

A PRACTICAL DCA-RTA-AI/ML WORKFLOW FOR OIL AND ASSOCIATED GAS PRODUCTION FORECASTING IN A SILTSTONE RESERVOIR: A CASE STUDY

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ABSTRACT:

This paper is framed as a field case study and applied forecasting workflow for hydraulically fractured vertical wells producing oil and associated gas from a siltstone interval in the Cambay Basin. The reservoir setting is characterized by low matrix permeability, solution-gas/depletion-drive behavior, rapid pressure loss, and dependence on hydraulic fracturing for sustained commercial deliverability. Daily production histories from Wells 101, 112, and 201 are used to integrate empirical decline-curve analysis (DCA), rate-transient-analysis (RTA) screening, and AI/ML-assisted short-term forecasting. The forecast is extended to 2030 and is conditioned by reservoir attributes including porosity, water saturation, net pay, production/drainage area, depth, bottomhole-pressure references, and oil gravity.

The case study demonstrates how a transparent, auditable workflow can be constructed when complete bottomhole-pressure, PVT, and fracture-treatment datasets are not available. DCA provides the deterministic production-forecast baseline, RTA screening provides diagnostic evidence for flow-regime and data-quality assessment, and AI/ML supplies a repeatable feature-based layer for holdout testing and interpretation. The contribution is therefore not a new machine-learning algorithm, but a practical field workflow that combines engineering diagnostics, reservoir conditioning, and data-driven validation for low-permeability fractured siltstone wells.

Keywords: *Siltstone reservoir; hydraulically fractured vertical well; production forecasting; decline curve analysis; rate transient analysis; artificial intelligence; machine learning; oil & associated gas.*

INTRODUCTION

Siltstone reservoirs commonly present forecasting challenges because their pore systems are fine grained, heterogeneous, and only weakly transmissive. In these reservoirs, hydraulic-fracture conductivity, fracture connectivity, and local depletion around the stimulated interval can dominate observed production behavior. Consequently, rate trends may be affected by transient flow, depletion, multiphase oil-gas effects, choke adjustments, shut-ins, variable flow hours, wellhead-pressure fluctuations, and measurement scatter.

The production response of hydraulically fractured vertical wells differs from that of long horizontal or pad-based developments. Drainage is typically more localized, fracture height and fracture half-length are important, and interference between nearby vertical wells is less regular but still possible. For that reason, this work uses an integrated approach: DCA provides transparent empirical decline parameters, RTA screening provides a flow-regime check, and AI/ML captures nonlinear production-memory effects from engineered features.

This paper applies the workflow to Wells 101, 112, and 201 as an applied field case study. The objective is to demonstrate how limited but realistic production and reservoir data can be organized into a defensible forecasting workflow suitable for technical screening, field planning, and future pressure-normalized validation.

PAPER OBJECTIVES AND CONTRIBUTIONS

The objectives of this paper are to:

- Incorporate available field and reservoir information from the Cambay Basin siltstone system into a DCA-RTA-AI/ML interpretation workflow.
- Build a repeatable decline-analysis workflow for three hydraulically fractured vertical wells using measured production histories.

- Generate rate-time, semi-log, log-log, and cumulative diagnostics for both oil and associated gas.
- Use Blasingame-, Agarwal-Gardner-, and Fetkovich-style RTA plots as screening diagnostics without presenting unsupported quantitative reservoir-property estimates.
- Connect DCA and RTA observations with AI/ML feature engineering based on production, pressure, operating, and reservoir inputs.
- Compare empirical and data-driven forecast behavior and identify the practical limitations of each method for the available dataset.

The principal contribution is the field-validated workflow rather than a standalone algorithm. The paper links DCA, RTA screening, reservoir-property conditioning, and AI/ML holdout testing into one auditable sequence so that each forecast result can be traced back to production behavior, diagnostic evidence, and reservoir context.

2.1 Case-Study Novelty and Applied Contribution

The novelty of this study lies in integrating three normally separate interpretation layers—empirical DCA, RTA screening, and AI/ML-assisted forecasting—within one field-case workflow for hydraulically fractured vertical wells in a siltstone reservoir. The available data represent a realistic mature-field condition: production records and selected pressure references exist, but continuous flowing bottomhole pressure, complete PVT data, and fracture-geometry information are not available. Therefore, the study is positioned as an applied workflow and screening-level field case study rather than as a universal AI/ML model or a quantitative PTA/RTA reservoir-property-estimation exercise. Table 2.1 clarifies the novelty claim, risk area, and the way each issue is handled in the manuscript.

Table 2.1 - Case-study novelty, risk mitigation, and applied contribution.

Novelty / risk area	How it is addressed in this manuscript
Integrated workflow rather than a single-method study	DCA, diagnostic plots, RTA screening, reservoir-property conditioning, and AI/ML holdout testing are combined into one traceable applied workflow.
Limited well count	The work is explicitly positioned as a field case study and workflow demonstration using Wells 101, 112, and 201, not as a universal AI/ML model.
Screening-level RTA	RTA plots are used only for qualitative diagnostic screening because corrected bottomhole pressure, complete PVT data, and fracture-geometry inputs are unavailable.
AI/ML contribution	AI/ML is used as an engineering-assisted holdout and feature-integration layer supported by production memory, DCA descriptors, RTA indicators, and reservoir properties.
Forecast uncertainty and field relevance	The 2030 forecast is reported as a deterministic technical base case. Probabilistic P10/P50/P90 forecasting, commercial-software validation, and pressure-normalized RTA are identified as future work.

FIELD AND RESERVOIR DESCRIPTION

3.1 Field Setting and Production Background

The study area lies in the southern Cambay Basin. Hydrocarbon production is obtained from an Eocene-age siltstone interval containing oil and associated natural gas. Because matrix permeability is reported to be less than 2 md and commercial flow depends on hydraulic fracturing, the reservoir is treated as a low-permeability fractured system. The drive mechanism is interpreted as solution-gas/depletion drive, making pressure decline and pressure support central to long-term well performance; the field context used in the study is summarized in Table 3.1.

The field contains seven wells, but this study uses Wells 101, 112, and 201 because these vertical, hydraulically fractured wells have post-fracture oil and associated-gas histories suitable for DCA, RTA screening, and machine-learning-based evaluation.

Table 3.1 - Field and reservoir context used in the study.

Item	Description / Value
Producing formation	Kalol Formation, Eocene age
Lithology	Siltstone
Hydrocarbon system	Oil with associated natural gas

Item	Description / Value
Drive mechanism	Solution-gas / depletion drive
Permeability character	Very tight; less than 2 md
Completion requirement	Hydraulic fracturing required for commercial production
Field challenge	Rapid reservoir-pressure decline and long-term pressure/production sustenance
Study wells	Vertical hydraulically fractured Wells 101, 112, and 201

3.2 Well-Specific Reservoir Properties

Well-level reservoir properties were incorporated so that the forecast interpretation is not based solely on production-rate fitting. These static descriptors are used as engineering context and as candidate explanatory variables for the AI/ML workflow. Porosity, water saturation, net thickness, reported drainage/production area, reservoir depth, pressure-depletion references, and oil gravity are summarized in Table 3.2 and help explain why wells with similar completion concepts may show different decline and cumulative-production responses.

Table 3.2 - Reservoir and completion properties for Wells 101, 112, and 201.

Parameter	Well 101	Well 112	Well 201
Porosity, %	17	16	15
Water saturation, %	45	45	45
Net thickness, m	9	14	8
Production/drainage area, km ²	0.25	0.017	0.196
Date of first production	July 2009	January 2009	April 2014
Avg reservoir depth, m TVDSS	1593	1584	1638
Initial BHP, psi	3340 at	3199	2837
Current/static BHP reference	1847 psi, April 2015	1968 psi, April 2016	1350 psi, August 2018
Oil gravity, deg API	42	42	42

3.3 Historical DCA Benchmarks From Prior Field Analysis

Earlier field-analysis results through 2029 are used only as engineering reference points for the current 2030 forecast extension. The benchmark decline and reserve values listed in Table 3.3 are not treated as final conclusions; instead, they provide comparison points for the current repeatable Excel/Python DCA workflow and the 2030 forecast extension.

Table 3.3 - Prior 2029 DCA benchmarks.

Parameter	Well 101	Well 112	Well 201
Best-fit decline type	Best fit / hyperbolic behavior	Best fit / hyperbolic period	Best fit / hyperbolic behavior
Arps b-value	1.04	1.20	1.40
qi, bopd	6.4	6.8	96.6
Initial decline ai, 1/year	0.013	0.010	0.009
Oil EUR, Mbbl	76.21	65.70	64.31
Gas EUR, MMscf	1355	1198.5	188.9
Balance oil reserves, Mbbl	14.24	17.60	21.90
Balance gas reserves, MMscf	553.05	783.06	67.2
Forecast reference year	2029	2029	2029

3.4 Implications for RTA and AI/ML Forecasting

The field setting directly affects the interpretation strategy. Hydraulic fracturing can produce early transient and cleanup-dominated behavior, so early production must be screened before decline fitting. Because solution-gas/depletion-drive behavior causes rapid pressure loss, observed rate changes may represent both reservoir

depletion and operating practice. The static descriptors in Table 3.2 are therefore used with the dynamic production indicators summarized later in Table 9.4.

LITERATURE REVIEW

4.1 Rate-Transient Analysis Applications in Tight and Siltstone Reservoirs

RTA is valuable for low-permeability reservoirs because it evaluates production behavior through rate, pressure-related response, cumulative production, and transformed-time variables. Unlike a purely empirical rate-time fit, RTA can indicate whether the well response is dominated by transient flow, fracture effects, boundary influence, or depletion. This is particularly important for hydraulically fractured siltstone wells, where production may be controlled by fracture conductivity, matrix contribution, pressure depletion, and operational constraints [7]-[9]. A gap remains in published field studies where DCA, RTA screening, reservoir conditioning, and AI/ML are applied together using the same production dataset and then interpreted transparently. Recent ML-based production forecasting studies show the value of data-driven methods, hybrid time-series models, and deep-learning approaches; however, field engineers also require traceability, diagnostic consistency, and awareness of missing pressure/PVT inputs [12]-[16]. The present work addresses that gap by treating AI/ML as one element of an engineering workflow rather than as a black-box replacement for reservoir analysis.

The diagnostic basis used in this study follows established production-analysis concepts. Blasingame-style plots are useful for variable-pressure-drop and variable-rate production systems [8]. Agarwal-Gardner concepts combine type-curve and decline-curve thinking through transformed time and cumulative-production relationships [9]. Fetkovich-type diagnostics provide a practical link between transient-flow interpretation and empirical decline behavior [7]. These approaches are appropriate for tight formations where boundary-dominated flow may occur only after an extended transient period.

For unconventional or tight reservoirs, decline-curve fitting must be applied with diagnostic control. Prior studies emphasize that unconstrained extrapolation of transient-flow data can overstate recovery, especially when high-b hyperbolic trends are extended too far [1]. Other work highlights the need to evaluate operating changes, pressure variability, and production history before selecting decline parameters [4], [5].

In the present siltstone dataset, RTA interpretation must account for lithological heterogeneity, low permeability, fracture stimulation, pressure decline, and multiphase oil-gas behavior. The available data include wellhead-pressure variables and selected BHP references, but not continuous flowing bottomhole pressure, complete PVT data, or fracture-treatment details. Accordingly, the RTA component is treated as a qualitative screening step rather than a final reservoir-property estimation exercise.

Blasingame-, Agarwal-Gardner-, and Fetkovich-style plots are used here to check whether the observed trends are consistent with transient behavior, fracture-controlled flow, depletion, or operational scatter. The plots are not used to report final permeability, skin, fracture half-length, or drainage-area values. A quantitative RTA workflow would require reconstructed flowing bottomhole pressure and appropriate fluid-property corrections.

4.2 Empirical and Analytical Decline-Curve Comparison

Empirical DCA is widely used because it is transparent and efficient for first-pass forecasting when adequate production history exists. The Arps exponential, harmonic, and hyperbolic forms provide the mathematical basis for the decline fits used in this paper [6]. In hydraulically fractured siltstone wells, however, these models should be interpreted carefully because early-time production may reflect transient or fracture-dominated flow rather than stabilized boundary-dominated behavior.

Analytical and semi-analytical methods, including Fetkovich type curves and material-balance-time transformations, can provide stronger physical insight but require more complete pressure, fluid, and reservoir inputs [7]-[9]. For the Cambay Basin dataset, the pressure history is represented mainly by wellhead measurements and selected BHP references rather than continuous bottomhole flowing-pressure data, so a screening-level interpretation is more defensible than a full parameter-estimation workflow.

The most appropriate workflow for Wells 101, 112, and 201 is therefore a combined one. DCA establishes a transparent forecast baseline; RTA screening evaluates whether the decline behavior is physically plausible; and AI/ML adds a short-term data-driven layer based on production memory and operating variables. This approach

follows the broader principle that forecasting method selection should reflect reservoir type, flow regime, well configuration, and production history [4], [5].

4.3 AI/ML in Production Forecasting

AI/ML methods are increasingly used in reservoir-performance forecasting because they can represent nonlinear relationships among production history, operating conditions, and reservoir descriptors. Their value depends strongly on careful feature design and validation that prevents leakage of future production into the training period [10], [12]-[16]. Sequence-based methods such as LSTM and hybrid ARIMA-LSTM/EEMD-LSTM models may be useful for long time-series datasets, but they require adequate data volume and independent examples before they can be relied upon for field-scale generalization [12]-[14].

In this three-well study, AI/ML is used as a support tool rather than as a standalone forecasting replacement. The wells provide useful daily production records, but the number of independent wells is small. Tree-based models and engineered production-memory features are therefore more appropriate than complex deep-learning architectures for this stage of analysis.

Feature design was guided by petroleum-engineering interpretation. Dynamic features include oil rate, associated-gas rate, cumulative volumes, rolling averages, operating pressures, bean size, and flow hours. Physics-informed features include DCA parameters, RTA screening indicators, porosity, water saturation, net thickness, production/drainage area, depth, BHP references, and oil gravity. This structure follows recent data-driven forecasting literature that emphasizes domain-informed input selection and careful interpretation of model outputs [15], [16].

4.4 Research Gap and Study Positioning

The literature shows that DCA, RTA and AI/ML are commonly discussed as separate analysis tools, but fewer field papers demonstrate how these tools can be combined under the data limitations typically encountered in mature fractured reservoirs. In practice, field engineers often have long production histories and selected pressure references, but do not always have continuous bottomhole-pressure, complete PVT and detailed fracture-treatment data. This study is positioned within that practical gap.

The paper therefore contributes an applied workflow rather than a new mathematical model. Its value is in showing how DCA, diagnostic plotting, RTA screening, reservoir-property conditioning and AI/ML holdout validation can be used together without overstating the certainty of reservoir parameters that require additional pressure and fluid data; this positioning is summarized in Table 4.1.

Table 4.1 - Research gap and positioning of the applied workflow.

Gap in common practice	Applied response in this paper
DCA is often used alone for long-term forecasting	DCA results are checked against diagnostic plots and RTA screening before interpretation.
AI/ML papers may emphasize prediction without reservoir context	AI/ML features are tied to production memory, operating variables, DCA descriptors and reservoir properties.
RTA can be over-interpreted without pressure correction	RTA is explicitly limited to screening because corrected bottomhole-pressure data are unavailable.
Field datasets are often incomplete	The workflow separates completed analysis from recommended future validation work.

DATA DESCRIPTION AND QUALITY CONTROL

The production dataset contains daily records for Wells 101, 112, and 201, and the production-window summary is provided in Table 5.1. The available fields include date, well name, oil volume, associated gas volume, shut-in and flowing tubing/casing pressures, bean size, flow hours, and operational remarks. The time-series behavior is shown in Figure 5.1, while the cumulative production response is shown in Figure 5.2.

Data preparation involved standardizing dates, excluding nonphysical negative values, retaining positive production intervals for fitting, and distinguishing calendar time from producing time where possible. The

conditioned dataset summarized in Table 5.1 forms the basis for the DCA model fitting in Table 6.2, the RTA screening in Figures 8.1 to 8.3, and the AI/ML feature construction in Table 9.1.

Table 5.1 - Production-data summary for Wells 101, 112, and 201.

Well	Production window	Calendar days	Oil days	Gas days	Cum. oil (m3)	Cum. gas (m3)	Avg oil (m3/d)	Avg gas (m3/d)
Well 101	2014-03-28 to 2020-03-23	2188	2170	2177	5,803	23,296,590	2.67	10,701
Well 112	2014-05-20 to 2020-03-23	2135	2101	2135	4,428	11,206,443	2.11	5,249
Well 201	2014-07-13 to 2020-06-17	2167	2145	2165	5,933	3,626,877	2.77	1,675

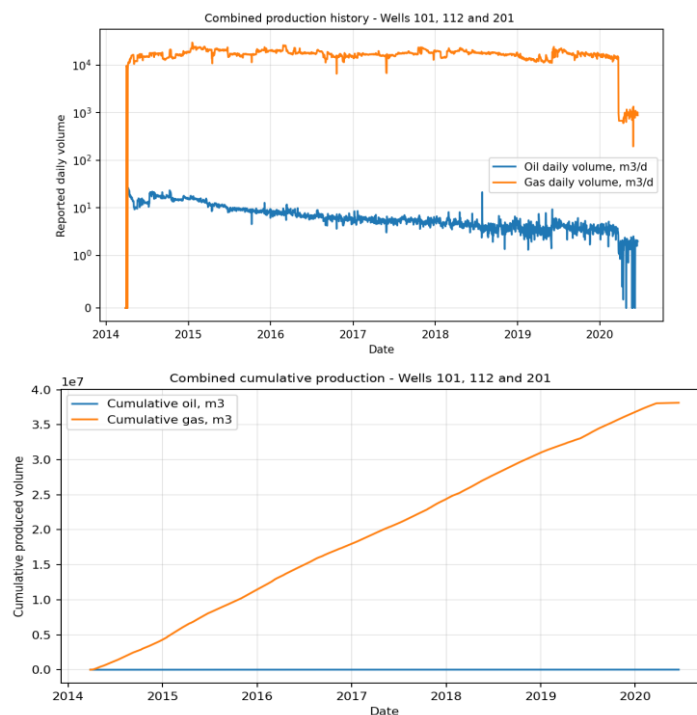


Figure 5.1 - Reported daily oil and associated gas production history for Wells 101, 112, and 201.

Figure 5.2 - Cumulative oil and associated gas production for Wells 101, 112, and 201.

5.4 Reservoir-Property Data Used for Model Conditioning

Reservoir-property information was used to condition production interpretation. Porosity, water saturation, net thickness, reported production/drainage area, depth, BHP references, oil gravity, lithology, and completion requirement were added as explanatory descriptors. These variables, listed in Table 3.2 and incorporated conceptually into Table 9.4, help explain inter-well differences; for example, Well 101 has the largest reported area and relatively favorable porosity, whereas Well 112 has the thickest interval but the smallest reported area.

DECLINE-CURVE ANALYSIS METHODOLOGY

Oil and associated-gas production were fitted independently for each well using exponential, harmonic, and hyperbolic Arps decline forms. The reproducible analysis sequence is summarized in Table 6.1, and the fitted DCA model selection is reported in Table 6.2. Model selection considered residual error, visual fit quality, and whether the resulting forecast shape was technically reasonable for a low-permeability fractured reservoir.

6.1 Reproducible Workflow Steps

To make the case study reproducible, the analysis was organized as a fixed sequence of data preparation, diagnostic evaluation, decline fitting, screening interpretation and forecast extension. The same sequence was applied consistently to oil and associated gas for Wells 101, 112 and 201.

Table 6.1 - Reproducible workflow steps used in the study.

Step	Action performed	Purpose
1	Compile daily oil, gas, pressure, bean-size, flow-hour and remarks data	Create a common production-analysis dataset.
2	Clean dates and remove nonphysical negative entries	Avoid distorted decline and AI/ML training behavior.
3	Inspect rate and cumulative trends	Identify production continuity, shut-ins and operational scatter.
4	Fit exponential, harmonic and hyperbolic DCA models	Select a transparent empirical forecast baseline.
5	Generate Cartesian, semi-log and log-log plots	Evaluate decline behavior and data quality.
6	Generate Blasingame, Agarwal-Gardner and Fetkovich plots	Screen qualitative flow-regime and transient/depletion behavior.
7	Create AI/ML features from production, operating, DCA and reservoir descriptors	Build an engineering-guided forecasting feature set.
8	Use chronological holdout testing	Evaluate data-driven performance without future-data leakage.
9	Extend DCA forecasts to 2030	Provide a deterministic technical base case.

The fitted decline models are:

Exponential decline: $q(t) = q_i \exp(-D_i t)$

Harmonic decline: $q(t) = q_i / (1 + D_i t)$

Hyperbolic decline: $q(t) = q_i / (1 + b D_i t)^{1/b}$

In these equations, $q(t)$ is the production rate at time t , q_i is the fitted initial rate, D_i is the nominal decline constant, and b is the hyperbolic exponent. The selected model parameters in Table 6.2 are later extended into the 2030 forecast summary in Table 13.1.

Table 6.2 - Arps DCA model selection and fitted parameters.

Well	Phase	Best DCA model	Fitted parameters	RMSE	R2
Well 101	Oil	Hyperbolic	$q_i=20.24, D_i=0.02012, b=1.42$	0.55	0.942
Well 101	Gas	Exponential	$q_i=12,335.26, D_i=0.00014$	2,181.29	0.158
Well 112	Oil	Hyperbolic	$q_i=4.99, D_i=0.00124, b=0.37$	0.68	0.722
Well 112	Gas	Harmonic	$q_i=5,206.34, D_i=0.00000$	1,783.00	-0.000
Well 201	Oil	Hyperbolic	$q_i=7.91, D_i=0.00292, b=1.25$	0.53	0.878
Well 201	Gas	Exponential	$q_i=2,752.09, D_i=0.00051$	248.45	0.818

DCA RESULTS AND DIAGNOSTIC PLOTS

Well 101

For Well 101, the oil response shows a pronounced early decline followed by a low-rate tail, as shown in Figure 7.1. The diagnostic plots in Figure 7.2 support this interpretation by comparing Cartesian, semi-log and log-log views. The associated-gas profile is more scattered than the oil response, so the gas interpretation is checked against both cumulative production and the fitted model in Table 6.2.

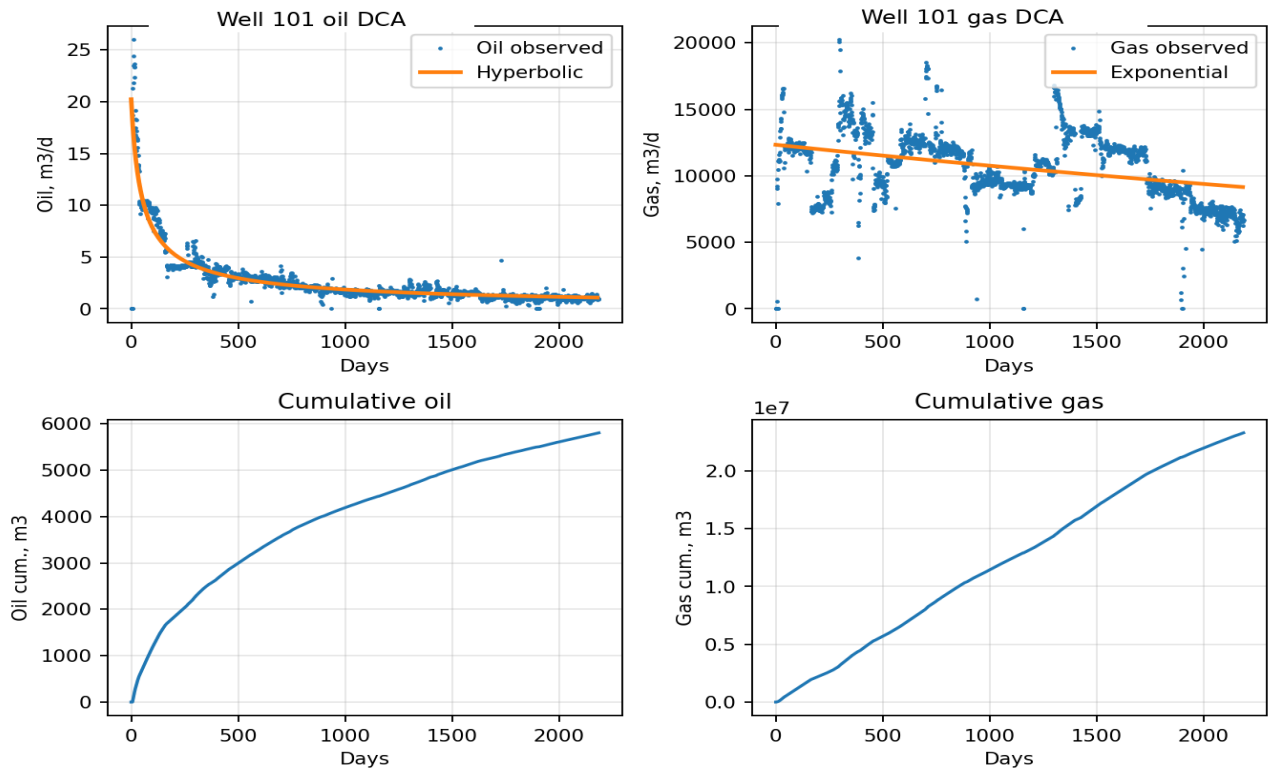


Figure 7.1 - Well 101 oil/gas DCA and cumulative production analysis panel.

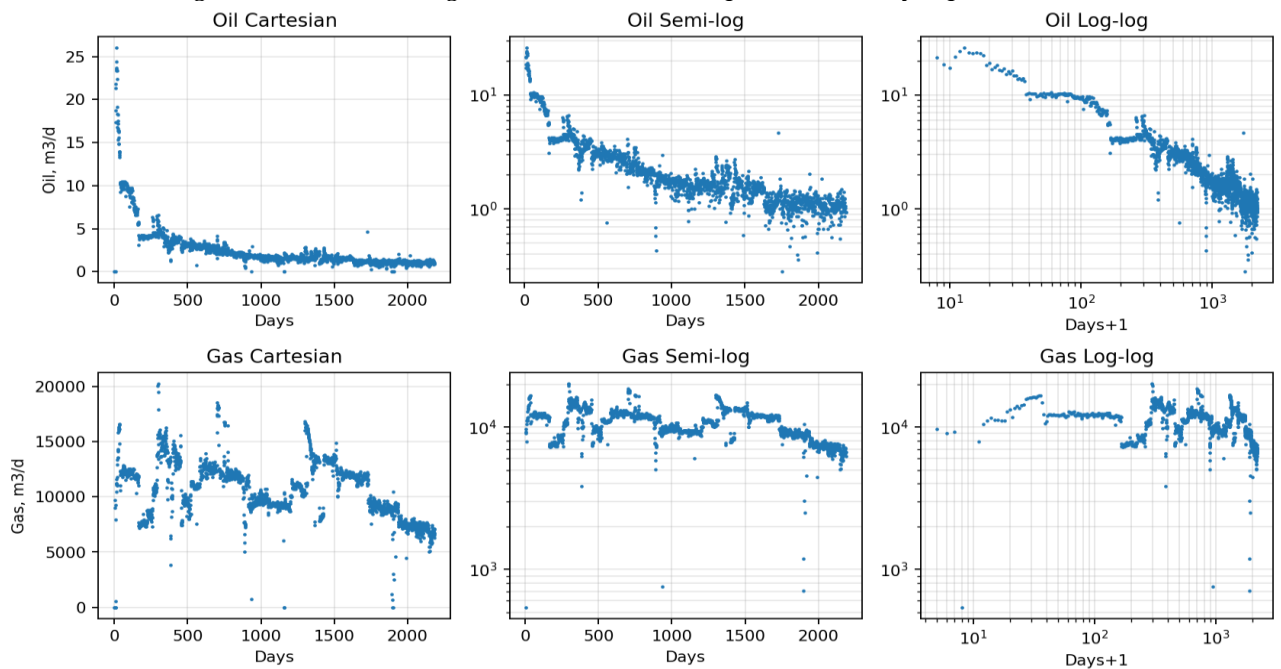


Figure 7.2 - Well 101 Cartesian, semi-log, and log-log diagnostic curves for oil and associated gas.

Well 112

Well 112 has a lower oil-rate range and a gas history that is more sensitive to late-time variability, as shown in the DCA/cumulative panel in Figure 7.3. The diagnostic curves in Figure 7.4 are used to distinguish genuine decline behavior from operational scatter, short-duration rate changes, and measurement effects.

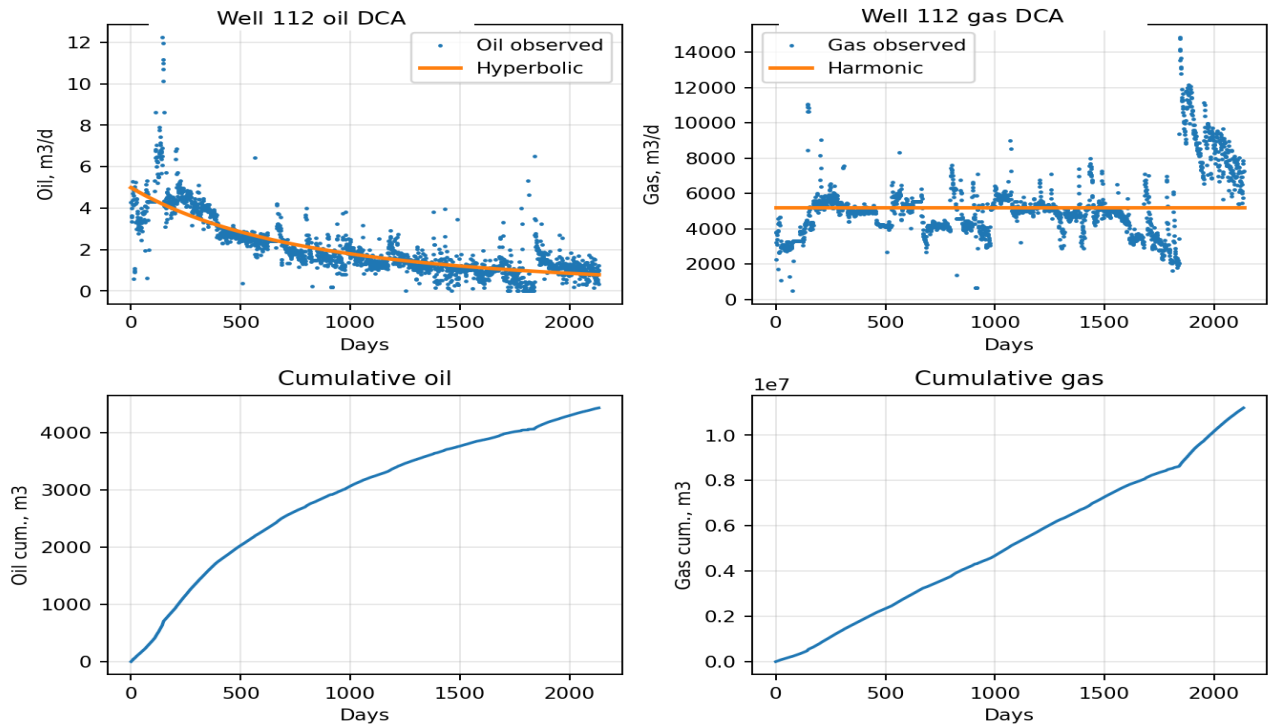


Figure 7.3 - Well 112 oil/gas DCA and cumulative production analysis panel.

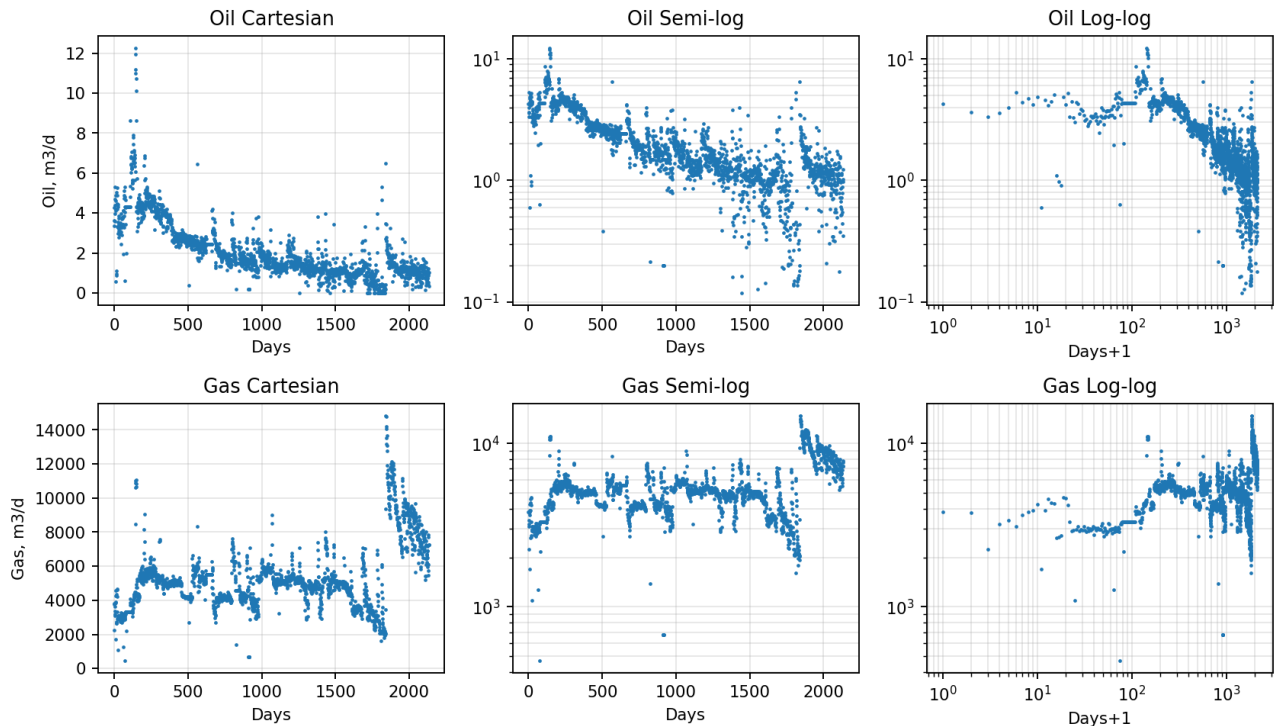


Figure 7.4 - Well 112 Cartesian, semi-log, and log-log diagnostic curves for oil and associated gas.

Well 201

Well 201 shows a clearer associated-gas decline trend than Wells 101 and 112, while its oil response remains consistent with a fractured vertical well in a low-permeability interval. This behavior is visible in the DCA/cumulative panel in Figure 7.5 and is further supported by the diagnostic plots in Figure 7.6.

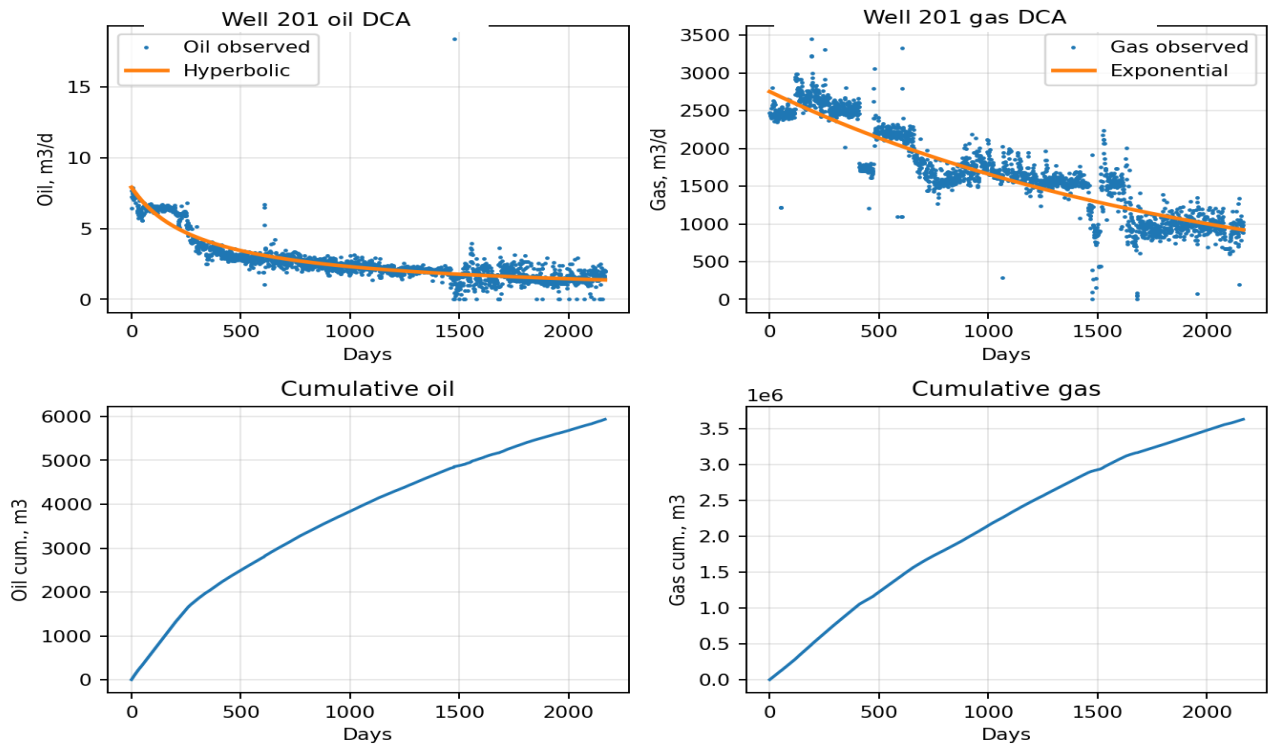


Figure 7.5 - Well 201 oil/gas DCA and cumulative production analysis panel.

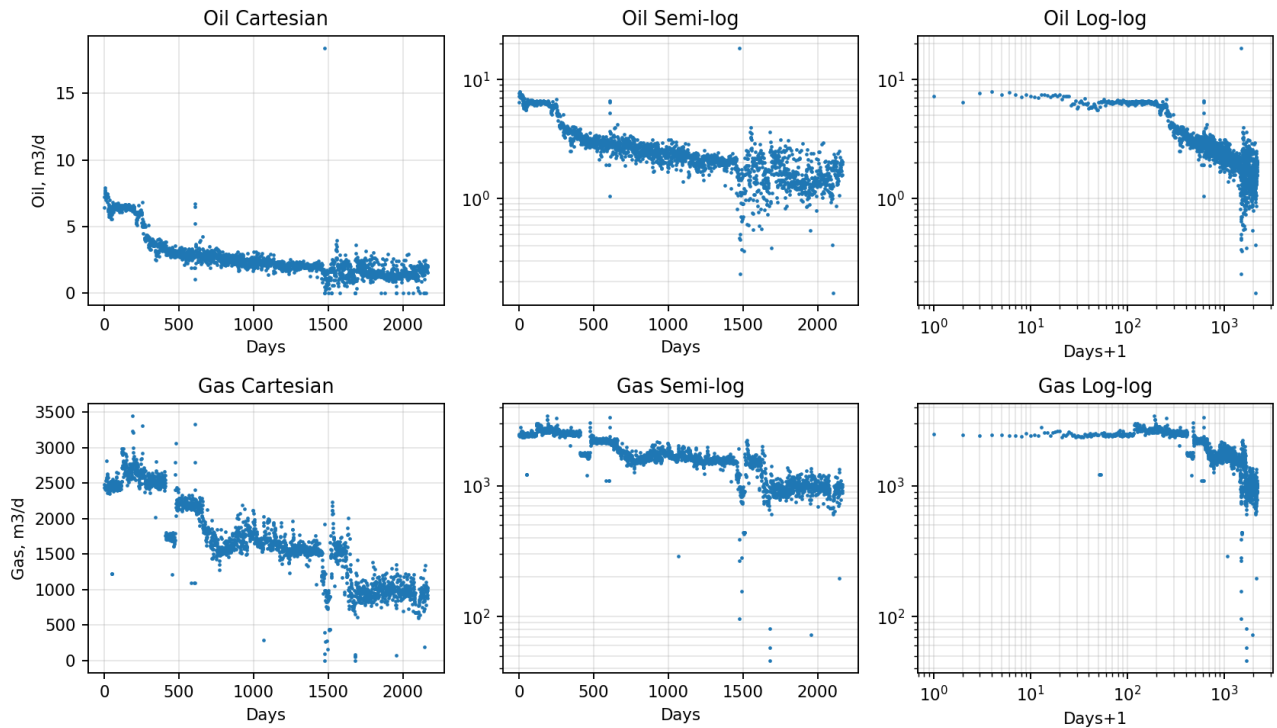


Figure 7.6 - Well 201 Cartesian, semi-log, and log-log diagnostic curves for oil and associated gas.

RATE-TRANSIENT-ANALYSIS SCREENING

The RTA component is used only as a screening layer. Although wellhead pressure variables are available, full pressure-normalized RTA would require reconstructed flowing bottomhole pressure based on wellbore hydraulics, PVT, measured depth, tubing/completion configuration, temperature, and fluid gradients. Therefore, Figures 8.1 to 8.3 are interpreted qualitatively and no permeability, skin, fracture half-length or drainage-area values are reported.

The diagnostic plots in Figures 8.1 to 8.3 were used to evaluate whether production behavior is more consistent with transient/fracture-controlled flow, operational variability, depletion, or boundary influence. Blasingame-style plots emphasize transformed-time and rate-normalized behavior, Agarwal-Gardner-style plots support comparison with cumulative-production response, and Fetkovich-style plots connect transient and decline-type behavior.

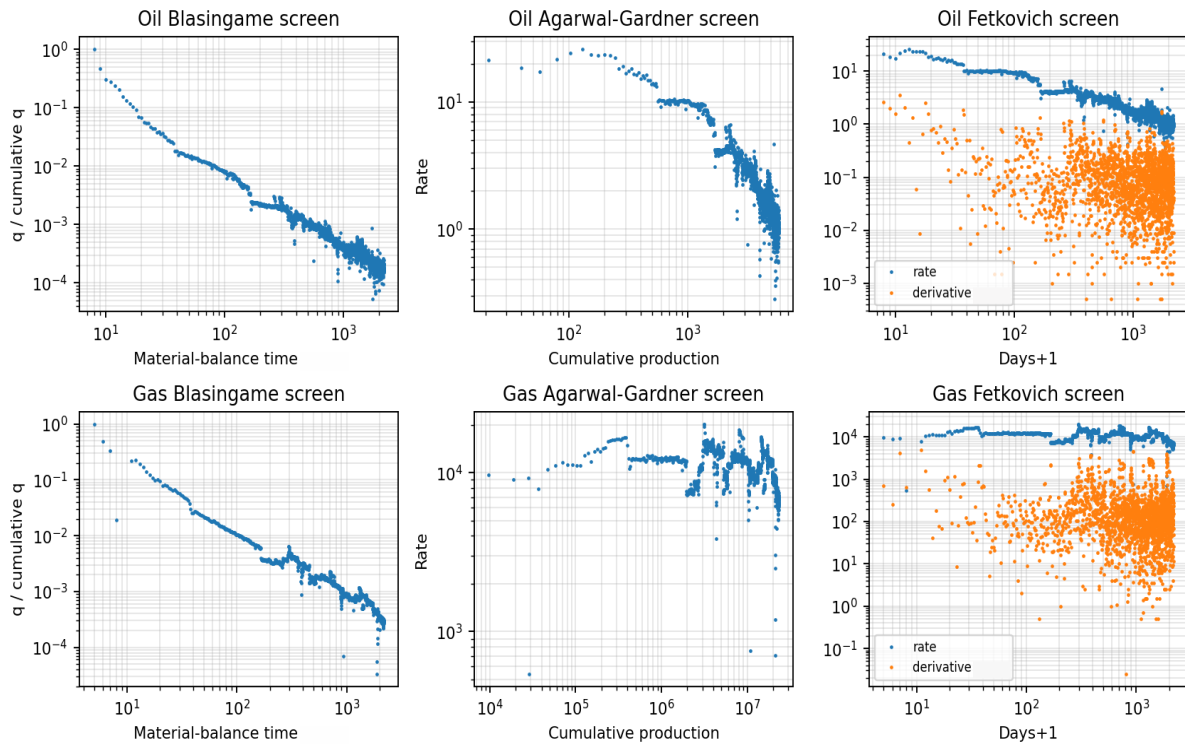


Figure 8.1 - Well 101 RTA screening: Blasingame-style, Agarwal-Gardner-style, and Fetkovich-style diagnostic views for oil and associated gas.

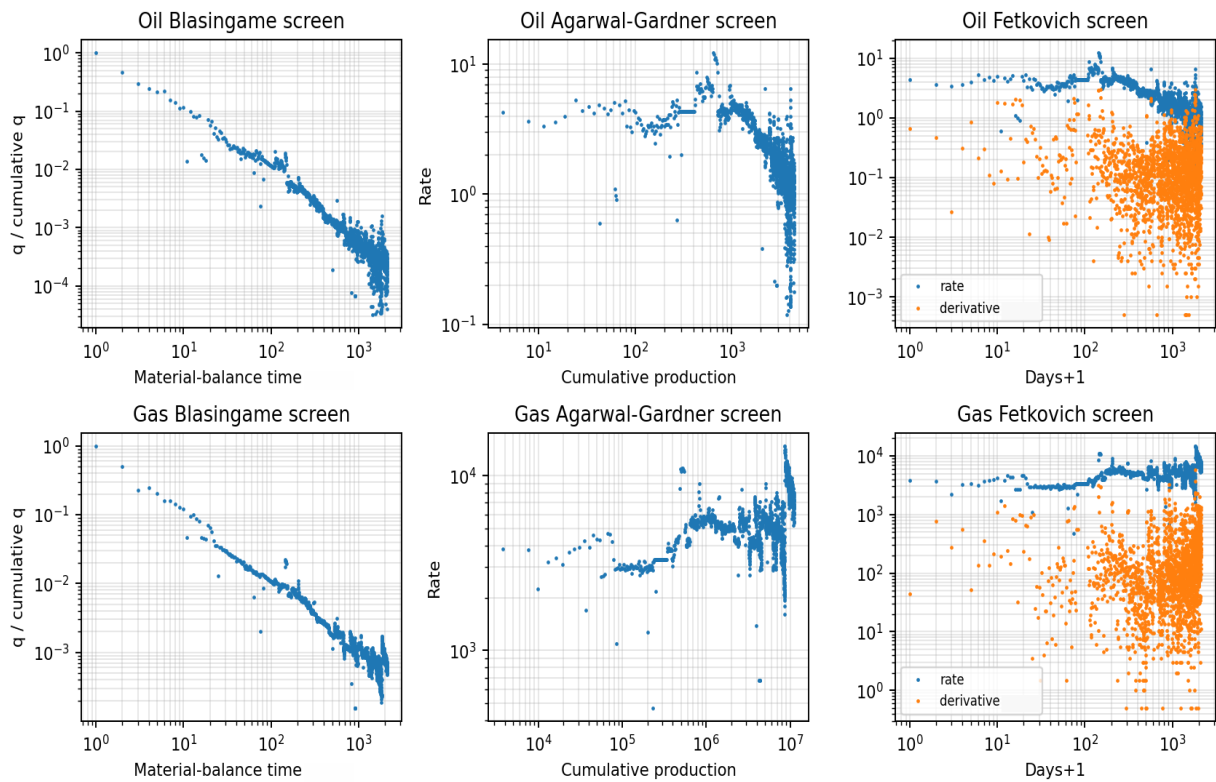


Figure 8.2 - Well 112 RTA screening: Blasingame-style, Agarwal-Gardner-style, and Fetkovich-style diagnostic views for oil and associated gas.

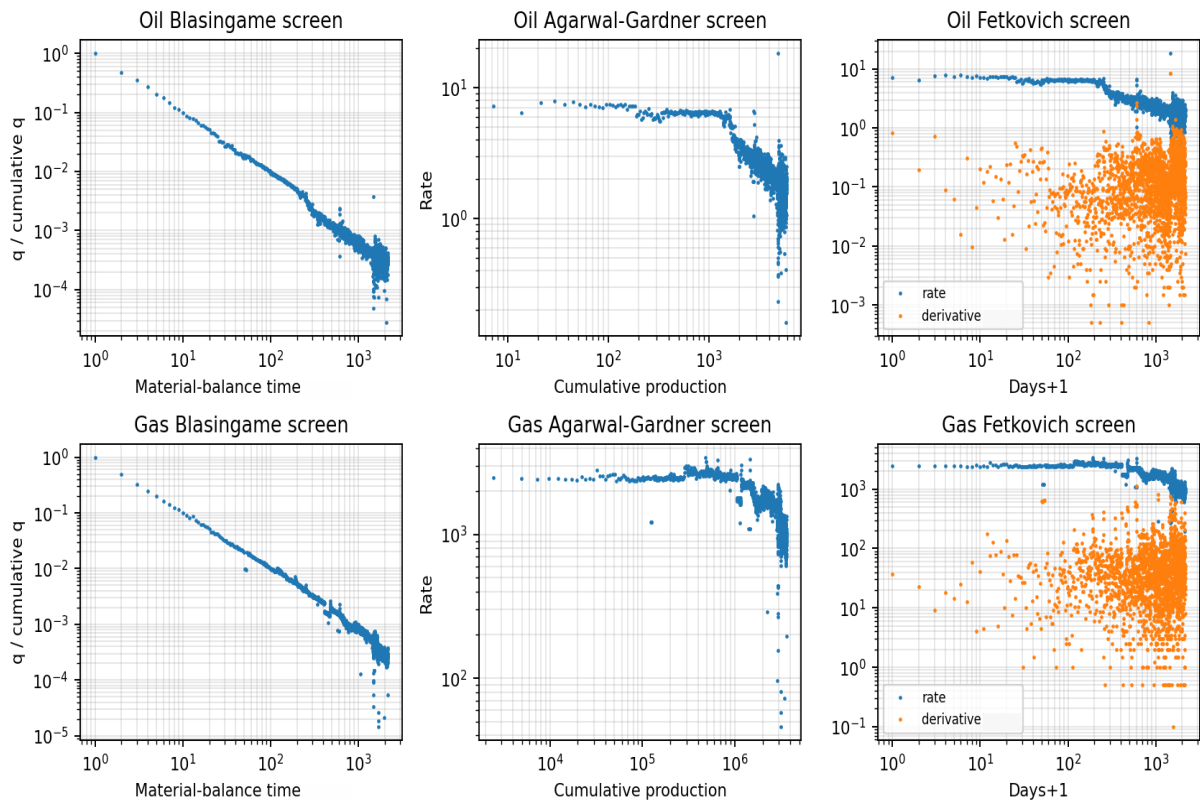


Figure 8.3 - Well 201 RTA screening: Blasingame-style, Agarwal-Gardner-style, and Fetkovich-style diagnostic views for oil and associated gas.

AI/ML FORECASTING WORKFLOW

The AI/ML workflow was built to complement, not replace, the DCA and RTA interpretation. It uses production memory, cumulative depletion, operating variables, and well identity to predict next-step oil and gas production. The feature groups are summarized in Table 9.1, the holdout performance metrics are reported in Table 9.2, and the validation logic is summarized in Table 9.3.

The engineered inputs include well identifier, time on production, current oil and gas volumes, 7-day and 30-day rolling averages, cumulative production, flowing tubing-head pressure, flowing casing-head pressure, bean size, and flow hours. These inputs are linked to the reservoir-conditioned feature framework in Table 9.4 and evaluated through the holdout plots in Figures 9.1 to 9.3.

Table 9.1 - Feature-engineering framework for DCA/RTA-informed AI/ML forecasting.

Feature group	Examples	Reason for inclusion
Production memory	Lag-1, lag-7, lag-30 oil/gas; rolling averages	Captures short-term production inertia.
Cumulative depletion	Cumulative oil, cumulative gas, time on production	Represents reservoir depletion and production maturity.
Operating conditions	FTHP, FCHP, bean size, flow hours	Separates reservoir decline from operational changes.
DCA features	qi, Di, b, residuals, decline class	Connects empirical decline behavior to the ML model.
RTA features	log-log slopes, material-balance-time proxies	Adds physics-informed diagnostic behavior.
Completion/reservoir inputs	Fracture half-length, conductivity, porosity, permeability	Required for future cross-well generalization.

Table 9.2 - Chronological holdout AI/ML forecasting performance.

Target	Model	RMSE	MAE	R2
Oil	Random Forest	0.56	0.36	0.044
Oil	Gradient Boosting	0.50	0.33	0.213
Gas	Random Forest	854.90	487.49	0.944
Gas	Gradient Boosting	783.57	429.33	0.953

Gradient Boosting produced the strongest holdout performance in this dataset, as shown in Table 9.2. Oil prediction remains difficult because the rates are low and affected by operational scatter, which reduces the apparent explanatory power of short-term models. Gas prediction performs better because the associated-gas signal has a stronger overall trend, particularly for Well 201, which is visible in Figure 9.3.

9.3 Model Interpretability and Field-Case Validation

The holdout results were interpreted using engineering judgment rather than statistical metrics alone. Table 9.3 shows how chronological holdout testing, DCA comparison, RTA screening, reservoir conditioning, and transparent limitations are combined.

Table 9.3 - Validation logic used for the applied field workflow.

Validation element	Purpose in the workflow
Chronological holdout split	Prevents future production information from entering the training period.
DCA comparison	Checks whether AI/ML forecasts remain consistent with long-term decline behavior.
RTA screening	Identifies whether the decline trend is likely affected by transient flow, depletion, or operational scatter.
Reservoir conditioning	Explains inter-well differences using porosity, thickness, area, pressure state, and fluid context.
Transparent limitations	Prevents overclaiming where bottomhole pressure, PVT, or fracture data are incomplete.

Figures 9.1 to 9.3 then provide the visual check of observed versus predicted oil and gas behavior.

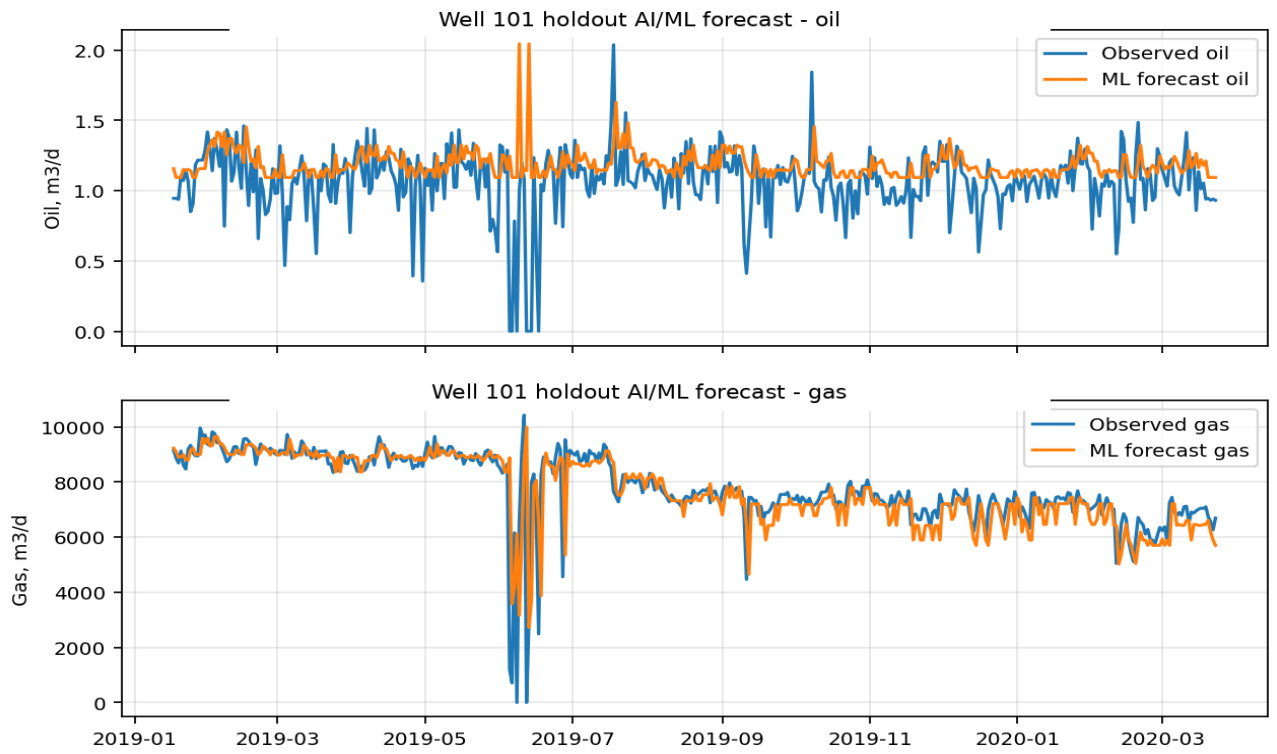


Figure 9.1 - Well 101 chronological holdout AI/ML forecast for oil and associated gas.

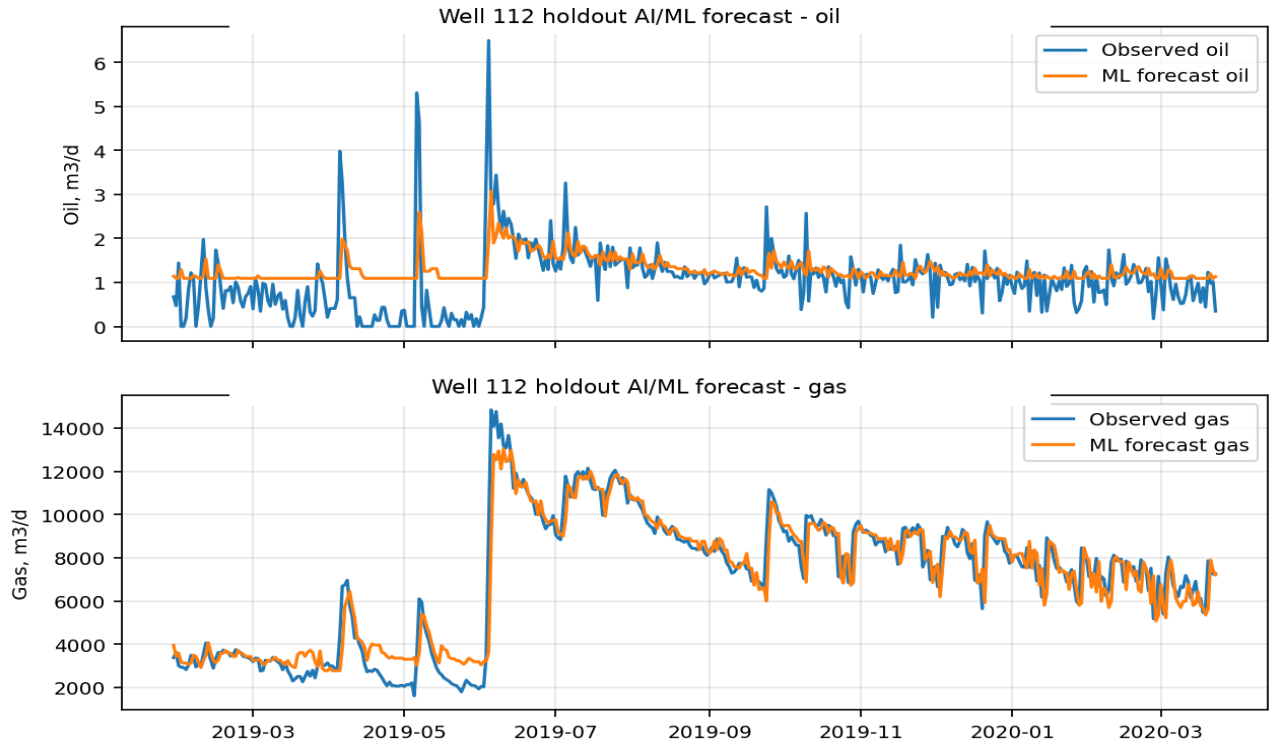


Figure 9.2 - Well 112 chronological holdout AI/ML forecast for oil and associated gas.

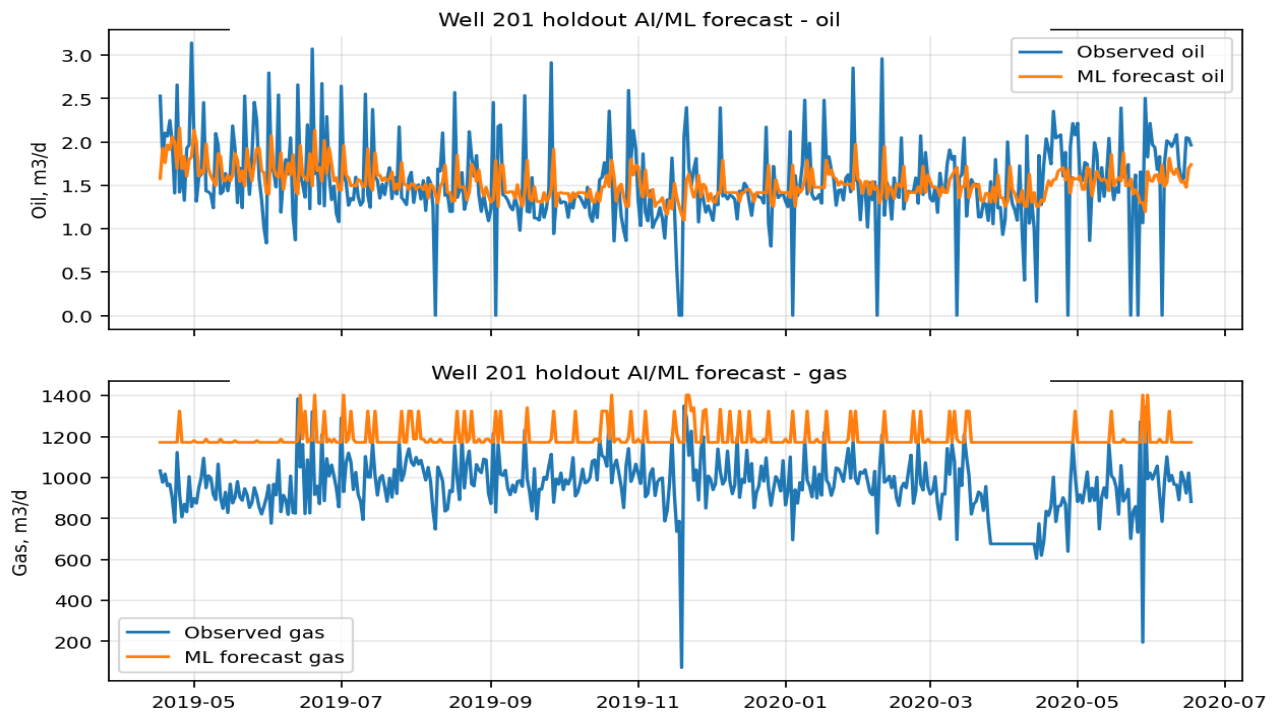


Figure 9.3 - Well 201 chronological holdout AI/ML forecast for oil and associated gas.

9.4 Reservoir-Conditioned AI/ML Feature Set

The reservoir-conditioned feature set in Table 9.4 combines dynamic production measures with static reservoir descriptors. Dynamic variables include time on production, oil rate, associated-gas rate, cumulative oil, cumulative gas, GOR, rolling decline, and normalized rate. Static variables include porosity, water saturation, net pay, drainage/production area, depth, oil gravity, BHP references, and well identity.

Table 9.4 - Proposed reservoir-conditioned AI/ML input-feature groups.

Feature group	Variables	Purpose
Production history	Oil rate, gas rate, cumulative oil, cumulative gas	Capture dynamic well performance
Decline diagnostics	Arps b, Di, decline model, rolling decline	Represent empirical decline behavior
RTA screening	Log-log slopes, rate-normalized trends, material-balance-time proxies	Indicate flow-regime behavior qualitatively
Reservoir quality	Porosity, water saturation, net thickness, lithology	Condition forecast by rock/fluid storage capacity
Pressure/depletion	Initial BHP, current/static BHP reference, pressure-depletion proxy	Represent solution-gas/depletion-drive effects
Geometry/area	Production/drainage area, vertical-well identifier	Represent effective contacted volume
Fluid property	Oil gravity, associated gas behavior/GOR	Support oil-gas production coupling

INTEGRATED TECHNICAL INTERPRETATION

The three wells exhibit the expected response of hydraulically fractured low-permeability wells: relatively high early deliverability, rapid decline or operational scatter, and later low-rate production. This interpretation is supported by the DCA results in Table 6.2, the diagnostic plots in Figures 7.1 to 7.6, and the RTA screening responses in Figures 8.1 to 8.3.

The integrated analysis gives three complementary views of the same production system. DCA provides transparent decline parameters (Table 6.2), RTA screening checks whether those trends are physically plausible (Figures 8.1 to 8.3), and AI/ML provides a data-driven forecast layer based on production memory and operations (Tables 9.1 to 9.4).

A central conclusion is that AI/ML should be used as a physics-informed aid rather than as an independent substitute for DCA or RTA. Decline parameters, RTA slopes, cumulative recovery, pressure indicators, and operating variables should be retained as model inputs so that the forecast remains interpretable and less vulnerable to black-box extrapolation.

LIMITATIONS AND UNCERTAINTY

The following limitations should be considered when interpreting the results in Tables 6.2, 9.2, 13.1, and 13.2 and the diagnostic figures throughout the paper:

Bottomhole flowing pressure was not available; therefore, RTA remains qualitative and screening-level. PVT, reservoir thickness, porosity, compressibility, saturation, and fracture geometry were not available; therefore, permeability, skin, contacted volume, and fracture half-length were not estimated.

The dataset contains only three wells; therefore, deep-learning models such as LSTM should be considered future work unless synthetic augmentation or transfer learning is introduced.

Operational changes, shut-ins, variable flow hours, and wellhead-pressure fluctuations introduce scatter that may not reflect reservoir quality alone.

DCA extrapolation should be constrained by terminal decline and physical recovery limits before use in reserves booking.

11.4 Reservoir-Data Limitations

The available reservoir-property data improve the technical grounding of the study, but important dynamic data gaps remain. Pressure information is limited to initial and selected static/current BHP references rather than full pressure-transient records. PVT tables, relative permeability, fracture-treatment details, proppant placement, fracture conductivity/half-length diagnostics, and pressure-normalized rate histories are not available. For these reasons, the RTA plots are presented as screening diagnostics, and commercial PTA/RTA validation is recommended as future work.

FUTURE WORK AND COMMERCIAL-SOFTWARE VALIDATION

Commercial software results were not available and were not used in the reported analysis. Future work should validate the DCA forecast parameters in Table 13.1 and the RTA screening behavior in Figures 8.1 to 8.3 using commercial reservoir-engineering tools after the necessary pressure, fluid, and completion inputs are assembled. Recommended future work includes:

Reconstruct flowing bottomhole pressure from wellhead measurements using wellbore hydraulics and PVT inputs.

Carry out pressure-normalized RTA and PTA/RTA software validation after reliable bottomhole-pressure data are available.

Include fracture-treatment details, reservoir thickness, porosity, permeability, water saturation, and geomechanical parameters to improve model generalization. Expand the dataset with additional vertical wells before applying LSTM, transfer-learning, or graph-based modelling approaches.

FORECAST EXTENSION TO 2030

Production was forecast deterministically to 31 December 2030 for Wells 101, 112, and 201 using the cleaned well-production dataset. The fitted model parameters and 2030 rate/cumulative results are summarized in Table 13.1, while Figures 13.1 to 13.10 provide the well-level and field-level visual forecast support.

13.1 Forecasting Method and Assumptions

Oil and associated-gas rates were normalized where flow-hour data were available, and monthly averages were calculated to reduce the influence of short-term shut-ins, choke changes, workovers, and measurement scatter. Exponential, harmonic, and hyperbolic decline forms were fitted to the declining monthly segment, and the preferred model was selected separately for each well and phase. Forecast volumes were then calculated from monthly forecast rates and calendar days.

The forecast is presented as a deterministic technical base case rather than a reserves-booking estimate. Its reliability is interpreted in Table 13.2, which separates moderate-confidence oil forecasts, lower-confidence gas cases, field-level screening use, and future uncertainty work.

The interpretation distinguishes observed production, fitted decline behavior, extrapolated forecast, and recommended future uncertainty analysis. This separation avoids overstating the certainty of the 2030 forecast while still preserving its usefulness as a field-planning and screening tool.

13.2 Decline Parameters and Forecast Summary

Table 13.1 - Decline parameters and 2030 forecast summary.

Well	Phase	Model	qi (m3/d)	Di (1/d)	b	R2	Dec-2030 Rate (m3/d)	Incremental Forecast to 2030 (m3)	Total Cum. to 2030 (m3)
Well 101	Oil	Hyperbolic	14.54	0.01094	1.33	0.972	0.49	2,707	8,510
Well 101	Gas	Exponential	14,025.41	0.00085	0	0.836	243.34	7,639,180	30,935,770
Well 112	Oil	Harmonic	5.55	0.00258	1	0.938	0.34	2,078	6,506
Well 112	Gas	Harmonic	10,194.06	0.00189	1	0.852	1,146.14	9,634,778	20,841,221
Well 201	Oil	Hyperbolic	7.53	0.00256	1.19	0.935	0.63	3,418	9,351
Well 201	Gas	Exponential	2,583.82	0.00053	0	0.870	117.39	1,464,609	5,091,486

From table 13.1, we can see that, the oil forecasts indicate low but persistent tail production through 2030. Gas forecasts carry higher uncertainty because gas production responds strongly to operating pressure, measurement scatter, and gas-oil-ratio behavior. The Well 112 gas forecast should therefore be interpreted with lower confidence than the oil forecasts.

13.3 Well-Level Forecast Plots

Figures 13.1 to 13.6 present the well-level oil and associated-gas decline forecasts and should be read with the fitted parameters in Table 13.1. These figures demonstrate how the selected decline models extend historical production trends to 2030 by well and phase.

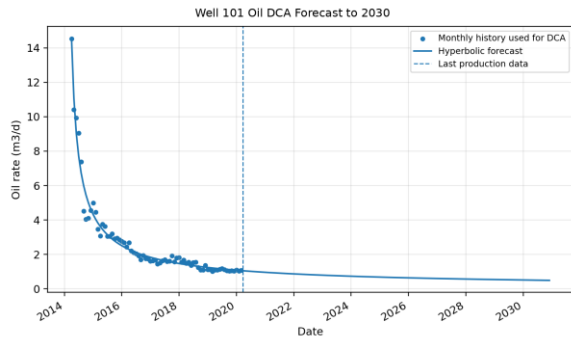


Figure 13.1 - Oil decline-curve forecast to 2030 for Well 101.

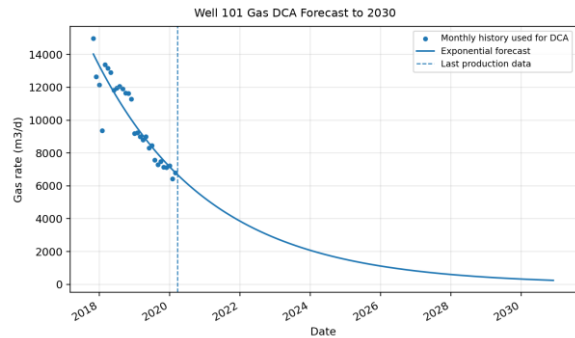


Figure 13.2 - Gas decline-curve forecast to 2030 for Well 101.

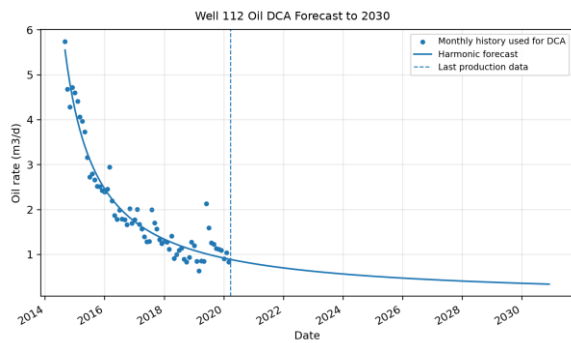


Figure 13.3 - Oil decline-curve forecast to 2030 for Well 112.

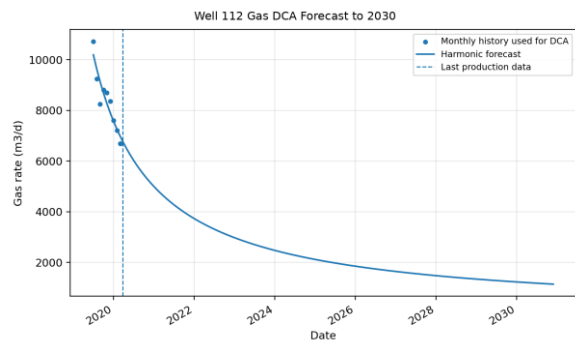


Figure 13.4 - Gas decline-curve forecast to 2030 for Well 112.

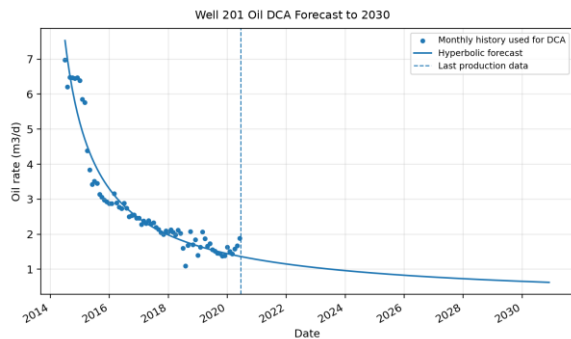


Figure 13.5 - Oil decline-curve forecast to 2030 for Well 201.

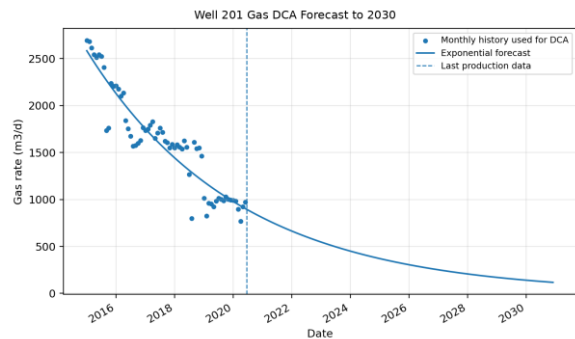


Figure 13.6 - Gas decline-curve forecast to 2030 for Well 201.

13.4 FIELD-LEVEL FORECAST SUMMARY

Figures 13.7 to 13.10 summarize the field-level oil and associated-gas rate forecasts and the corresponding cumulative forecast behavior. These figures aggregate the well-level forecast results reported in Table 13.1 and support the reliability interpretation summarized in Table 13.2.

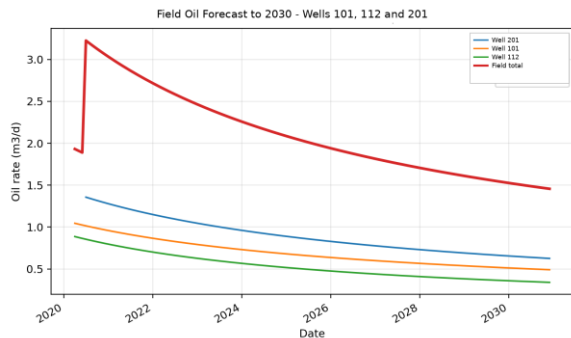


Figure 13.7 - Combined oil-rate forecast to 2030 for Wells 101, 112, and 201.

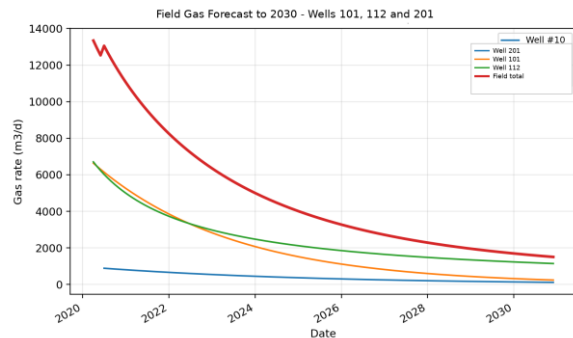


Figure 13.8 - Combined associated-gas-rate forecast to 2030 for Wells 101, 112, and 201.

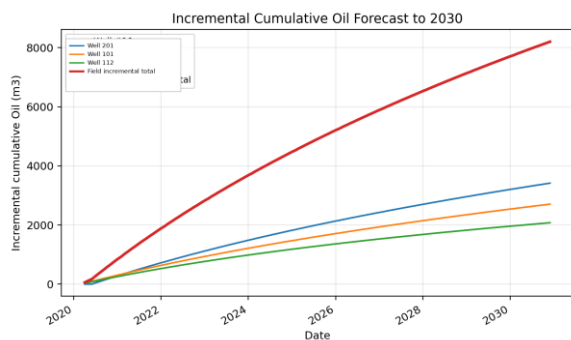


Figure 13.9 - Incremental cumulative oil forecast from the forecast start through 2030.

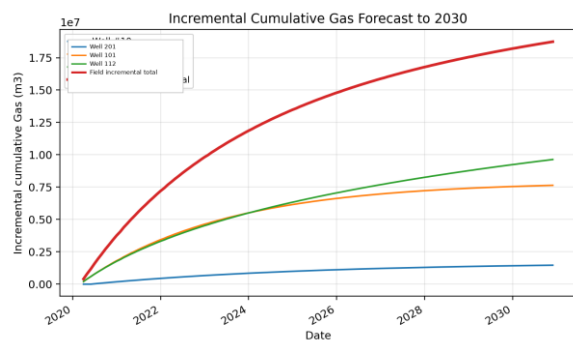


Figure 13.10 - Incremental cumulative associated-gas forecast from the forecast start through 2030.

13.5 Forecast Reliability and Uncertainty Interpretation

The 2030 forecast is interpreted as a deterministic engineering base case. Confidence is not uniform across wells and phases because oil and associated gas respond differently to depletion, operating pressure, measurement scatter and gas-oil-ratio evolution. The reliability comments below are intended to guide field use of the forecast without presenting it as a reserves-booking estimate.

Table 13.2 - Forecast reliability and uncertainty interpretation.

Forecast element	Reliability interpretation	Reason
Oil forecasts	Moderate confidence as technical base cases	Oil decline trends are more coherent than gas for the analyzed wells, although low rates and shut-ins still create scatter.
Well 101 gas	Moderate to lower confidence	Gas rates are affected by operational variation and pressure-sensitive behavior.
Well 112 gas	Lower confidence	Gas behavior is flatter/noisier and more sensitive to operating changes.
Well 201 gas	Relatively stronger confidence among gas cases	The gas decline trend is clearer and more consistent with exponential behavior.
Field-level forecast	Useful for screening and planning	It aggregates deterministic well-level forecasts but does not include downtime, recompletion or economic limits.
Future uncertainty work	Required before reserves use	P10/P50/P90 cases should be generated after pressure, PVT, completion and economic-limit assumptions are available.

13.6 Integration With AI/ML Forecasting Workflow

The 2030 DCA forecast in Table 13.1 supplies an interpretable baseline for the AI/ML workflow. Decline parameters, normalized rates, cumulative volumes, rate ratios, and time-on-production variables can be converted

into engineered features alongside the production-memory and reservoir-conditioned inputs listed in Tables 9.1 and 9.4.

Future studies should compare the deterministic DCA forecast with commercial reservoir-engineering and pressure-/rate-transient tools once pressure, PVT, and completion datasets are available. Until those inputs exist, such validation should be presented as a recommended next step rather than as a completed result.

13.7 Practical Field Application of the Workflow

For field implementation, the workflow can be used as a surveillance and screening tool. Table 13.3 shows how DCA, RTA screening, AI/ML holdout behavior, and reservoir conditioning can be translated into practical field-use decisions such as routine forecast updating, pressure reconstruction prioritization, and future PTA/RTA validation.

Table 13.3 - Practical outputs of the applied DCA-RTA-AI/ML workflow.

Workflow output	Field-use implication
DCA forecast	Provides a transparent deterministic base case for short- to medium-term planning.
RTA screening	Flags whether pressure-normalized analysis is needed before reservoir-property estimation.
AI/ML holdout	Tests whether production-memory features can reproduce recent behavior without random data leakage.
Reservoir conditioning	Improves explanation of well-to-well differences using available static descriptors.
Future data plan	Identifies bottomhole pressure, PVT, and fracture data as highest-value additions for validation.

The workflow can be transferred to similar mature fractured reservoirs where production data are available, but complete dynamic reservoir data are incomplete. Its practical value lies in forcing the analyst to reconcile rate decline, cumulative production, diagnostic plots, operating variability, and reservoir properties before extending forecasts. This makes the approach useful for screening, surveillance planning, and identifying which pressure/PVT/completion data should be prioritized next.

13.8 Objective-Wise Achievement Summary

Table 13.4 summarizes how the stated study objectives are addressed by the workflow, results, and interpretation. It links each objective to its supporting section, table, or figure so that the objective-to-result relationship is clearly established.

Table 13.4 - Objective-wise achievement summary.

Study objective	Addressed at	Achievement status	Evidence / comment
Integrate field and reservoir data into the workflow	Sections 3, 5.4, 9.4, 10	Achieved	Reservoir descriptors such as porosity, water saturation, net thickness, drainage/production area, depth, BHP references, and oil gravity are used to condition the interpretation.
Build a repeatable DCA workflow for three hydraulically fractured vertical wells	Sections 6, 7, 13	Achieved	Oil and associated-gas production are fitted independently using Arps decline forms, and 2030 forecasts are reported by well and phase.
Generate Cartesian, semi-log, log-log and cumulative diagnostics	Section 7	Achieved	Diagnostic plots are presented for Wells 101, 112, and 201 to visually assess decline behavior, scatter, and phase-specific production response.
Apply Blasingame, Agarwal-Gardner and Fetkovich RTA screening	Section 8	Achieved as screening-level analysis	RTA plots are used for qualitative flow-regime and data-quality screening; quantitative reservoir-property estimates are not claimed because complete bottomhole-pressure and PVT data are unavailable.

Connect DCA/RTA observations with AI/ML engineering feature	Sections 9.3, 9.4	9,	Achieved	Production memory, cumulative depletion, operating variables, DCA descriptors, RTA indicators, and reservoir descriptors are combined into an engineering-guided AI/ML workflow.
Compare empirical decline behavior with data-driven forecast behavior	Sections 10, 13	9,	Achieved with stated limitations	DCA provides the deterministic base forecast, while AI/ML holdout results provide data-driven validation. The comparison is interpreted as field-screening evidence rather than reserves certification.
Identify practical limitations and future validation requirements	Sections 11, 12, 13.1, 13.6	11,	Achieved	The manuscript explicitly identifies the need for bottomhole-pressure reconstruction, PVT correction, commercial PTA/RTA validation, and probabilistic P10/P50/P90 forecasting as future work.

This summary shows that all stated objectives are addressed in the manuscript. The only intentionally limited component is quantitative RTA/reservoir-property estimation, which is correctly presented as future work because the required bottomhole-pressure, PVT, and fracture-treatment inputs are not yet available.

CONCLUSIONS

The main findings are organized below according to the analytical components of the applied workflow.

DCA: Production histories from Wells 101, 112 and 201 were fitted using Arps decline forms and extended to 2030 as deterministic technical base cases. Oil-rate behavior is best represented by hyperbolic decline, supporting the interpretation of prolonged transient or fracture-influenced production.

RTA screening: Cartesian, semi-log, log-log, Blasingame-style, Agarwal-Gardner-style and Fetkovich-style plots provide qualitative diagnostic evidence for decline behavior, operational scatter and possible transient/depletion effects. Quantitative RTA should be deferred until bottomhole pressure, PVT and fracture data are available.

AI/ML workflow: Gradient Boosting produced the strongest tested holdout performance for oil and associated gas in this limited dataset. The AI/ML workflow is most defensible when it is guided by production memory, operating variables, DCA descriptors, RTA indicators and reservoir properties.

Reservoir-conditioned interpretation: Well-specific porosity, thickness, pressure state and production/drainage area improve the explanation of inter-well differences and make the workflow more useful for field-level screening than a rate-only forecast.

Forecast interpretation: The 2030 forecast should be treated as a DCA/AI-assisted engineering forecast, not as a substitute for reserves booking, dynamic simulation or pressure-transient interpretation.

Future validation: Bottomhole-pressure reconstruction, PVT correction, completion/fracture data integration, probabilistic P10/P50/P90 forecasts and commercial PTA/RTA validation are required to move the workflow from screening level to quantitative reservoir-property estimation.

Additional field-enhanced conclusions are as follows:

The siltstone setting supports the need for hydraulic-fracture-aware diagnostics rather than unconstrained empirical extrapolation.

Porosity, thickness, pressure state, and reported drainage/production area strengthen the engineering basis of the AI/ML feature set.

The solution-gas/depletion-drive mechanism and rapid pressure decline justify pressure-aware validation and cautious interpretation of rate-only forecasts.

The 2030 forecast should be treated as a DCA/AI-assisted technical forecast conditioned by available production and reservoir-property data, not as a substitute for dynamic simulation or pressure-transient interpretation.

NOMENCLATURE

Table N.1 - Nomenclature.

Symbol / term	Description	Symbol / term	Description
AG	Agarwal-Gardner diagnostic method	md	Millidarcy, unit of permeability
AI/ML	Artificial intelligence / machine learning	ML	Machine learning
API	American Petroleum Institute oil-gravity scale	MMscf	Million standard cubic feet of gas
b	Hyperbolic decline exponent	Mbbl	Thousand barrels of oil
BHP	Bottom-hole pressure	P50	Deterministic median or base-case forecast
DCA	Decline curve analysis	PTA	Pressure-transient analysis
Di	Initial nominal decline constant	PVT	Pressure-volume-temperature fluid properties
EUR	Estimated ultimate recovery	q	Production rate
FCHP	Flowing casing-head pressure	qi	Initial fitted production rate
FTHP	Flowing tubing-head pressure	R2	Coefficient of determination
GOR	Gas-oil ratio	RF	Random Forest model
LSTM	Long short-term memory neural network	RMSE	Root mean square error
t	Time	RTA	Rate-transient analysis
TVDSS	True vertical depth subsea		

REFERENCES

- [1] Okouma, V., Symmons, D., and Blasingame, T. A. "Practical Considerations for Decline Curve Analysis in Unconventional Reservoirs: Applications of Recently Developed Time-Rate Relations." SPE 162910, SPE Hydrocarbon Economics and Evaluation Symposium, Calgary, September 2012.
- [2] Pratikno, H., Rushing, J. A., and Blasingame, T. A. "Decline Curve Analysis Using Type Curves-Fractured Wells." SPE 84287, SPE Annual Technical Conference, USA, October 2003.
- [3] Rahuma, K. M., Mohamed, H., Hissein, N., and Giuma, S. "Prediction of Reservoir Performance Applying Decline Curve Analysis." International Journal of Chemical Engineering and Applications, Vol. 4, No. 2, April 2013.
- [4] Cox, S. A., Lee, J., Sutton, R. P., and Cox, J. "A Comprehensive Approach to Rate-Time Production Analysis for Unconventional Resources." SPE/CSUR Unconventional Resources Conference, Calgary, Canada, October 2015.
- [5] Dutta, R., Meyet, M., and Burns, C. "Comparison of Empirical vs Analytical Methods for Production Forecasting in Unconventional Reservoirs: Lessons from North America." SPE/EAGE European Unconventional Conference, Austria, February 2014.
- [6] Arps, J. J. "Analysis of Decline Curves." Transactions of the AIME, Vol. 160, 1945, pp. 228-247.
- [7] Fetkovich, M. J. "Decline Curve Analysis Using Type Curves." Journal of Petroleum Technology, 1980.

- [8] Blasingame, T. A., McCray, T. L., and Lee, W. J. "Decline Curve Analysis for Variable Pressure Drop/Variable Flowrate Systems." SPE 21513-MS, SPE Gas Technology Symposium, Houston, Texas, 23-24 January 1991.
- [9] Agarwal, R. G., Gardner, D. C., Kleinsteiber, S. W., and Fussell, D. D. "Analyzing Well Production Data Using Combined Type-Curve and Decline-Curve Analysis Concepts." SPE 49222-MS, SPE Annual Technical Conference and Exhibition, New Orleans, Louisiana, 27-30 September 1998.
- [10] Jeong, H., Sun, A. Y., Lee, J., and Min, B. "A Learning-Based Data-Driven Forecast Approach for Predicting Future Reservoir Performance." *Advances in Water Resources*, Vol. 118, 2018, pp. 95-109.
- [11] Wang, S., and Chen, S. "Application of Long Short-Term Memory Networks for Well-Testing Data Interpretation in Low-Permeability Reservoirs." *Journal of Petroleum Science and Engineering*, 2019.
- [12] Fan, D., Sun, H., Yao, J., Zhang, K., Yan, X., and Sun, Z. "Well production forecasting based on ARIMA-LSTM model considering manual operations." *Energy*, 2021.
- [13] Liu, W., Liu, W., and Gu, J. "Forecasting oil production using ensemble empirical mode decomposition based long short-term memory neural network model." *Journal of Petroleum Science and Engineering*, 2020.
- [14] Li, X., Zhang, R., and related coauthors. "A well rate prediction method based on LSTM algorithm considering manual operations." *Journal of Petroleum Science and Engineering*, 2022.
- [15] de Oliveira Werneck, R., Prates, M. O., and related coauthors. "Data-driven deep-learning forecasting for oil production and pressure." *Journal of Petroleum Science and Engineering*, 2022.
- [16] Rahmanifard, H., and coauthors. "A comprehensive review of data-driven approaches for production forecasting of unconventional reservoirs." *Artificial Intelligence Review*, 2024.