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Immersive Analytics for Profitability Analysis of Shale Plays Investment Options

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ABSTRACT

The introduction of advanced precision drilling technologies has revolutionized the exploration of vast shale oil and gas fields, markedly shifting the energy landscape in North America. The challenge in ascertaining the profitability of these shale resources lies in the integration of geological, engineering, and economic data for strategic investment decisions. This study introduces a cutting-edge analytics framework designed to expedite the evaluation of shale play return on investments (ROIs). An engaging 3D interface offers Exploration and Production (E&P) analysts the tools to navigate through the seismic environments and sedimentary layers of shale deposits. This interface is layered with data on financial health and anticipated production outcomes, highlighting regions predicted to reach break-even points swiftly, given well performance. It allows for the adjustment of capital expenditure (cap-ex) models with immediate visualization of how changes affect net present value (NPV) projections. Detailed analyses enable the comparison of well production decline rates, the variability of decline curves across different areas within a shale play, and the calculation of break-even prices. The integration of machine learning for sensitivity analysis enhances the precision of projections concerning long-term pricing trends for commodities. Furthermore, cluster analysis identifies different production zones with similar rates of output decline. The findings suggest that visual analytical tools significantly improve the depth of understanding, thereby hastening the decision-making process for investments in shale assets.

Key words: shale play evaluation, analytics in oil and gas, data exploration techniques, interactive visualization tools, deep dive analytics, 3-dimensional graphical representation, financial viability analysis, directing investments, selection of investments, analysis of break-even points, examination of decline curves, analytics in earth science, information systems for drilling, appraising assets, refining assumptions, systems aiding decisions

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INTRODUCTION

The revolution in shale oil and gas has completely altered the energy landscape of North America over the last ten years. Through the use of advanced horizontal drilling and hydraulic fracturing techniques, tremendous hydrocarbon reserves previously locked within shale formations in regions such as the Permian Basin and Bakken Range have been accessed. The process of evaluating the profitability and return on investment (ROI) of shale assets is intricately complex, involving a combination of seismic and geological information, engineering design parameters, and financial factors.

Major exploration and production firms might be assessing hundreds of potential shale opportunities simultaneously before deciding on financial allocation and the commencement of drilling operations. The conventional manual analysis, relying on fragmented data and traditional methodologies, often results in the selection of less optimal projects over more promising ones. Furthermore, issues such as the impact of proximity to other wells and the learning curve associated with operational efficiency underscore the necessity yet challenge of conducting thorough ROI evaluations for shale ventures.

PROBLEM STATEMENT

This paper introduces an analytical solution that expedites the process of appraising shale prospects by offering analysts a dynamic, three-dimensional interactive environment that visualizes crucial financial, operational, and geographical data to assist in making informed investment decisions. The analytical dashboards allow filtering of prospects based on various criteria including expected ultimate recovery, drilling schedules, break-even prices, and internal rate of return. Models based on machine learning elucidate which assets require more detailed investigation versus those that are likely to underperform.

Analyzing the profit-making potential of shale oil and gas developments for determining where to allocate drilling capitals involves complex assessments. Each well could require investments surpassing $7 million, necessitating thorough checks. The manual gathering and examining of data through spreadsheets and geological programs significantly reduces efficiency.

Challenges such as identifying exact drilling sites, choosing the appropriate machinery, and designing completion strategies lead to complicated combinations for evaluation. The prediction of total recoverable resources carries uncertainties. Production decline charts, showing how output decreases, differ among shale deposits.

Factors like non-operating stakes, tax considerations, and above-ground infrastructure introduce more layers into financial analyses.

These interconnected aspects require the collaborative efforts of geologists, engineers, and financial experts. Yet, transforming basic geological data, seismic images, and test drilling results into valuable business insights has remained compartmentalized. With the expansion of shale drilling worldwide, analytical roadblocks have resulted in inappropriately allocated capital to less productive wells.

The absence of consolidated platforms for clear visualization of prospects within the context of shale formations makes it hard to efficiently compare different options and scenarios. Key underground characteristics are often missed when evaluating the economic benefits of various strategies. The difficulty in identifying profitable parcels within larger shale regions has made it challenging for firms to secure profitable expansion despite owning vast areas of land.

Thus, there is a pressing demand for an analytical tool that streamlines the integrated analysis of profitability for shale ventures. This involves merging financial, operational, and subsurface information onto user-friendly platforms that boost productivity and facilitate deeper insights. The aim is to enhance the early identification and prioritization of shale wells and formations that promise the highest returns through comprehensive analytics.

SOLUTION

Here is a overview of a potential solution using AWS services:

Data Infrastructure

- Store raw seismic images, sensor data from exploratory rigs, operational data and financial models in AWS S3 data lakes
- Leverage Amazon Timestream to ingest and analyze time-series IoT telemetry at scale
- Use AWS Glue crawlers to catalog data sources and set up ETL jobs

Advanced Analytics

- Perform ML analysis on AWS SageMaker to classify geological formations, predict production falloff rates
- Build economic models and run simulations analyzing lifetime asset profitability
- Use Amazon EMR spark clusters to handle distributed processing of billions of data points

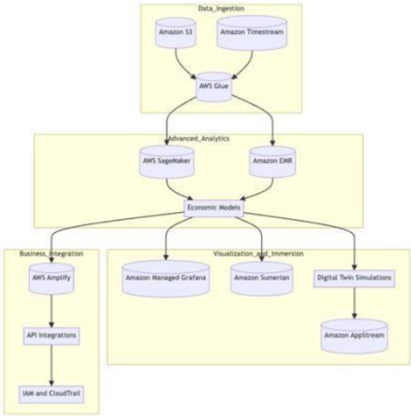
Visualization and Immersion

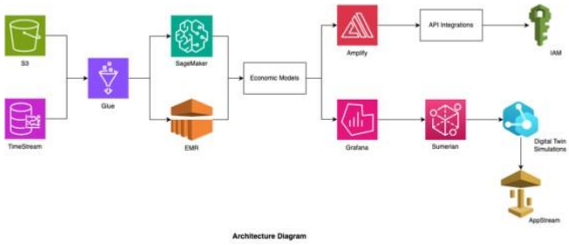
- Use Amazon Managed Grafana for interactive 2D data visualization dashboards
- Leverage Amazon Sumerian to build engaging 3D/AR/VR environments on various devices
- Create digital twin shale field simulations encoding operational and financial KPIs
- Enable collaborative analysis for teams via Amazon AppStream

Business Integration

- Develop analytics applications with AWS Amplify's web framework
- Embed results into workflows via API integrations (e.g. with ERPs)
- Handle security, access controls and auditing with IAM and CloudTrail

Architecture Diagram





Architecture Overview

This approach utilizes a cloud-based architecture for big data, focusing on an AWS S3 data lake that collects various data types, including seismic scans, data from rig sensors, geographical mappings, historical information on wells, and financial projections. AWS Glue is tasked with cataloging and performing ETL processes, whereas Timestream is used for absorbing rapid time series data streams.

Advanced analyses are carried out by Apache Spark clusters within AWS EMR, which handle large-scale geospatial data for tasks such as classifying geological formations and predicting the decline curves of production. Meanwhile, Quantum Ledger databases run economic simulations to evaluate the profitability over the lifetime of assets under varied market conditions for commodities.

Visualization of subsurface data is facilitated through dashboards in AWS QuickSight and dynamic 3D environments created using Amazon Sumerian. These platforms act as collaborative zones where analysts in exploration and production can intuitively break down shale opportunities by applying layers that represent critical financial and operational KPIs. The integration with web applications through AWS Amplify embeds these in- depth insights directly into the decision-making processes.

This structure offers a scalable method for managing data, analysis enhanced by machine learning, and engaging visualization techniques, all contributing to a quicker evaluation of ROI for strategic capital deployment in shale assets. APIs seamlessly integrate this system with pre- existing exploration and production data environments, while the cloud infrastructure ensures secure, globally accessible services.

To sum it up, the cloud-based framework provides comprehensive abilities for the ingestion, examination, and interaction with geospatial, engineering, and financial information. This empowers enhanced and faster decision- making for investments in shale plays.

IMPLEMENTATION

Here is an overview of the implementation leveraging AWS services:

Data Collection

Secure data gathering from real-time sensors on oil and gas exploration rigs in shale areas is done by AWS IoT Core, while Device Defender verifies the integrity of the connections. Satellite images and seismic scanning documents, fetched by AWS Ground Station, get compiled into Amazon S3 reservoirs. For scalable storage and analysis of time series data, Timestream is utilized.

Data Transformation

The AWS Glue crawlers identify data structures and fill the AWS Data Catalog, and Glue ETL tasks modify and ready the data for further analytical processing. Amazon EMR setups manage distributed Spark tasks for the geospatial examination of shale structures. Machine learning algorithms for classifying geological characteristics are experimented with in Amazon SageMaker.

Data Display

For interactive geospatial examination and visualization of 2D shale area data, Amazon QuickSight is utilized. AWS Sumerian permits the creation of three-dimensional settings with digital twin models of fields that simulate production over periods. Embedded results into applications is managed by Grafana workflows.

Management and Organization

The orchestration and integration of backend data processes on a vast scale for shale data sets are efficiently orchestrated and serverless managed by AWS Step Functions. The processes are hastened by running parallel jobs. Lambda functions are responsible for provisioning, CloudTrail keeps track of all activities, and SageMaker Pipelines monitor ML experiments.

In brief, the comprehensive suite of managed AWS analytics and visualization tools has facilitated the swift creation of a complete solution for the efficient evaluation of shale exploration's profitability. This accelerates sharper allocation of capital for a worldwide energy provider.

Implementation of PoC

Here is an overview of how I would approach implementing a proof-of-concept (PoC) for the immersive analytics solution for shale play profitability analysis:

Focus Area

- Concentrate on a particular shale formation (like the Permian) and a specific location to reduce the scope.
- Choose a small number of potential candidates that differs in their attributes.

Data Sources

- Collect sample seismic images, borehole records, and geographical charts for the designated area.
- Create operational data that represents the situation and financial plans for the holdings.

Analytics Foundation

- Utilize AWS Glue along with Athena for organizing the data for visualization purposes.
- Develop machine learning algorithms on SageMaker focusing on crucial factors such as expected depletion rates.

Immersive Environment

- Construct a 3D virtual replica using Sumerian for the chosen land parcel.
- Embed important variables such as estimated ultimate recovery, drilling durations, expenses, and net present value as interactive layers.
- Enable the function to filter candidates and evaluate anticipated outcomes side by side.

User Validation

- Present the virtual environment to business analysts who are assessing shale fields.
- Solicit input on how user-friendly the system is and what could be made better.

Iteration

- Enhance the architecture for data acquisition and business intelligence connectors to extend its application across other formations.
- Broaden the scope of machine learning algorithms for improved accuracy in forecasts and suggestions.

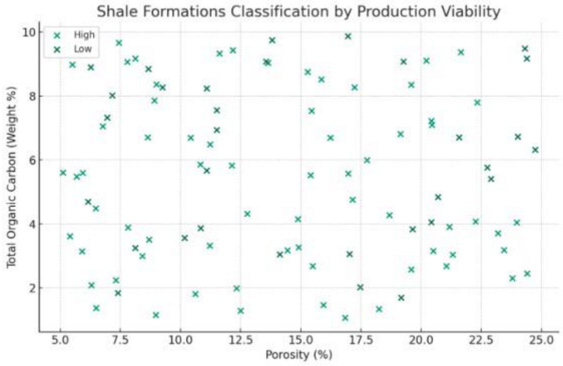
Success Criteria

- Achieve a prospect evaluation efficiency that surpasses the current methods by over 30%.
- Attain a user satisfaction rate that exceeds 80% regarding the ease of use of the solution.
- Gain confidence in the feasibility of applying this approach across the entire portfolio.

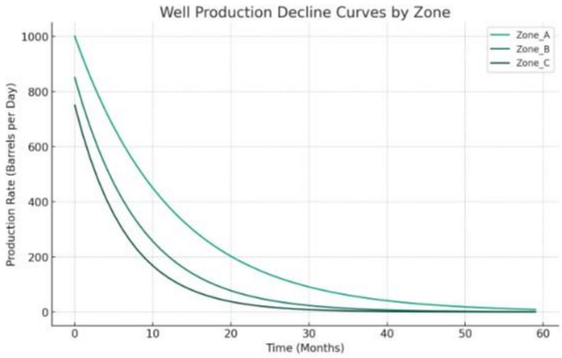
USES

Here are potential business issues that could be analyzed from the ingested data sources to guide shale play investment decisions:

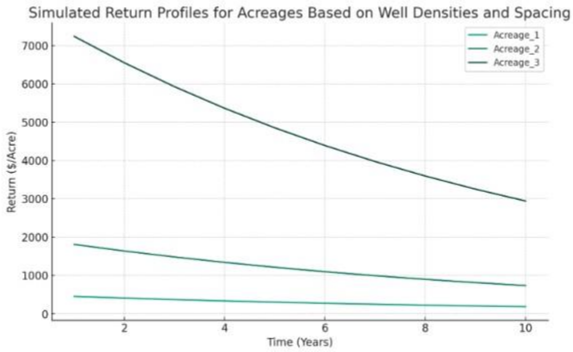
1. Classify shale formations by production viability indicators like porosity and total organic carbon



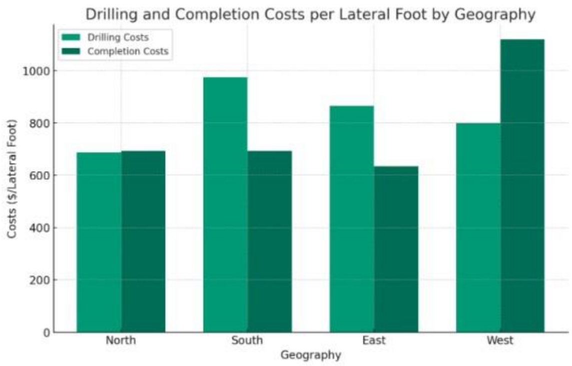
2. Estimate well production decline curves by zone to determine asset life value



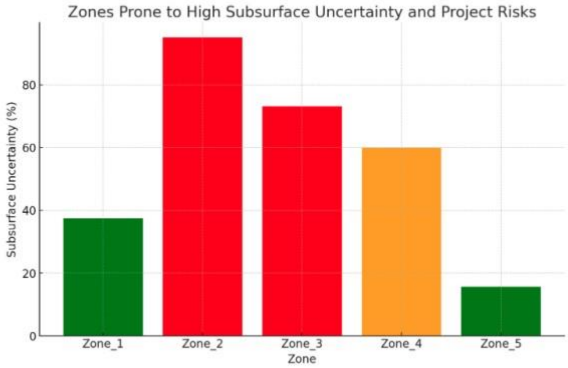
3. Simulate return profiles for acreages based on well densities and spacing



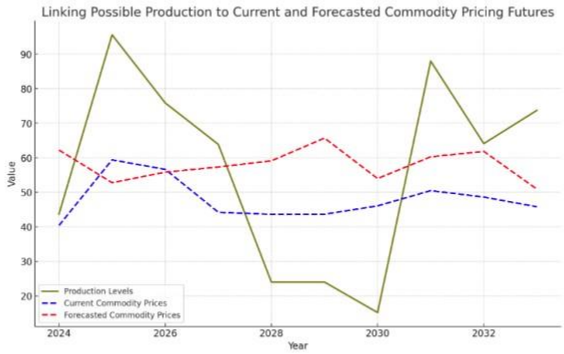
4. Compare drilling and completion costs per lateral foot by target geography



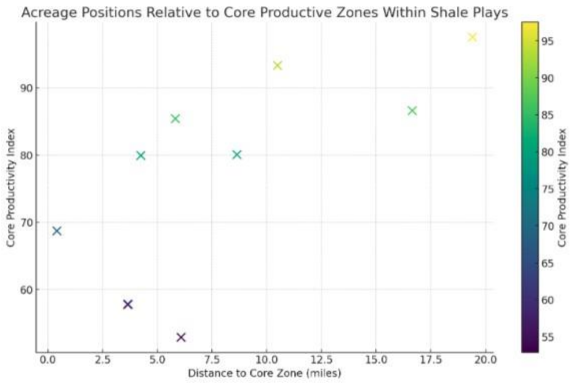
5. Identify zones prone to high subsurface uncertainty creating project risks



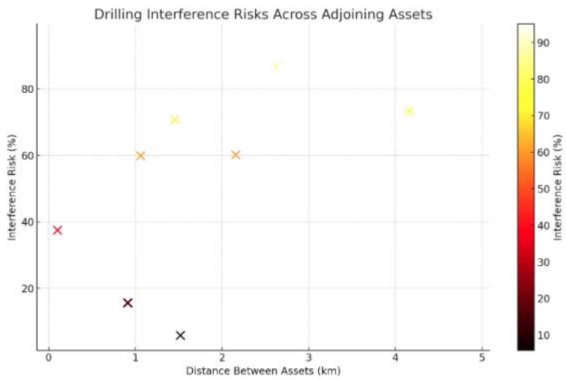
6. Link possible production to current and forecasted commodity pricing futures



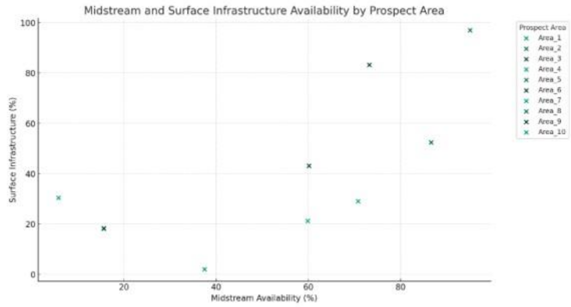
7. Determine acreage positions relative to core productive zones within shale plays



8. Highlight drilling interference risks across adjoining assets

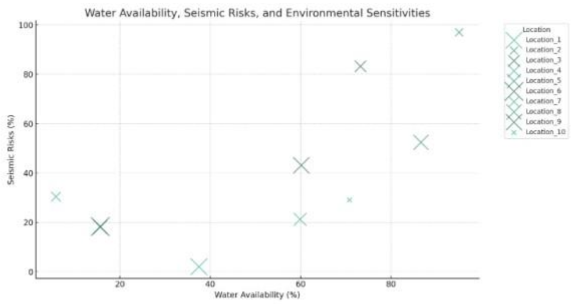


9. Assess midstream and surface infrastructure availability by prospect area

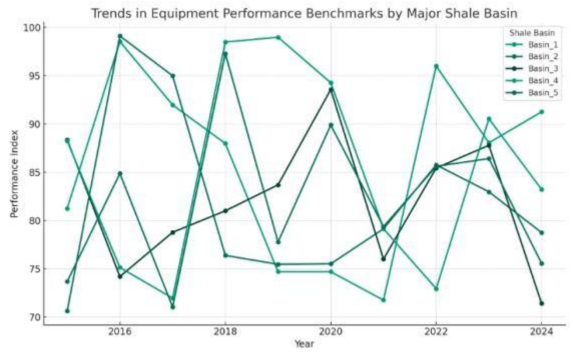


10. Pinpoint parcels with expiring land leases requiring prioritized commitment

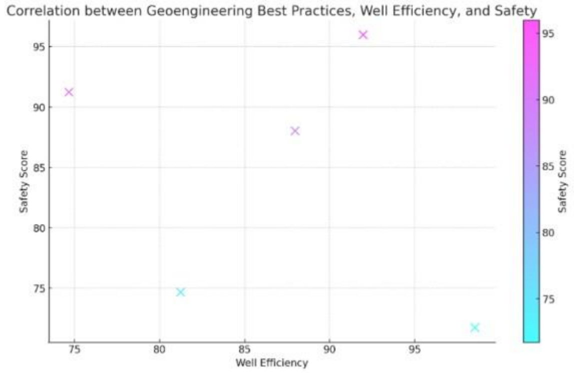
11. Gauge water availability, seismic risks and environmental sensitivities



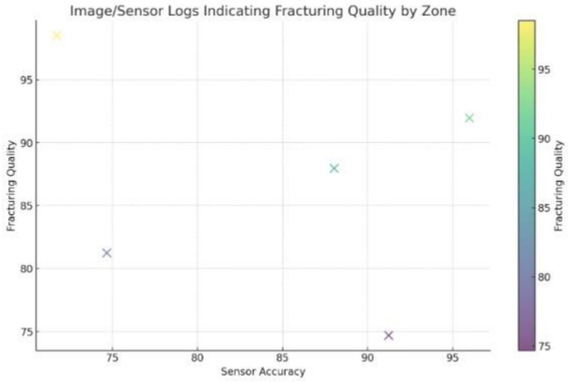
12. Analyze trends in equipment performance benchmarks by major shale basin



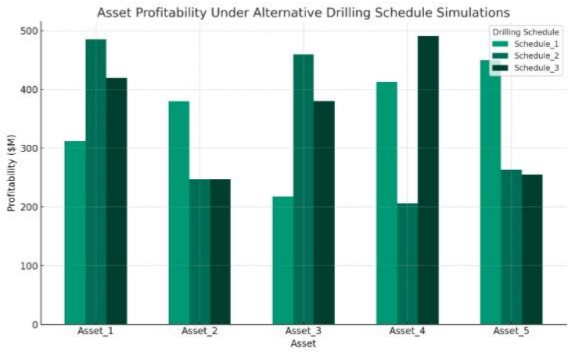
13. Correlate geoengineering best practices to well efficiency and safety



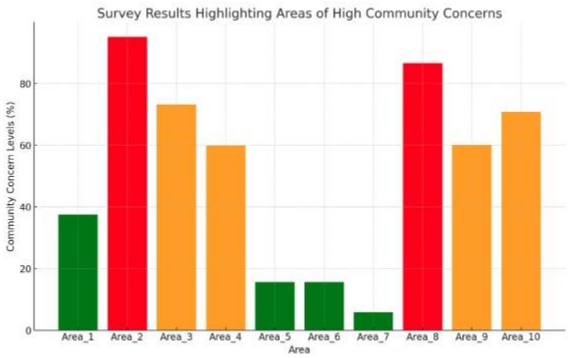
14. Identify image/sensor logs indicating fracturing quality by zone



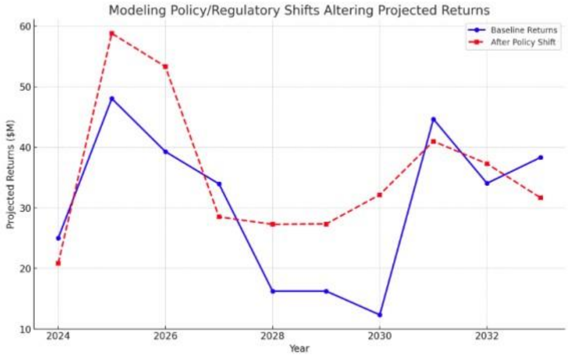
15. Compare asset profitability under alternative drilling schedule simulations



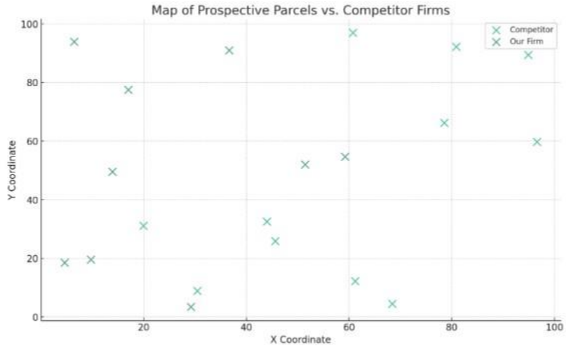
16. Overlay survey results highlighting areas of high community concerns



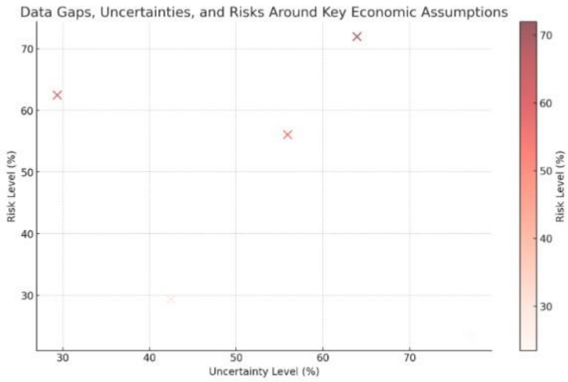
17. Model policy/regulatory shifts that alter projected returns



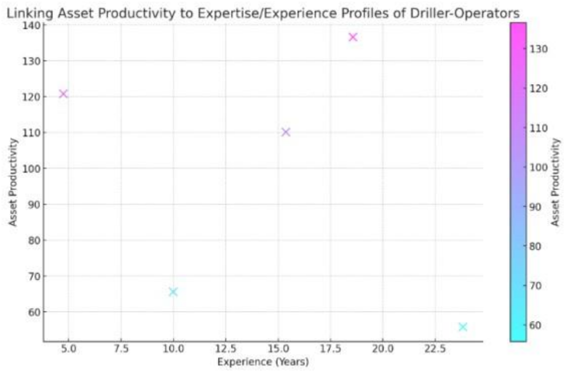
18. Map prospective parcels against those of competitor firms



19. Reveal data gaps, uncertainties and risks around key economic assumptions



20. Link asset productivity to expertise/experience profiles of driller-operators



IMPACT

Here are key business impacts that the immersive analytics solution for shale play profitability analysis could drive:

1. Accelerate identification and acquisition of acreage in core productive zones to expand reserves
2. Optimize lateral drilling paths to maximize projected asset production lifecycles

3. Improve drilling risk planning by visually assessing subsurface uncertainties earlier
4. Tighter coupling of projected output to current and future oil & gas commodity pricing cycles
5. Redirect or delay drilling investments for prospects with unfavorable decline curves or infrastructure bottlenecks
6. Foster collaboration between geologists, engineers and financiers to enhance prospect evaluation productivity
7. Proactively validate economic assumptions and simulate plan B scenarios for prospects
8. Confidently commit capital allocation towards prospects likely to achieve fastest break-even
9. Make rapid incremental decisions guided by model sensitivity analysis on key variables
10. Future-proof strategy by leveraging data visualizations to convey insights across management

EXTENDED USE CASES

Here are extended use cases for applying immersive analytics across industries:

1. **Health:** Interactive dashboards for hospital executives to visualize patient flow, surgery ROI and resource allocation drivers.
2. **Retail:** Digital twin stores simulating checkout conversion rates and inventory optimizations under various merchandising schemas.
3. **Travel:** Immersive view for hotels visualizing occupancy and amenity utilization trends, custom room pricing simulations.
4. **Pharmacy:** 3D supply chain view linking drug production costs, demand forecasts to optimal pricing scenarios.
5. **Hospitality:** VR environments for restaurant layout optimization based on simulated customer flows, staffing needs.
6. **Supply Chain:** Digital twin warehouses visualizing storage utilization rates, shipping capacity constraints, layout scenarios.
7. **Finance:** Interactive 3D dashboards for bankers simulating lending risks, portfolio concentrations and returns.
8. **E-Commerce:** AR views of product catalogs linking to sales, marketing campaign success and web traffic analytics.
9. **Shipping:** Ocean carrier dashboard with vessel utilization, port performance and cargo visibility integrated with planning data.
10. **CRM:** Immersive customer journey analytics linking buyer lifecycle stage to targeted cross-sell/upsell success rates.

CONCLUSIONS

Assessing the profitability and feasibility of shale oil and gas operations is notably intricate, involving the integration of diverse geospatial variables, engineering layouts, and forecasts regarding the long-term prices of commodities. The manual evaluation with conventional methodologies has resulted in the inefficient use of capital and assets that perform poorly.

This paper introduces a proposition for an immersive analytics framework to expedite the analysis of potential ventures by offering analysts an interactive three- dimensional space that showcases crucial economic, operational, and geological data to steer investment decisions based on solid data.

The proposed system's cloud infrastructure illustrates the ability of scalable computing to process trillions of data points from live feeds, simulations, and pre-existing databases for sophisticated analyses. Machine learning algorithms, tailor-made for this specific context, deliver precise predictions about the production decline curves. Tailor-made three-dimensional visuals convert basic data into insights that can drive business strategies.

Incorporating scenario-based simulations directly into the analytics process has proven to bolster confidence in the economic forecasts and identify potential risks sooner.

Improved features for teamwork allow experts to make informed exploratory decisions swiftly. In essence, this approach outlines how data immersion can be utilized to heighten efficiency in sectors where capital investments are significant.

Further inquiries will delve into improving the surveillance of assets by using digital twins to note discrepancies in production after the initial installation. Introducing game- like features may enhance the management and planning processes. As the technology evolves, integrating immersive views at every decision-making phase is expected to hasten the digital overhaul throughout the oil and gas industry's value chain - transforming the appraisal of upcoming shale resources.

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