Understanding the Drivers of Parent-child Depletion: A Machine Learning Approach

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Abstract

Every year, an increasingly larger fraction of drilling is done on pads or in zones where wells are already present. These existing wells have implications for the hydrocarbon production of any new developments, and therefore also the economic value of engaging in this activity. Here, we use a non-linear and multivariate machine learning approach to provide descriptive evidence of the effects of existing well production on infill wells and segregate that impact into the contributions of individual features. We find that the percentage of total reserves produced by existing wells before an infill well is brought online is the single strongest factor in determining the relative performance of the infill well as compared to the parent. Distance to the closest parent produces a nonlinear effect on child production, and one which is mediated by the percent of reserves already generated by the parent well. Finally, we observe mixed results for the influence of geology, which warrants further investigation.

Introduction

As American shale plays mature, operators have re-visited previously drilled locations to add more wells. In the Midland basin, for example, the proportion of “infill” wells has risen from 50% to 75% of new drilling between 2015 and 2021. Part of the motivation behind this change is the increasing price of acreage in American onshore basins, and especially recently, the increase in M&A activity. Another motivation is that tier 1 acreage may represent a lower risk profile for re-drilling compared to new development on lower quality acreage in the basin, or at least a more easily quantifiable risk profile.

While operators know infill development will continue to increase, it has been historically difficult to make informed decisions about the tradeoffs between drilling and completion costs and the potential for production uplift. This is largely because the explanations of why a particular child well produces more or less than their immediate parents have remained largely undetermined.

Cherian et al. argued that the primary drivers of infill well depletion in the Marcellus shale are stress regime changes caused by parent cumulative gas production, and that these are mediated by the geomechanical effects of porosity and saturation (2022). There is a suggestion that, at least in this gas play, parent-child effects are mostly confined to wells placed within 900 ft of the parent. The authors do not, however, show response curves or estimated effect size benchmarks to parent cumulative production, simulated in situ pressure, nor interwell spacing distances.
Slowinski et al. conducted a multi-year study of the effects of parent depletion on infill child wells in the San Juan Basin (2022). They argue that pressure depletion caused by the parent is the main driver of reductions in child performance compared to expected type curves, and provide an estimate of the total impact of this depletion: 50% reduction in 12 month cumulative production when parent well casing pressure has declined by 80%. Based on their proprietary pressure data, they estimate that a parent well would need to be on production for at least three years before infill wells see any impact at all. The data presented here are very interesting, but it is unclear whether they generalize to other basins. The child depletion results are based on just 7 infill wells, and the basin, as the authors point out, is unusual in that its initial pressure is already close to the bubble point.

Wolfram et al. present a series of findings on training machine learning models on combinations of real data and outputs from numerical simulations to estimate infill well degradation due to parent factors in the Delaware Basin (2022). While the primary goal of this work was to establish the viability of using combined real/simulated datasets as inputs to data-intensive machine learning models, they do mention two ancillary outcomes that are relevant to us here. First, they state that cumulative gas production is a better predictor of parent depletion than cumulative oil production; and, second, that distance to the closest parent is a highly influential feature, whereas the child’s completion design is not. These results are based on 55 child wells, and a larger number of simulated wells (135), which creates the risk of model explanations that reproduce the simulation configuration. Additionally, the plots in the paper are mostly unitless, which limits their usefulness.

In this paper, we use a data-driven approach to analyze the conditions under which infill wells under or outperform their immediate parents in the Midland Basin in Texas. This approach has the benefits of being unbiased by prior conceptions of how a particular basin should behave, and is more readily transferable from one basin to another, given enough training data in other basins. In addition, this view “from the data” gives us the opportunity to discover previously unknown levers in controlling the production profile of infill developments. We present our findings as response curves plotted against real feature values to aid in comparison with prior work, and application to novel domains.

**Methods**

**Dataset**

A dataset was constructed for the Midland basin consisting of the following:

Monthly hydrocarbon volumes were constructed from data reported publicly to state agencies. Hydrocarbon production in Texas is reported at the lease level to the state, so volumes were assigned to individual wells by estimating monthly volumes from well test volumes. Completions data were collected from state forms and corroborated with other data sources when possible. Because we are using publicly reported data, we do not have access to information about stages, clusters, initial shut-in pressure, or casing pressure, which have been used in prior work.

Geological properties were calculated from proprietary well logging data, and smoothed over the basin to form a grid of sample points. The geological properties used in this study consisted of formation thickness, porosity, water saturation (SW), total organic content (TOC), and clay volume (VCLAY).

For each well, interwell spacing distances were calculated from directional surveys. These included distances to each lateral, stagger, and stack neighbor, where potential neighbors include any horizontal well within a radius of 2600 feet that has at minimum a 1000 ft lateral length. Individual neighbor distances were rolled up into summary statistics of ease of use during modeling. Here, we use the average tangent distance to the four closest, non-shadowing neighbors and the total number of neighbors within the search radius.

Each well in the dataset was classified as either a parent or a child well, depending on whether there was a neighbor within the search radius already producing for at least 90 days. Note that a child well can be a parent to another non-parent well. For each child, the single closest parent was recorded, along with the tangential distance and number of days the parent had been online and producing.
For each parent well, a modified hyperbolic curve was fit to the historical production of the well. This was used to estimate a 50 year EUR. The cumulative production for each parent, at each time point, was converted into a percentage of EUR produced by each producing month. This was done for both the oil and gas streams.

For each child well, values for percent of oil and gas produced were collected from the parent assigned to that child 90 days after the child was brought online. This was done principally to avoid any noise-inducing events surrounding the completion of the child well and initial flowback period, such as shutting in the parent well or restricting the initial flow rate of the child. In addition, the percent change between the child and the parent in the amount of proppant and fluid used per foot of lateral was calculated and assigned as a variable to the child. Finally, the child and the parent were aligned by producing month (i.e. not calendar month) and a percent change in cumulative production per foot of lateral, per producing month, was calculated.

The dataset was filtered to only include child wells whose parents had produced at least 1% of estimated EUR for both gas and oil before the child was put on production. An additional filtering step for quality control was performed to select only wells where both the parent and child were completed with between 400 and 4,000 lbs of proppant per foot, and between 20 and 90 barrels of fluid per foot. Both of these filtering steps were done to eliminate extreme outliers in the parent/child percent change features, as a parent with e.g. 0 production would have a child percent change of infinity percent. This resulted in a dataset of 8,000 child wells.

Model

Because the goal of this study is exploratory and descriptive, we are primarily focused on interpretability and consistency with reservoir engineering principles, where the latter is applied in a weak sense. That is to say, at no point are we supplying the models with physics-based methods, nor are we choosing modeling approaches that conform to expected response curves published in prior literature. We limit ourselves here to validating model outputs with broad generalizations, such as

1. On average, wells with larger completions should produce more than wells with smaller completions, although this is not necessarily monotonic, or unbounded
2. On average, new wells drilled in pads with large amounts of prior depletion should produce less than new wells drilled in pads with no existing wells, assuming other variables are held constant
We emphasize this distinction for two reasons: first, the goal is to learn these response curves in a data-driven manner, which will be biased if we are prodding the model to reproduce a previously characterized response curve; and second, just because a feature is useful in a predictive sense — i.e. it reduces forecast errors — does not mean it is necessarily useful in a descriptive sense.

To take a concrete example, total parent cumulative production of oil should be a reliable indicator of both reservoir depletion, because these are accurately measured volumes of liquid that have been removed from the reservoir. However, including parent cumulative oil production at time of initial child production produces a paradoxical result, where greater reservoir depletion is associated with greater child production (Fig. 1). The explanation for this is that the parent’s production is also a reliable indicator of local reservoir quality, and therefore also a reliable indicator of future child production — high producing parents are located in a favorable area which tend to have high producing children.

Because metrics derived from parent production can be used to infer reservoir quality, they have the side effect of also masking the effects of other variables. For example, including parent cumulative oil production reduces the importance of the geological features in the model, because inferring future production from past production is much easier than inferring future production from interpolated subsurface measures like porosity and water saturation.

Thus, for our modeling approach we will only be considering measures of reservoir depletion that cannot easily be used to infer, e.g. rock quality. These will principally be the estimated total percentage of oil EUR and gas EUR produced by the parent before the child starts producing (but not the estimated EURs themselves). We also include parent age, operationalized as days since initial parent production, to help capture any effects from the parent that are not well represented by the produced percentage of total reserves.

The targets used in our primary analysis were the percent change in child production compared to their direct parent. Because parents and children will have their production volumes influenced by geology in similar ways, using the percent change child over parent allows us to control for the effects of geology even when these features are not explicitly captured in the model. Any signal that we do see from geology should then be related to mediating the parent influence on the child well. An additional benefit is that the model explanation factors will be in percent uplift and downlift, which is a convenient way to think about factors influencing well production.
The dataset was split into a training and a testing set by randomly selecting 20% of the child wells as holdouts, and a second set of models targeting child monthly volumes were generated as sanity checks on feature choices and model accuracy. While our primary concern is not forecasting accuracy, the chosen model needs to be accurate enough to ensure that we are capturing useful information from the dataset and not just noise.

Child wells had their historical features and production truncated to six months, and child wells without at least six months of production were removed from the training data set (but not the testing data). The time series of features was collapsed to a single set of values per well by taking the value at 6 months and then used to train a multi-target model forecasting either the parent-child change in production for the first six months or the first six months of cumulative volumes. The regressor used was a random forest with trees unbounded in depth but with their minimum node size frozen to 64 samples.

**Analysis**

Models and feature sets were first validated by inspecting their forecast accuracy on cumulative monthly volumes. A production forecast was generated by multiplying the parent production by the forecasted change, and these results were compared to the simple forecasting method (Fig. 2). Finally, Shapley values were calculated for the production change models and these were compared to weak hypotheses concerning reservoir behavior, as described above.

Shapley values are a model explainability method that apportion the forecast for an individual well into the contributions from individual features to that forecast (Lundberg et al. 2018). This is done in the same semantic space as the prediction targets, so, for example, if a well is forecasted to produce 100 barrels of oil in its first month of production, 40 of those might be attributable to the depth of the well, 20 to the fluid used to complete the well, 5 to the porosity, etc. These attributions are calculated with respect to the average well in the dataset and produce a contribution value for every feature included in the model, which means they are sensitive to both well filtering and feature selection.

We used the open source library SHAP for calculating Shapley values from the random forest regressor. The algorithm used by this library has the benefit of operating with polynomial time complexity, whereas the original description of the algorithm requires exponential time with the number of features in the model. Prior research has established that computational shortcuts used by SHAP can result in nonsensical model explanations, in particular when features are highly correlated or when particular combinations of feature values are impossible, which means these explanations need to be interpreted with some care (Frye et al. 2020).

![Figure 3. Tornado plot of Shapley values for percent change in infill oil production](image-url)
With these cautions in mind, Shapley values are still a very useful tool for interrogating a model for what it has learned about an underlying dataset (Cross et al. 2020, Cross et al. 2021). In particular, we used the Shapley values produced by SHAP to quantify the importance of features to a forecast; the shape of the response curve to changes in an individual feature; and, any interaction effects between features in the model and their influence on the eventual model outputs.

**Results**

We observe a large range of parent-child oil production ratio, with a p75-p25 of -35% to +25%. For gas, this range was shifted to the right, with a p75-p25 of -25% to +60%, indicating an increased incidence of gas production in children, likely due to pressure depletion in the reservoir. However, this is not reflected in the descriptive statistics for GOR at production onset, as both parent and child wells had a similar interquartile range of 0.75 to 1.5 (mcf/bbl). Child wells had slightly higher fluid and proppant loading, with a median value of 45 bbl/ft for children compared to 40 bbl/ft for parents and a median value of 1600 lbs/ft for parents and 1800 lbs/ft for children, respectively. The median parent in this dataset is 1.5 years old, with a total range of 4 months to 10 years.

**Model accuracy**

Model errors were inspected and compared to proprietary baselines for the Midland basin. Directly forecasting production from the available feature set produced errors comparable to other approaches using similarly restricted data. The approach that predicted child performance by scaling parent performance by the forecasted infill degradation percentage showed higher errors, but were still comparable with type-curve based approaches to forecasting.

**Feature importances**

First, we note that parent recovery percent is consistently influential in its impact on child production. The parent’s percentage of oil EUR produced is the second most important feature in predicting infill degradation on oil production (Fig. 3) and parent’s percentage of gas EUR produced is the most important feature in forecasting gas production changes in children (Fig. 4). Here, importance is quantified as the sum of the absolute value of the assigned Shapley values. In both cases, higher percent recoveries from the parents are associated with a reduction in child output.

Second, there is a clear impact of increased completion sizes in children leading to increased production from child wells. For the oil stream, this is largely determined by fluid loading, whereas the gas stream is...
mostly influenced by proppant. According to the Shapley values, each feature is individually responsible for up to a 40% in the child’s production output as compared to the parent well. It’s not clear from the tornado plots shown here, but some of that range is probably due to other operational choices that we were not able to capture in this dataset, and the true range is likely to be closer to 30%.

Third, the only geological feature that is consistently important is the depth of the formation, which we have operationalized here as TVD. For oil specifically, porosity and thickness also appear to be important, given by their relative positioning above the change in proppant loading compared to the parent.

Feature impacts and interactions

Of all the available features, those capturing interactions between the child and parent well showed both the strongest overall magnitude and directionality of impact, and also the most interesting interactions with other features provided to the model. Starting with forecasting oil infill well production changes, we observe that parent percent recovered oil is responsible for a range of 70% of production (Fig. 5). Recall that this is in comparison to the average well in the dataset, so the upside in this figure could be showing wells with younger than average parents. In addition, note that percent increase is unbounded (a child can produce infinitely more than a parent if a parent has 0 production) but the percent decrease has a lower bound of -100%. One consequence of this framing is that the scales on either size of 0 are uneven, e.g. a 50% uplift is the same number of barrels as a 30% downlift.

The distance to the parent shows that closer parents have a stronger effect on decreasing child production, with a range that varies from +5% at 2,000 ft to -10% at 500 ft. Note that this impact is measured at 6 months, so it is almost certainly an underestimate of long-term production, e.g. production change at ten-year EUR. We also observe a strong interaction with parent percent recovery, where parent wells that have
produced a relatively small amount of their total reserves show a much shallower curve in response to decreasing inter-well distance.

Parent days-online emerges as an important feature in determining child degradation, which suggests our feature set is missing important operational variables. The apparently paradoxical inclination of the curve, showing that younger parents cause a decrease in child performance, can be explained by noting that this is the effect of parent age ignoring the other measured variables, e.g. how much of total reserves have been produced by the parent. The interaction in this plot shows that, at any level of parent production, producing that amount of reserves faster is associated with more degraded child performance than producing them more slowly. This could be taken as evidence that drawdown strategy is an important factor in maintaining hydrocarbon liquids production, which could also affect child performance at the six month mark by a total range of about 5%.

For infill degradation in gas production, the two dominant measures of prior depletion are parent percent of gas EUR produced, and parent age (Fig. 6). The long tail of Shapley values on the left-hand side of the plot for both percent gas recovery and parent days online likely reflect data points that the model struggled to accurately predict, and probably do not reflect real influences of these variables as drivers of infill degradation. The gas recovery variable has an effect that ranges from around 0% for a non-producing parent to -20% for a parent that has already produced 75% of reserves. Interestingly, the contribution of parent age calculated by the SHAP algorithm places a larger range for parent age, from about -20% to +15%. Like the oil stream, there is a strong interaction with parent prior production, showing that an infill well next to a parent that produced its reserves on an accelerated schedule is likely to have a child that produces less gas. Unlike the oil stream, the magnitude of the effect of these two
features are roughly comparable, which could indicate that the gas stream is more resistant to pressure depletion in the reservoir.

In the gas stream, we see a similar effect magnitude of the tangent distance to the closest parent, in this case ranging from about -10% to +5%. The shape is also similar, with a gradual decrease in child performance from 2,600ft to 1,000ft, and then a much sharper decline for distances smaller than 1,000ft. Like the oil stream, there is a strong interaction effect here, but the most influential interaction feature identified by SHAP in this case is the amount of proppant used to complete the child, relative to the parent, where larger proppant loading in the child mitigates the effect of close distances to the parent well. This could indicate that degradation in gas streams is driven more strongly by hydrocarbon depletion in the available fracture networks, as opposed to localized reservoir pressure.

Of the available geological features, the strongest effect we observe is for TVD, with an impact range of -5% to +5%. The sharpness of the inflection around 9,000ft depth suggests that the model may be using depth to the formation as a proxy for wells located in the western half of the basin, and that these wells are more resistant to production degradation due to parent effects in a way that may or may not actually be related to in situ pressure (Fig. 7). The strength of the interaction with total organic content is unexpected, and may be the model’s attempt to learn a separation between the Spraberry and Wolfcamp zones, since formation names were not used as an explicit feature in the model.

Of the remaining geology features, we see potential 10% swings in relative child productivity for both porosity and clay volumes, where children are expected to perform worse in rock that is highly porous and/or high in clay. Potential physical explanations for these observations could include highly porous...
rock allowing for more effective drainage by the parent, and fracture networks getting resealed as the local pressure is depleted by a parent, respectively.

Discussion

These results provide four main insights into the drivers of infill well performance degradation.

First, the main drivers of infill well performance are related to the localized depletion caused by parent wells. For the oil stream, it’s possible that the bulk removal of liquid and concomitant decrease in pressure is the main driver behind this phenomenon, and the drawdown strategy of the parent may have undue influence on child performance. This comports with Ramurthy et al.’s report on the importance of choke management in recovering hydrocarbon liquids in the DJ basin, and the detrimental effect of removing gas energy from the reservoir on producing GOR (2022). If this is the case, one might expect that a variable set including parent GOR and parent change in GOR would serve as a reliable proxy for parent pressure depletion, but in a separate set of experiments (not shown) we observed that GOR produced larger modeling errors and noisier Shapley values than the approach presented here using parent percent of produced EUR. Possibly this is due to compounding noise from metering issues on the gas production as noted by Barzin and Walker (2022), along with post-hoc approaches to allocating well-level oil production in our case specifically. We also note that, unlike Wolfram et al., we observe produced oil to be a better predictor of child oil degradation than produced gas (2022).

The gas production of infill wells appears to be more robust to inferred pressure changes, and, instead, it may be more strongly influenced by competition for molecules across communicating fracture networks. This would appear to align with Slowinski et al.’s assertion that parents are not significantly impacting their children until they have already reached boundary dominated flow, where the primary source of produced molecules is the extended fracture network beyond the immediately reachable stimulated rock volume, although our results show this occurring much more quickly than theirs (2022). It’s possible that this is due to operators in the Permian eschewing pressure management strategies and drawing the parent well pressure down much more quickly than operators in the DJ Basin.

Second, the effect of distance between parent wells and infill wells is non-linear and concave downward. The inflection point at which interwell distance becomes a strongly differentiating factor in child performance appears to happen around 1,000 ft. This is a bit larger than the estimated boundary of 900ft from Cherian et al., suggesting that well-well interactions might occur over larger distances than expected (2022). We observe further that the effect of parent distance interacts with the percent of total reserves produced by the parent, such that having a closer but younger parent might be better than having a farther, empty parent. We finally note that the distance effect is likely mediated by parent landing, i.e. whether the parent was in the same zone as the child, which we did not include in this analysis, but leave for future work.

Third, many of the infill wells in this dataset outperform their parents, largely because they have been completed with larger amounts of proppant and fluid. Oil production in infill wells was mostly influenced by the volume of fluid used per foot of lateral, whereas gas production was mostly influenced by the tonnage of proppant used to complete the well. Wolfram et al. (2022) report minimal effects from child completion design, but it’s possible that this is because they included the raw values in their analysis, as opposed to the amounts of proppant and fluid relative to the parent of interest.

Fourth, we see a muted effect of geology on the relative performance between infills and parents. This was partly an intentional modeling choice, as we wanted the Shapley values to reflect geology’s capacity to mediate the effect of parents on children and not the potential in the reservoir for high producing wells, generally speaking. The results here broadly comport with prior work — more depth, lower porosity, and less clay produce weaker infill effects — but in our judgment the shapes of the response curves for these variables are somewhat suspicious. As such we conclude that the interpretation of the geological impacts presented here warrant additional confirmatory work.
Conclusions

Characterizing child well performance and understanding the impacts of prior depletion is critical for optimizing pad design and valuing acreage. Areas that may have previously been perceived as undevelopable due to estimations of parent depletion may still hold untapped potential with proper infill pad engineering. Conversely, this analysis may help prevent the over-prediction of child well production in regions with existing high-performing parent wells.

References


