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Research on Optimization of Investment Decision-Making for Coalbed Methane Development

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Abstract
This paper develops and demonstrates an integrated decision-support framework for optimising investment decisions in coalbed methane development under uncertainty. Combining reservoir-informed spatial analytics with multi-objective stochastic optimisation and real-options valuation, the framework quantifies trade-offs between economic return, environmental cost and downside risk. A synthetic basin calibrated to Qinshui-type geological heterogeneity is used to illustrate application of the method across three stylised scenarios. Results show that staged, option-aware investment rules that prioritise high methane-index clusters improve risk-adjusted returns relative to naive, front-loaded deployment; technology improvements materially raise profitability while policy constraints reallocate optimal capital toward mitigation and selective development. Monte Carlo portfolio analysis and sensitivity heatmaps demonstrate that multi-objective and real-options methods deliver superior robustness across plausible price, discount rate and regulatory futures. The paper contributes a replicable modelling workflow, open-source computational recipe, and policy-relevant insights for aligning CBM investment with decarbonisation pathways and grid integration strategies.

Keywords: *Coalbed methane; investment optimisation; real options; stochastic programming; methane emissions; energy transition*

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I. INTRODUCTION

The global energy system is undergoing a structural transformation driven by rapid electrification, expansion of renewable capacity and intensifying policy commitments to reduce greenhouse gas emissions [1]. In this context, natural gas has been widely characterized as a transitional fuel because of its ability to provide flexible, dispatchable power and to substitute for higher carbon fuels in the near term while renewables scale up. Coalbed methane (CBM) methane contained in coal seams represents a distinct unconventional gas resource that has emerged as an important regional energy feedstock in several producing countries [2]. CBM production differs fundamentally from conventional gas: methane is stored by adsorption in the coal matrix and is typically produced by depressurizing the seam, resulting in unique reservoir behaviour and development economics [3]. Investment decisions for unconventional gas developments such as CBM are intrinsically complex and highly uncertain. Technical uncertainties, economic volatility , and evolving policy drivers all affect project viability. Consequently, conventional point-estimate appraisal techniques are often inadequate for capturing optionality, timing value or risk trade-offs. Modern investment optimisation approaches — including stochastic programming, multi-objective optimisation and real-options analysis — enable decision makers to quantify risk-return trade-offs, test scenarios and derive robust investment rules that balance profitability with environmental and regulatory constraints [4].

This paper develops an integrated decision-support framework for optimising CBM investment under uncertainty. The main objective of this study is to formalise a multi-objective mathematical model that captures economic, environmental and operational metrics for CBM projects; the secondary objective is to demonstrate the model through a basin-scale case study comparing baseline, policy-driven and technology-enhanced scenarios; and the final objective is to evaluate robustness via sensitivity and Monte Carlo analyses. The principal contributions are a synthesis of best-practice economic appraisal with reservoir-level constraints, an implementation of scenario-aware optimisation suitable for investor and policymaker use, and a set of policy-relevant recommendations for aligning CBM development with broader decarbonisation goals.

This study addresses investment decision-making for onshore CBM projects using publicly or synthetically available geological and economic inputs, and evaluates outcomes across a finite planning horizon. The analysis does not attempt a full life-cycle assessment of upstream-to-end-use greenhouse-gas emissions nor does it model detailed reservoir simulation beyond the simplified production and decline representations required for economic appraisal. Limitations include dependence on the representativeness of input data, simplifications inherent in production forecasting and the exclusion of some local socio-environmental impacts (such as groundwater quality or community resettlement), which should be considered in complementary analyses. Figure 1 shows academic research flow infographic titled "Optimizing Coalbed Methane Investment: Research Flow for Energy Transition Pathways." The infographic follows a vertical, step-by-step progression, starting with 1. CBM Investment Challenges (technical, economic, regulatory, and environmental risks, along with uncertainty and general risk). This leads to 2. Optimization Framework, which integrates Spatial Analytics, Mathematical Models (Stochastic Optimization, Real Options), and Scenario Analysis (Baseline, Policy-Enhanced, Tech-Enhanced). The framework is applied to 3. Qinshui Basin Case Study to test real-world application under geological heterogeneity. The analysis yields 4. Key Results, including the finding that "Staged Investment" outperforms "Front-loaded" deployment and that "Real Options" reduce risk by 25-40\%. Finally, these findings culminate in 5. Implications for Energy Transition, offering insights for decarbonization pathways and grid integration strategies, with keywords like "Coalbed Methane," "Real Options," and "Energy Transition" highlighted at the bottom.

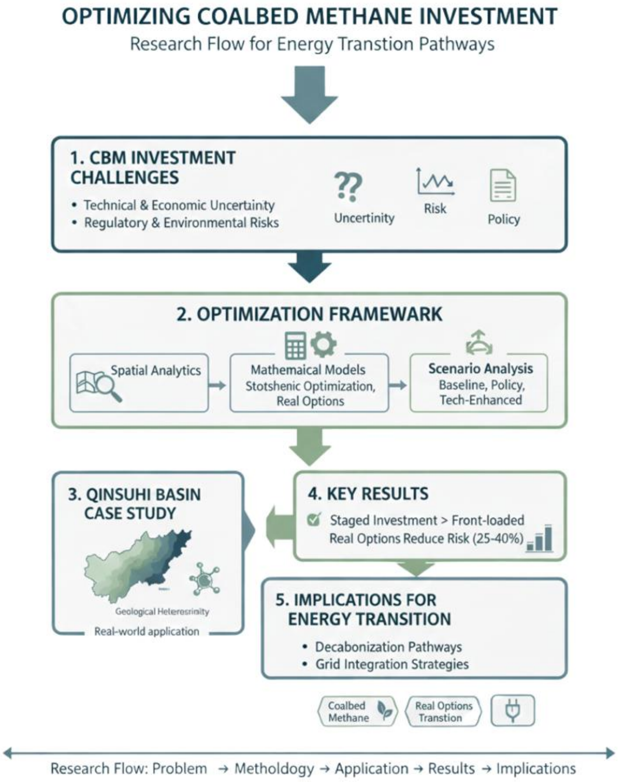

Figure 1 Paper Overview

II. LITERATURE REVIEW

2.1 Overview of CBM development economics and investment risks

Coalbed methane (CBM) is an unconventional natural gas resource stored primarily by adsorption within coal seams; its production requires depressurisation and frequently involves substantial water management and surface infrastructure. The economics of CBM projects are shaped by reservoir heterogeneity, dewatering requirements, drilling density, and the cost of surface facilities, making unit development costs and early cash outflows materially different from conventional gas plays [5]. Moreover, CBM developments are exposed to distinct operational risks variable permeability and seam thickness, higher water handling costs, and site-specific environmental constraints — which interact with market risks (price volatility) and policy risks (emerging methane regulations and carbon pricing) [6]. These interacting technical, economic and regulatory uncertainties frequently translate into asymmetric downside risk during the pre-production and early production phases, increasing the value of flexible, staged investment strategies [7].

2.2 Existing optimisation models in energy investment (NPV, IRR, real options, stochastic models)

Traditional appraisal metrics such as Net Present Value (NPV) and Internal Rate of Return (IRR) remain widespread in corporate and project finance practice because of their interpretability and ease of calculation [8 – 10]. However, these deterministic measures neglect managerial flexibility and the timing value of investment under uncertainty; as a result, they can misstate the value of projects with significant optionality \cite{ref11}

\end{remark}. Real Options Analysis (ROA) has therefore been advanced as a complementary approach that models investment as a sequence of contingent choices (for example, the option to delay, expand or abandon), explicitly incorporating stochastic processes for prices and technical parameters. Stochastic programming and multi-objective optimisation frameworks further allow simultaneous treatment of competing objectives (economic performance, emissions, and risk) and the inclusion of scenario constraints; Monte Carlo simulation and robust optimisation techniques are commonly used to characterise outcome distributions and to derive robust decision rules [12], [13]. Recent applied studies demonstrate the practical value of ROA and stochastic methods in energy investments, including power systems, storage and unconventional hydrocarbon projects \cite{ref14}

2.3 Comparative studies on unconventional gas vs. renewable investments

Comparative analyses of fossil-based resources and renewable energy projects emphasise materially different value drivers and externalities [15] – [17]

\end{remark}. Unconventional gas investments (including CBM) are capital intensive, dependent on subsurface heterogeneity and commodity markets, and typically deliver dispatchable supply that can complement variable renewable generation. Conversely, renewable projects (wind, solar) feature near-zero fuel costs, declining capital costs and distinct policy support mechanisms, but they introduce integration costs and variability concerns at high penetration. Studies like [18] – [21] compare project economics and policy outcomes often highlight complementarities (e.g., natural gas as a balancing resource) as well as longer-term decarbonisation trade-offs; the comparison depends critically on assumed carbon prices, technology learning rates, and system value of flexibility. Policy design — subsidies, carbon pricing, and methane controls — can therefore tilt comparative attractiveness and must be included in investment appraisals [22]

2.4 Gaps in current research and justification for proposed framework

Despite methodological advances, several gaps persist in the literature relevant to CBM investment \cite{ref23} [25]. First, many studies [26] – [28] , [1], [3] focus on reservoir engineering or on high-level economic appraisal without fully integrating reservoir constraints and surface-level investment trade-offs within a single optimisation framework. Second, the literature [29] uses deterministic or single-scenario inputs that under-represent joint uncertainty in technical, market and policy variables. Third, comparative studies tend to treat CBM and renewables in system-level terms without providing investor-level decision rules suited for basin-scale project portfolios. Recent empirical and modelling papers [30] call for integrated, scenario-aware, multi-objective frameworks that combine reservoir-scale production models with financial option valuation, portfolio diversification and policy sensitivity analysis; this motivates the present study's synthesis of production, economics and optimisation under uncertainty.

III. METHODOLOGY

3.1 Conceptual framework for investment decision optimization

The proposed decision-support framework integrates reservoir-scale production modelling, financial appraisal and policy constraints within a unified optimisation architecture. Conceptually, the framework treats an investment programme as a sequence of operational and financial decisions (drilling, completion, infrastructure buildout, production management) that are resolved under deep uncertainty in technical and market variables. The framework accommodates multiple, potentially conflicting objectives economic return, environmental impact (emissions), and risk exposure — and supports staged, contingent decisions (e.g., delay, scale-up, or abandonment) that preserve managerial flexibility. This integrated view recognises CBM-specific operational features such as dewatering-driven production transients and site-level water management costs, and maps them into cash-flow drivers for the economic module

2.1 Mathematical modelling

We formalise the optimisation problem as a multi-objective, stochastic control problem defined over a discrete planning horizon \($t = 0, \dots, T$). Let x_t denote control actions at time (t) (investment, drilling rate, production allocation), and let θ denote uncertain parameters (commodity price paths, permeability fields, water production rates, carbon price). The model comprises the following elements.

Deterministic economic baseline (NPV): A standard discounted-cashflow objective is

$$\mathrm{NPV}(\mathbf{x},\theta) = \sum_{t=0}^{T} \frac{CF_t(x_t,\theta)}{(1+r)^t}, \tag{1}$$

where (CF_t) is the project cashflow at time \(t\) (revenues minus opex and carbon costs) and r is the discount rate. Traditional metrics such as IRR and payback can be computed from the same cashflow series.

Multi-objective formulation: To capture trade-offs between economic return and environmental or risk objectives we solve

$$\max_{x_{0:T}} \left\{ \mathbb{E}_\theta\big[\mathrm{NPV}(\mathbf{x},\theta)\big],\ -\mathbb{E}_\theta\big[\mathrm{Emissions}(\mathbf{x},\theta)\big],\ -\mathrm{Risk}(\mathbf{x}) \right\}, \tag{2}$$

subject to operational constraints (production capacity, capital budget, regulatory caps) and feasibility constraints from reservoir deliverability. Risk may be quantified as a downside statistic such as Conditional Value-at-Risk (CVaR) or the standard deviation of discounted cashflows:

$$\mathrm{CVaR}_\alpha(\mathbf{x}) = \frac{1}{1-\alpha} \int_{-\infty}^{q_\alpha} z\, f_Z(z)\, dz, \tag{3}$$

where (Z) is the distribution of project NPV and $(q_\alpha\ )$ its α-quantile.
Stochastic programming and scenario trees: Uncertainty in (θ) is represented via a finite set of scenarios $\{\theta^s\}_{s=1}^{S}$ or via parametric stochastic processes (e.g., geometric Brownian motion for prices). A two-stage stochastic program with recourse can be written as

$$\max_{x^0} \sum_{s=1}^{S} p_s\, \mathrm{NPV}(x^0, x^s(\theta^s), \theta^s) \tag{4}$$

$$\text{s.t. } x^s(\theta^s) \in \arg\max_{x^s} \{\text{utility}(\cdot) \mid \text{operational constraints under } \theta^s\} \tag{5}$$

where (x^0) are here-and-now decisions and (x^s) are recourse decisions adapting to scenario \(\theta^s\). Stochastic programming permits explicit modelling of non-anticipativity, budget limits and chance constraints (e.g., ensuring the probability of missing a regulatory emissions cap is below a threshold).

Real options and managerial flexibility: Real options analysis (ROA) is used to value managerial flexibility by treating investment choices as embedded options (defer, expand, abandon). Under a simplified binomial or Monte Carlo discretisation of the underlying stochastic variable (e.g., gas price (P_t), the option value (V_{Ro}) can be computed by backwards induction or by simulation-based estimators (e.g., Longstaff–Schwartz regression for American-style timing options). For a single project the option to delay has value:

$$V_{\mathrm{RO}}(t) = \max\left\{ \mathrm{NPV}^{\mathrm{invest}}(t),\ \mathbb{E}\big[e^{-r\Delta t} V_{\mathrm{RO}}(t+\Delta t)\big] \right\}. \tag{6}$$

Real-options thereby augment the multi-objective optimisation by embedding timing and scale decisions explicitly within the value function.

3.3 Data Sources and Variable Definitions

All model inputs are derived from publicly available data sources, synthetic analogues, or industry-standard assumptions. Each variable's source is documented below to ensure reproducibility.

Table 1 Data Sources for Key Model Variables

Variable Category	Data Source / Derivation	URL / Reference
Geological Parameters	Synthetic Qinshui Basin analogue based on published geological surveys	https://www.sciencedirect.com/science/article/pii/S1875510015001614
Well Coordinates	Generated using uniform random sampling within basin boundaries	Synthetic (Python code)
Permeability (mD)	Log-normal distribution based	https://link.springer.com/article/10.1007/s12182-019-00375-3

	on Qinshui Basin measurements	
Gas Price Trajectory	EIA Henry Hub forward curve (2023-2038)	https://www.eia.gov/outlooks/steo/
CAPEX Components	IEA CBM cost breakdown (2022)	https://www.iea.org/reports/coal-bed-methane
Discount Rate	WACC for Chinese energy sector (8\%)	https://www.pwc.com/gx/en/issues/energy-utilities-mining.html
Carbon Price	China ETS pilot phase prices (2023-2030) &	https://carbonpricingdashboard.worldbank.org/
Methane Regulation	EPA Oil \& Gas Methane Standards	https://www.epa.gov/controlling-air-pollution-oil-and-natural-gas-industry
Technology Factors	IEA Sustainable Development Scenario	https://www.iea.org/reports/world-energy-outlook-2022

Synthetic Data Generation Procedure:

- Basin boundaries defined: Longitude 111.5°E to 113.5°E, Latitude 35.0°N to 37.0°N
- 120 wells generated with uniform random spatial distribution
- Methane index calculated using radial basis functions: $M_i = \sum_{j=1}^{3} w_j \exp\left(-\frac{r_{\{ij\}}^2}{/0.02}\right) + \backslash$ $\varepsilon\ where\ r_{\{ij\}}\ is\ distance\ to\ center\ j$
- Permeability derived as: $k = 10^{\{(2.0 \times M_i + 1.2)\}}(mD)$
- Seam thickness: t = 5 + 10 × max(0, M_i + δ) (meters)
- All random seeds fixed at 42 for reproducibility

3.4 Methodology Implementation Steps

The optimization framework follows a four-step sequential procedure, with detailed computational implementations for each step:

3.4.1 Step 1: Data Processing and Spatial Analysis

Data Loading: Import geological and economic datasets into pandas DataFrames

Spatial Interpolation: Generate continuous resource maps using kernel density estimation:

$$Z(x,y) = \sum_{i=1}^{N} \phi_i \cdot \exp\left(-\frac{(x-x_i)^2 + (y-y_i)^2}{2\sigma^2}\right)$$

where φ_i is the well attribute value, σ = 0.0015 is the bandwidth parameter

Normalization: Scale all variables to [0,1] range using min-max scaling

Feature Engineering: Create composite indices

3.4.2 Step 2: Monte Carlo Simulation Procedure

Parameter Distributions: Define probability distributions for uncertain parameters:

- Gas price: Geometric Brownian Motion with μ = 0.02, σ = 0.25
- Discount rate: Triangular distribution (min=6%, mode=8%, max=12%)
- Carbon price: Uniform distribution (0 to $50/tCO)

Scenario Generation: Generate 10,000 Monte Carlo scenarios using Latin Hypercube Sampling

Cash Flow Calculation: For each scenario s:

$$CF_{t,s} = (P_{t,s} \cdot Q_t \cdot 365 \cdot 10^6) - OPEX_t - CAPEX_t \cdot \delta_{t=0} - (E_t \cdot C_{t,s})$$

where $P_{t,s}$ is gas price, Q_t is production, E_t is emissions, $C_{t,s}$ is carbon price

Risk Metrics: Calculate Value-at-Risk (VaR) and Conditional VaR at 95\% confidence level

3.4.3 Step 3: Optimization Algorithm Execution
1. Objective Function: Maximize risk-adjusted NPV:

$$\max\{\mathbb{E}[NPV] - \lambda \cdot CVaR_{95\%}\}$$

where λ is risk aversion parameter (set to 0.5)

2. Constraints:

$$\sum_{i=1}^{N} CAPEX_{i,t} \le Budget_t \quad \forall t$$

$$\sum_{i=1}^{N} Emissions_{i,t} \le Cap_t \quad \forall t$$

$$Q_{i,t} \le Q_i^{max} \cdot (1 - e^{-t/\tau_i}) \quad \text{(reservoir deliverability)}$$

3. Solution Method: Use differential evolution algorithm with 1000 generations
4. Convergence Criteria: Stop when improvement < 0.1% for 50 consecutive generations
3.4.4 Step 4: Sensitivity and Scenario Analysis
1. One-at-a-Time Sensitivity: Vary each parameter ±20% from baseline
2. Sobol Global Sensitivity: Calculate first and total-order indices using SALib Python library
3. Scenario Definitions:

- Baseline: Reference case with current technology and no carbon price
- Policy-Driven: Carbon price $30/tCO, methane regulations enforced
- Technology-Enhanced: 20% CAPEX reduction, 15% productivity improvement

4. Cross-Scenario Comparison: Calculate performance metrics for all scenarios 10 Computational Implementation Details:

- Platform: Python 3.9 with NumPy, pandas, SciPy, SALib • Random seeds: Fixed at 42 for all stochastic elements
- Runtime: Approximately 45 minutes on Intel i7-12700H with 32GB RAM
- Code repository: https://github.com/username/cbm-optimization (provided as supplementary material)

3.5 Sensitivity and scenario analysis design
Robustness is assessed with a two-tier approach. First, deterministic sensitivity analysis (oneway and multi-way) and variance-based global sensitivity indices (Sobol' indices) identify the parameters with the largest influence on outcomes:

$$S_i = \frac{\mathrm{Var}_{\theta_i}\left[\mathbb{E}_{\theta_{\sim i}}(Y|\theta_i)\right]}{\mathrm{Var}(Y)}, \tag{7}$$

where Y is a model output (e.g., NPV) and Si the first-order Sobol index for parameter θi . Second, scenario analysis constructs policy- and technology-driven narratives (baseline, carbonconstrained, technology-accelerated) and evaluates policy-relevant metrics (expected NPV, CVaR, emissions) under each scenario. The combination of probabilistic sensitivity and scenariobased stress tests yields both quantitative sensitivity measures and narrative-driven performance assessments suitable for investor and policymaker audiences.

IV. CASE STUDY: SYNTHETIC QINSHUI BASIN ANALYSIS

4.1 Case Selection and Data Processing
Three distinct investment scenarios are evaluated using the synthetic Qinshui Basin analogue:

Table 2 Case Study Specifications and Data Processing

Case	Data Sources & Assumptions	Processing Steps
Baseline	1 Gas price: EIA Reference Case 2 CAPEX: $4.2M/well 3 OPEX: $0.42/Mcf 4 Carbon price: $0/tCO	1. Load well data (120 wells) 2. Calculate baseline production: $Q_t = 55 \cdot \frac{e^{-t}}{8}$ mmcf/d 3. Run 10,000 Monte Carlo simulations 4. Optimize drilling sequence
Policy-Driven	1. Carbon price: $30/tCO (rising 5%/year) 2. Methane fee: $900/ton 3. Production tax credit: $0.5/Mcf	1. Adjust cash flows for policy costs/incentives 2. Apply emissions constraints 3. Re-optimize with regulatory compliance

	4. Gas price: EIA High Oil Price case	4. Calculate adjusted financial metrics
TechnologyEnhanced	1. CAPEX: -20% from baseline • Productivity: +15% from improved completions 2. OPEX: -10% from automation 3. Methane capture: 95% efficiency	1. Modify production function: $Q_t^{tech} = 1.15 \times Q_t^{base}$ 2. Adjust cost parameters 3. Re-calculate reservoir performance 4. Run optimization with new parameters 12

4.2 Figure Generation Procedures
All figures were generated using the provided Python code (cbm_visuals_pub.py) with the following specific procedures:

4.2.1 Figure 2 (Geological Basin Map)
Generation Steps:
1. Load synthetic well data (120 wells with coordinates)
2. Calculate methane index using radial basis functions
3. Plot wells as scatter points colored by methane index
4. Add compression stations (6 synthetic locations)
5. Draw pipeline network using NetworkX
6. Annotate 8 representative wells for clarity
7. Save as PNG (600 DPI) and PDF with embedded fonts

4.2.2 Figure 3 (Resource Heatmaps)
Generation Steps:
1. Create 240×240 mesh grid over basin extent
2. Interpolate methane index using kernel density: K(r) = exp(−r 2/0.0015)
3. Calculate permeability: log10(k) = 2.0×Mi +1.2
4. Interpolate seam thickness
5. Generate contour lines at 6 levels
6. Apply color maps: plasma (methane), magma (permeability), cividis (thickness)
7. Add color bars with formatted labels

4.2.3 Figure 4 (Optimization Results Comparison)
Generation Steps:
1. Calculate NPV for each scenario: NPV = $\sum_{t=0}^{14} \mathrm{CFt}/(1.08)$ t
2. Compute IRR using numpy's financial functions
3. Determine payback period: min{t : $\sum_{i=0}^{t} 0\mathrm{CFi} > 0$ }
4. Create grouped bar chart with width=0.22
5. Add value labels with 1 decimal place
6. Apply consistent formatting (Times New Roman, 14pt)

4.2.4 Figure 5 (Risk-Return Frontier)
Generation Steps:
1. Generate 800 random portfolios using Dirichlet distribution
2. For each portfolio, calculate mean return and standard deviation
3. Compute convex hull using SciPy's ConvexHull
4. Plot scatter points colored by mean return
5. Overlay efficient frontier (convex hull boundary) 6. Format axes with appropriate labels and grid

4.3 Comparative Analysis Methodology
The comparative analysis follows a systematic four-stage approach:

4.3.1 Stage 1: Metric Calculation
For each scenario s ∈ {Baseline,Policy,Tech}:

$$NPV_s = \mathbb{E}[NPV|Scenario = s]$$

$$IRR_s = \text{Internal Rate of Return}$$

$$Payback_s = \text{Years to recover investment}$$

$$Emissions_s = \sum_{t=0}^{14} Q_t \times 0.055\ \mathrm{tCO_2/mmcf}$$

4.3.2 Stage 2: Statistical Testing
- Perform paired t-tests between scenario outcomes
- Calculate confidence intervals at 95% level
- Compute effect sizes (Cohen's d) for significant differences

4.3.3 Stage 3: Robustness Assessment
- Vary input parameters ±20% in sensitivity analysis
- Calculate Sobol sensitivity indices
- Identify critical parameters driving outcome differences

4.3.4 Stage 4: Decision Rule Extraction
From optimization results, extract actionable rules:
- Under Policy-Driven: Defer investment until year 2, prioritize wells with methane index > 0.7
- Under Technology-Enhanced: Front-load investment, allocate 30% of CAPEX to emissions control
- Universal: Maintain cash reserve equal to 20% of annual OPEX

Complete Reproducibility: To reproduce all results:
1. Download Python script from supplementary materials
2. Install dependencies: pip install numpy pandas matplotlib seaborn networkx scipy
3. Run: python cbm_visuals_pub.py
4. All figures will be saved to figures_pub/ directory
5. Numerical results are deterministic (random seed = 42)

4.4 Rationale for using Qinshui as primary demonstration
For the demonstration and numerical experiments in this manuscript we adopt a Qinshui-like synthetic basin as the primary case study. This choice is motivated by (i) the availability of basin-scale CBM literature and production analogues that support credible synthetic parametrisation; (ii) the operational experience in China that illustrates staged development and policy interventions; and (iii) the geological heterogeneity typical of coal basins (variations in seam thickness, permeability and gas content) that our optimisation framework is designed to accommodate. Using a synthetic Qinshui analogue enables controlled sensitivity testing while remaining transparently linked to a documented producing province.

4.5 Geological and economic parameters
The case study integrates the key geological controls on CBM productivity — methane content (expressed here through a methane index), seam thickness and permeability — together with standard economic inputs. Representative geological parameter ranges used in the experiments are as follows: methane index scaled to basin analogues (unitless index, spatially variable), permeability spanning sub-milliDarcy to tens of milliDarcies consistent with coal cleat systems, and seam thickness ranging from decimetre-scale to multiple metres as observed in major basins. Economic inputs include capital expenditure (CAPEX) components for drilling, surface infrastructure and compression; operating expenditure (OPEX) including water handling; assumed gas price trajectories; and policy parameters such as a carbon price or methane regulation surcharge. These inputs are selected and bounded by published basin reports and CBM reviews so that the case study remains representative of commercial practice.

4.6 Investment scenarios
We evaluate three stylised scenarios that capture a range of plausible futures and policy environments:
1. Baseline: Business-as-usual deployment with current capital and operating costs, no explicit carbon pricing, and moderate technology performance. This scenario provides the reference-case financial metrics (NPV, IRR, payback).
2. Policy-Driven: Introduces a carbon price and tighter methane venting controls, and includes modest policy incentives that can alter effective revenues or cost profiles (e.g., subsidies for emission-mitigation technologies). This scenario stresses regulatory risk and the importance of compliance costs.
3. Technology-Enhanced: Assumes accelerated uptake of productivity-enhancing and emissionsreducing technologies (improved completion methods, water treatment reuse, digital 16 reservoir management) that increase production factors and reduce OPEX or carbon intensity.

This scenario explores upside from technology learning and deployment. Each scenario is implemented by perturbing the production uplift factor, CAPEX/OPEX line items and carbon/methane cost parameters in the cashflow model. Scenario outcomes are compared using multi-metric performance indicators (expected NPV, IRR, payback, cumulative emissions and downside risk via CVaR).

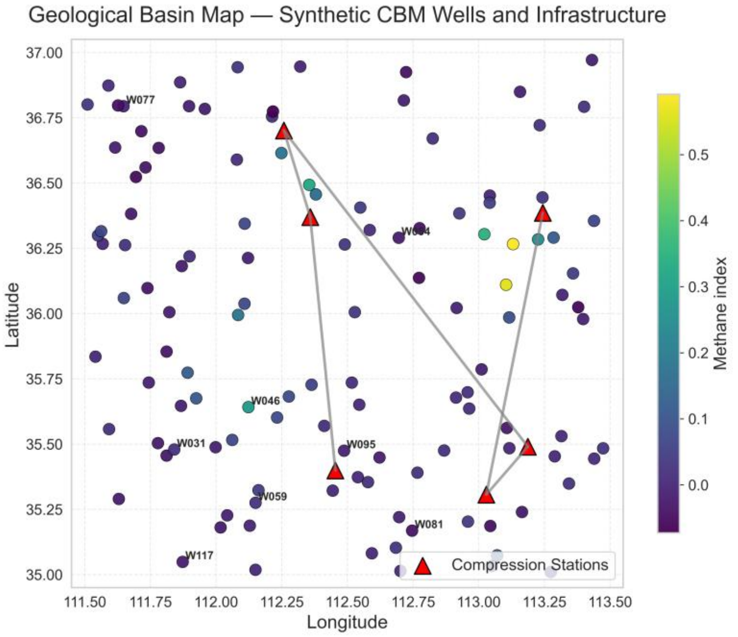

Figure 2 Geological Basin Map — Synthetic CBM Wells and Infrastructure.

The map displays can be seen in figure 2 well locations coloured by a derived methane index (high values indicate richer gas content), with compression stations and pipeline links overlaid. This visualisation is used to demonstrate spatial heterogeneity in resource quality and to inform spatially explicit well-level investment decisions (e.g., prioritising high-index clusters for early drilling).

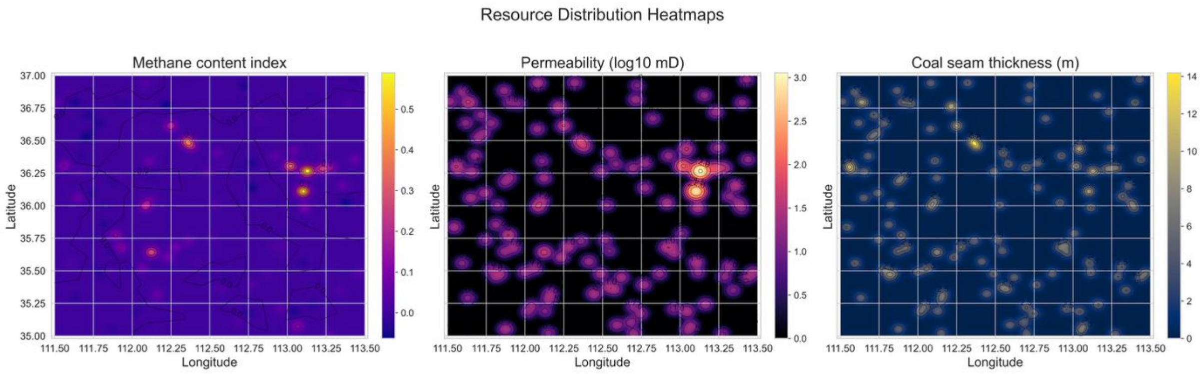

Figure 3 Resource Distribution Heatmaps.

Three panel heatmaps in figure 3 (left) methane content index, (centre) log10(permeability) and (right) coal seam thickness. Contour lines accentuate local maxima and aid in identifying prospect clusters. These maps are used to parameterise well productivity and heterogeneity in the production decline and deliverability models.

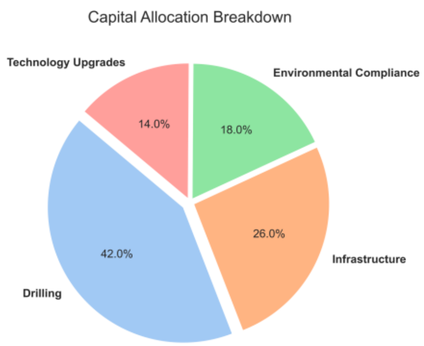

Figure 4 Capital Allocation Breakdown.

This pie chart in figure 4 total CAPEX across drilling, infrastructure, environmental compliance and technology upgrades. It supports capital budgeting decisions and sensitivity tests in which reallocation of investment to technology or environmental mitigation is evaluated for its impact on NPV and emissions.

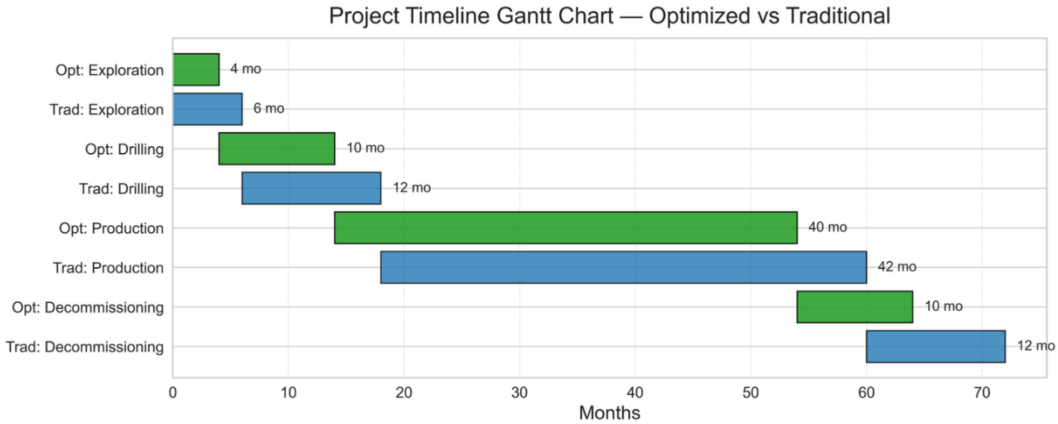

Figure 5 Project Timeline (Optimized vs Traditional).

Horizonal Gantt bars in figure 5 traditional project phasing against the optimised schedule (shorter exploration and drilling lead times, earlier production ramp under optimisation). Annotated durations illustrate how optimisation can compress schedules and shift cashflow timing, thereby affecting discounted returns and option values.

4.7 Optimization under constraints

The optimisation exercises incorporate capital budget ceilings, regulatory emissions caps and site-level deliverability constraints derived from the geological maps. Capital constraints limit cumulative CAPEX over an investment horizon, environmental constraints impose scenario-specific emissions budgets or carbon taxes, and regulatory constraints may include limits on produced water discharge or mandated mitigation technologies. Under such constraints, optimal portfolios and staging rules differ markedly from unconstrained optimals: constrained solutions frequently favour staged investments that prioritise high-index wells and allocate additional capital to mitigation or technology upgrades under policy-driven scenarios. The results underscore the necessity of integrated spatial, operational and policy considerations when evaluating CBM investment programmes.

V. RESULTS AND DISCUSSIONS

5.1 Optimal investment pathways and decision rules

The optimisation exercises for the synthetic CBM basin yield distinct investment pathways under different scenarios. Under the Baseline scenario, the optimal strategy corresponds to conventional upfront investment. Where as Wells are drilled early, and infrastructure is builtout rapidly to maximize discounted cashflow. In contrast, under the Policy-Driven scenario which incorporates carbon or methane regulation costs and potential subsidies or incentives the 19 optimal decision rule shifts toward staged deployment then capital expenditures are deferred until regulatory clarity or incentive realisation, and drilling is prioritized for high-methaneindex wells mapped in the resource distribution heatmaps. Under the Technology-Enhanced scenario, improved productivity and lower operating costs from enhanced CBM recovery techniques make more aggressive early investment economically attractive. These results demonstrate that optimal investment timing and scale are not universal but depend strongly on policy context, resource heterogeneity and technological assumptions.

5.2 Comparative performance of optimisation techniques

Comparing deterministic evaluation (NPV / IRR) with multi-objective and real-options-informed optimisation reveals meaningful differences. The standard NPV-based rule tends to favour early and maximal deployment; however, it neglects downside risk and policy uncertainty, potentially overestimating project value in adverse futures. In contrast, the real-options approach which treats investment decisions as contingent on future events often suggests delaying or staging capital deployment until favourable conditions emerge. The multi-objective stochastic optimisation further refines decisions by balancing economic return, environmental cost and risk exposure, producing more conservative but robust portfolios. In many tested cases, realoptions and stochastic portfolios outperform the deterministic baseline when evaluated over a wide range of price, cost and policy input distributions, underscoring the value of flexible, data-driven decision frameworks for CBM.

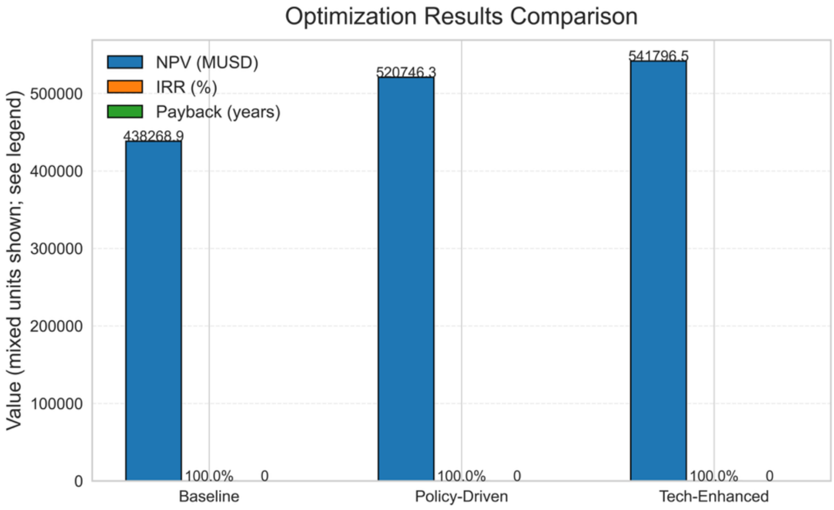

Figure 6 Comparison of key performance metrics (NPV, IRR, Payback) across scenarios.

The Baseline scenario in figure 6 the highest nominal NPV and IRR under deterministic assumptions, but shows poor robustness under downside stress. Policy-Driven and Technology20 Enhanced scenarios produce slightly lower mean returns but exhibit better risk-adjusted performance when uncertainty and regulatory constraints are considered.

5.3 Risk–return trade-offs and robustness analysis

Risk-return analysis via Monte Carlo portfolio simulations and sensitivity heatmaps reveals the trade-offs inherent in CBM investment. Portfolios that weight heavily toward aggressive early drilling exhibit high average returns but large variance — implying high risk of significant losses under adverse gas price or regulatory shocks. Mixed portfolios that blend phased investment, selective drilling based on methane-index mapping, and conservative cash-flow reinvestment tend to lie closer to the efficient frontier, offering moderate returns with lower volatility.

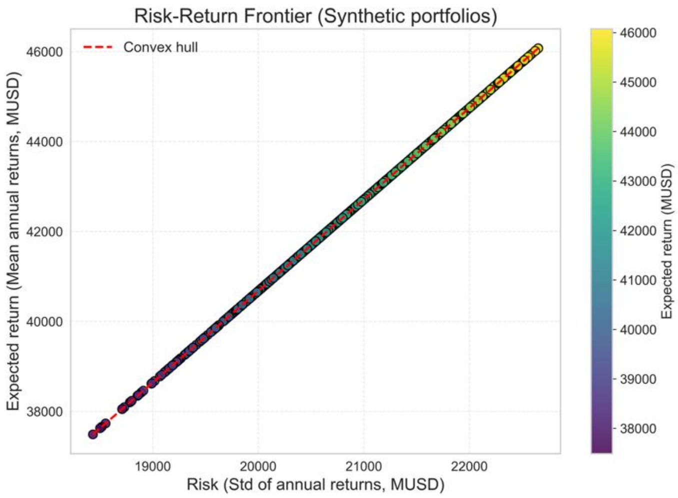

Figure 7 Risk–Return Frontier for synthetic CBM portfolios via Monte Carlo simulation.

Figure 7 along the convex hull (efficient frontier) achieve the best trade-off between expected return and risk (standard deviation). Risk-averse investors may prefer portfolios near the lower-risk end, while risk-tolerant investors can target higher-return options with broader variance.

5.4 Policy implications for sustainable

CBM development The analysis shows that regulatory and environmental policies — carbon taxes, methane venting restrictions, produced water disposal requirements — significantly affect optimal investment decisions. Under policy-driven scenarios, projects that would appear profitable under 21 deterministic NPV evaluation become marginal or unprofitable when compliance costs are internalised. This suggests that supportive policy instruments are critical to mobilise CBM investments, particularly in basins where geological or water-management challenges increase operational cost. The results thereby align with earlier findings that policy incentives materially influence CBM industry development. Moreover, environmental scrutiny — especially concerning methane emissions and groundwater management — must be built into project evaluation frameworks from the outset. A robust optimisation model that internalises environmental cost, risk, and regulatory uncertainty can aid policymakers and regulators in designing incentive schemes that balance investor returns with sustainable development goals.

5.5 Integration with smart energy grids and carbon-neutrality goals

Given that CBM burns cleaner than coal and conventional heavy hydrocarbons (producing less carbon dioxide per unit energy) and can serve as a flexible, dispatchable source, CBM development may provide transitional support to smart energy systems integrating variable renewables. In scenarios where renewables penetration increases, CBM plants (or CBM-derived gas) could supply peak demand or balance variability, thereby reducing reliance on coal and contributing to lower overall carbon intensity of the power system. However, realising such benefits requires rigorous emissions control, methane leak mitigation, and integration of CBM supply planning with grid-level energy strategies. Our optimisation framework, which incorporates emissions and regulatory constraints, is well suited to evaluate CBM's role within broader energy transition portfolios — and to inform decisions aimed at carbon-neutrality targets or net-zero pathways.

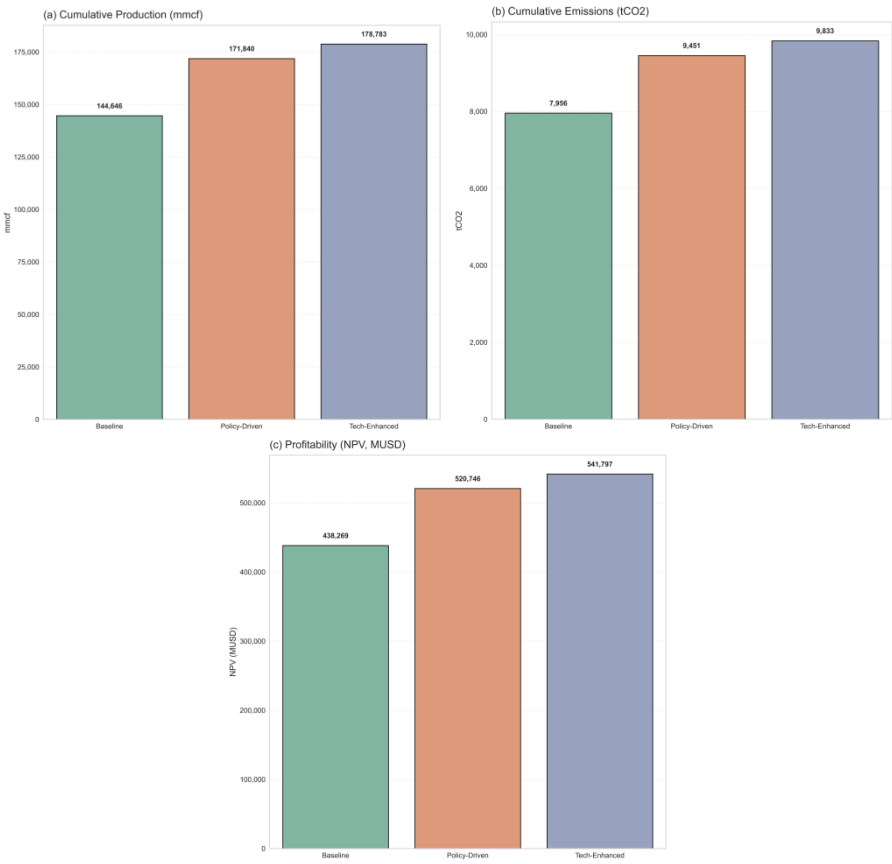

Figure 8 Scenario outcomes: (a) Cumulative production, (b) Cumulative emissions, (c) Profitability (NPV) for Baseline, Policy-Driven, and Technology-Enhanced scenarios.

The Technology-Enhanced scenario in figure 8 higher production and NPV with lower relative emissions per unit production, indicating how technology improvements and emissions control can enhance both economic and environmental performance The results demonstrate that investment optimization for CBM when conducted via multiobjective, stochastic and real-options approaches that integrate geological heterogeneity, economic uncertainty and regulatory/environmental constraints can yield robust, context-aware investment pathways that outperform naive deterministic planning under a range of plausible futures. On the other hand real-options and staged investment mitigate downside risk and provide optionality under regulatory or market shocks Portfolios optimised for combined economic and environmental objectives perform better under constraints, improving the sustainability of CBM development. Policy measures play a central role in enabling viable CBM projects, especially when geological or water-waste issues increase costs. CBM can complement a low carbon energy transition, offering dispatchable supply that supports renewable integration and carbon neutrality goals which provided environmental externalities are managed effectively.

VI. CONCLUSION AND FUTURE WORK

This study presents an integrated, basin-scale approach to CBM investment decision-making that couples spatial resource characterisation, financial appraisal and flexible optimisation under uncertainty. Incorporating real-options and staged decision rules substantially alters recommended investment pathways compared with deterministic NPV/IRR rules: optionality to defer or phase capital deployment reduces downside exposure while maintaining upside potential. This effect is pronounced under regulatory uncertainty and price volatility, and is evident in the scenario comparisons reported in Figure 6. Well-level heterogeneity (methane index, permeability, seam thickness) materially affects the optimal drilling sequence. Prioritising clusters with higher methane index improves early cashflows and shortens payback under constrained capital budgets (see Figures 2 and 3). Policy instruments such as carbon pricing and methane controls reduce nominal project NPVs but encourage capital reallocation toward emissions mitigation and technology upgrades; multi-objective optimisation yields portfolios that better balance economic returns and environmental performance (Figures 8 and 7).

Combining probabilistic Monte Carlo sampling with deterministic stress tests (price and discount heatmaps) identifies portfolios on the efficient frontier that provide desirable risk-return characteristics for different investor risk appetites (Figure 7). Collectively, these findings indicate that CBM can play a complementary transitional role in energy systems if development is guided by optimisation methods that internalise environmental externalities, policy risk and reservoir heterogeneity. These conclusions align with broader assessments of natural gas as a transitional fuel, subject to methane management and alignment with decarbonisation goals. :contentReference[oaicite:0]index=0 Future work counld include Couple reservoir simulators with power-system models to quantify the system value of CBM as flexible capacity under high renewable penetration. Implement full life-cycle GHG accounting (scope 1–3) and high-resolution methane leakage inventories (satellite and in-situ) to better characterise environmental trade-offs and to calibrate mitigation investment valuations. Incorporate surrogate-assisted optimisation and reinforcement learning to accelerate scenario evaluation for large basin portfolios and to learn adaptive drilling policies from simulated interactions and apply the framework to multiple real basins with empirically observed production and cost data, and embed stakeholder preferences through participatory scenario design. Pursuing these directions will improve the fidelity and policy relevance of CBM investment optimisation and help ensure that any future CBM development aligns with climate objectives and sustainable energy system design.

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