Mine Closure 2025 – S Knutsson, AB Fourie & M Tibbett (eds)

doi:10.36487/ACG_repo/2515_29

A probabilistic framework for mine closure financial liability assessment

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Abstract

Mine closure remains a critical challenge for the global mining industry, particularly in ensuring adequate financial provisions to mitigate environmental risks and long-term liabilities. Traditional cost estimation models rely on deterministic approaches that often underestimate closure liabilities by failing to account for uncertainties related to future environmental conditions, regulatory changes, and economic variability.

This paper introduces a probabilistic framework for assessing mine closure liability, which integrates an uncertainty-based cost estimation model. Unlike conventional models that provide single-point cost estimates based on itemised engineering breakdowns, this framework employs a Monte Carlo simulation approach to generate a probabilistic range of potential closure costs. The model incorporates multiple closure options per action/component, each assigned a probability of occurrence. Additionally, quantities and unit rates are represented as probability distributions rather than fixed values, ensuring a comprehensive assessment of variability and risk.

The model dynamically refines closure cost projections using an interactive database integrating satellite imagery, computer vision, historical knowledge, artificial intelligence, and statistical modelling. This framework enhances accuracy and facilitates data-driven decision-making by applying the Pareto principle to action/components that are key cost drivers, such as water treatment and material movement. The output from the framework generates a probabilistic cost distribution, accounting for uncertainties and enabling the determination of confidence intervals for closure costs. This approach improves transparency, supports risk-adjusted financial assessments, and ensures a robust evaluation of closure liabilities.

The proposed probabilistic model offers stakeholders, regulators, and financial auditors a comprehensive, data-driven assessment of mine closure costs. It facilitates rigorous financial provisioning by aligning closure liabilities with site-specific risk profiles. Ultimately, this framework enhances regulatory compliance and promotes financial transparency. Integrating risk-adjusted planning and informed decision-making supports more sustainable approaches to post-mining land rehabilitation. Doing so helps ensure that environmental restoration is adequately funded and that mine closure processes align with long-term, sustainable land use goals.

Keywords: *mine closure, financial provisioning, probabilistic cost estimation, Monte Carlo simulation, environmental risk management, closure liabilities, unknown-unknowns*

1 Introduction

Assessing financial liabilities is a fundamental yet often poorly understood component of the mining lifecycle. Globally, mining operations must account for the costs associated with mine rehabilitation to meet regulatory obligations, secure financial guarantees, and contribute to long-term environmental stewardship (International Council on Mining and Metals 2019). Even with established models and formalised processes

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for closure costing, aligning on-the-ground rehabilitation efforts with financial provisions meant to support them remains a persistent challenge (Hutchinson & Dettore 2011). These misalignments are frequently attributed to inconsistent estimation methodologies, limited integration between financial provisioning and progressive rehabilitation, and inadequate treatment of uncertainty and regulatory complexity. Tackling these challenges requires a shift toward more open, evidence-based approaches to closure costing; approaches that connect financial provisions to on-the-ground, changing realities of mine rehabilitation (Brock et al. 2019).

These global trends are echoed in national contexts with significant mining legacies. South Africa reflects many of these global challenges, with a well-established and highly active mining sector, yet actual mine closures (particularly those with significant environmental impacts) remain rare. As Watson & Olalde (2019) observed, not a single large, environmentally significant mine was formally closed between 2011 and 2016, and more recent reports suggest that minimal progress has been made since (Department of Mineral Resources and Energy 2022).

In an effort to address these challenges, the South African government introduced Financial Provision Regulations under the National Environmental Management Act (NEMA), through General Notice Regulation (GNR) 1147 of 2015. These regulations, still pending final implementation, seek to ensure that mining companies set aside sufficient funds to support rehabilitation throughout the life of the operation and after closure (Department of Environmental Affairs 2015). The regulations require that financial provisions be secured through mechanisms such as trust funds or bank guarantees and that these provisions be updated annually to reflect changes in site conditions and rehabilitation costs (Rapson & Novotny 2022). Grounded in “the polluter pays” principle, these regulations aim to reinforce accountability and reduce the likelihood that rehabilitation liabilities are transferred to the state or affected communities.

Despite regulatory efforts, questions persist about the adequacy and enforcement of financial provisioning. Studies have pointed to underfunded or inaccurately calculated provisions, with some assessments either overengineered (leading to inefficient capital use) or oversimplified, thereby overlooking key elements of environmental rehabilitation (Centre for Environmental Rights 2019). Such discrepancies create a disconnect between projected and actual costs, increasing the risk that mining companies may exit operations without fulfilling their closure responsibilities.

This research project addresses the above concerns by proposing a probabilistic framework for estimating financial liabilities, commonly called closure costing. The approach integrates remote sensing, artificial intelligence (AI), computer vision, and statistical modelling. By leveraging these advanced technologies, the framework offers a more accurate and dynamic method for assessing closure costs in complex mining environments. While earlier work, such as Hutchison & Dettore (2011), highlighted the value of probabilistic methods in closure costing, integrating high-resolution geospatial data and AI techniques offer new opportunities for evaluating rehabilitation progress in a spatially explicit manner. The proposed framework does not aim to provide a single, deterministic figure but rather a credible range of possible cost outcomes, enhancing the accuracy and defensibility of financial provisions.

By enabling the identification of multiple closure scenarios, the framework additionally supports more robust decision-making, which aligns with the intent of GNR 1147, and offers a tool for both regulatory oversight and internal auditing. Ultimately, this approach contributes to more resilient closure planning, supports the responsible allocation of financial resources, and advances the broader goal of achieving sustainable post-mining land uses.

2 Current approaches to estimating mine closure costs

Mine closure cost estimation in South Africa commonly follows a deterministic approach, similar to an engineering Bill of Quantities, where quantities are multiplied by unit rates to determine overall costs. These unit rates are typically based on industry benchmarks and do not take into account site-specific conditions, such as the remoteness of the site, which can increase transport and labour costs, or the presence of sensitive ecosystems requiring specialised rehabilitation measures (such as geographic location, regulatory context, market fluctuations, and operational scale).

Closure cost estimates should aim to capture the full scope of financial liability associated with mine rehabilitation and closure. However, these estimates' reliability largely depends on the design detail level available at the assessment time. Early-stage estimates often involve significant uncertainty due to limited information. In contrast, later estimates tend to be more accurate, benefiting from detailed engineering designs and comprehensive planning data. NEMA and GNR 1147 recognise the importance of financial preparedness and the need to ensure that mine rehabilitation is adequately funded throughout an operation's life of mine (Department of Forestry, Fisheries and the Environment 2022; Republic of South Africa 1998). These regulations emphasise the importance of continuously updating closure cost estimates throughout a mine's operational life. Such refinements help ensure that financial provisions remain both realistic and responsive. As closure requirements evolve and the timeline to final closure becomes clearer, estimates should be adjusted to reflect changing conditions and responsibilities. GNR 1147 provides a structured guideline for how this progression should unfold.

In accordance with the Financial Provisioning Regulations, the required level of design effort and the expected accuracy of closure cost estimates are aligned with the remaining life of operation, as outlined in Table 1.

Table 1 Design effort and cost estimate accuracy by remaining mine life

End of life of operation (or components of operation) from year of assessment	Design effort	Degree of accuracy in cost estimation
> 30 years	Pre-conceptual/Class 5 estimate/up to 2% of complete definition	-50 to +50%
10 to 30 years	Conceptual/pre-feasibility/Class 4 estimate/up to 15% of complete definition	-30 to +30%
5 to 10 years	Preliminary/feasibility/Class 3 estimate/up to 40% of complete definition	-20 to +20%
Less than 5 years	Detailed designs/bid/tender/Class 2 estimate/up to 75% of complete definition	-10 to +10% (or less)

Closure cost estimate accuracy improves as mines near the end of life, progressing from broad Class 5 estimates (>30 years) to more precise Class 2 estimates (<5 years). Importantly, improvements in accuracy must be supported by documented methods and data, ensuring transparency and accountability in line with GNR 1147 and international standards. This requirement promotes transparency and strengthens accountability in how financial provisions are assessed and justified (Bocking et al. 2009). The approach outlined in GNR 1147 aligns closely with international cost estimation practices, such as those set by AACE International, which also rank estimates on a scale from Class 5 (least accurate) to Class 2 (most definitive) (AACE International 2020).

Often, contingencies are applied to mine closure estimates using standard percentages. While intended to safeguard against uncertainty, these values are usually chosen without clear justification or supporting evidence (Byrne 2024). A cost estimate that might appear precise but masks a much wider margin of error. Current models are designed to handle "known unknown" risks that are acknowledged but hard to quantify.

They rarely account for surprises: the “unknown-unknowns” that emerge in real-world rehabilitation, where conditions shift and new challenges appear unexpectedly (Shrivastava 2014).

A probabilistic framework was developed to improve closure cost estimation by integrating uncertainties and site-specific data. Unlike fixed models, it generates a dynamic, auditable cost range using remote sensing and computer vision, aligning with GNR 1147’s adaptive intent. This supports more credible, accountable, and forward-looking mine closure planning.

3 Sources of uncertainty

Mine closure involves inherent uncertainty. NASA defines two types: aleatory (natural variability) and epistemic (limited knowledge), both of which affect all aspects of closure costing (National Aeronautics and Space Administration 2011). Complicating this are “unknown-unknowns”, unforeseen factors with potentially significant consequences. Managing such uncertainty requires adaptable, robust methods as new information emerges.

3.1 Action/component required

Hutchison & Dettore (2011) highlighted that a key source of uncertainty in mine closure cost estimation arises from the selection and definition of closure actions or components. Estimates often rely on a single preferred scenario, overlooking alternatives that reflect the true variability of closure planning (Eldarov 2025). Scenario-based approaches, which consider multiple closure paths with distinct actions, quantities, and rates, improve robustness (Brock et al. 2019). Expert judgment is needed to anticipate evolving components and site changes.

3.2 Quantity

Uncertainty in quantity arises from inherent difficulty in accurately measuring or quantifying the physical extent of mine closure actions/components, such as open pits, tailings storage facilities, waste dumps, and infrastructure (McKenna et al. 2020). These uncertainties are driven by factors such as outdated site data, changes in operational boundaries over time, and variations in how features are defined or classified.

3.3 Rates

Uncertainty in unit rates remains a major source of variability in mine closure cost estimates. Industry practice often relies on benchmarked average rates derived from datasets, encompassing a wide range of mining operations from small-scale quarries to large open pit mines. Relying on averages or judgment-based values can misrepresent actual costs, increasing the risk of over- or underestimation. Transparent rate selection is essential. As a result, generic rates may misrepresent closure costs, especially for sites with unique logistical or environmental constraints (Neubauer 2022).

3.4 Unknown-unknowns

A comprehensive understanding of uncertainty in mine closure costing must also address the distinction between known knowns, known unknowns, and unknown-unknowns. Known knowns refer to closure actions/components with clearly defined scopes, quantities, and rates. Known unknowns represent actions/components for which the need is known but where quantities or costs remain uncertain, typically due to data limitations, site complexity, or variability in implementation approaches. These uncertainties can be systematically addressed through structured frameworks. For example, action/component-based decision trees and application of probability distributions to reflect variability in both rates and quantities.

Unknown-unknowns refer to actions/components that have not been anticipated due to limitations in site data, evolving regulatory contexts, or human oversight. These unanticipated elements introduce an additional layer of uncertainty, often not captured in formal modelling exercises. To mitigate this residual uncertainty, it is essential to incorporate a contingency reserve into cost estimates, acknowledging the potential for risk events that may occur beyond the current scope of planning. These layers of uncertainty reinforce the value of probabilistic approaches, which provide a structured way to incorporate a broader range of outcomes and ensure financial provisions that remain credible even as conditions evolve (Byrne 2024).

4 Proposed probabilistic framework

Estimating mine closure costs remains a global challenge. Despite regulations, cost estimates often overlook high-impact rehabilitation needs while overemphasising minor line items. This imbalance can lead to funding shortfalls and increased environmental and financial risks. A more targeted, data-driven approach is needed, one that focuses on the few cost drivers that contribute most significantly to overall liability.

The framework outlined here offers a more accurate and transparent view of closure costs by combining probabilistic modelling, geospatial analysis, and contextual data. It does not aim to predict a single figure but rather to define a realistic range of potential outcomes. In doing so, it supports financial provisioning that is better aligned with operational realities and regulatory expectations. The following sections detail the framework's key components, underlying data, and practical applications.

Figure 1 provides a high-level overview of the proposed probabilistic framework, illustrating how multiple closure options, cost distributions, and unknown uncertainties are integrated through Monte Carlo simulations to generate a realistic distribution of total closure costs.

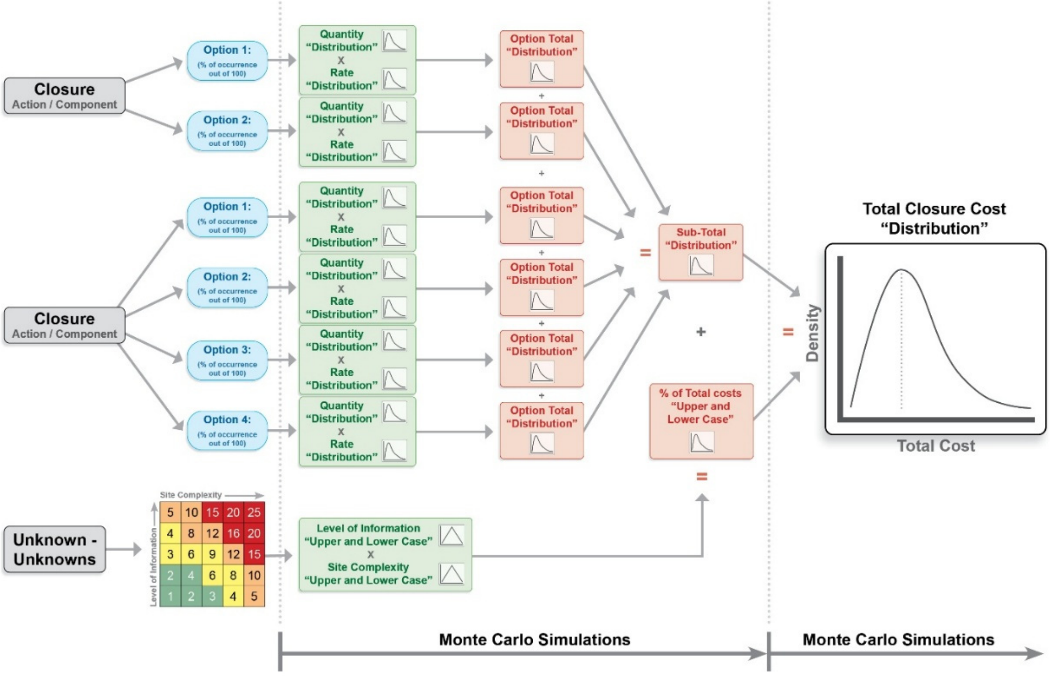

Figure 1 Workflow diagram illustrating the proposed probabilistic framework for mine closure cost estimation

4.1 Materiality and level of definition

When it comes to mine closure costs, accounting materiality is about identifying which elements are significant enough to influence financial or regulatory decisions. In practice, this means focusing attention on cost items that could meaningfully affect the overall closure liability. Financial reporting standards similarly emphasise focusing on material provisions that could impact stakeholders' decisions (Bocking et al. 2009). As closure liabilities often involve long timelines and complex technical assumptions, determining what matters most and how much detail is needed plays a crucial role in ensuring closure estimates are both defensible and useful.

Minor actions/components or uncertainties that are unlikely to impact the financial picture materially may be grouped or excluded as long as their omission does not distort the overall estimate. However, for large or high-risk sites, even small variations in assumptions, such as unit rates or closure actions/components, can lead to significant financial discrepancies. Materiality must be evaluated not in isolation but relative to the total liability and the specific reporting or auditing context. The "level of definition" refers to the degree of detail required for the inputs to meet this threshold. While some components require high precision and detailed data, others may be sufficiently represented by indicative values or assumptions, especially in early-stage or high-level assessments.

4.2 Effort versus precision (Pareto principle)

The Pareto principle (often summarised as the 80/20 rule) particularly holds true in the context of mine closure costs. A relatively small number of high-impact actions/components tend to drive the majority of total closure expenses. Research confirms this, highlighting that items such as long-term environmental liabilities, major earthworks, and structural demolition frequently account for the bulk of financial provisions (Watson & Olalde 2019).

This insight changes the way we approach cost estimation. Rather than trying to account for every possible closure task with equal effort, it makes more sense to focus on the big-ticket items that truly shape the final cost, where it matters most. These are the actions/components that make the biggest differences. By identifying them early and applying the right level of detail (especially when uncertainty is high), we can create more efficient and far more reliable estimates. In doing so, practitioners can reduce dependence on exhaustive site-specific data while maintaining the integrity of the estimate. By focusing modelling efforts on these "vital few" components and assigning ranges to their quantities and unit rates, the probabilistic framework delivers cost outputs that are more encompassing of all possible costs and more adaptable to site-specific constraints and future uncertainty.

The distinction between what is material for decision-making and what is impactful from a modelling effort perspective is central to achieving efficiency and accuracy in closure cost estimation.

4.3 Level of information required

Given that a small number of key actions/components typically account for the majority of closure costs, the next step involves determining the information required to effectively evaluate each action/component scenario. When closure cost assessments are conducted for audit or review purposes rather than for detailed closure planning, the required level of detail is higher. This enables the probabilistic framework to use publicly available data sources and established information on commodity characteristics and regional climatic conditions to generate meaningful estimates. Estimates are made without requiring access to detailed, site-specific inputs. For example, using global mine data and climate models, one can estimate a site's rehabilitation cost range early, even if site-specific monitoring data are not yet available (Helmholtz Association of German Research Centres 2024).

In South Africa, the probabilistic framework could be applied to mines in the Mpumalanga Coalfields. The framework can generate informed estimates of likely water quality conditions and potential water-related challenges by incorporating historical climatic data and local geological information. Scenario development using these inputs enables the estimation of a range of possible water treatment volumes and treatment quality requirements. Similarly, geological characteristics, such as the depth and distribution of coal seams, can be used with aerial imagery to model typical pit depths and assess material movement requirements under various scenarios. Lastly, mine infrastructure can be readily identified, measured, and quantified using computer vision techniques applied to high-resolution aerial or satellite imagery, further enhancing the reliability of closure cost estimations

4.4 Action/component

Each mine closure cost estimate comprises multiple actions/components that should be explicitly identified and quantified at the correct level of detail. In deterministic closure cost assessments, practitioners are typically required to select a single course of action for each action/component, often defaulting to the preferred or most likely scenario. However, given mining operations' inherent complexity and variability, this approach fails to account for the full range of plausible alternatives. In contrast, a probabilistic closure cost framework allows for the incorporation of multiple potential actions/components, each assigned a likelihood of occurrence (Hutchison & Dettore 2011).

This approach begins by assessing the availability and quality of relevant data. After applying the Pareto Principle, it becomes evident that only a limited number of actions/components are responsible for most closure expenditures. While mine closure encompasses a wide array of technical and environmental actions/components, the most significant costs typically fall within three primary categories: (1) movement and reshaping of large volumes of material, such as waste rock and tailings (Sanders et al. 2024); (2) management and treatment of water to mitigate pollution risks (Sanders et al. 2024); and (3) demolition and remediation of site infrastructure (Fletcher et al. 2011). Tailings stabilisation may also represent a substantial cost that has not already been addressed through general earthworks.

The relative importance of specific cost drivers may vary with site characteristics, such as mineralogy, climate, and regulatory requirements. However, material movement, water management, and infrastructure decommissioning consistently emerge as the dominant closure liabilities. These "vital few" components typically account for the bulk of closure costs and are central to effective financial provisioning and closure planning (Knight 2024; Office of Surface Mining Reclamation and Enforcement 2020).

Since the vital few actions/components are known, the probabilistic framework needs to determine the best-case and worst-case scenarios for each element and, based on this understanding, identify a number of possible rehabilitation actions/components. This probabilistic approach accounts for uncertainties inherent in mine closure planning. For example, water treatment may involve active or passive methods, while waste cover options could include evaporative, water-shedding, or synthetic covers. Each option is assigned a probability weight based on its likelihood of implementation.

Much like a decision tree, this structured framework explores multiple closure scenarios by mapping out different possible pathways for each component. It does not assume a single, fixed course of action. Instead, it accounts for uncertainty, recognising that conditions onsite and regulatory expectations can change over time. By embracing this variability, the approach facilitates a more comprehensive and adaptable cost assessment that accurately reflects the inherent complexity of mine closure planning.

4.5 Determining the quantities

Measuring key mining actions/components, such as infrastructure and open pit operations, can be efficiently conducted by integrating Google Earth Engine (GEE) and computer vision techniques that can accurately delineate open pits, tailings dams, waste dumps, and various other types of mine infrastructure. Consequently, the measurements derived from this satellite imagery can be represented as a distribution of potential sizes rather than fixed values. Statistical analysis of extracted features enables the generation of probability distributions for pit dimensions and infrastructure footprints, allowing for site classification based on mining phase and operational scale.

By combining object detection algorithms with GIS-based spatial analysis, this method provides a powerful tool for estimating closure components and their associated costs. Perhaps most importantly, it allows for remote assessment using publicly available satellite imagery. This reduces dependence on direct site access while delivering accurate, timely, and reliable closure cost estimates.

4.6 Determining the rates

Default unit rates in closure cost estimates often rely on broad industry averages, but these rarely reflect unique conditions of individual sites. Factors like location, market context, and scale can significantly affect actual costs. As a result, standardised rates may lead to inaccurate estimates and misaligned financial provisions for mine closure.

To account for this variability, the probabilistic framework draws on a database of third-party contractor rates to define a realistic range of potential costs for each closure action/component. These rate distributions reflect geographical differences, market fluctuations, and broader economic conditions, resulting in more accurate and site-specific estimates. Rather than relying on a single figure, the approach captures uncertainty by establishing a range between minimum and maximum values.

4.7 Contingencies

Closure cost estimates often rely on various contingencies, with blanket contingencies being used most widely (Byrne 2024). Another common approach involves assigning specific risk-related contingencies based on the degree of project definition or the level of remaining uncertainty (Neubauer 2022). While convenient, blanket contingencies are frequently criticised for lacking clear evidence and for potentially masking real cost uncertainties.

The probabilistic framework offers an alternative, by building contingency directly into each closure action/component and the unit rates themselves. Instead of globally applying a single percentage, it systematically accounts for the full range of possible quantities and cost outcomes. This way, components with higher uncertainty naturally reflect a broader cost range, while those with more reliable inputs have narrower distributions. By tailoring contingencies to specific uncertainties, the approach enhances both the transparency and credibility of closure cost estimates, moving away from general assumptions toward data-driven, defensible estimates.

4.8 Dealing with unknown-unknowns

By integrating an action/component-based decision tree on “vital few” items, closure cost estimation can more effectively capture both “known knowns” and “known unknowns”. This structured approach enhances the transparency and completeness of the costing process. However, it is equally important to consider the impact of “unknown-unknowns”. The probabilistic framework addresses this challenge with a structured yet practical approach. It uses a matrix that evaluates two key factors: the complexity of the site and the quality of available information. By scoring a site across these dimensions, the method offers a straightforward way to assess uncertainty. The outcome is both visual and quantifiable, with a simple five-by-five matrix that helps account for often-overlooked “unknown-unknowns” in closure cost modelling.

Site complexity can be scored on a scale from 1 (simple) to 5 (very complex), using visual indicators from aerial imagery. These include the number and variety of mining features (e.g. pits, dumps, tailings), infrastructure density (e.g. roads, conveyors, buildings), the presence of water systems (e.g. ponds, trenches), signs of legacy disturbance, and proximity to sensitive areas (e.g. rivers, communities, protected zones).

The level of available information is also scored from 1 (poor) to 5 (very good), based on the quality and completeness of the datasets used for closure planning. This includes the clarity of satellite imagery, the performance of computer vision models in interpreting site features, and the availability of supporting datasets, such as rainfall records, geology, and historical mining data. A low score indicates high uncertainty due to patchy or outdated data; a high score suggests a strong and reliable information base.

By multiplying the site complexity score by the information score, practitioners can generate a numerical factor to represent ‘unknown-unknowns’. This scoring system is illustrated in Figure 2. This ensures that even unpredictable elements are accounted for in a structured and transparent way. This score can be translated into a percentage adjustment and applied to the closure cost distribution, which is also expressed as a probability range. This ensures that even unpredictable elements are accounted for in a structured and transparent way.

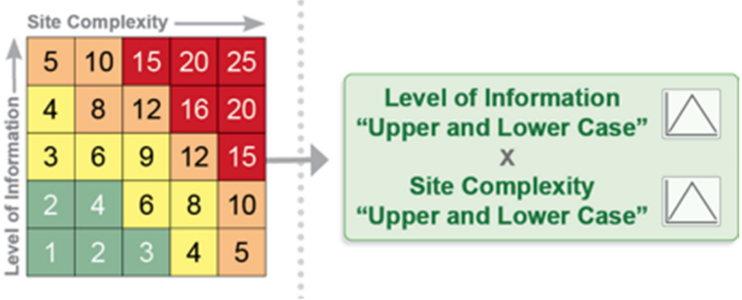

Figure 2 Example of 5 × 5 matrix for "unknown-unknowns"

5 Sources of Information

5.1 Historical knowledge

Historical information often serves as a crucial supplement to current site data, especially for legacy operations. Common sources include geological and topographical maps, historical aerial imagery, environmental impact assessments, feasibility studies, and technical reports. These resources are available through public databases, regulatory archives, or institutional repositories. Online tools, including government geospatial portals, academic databases, and industry reports, offer valuable insights into historical mining activities, infrastructure layouts, and past environmental conditions. These records can help identify the location and dimensions of legacy features, fill data gaps, and reconstruct the site's development history. Case studies have shown that integrating historical geographic information system (GIS) data helped avoid missing legacy contamination, leading to more defensible closure plans (Poole 2023).

5.2 Computer vision

In mine closure costing, computer vision offers a robust and scalable tool for identifying and measuring key mining components, particularly where direct, site-specific data are unavailable or incomplete. By integrating satellite imagery with cloud-based platforms like GEE, practitioners can access multi-temporal datasets from sources such as Sentinel-2 and Landsat-8. For instance, cloud platforms enabled the analysis of 30+ years of Landsat images to map how tailings facilities grew over time, providing data for closure volume estimates (Samaei et al. 2024). For example, McKenna et al. (2020) demonstrated that automated classifications of rehabilitated versus disturbed land achieved an accuracy of over 80%, which further improved when multiple indices and methods were combined. These methods contribute to a more reliable remote sensing-based approach to obtaining further information, which can be used in the closure costing.

5.3 Contextual data: mining practice and regional conditions

Reliable closure planning depends on high-quality contextual data, particularly information related to mining practices and regional environmental conditions. Depending on the extraction method, geology, and operational scale, mining operations vary significantly in layout and disturbance footprint. These characteristics can be identified through satellite imagery, aerial photography, or publicly available online data. Such spatial sources provide insight into mining activities' physical configuration and extent across different contexts.

In addition to mining-specific data, regional environmental conditions serve as essential sources of information for understanding site characteristics. Factors such as climate, rainfall, temperature extremes, and evapotranspiration influence ecological processes and post-mining land performance. Publicly accessible datasets, such as those provided by WorldClim, CHIRPS, and national meteorological services, can be integrated with geological, topographical, and land cover data to create a detailed environmental profile.

Researchers have used WorldClim and similar datasets to cluster mine sites by environmental conditions, helping predict rehabilitation difficulty and cost needs for each cluster (Poole 2023).

6 Simulation tools

6.1 Monte Carlo simulations

The proposed probabilistic framework uses Monte Carlo simulations, implemented in R, to account for uncertainty across closure actions/components, quantities, rates, and allowances for “unknown-unknowns”. This method works by running thousands, or even millions, of simulation iterations, each of which randomly samples probability distributions defined for each input variable.

Instead of producing a single fixed number, this approach generates a full distribution of potential closure costs. Actions/components marked by greater uncertainty yield a wider range, whereas well-defined items result in narrower spreads.

7 Interpretation and application of cost distributions

7.1 A range of potential closure costs

Adopting the probabilistic framework outlined above allows closure cost estimates to be represented as a distribution of potential financial liabilities rather than a single-point estimate, as illustrated in Figure 3. This distribution serves as a benchmark, enabling stakeholders to assess whether a proposed closure liability falls within the predicted range of values.

This approach allows stakeholders to assess the level of financial risk they are prepared to accept. Choosing a liability estimate near the lower end of the distribution implies a higher tolerance for risk, acknowledging that actual closure costs may exceed the budgeted amount. Opting for a more conservative figure, such as the 95th percentile, lowers risk by accounting for a broader range of possible outcomes. Even then, underfunding remains possible as there is a 5% chance that real-world costs could exceed the estimate. By making these trade-offs explicit, the method brings greater transparency to closure cost estimation and supports more informed, risk-aware financial planning.

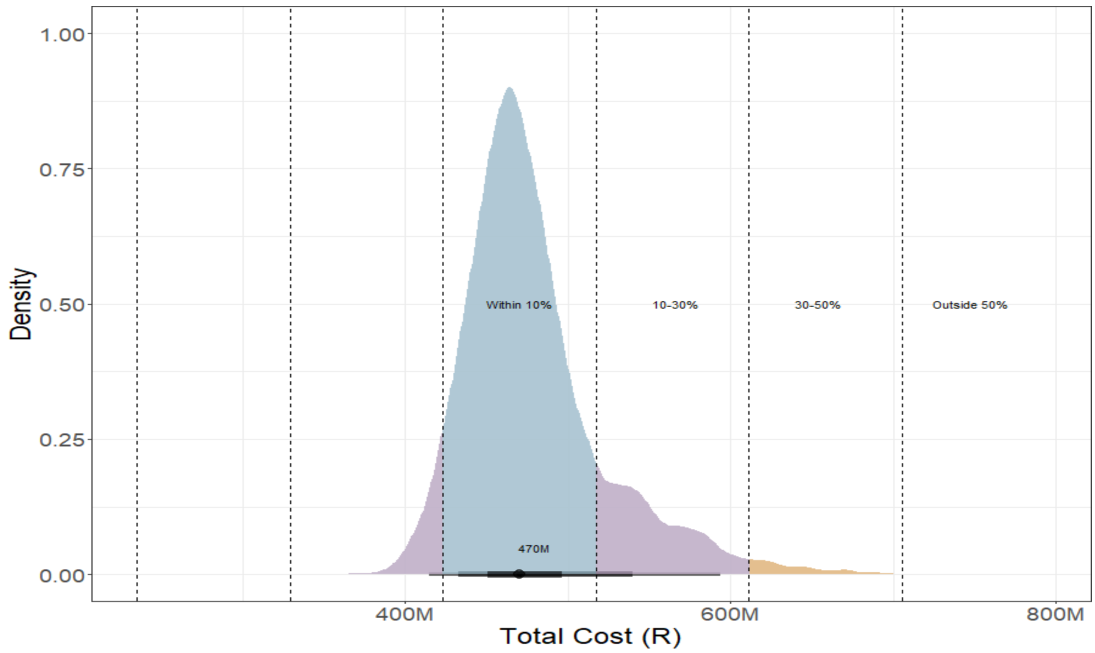

Figure 3 Example of final distribution of potential closure costs

7.2 Practical and regulatory considerations

In the South African context, GNR 1147 requires a detailed and auditable closure cost report based on site-specific assessments, including selecting closure methods and justifying unit rates supported by specialist inputs. Currently, the regulation favours a deterministic model that yields a single, defendable figure for financial provisioning.

Introducing probabilistic distributions into this process may raise questions about compliance, particularly regarding how risk-based ranges or percentiles align with the legal requirement for a defined financial provision. One practical solution could involve aligning the probabilistic estimate with a high percentile value (such as P90 or P95) to reflect a conservative, risk-buffered figure consistent with the intent of GNR 1147. Auditors have welcomed the shift to a probabilistic approach, noting it brings greater transparency to decisions and uncertainties previously masked by a single deterministic figure, though it's still early days for widespread adoption. While this interpretation may align conceptually, formal regulatory guidance or updates may be needed to explicitly support probabilistic approaches.

7.3 Reducing uncertainty

The probabilistic approach reduces uncertainty in closure cost estimation by replacing practitioners' implied assumptions with clearly defined distributions of possible outcomes, based on observed variability or expert judgment. The approach highlights which actions, components, or rates carry greater uncertainty than others. This insight helps practitioners identify where to focus their efforts, prioritising areas requiring more detailed data or refined assumptions to improve accuracy. As a result, uncertainty is no longer buried within a single number or masked by modelling shortcuts. It becomes visible and measurable. Practitioners can evaluate the likelihood of different outcomes, identify thresholds they are comfortable with, to make more risk-aware decisions.

7.4 Managing risk

From a corporate governance perspective, probabilistic estimates enable internal teams to assess financial exposure, run scenario analyses, and plan capital allocation more efficiently. They also allow companies to communicate risk transparently to regulators, auditors, and investors. Over time, as more site-specific data becomes available, these models can be refined, allowing for dynamic adjustments that reflect reduced uncertainty. In this way, probabilistic methods help build closure cost estimates that are not just accurate but also strategic and adaptable.

8 Discussion

8.1 Implications for financial provisioning

The proposed probabilistic framework significantly advances the accountability and transparency of mine closure cost estimation. Traditional approaches often rely on fixed, deterministic inputs, such as standard quantities, unit rates, and contingencies, combined with broad assumptions. These methods frequently result in overestimation or underestimation of financial provisions, limiting their reliability. In contrast, the proposed framework adopts a more flexible and holistic methodology. Instead of producing a single-point estimate, it generates a distribution of potential closure costs, offering a more realistic and nuanced representation of uncertainty.

Uncertainty presents a critical challenge in mine closure costing, particularly regarding rehabilitation requirements, material volumes, contractor rates, and long-term environmental liabilities. Conventional approaches typically address these uncertainties by applying blanket contingency percentages; however, these often lack a robust rationale and fail to account for all-encompassing risks. The proposed probabilistic framework addresses uncertainty at its source by defining multiple scenarios for each closure action or component, assigning probabilistic distribution, typically in the form of minimum and maximum values for both quantities and rates. It also incorporates allowances for “unknown-unknowns”. The framework captures the full range of possible outcomes by running thousands of iterations through the Monte Carlo simulation.

Monte Carlo simulation facilitates a risk-based evaluation of closure liabilities, allowing stakeholders to align financial provisioning with their risk appetite. For instance, budgeting at the lower end of the resulting cost distribution implies a higher likelihood of underfunding, whereas selecting a more conservative percentile reduces financial risk but requires a larger upfront allocation. This flexibility enables a more strategic and evidence-based approach to financial provisioning, moving beyond the limitations of standardised deterministic methods.

8.2 A shift from traditional approaches

The probabilistic framework challenges this rigidity by introducing cost distributions in place of fixed averages. Instead of assuming that a particular rehabilitation activity will always cost a specific amount per hectare or cubic metre, it accounts for a range of potential rates. These rates can vary significantly based upon contractor availability, market fluctuations, site accessibility, and other site-specific factors.

Another major benefit of the proposed approach includes the measurement of quantities. Traditional methods often rely on direct site measurements or engineering reports, which can be time-consuming and expensive. The proposed framework leverages remote sensing, machine learning, and GIS-based analysis to automate the detection of mining features using satellite imagery and cloud computing. This makes the process more scalable, efficient, and capable of independent verification, an advantage for both regulators and external reviewers.

8.3 Practical and regulatory considerations

As mine closure regulations tighten, there is increasing pressure on mining companies to provide more accurate and defensible financial provisions. In South Africa, for example, GNR 1147 requires closure cost estimates to be scientifically defensible, underpinned by specialist inputs and site-specific assessments. Similarly, international regulatory frameworks are moving toward more transparent and risk-based financial assurance models.

The probabilistic framework is well aligned with these evolving requirements. It provides a structured, repeatable, and auditable method for estimating closure costs that explicitly addresses risk. For mining companies, this means they can present closure liabilities based on a clear rationale and grounded in site-specific evidence, rather than relying on standardised assumptions or fixed contingencies. This enhances internal financial planning and fosters greater confidence among investors and regulators.

The framework provides regulators with a means to assess whether provisions are realistic and robust. By capturing a full range of potential costs and documenting the basis for each assumption, the framework helps reduce the risk of underfunding. In doing so, it prevents environmental liabilities from being transferred to the state.

8.4 Limitations and future work

While this framework significantly improves cost estimation, it is not without its challenges. First, the accuracy of the output depends on the quality of the input data. If the available data on closure quantities, contractor rates, or rehabilitation methods is limited or outdated, the cost distribution may not fully reflect actual conditions. To help manage this, the framework includes an additional factor for “unknown-unknowns”. Still, having access to reliable, up-to-date baseline data remains crucial for maximising the approach’s effectiveness. Equally important is the governance of this data, which would include access to proprietary rate databases, transparency in source documentation, and quality control measures to ensure that the inputs used are valid, traceable, and fit for purpose.

Second, Monte Carlo simulations need some processing power and technical skill. Cloud tools help, but simpler, user-friendly software could make these methods more accessible to a broader range of users, including regulators.

Pilot testing of the framework in real-world scenarios could also help validate its effectiveness and guide future improvements. These efforts would support broader adoption and ensure that the approach continues to meet both technical demands and regulatory expectations.

9 Conclusion

The probabilistic framework for estimating mine closure costs represents a step forward from traditional deterministic methods. Integrating uncertainty analysis, geospatial data, and Monte Carlo simulations delivers a more transparent, realistic, and defensible assessment of financial liability. Unlike conventional approaches that rely on fixed unit rates and general contingencies, this framework generates a data-driven distribution of potential closure costs, capturing both known uncertainties and allowances for "unknown-unknowns".

Through action/component scenario analysis and the incorporation of variable quantities and fluctuating unit rates, the framework enables more flexible, risk-informed decision-making. Stakeholders can determine provisioning levels based on their specific risk tolerance. The use of GEE, computer vision, and machine learning adds further value by automating closure quantity estimation, minimising the need for costly and time-intensive site visits.

This approach also has important regulatory and practical implications. It aligns with evolving mine closure requirements, such as South Africa's GNR 1147, and supports international best practices that call for scientifically grounded, risk-based financial assurance. By explicitly incorporating uncertainty into closure estimates, rather than relying on arbitrary contingencies, it provides a more transparent, auditable, and defensible method for regulators, mining companies, and investors alike.

The framework's effectiveness depends on access to high-quality data and suitable computational resources. Future development should improve input data, simplify long-term environmental modelling, and create user-friendly tools to expand accessibility. Incorporating emerging post-closure risks, such as those related to climate change or shifting rehabilitation standards, will further enhance its long-term relevance.

This framework modernises the assessment of mine closure costs, bridging the gap between financial accountability and environmental responsibility. Integrating probabilistic modelling, remote sensing, and AI-driven tools helps ensure that closure liabilities are accurately estimated, not underestimated or over-provisioned. The result is a more balanced, data-driven approach that supports responsible closure planning and promotes sustainable post-mining land use.

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