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# SustMine: A Framework for Integrating Sustainable Development Dimensions into Strategic Mine Planning

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**Abstract**
Strategic mine planning involves optimizing resource extraction to achieve economic, environmental, and social objectives. However, only a few frameworks offer a unified approach that simultaneously employs systematic indicator selection and weightless trade-off evaluation. This study addresses these issues by proposing a comprehensive framework for integrating sustainability into strategic mine planning, named SustMine. SustMine introduces two key advancements: (1) a rigorous, systematic, criteria-based process for selecting site-specific sustainable development indicators (SDIs), and (2) a weightless evaluation strategy that utilizes Pareto front analysis to construct composite indices. This allows decision-makers to identify non-dominated (optimally balanced) alternatives without relying on arbitrary or subjective weighting schemes, ensuring that trade-offs among all three dimensions are optimally balanced. A case study applying SustMine to the evaluation of 20 production schedules shows that five of these are on the Pareto optimal front. This validates SustMine's utility in identifying robust and sustainable long-term strategies.

**Keywords** Mine design evaluation · Sustainability assessment · Multi-objective optimization · Hybrid case study · Indicator selection criteria · Long-term planning

## 1 Introduction

Over the past few decades, sustainable development (SD) has gained significant attention across various countries and industries. SD adopts a holistic approach that integrates economic, environmental, and social dimensions, referred to as the "triple bottom line." Decision-makers must jointly consider these dimensions to ensure a balanced and comprehensive sustainability assessment [1, 2]. Since mining is inherently finite and non-renewable, debates have long persisted on whether the industry can ever be truly sustainable [1, 3]. While mining poses environmental and social challenges, it can contribute to sustainable development through responsible resource management, efficiency improvements to mining operations, technological advancements, and adherence to environmental regulations and guidelines. Sustainable mineral development should minimize negative impacts on SD dimensions while ensuring resource availability for future generations [4].

The mining industry is crucial in securing minerals essential for advancing clean energy technologies, driving increased demand for valuable, deep, and low-grade deposits [5]. This growing demand presents significant SD challenges, affecting economic, environmental [6, 7], and social dimensions [8]. The extraction of low-grade deposits and more complex ores are associated with numerous sustainability issues, including the need for more intense grinding and updated processing technologies, resulting in larger

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volumes of tailings per unit of ore extracted [9, 10]. Additionally, as society becomes more aware of the environmental and social impacts of mining, companies are increasingly pressured to adopt sustainable strategies to maintain their social license to operate [11]. Therefore, the emphasis on integrating SD dimensions into the decision-making process is a crucial topic. As Douglas Yearly [1] noted, achieving sustainable mining requires integrated approaches to decision-making that not only fulfill obligations to shareholders, but also strike a balance supported by science, as well as social, environmental, and economic analysis. Among all stages of mining life cycles, strategic mine planning stands out as the phase where decisions with the most far-reaching operational impacts are made. Given these challenges, it is critical for the mining industry to integrate SD principles into strategic mine planning decisions early.

Strategic mine planning is the process of developing and executing a long-term strategy for a mining operation to optimize its value, sustainability, and profitability. It entails incorporating technical, economic, environmental, and social factors into a flexible and comprehensive plan that accounts for the uncertainties and risks associated with mining [12]. Despite growing awareness of sustainability in mining, evidence of its integration in feasibility studies and strategic planning remains scarce. Current standard practices for resource evaluation, feasibility studies, planning, and mine design have not effectively integrated SD dimensions. Mining companies make decisions on mine planning and design predominantly based on economic analysis and considerations. This gap arises for several reasons: (1) sustainability considerations are often introduced at later stages, after critical decisions impacting social and environmental factors have already been made, and (2) sustainability efforts primarily focus on mitigating impacts and implementing control measures rather than being embedded in the initial mine design and operational planning phases [13]. Therefore, a new, practical framework is needed, designed to overcome the shortcomings of previous attempts of integrating SD in strategic mining planning, thus providing decision-makers (DMs) with a valuable tool to assess their alternatives in this stage of the planning activity.

In this work, we propose a practical sustainability assessment framework that is designed to integrate all dimensions of SD into the strategic mine planning stage. The authors name the framework "SustMine," which stands for sustainable mine planning. SustMine supports DMs in selecting site and stage specific indicators. Establishing a robust set of sustainable development indicators (SDIs) is essential to ensure that sustainability assessments accurately capture the issues most relevant to stakeholders throughout the decision-making process [14]. SustMine constructs composite sustainability indices to evaluate long-term planning activities, including production schedules, cut-off grades (COG), and ultimate pit limits (UPL). The framework uses Pareto front mathematical optimization to balance trade-offs among SD dimensions. Its primary contribution addresses an important gap in the literature, which is the lack of a clear method to select relevant SDIs for integrating sustainability into strategic mine planning.

## 2 Literature Review

This literature review is structured around two objectives: (1) it examines previous efforts to integrate SD into strategic mine planning, identifying existing shortcomings and challenges; and (2) it investigates how the previous work selected SDIs. This second objective is necessary for defining the research gap and guiding the creation of a more robust, transparent framework for selecting relevant SDIs during strategic mine planning.

### 2.1 Prior Work on Integrating Sustainable Development in Strategic Mine Planning

Efforts to incorporate SD across the mining life cycle (MLC) have emphasized the mine design and planning stage due to its long-term and significant implications for economic, environmental, and social outcomes [3]. Despite these efforts with some visible progress in this field, only a limited number of studies holistically consider all three SD dimensions simultaneously; the majority focus on integrating only one or two [3, 15]. Although addressing a single dimension can provide significant results, SD requires a holistic approach for meaningful integration into planning decisions. Existing efforts in mine design and planning primarily target three key activities: production planning, determining ultimate pit limits, and cut-off grade optimization [3]. Tables 1, 2, and 3 summarize major studies within each activity based on case study, method, SD dimension addressed, and selection of SDIs.

Researchers have proposed various methods and approaches to incorporate SD dimensions into these activities, primarily focusing on incorporating the environmental dimension in the optimization process. Most of these efforts includes environmental costs such as reclamation/rehabilitation costs, or sustainability goals in optimization models [16–20]. These studies limit integration to one or a few environmental impacts, such as tailings management, reclamation cost, or acid mine drainage (AMD). Despite addressing some critical environmental impacts, researchers developed most of these attempts from an economic point of view, with the maximization of economic value (e.g., net present value i.e. NPV) being the main objective. For example, Burgher et

**Table 1** Summary of major studies on integrating SD in production planning

| Reference | Case study | Method | SD Focus | Selection of SD indicators |
|---|---|---|---|---|
| Burgher et al. (1984) [16], | Coal mine production schedules | Linear programming (LP) | • Economic<br>• Environmental (reclamation cost) | None |
| Caccetta et al. (2001) [17], | Conceptual | Mixed integer linear programming (MILP) | • Environmental | None |
| Ersan et al. (2003) [7], | Conceptual | Theoretical study | • Environmental (Acid Mine Drainage) | None |
| Roumpos et al. (2013), [30] | Mavropigi surface lignite mine | Conceptual framework | • Economic<br>• Environmental<br>• Social | None |
| Badiozamani et al. n.d [18]. | Real dataset of oil sands surface mine | Mixed integer linear programming (MILP) | • Economic<br>• Environmental<br>(reclamation costs, tailings, and NPV) | None |
| Awuah-Offei et al. (2021) [31], | Production planning of a gold deposit | Decision-based design integrated with discrete choice analysis | • Social | None |
| Kamrani et al. (2025) [32], | Iron ore deposit case study | Mixed integer linear programming (MILP) | • Economic<br>• Environmental | None |
| Xu et al. (2018) [33], | Iron ore open pit mine, China | Dynamic programming (DP) approach | • Environmental (carbon emission cost, and damaged land) | None |

**Table 2** Summary of major studies on integrating SD in ultimate pit limit

| Reference | Case study | Method | SD Focus | Selection of SD indicators |
|---|---|---|---|---|
| Odell (2004) [34], | A hypothetical mining project based on actual porphyry copper deposit | Multi-Criteria Decision Making (MCDM) | • Economic<br>• Environmental<br>• Social | Framework-guided |
| Muñoz et al. (2014) [13], | A hypothetical block model based on a real porphyry copper deposit | Include environmental and social attributes into the block model | • Environmental<br>• Social | Literature review and expert input |
| Moradi et al. (2015) [35], | A conceptual open pit mine design | Combining Preference Voting System (PVS) and Data Envelopment Analysis (DEA) | • Economic<br>• Environmental<br>• Social | Literature review and expert input |
| Adibi et al. (2015) [36], | Jalalabad iron ore, Iran | A hierarchical aggregation method | • Economic<br>• Environmental<br>• Social | Sources: literature and Global Reporting Initiative (GRI)<br>Criteria: quantitative and measurable indicators |
| Rahmanpour et al. (2017) [37], | Sungun copper mine, Iran | A Decision-Support System (DSS) | • Economic<br>• Environmental<br>• Social | None |
| Xu et al. (2024) [20], | Heishan open pit coal mine | Floating Cone-based UPL optimization | • Economic<br>• Environmental (ecological values loss) | None |
| XU et al. (2021) [38], | Open pit metal mine in China | Incorporating costs into pit limit optimization | • Economic<br>• Environmental<br>• Social | Pre-defined set of indicators |

al. (1984) [16], incorporated reclamation costs and interest rates into the optimization of coal mine production schedules using linear programming (LP). Their aim was to demonstrate the effectiveness of LP as a method to incorporate a legal obligation such as reclamation costs into production planning to maximize NPV. Despite the economic consideration of these environmental efforts in the most of studies, one clear observation is the interchangeable use of SD and environmental considerations.

Consequently, multi-criteria decision making (MCDM) presents a powerful tool to solve problems that involve multiple sustainability criteria [21, 22]. Researchers have applied MCDM to a wide range of applications across various disciplines, including forest management and planning

**Table 3** Summary of major studies on integrating SD into cut-off grades

| Reference | Case study | Method | SD Focus | Selection of SD indicators |
|---|---|---|---|---|
| Gholamnejad (2008) [19], | A hypothetical example | Lane Algorithm | • Economic<br>• Environmental (rehabilitation cost) | None |
| Rashidinejad et al. (2008) [39], | A hypothetical copper deposit | Lane Algorithm | • Environmental (Acid Mine Drainage) | None |
| Osanloo et al. (2008) [40], | A hypothetical copper deposit | Lane Algorithm | • Environmental | None |
| Narrei et al. (2015) [41], | Gol-Gohar iron mine, Iran | Lane Algorithm | • Economic<br>• Environmental | None |
| Rahimi et al. (2015) [42], | Sungun copper mine, Iran | Linear Programming (LR) | • Economic<br>• Environmental<br>• Social | None |

[23], sustainable bridge design [24], bioenergy systems [25], construction [26], and infrastructure management [27]. The multi-dimensional nature of SD requires a tool that can analyze and evaluate alternatives subjected to a set of criteria. Multi attribute decision making (MADM) is one basic branch of MCDM that focuses on selecting from a limited set of predefined alternatives, evaluating each based on multiple criteria. The process entails sorting and ranking alternatives using their attributes and inputs available in various literature and expert reports [21, 28]. Previous studies that proposed a MCDM approach have encountered challenges related to assigning subjective weights. Subjective weighting reflects the opinion of an individual or a group, such as experts or stakeholders. These weights often lack transparency and may differ widely depending on who assigns them. Even objective weighting methods (e.g., based on statistical variation or entropy) can embed implicit assumptions or depend heavily on the dataset's properties [29]. This inherent subjectivity fundamentally compromises the scientific rigor and objectivity required for the evaluation of long-term strategic planning alternatives.

Studies that utilize MCDM approach require a careful assigning of weights, a process that demands significant time and often introduces ambiguity in expert judgment [34–37, 43]. Additionally, these studies have integrated SD dimensions by aiming to promote a single "best" alternative. However, during the early stages of mine planning, the focus should be on integrating SD to evaluate the performance of all generated alternatives. While ranking alternatives is acceptable, the intent, in these referenced studies, appears to be selecting an optimal solution. This approach may overlook the broader value of examining and observing across multiple alternatives, which is crucial for informed and balanced decision-making in sustainability assessments. We are in favor of the approach of evaluating the sustainability performance of generated planning alternatives, given the limited quality and high uncertainty of data typically available during the early stages of mine planning.

In other disciplines, researchers have used Pareto-based evaluation to assess SD dimensions of various systems [29]. Recently, some have applied this to evaluating mining SD dimensions [44]. We build on such work to advance a Pareto-based multi-criteria optimization framework integrating SD dimensions into strategic mine planning.

## 2.2 Selection Criteria for Sustainable Development Indicators

Every mining project is characterized by a unique combination of factors, including the mineral deposit, the size and scale of mining operations, the mining method, the site's topography, the regulatory jurisdiction within which it operates, etc. These factors, in turn, define the sustainability issues and the severity of their associated current or future impacts that arise with developing the project [41]. Consequently, this uniqueness in terms of the mining site and mining operations must be reflected in the final set of SDIs selected for the sustainability assessments of mine design and planning alternatives. Therefore, there is a need for a systematic and transparent approach to selecting SDIs that do not bias or predetermine the outcomes of the decision-making process.

Indicator selection is an important component of a comprehensive sustainability assessment in mining, but it presents a significant challenge for both researchers and practitioners. Determining what aspects to measure, which indicators to use, and what the right metrics are crucial for accurately assessing SD [45]. It is evident from the literature summarized in Tables 1 and 2, and 3 that only a few studies, particularly those integrating all three dimensions of SD, have defined a set of SDIs prior to applying their proposed methods. Furthermore, most of the literature on SDIs focuses on the development of a comprehensive set of indicators rather than the process of selection [14]. The key question is: which SDIs best describe the specific mine site? This is where selection criteria play a major role, serving as a filter to ensure that selected SDIs are tailored to the specifics of the mine-site and the strategic level of planning.

The selection criteria for SDIs rarely appear explicitly in mining-related studies. In most cases, “relevance” to the mining method or planning activity is the only selection criterion. To the best of our knowledge, Poveda [45] provided one of the very few explicit examples of the relevance criterion applied in a mining context. Although this study presents a unique approach for selecting SDIs for surface mining in oil sands projects, the methodology remains a pre-selection process rather than a fully developed selection framework. Poveda structured six potential sources for SDI identification into three groups: consensus-based indicators, academically or practitioner-derived indicators, and organization-established indicators. Through a comprehensive review, Poveda compiled a preliminary list of indicators from these sources and assessed each indicator for its relevance to surface mining and classified it by its origins. To reflect the breadth of consensus, indicators received one point for each source in which they appeared, with a maximum of six if present in all. In the literature, the terms “relevance” and “applicability” often function interchangeably when evaluating indicators for mining contexts.

Munoz et al. (2014) [13], selected indicators that are relevant to the Chilean mining context, namely energy consumption, GHG emissions, freshwater consumption, AMD generation, and direct employment generation. Moradi et al. (2015) [35], relied solely on the literature review and experts’ opinions to select SDIs. However, they implicitly applied a criterion for selecting an indicator set that is relevant to open pit mine design. Studies by Adibi et al. (2015) [36, 43] selected indicators based on literature and GRI. These studies identified several criteria for the selection of indicators in their approach, such as maintaining a limited number of indicators, considering only those that are quantitative and measurable, and excluding those that yield identical values across all generated UPLs. These examples confirm that existing selection criteria are sparse, often implicit, and lack the comprehensive structure needed for site-specific, rigorous SDI development.

A major takeaway of the literature review, particular in reference to strategic mine planning, is that existing prioritization efforts often focus on ranking alternatives based on a predefined set of SDIs. However, SustMine proposes a rigorous approach for identifying and prioritizing the sustainability issues (i.e., material topics, meaning the key issues that represent the most significant impacts on the triple bottom line) that are most relevant to the specific mining site. These material topics should guide the selection of indicators to ensure that the evaluation framework reflects genuine sustainability concerns.

Furthermore, this study challenges the conventional notion that integrating SD should yield a single ‘optimal’ solution. Given the nature of the data available at the early stages of mine planning, researchers should not treat sustainability as an optimization problem with one definitive answer. Rather, it should provide a structured framework to evaluate and understand the performance of multiple generated alternatives. Consequently, this study aims at proposing a framework that assists decision-makers by delivering a relevant sustainability assessment, thereby facilitating a more balanced and transparent decision-making process.

## 3 A Weightless Framework for Sustainable Strategic Mine Planning

SustMine consists of two interconnected sub-frameworks: indicator selection and Pareto front-based evaluation. While each sub-framework can operate independently, comprehensive sustainability assessment requires their integration. The indicator selection sub-framework identifies relevant indicators for each SD dimension. These indicators should reflect the key sustainability issues of a given mine project while remaining applicable to the strategic mine planning stage and its associated activities. The Pareto sub-framework then evaluates the sustainability of mine planning alternatives by constructing a composite index structure that uses the order of Pareto fronts as a weightless strategy. Together, these components serve SustMine’s overarching objective of integrating SD dimensions simultaneously into strategic mine planning without assigning explicit weights to indicators, while ensuring that the relevance of each indicator to the specific site and planning activity is respected. Figure 1 shows the schematic flowchart of SustMine and its key steps. While the framework identifies optimal (most sustainable) solutions, its primary aim is to enable DMs to better understand the sustainability performance and trade-offs of all generated planning alternatives.

The first step in the proposed framework is to identify the type of planning activity being evaluated. The initial step is necessary because evaluation criteria differ according to the factors associated with each activity. For example, time serves as a critical factor when evaluating production schedules, but it is irrelevant when assessing COGs. As a result, indicators that rely on time as an input for measurement would not be suitable when assessing COGs. This distinction emphasizes the need for activity-specific evaluations to ensure that the selected indicators are applicable. The next step involves identifying sustainability issues that are relevant to the mining site. Once these issues are defined, we prepare indicator sources by gathering potential

SDIs from various sources such as GRI standards, literature, expert consultations, or site-specific reports. We then evaluate these indicators against predefined selection criteria to assess their applicability, relevance, measurability, data availability, and quality. If an indicator does not meet the criteria, the process loops back to refine the selection, otherwise, we store accepted indicators for the Pareto front sub-framework.

After selecting indicators, the Pareto front sub-framework begins with the generation of mine planning alternatives, creating different scenarios such as variations in UPL, production schedules, and COGs. For each alternative, we calculate the values of selected indicators. We then rank these alternatives using Pareto ranks (Composite indices), applying a multi-objective optimization method to evaluate trade-offs between different sustainability dimensions. The final step, selection of optimal alternatives, identify the best-performing scenarios. Alternatives on the first Pareto front (composite index of 1) represent the most sustainable options. This structured approach ensures that SD dimensions are systematically integrated into strategic mine planning, supporting DMs in selecting mine designs that balance economic, environmental, and social objectives effectively. Additionally, constructing a composite index structure provides the DM the ability to view not only the overall sustainability performance of all generated alternatives, but also the performance for each SD dimension individually. The following subsections will provide necessary discussion in more detail for each step in Fig. 1.

### 3.1 Selection of Sustainable Development Indicators (SDIs)

Section 2 demonstrated that most prior research focuses on evaluation methods used for assessing planning alternatives, with comparatively little attention given to the

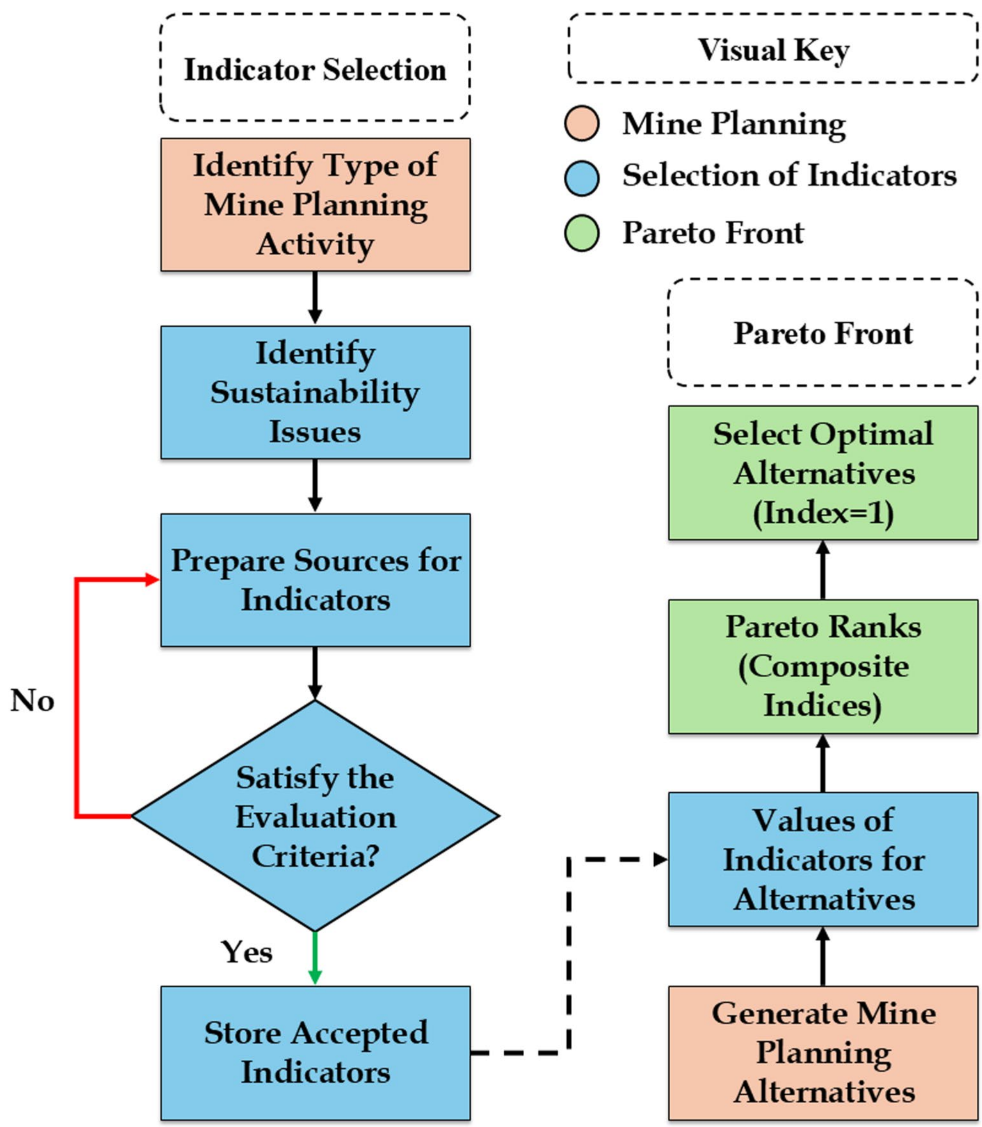


**Fig. 1** SustMine schematic flowchart

selection and evaluation of sustainability indicators applied in the proposed case studies. Consequently, this has resulted in selecting biased, random, and sometimes limited sets of indicators to fit their context without a solid scientific foundation or a clearly defined selection process. On the other hand, mining companies typically report on sustainability in a standalone report using the GRI standard, which has its own limitations when applied to the mining context [14]. Therefore, we present a framework for the systematic and transparent evaluation and selection of SDIs, designed to be adaptable to different mining sites and suitable for strategic mine planning activities, unlike previous approaches, which constrained their works to specific case studies and activities.

The selection sub-framework, illustrated in Fig. 2, adapts the approach in Gebara et al. (2024) [46],. In that study, the authors proposed a structured approach for selecting sustainability indicators for measuring progress toward sustainable development goals (SDGs). They conducted a systematic review to define selection criteria, and they ended with defining a comprehensive list of 12 criteria for single indicators and 6 for developed set of indicators. They structured the framework around three steps: (1) pre-steps for identifying potential indicators, (2) evaluating or selecting indicators, and (3) reporting of the resulting indicator set. Step 2 is the core of their framework, and it was based on the findings from the literature review. It includes identifying and categorizing indicator selection criteria.

In our implementation, we adopted Variant 2 in [46] with some modifications. We selected this variant because it provides a more detailed and interactive process, allowing users to actively participate in evaluating and selecting a new set of SDIs. Since we implemented this in the mining sector and at a specific stage of planning, it required us to pay more attention to the preliminary steps taken prior to the evaluation criteria. SustMine begins by identifying the specific type of mine planning activity under evaluation (e.g., UPL, COGs, or production scheduling). We aim to

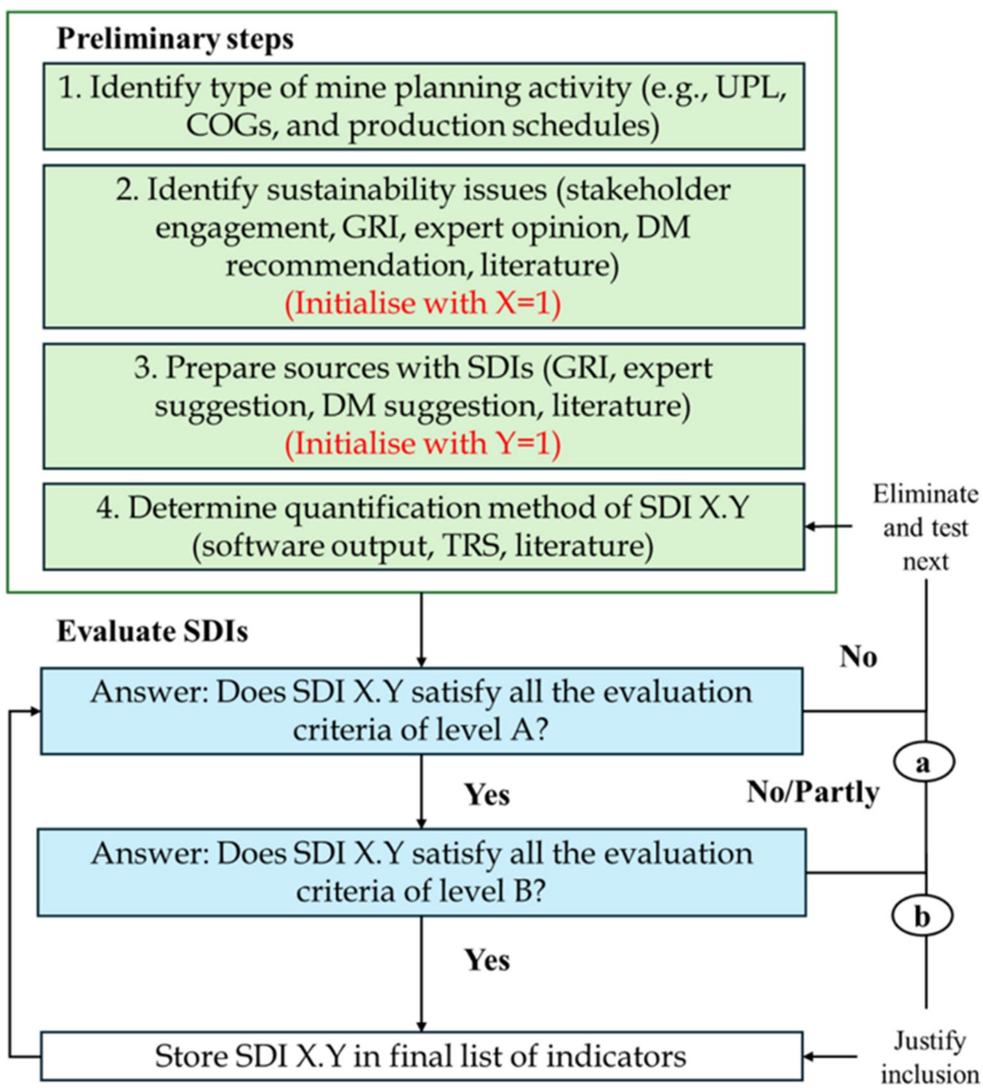


**Fig. 2** SDI selection sub-framework, showing steps from identifying mine planning activity to evaluating and storing accepted SDIs. The small circles labeled 'a' and 'b' represent alternative courses of action for indicators that fail to fully meet the Level B criteria. The 'a' option refers to the possibility of eliminating an individual indicator and test next. The 'b' option allows the assessment to proceed even if the indicator does not fulfill or partially fulfills the Level B requirements. Image reproduced with permission from ref [46]. Copyright 2024. CC BY 4.0 (http://creativecommons.org/licenses/by/4.0). Elsevier

help DMs to clearly understand the activity under assessment and its components, as this understanding is necessary to address specific evaluation questions when applying the evaluation criteria. Once we identify the planning activity, the next step is to identify the sustainability issues related to the mining project (i.e., mining-site) under evaluation. This process, illustrated in Fig. 3, is similar to the GRI process of determining material topics, except for the last two steps, as we are not concerned with assessing significance or prioritizing issues for reporting. We are interested in all actual and potential impacts of the mining site. The process starts with understanding the project's context, including its geology, mining method, processing methods, location, and operational constraints. A comprehensive understanding of these aspects allows DMs to anticipate potential impacts of the long-term planning activity across SD dimensions. Furthermore, users can utilize tools to understand the context such as engaging with stakeholders (e.g., local community), obtaining experts' opinions (e.g., qualified person), and using GRI and literature for a better understanding of the mining project. After defining the sustainability issues, the user can assign the first issue to X = 1, where X = 1: n represents the total number of identified issues. This approach of identifying sustainability issues strengthens the credibility and practicality of the sustainability assessment by grounding it in site-specific conditions and informed stakeholder perspectives.

Potential indicators are then compiled from sources such as international reporting standards (e.g., GRI, SASB, SDGs), regulatory requirements, expert consultations, and peer-reviewed literature, as summarized in Table 4. We assign each SDI a value of Y, where Y = 1: h represents the total number of indicators. This yields a unique identifier in the format SDI X.Y, where a single sustainability issue may have one or more indicators linked to it. For example, we can represent the first sustainability issue (X = 1) by SDI 1.1 and SDI 1.2, and so forth. After collecting all SDIs from different sources and prior to applying the evaluation criteria, we define a quantification method for each indicator to specify how we determine it and what data sources it requires. This step clarifies whether we can quantify the indicator using internal model outputs (e.g., Whittle) or the indicator requires external inputs, enabling an informed assessment of its measurability, data availability, and quality. It is also important to note that we use the first three evaluation criteria to assess the indicators themselves, whereas we use the last two criteria; Data Availability and Data Quality, evaluate the data to quantify the selected indicators. These two criteria, together with Measurability, require the determination of the quantification method in advance. Therefore, we consider it a good practice to define the quantification method before conducting the evaluation criteria check.

As we discussed in Sect. 2, previous attempts have failed to establish a systematic approach for selecting SDIs.

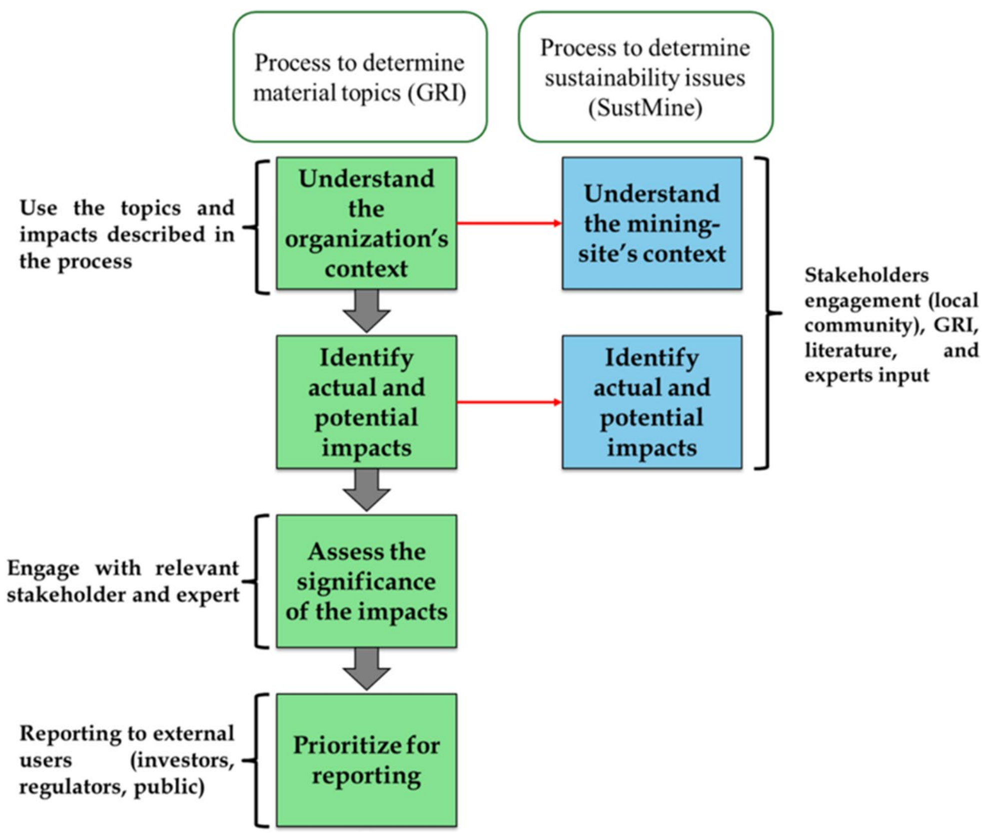


**Fig. 3** Comparison between the GRI process for determining material topics and the SustMine process for determining sustainability issues

**Table 4** Sources for identifying candidate sustainable development indicators (SDIs) for strategic mine planning

| Source Category | Examples |
|---|---|
| Regulatory and Governmental Standards | • Government regulations and policies<br>• Environmental protection laws<br>• Health and safety guidelines |
| International Reporting Standards | • Global Reporting Initiative (GRI)<br>• Sustainability Accounting Standards Board (SASB)<br>• International Council on Mining and Metals (ICMM)<br>• United Nations Sustainable Development Goals (SDGs) |
| Experts Consultations, Academic and Scientific Literature | • Input from experts<br>• Peer-reviewed journal articles<br>• Conference proceedings<br>• Research reports on sustainable mining |
| DM Suggestion | • Developing indicators by DMs |

Therefore, the SustMine framework introduces five evaluation and selection criteria: applicability, mine-site relevance, measurability, data availability, and data quality, as we summarized in Table 5. We selected the evaluation criteria based on observations from the literature on integrating SD into long-term mine planning, the nature of strategic mine planning stage, and the characteristics Pareto front-based evaluation method acquires. The Pareto front strategy offers advantages such as its ability to handle different types of indicators, its applicability to correlated indicators, and its capacity to manage a large number of indicators without computational limitations. The need to balance conceptual soundness with practical applicability guides the selection of these five criteria in the early stages of strategic mine planning, where uncertainty and data limitations are inherent. Because of this, we adopted the two levels proposed by [46] in categorizing the evaluation criteria. Each SDI must satisfy level A criteria so that we can consider in the final list of indicators. We can exclude the indicators that fail to meet any level A criterion from further consideration, as they lack essential applicability, relevance, or measurability.

Level A criteria are designed as a strict filter to ensure that only indicators that are applicable, site-relevant, and measurable enter the Pareto evaluation. If most or all candidate indicators for a given sustainability issue fail level A, this outcome should be treated as information. It signals a conceptual or data gap that warrants further investigation. In such cases, SustMine encourages users to redefine the issue to ensure it is sufficiently specific and scoped to the planning activity under evaluation, search for alternative or proxy indicators from additional sources, and explicitly document that the issue is recognized as material but cannot yet be robustly quantified. When no suitable indicator can be identified after exhausting available sources, the issue is handled in two ways: it is excluded from the numerical Pareto analysis to preserve methodological rigor and avoid introducing non-measurable noise, but it is retained in a qualitative decision narrative so that DMs remain aware of its importance and can treat it as a topic for future data collection.

Level B criteria acknowledge what we mentioned earlier about the inherent uncertainty of the early planning stage,

**Table 5** Selection criteria for sustainable development indicators (SDIs) in SustMine

| Criterion | Description | Evaluation Checks | Level |
|---|---|---|---|
| 1. Applicability | The indicator must be obtainable and applicable for the specific strategic mine planning activity (e.g., UPL, COG, production scheduling). | Yes: Indicator can be obtained for this specific type of activity.<br>No: If cannot be obtained; therefore, not applicable. | A |
| 2. Mine-Site Relevance | The indicator is relevant to the identified sustainability issue. | Yes: Indicator is relevant to the sustainability issue.<br>No: If not relevant or generic (overly broad). | A |
| 3. Measurability | The indicator must be measurable quantitatively or qualitatively. | Yes: Can be measured directly or via proxy using numerical, categorical, or binary scale.<br>No: If not measurable. | A |
| 4. Data Availability | Indicator data should be accessible or realistically obtainable during the strategic planning stage. | Yes: Data can be sourced from feasibility studies, technical report summaries, or historical records.<br>No: If data is not available.<br>Partly: Only some of the required data is available, or data must be estimated or assumed. | B |
| 5. Data Quality | The indicator should be based on data that is reliable, accurate, and consistent across different sources and timeframes to ensure meaningful assessment. | Yes: the data comes from a reliable/accurate/consistent source.<br>No: If the source is not reliable.<br>Partly: The data source is generally reliable but may lack full consistency, completeness, or transparency. | B |

where data may be limited or incomplete. Indicators failing to meet level B criteria have three options: if the evaluation check is ‘Yes’, the indicator proceeds to the next step. If the answer is ‘No’ or ‘Partly’, the decision to include the indicator depends on the user’s confidence in the data. In such cases, the user must provide a clear justification for inclusion, documenting the assumptions made, the nature of the data limitations, and any plans for future data improvement or verification.

Applicability and mine-site relevance ensure that indicators are context-specific and within the scope of our assessment. Measurability guarantees that we can quantify each indicator or assess them qualitatively, supporting repeatability of results. Finally, data availability and data quality acknowledge the practical constraints inherent in early-stage evaluations, ensuring that SustMine remains operational even when complete datasets are not yet available, while still promoting continual improvement in data confidence over time. This framework sequentially processes each sustainability issue, beginning with (X = 1), then the next issue (X = 1 + 1), and continuing in the same manner. Within each X, the framework also iterates through the corresponding indicators, starting with SDI X.1 (Y = 1), followed by SDI X.2 (Y = 1 + 1), and so forth.

### 3.2 Pareto Front-Based Approach: A Weightless Strategy

The second sub-framework of SustMine evaluates the sustainability performance of mine planning alternatives using a weightless Pareto front-based approach [29]. In Sect. 2, we identified several limitations associated with ranking alternatives when design objectives compete. For example, many methods rely on subjective weighting schemes that are based on expert judgment and stakeholder preferences. While these methods provide some structure, they suffer from ambiguity and potential bias, as the relative importance of SDIs may differ depending on who assigns the weights or what dataset is used. Even objective weighting techniques (i.e., statistic-based), such as entropy weight coefficient, have the potential to assign misleading weights as they depend on indicator values to determine them [29].

To overcome these challenges, we adopted a weightless strategy for constructing a composite sustainability index. A composite index is a single measure that combines multiple economic, social, or political variables into an aggregated indicator, allowing for easier comparison and evaluation across contexts [29]. In other words, we use composite indices to represent indicators because they capture the multidimensional nature of sustainability while simplifying comparability, supporting decision-making, and improving communication with the public. Since technical report summaries, which present most strategic mine planning decisions, reach stakeholders who may lack the expertise to interpret raw indicator values, composite indices offer a more accessible way to compare alternatives and understand the rationale behind planning decisions. The strategy employs the concept of Pareto dominance from multi-objective optimization. The goal in multi-objective optimization is to find good compromises. We can consider a solution to a multi-objective optimization problem optimal when no other feasible solution can achieve better performance across all objectives simultaneously. We refer to the set of solutions identified as Pareto minimizers or optimizers as the Pareto front, as illustrated in Fig. 4 [47]. In our implementation, we calculate indicator values for each strategic planning alternative and evaluated through Pareto ranking. We apply the principle of Pareto dominance to identify non-dominated alternatives, which form the Pareto front, while we rank dominated alternatives based on their trade-off performance across the SD dimensions. From these rankings, we construct composite indices, allowing DMs to compare planning alternatives according to their position in the Pareto order. Following the recommendation of the authors in [29], we adopted the hierarchical implementation of this approach, ensuring that the goodness of variance fit (GVF) is maintained at 0.80. This means that we can assign to each alternative four Pareto scores, one for each SD dimension and an overall Sustainability Composite Index (SCI).

The computational cost of the SustMine Pareto analysis is governed by two components: the Jenks natural breaks discretization, with a complexity of approximately $O(n^2 \times k)$, and the Pareto front ranking algorithm, with a worst-case complexity of $O(n^2 \times m)$, where n is the number of alternatives, k is the number of break classes, and m is the number of objectives. For the composite-level analysis, m = 3, corresponding to the three SD dimension indices, which keeps the problem highly tractable at the scale of strategic mine planning problems.

## 4 Production Scheduling: A Hybrid Case Study

To demonstrate the application of the SustMine framework, we developed a hybrid case study. The hybrid nature of the study arises from the combination of technical and economic data from a real mining project with social data derived from an established academic study that the authors are familiar with. This approach was necessary because of confidentiality often constraint access to real mining project data, while social data, when available, authorities can rarely disclose in publicly and comprehensive available reports. By combining two validated sources, the hybrid

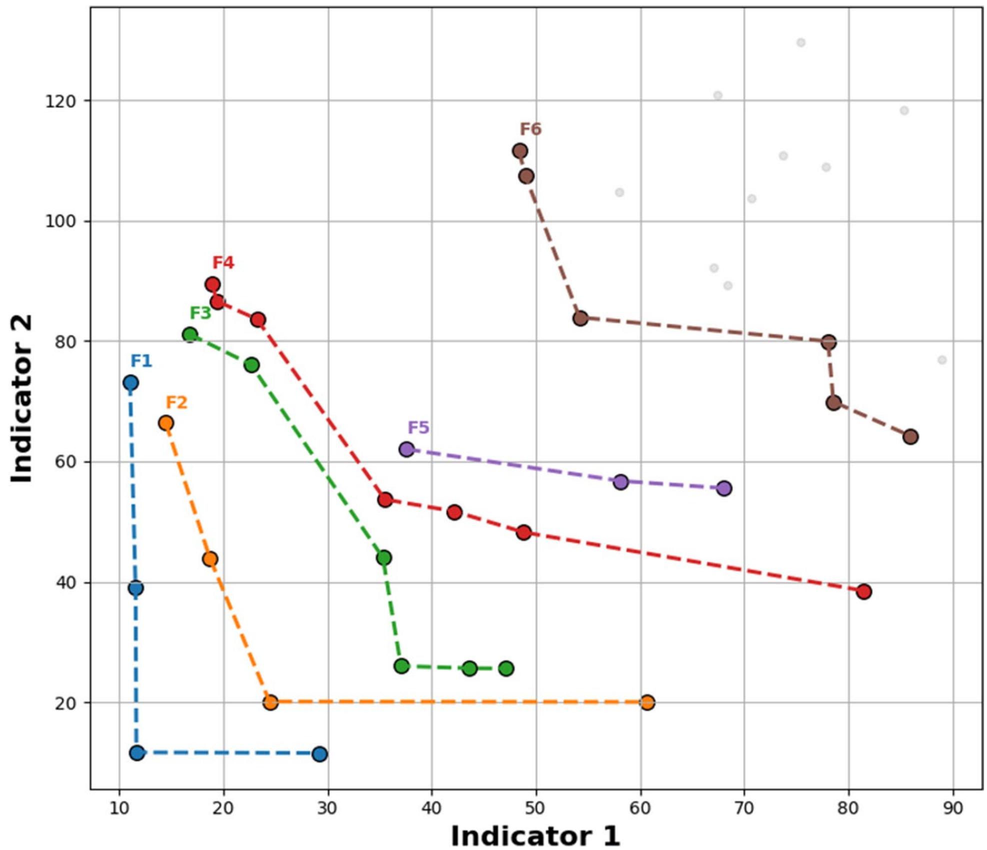


**Fig. 4** Illustration of iterative Pareto fronts for two objective functions (minimization-minimization)

case study provides a realistic and comprehensive basis for identifying sustainability issues and then selecting SDIs across economic, environmental, and social dimensions. We obtained the technical and economic parameters from the Technical Report Summary (TRS) of the real mining project. This report provides detailed information on resources, reserves, production schedules, mining methods, processing flowsheets, and cost structures. These data elements establish a credible mine model that reflects real-world operating conditions and constraints.

To complement this technical foundation, the study integrates the community acceptance framework developed in [8], which applied discrete choice experiments (DCEs) to identify determinants of local community support for a mining project in Salt Lake City, Utah, United States. We are going to adopt [8] to provide the social context of the case, including the location of the mining project and regulations of the mining sector in Utah. She classified 16 project characteristics including social, environmental, and governance aspects, and 4 demographic factors that influence community preferences. This social context is necessary for our application of the SustMine framework for two specific reasons: (1) it informs the identification of sustainability issues and the subsequent selection of SDIs, and (2) it provides project-specific contextual parameters used in calculating certain indicators. The reader should note that using a different social, regulatory, or technical context might lead to a different set of identified sustainability issues and consequently a different selection of SDIs. However, the case study only serves to illustrate the method and the reader should not put too much emphasis on the specific results from applying SustMine (which would be influenced by this disparity between the technical data and social context).

Together, these two sources create a hybrid case study as illustrated in Fig. 5, that is both technically robust and socially grounded. This approach ensures that we can test SustMine framework under conditions that reflect the practical realities of mining projects.

### 4.1 Hybrid Case Study Overview

The hybrid mine, located in Salt Lake City, Utah, represents a conceptual open pit gold operation designed to reflect the geological and operational characteristics of a sulfide deposit. We assumed the operation used a conventional truck-and-shovel method. The deposit has a north to northwestern orientation and a thickness exceeding 200 m. Figure 6 illustrates a northing cross-section of the block model. The project processes ore through heap leaching followed by a carbon-in-column (CIC) circuit for gold recovery.

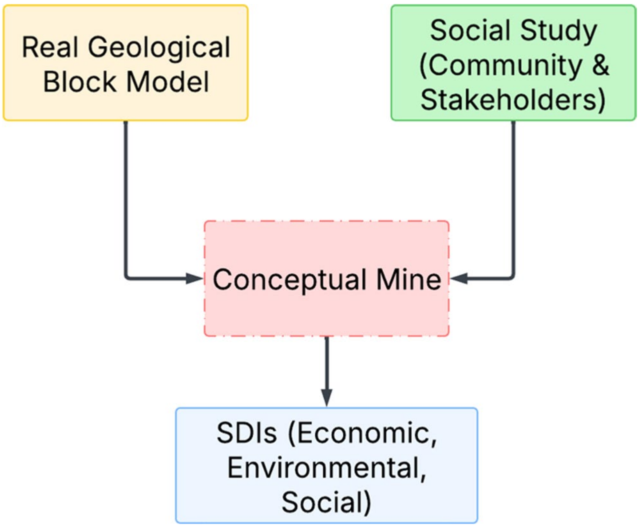


**Fig. 5** Development of a hybrid case study by integrating technical report data and social study results

## 4.2 Block Model & Design

We applied the input parameters presented in Table 6 in the strategic mine planning exercise carried out in GEOVIA Whittle to generate 20 production schedules, with the process steps shown in Fig. 7. We employed the pseudoflow algorithm [48] to generate the optimal pit outline due to its computational efficiency and robustness in solving large-scale maximum closure problems [49]. We generated the 20 production schedules in Table 7 by varying design variables such as initial capital cost, mining production rate, processing capacities etc. We varied design variables in a way that ensures the range captures the full spectrum of potential planning scenarios that we are interested in. The lower bounds represent conservative low-intensity scenarios that remain technically feasible given the deposit size and characteristics reported in the TRS, while the upper bounds represent high-intensity scenarios approaching the practical limits of the mineral deposit's volume.

In the following subsection, we are going implement SustMine to the generated production schedules to assess their sustainability performance across economic, environmental, and social dimensions.

## 4.3 SustMine Implementation

We applied SustMine and its two sub-frameworks to the hybrid case study. The implementation followed the methodological structure described in Sect. 3. In the following, we describe how we implemented each sub-framework in our hybrid case study and discussed results of the 20 production schedules. All files related to this project are available on the Github repository for this project (https://github.com/Somatalhi/SustMine-.git). The repository includes a spreadsheet for the SDIs selection, which serves as the input to the MATLAB scripts to find the composite indices for the 20 production schedules.

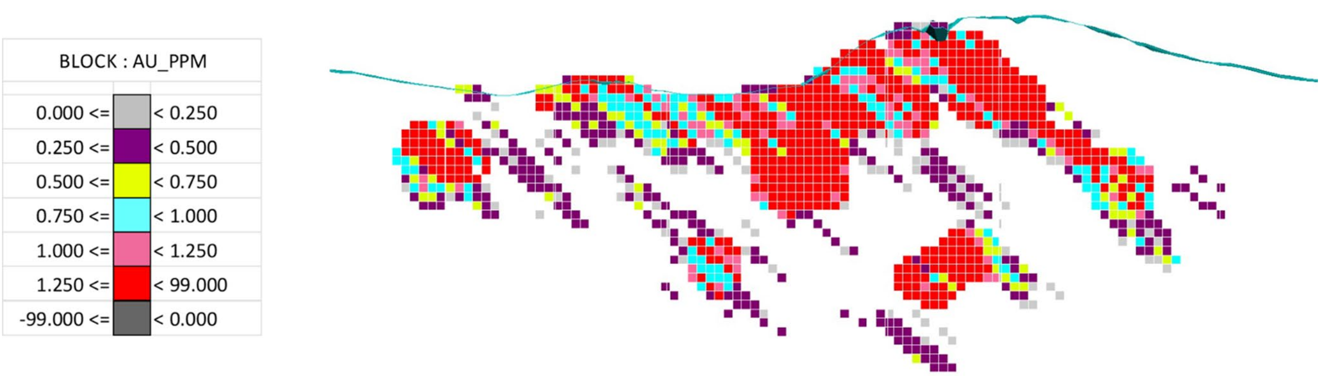


**Fig. 6** Cross-sectional view of the hybrid case study ore body (Northing)

**Table 6** Input data for mine planning and design

| Item | Input Value |
|---|---|
| Overall pit slope | $55^{\circ}$ |
| Unit mining cost | \$3.28/t |
| Unit Processing cost | \$19.25/t |
| Processing recovery | 82% |
| Gold Price | \$4000/oz. |
| Reclamation costs | \$3 million |

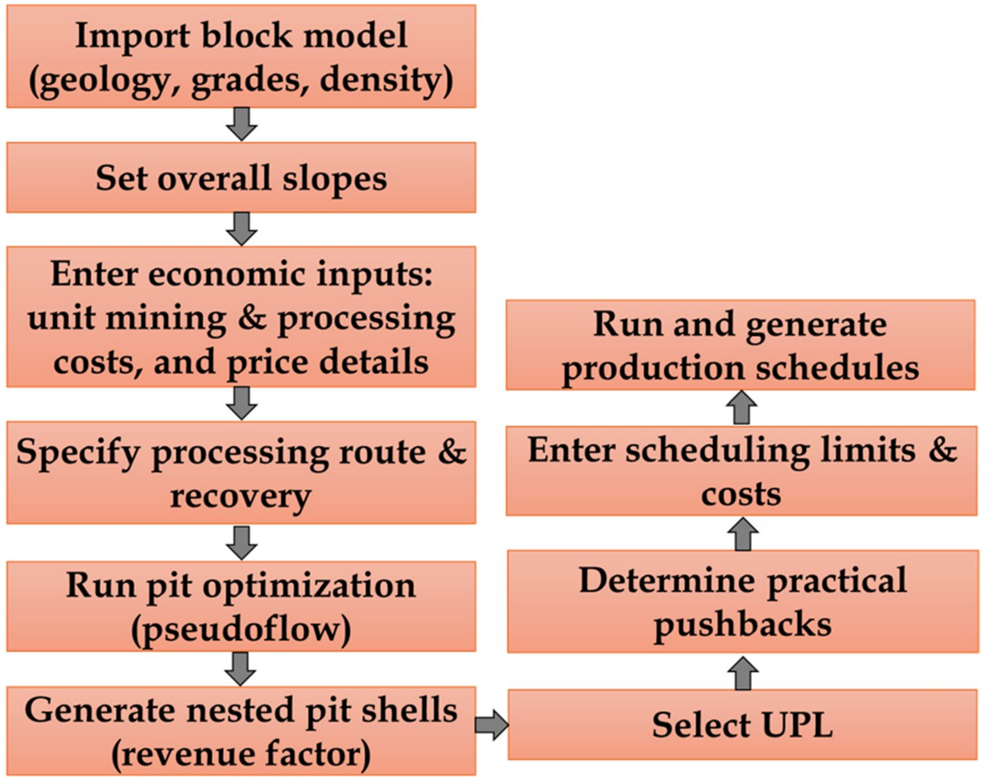


**Fig. 7** Workflow in GEOVIA Whittle for the hybrid case study

**Table 7** Hybrid case study production schedules

| Schedule ID | CAPEX ($million) | Production Rate (Million Tonnes) | Processing Throughput (Million Tonnes) | NPV ($million) | Mine Life (yrs) |
|---|---|---|---|---|---|
| Schedule_1 | 500 | 13 | 8 | 4,809 | 32 |
| Schedule_2 | 550 | 14 | 8 | 5,018 | 33 |
| Schedule_3 | 600 | 15 | 9 | 5,201 | 32 |
| Schedule_4 | 650 | 16 | 9 | 5,361 | 29 |
| Schedule_5 | 700 | 17 | 10 | 5,512 | 25 |
| Schedule_6 | 750 | 18 | 9 | 5,133 | 27 |
| Schedule_7 | 800 | 19 | 11 | 5,827 | 26 |
| Schedule_8 | 850 | 16 | 9 | 5,168 | 28 |
| Schedule_9 | 900 | 17 | 10.5 | 5,420 | 28 |
| Schedule_10 | 950 | 19 | 11.4 | 5,664 | 27 |
| Schedule_11 | 1,000 | 21 | 12.9 | 6,078 | 21 |
| Schedule_12 | 1,050 | 15 | 10 | 4,862 | 26 |
| Schedule_13 | 1,100 | 22 | 13.8 | 6,227 | 21 |
| Schedule_14 | 1,150 | 23 | 14 | 6,114 | 24 |
| Schedule_15 | 1,200 | 18 | 9 | 4,631 | 31 |
| Schedule_16 | 1,250 | 24 | 14.5 | 6,257 | 20 |
| Schedule_17 | 1,300 | 17 | 10 | 4,878 | 28 |
| Schedule_18 | 1,350 | 18 | 9 | 4,430 | 34 |
| Schedule_19 | 1,400 | 19 | 11 | 5,141 | 26 |
| Schedule_20 | 1,500 | 16 | 9.6 | 4,480 | 31 |

#### 4.3.1 SDIs Selection Sub-Framework

Selecting the right SDIs was a collaborative and thoughtful process. The evaluation began by applying the SustMine selection sub-framework, carefully considering each potential sustainability issue. Table 8 shows the 12 sustainability issues we identified for our hybrid case study. We relied on the local community engagement, general knowledge of the mining method, ore type, and other technical information (i.e., technical report summary) to identify the

**Table 8** Identified sustainability issues for the hybrid case study

| SD dimension | Sustainability issues (X = 1:12) |
|---|---|
| Economic | - Economic impacts<br>- Payments to governments |
| Environmental | - GHG emissions<br>- Energy use & efficiency<br>- Air emissions<br>- Biodiversity<br>- Waste<br>- Water and effluents<br>- Closure and rehabilitation |
| Social | - Local community<br>- Land and resource rights<br>- Occupational health and safety |

sustainability issues. According to [8], local community seems to care more about job opportunities, water shortage and pollution, air pollution, and land pollution. We used these findings to guide the identification of related sustainability issues. These include local community impacts, water and effluents, GHG emissions, air emissions, waste, closure and rehabilitation, biodiversity, and land and resource rights.

Users identified the remaining issues directly, including economic impacts, payments to governments, energy and efficiency, and occupational health. With the exception of energy use and efficiency, all identified issues are consistent with GRI material topics. However, this consistency should not constitute a requirement. As we noted earlier, users may select issues from any credible source, provided each issue falls within the scope of the mining project under consideration. For example, we did not include the issue of tailings in the hybrid case study because the project assumes the use of heap leaching as the only processing method, and heap leaching does not produce tailings.

After we identified the sustainability issues, we compiled all potential indicators associated with each issue. We drew them from literature, established reporting standards, and the unique features of our site. We documented each indicator together with its quantification method, including the parameters, assumptions, and factors required for its calculation. We reviewed each indicator for its practical fit with our goals, focusing on how well it matched five essential criteria: applicability, relevance to the mine site, measurability, data availability, and data quality. When an indicator completely failed to meet the primary requirements, it was set aside. In some cases, where an indicator only partially fulfilled the secondary criteria, it still included if its value outweighed any concerns, especially when this helped us make the most of the available data at the planning stage. The indicators that made it through this process truly reflect the key issues facing the case study. They cover economic performance, environmental impacts, and the social dynamics of the project. This careful review allowed us to remove any indicators that were redundant, vague, or difficult to measure. As a result, the set we used is both focused and defensible, providing a solid foundation for the later stages of our analysis (Table 9). By tailoring the approach to the uncertain and sometimes incomplete nature of early-stage planning data, this method supports decision-making that is both informed and realistic.

#### 4.3.2 Pareto Sub-Framework

The SDIs retained in the final list serve as the input for the Pareto sub-framework. We quantified ach SDI for all twenty production schedules and compiled into a structured matrix in which rows represent the schedules and columns represent the indicators. The complete quantification methods, formulas, parameters, emission factors, and data sources for all 15 retained SDIs are available in the GitHub repository for reproducibility and practical application of the framework (https://github.com/Somatalhi/SustMine-.git). We used MATLAB (R2024a) to develop the Pareto analysis scripts for constructing composite index structure for the production schedules. As Gao et al. (2023), suggested [29], we implemented the hierarchical Pareto front approach with a goodness of variance fit set at 0.80 to ensure reliable results. We began the data preparation process by normalizing all values to a scale from zero to ten to ensure comparability among SDIs with different units. We then discretized the normalized values using the Jenks natural breaks optimization method, with a minimum goodness of variance fit threshold of 0.80. We then used these discretized SDI values as the input for the Pareto analysis.

We applied the Pareto front analysis independently for each sustainability dimension. As a result, each dimension has its own composite index structure in which the SDIs serve as the objective functions. We then combine the Pareto ranks generated for each dimension into a composite matrix that represents the overall sustainability profile of each schedule. We then applied a second-stage Pareto front analysis to this composite matrix to classify schedules into non-dominated and dominated fronts. This final index

**Table 9** Sustainable development indicators (SDIs) selected for the hybrid case study, categorized by SD dimension and sustainability issue

| SD dimension | Sustainability issues | SDI X.Y |
|---|---|---|
| Economic | - Economic impacts | - SDI 1.1 NPV<br>- SDI 1.2 Post Mining Income per Year<br>- SDI 1.3 Mining Indirect Benefit<br>- SDI 1.4 Proportion of Spending on Local Suppliers |
| | - Payments to governments | - SDI 2.5 Taxations<br>- SDI 2.6 Royalties |
| Environmental | - GHG emissions | - SDI 3.7 GHG Intensity |
| | - Energy use & efficiency | - SDI 4.8 Energy Consumption |
| | - Air emissions | - SDI 5.9 Nitrogen oxides (NOx)<br>- SDI 5.10 Particulate matter ($PM_{10}$) |
| | - Biodiversity | - SDI 6.11 Land Occupation (ha.year) |
| | - Waste | - SDI 7.12 Waste Production |
| | - Water and effluents | - SDI 8.13 ARD |
| | - Closure and rehabilitation | - SDI 9.14 Reclamation |
| Social | - Local community | - SDI 10.15 Number of Employees<br>- SDI 10.16 Job Security |
| | - Land and resource rights | - SDI 11.17 Report the number of persons who have been or will be displaced (GRI 14.12.2)<br>- SDI 11.18 List the locations of operations where conflicts or violations of land and resource rights (GRI 14.12.3)<br>- SDI 11.19 Pit Utilization |
| | - Occupational health and safety | - SDI 12.20 Operational Safety |

structure reflects the overall sustainability performance of the 20 production schedules across all three SD dimensions. Lastly, we computed two effectiveness measures to assess the discrimination of our analysis: the number of Pareto fronts (NPF), and the Shannon entropy of the front distribution.

## 4.4 Results and Discussions

This section presents and discusses the main findings that we obtained from applying the SustMine framework to the hybrid case study. We evaluated each of the 20 production schedules using the selected sustainability indicators across economic, environmental, and social dimensions. To enable meaningful comparisons, we calculated and normalized the indicator values for each dimension. The results revealed significant differences in how the schedules perform across these dimensions. These differences highlighted the natural trade-offs that arise when economic benefits conflict with environmental impacts or social concerns. Some schedules consistently delivered strong economic results but did tend to have weaker environmental performance due to factors like increased material movement or higher energy use. Others maintain moderate performance across all indicators, suggesting a more balanced approach to sustainability.

After evaluating the 20 SDIs against the selection criteria, we excluded five indicators from the final list. As shown in Fig. 8, four SDIs (1.3, 1.4, 11.17, 11.18) failed the applicability criterion (Level A); because it is a primary criterion, those indicators were immediately removed. SDI 1.2 (Post Mining Income per Year) satisfied all level A criteria but did not meet level B criteria. Although conceptually relevant, we excluded it due to insufficient data availability and quality. Specifically, the lack of reliable information on land income before and after mining. This emphasizes the importance of defining the quantification method early, as it helps users to understand data requirements and tells them whether an indicator can be meaningfully evaluated or not. We answered most data availability and quality checks as “partly,” which is expected at this early stage of planning. However, we anticipate that these limitations can be improved as more consistent data become available in future evaluations. The final list of SDIs includes three economic indicators, eight environmental indicators, and four social indicators. A more detailed evaluation on the selection of SDIs can be found in the spreadsheet in the GitHub repository.

We calculated the values of the SDIs in the final list for each schedule and incorporated them into the Pareto front analysis. The composite indices derived from the Pareto analysis provide a clear assessment of the relative sustainability performance of the twenty production schedules. Table 10 presents the dimension level index values for the economic, environmental, social, and the overall sustainability composite index (SCI). These values range from one to four for the economic dimension, one to seven for the environmental, one to three for the social, and one to five for the SCI. In all cases, lower scores indicate stronger performance.

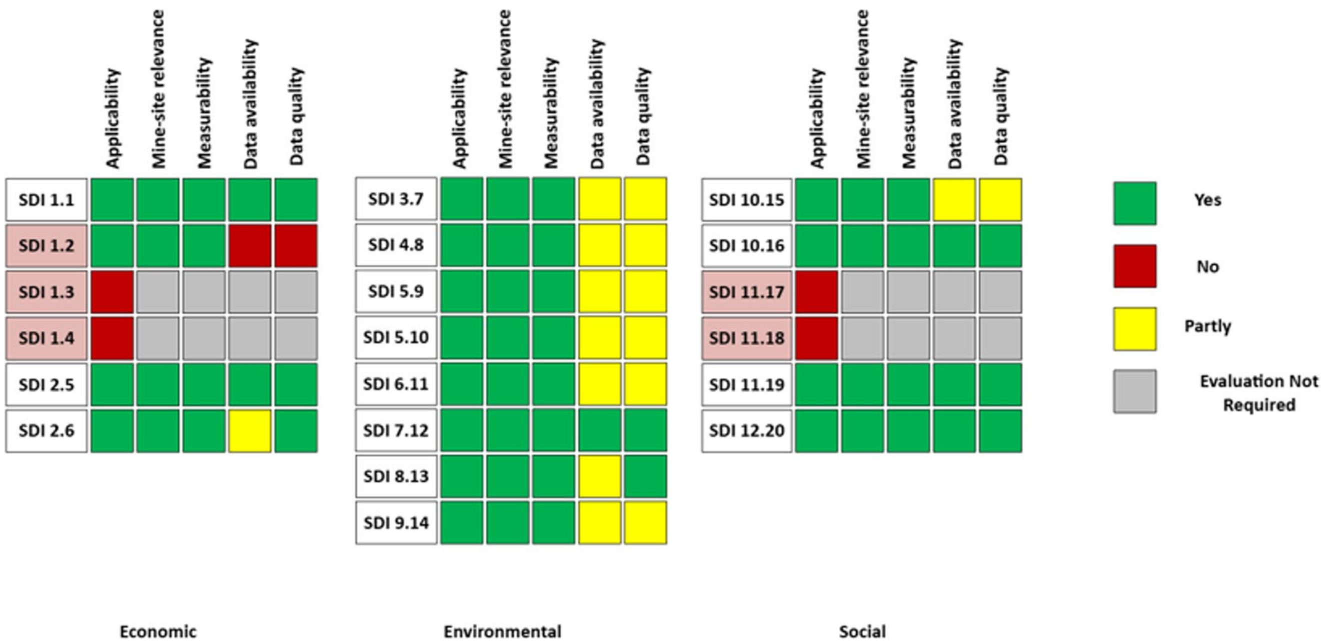


**Fig. 8** Evaluation of sustainable development indicators (SDIs) against level A and level B criteria in the SustMine selection sub-framework

**Table 10** Composite indices of production schedules based on Pareto front evaluation for SD dimensions and overall sustainability index

| Schedule_ID | Economic | Environmental | Social | Sustainability Index (SCI) |
|---|---|---|---|---|
| Schedule_1 | 2 | 2 | 1 | 1 |
| Schedule_2 | 2 | 2 | 1 | 1 |
| Schedule_3 | 2 | 5 | 2 | 4 |
| Schedule_4 | 1 | 2 | 2 | 2 |
| Schedule_5 | 1 | 1 | 2 | 1 |
| Schedule_6 | 3 | 1 | 1 | 1 |
| Schedule_7 | 2 | 3 | 3 | 4 |
| Schedule_8 | 2 | 1 | 2 | 2 |
| Schedule_9 | 1 | 4 | 3 | 3 |
| Schedule_10 | 2 | 5 | 2 | 4 |
| Schedule_11 | 3 | 1 | 1 | 1 |
| Schedule_12 | 2 | 1 | 3 | 3 |
| Schedule_13 | 3 | 2 | 1 | 2 |
| Schedule_14 | 3 | 6 | 1 | 3 |
| Schedule_15 | 4 | 7 | 1 | 4 |
| Schedule_16 | 3 | 3 | 2 | 3 |
| Schedule_17 | 2 | 4 | 2 | 3 |
| Schedule_18 | 4 | 7 | 2 | 5 |
| Schedule_19 | 3 | 3 | 3 | 5 |
| Schedule_20 | 3 | 6 | 1 | 3 |

The economic scores fall mostly between two and three, with only three schedules getting a score of one (more economically sustainable than the others). This narrow spread suggests that economic outcomes are relatively uniform across the alternatives. The environmental dimension displays the greatest variation, with values ranging from one to seven. Schedules such as Schedule 15 and Schedule 18 scored an environmental index of seven, whereas several schedules, including Schedule 11 and Schedule 12, scored an environmental index of one. This large variation reflects the influence of indicators such as GHG intensity, air emissions, land occupation, waste production, and acid rock drainage potential. The social scores fall within a narrow range one to three, indicating relatively limited variation in social performance compared to the economic and environmental dimensions. Several schedules (e.g., 1, 2, 6, 11, 13, 14, 15, and 20) achieve the strongest social score of one, suggesting that most alternatives perform well socially.

Only a few schedules reach the weakest social score of three, indicating that social impacts are generally less discriminating among alternatives.

This limited discrimination of the social dimension is primarily a characteristic of the planning activity under evaluation, which does not affect many social indicators. Two of the four retained social indicators, SDI 11.19 (Pit Utilization) and SDI 12.20 (Operational Safety), are nearly constant across all 20 schedules because both are fundamentally tied to pit geometry, which varies only modestly across the scheduling alternatives. Operational Safety shows the least variation, taking a value of 48 for 17 of the 20 schedules, with only minor deviations in three schedules, because it is measured as pit depth, which is highly insensitive to production scheduling variables. Pit Utilization shows slightly more variation, ranging from 75.6% to 77.9%, reflecting the modest differences in pit geometry across the nested pit shells generated in this study. Had the pit geometry varied more substantially, as would be the case in a UPL optimization exercise, these indicators would likely exhibit significantly greater discrimination. The remaining two social indicators, SDI 10.15 (Number of Employees) and SDI 10.16 (Job Security), do exhibit meaningful variation across schedules, ranging from 643 to 1,180 employees and from 20 to 34 years of mine life, respectively, but their discriminating contribution is weakened in the Pareto analysis by the near-constant values of SDI 11.19 and SDI 12.20.

When an SD dimension exhibits limited discriminating power, as observed here for the social dimension, users are advised to first examine the underlying indicator values to identify which specific indicators are driving the uniformity. If the uniformity is attributable to indicators that are insensitive to the planning activity's design variables, as is the case for SDI 11.19 (Pit Utilization) and SDI 12.20 (Operational Safety) in a production scheduling exercise where pit geometry varies only modestly, this finding should be documented and interpreted as a scope characteristic. Consistent with the iterative nature of SustMine, users are encouraged to report these findings and include specific recommendations for the next iteration, such as identifying alternative indicators that are more directly sensitive to the planning variables under evaluation or revisiting the quantification method step to better align indicator measurement with the specific variables and outputs of the planning activity being assessed. This limited discriminating power is therefore not inherent to social indicators as a class, but rather arises from the specific selection of indicators and the characteristics of the planning activity considered in this case study. In early-stage strategic planning, certain social indicators, particularly those tied to physical design parameters, may exhibit low sensitivity to scheduling decisions, while others remain more responsive. From a decision-making perspective, dimensions with limited discrimination contribute less to the identification of Pareto front solutions, as they do not significantly differentiate among alternatives. Therefore, practitioners applying the SustMine framework should carefully evaluate the sensitivity of selected indicators and consider supplementing or replacing low-variance indicators with more responsive metrics where appropriate. This ensures that all sustainability dimensions meaningfully contribute to the trade-off analysis and decision-making process.

The overall sustainability index ranges from one to five, and Schedules 1, 2, 5, 6, and 11 achieve a SCI value of one. These schedules combine low (i.e., strong) economic, environmental, and social scores. Schedules 6 and 11 are clear examples of trade-offs in the Pareto analysis. Although both schedules scored 3 in the economic dimension, they still achieved a SCI of 1 because their environmental and social performances are among the strongest in the dataset (score 1). In contrast, schedules assigned to later fronts are dominated because they underperform in one or more areas. For example, Schedule 12 shows very strong environmental performance (score 1) but a weak social score (3), while Schedules 15 and 18 are penalized by poor environmental scores (7) and correspondingly lower SCI (4 and 5, respectively). These trade-offs reduce their overall standing in the sustainability ranking. Although Schedule 9 achieved a strong economic score of 1, its overall SCI is 3 because this alternative combines strong economic performance with only moderate outcomes in the environmental and social dimensions.

The effectiveness metrics further support the robustness of the indicator set. The presence of five Pareto fronts combined with a Shannon entropy value of 2.23 indicates that the indicators generate meaningful discrimination among alternatives. We computed the Shannon entropy using log base 2. The theoretical maximum entropy for a perfectly uniform distribution of 20 alternatives across 5 Pareto fronts is 2.322. The observed value of 2.23 represent 96% of this maximum, confirming that the schedules are distributed nearly uniformly across all five fronts and that the selected indicator set provides a diverse set of trade-offs across the solution space. A smaller or unbalanced indicator set would likely collapse the solution space into fewer fronts and reduce analytical value, while inconsistent normalization would increase the entropy and weaken interpretability. In this study, the environmental indicators introduce the largest variation, while the economic and social indicators help prevent the analysis from becoming environmentally dominant. Together, these characteristics ensure that the resulting decision space is consistent and suitable for multi objective evaluation.

Ultimately, it is up to the DM to interpret the sustainability performance of generated alternatives and communicate a justified decision to stakeholders. In our case (as the user), we proceed with Schedule 5, which achieves strong performance in both the economic and environmental dimensions (score of 1) and a moderate score in the social dimension (2). Given that the social dimension shows limited discriminating power across alternatives, Schedule 5 represents a robust and well-balanced option.

Overall, the results demonstrate that the SustMine framework provides a comprehensive and transparent basis for comparing long term production strategies. By revealing variation in sustainability outcomes and identifying non dominated alternatives, the framework supports more balanced decisions and helps align production scheduling with broader sustainability objectives.

#### 4.4.1 Sensitivity Analysis

To assess the robustness of the SustMine framework, we conducted a sensitivity analysis examining three key methodological choices: normalization method, GVF discretization threshold, and indicator inclusion. Results of this analysis can be found in the GitHub repository (https://github.com/Somatalhi/SustMine-.git).

For normalization sensitivity, we compared the baseline min-max normalization against z-score standardization and rank-based normalization. Z-score normalization produced results identical to the baseline across all 20 schedules (20/20 agreement) and identical Front 1 composition, confirming that the results are robust to the choice between these two methods. Rank-based normalization produced substantially different results, as this method completely alters the magnitude of differences among indicator values and is not appropriate for this application.

We tested thresholds of 0.70, 0.75, 0.80, 0.85, and 0.90 to examine the sensitivity of different GVF thresholds. Schedules 5 and 11 appeared on Front 1 across all five thresholds, confirming that these schedules are the most robustly non-dominated alternatives. The remaining Front 1 schedules showed some sensitivity to the threshold, particularly at higher values, where some indicators could not achieve the specified GVF level due to limited variability in the data. The (GVF = 0.80) threshold adopted in this study represents a reasonable balance between classification quality and practical applicability under early-stage data constraints.

For indicator sensitivity, a leave-one-out analysis showed that 10 of the 15 retained indicators did not change in the composition of Front 1 or composite rankings, when excluded individually, demonstrating that the framework is not driven by any single indicator. The four indicators that produce changes when excluded are NPV, Land Occupation, Number of Employees, and Job Security, which represent the primary drivers of discrimination in their respective dimensions, and their influence is expected and methodologically appropriate. Schedules 5 and 11 remain on Front 1 in all leave-one-out cases, further confirming the robustness of the optimal solution identification.

## 5 Conclusion

This study introduced SustMine, a comprehensive and practical framework designed to integrate sustainable development principles into the strategic mine planning stage. SustMine addresses key gaps identified in the literature, particularly the lack of systematic methods for selecting SDIs and the persistent reliance on subjective weighting schemes. By combining a transparent indicator selection procedure with a weightless Pareto front-based composite index, the framework enables DMs to evaluate mine planning alternatives across economic, environmental, and social dimensions without introducing bias from arbitrary weighting.

The proposed approach demonstrates that meaningful sustainability integration is possible at the earliest stages of mine development, where decisions have the most far-reaching implications. SustMine's dual sub-framework, consisting of indicator selection and weightless evaluation, ensures that each indicator is context specific, measurable, and feasible to implement even in data-limited planning environments. The use of a composite sustainability index further enhances comparability among alternatives and facilitates communication with stakeholders by translating complex multidimensional results into interpretable performance measures.

The hybrid case study validated SustMine's applicability and demonstrated its ability to reveal balanced production schedules that align economic performance with environmental responsibility and social well-being. By combining technical and economic data from a real mining project with social indicators from an established community acceptance study, the case study confirmed that sustainability can be quantitatively and transparently integrated into mine planning decisions. These findings suggest that SustMine can serve as an effective decision-support tool, offering a replicable blueprint for researchers and practitioners seeking to embed sustainability into early-stage planning.

Future work should extend SustMine's application to different mine types, geological settings, and planning activities, including cut-off grade and ultimate pit limit optimization. Additionally, future case studies should aim to apply SustMine using case studies where all the data (technical and social context) are available, so that the identification of sustainability issues and the subsequent selection of SDIs are grounded in the specific community, regularity, and operational characteristics of the project under evaluation. Moreover, incorporating uncertainty quantification techniques such as Monte Carlo simulation or fuzzy logic would enhance its capability to model data variability and support robust decision-making under uncertainty. By refining and expanding this framework, SustMine can evolve into a cornerstone methodology for developing more resilient, transparent, and sustainable strategies across the global mining sector.

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## Declarations

**Competing interests** Dr. Kwame Awuah-Offei is an Associate Editor of Mining, Metallurgy, and Exploration. He will not be involved in the review of this manuscript in any way. The section editor will ensure he has no influence on the outcome of the review process.



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