Uncertainty Models for Exploration and Appraisal of Shale Gas

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Various models are available to quantify uncertainty given global statistics (histogram and variogram), size of the area of interest and potential well positions. These may quantify uncertainty given the number and position of wells; therefore, with generalization, assess the number of wells required to constrain uncertainty to an acceptable level. The two major components of uncertainty are; (1) uncertainty given known global analog statistics and (2) uncertainty in the global analog statistics. For the first component, the standard methods are applicable, for the second component it is unlikely that these methods are feasible and empirical methods may be required. Regardless of the uncertainty method applied, visualization and the application of selection criteria are useful to assist in the determination of the required number of wells.

Introduction

To answer the question; how many wells are required to reduce uncertainty to an acceptable level?, there are four fundamental associated questions; (1) How much uncertainty is there in the global statistics? (2) What are the representative statistics and associated uncertainty at well scale? (3) How does well scale uncertainty scale to exploration blocks? (4) How much information do wells provide? We will deal with each of these questions separately. In addition to a high-level discussion on prerequisites and these components, an example / demonstration is provided of the workflows for shale gas Initial Production (IP) uncertainty in a given exploration block.

These questions relate to two components of uncertainty; (1) uncertainty given known global statistics (or uncertainty given an accepted analog distribution) and (2) uncertainty in the global statistics (uncertainty in the accepted analog distribution). The influence of scale on these is shown in Figure 1. Uncertainty given known global statistics (blue curve) – as the scale of the estimation problem increases, uncertainty given known global statistics decreases as averaging tends to remove most uncertainty (as scale of the estimate increases it is easier to estimate the average given the global statistics are known). This relationship is known analytically. Uncertainty in the Global Statistics (red curve) – as the scale of the estimation problem increases, the reservoir statistics are less likely to stationary (invariant across the area of interest) and more likely to exhibit trends or change geologic setting; therefore, uncertainty in the global statistics increases.

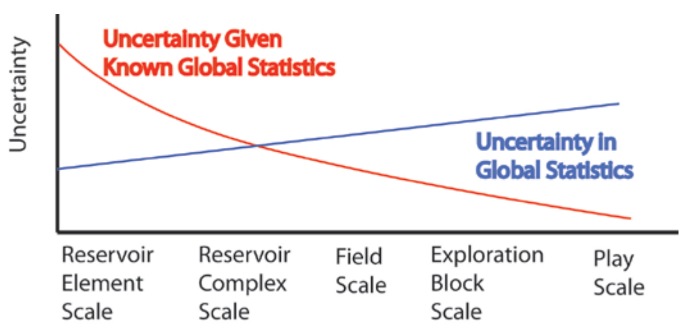

Figure 1: The influence of scale on global and local uncertainty. At large scales there is almost no local uncertainty due to averaging and at small scales there is less global uncertainty due to local conditioning constraints.

Geologic expertise and mapping and reservoir engineering expertise in filtering, pooling and characterizing IP are central to this problem. This is critical and assumed to be considered in every step of this process. For example, the area of interest for the investigation is mapped as a geologically consistent region and the representative statistics are constrained by geological concepts. Thus the first wells drilled and / or supporting geologic evidence are required to confirm and define the broad area of a postulated play concept, and thenceforth its general presence is assumed. When local information deviates from the domestic analog information then the prior statistics from the analogs may be updated with the local information. One method for accomplishing this is Bayesian updating. Significant deviation may indicate a failure in the analog assumption; this is later discussed as the decision to reassess the area of interest and / or to "walk away".

Shale gas plays are assumed to be statistical plays. With a traditional play, the local data measures are reasonably accurate and in combination with local geologic factors allow for the mapping of reservoir properties that are predictive of production after the application of flow simulation (see Figure 2). In contrast, for our statistical play, well measures are highly uncertain, and the relationships between the measured values production is weak. In the face of this difficulty, Olea (2011) recommended working directly with a production proxy, such as initial production (IP). Well IP is then mapped directly and production potential is assessed by summarization of mapped IP. Note, while geologic factors naturally enter the traditional workflows through hierarchy, depo- and lithofacies and porosity, permeability and saturation distributions and relations, the challenge is to integrate geologic factors in this statistical play workflow. Careful sub-setting and selection of analogs and matching and sub setting exploration and appraisal settings with consideration of geologic setting and similarity is important.

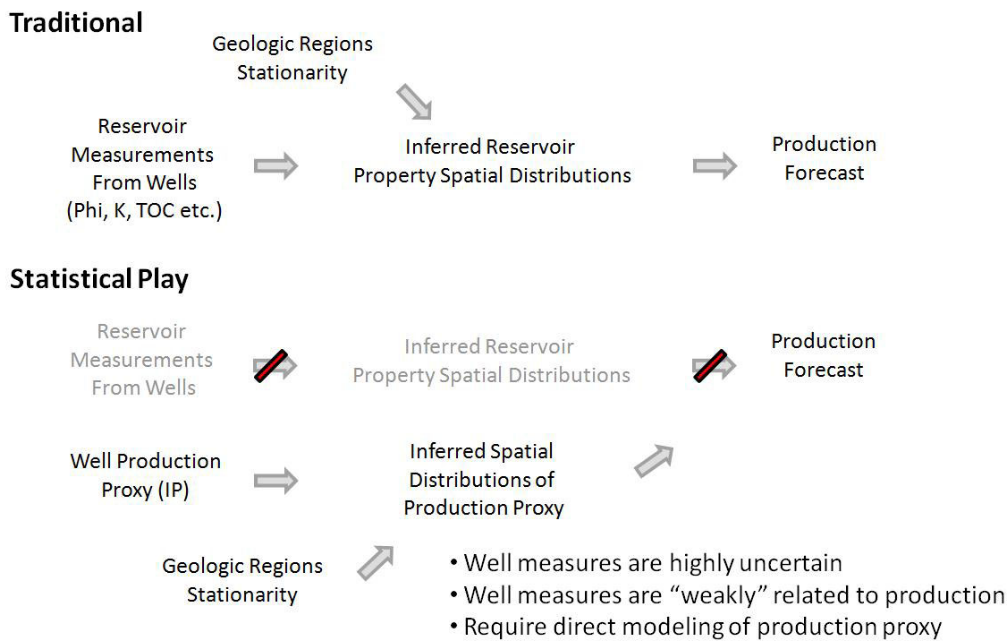

Figure 2: Difference between statistical play and traditional play workflows.

Certainly some level of geologic information is available. In fact, we do not recommend a completely statistical approach. There is a balance between the use of statistical (unknown) components and geologic (known), similar to the choice to combine trend models and stochastic models in traditional reservoir modeling. Given the context of the statistical play and the uncertainty methods and metrics described subsequently, it is important describe how geologic information may be integrated. This may be to improve the choice of analog, choice of area of interest or inclusion of ma-able properties or trends.

Analog choice has a first order control on the uncertainty model results. Geologic information must be utilized to choose the best mature analog field to borrow statistics (i.e. IP histogram and IP spatial continuity). When this choice is uncertain then multiple analogs may be applied or uncertainty in the analog statistics may be considered.

A choice must be made concerning the specific area in the exploration / appraisal target over which the analog statistics may be applied. For example, if the Haynesville is an analog of our exploration play, over what area in that play may we consider that the Haynesville is analogous?

If secondary data is available, then it would be possible to integrate this secondary data into present uncertainty models. For example, a map of expected IP from primary IP data and calibrated to secondary data may be constructed. Then the local uncertainty distributions (at block or well scale) may be updated with this information.

In this work we follow up the previous work of Wilde and Deutsch (2010a and 2010b) that addressed methods to relate uncertainty to data spacing. We include consideration of various uncertainty models and visualization of the impact of spatial continuity in addition to data spacing.

The Critical Questions to Uncertainty

This following discussion provides details on the four questions that must be answered to determine how many wells are required. As mentioned before these are: (1) How much uncertainty is there in the global statistics? (2) What are the representative statistics and associated uncertainty at well scale? (3) How does well scale uncertainty scale to exploration blocks? (4) How much information do wells provide? We will deal with each of these questions separately below.

1. What is the Uncertainty in the Global Statistics?

The subsequent discussion for questions 2, 3 and 4, assume known and stationary global statistics. That is, the global statistics over the entire study area are known and constant and local fluctuations occur within the constraint of the variogram. At the very least, this is the assumption that "maximum variability / uncertainty" is known. This maximum uncertainty is the uncertainty given no local data and complete reliance on analog statistics. Yet, there may be intrinsic nonstationarities in shale gas IP beyond the fluctuations predicted by the variogram.

These nonstationarities in the statistics result in increased exploration uncertainty. Empirical studies may be applied to understand these nonstationarities by calculating and modeling nonstationarities directly from the analog fields.

It is not likely that a completely objective method is available to rigorously account for uncertainty in the global statistics (unlike the second component of uncertainty given known global statistics and limited data). While these numerical methods may guide, expert judgment calibrated by experience will be critical on this part of uncertainty analysis.

Large scale trends and their impact on local uncertainty on the global statistics can be observed directly from the analog data sets. The empirical study method discussed later provides a method to calculate the uncertainty and compare this result to the theoretical global kriging method. This provides a means to directly assess the contribution of nonstationarity (large scale trends) in a domestic shale gas project on uncertainty.

2. What is the Representative Statistics and Associated Uncertainty at Well Scale?

This question requires the inference of the representative well scale, property distribution over the area of interest. That is, if a well is drilled anywhere without any additional information, what would the well IP uncertainty. While this component is aided by statistical methods it is largely the subject of expert geologic judgment.

This distribution should be representative of the target area. This step requires the pooling of all available information and correction of the data for sampling representativity (clustered and biased sampling). These corrections may include declustering to correct for sample clustering and soft data debiasing to correct for un- or under-sampled parts of the property distribution (Deutsch and Journel, 1998, Deutsch, 2002).

Even with these large domestic IP datasets, data representativity is a major concern. See the following results for domestic shale gas. Note: perfect declustering is not possible. While declustering does generally improve results, it is not guaranteed to do so in all circumstances.

3. How Does Well Scale Uncertainty Scale to Exploration Blocks?

Volume variance relations are not widely utilized in a rigorous manner, but their principles are quite intuitive and their mathematical representations are extensions to the common notion of variance and spatial continuity. Volume-variance dictates that the distribution variance should decrease as scale increases. The uncertainty in estimating the reservoir properties for a specific location in the reservoir decreases as we scale from point (a single well) to model cell to exploration block to entire area of interest.

For our problem we are primarily concerned with how variance scales as we move from well scale to exploration block scale. The dispersion variance is a generalization of variance that accounts for size support volume. Dispersion variance provides a mathematical description of the variability of volumes within other volumes. For example, dispersing variance describes the variability of wells within exploration / lease blocks and exploration blocks within the play etc.

$$D^2(\text{well, play}) = D^2(\text{well, lease}) + D^2(\text{lease, play})$$

Furthermore, dispersion variance is calculated directly from our model of spatial continuity. This model of spatial continuity is central to the concept of how much do wells tell us. Mathematical details will be provided after this summary. For all subsequent discussions we will generally truncate dispersion variance as variance.

4. How Much Information Do Wells Provide?

A variogram provides a mathematically consistent model of spatial continuity for a variable of interest. This model indicates the level of correlation for all distances and directions. An experimental variogram is calculated directly from the data as the average of the square difference of data offset by a lag of vector h. Averaging is accomplished by pairing all data with the same offsets (within tolerance). Intuitively, the variogram provides a measure of variability (squared difference) for a distance and direction of offset. When standardized by the variance (at the appropriate size support), the variogram provides a direct measure of correlation, no correlation or negative correlation between any two points for the variable of interest.

A simple application of the variogram is to determine the maximum extent of information from a well in map view. For a single well this is easy to visualize and calculate. At the well location there is no uncertainty and perfect correlation. At some small distance, below the minimum samples spacing, the correlation decreases to the nugget effect. At the range no correlation exists any longer, that is the well provides no information. Beyond the range there may be some small negative correlation to provide some information, but this is not likely significant and may be more related to local trends. In general, wells that are 2 x the range apart are not redundant and carry the maximum information content.

Information from wells that confirm or change the conceptual model and associated global statistics are not considered here (see the discussion in question one on assessing uncertainty in global statistics).

While the schematic is useful, real situation are more complicated due to multiple wells and the need to estimate IP over of volume as opposed to a point.

Uncertainty Methods

This section reviews the various uncertainty methods that may be applied to calculate uncertainty as a function of data spacing and spatial continuity. They are separated into three groups: well scale methods, block scale methods and empirical methods. The well scale methods provide uncertainty at the well scale while block scale methods provide uncertainty at the scale of a block. The empirical method is unique as it extracts an uncertainty model directly from a densely sampled analog. The well scale and block scale methods assume the analog statistics are stationary (uncertainty given known global statistics), while the empirical method does not require this assumption and provides a method to calibrate the impact of uncertainty in the global statistics.

The Synthetic Example

Demonstrate the uncertainty methods a synthetic exploration block (24 km x 35 km) is assumed within a play that we assume has the similar statistical behavior as the Haynesville IP (histogram and variogram from publically available sources). The variogram includes low, mid and high case IP spatial continuity ranges of 8 km, 15 km and 30 km respectively. Within the exploration block all wells will be assumed to be uniformly sampled (see Figure 3).

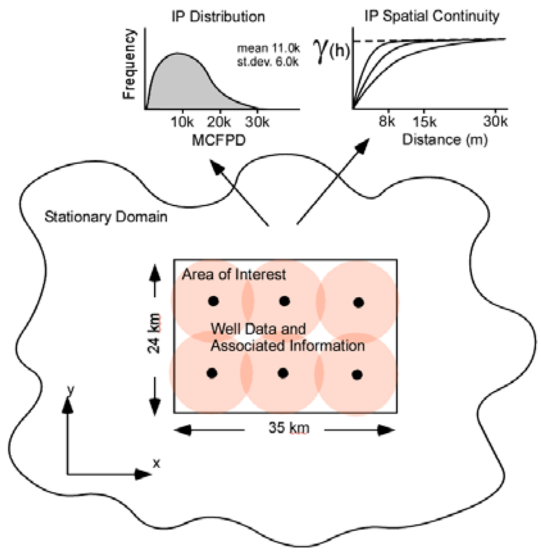

Figure 3: Example exploration problem - what is the uncertainty in the block, given the IP statistics are similar to the Haynesville.

Visualizing Uncertainty

We attempt to visualize the influence of number of wells and spatial continuity on uncertainty. This can be accomplished with a response surface with number of wells on the Y axis and spatial continuity on the X axis and color scale and contours based on the level of uncertainty (see Figure 4).

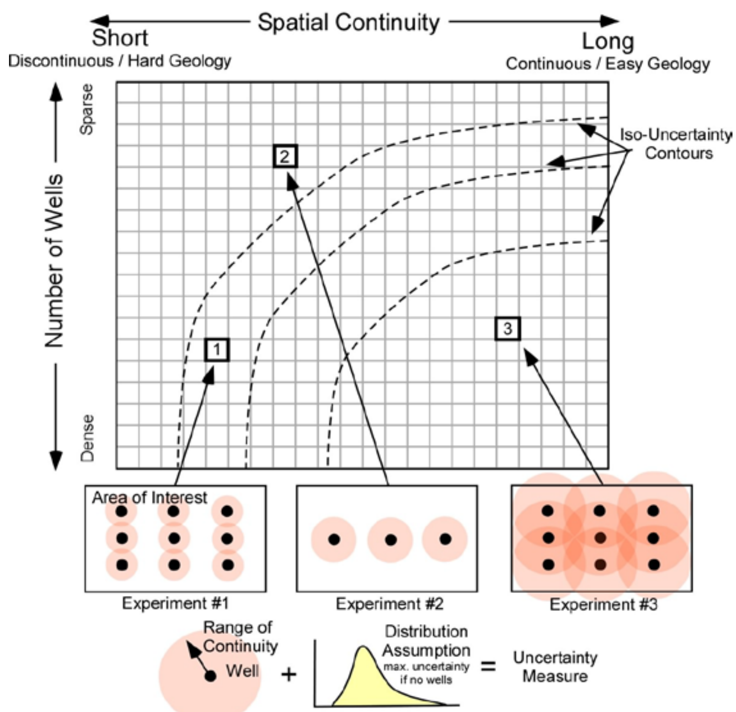

Figure 4: Illustration of method to visualize uncertainty. Uncertainty is shown from a full factorial investigation of all combinations of spatial continuity and number of wells. Note: for each number of wells the volume of interest is sampled uniformly (wells are not added sequentially).

The plot is the result of the full factorial experiment, running all combinations of number of wells and spatial continuity. Each grid location on the plot represents a single experiment with uniform well spacing and a specific spatial continuity model. All results in the plot rely on the same distribution assumptions (global distribution for IP from an analog). The color scale is set relative to red for highest uncertainty and blue for the lowest uncertainty. At times, iso-uncertainty contours are added and labeled to illustrate the uncertainty behavior of the model.

Well Scale Uncertainty Methods

The following is a discussion on traditional statistical methods, the bootstrap and spatial bootstrap and a new geometric method.

Bootstrap and Spatial Bootstrap

Bootstrap is a statistical method of assessing uncertainty in a sample distribution. The method relies on repeated sampling with replacement from the sample distribution to construct multiple realizations of the distribution to quantify uncertainty in any statistical description. Spatial bootstrap is simply a variant of bootstrap that accounts for the correlation between the data during the resampling process using the data locations and a variogram model. Neither method accounts for the size of the area of interest and closeness to wells. Below are response surfaces for bootstrap and spatial bootstrap uncertainty vs. number of wells and spatial continuity (denoted as effective variogram range)(see Figures 5 and 6 respectively).

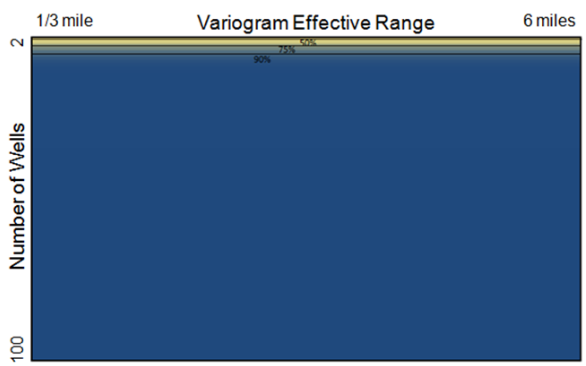

Figure 5: Uncertainty model from bootstrap vs. number of wells and spatial continuity. Note: spatial context, spatial continuity, well locations and model size are not considers. All data assumed to be independent, identically distributed (blue – low uncertainty and red – high uncertainty).

As seen above, bootstrap does not account for any spatial information and is simply related to number of samples (wells).

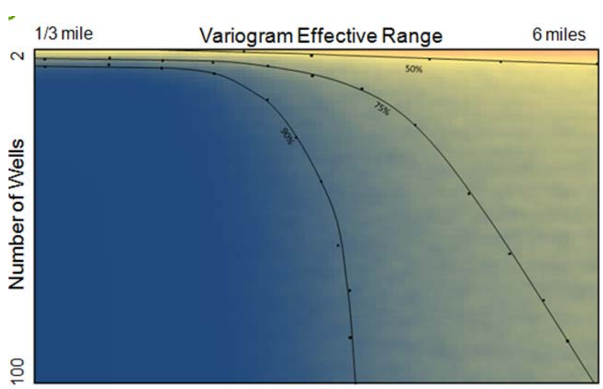

Figure 6: Uncertainty model from spatial bootstrap vs. number of wells and spatial continuity. Note: only the redundancy between the data is considered, not the block size or well locations within the block.

Therefore, more spatial continuity actually increases uncertainty due to redundancy (blue – low uncertainty and red – high uncertainty).

As seen above spatial bootstrap only accounts for data redundancy, so increase in spatial continuity actually increases uncertainty. In other words, more predictable geology is more uncertain.

We can apply spatial bootstrap for any well scenario given the global analog distribution, location of the wells and analog spatial continuity model. We do not require data values to calculate the equivalent number of independent data (n') and then to use the standard error equation (below) to calculate the variance reduction (well information content). See equation below where $\sigma_{\bar{x}}$ standard deviation of the mean, σ_s , is the standard deviation of the well scale analog IP distribution and n' is the effective number of data calculated from spatial bootstrap.

$$\sigma_{\bar{x}} = \frac{\sigma_s}{\sqrt{n'}}$$

We can reform this equation in terms of variance reduction that is the variance of the sample mean as a fraction of the variance of the samples.

$$\frac{\sigma_{\bar{x}}^2}{\sigma_s^2} = \frac{1}{n'}$$

The spatial bootstrap methodology assumes well scale support size, the result should be scaled to the lease area, using the same scaling factor discussed previously.

Geometric Method

It is natural to consider that wells inform a local area (illustrated by a circle or an eclipse); more wells or larger local areas result in less uncertainty (see Figure 7).

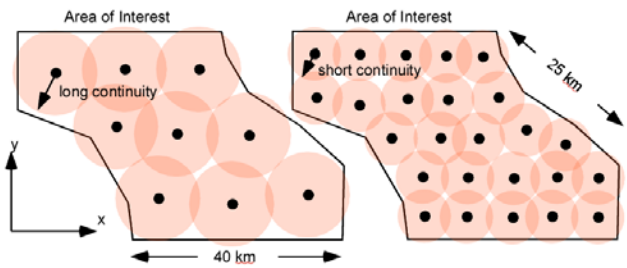

Figure 7: Geometric method to assess the required number of wells.

Kriging provides a more robust method to apply this type of criteria to select the required number of wells. Kriging is a standard tool within geostatistics for calculating least squares estimates given local conditioning data and spatial continuity as modeled with the variogram.

Kriging provides not only the least squares estimate, but also a measure of estimation variance (the uncertainty associated with the estimate). This estimation variance is a measure of the information that data provide at all locations within the model. As shown below, we can see lower uncertainty at the well locations (3 x 3 template and 5 x 5 template). Note: due to the nugget effect the estimation variance does not reach 0.0 at the well locations (see Figure 8).

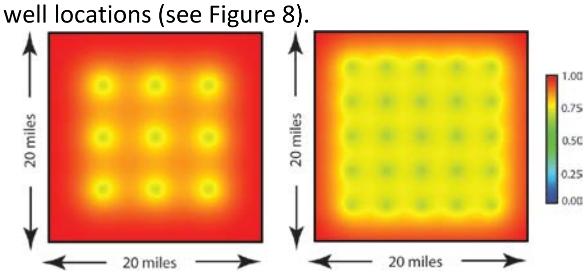

Figure 8: Local uncertainty (local variance / total variance) for two well templates over a Poland exploration block.

This estimation variance provides local uncertainty at all locations within the model. This map of local uncertainty is useful to visualize and assess the information at locations away from wells.

It can be seen that the kriging variance map is analogous to the simple geometric method. It is possible to summarize the kriging variance in a couple ways to provide the relationship between well density, spatial continuity and uncertainty. This includes:

1. proportion of the model with less than a maximum kriging variance (minimum information from wells)
2. average kriging variance
3. incremental information of well data

The first criterion is similar to the simple geometric method, yet it accounts for the spatial continuity model and interactions between wells. For example, if we assign a threshold of 50% kriging variance or less to the kriging variance map shown in Figure 9.

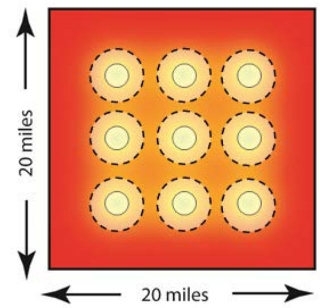

Figure 9: Circles indicate the areas with at most 75% and 80% kriging variance (solid and dashed lines respectively). At 75% threshold about 7% of the area is informed at a threshold of 80% about 28% of the area is informed.

If we apply this method to an area the size of the example exploration block with the spatial continuity model from Haynesville we get the following resulting response surface for uncertainty as a function of number of wells and spatial continuity (see Figure 10).

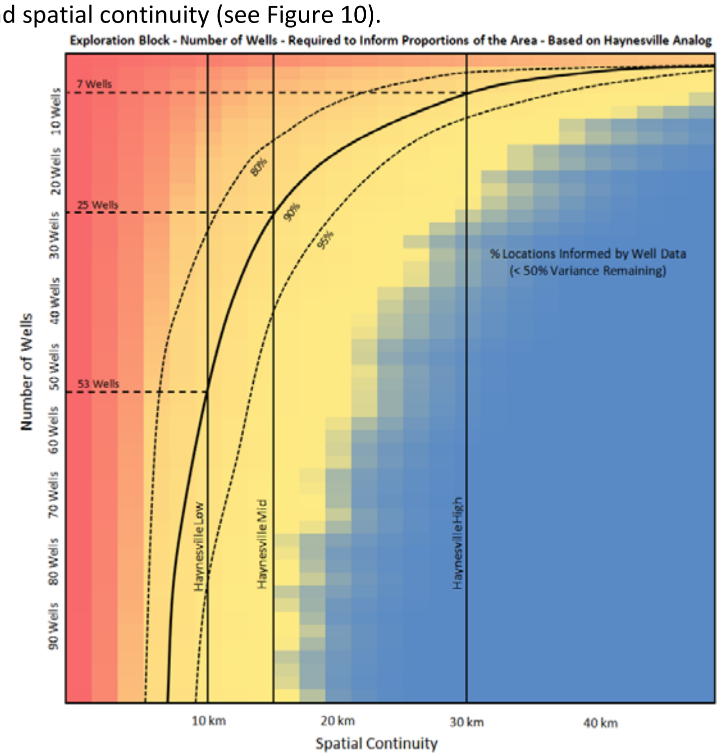

Figure 10: Response surface for proportion of area of interest informed (kriging variance < 50%) as a function of number of wells and spatial continuity.

From this result we observed that for the Haynesville low, mid and high spatial continuity model, a requirement of 53, 25 and 7 wells respectively to reach a state where 90% of the model is well informed. "Well informed" is defined as 50% kriging variance or less.

For specifically the mid-level spatial continuity case, the relationship between well density and area informed may be illustrated as shown below. From this graph, well densities of 1 well / 7,000 acres are required to provide 90% of area informed, while 1 well / 26,000 acres for 70% of area informed and 1 well / 64,000 for 50% of are well informed. This result is an average result over the area, at any point maps of local uncertainty could be visualized of summaries of uncertainty at specific locations (see Figure 11).

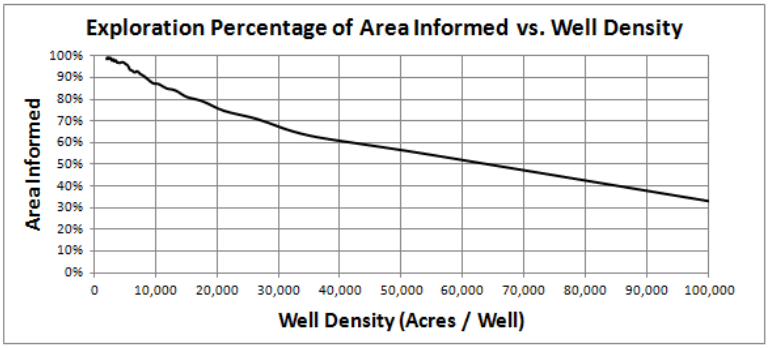

Figure 11: Area informed vs. well density based on the example exploration block area and Hayneville analog statistics for geometric method.

Conversely one may summarize the local kriging variance over the area of interest as the average kriging variance. This is a measure of the expected well scale uncertainty over the area of interest. This result may be applied to scale the global analog distribution to calculate a new distribution given well information. For example, for the analog Haynesville distribution, the original global standard deviation of 5,992 MCFPD. If the average kriging variance is applied to scale the global distribution the resulting well scale uncertainty in the presence of wells can be represented (see Figure 12).

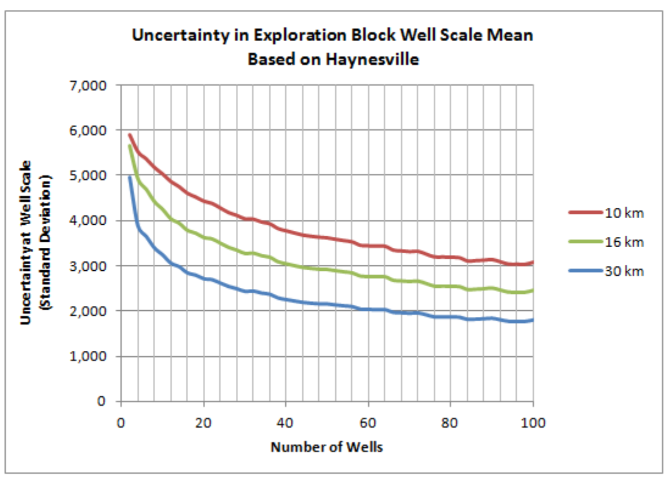

Figure 12: Uncertainty in well scale IP vs. number of wells for low, mid and high spatial continuity cases for geometric method.

Finally, one can observe that with increasing well counts there is a significant decline in the incremental information add of additional wells. One can visualize this with the following plot (see Figure 13).

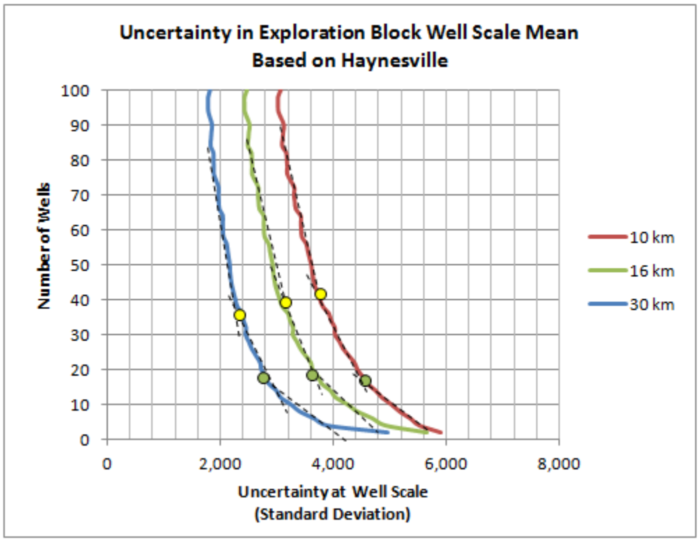

Figure 13: Information from incremental well data for geometric method.

Note that this plot is the same as the previous with the axis reversed and lines and points representing the stages of incremental data value. For the first 15 – 20 wells there is large information add from well data, then from these wells to the 35 – 42 wells there is a significant decline in the incremental decrease in uncertainty with new wells. Any additional wells have a minor contribution that continues to diminish. In the following section a method is introduced to provide block scale or uncertainty in the average over the entire reservoir. This is contrasted with the previous discussion that was concerned with the uncertainty over the scale of individual wells.

Block Scale Uncertainty Methods

The two methods to quantify block scale (or any area of interest scale) uncertainty are global kriging and empirical studies. They each have their assumptions and limitations, but as we show they can be related to each other for insights on the impact of nonstationarity on uncertainty as shown after discussing each.

Global Kriging

Kriging was described and applied previously for well scale uncertainty (Deutsch and Deutsch, 2010). Kriging is completely general, it can estimate IP at many locations (points) in the reservoir using wells (points in 2-D). Kriging can also estimate the IP over the entire reservoir (accounting for area) using the wells. For the latter, the kriging variance represents the uncertainty in the estimate for the entire reservoir (at reservoir size support). From the previous discussion on uncertainty scale; this large scale uncertainty is expected to be lower than the previously discussed well scale uncertainty. That is, it is easier to estimate IP over an entire reservoir than at the next well.

The kriging variance equation is included in all standard geostatistics textbooks (Deutsch, 2002). There are three components in the equation:

1. Maximum Uncertainty Possible at Volume Support – this is the uncertainty at well scale (IP distribution from analog) scaled up to reservoir scale. This is typically much smaller, consider for the example exploration block scale IP uncertainty is 12% of the well scale if we use Haynesville as an analog.
2. Closeness of Well Data to Area of Interest – this accounts for the size of the model and the coverage of the data over the reservoir. If for a dataset, the area of interest expands further away from the data, overall closeness decreases and the kriging variance increases.

3. Redundancy of the Well Data – this considers the redundancy of the well data with each other. For example, if the spatial continuity range relative to well spacing is large then the well data redundancy is large and the kriging variance increases.

From these three components complicated, but understandable behavior emerges in the uncertainty model (see Figure 14).

1. Increase in spatial continuity increases the maximum uncertainty possible as short range fluctuations average out quickly as we scale up (small highs and lows average out to the representative mean quickly).
2. Increase in spatial continuity increases the redundancy between the well data.
3. Increase in spatial continuity increases the closeness between well data and the entire reservoir.
4. Increase in number of wells always decreases uncertainty.

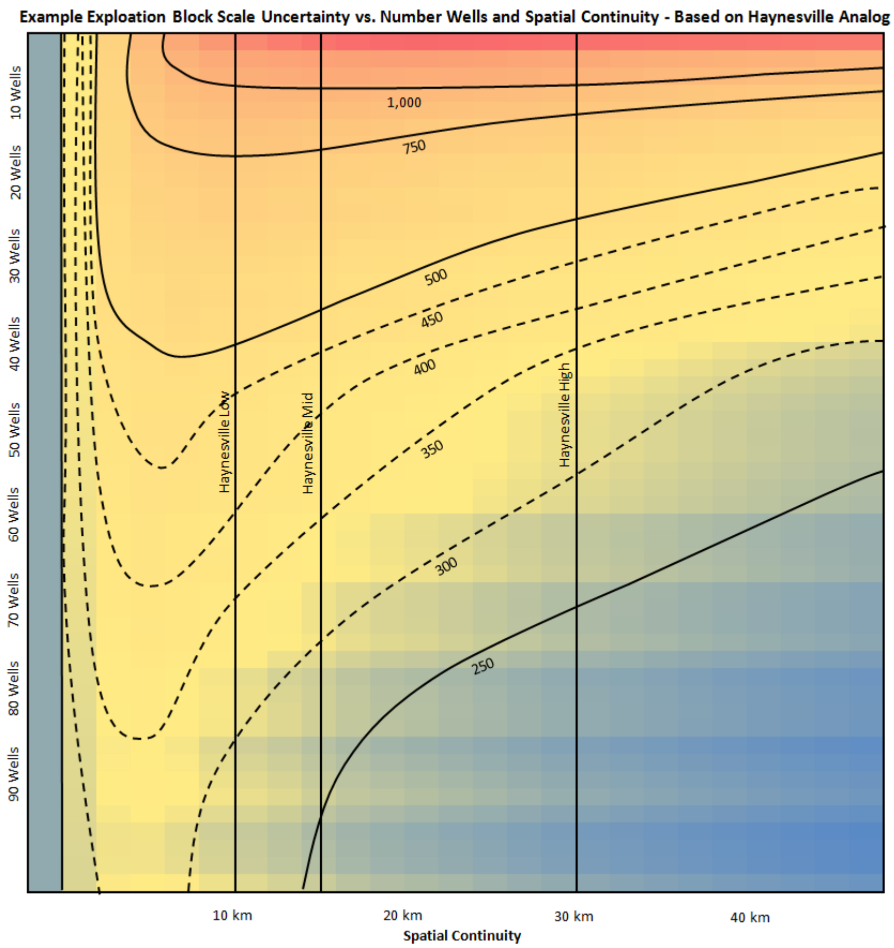

Figure 14: Global kriging uncertainty vs. number of wells and spatial continuity.

It can be observed that at very short spatial continuity ranges that the uncertainty is very low due to very low maximum uncertainty, given the "rapid" averaging of small scale highs and lows. This is counter intuitive, but is due to the strong assumption of statistical stationarity with this method. It is assumed that the reservoir has specific analog statistics that are constant. As spatial continuity increases from 2 to 5 km there is a general increase in uncertainty, due to increasing maximum uncertainty (due to scale alone). At 5 km and on, closeness overwhelms maximum uncertainty (due to scale alone). At about 30 km and on, redundancy starts to limits the decrease in uncertainty (the iso-uncertainty contours level off).

Another way to visualize this relationship is to standardize (or divide) by maximum uncertainty. The result is a relative uncertainty a measure of well information content (equal to uncertainty divided by maximum uncertainty if no wells (see Figure 15).

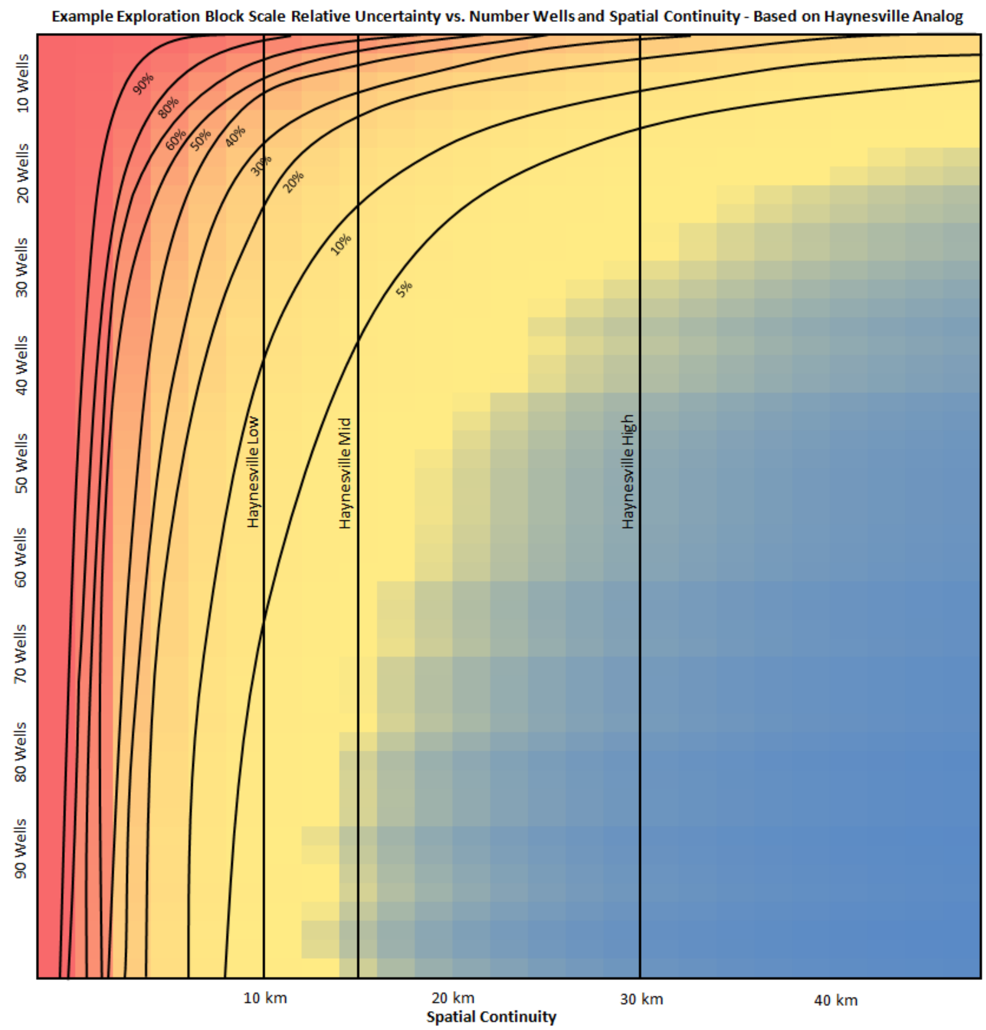

Figure 15: Relative uncertainty provides of measure of the information content of the well data to estimate the mean of the reservoir.

This result has the same form as the average kriging variance result, but the decrease in uncertainty is more rapid. This suggests that well scale uncertainty falls at a slower rate with additional wells than reservoir scale uncertainty.

Similar to the well scale results, the block scale global kriging results may be applied to formulate criteria for selecting the number of wells required. For example, an acceptable level of uncertainty in reservoir IP may be assigned as a standard deviation of 600 MCFPD. The following plot indicates the number of wells for this criterion, resulting in 28, 24 and 15 wells for the low, mid and high Haynesville spatial continuity and representative IP distribution (see Figure 16).

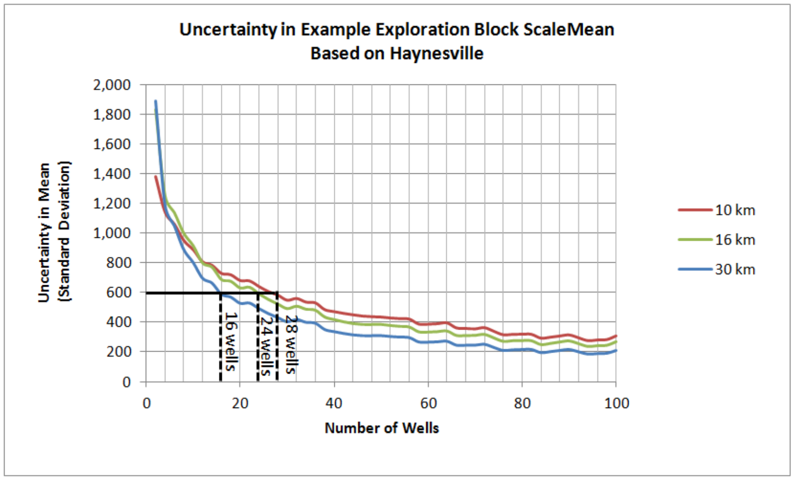

Figure 16: Example exploration block scale uncertainty in IP vs. number of wells for low, mid and high spatial continuity cases, based on Haynesville.

Empirical Studies

Our fundamental question is, "If we had the example exploration block in the Hayenville and limited well data how good would our estimate be?" "How would uncertainty decrease as we add well data?" The answer these questions, the empirical study proceeds as follows:

1. Load a domestic shale gas dataset with x, y, IP values and a set of secondary data (e.g. year drilled, well type, horizontal length, number of fractures etc.)
2. Apply a set of filters to restrict the data to similar well type and completion methods (mixing various well types and completion methods would result in a pessimistic assessment of estimation accuracy).
3. Determine an area of investigation for the domestic shale dataset. An effort should be made to exclude regions that are poorly sampled (will not provide a good truth value for the error calculation).
4. Build a smooth "truth" model map from the available IP data. This smooth map is used to calculate the "truth" value over a sampled window. The smooth map provides a declustered truth value, so data clustering issues are reduced and the truth value is improved (see Figure 17).

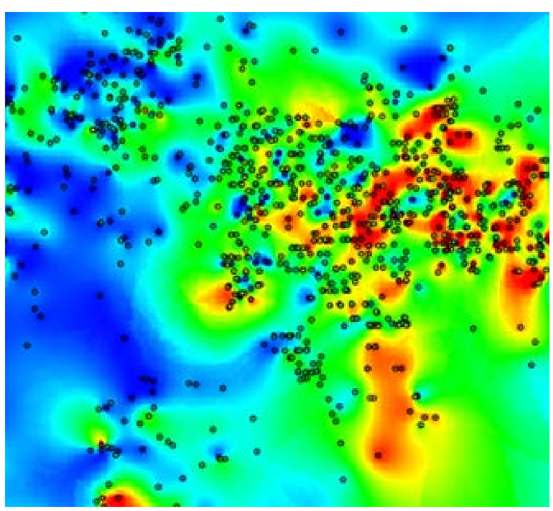

Figure 17: Map of region of the Haynesville with filtered well IPs and smooth IP map.

5. Randomly place a window the size of the exploration block (35 km x 24 km for our exploration block) within the area of investigation. See window and blow up below.
   a. Within the window calculate the "truth" average IP as the average of the smooth IP map over the window. This provides a declustered IP value given all of the available wells.
   b. Within the window place a well template with "n" equally spaced wells. Note: equal spacing is a simple assumption for this initial effort. It would be straightforward to encode any other type of drill strategy such as a clustered well template. In more advanced workflows, the wells are drilled sequentially and the well results impact the subsequent well placement.
   c. Then the closest wells are retained to calculate average IP for the window. This is an attempt to systematically sample n equally spaced wells from the available data.
   d. calculate the squared difference between the estimated IP from the mean of the "n" wells and the "truth" IP.
6. Repeat this process with many random window locations and calculate the root mean square error. Repeat this calculated for a range of number of, "n", wells to calculate the relationship between estimation of average IP and number of wells available for the specified window (example exploration block size) in the data example (Haynesville in this example).

The results from this experiment are shown in Figure 18.

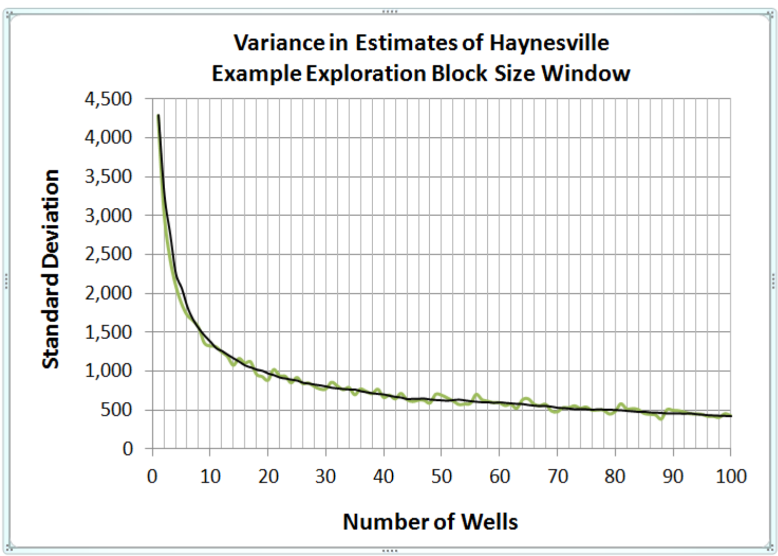

Figure 18: Results for the empirical study of the relationship between number of wells and uncertainty for the example exploration block with Haynesville analog.

Similar to the previous methods, the empirical study method may be applied with a criterion to determine the number of required wells. For example, one can select number of wells with the incremental well information method. As shown in Figure 19, there is a strong decrease in the incremental value of wells at 12 wells and 40 wells.

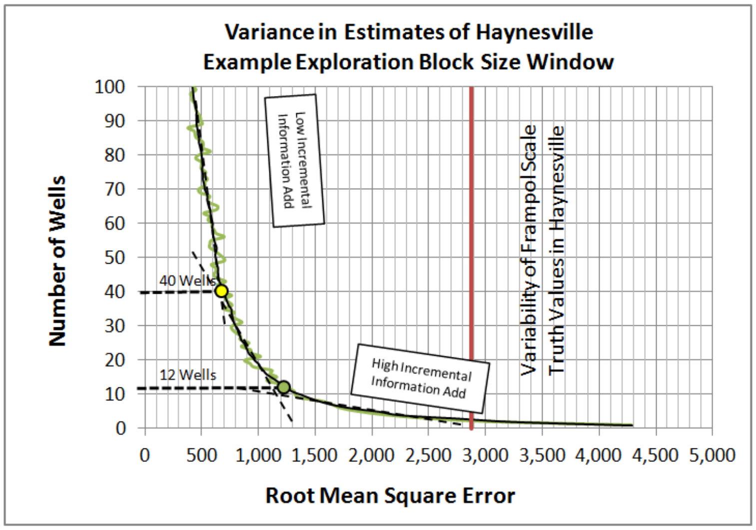

Figure 19: Number of wells by well incremental information criterion for the empirical study.

Also, another criterion is the acceptable level of uncertainty. The root mean square error provides a direct indication the expected error in estimating IP due to sparse data. One can determine an acceptable level of error and apply this to determine the number of wells required (see Figure 20).

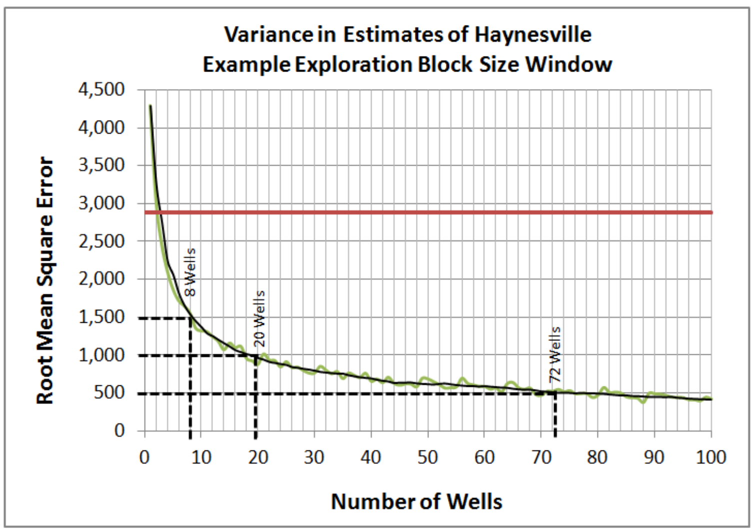

Figure 20: Number of wells required to reduce error to an IP RMS of 1,500, 1,000 and 500 MCFPD. The red line is the variability observed in the truth values over all windows. This is a theoretical maximum uncertainty given no well data and the global mean used as the estimate for all windows.

Conclusion

In statistical plays, as shale gas may be considered, a greater dependence is placed on statistical models for uncertainty. The comparison and visualizations provided in this paper provide a review of these methods and communicate their behavior. Each of these models is applicable at different scales and responds differently to well density, the area of interest and spatial continuity. This has been demonstrated for a typical shale gas exploration setting, but is general to resource problems. Recognizing the behavior of uncertainty in of itself is a valuable tool for decision making, and with specified criteria well counts may be rationally determined.

In general, the bootstrap does not provide a reasonable uncertainty model due to the inability to account for the spatial context of the problem, including the position of the wells, spatial continuity and the area of interest. Spatial bootstrap attempts to account for spatial continuity, but results in the counter-intuitive behavior that increasing spatial continuity of the phenomenon, increases uncertainty.

Geometric-based uncertainty methods are intuitive, can be related to geometric criteria used in resource assessment and may be summarized for measures of local, well scale uncertainty. These methods are sensitive to the specification of the metric, for example the level of uncertainty to calculate the area informed by wells.

Global kriging provides a rigorous method to calculate the uncertainty the property of interest over an area of interest. The interaction of volume support, closeness and redundancy with respect to spatial continuity results in some complicated behaviors. Yet, these are valid and it is valuable to understand their features for the specific problem.

Empirical studies offer a valuable opportunity to “look back” and address exploration, uncertainty questions through scenarios of development. High level of data density is important and changes in sampling scheme and well completions may pose issues. Good data filtering and experiment formulation is essential.

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