regressive cycles (Blood, 2011). The same interdependence exists between the quartz content that controls the brittleness and the porosity that is critical to the reserves. Higher quartz content in the Marcellus translates into higher porosity. Finally, the natural fractures are also highly dependent on this quartz content thus making every shale driver interdependent on the others.

The geology of shales resembles a card game more than a dice game. When playing a card game, e.g., poker, the probability of getting a royal or straight flush depends on what cards are in the hands of the other players. In contrast, in a dice game, the probability to score a six in each die is independent of the other die. So modeling shale properties with linear regression tools that assumes that the underlying drivers are linearly INDEPENDENT is like using dice to play poker! The reality is that shale drivers and the multiple seismic attributes used to model them are dependent variables that require mathematical tools that follow a set of rules designed to solve the problem. In layman's terms, **the modeling of shale reservoirs is a card game not a dice game.** It is this geologic reality that makes neural networks, which are specifically designed to model interdependent variables and the coupled non-linear relation that exist between them, the appropriate modeling tool for predicting these properties. Various aspects related to the use of artificial intelligence tools in reservoir modeling and their successful application to fractured reservoirs can be found in Ouenes (2000) and Jenkins et al (2009).

To better illustrate the process that takes the shale drivers and turn them into the Shale Capacity, we consider a Marcellus example where narrow azimuth post- and pre-stack seismic data were available along with five wells that have reasonably complete sets of logs including a well with an image log. The workflow that turns these raw data into useful 3D models showing the distribution of the shale drivers is summarized below.

The first step is to enhance the resolution of the seismic data using broadband spectral inversion. The enhanced seismic is used as input in the extended elastic inversion (EEI) to create the elastic properties needed to compute the brittleness and used as input in the geologic and fracture modeling effort that uses the neural network (Ouenes, 2012, Jenkins et al., 2009, Ouenes et al., 2010). The stochastic inversion was used in the EEI to create seismic attributes with a resolution of 1 msec which will allow the building of geologic and fracture models that have a vertical resolution of 3 to 5 m, a necessary requirement for proper quantitative characterization of shale reservoirs. The enhanced seismic is also used as in input for spectral imaging and volumetric curvature to create additional seismic attributes needed for the geologic and fracture modeling effort. The sequential geologic modeling approach is used to estimate sequentially the gamma ray model (GR), followed by the density (RHOB), the porosity (φ), and finally the resistivity (RT) and fracture density (FD). The entire modeling effort is done in a 3D geocellular grid that takes into account the complex stratigraphic features of the shale reservoir. Six wells produced in 2010 and 2011 with different IP's and different number of days and their productivities were retrieved from the Pennsylvania Department of Oil & Gas Reporting Website. The longest producing well had 344 days of production and the shortest one had only 11 days of production. The highest IP of the 6 wells was 5383 Mcf/day and the lowest IP was 1314 Mcf/day. Given the lack of well history and long production time, we have no other choice than to mix IP values computed with different number of days varying between 344 and 11 days. Figure 6 shows the distribution of the four drivers used to compute the shale capacity at a poor well that had an IP of 1314 Mcf/day with 63 days of production. Figure 7 shows the same four shale drivers for a good well that had an IP of 4389 Mcf/day with 344 days of production. The shale drivers used to compute the shale capacity include many areas that have a zero value (purple cells in Figures 6 and 7), which corresponds to reservoir zones that are below the cut-off value. The Shale Capacity is simply the product of the four shale drivers shown in Figures 6 and 7. The resulting shale capacity in a good and a poor well is shown in Figure 8. We notice that the wellbore of the poor well crosses a very small zone of useful positive shale capacity while the good well is intercepting a larger zone of high shale capacity. Could these empirical observations be translated into quantitative relationships that relates to the IP to the shale capacity? This is the subject of the next section.

Well Performances Explained with Relative Intercepted Shale Capacity (RISC)

When examining the positive shale capacity intercepted by the wellbore, an anomaly appears when comparing longer and shorter laterals and their relationship to the IP. The same puzzling anomaly appears when comparing wells with different frac stages all placed in the zone of high shale capacity. The same anomaly was reported by Swindell (2012) for the Eagle Ford. This anomaly indicates that the intuitive absolute length of the wellbore intercepting the high shale capacity would correlate very well with the IP of that well. Unfortunately, this is not the case, and it appears from various data examined that the relative length of the wellbore intercepting the shale capacity is the key factor controlling the well performance. Therefore, what matters the most in these wells is not their absolute length that penetrates the good shale capacity but their relative length in it compared to the total length of the lateral. The relative well performance seems to be sensitive to the length of the wellbore crossing the zone of high shale capacity divided by the total length of the wellbore. We define this entity as the Relative Intercepted Shale Capacity (RISC). When using the IP for the limited 6 wells that produced in 2010 and 2011, we find a strong correlation with an $R^2 = 0.73$ between the Relative Intercepted Shale Capacity (RISC) and the IP as shown in Figure 9. Could this relationship be used to predict the relative well performance of the wells drilled in 2012?

Predicting Well Performances Using Relative Intercepted Shale Capacity (RISC)

From Figure 8, we notice that the good well did not intercept the very high values of the shale capacity. Thus the six IP values available at the end of 2011 may not provide the entire spectrum of possible well performance. Nevertheless, we can use the derived correlation shown in Figure 9 to predict the relative IP of the seven new wells that were drilled and produced in 2012. The absolute IP of the predicted wells will depend on the number of frac stages and their successful execution. Here again the number of days of production varied between a low of 33 days to a high of 182 days. The resulting absolute IP retrieved from the Pennsylvania Department of Oil & Gas Reporting Website varied between 876 Mcf/day computed with 82 days of production to 17,250 Mcf/day computed with 57 days of production. Again we are mixing IPs of different days because of the scarcity of the data. Despite this mix of IP values computed with different number of days, the predicted relative IP is good in 5 out of 7 wells as shown in Figure 10. In other words the predicted relative high IP wells turned out to have the absolute highest producing rates while the predicted relative low IP wells turned out to be the lowest absolute producers. Notice that none of these predictions involved the use of the number of frac stages, the type of fracing technology, or anything related to the completion of these wells. Figure 11 shows the (RISC) at a good and a poor well drilled and produced in 2012. The RISC shown at the 2 wells of Figure 11 is able to explain the difference in well performance between the 2 wells.

These empirical observations have been verified with multiple studies and seem to be robust from one area to another in the same basin and across different shale basins. The most striking of all these observations is the link between the (RISC) and the distribution of the shale productivity described in the previous sections as red, yellow and green boxes. After examining many data sets, it appears that a RISC < 50% will put the well in the red box of uneconomical wells, and the average to good wells (yellow and green boxes) seem to be achieved with a RISC > 50%. This shows that to get the best wells the shale operator needs to be able determine the Shale Capacity 3D volume in order to compute the RISC of future wells and adjust their landing zone, azimuth, and length accordingly to reduce drilling and fracing costs, to achieve the best return on his investment, and to accelerate the payout.

Acknowledgements

The author would like to thank AAPG Search and Discovery editors, Alan Huffman, Dave Balogh, Peter O'Connor, and Kathy Ashmore for their editorial comments. For the Marcellus example, the contribution of Raul Cabrera for the broadband spectral inversion, Matt Fackler, Chelsea Newgord, Dave Balogh, Moussa Bari, Eric Bard, and Amares Aoues for the geophysical tasks, Mohamed Mediani, and Badia Daoudi for the geologic and fracture modeling tasks, Aissa Bachir and Djamel Boukhelf for the engineering tasks are greatly appreciated.

References Cited

Blood, D.R., 2011, Sequence stratigraphy crucial to lateral placement in Marcellus shale play: The American Oil & Gas Reporter, v. 54/8, (August), p. 52-60.

Gale, J.F., R.M. Reed, S.P. Becker, and W. Ali, 2010, Natural fractures in the Barnett Shale in the Delaware Basin, Pecos County, West Texas: Comparison with the Barnett Shale in the Fort Worth Basin: Search and Discovery Article #10226 (2010), Web accessed June 27, 2013. http://www.searchanddiscovery.com/documents/2010/10226gale/ndx_gale.pdf

Jenkins, C., A. Ouenes, A. Zellou, and J. Wingard, 2009, Quantifying and predicting naturally fractured reservoir behavior with continuous fracture models: AAPG Bulletin, v. 93/11, p. 1597-1608.

Mitchell, G.C., and T.B. Berge, 2009, Structural attribute analysis used in Barnett resource development: Search and Discovery Article #110095 (2009), Web accessed June 27, 2013. http://vidego.multicastmedia.com/player.php?v=hnc0763t

MIT, 2011, The future of natural gas, An interdisciplinary MIT study: 178 p. Web accessed 26 June 2012. http://mitei.mit.edu/system/files/NaturalGas_Report.pdf

Ouenes, A., 2000, Practical application of fuzzy logic and neural networks to fractured reservoir characterization, *in* Shahab Mohagegh (ed.), Computers and Geosciences: v. 26/7.

Ouenes, A., T. Anderson, D. Klepacki, A. Bachir, D. Boukhelf, U. Araktingi, M. Holmes, B. Black, and V. Stamp, 2010, Integrated characterization and simulation of the fractured Tensleep reservoir at Teapot Dome for CO_2 injection design: SPE paper 132404.

Ouenes, A., 2012, Seismically driven characterization of unconventional shale plays: CSEG Recorder, v.37/2 (February), Web accessed 27, June 2013. http://csegrecorder.com/articles/view/seismically-driven-characterization-of-unconventional-shale-plays

Pearson, C.M., L. Griffin, C. Wright, and L. Weijers, 2013, Breaking up is hard to do: Creating hydraulic fracture complexity in the Bakken central basin: SPE paper 163827.

Swindell, G., 2012, Eagle Ford Shale-An early look at ultimate recovery: SPE paper 158207.

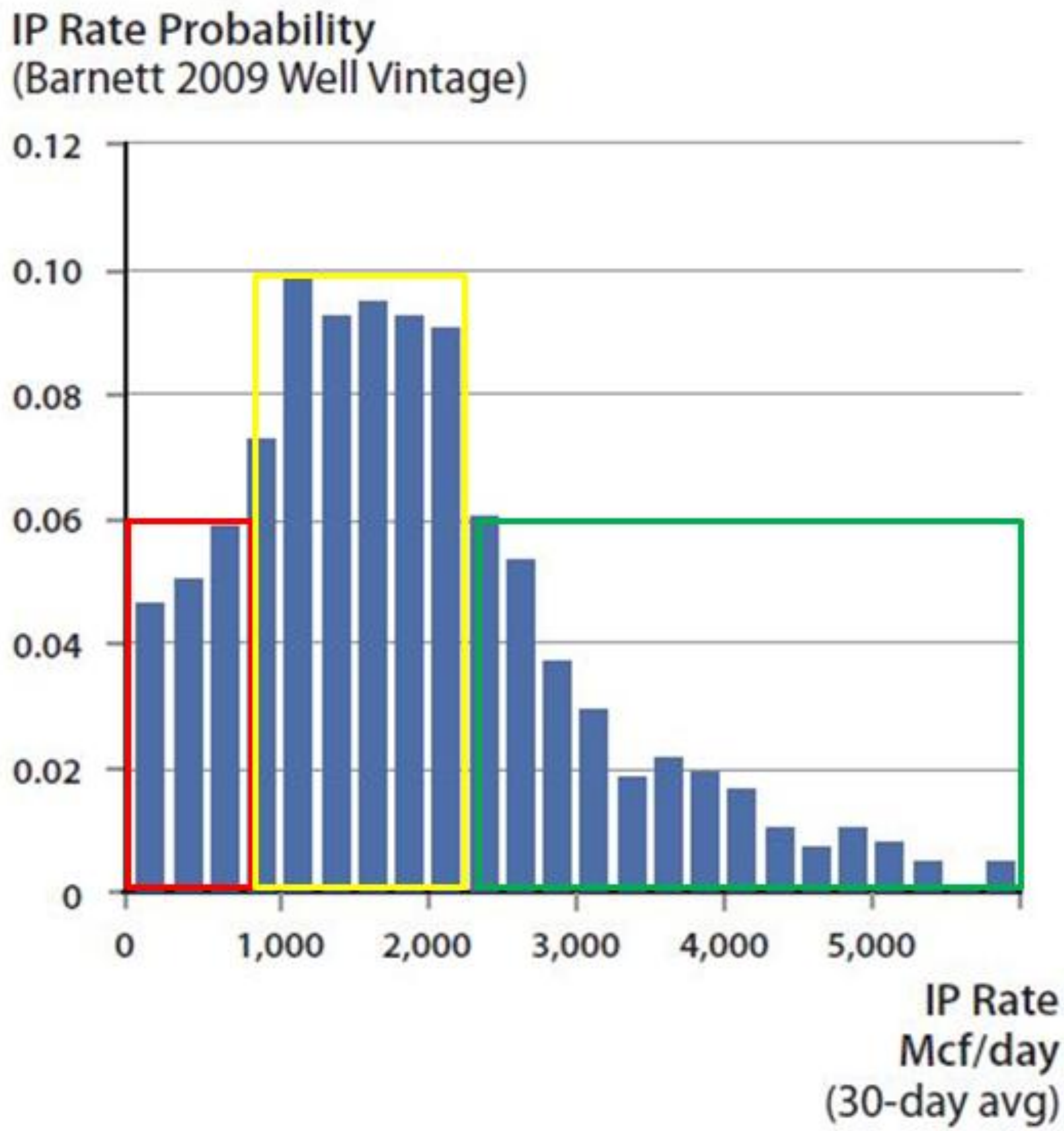

Figure 1. IP rate for 2009 Barnett Shale wells (from MIT, 2011,"The Future of Natural Gas").

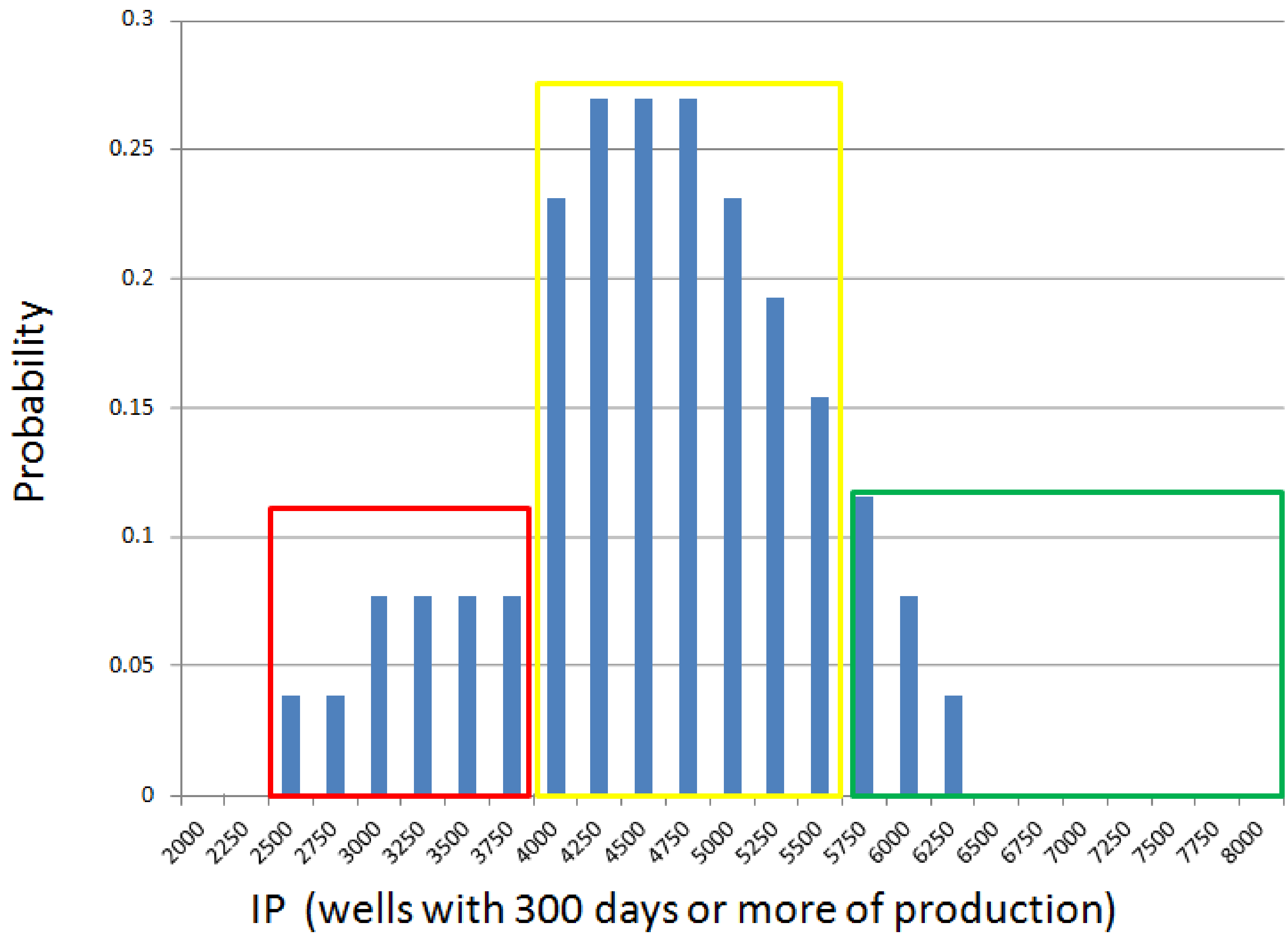

Figure 2. Marcellus IP rates for 26 wells that produced more than 300 days. The 26 wells cover an area about 50 sq miles.

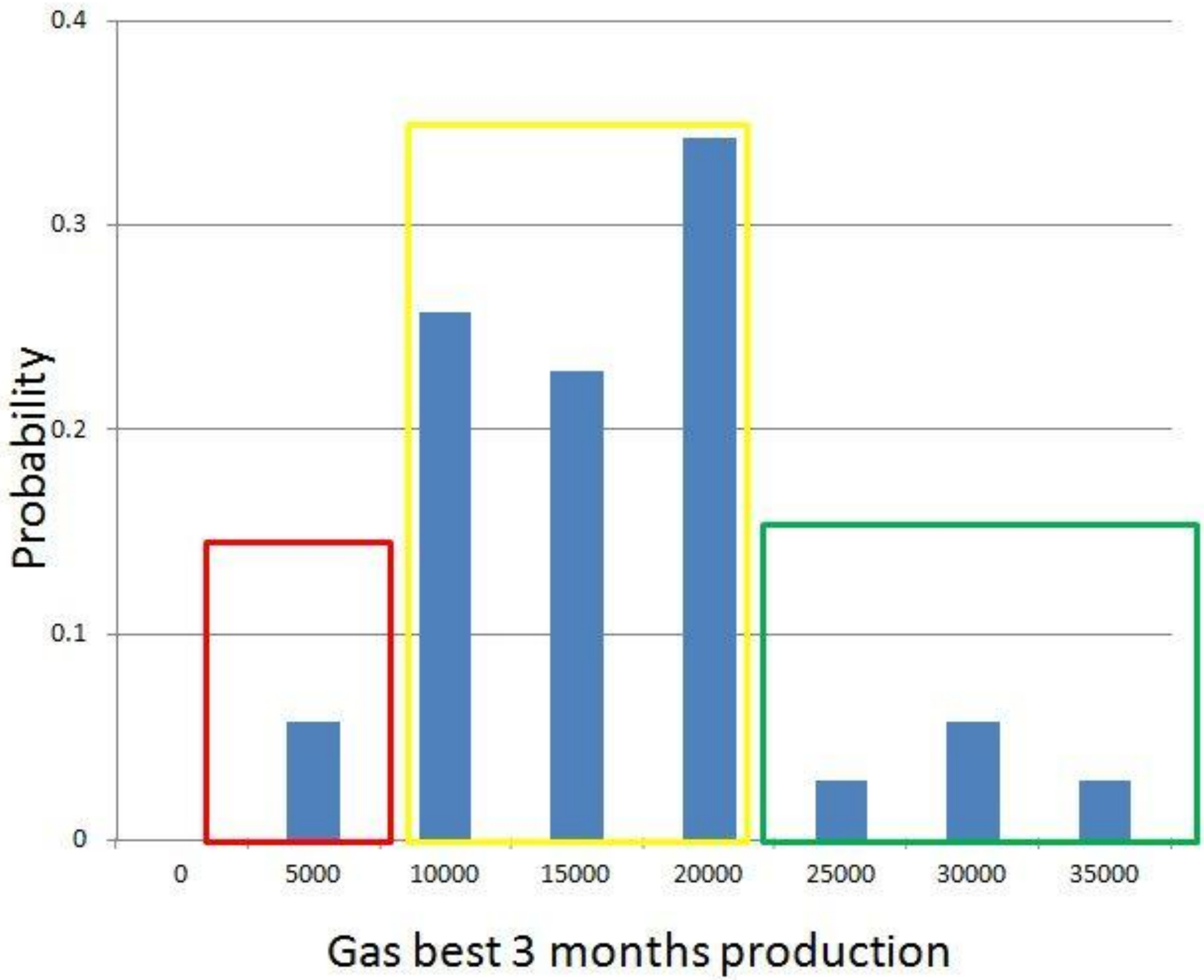

Figure 3. Eagle Ford Gas: Best three months production for 36 wells that cover an area about 60 sq miles.

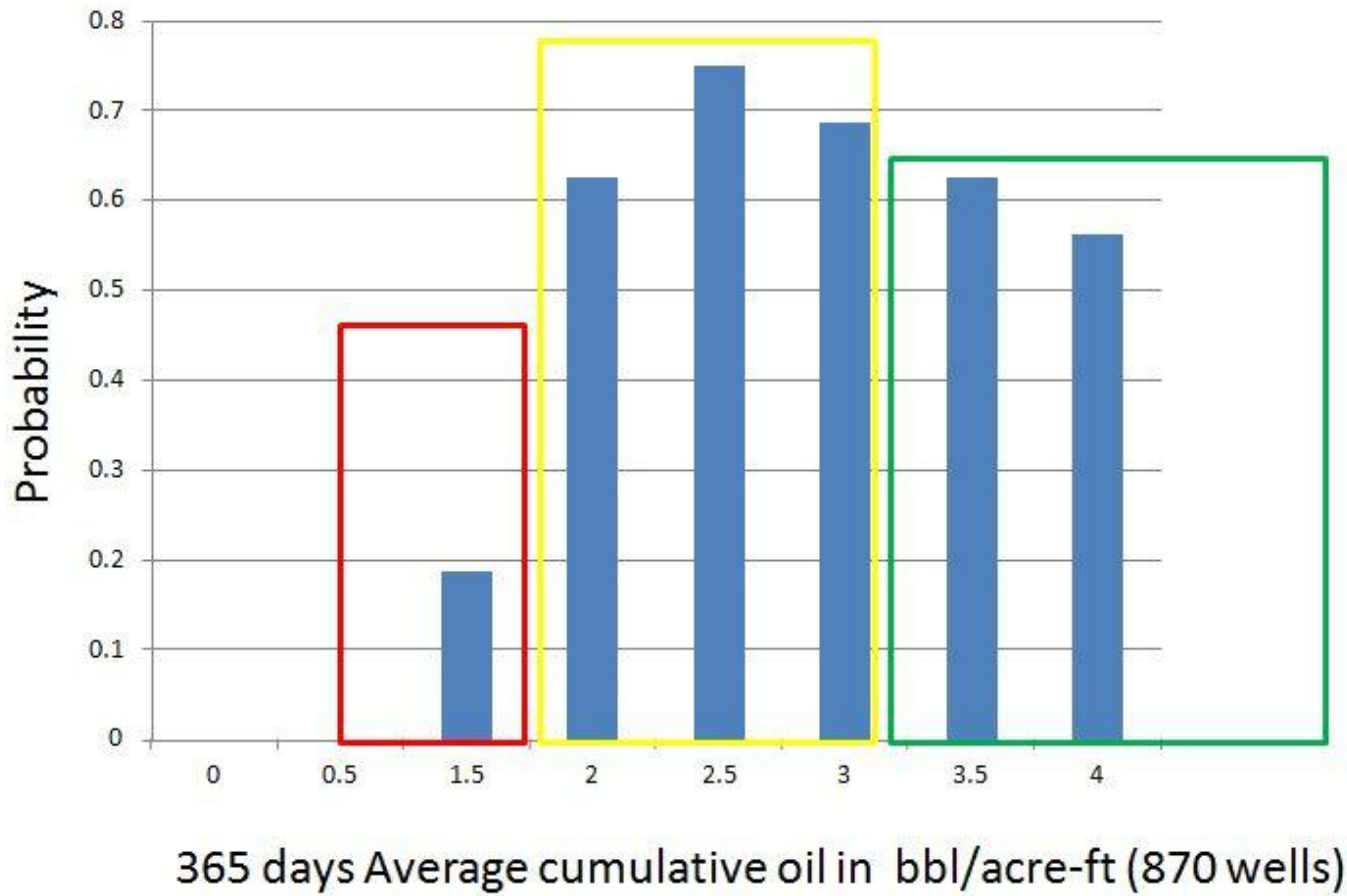

Figure 4. Bakken Oil: 365-day average cumulative oil from 870 wells in the central basin.

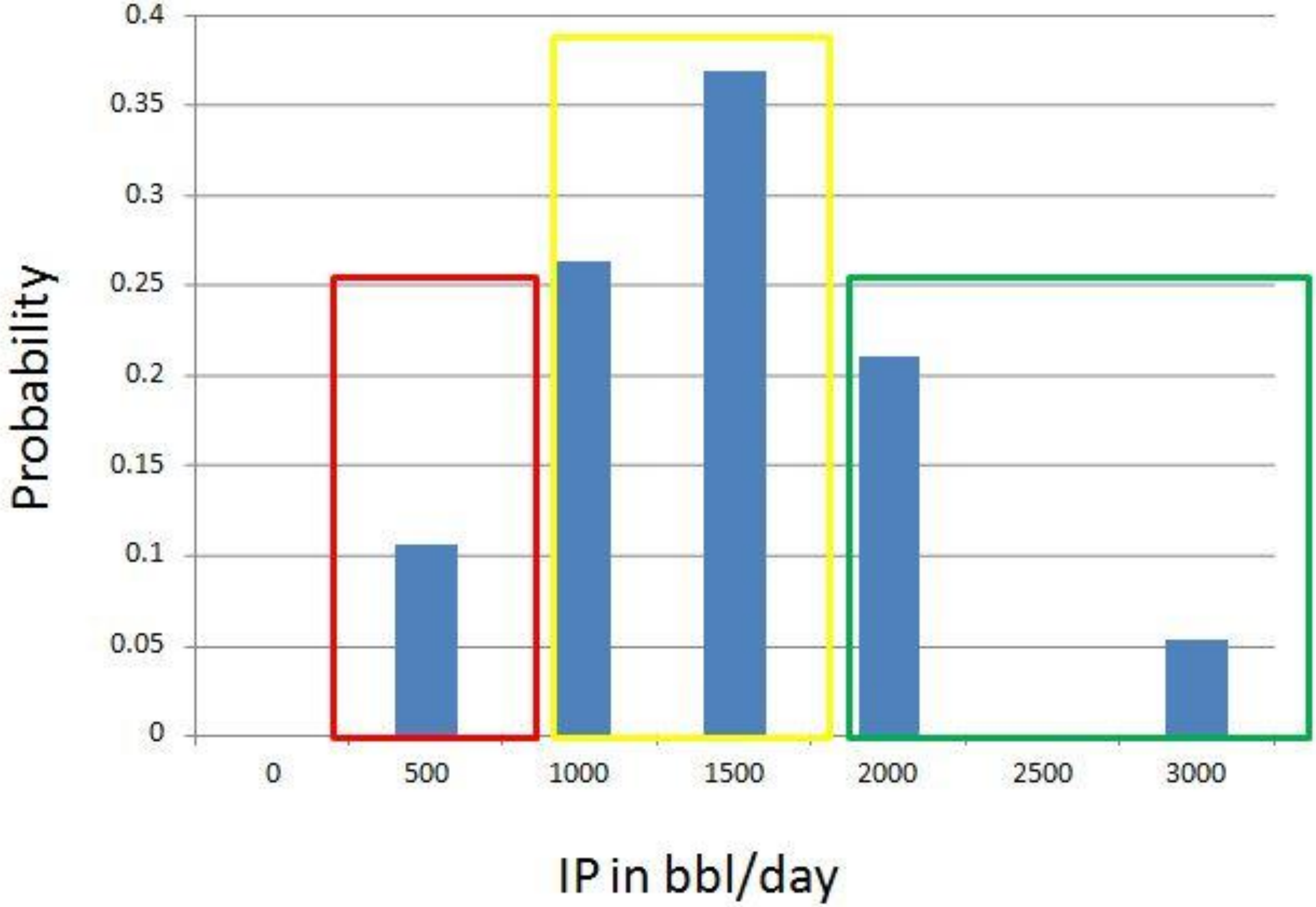

Figure 5. Niobrara initial production rates from 19 wells which include the ten highest IP rates.

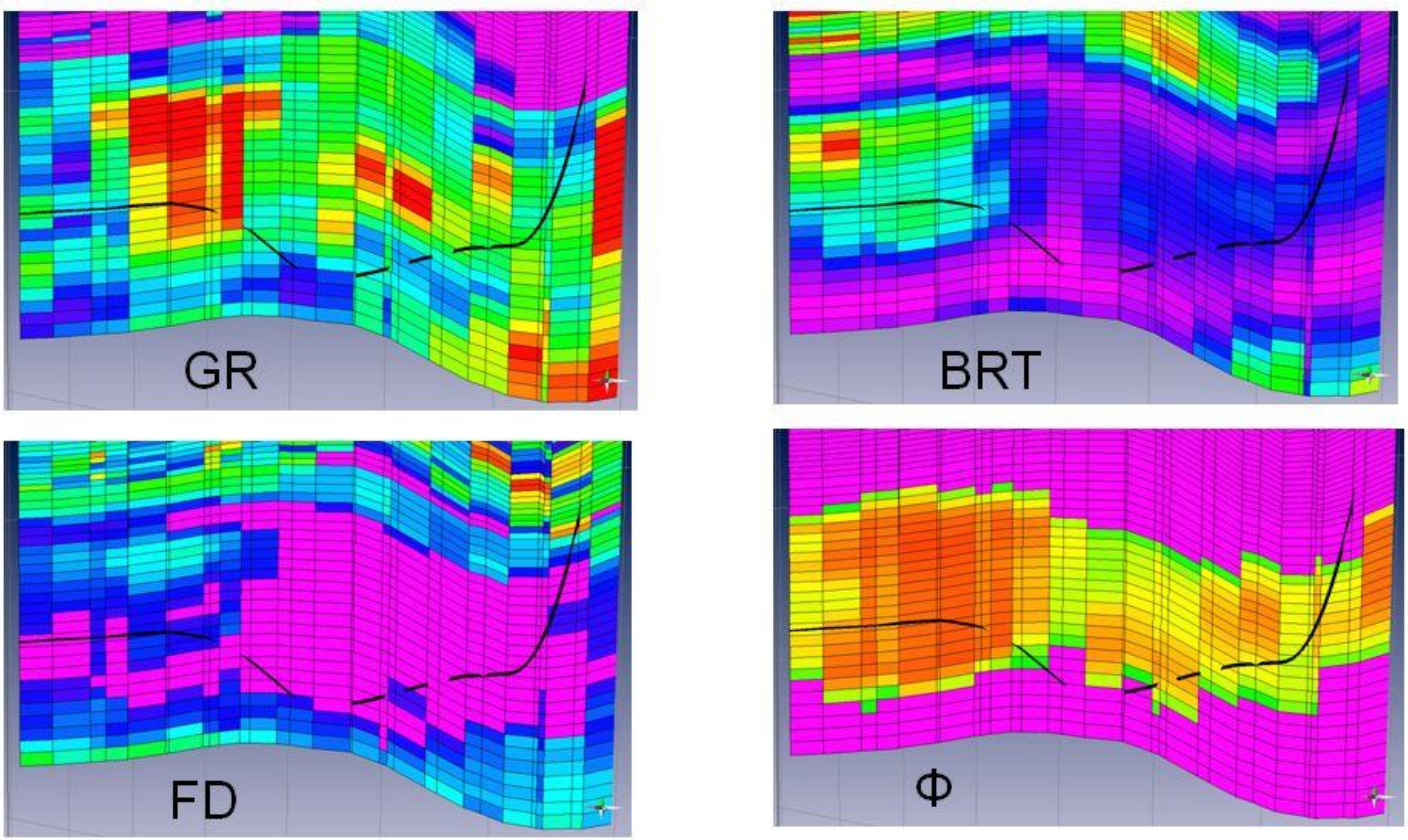

Figure 6. Cross section along a poor well (shown in black). IP = 1314 Mcf/day of the four shale drivers used to compute the shale capacity: GR as a proxy for TOC; Brittleness BRT; Fracture density FD; Porosity φ. Red cells correspond to high values, blue correspond to low values, and purple cells correspond to zero, which means the driver is below the cut-off value.

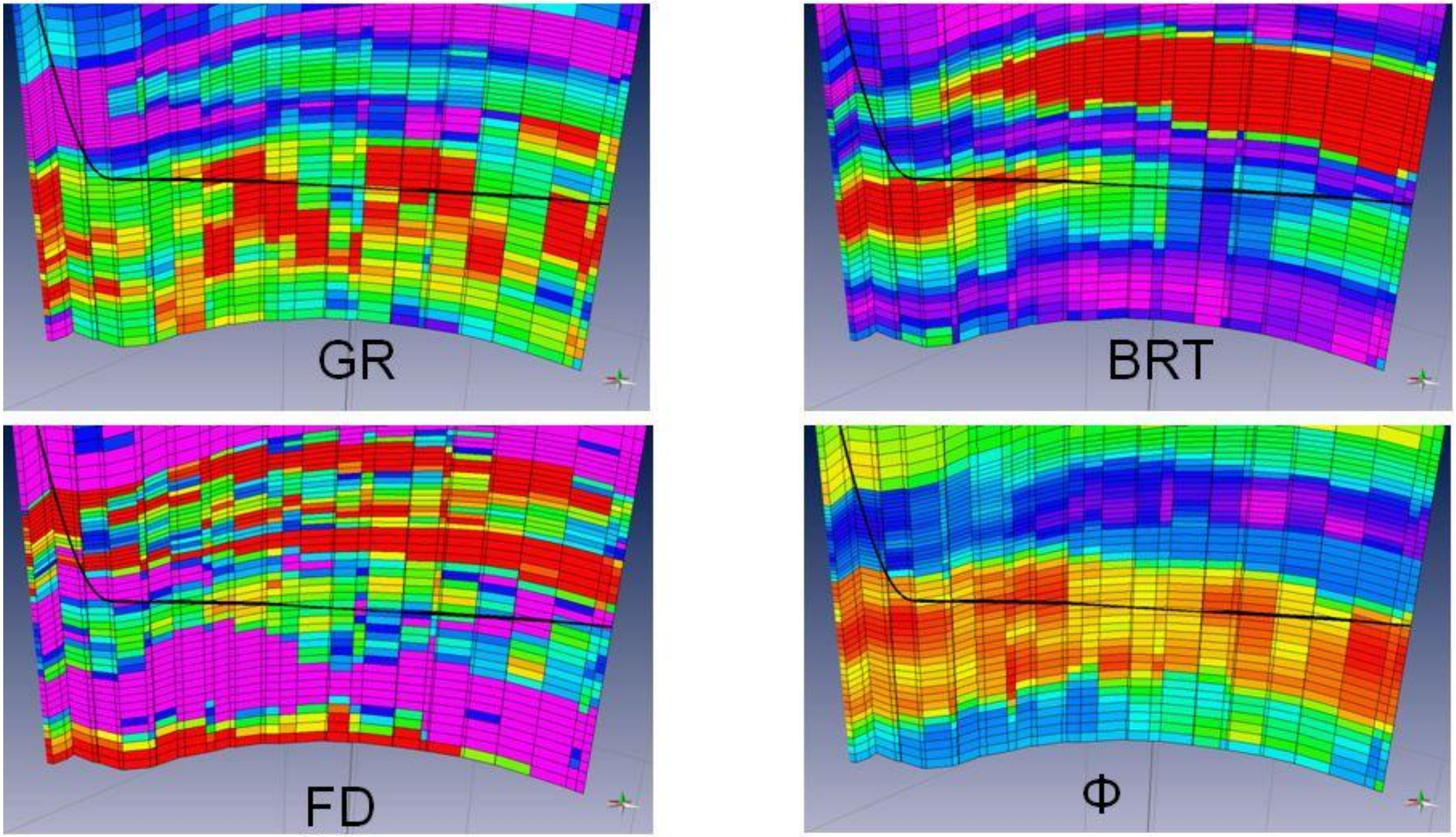

Figure 7. Cross section along a good well (shown in black). IP = 4389 Mcf/day of the four shale drivers used to compute the shale capacity: GR as a proxy for TOC; Brittleness BRT; Fracture density FD; Porosity φ. Red cells correspond to high values, blue correspond to low values, and purple cells correspond to zero, which means the driver is below the cut-off value.

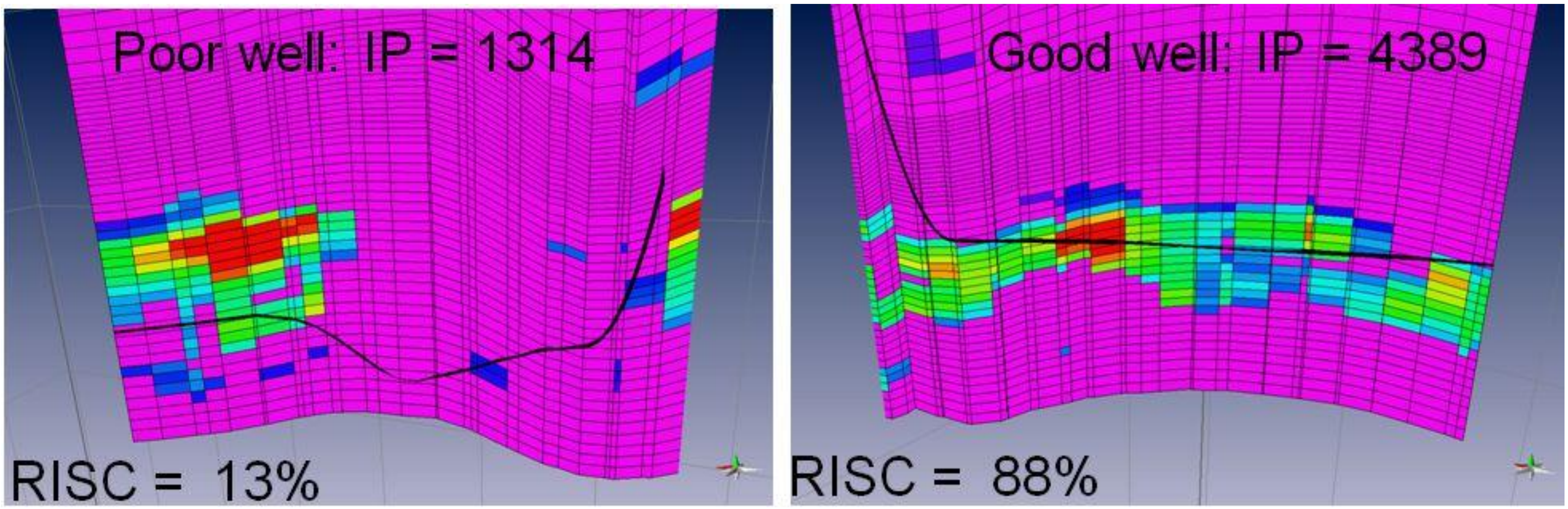

Figure 8. Shale Capacity resulting from the product of the four shale drivers for both the poor and the good well. All purple cells indicate shale capacity equal to zero, which means a shale reservoir that cannot contribute to production and a wellbore crossing this zone will yield no production whatever fracing technology is applied. Higher values of shale capacity (red and yellow cells) indicate the best sweet-spots that will yield the highest rates and reserves.

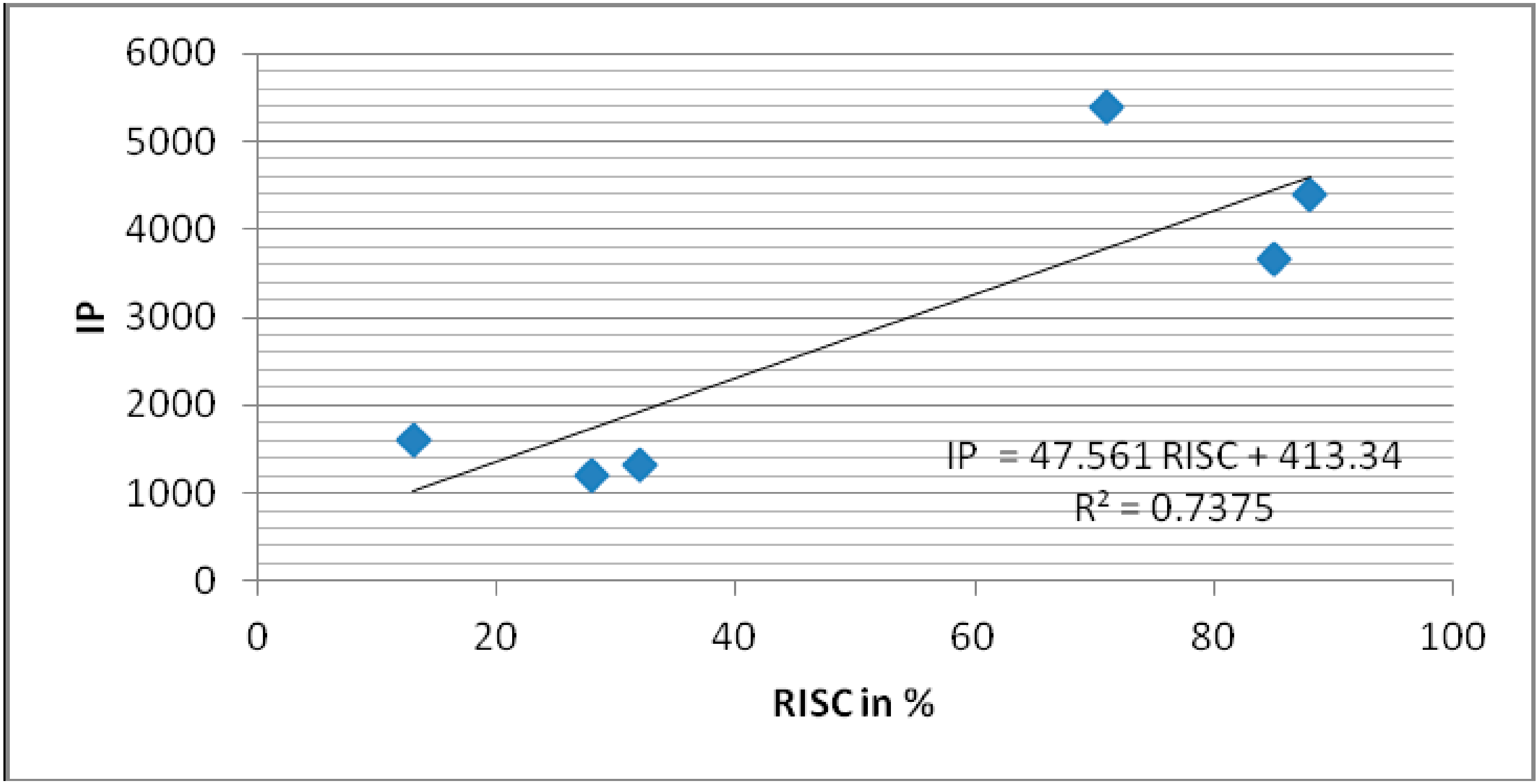

Figure 9. Strong correlation between Relative Intercepted Shale capacity (RISC) and the IP of 6 wells producing in 2010 and 2011.

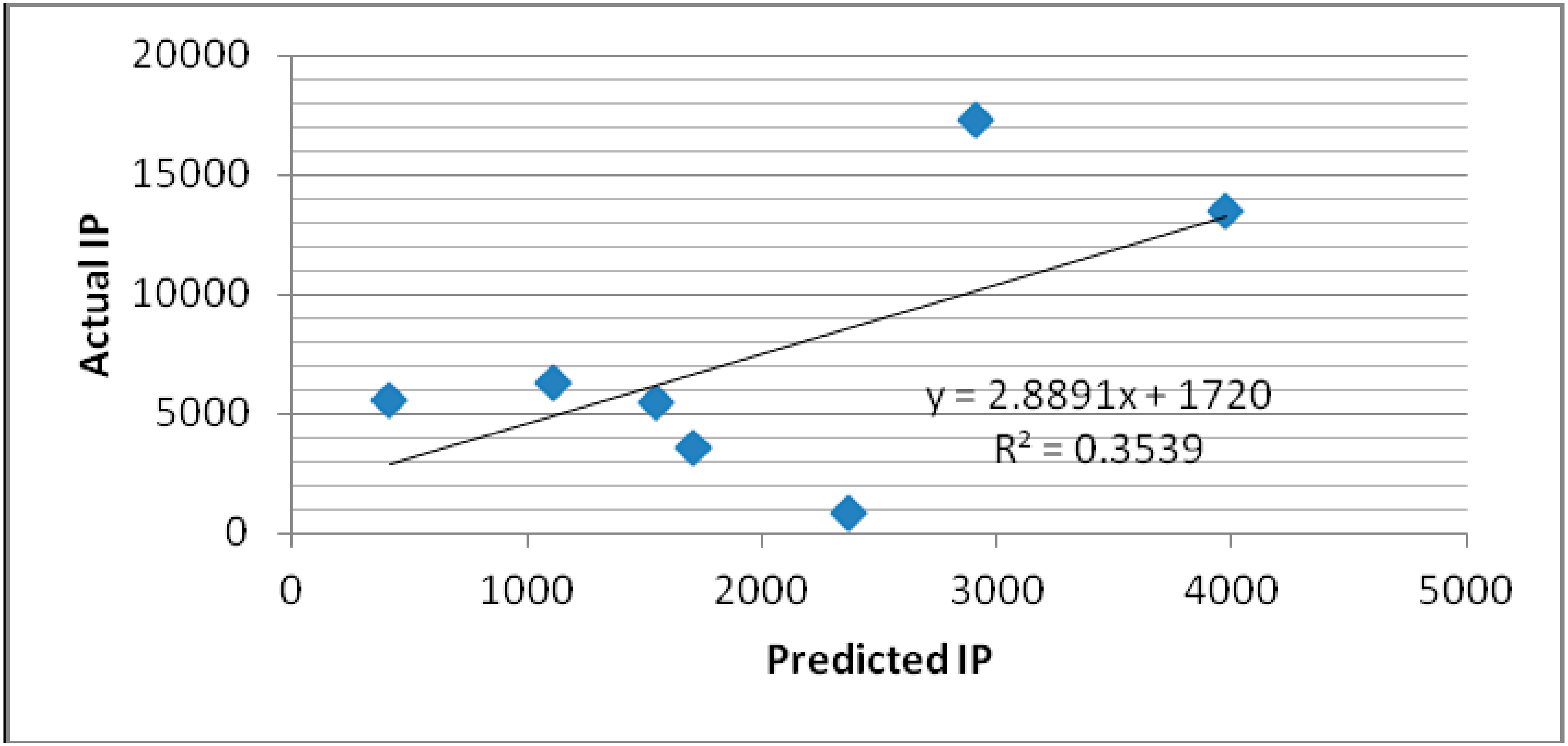

Figure 10. Using the relationship derived with 6 wells of 2010-2011; the relative IP rates of 7 wells that started production in 2012 are predicted. Despite the mix of IP derived with various number of days, the predicted relative values fare well in 5 wells out of 7.

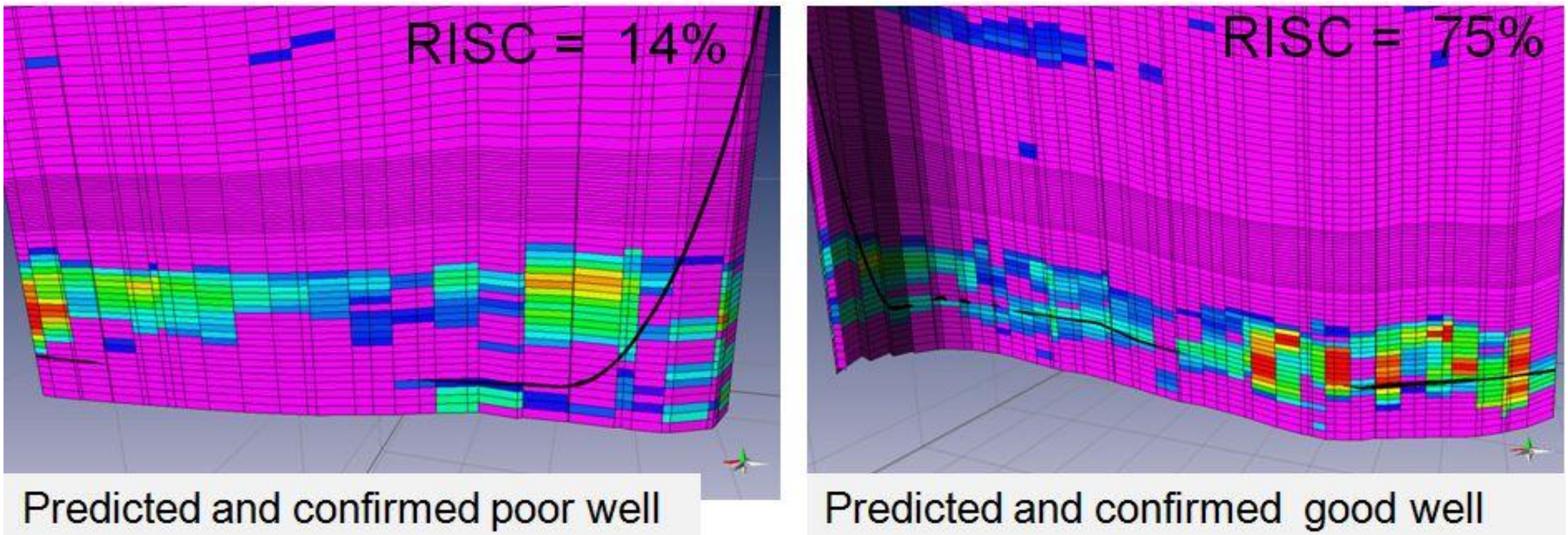

Figure 11. Cross section showing the Shale Capacity and the resulting Relative Intercepted Shale Capacity (RISC) along two wells drilled in 2012. The (RISC) explains the performance of the predicted and confirmed poor and good wells.