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Regional Productivity in the Austin Chalk with Emphasis on Fault Zone Production in the Karnes Trough Area, Texas

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ABSTRACT

In spite of several thousand horizontal wells drilled in the Austin Chalk, regional productivity analyses are limited. These studies predate modern hydrofracture treatments and increased drilling in the Karnes Trough region. This study incorporates recent production trends and includes recent completion techniques within the Austin Chalk play in Texas. Furthermore, we have investigated the Karnes Trough fault and fractured trend to determine potential influence on productivity.

We performed an exploratory analysis to investigate the impact of these faults on well production. Following this, we used completion and fault-distance data to build a gradient-boosting model predicting per-well productivity. The gradient-boosting model was tuned through cross-validated Bayesian optimization. Finally, we interpreted the gradient boosting model by generating SHAP (SHapley Additive exPlanations) values to explain the factors that influence model predictions.

The best wells are drilled downdip within two miles of major faults, but the variance in productivity is high in these areas. Analysis of the machine learning results shows the most important fault parameters are sinuosity and the closest distance between a well and its nearest fault. Fault bearing and length are of secondary importance. Apart from fault properties, early producing gas-oil ratios and well spacing are key to productivity.

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INTRODUCTION

The Austin Chalk has been a drilling target for nearly 100 years. The U.S. Geological Survey (USGS) resource evaluation (Pearson, 2010) predicted the chalk in Texas had the potential for producing 1,348 million barrels of oil and condensate; they estimate that 985 million barrels of that total come from the Pearsall and Giddings areas (Fig. 1). Given recent drilling results, the USGS estimate for oil resources west of Giddings may be low.

Early production from the Austin Chalk illustrated that most hydrocarbon was recovered from natural fractures that comprise a permeability network and facilitate drainage within low-permeability matrix (Corbett et al., 1994). In the 1980s, operators started drilling horizontal wells to better connect to the natural fractures and improve recovery (Haymond, 1991). The Austin Chalk has seen renewed activity with the advent of horizontal, multi-stage, hydrofractured wells in the past five years.

Through the 1990s, the typical Austin Chalk lithology was seen as chalk with streaks of marly mudstone, forming individual beds up to 25 feet thick (Durham and Hall, 1991; Haymond, 1991; Hovorka and Nance, 1994). More recently, Loucks et al. (2020) distinguished several lithofacies of variable thickness but characterized a common interval within the Austin Chalk containing laminated, total organic carbon (TOC) rich rocks that may be a good source of hydrocarbons. We do not know the extent to which the oil in the Austin Chalk is internally sourced versus sourced from underlying formations such as the Eagle Ford.

Martin et al. (2011) investigated whether the Eagle Ford and Austin Chalk were part of the same system. They concluded that Eagle Ford hydrocarbons migrated to the Austin Chalk in the Pearsall area, but near the Karnes Trough where fault-related fractures are high, it was difficult to determine two distinct source rock influences on hydrocarbon accumulations. Gherabati et al. (2018) found that recoveries for wells targeting the Eagle Ford in the Karnes Trough sometimes exceeded their oil in place estimates, indicating some flow between the Eagle Ford and Austin Chalk there.

Both published resource assessments (Pearson, 2010; Martin et al., 2011) predate massive hydraulic fracture treatments on par with other US resource plays (Fig. 2). Starting in 2014, the amount of fluid and proppant used in hydraulic fracturing has increased significantly in each region of the Austin Chalk, but those studies have relied on data from before 2010.

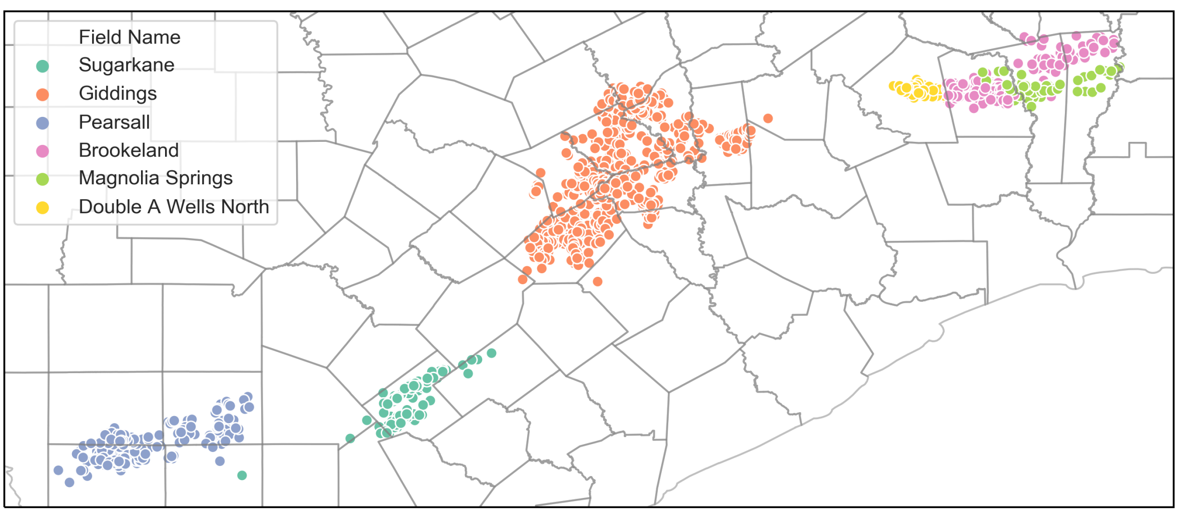

Figure 1. Horizontal wells separated into major fields of the Texas Austin Chalk. From East to West, the regions are Brookeland (Brookeland, Magnolia Springs, and Double A Wells North fields), Giddings, Karnes Trough (Sugarkane Field), and Pearsall in the Maverick Basin (Pearsall Field).

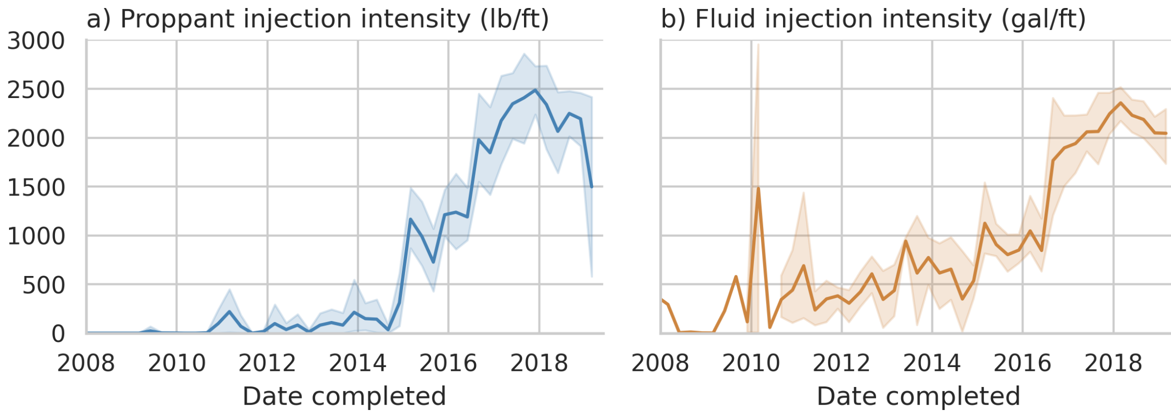

Figure 2. Average proppant and hydrofracture fluid injection intensity by quarter. Shading shows bootstrap-calculated 95% confidence intervals in the mean value. Proppant use has gone from none to 2200 pounds per foot since 2008. Fluid used in completions has intensified from 250 gallons per foot to about 2000 gallons per foot.

With current completion practices, how much do fault-related natural fractures influence productivity? We address this question in this study. To do this, we gathered production data and perform physics-based production analysis to determine productivity for every well. We then gathered fault and well data to build a machine learning model that could predict productivity.

Several groups have utilized machine learning to predict performance in tight oil plays (LaFollette et al., 2014; Attenasi and Freeman, 2020; Liao et al., 2020). These papers considered the Eagle Ford, Bakken, and Cardium, respectively, but no such papers focused on the Austin Chalk. Also, these studies consider early production metrics like the first 6 months or yearly production, which might not be indicative of full recovery (Male and Duncan, 2021).

Other studies have gone further using post-hoc analysis to interpret machine learning models (Molnar, 2019). In oil and gas, partial dependence plots (Male et al., 2017), permutation feature importance (Male and Duncan, 2020), and SHAP (SHapley Additive exPlanations) (Sathaye et al., 2020; Yang et al., 2020) have been used to find the predictive power of different inputs.

This study is a regional analysis of production for the Texas Austin Chalk horizontal well play. It used interpretable machine learning to determine the factors influencing ultimate recovery for Austin Chalk wells drilled near faults in the Karnes Trough region. We found that all of the best performing wells were within two miles of the nearest fault. Among those wells, the most important parameter was the hydraulic fracturing intensity.

METHODS

First, we collected geologic and well-specific data. Then, we analyzed the well data to estimate hydraulic fracturing intensity and productivity. Next, we matched wells to their corresponding faults. Then, we used the data and interpretations to build a machine learning model to predict productivity. Finally, we interpreted the model to understand the primary drivers of well productivity.

Fault locations and attributes come from several sources, including proprietary seismic information and published results, such as Ewing and Lopez (1991). In all, 224 faults were mapped, and their length, bearing, and sinuosity were measured.

Production data, completion data, and directional surveys came from IHS Enerdeq, which draws data from the Texas Railroad Commission and FracFocus. In Texas, operators report production from oil wells by lease with yearly well tests. IHS uses well test and lease data to back-allocate production to the individual well.

For each well, we calculated a 20–year Estimated Ultimate Recovery (EUR). We used a physics-based scaling method for predicting production from hydrofractured wells completed in undersaturated oil reservoirs (Male, 2019), which is an extension of a shale gas model (Patzek et al., 2013). This method has been used before; Male et al. (2016) applied the physics-based approach to production from the Eagle Ford formation that underlies the Austin Chalk.

We de-surveyed wells, converting their directional surveys to 3D well paths, to determine interwell distances and well-to-fracture distances. This included identifying parent and child wells. For wells within 2 miles of a fault, fault properties for the nearest fault were assigned to the well. Geopandas and Shapely took care of storing and manipulating geographic information and handling geodetic systems.

We chose granient-boosting trees to predict per-well productivity from geologic, spacing, completion, and fluid parameters. Physical understanding of the impact of several parameters on recovery is limited, and there is no reason to believe that trends are linear. Therefore, a non-parametric tree-based approach is appropriate for modeling productivity. With gradient-boosting trees, the model uses an ensemble of hundreds of weak tree learners. The model trains each learner on the residuals of the previous model (Friedman, 2001). With this approach, the final model can learn complicated relationships between input variables and the per-well productivity, without overfitting.

We used the LightGBM (Ke et al., 2017) and XGBoost (Chen and Guestrin, 2016) machine learning tools to model productivity. These are fast implementations of gradient-boosting decision trees.

Gradient-boosting decision trees have several hyperparameters that must be tuned to ensure the best performance and generality. Hyperparameters control the complexity of a machine learning model and are tuned to maximize the accuracy on data that was held back from training with cross-validation. After setting the learning rate to 0.05, we used the Bayesian Optimization python package to find the best hyperparameters. Scores were calculated on five-times repeated five-fold cross validation with a training set of 75% of wells. The objective function was squared error of the logarithm of oil EUR per length, and the metric used was root mean squared error (RMSE).

Several interpretable machine learning approaches are available for interpreting machine learning models. We chose to use Shapely additive explanations (Lundberg et al., 2018), which are model agnostic and assign feature importance for every decision using a cooperative game-theory approach.

SHAP values allow us to interpret the machine learning models (Lundberg et al., 2018). The SHAP approach uses cooperative game theory to assign the influence of each input variable on the model output for each well. High SHAP values indicate a strong positive influence, near-zero SHAP values a weak influence, and strongly negative SHAP values a sizable negative influence. Recently, oil and gas researchers have used SHAP to explain well productivity (Sathaye et al., 2020; Yang et al., 2020).

We calculated SHAP values for each input on each well productivity prediction after training. This allowed a direct comparison between, for instance, the impact of a particular distance from the well to the fault and the impact of the gas-oil ratio for that same well. The average absolute SHAP value for an input parameter is a useful rank of its relative importance to the model's predictions. In addition, the shape of the SHAP value versus input value plot shows how changes to the input impact the output prediction. If this relationship agrees with physical intuition, then that adds confidence to the model, and relationships that disagree with expectation can provide avenues for further investigation to determine root causes or invalidate the model.

RESULTS

Figure 3 shows a map of estimated ultimate recoveries for Austin Chalk horizontals. Similar to Martin et al. (2011), we divided the Austin Chalk into four regions: (from East to West) the Brookeville, Giddings, Karnes Trough, and Pearsall. The results are structured thus: We compared completions and productivity for each region from 2004 to present day. Then, we focused on the effect of faults in the Karnes Trough region.

Completions Trends

Operators have employed large hydrofracture treatments in the Austin Chalk since the 1970s, with single-stage horizontal wells appearing in the 1980s (Haymond, 1991). This remained typical until the 2010s.

From 2003–2014, operators drilled 60–100 wells per year in the Austin chalk, concentrated in the Giddings region. After 2014, development shifted to the Karnes Trough area. In both 2017 and 2018, over 100 wells were drilled near the Karnes Trough.

Since 2008, more stages have been hydrofractured and completions jobs inject four times more fluid per foot of lateral (Fig. 2). A step change in completions intensity occurred around 2016. Since that point, completions are comparably intense to those seen in the Permian basin. However, while a typical well in the Midland basin is 10,000 feet long, average lateral lengths have remained around 5000 feet in the Austin Chalk.

Productivity

From 2004 through 2015, 20–year EURs have remained around 30 barrels per foot, of which about one-third is in the first year. Since that time, EURs have increased to 60 barrels per foot, roughly in line with wells drilled in Wolfcamp and Bone Springs formations of the Delaware Basin (Fig. 4).

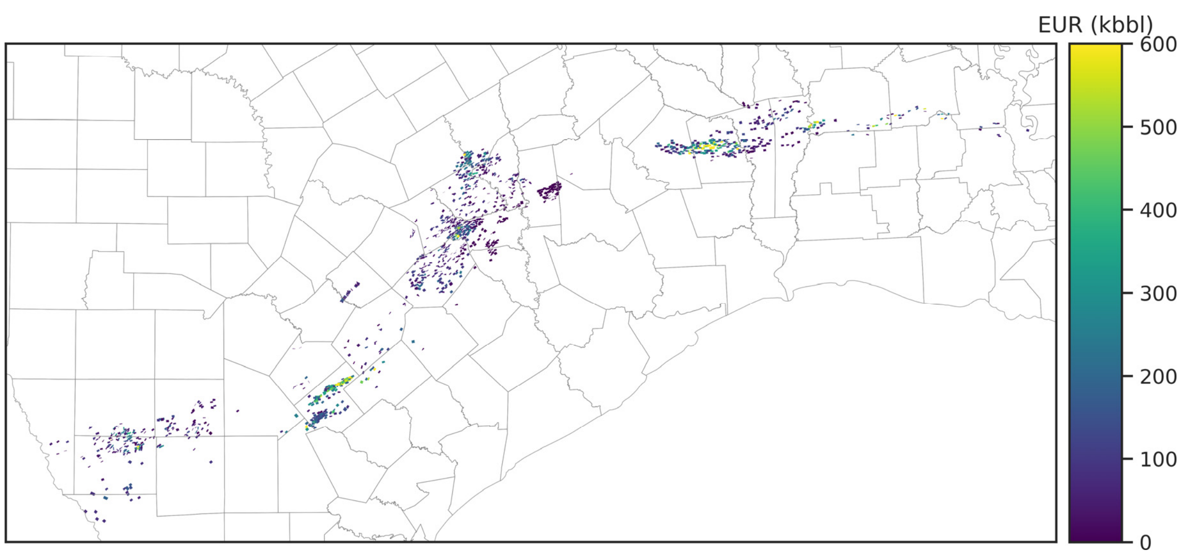

Figure 3. A map of Estimated Ultimate Recovery (EUR) for horizontal wells in the Austin Chalk play. County lines are gray. Wells with more than 0.5 million barrels of expected recovery are concentrated in the Brookeland (Easternmost) and Karnes Trough (second Westernmost) areas. Texas does not require strict field boundaries.

Increased productivity has coincided with more intense hydrofracture treatments and the shift of focus to wells in the Karnes Trough region. Aggregating wells by region indicates that, although each region has seen larger hydrofracture treatments, the best response to treatments has come from near the Karnes Trough.

Influence of Fault Zones—Karnes Trough

Comparing the locations of faults and horizontal wells, operators drilled wells near and perpendicular to faults (Fig. 5). A histogram of the distance of closest approach between well laterals and faults shows operators drill most wells within two miles of the nearest fault in the Karnes Trough (Fig. 6a). High producing wells do abut the faults, but the variation in productivity is high (Fig. 6b).

The best trained XGBoost model had a cross-validation mean absolute error (MAE) of 0.47 for log-productivity per foot. On the testing data (25%), it had an MAE of 0.52, versus an MAE of 0.49 for LightGBM. The testing R^2 was 0.38 for XGBoost and 0.41 for LightGBM. For comparison, we ran a naive baseline predictor. Predicting the mean value gave an MAE of 0.63. The MAEs for the LightGBM and XGBoost models are lower than the baseline, indicating better performance, with LightGBM showing the best performance. Figure 7 compares predicted and actual 20–year estimated ultimate recoveries for the testing dataset. The best hyperparameters for LightGBM were bagging fraction = 072, feature fraction = 0.57, learning rate = 0.05, maximum tree depth = 8, minimum child weight = 2, and number of leaves = 20.

The most explanatory attributes by SHAP value were first year hydraulic fracturing fluid per foot lateral, distance to the nearest fault, distance to the nearest well, proppant per lateral length, gas-oil ratio (GOR), and fault sinuosity (Fig. 8). Particularly low fracking fluid or particularly high proppant values result in poor performance. Drilling within one mile of a fault led to higher production. Either high or low GOR was deleterious to productivity, but there was a positive influence for 1.2 thousand cubic feet per barrel < GOR < 3 thousand cubic feet per barrel. Good wells tended to have neighboring wells within 1000 feet, and wells drilled within 2 miles of particularly sinuous faults performed poorly. The highest SHAP values for lateral length were from 2000–4000 feet.

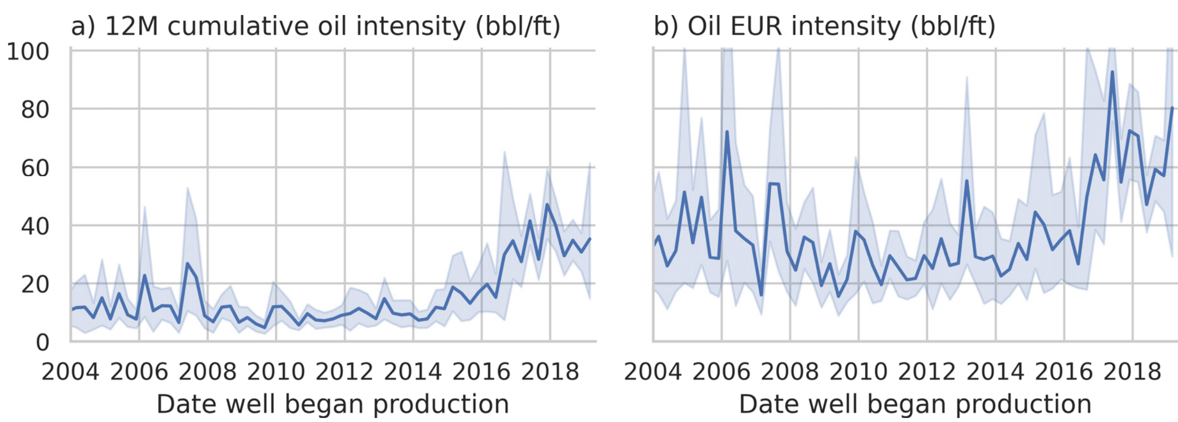

Figure 4. (a) Average first year cumulative production and (b) 20–year EUR per foot of lateral, split by quarter-year. The solid line indicates the mean performance, with shading to show the 95% bootstrap confidence interval in the average. By both metrics, wells improved significantly from 2015 to 2019.

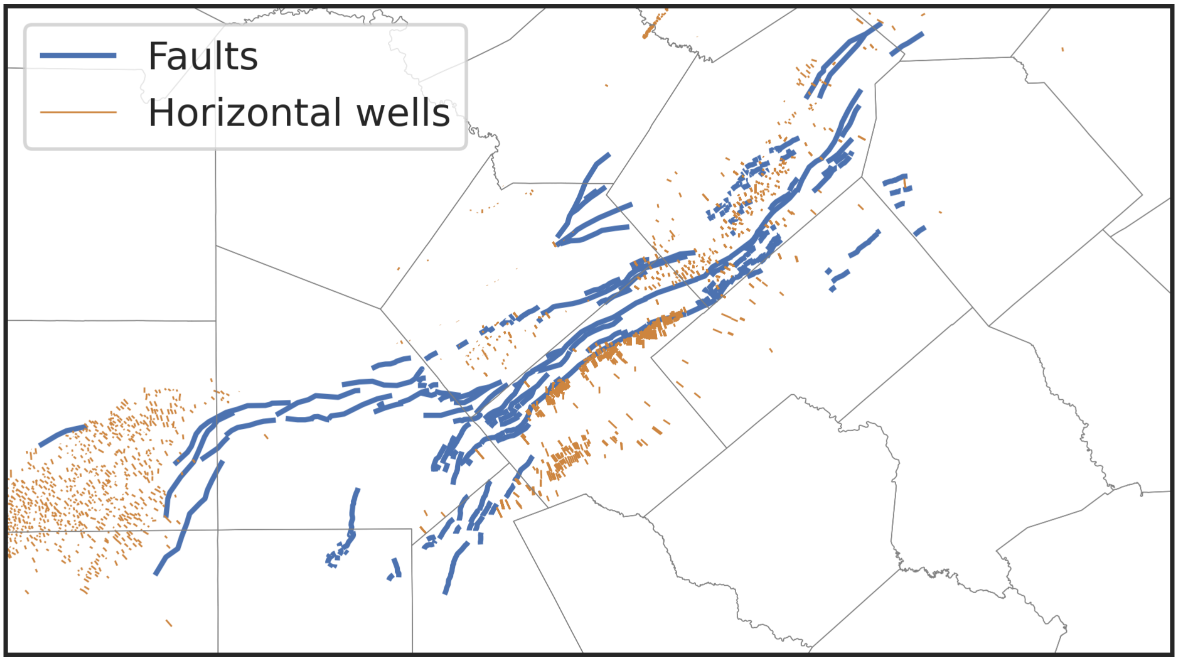

Figure 5. Locations of faults (blue) in the Karnes Trough in relation to horizontal wells (burnt orange) drilled in the Austin Chalk. Counties lines are shown in gray.

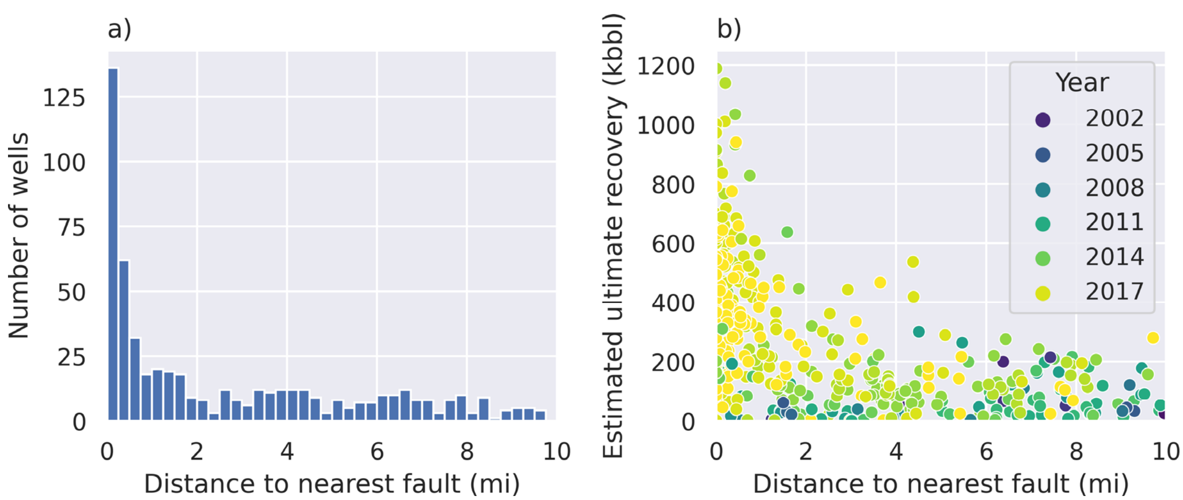

Figure 6. Nearest distances between well laterals and faults in the Karnes Trough. (a) Histogram of lateral-to-fault distances. (b) Cross-plot of distance and EUR. Color indicates the year wells were put on production.

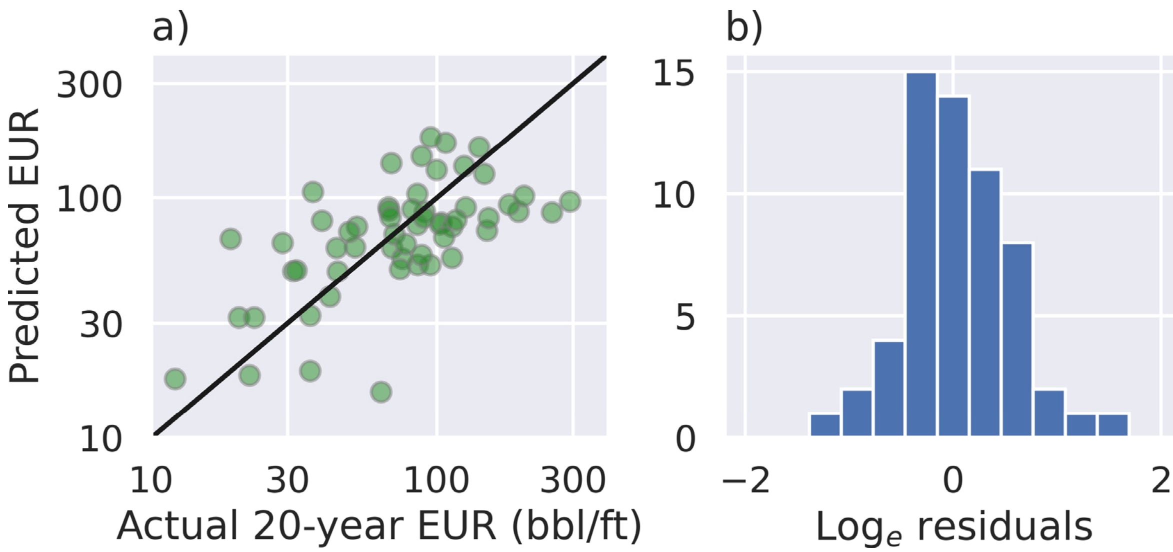

Figure 7. (a) Predictions versus actual 20-year ultimate recoveries for the testing dataset. (b) Histogram of prediction residuals in log-space.

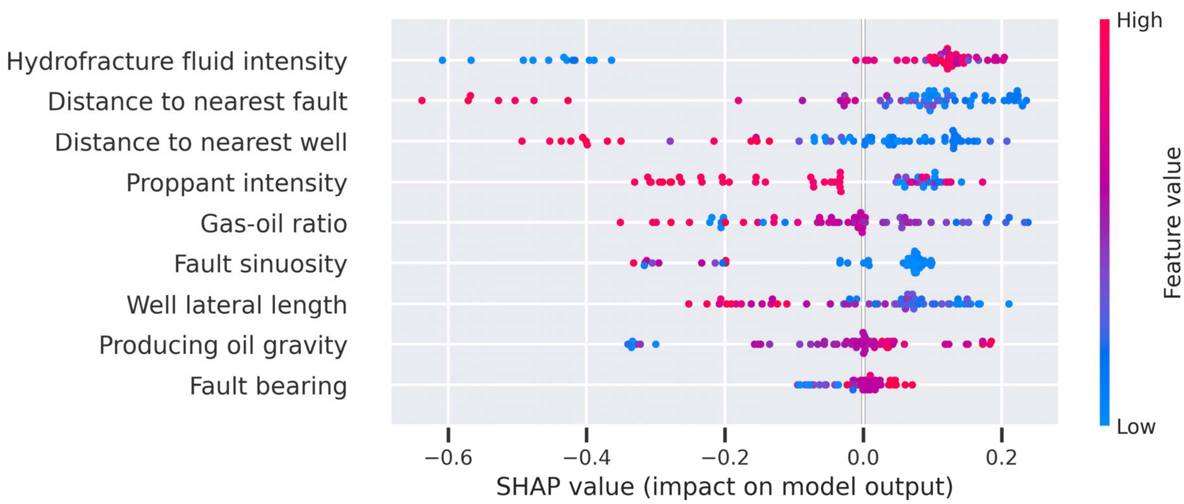

Figure 8. SHAP values for a LightGBM trained to predict ultimate recoveries from Karnes Trough area Austin Chalk wells. High SHAP values indicate predictions of better performance, while low SHAP values indicate worse predicted performance. High feature values are red, and low feature values are blue. The features are ordered by average absolute impact on the ultimate recovery prediction.

SUMMARY AND CONCLUSIONS

The Austin Chalk trend is a valuable drilling target. In the area of the Karnes Trough, the underling Eagle Ford Shale strata are characterized by thick sections of organic-rich intervals

(Gianoutsos et al., 2020). This could improve productivity in the area. Productivity from wells drilled in the Karnes Trough Area is comparable to Permian basin and Williston basin tight oil plays (Male, 2019). Infrastructure for hydrofracture treatment and pipeline capacity is available due to the extensive infrastructure built for the Eagle Ford.

Further work could include exploring several additional factors that could explain fault zone productivity. Among these factors are well landing, parent-child effects, petrophysical properties such as rock strength, TOC, and water saturation, fault trap potential, stress direction and magnitude, and interference from Eagle Ford wells.

Hovorka and Nance (1994) and Loucks et al. (2020) previously performed depositional and diagenetic analysis. In the future, these results could be brought into a machine learning model to improve productivity estimation and understanding of the impact of fault zones on productivity.

In this regional study of oil well productivity in the Texas Austin Chalk, we found that each of the four major regions have followed the same trends toward increasingly aggressive completions, but with uneven results. The best responses to newer completions came from the Karnes Trough. In the Karnes Trough region, mapping of faults and well laterals indicated that the highest producing wells are all within 2 miles of the nearest faults.

In order to find the impact of fault zones on productivity, we built a machine learning model predicting EUR per length. Our results showed that the most important fault parameters are the closest distance between a well and its nearest fault and fault sinuosity. Fault bearing and length were of lesser importance.

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