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Strip mining of stratiform deposits with thick overburden: environmental challenges and constraints to sustainable extraction

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ABSTRACT

The resource extraction industry relies heavily on strip mining to produce various minerals. Its popularity arises from its cost-effectiveness, making it a key surface mining method to meet the growing global demand for raw materials. The depletion of shallow ore deposits has led to an increased reliance on strip mining under extremely thick overburden layers, intensifying the environmental impact of mining operations. The first aim of this study was to evaluate the environmental effects of mining operations under these complex conditions, with a particular focus on their impact on land use, energy consumption, and climate change. Drawing upon multiple case studies, the research quantitatively explores how increasing overburden thickness affects the technical feasibility, energy demand, and footprint of mining activities. This analysis highlights the delicate balance between geological conditions and mining strategy which offers new insights into optimizing extraction efficiency while minimizing ecological disturbance. The feasibility of the utilization of an artificial neural network (ANN) based conceptual model was then explored to outline a predictive framework for environmental impacts under these conditions, intended to support future practical applications by combining the important operational factors studied with site-specific characteristics. The conception of the ANN model was structured with one hidden layer that is meant to capture complex connections between key mining factors and each one of the expected outcomes.

Keywords: *Artificial neural network, Climate change, Environmental impact, Strip mining, Strip ratio.*

1. Introduction

Mineral resource extraction widely employs surface mining methods due to their productivity, good recovery rates, and lower safety risks compared to underground mining systems [1, 2]. Strip mining, a key technique in the resource extraction industry, is one of the most employed methods in producing essential commodities such as coal, oil shale, phosphate, ironstone, and various other bedded deposits. This method has gained the attention of mining companies due to its economic efficiency, as it enables the industries to satisfy the rising global demand for raw materials [3]. This rising reliance on strip mining is confronting a depletion of shallow ore deposits worldwide [4], compelling mining operators to seek deeper and more complex resources where the progressive expansion of mining boundaries and the advancement of extraction stages are associated with increasing overburden thicknesses, historically extending from values of less than 3.5 m in the late nineteenth century to thicknesses exceeding 14 m with the introduction of large excavators and draglines in the early twentieth century, and progressively reaching economically viable overburden thicknesses greater than 60 m as mining equipment and stripping performance continued to improve [5–7]. However, as this type of exploitation expands, there is growing concern about its significant environmental impacts under those new geological conditions [8–10] which necessitates a thorough examination of its aspects, particularly in such challenging contexts.

Thick and extremely thick overburden layers are a relevant example of these complexities facing strip mining today [11], especially because of their environmental impact in different stages of the extraction process: ground preparation, drilling, blasting, overburden removal, ore extraction, and land reclamation (Figure 1). However, there is a lack of targeted studies addressing this specific issue, even though stricter environmental regulations are being implemented worldwide, impacting the feasibility of this type of exploitation. In particular, existing studies rarely provide a quantitative assessment of how increasing overburden thickness influences the combined technical feasibility and environmental footprint of strip mining operations. This makes it more important to research how thick overburden affects strip mining suitability and what can be done to reduce its environmental impact. This is of huge importance, especially since it is assumed that extending the applicability of the method to cover areas with thicker overburden may offer significant opportunities for an economically viable extraction of raw materials [5].

Technically, high overburden conditions are associated with distinct complications compared to operations with thinner overburden layers where the environmental impacts can be relatively less significant and more controllable. In fact, in deeper mining scenarios, the displacement of substantial volumes of overburden may disrupt local ecosystems and contribute to heightened resources consumption, extensive land disturbance, and increased air pollution caused by excessive greenhouse gas emissions from a larger machine fleet and more hours of work in removing overburden material, with a strip ratio much greater than in normal conditions. The analysis will seek to assess how these extreme

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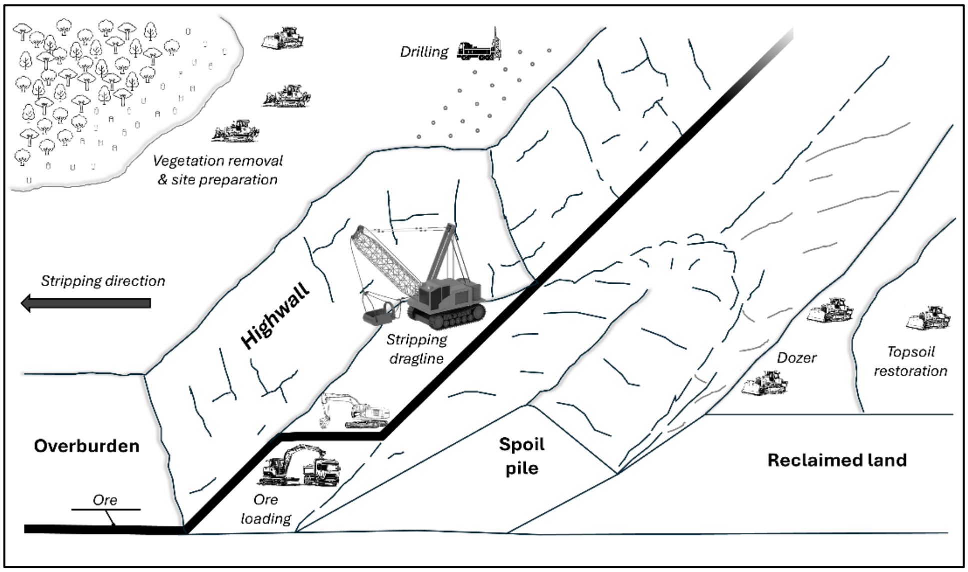

Figure 1. Schematic representation of the strip-mining process and exploitation steps.

geological conditions are impacting the efficiency of strip mining as an extraction method and, at the same time, the overall environmental consequences in such contexts reported per ton of extracted ore.

To discuss these aspects, a detailed analysis of mining operations through various contexts is proposed. By examining each case, the amplification of environmental effects observed with strip mining under different overburden thicknesses is highlighted. Accordingly, the objectives of this study are to (i) identify the key operational and geological factors governing environmental impacts under thick overburden conditions, and (ii) evaluate their influence across different mining contexts. While such analyses provide valuable insights into the mechanisms governing environmental footprints, their complexity and strong interdependence suggest that these effects could be more effectively anticipated using advanced predictive approaches capable of handling nonlinear relationships and multiple influencing factors. In this context, recent developments in data-driven and intelligent methods offer promising perspectives for structuring and forecasting the environmental performance of mining operations. Thus, the insights gained from the analysis will serve as a foundational step toward the development of an artificial neural network (ANN) based conceptual framework which could subsequently be developed in other contexts into a practically applicable model for predicting the discussed environmental outcomes.

The present paper comprises five main sections. The next section describes the method used to analyze the problem while section 3 presents the data and results of the case study analysis. The last two sections include discussion where the results and literature are used to reach findings and where a preliminary ANN approach is proposed as a tool for predicting environmental impacts, along with an analysis of its strengths and its limitations. Finally, the conclusion summarizes the study and synthesizes its key points.

2. Materials & methods

The data utilized in this study were sourced from a database compiled in a previous study by Ditsele and Awuah-Offei [12], who compiled data from environmental impact statements, coal mining permit applications, government reports, and published literature for four U.S. coal mines representing different geological contexts. The following analysis is therefore based exclusively on secondary data, and no additional site-specific data collection was undertaken. In fact, the considered dataset is assumed to be sufficiently representative for the objectives of this study, as it draws on multiple authoritative sources and encompasses contrasting mining and geological conditions which allows for a comparative assessment of environmental impacts under varying overburden characteristics. In the present paper, particular attention is given to land use, energy consumption, and climate change impacts. These aspects are systematically assessed across the different geological contexts to provide a deeper understanding of how overburden thickness and mining techniques influence the environmental performance of strip-mining operations. These three parameters were chosen because of their significant relationship to environmental impact and their unique relevance to the strip-mining method and surface mining activity in general.

The main data used in the study focuses on the technical characteristics of mining exploitation (machine types, overburden removal method, transport mode, ore production...etc.) and the geological features specific to each case study context. While the main part of data originates from earlier assessments [12], they remain representative of standard strip-mining operations with comparable methods and equipment. Table 1 provides a clear synthesis of these characteristics, presenting them in a comprehensive manner to highlight the differences in geological conditions and exploitation techniques at each mine.

One of the key parameters used to characterize each context is the strip ratio (SR) which represents the volume in cubic meters of overburden moved per volume of mineral extracted during the strip-mining process [13]. The general equation used for its calculation is provided by the following formula:

$$\mathrm{SR} = \frac{V_{ob}}{V_{ore}} \quad (1)$$

where:

- V_{ob} : the volume of overburden to be removed (m^3)
- V_{ore} : the volume of ore to be mined (m^3)

In the case of stratiform deposits and relatively regular terrains, and assuming uniform ore and overburden thicknesses over the mined area, a simplified form can be proposed. The strip ratio formula in this case involves dividing the overburden thickness by the ore thickness, as shown in the following formula:

$$\mathrm{SR} = \frac{H_{ob}}{H_{ore}} \quad (2)$$

where:

- H_{ob} : Average overburden thickness (m)
- H_{ore}: Average ore thickness (m)

Table 1. Technical characteristics of the four mining sites considered for the study (data from [12]).

	Site 1	Site 2	Site 3	Site 4
Exploitation method	Area strip mining	Area strip mining	Area strip mining	Area strip mining
Overburden removal method	Overburden thickness > 4.6 m: dragline; 0.9–4.6 m: shovel, front-end loader, and dump truck; < 0.9 m: dozer	Dozers, shovels, front-end loaders, and haulage trucks	Dozers, excavators, front-end loaders, and dump trucks	Dozers, excavators, small front-end loaders, and trucks
Ore extraction and transport mode	Shovels, front-end loader, and dump truck	Shovels, front-end loaders, and haulage trucks	Ripping with dozers, and loading into trucks	Shovels, front-end loaders, and haulage trucks
Average Ore thickness (m)	2.00	2.00	0.66	0.89
Average overburden thickness (m)	11.6	27.0	14.6	17.1
Calculated strip ratio	5:1	13:1	22:1	19:1
Annual production (million tons)	11.8	0.61	0.18	0.056
Permit land area (ha*)	2.61×10^4	3.62×10^2	2.81×10^2	2.63×10^2

3. Results

3.1. Climate change impact

To quantify the impact of climate change in each surface mining exploitation, a process of calculating the combined effects of different emissions is used. For this, a measure called the Global Warming Potential, GWP, for each of the greenhouse gases (GHG) has been utilized.

GWP makes it possible to calculate the combined impact of many different GHGs within an inventory. To do so, the estimated quantity of each GHG generated by extraction activity is multiplied by its GWP to get to a CO2 equivalent value (the unit of mass of the GHG will determine the unit of the CO2 equivalent, generally kg CO2). Particular attention has been given to carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) because they are the three most significant long-lived greenhouse gases directly emitted by mining activities and are consistently identified as key drivers of climate change by the Intergovernmental Panel on Climate Change (IPCC) [14]. The estimated quantity of GHG emissions resulting from strip mining at each site is given in Table 2.

Table 3 presents the global warming potentials of CO_2, CH_4, and N_2O over a 100-year time horizon, relative to CO_2. The values of the table represent the effects of these elements, expressed in terms of their relationship to CO_2. That means, if 1 kg of CH_4 is emitted into the atmosphere, that is the equivalent of emitting 25 kg of CO_2. Having converted all GHGs into their CO_2 equivalents, the addition of all these calculated values together will allow the estimation of the total impact as given by formula (3):

$$\text{Total climat change impact} = \sum_{j=1}^{n} (GWP_j \times Q_j) \tag{3}$$

where:

- Q_j: Quantity of greenhouse gas *j* emitted (kg/ton)
- GWP_j: Global Warming Potential of GHG *j* relative to CO_2 over a 100-year time horizon (kg CO_2-eq per kg of gas)
- *j* denotes the GHG type (CO_2, CH_4, N_2O or other GHG considered)
- *n* is the total number of GHG considered

  The total climate change impact is expressed in kg CO_2-eq per ton of extracted ore.

Considering that the choice of metric is influenced by the time horizon of the analysis, it was assumed that GWP100 which reflects the cumulative climate impact over a 100 year period, would be more appropriate to this study (instead of GWP20 which emphasizes short-term impact over 20 years, and GWP500 which represents long-term impact over a 500 year horizon).

This assumption stems from the typical duration associated with surface mining activities and their effects. Calculation details and obtained results for each site are represented in Table 4 while a visual representation of these values is shown in Figure 2.

3.2. Land use

Land use impact, including both the immediate area required for extraction and the land occupied over a one-year period, was assessed across the four mining sites. This assessment involved the estimation of the land area directly impacted by strip mining per ton of extracted ore, thus providing a measure of the immediate footprint of the mining activity. Direct land disturbance per ton of extracted ore is determined by dividing the total land area expected to be disturbed over the life of the mine by the total recoverable ore reserves:

$$L_d = \frac{L_{\text{dist}}}{R} \tag{4}$$

where:

L_d : direct land disturbance per ton of extracted ore (m^2/ton)

L_{dist} : total disturbed land area within the mining permit (m^2)

R : total ore reserves (tons).

Additionally, the land use over a one-year period for each site can be assessed by accounting for the duration of land occupation associated with mining and reclamation activities. The annual land use indicator is given by the following formula:

$$A_{\text{occ}} = \frac{1}{R} \sum_{t=1}^{T} (A_{d,t} \times \Delta t) \tag{5}$$

Table 2. Greenhouse gas emissions to air (in grams per ton of extracted ore, g/ton).

	Site 1	Site 2	Site 3	Site 4
CO_2	17 907.3	36 410	45 495.5	70 888.5
CH_4	797.6	697.8	793.7	822.6
N_2O	0.14	0.11	0.12	0.21

Table 3. GWPs relative to CO2 for a 100-year time horizon (data from [15]).

Industrial designation of the element	Chemical Formula	GWP_{100}
Carbon dioxide	CO_2	1
Methane	CH_4	25
Nitrous oxide	N_2O	298

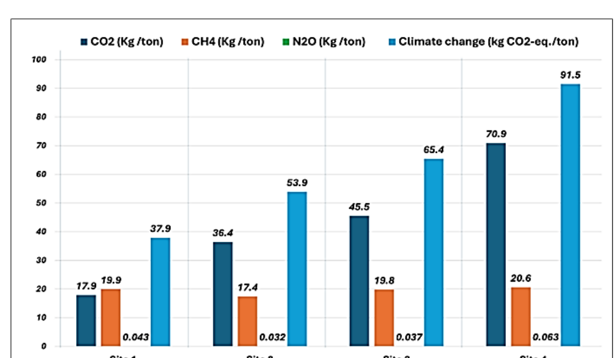

Figure 2. Climate change impact (kg CO2 eq./ton) for each site.

Table 4. Calculation details of climate change impact for each site.

Site	CO_2 (kg/ton)	CH_4 (kg/ton)	N_2O (kg/ton)	GHG contribution (kg CO_2-eq/ton)			Total climate change impact (kg CO_2-eq/ton)
				CO_2	CH_4	N_2O	
Site 1	17.907	0.7976	0.00014	17.91	19.94	0.04	**37.9**
Site 2	36.410	0.6978	0.00011	36.41	17.44	0.03	**53.9**
Site 3	45.495	0.7937	0.00012	45.50	19.84	0.04	**65.4**
Site 4	70.889	0.8226	0.00021	70.89	20.57	0.06	**91.5**

where:

A_{occ} : land use impact expressed in m² year per ton of extracted ore (m² year/ton)

$A_{d,t}$: land area disturbed during year t (m²)

Δt : is the occupation time before effective reclamation (year)

T : total mine life in years

R : total ore reserves (tons)

3.3. Energy consumption

The energy consumption was assessed at the four mining sites by quantifying its use in machines and equipment utilized in the strip-mining process through different stages of the production cycle. This involved measuring the consumption of electricity, diesel fuel, and explosives used for site preparation, overburden removal, and ore extraction at each mine.

These energy inputs are also given by a common unit of energy, megajoules (MJ), to allow for a direct comparison of total energy consumption for each mining context.

To ensure consistency and comparability across sites, the consumption of electricity, diesel fuel, and explosives was quantified per ton of extracted ore and then converted to a common energy unit using standard energy content factors as reported in [16]. The total energy input per ton of extracted ore was calculated as:

$$E_{\text{total}} = E_{\text{elec}} \times \alpha_{\text{elec}} + F_{\text{diesel}} \times \alpha_{\text{diesel}} + M_{\text{ANFO}} \times \alpha_{\text{ANFO}} \tag{6}$$

where: E_{elec} : electricity consumption (kWh/ton)

F_{diesel} : diesel fuel consumption (L/ton)

M_{ANFO} : explosives consumption (kg/ton)

α_i: denotes the corresponding energy conversion factors

E_{total}: The resulting total energy consumption in Megajoules per ton of extracted ore (MJ/ton).

Energy inputs and the corresponding total energy consumption per ton of extracted ore for each site are presented in Figure 4. Additional details on the calculation procedures applied to the same dataset used in sections 3.1, 3.2, and 3.3 can be found in [16].

4. Discussion

At this stage of the study, it is therefore clearer that strip mining carried out under thick overburden conditions has an influence on energy use, land disturbance, and greenhouse gas emissions which places these indicators at the core of the sustainability discussion [17–19]. For this reason, the results presented in this section are mainly interpreted in relation to the United Nations Sustainable Development Goals (SDGs) [20–22]. Specifically, SDG 7 (energy demand), SDG 12 (resource use and land efficiency), SDG 13 (CO_2 emissions), and SDG 15 (land and ecosystem disturbance) are considered which offers a coherent basis for the discussion of the environmental implications of the analyzed parameters.

4.1. Parametric analysis of environmental impacts

Concerning climate change impacts, mining sites with higher overburden thickness and strip ratios, such as site 3 (14.6 m, 22:1) and site 4 (17.1 m, 19:1), exhibit significantly higher climate change impacts, with CO2 equivalent emissions of 70.9 kg/t and 91.5 kg/t, respectively. From an operational perspective, these elevated impacts are primarily driven by the increased intensity and duration of earthmoving operations required to handle larger volumes of overburden per unit of extracted ore. In fact, these values are associated with the increased energy requirements for these operations, employing equipment such as dozers, excavators, loaders, and haulage trucks which exhibit significant fossil fuel consumption.

In contrast, site 1, characterized by the lowest overburden thickness (11.6 m) and the lowest strip ratio (5:1), shows minimal climate change impact, quantified at 37.9 kg CO2-eq./t. This indicates an apparent relationship between overburden thickness and the impacts of climate change associated with strip mining operations. This outcome arises from the heightened energy consumption of machinery used in overburden removal and transportation, necessitating the removal of larger material volumes to extract a certain ore tonnage. Similar relationships between stripping intensity, energy demand, and emissions have been reported in surface mining studies, where strip ratios are identified as a dominant driver of climate-related impacts [23, 24].

The land use indicators of each site differ significantly due to differences in stripping ratios, production scales, and site-specific characteristics. Sites 3 and 4, with the highest stripping ratios (22:1 and 19:1, respectively), show elevated land use impacts. These impacts are driven not only by the extent of surface disturbance, but also by how long that land remains occupied when production rates are low and mine life is extended. In this context, high stripping ratios translate into large volumes of overburden removal that when combined with limited production capacity, lead to longer operating periods and sustained land occupation. In contrast, site 2 stands out with the lowest land use impact of 3 m² year/t, probably due to its more moderate stripping ratio of 14:1, efficient production scale, and smaller infrastructure footprint. Interestingly, while site 1 has the most favorable stripping ratio of 6:1 and minimal land disturbance per ton of ore of around 0.22 m²/t, its impact on land use (5 m² year/t) is higher compared to site 2, which can be explained by other parameters linked to the specifications of each region.

Land use impacts in each mine are therefore strongly influenced by both stripping ratios and production scales. In fact, high stripping ratios increase the spatial footprint of disturbance while small production scales extend the temporal dimension of land occupation, jointly amplifying land use impacts. In contrast, efficient production mitigates these impacts by reducing the duration of active disturbance per unit of extracted material. A previous study by Bendouma et al. supports this

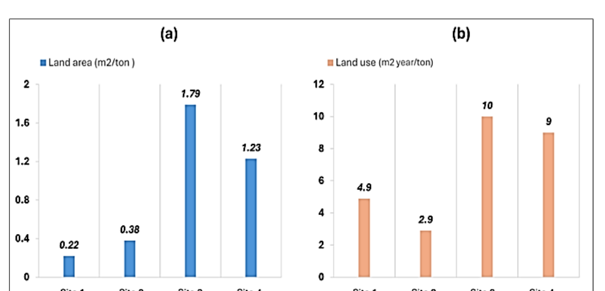

Figure 3. Land use impact per ton of extracted ore on each site: (a) Direct land area impacted by strip mining (m²/ton), (b) Annual land use (m² year/ton).

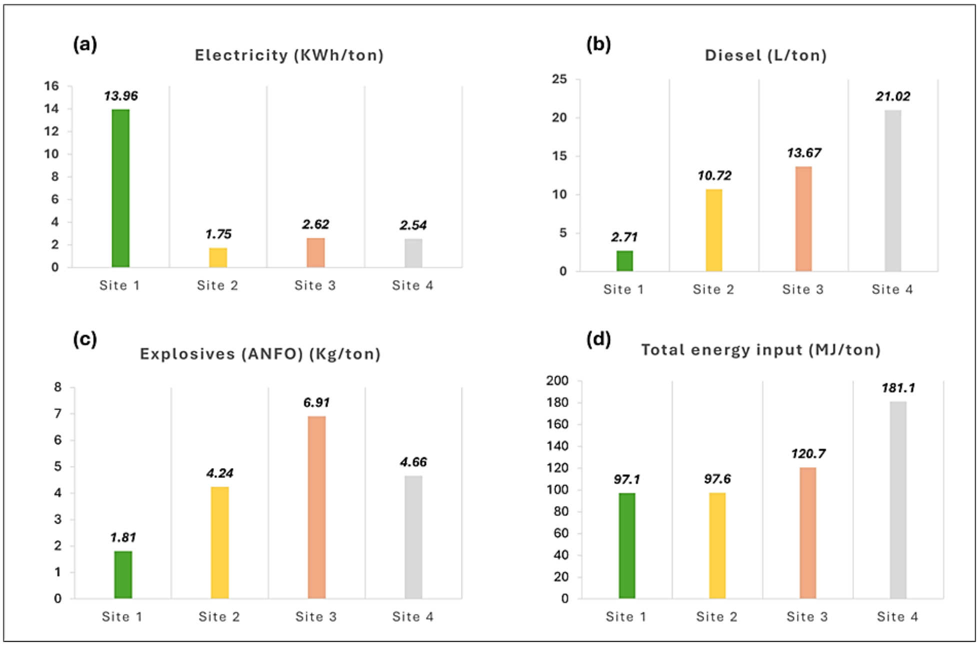

Figure 4. Comparative analysis of energy consumption per ton of extracted ore at each site: (a) Electricity consumption related to mining operations, (b) Diesel fuel consumption for on-site equipment, (c) Explosives used in blasting operations, (d) Total energy input by site.

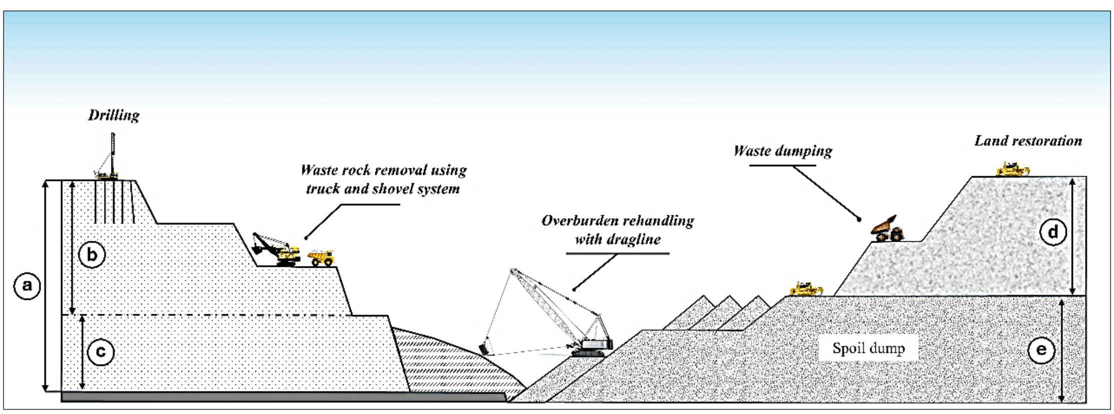

Figure 5. Scheme of a combined mining system in the case of strip mining with extremely thick overburden: (a) Overburden thickness, (b) Upper overburden strata mined out and hauled to internal/external dumps, (c) Lower overburden strata mined with rehandling, (d) Spoil dump reconstituted with a haulage system, (e) Spoil dump reconstituted with direct dumping.

result through an evaluation of limestone quarrying's environmental impact [25]. The authors found that smaller-scale mining operations with traditional management practices tended to have a greater land use impact than larger and more modern operations. This result reinforces the importance of operational scale and management efficiency as key moderators of land use impacts in surface mining systems

In addition to land use, overburden thickness significantly influences the rehabilitation of mining sites. Indeed, unusually thick overburden layers complicate material removal and handling, often requiring the management of large waste volumes. Removing the overburden in this case requires a two-step approach: waste rock removal for upper layers, then direct rehandling with draglines for lower layers [26]. These wastes may necessitate transfer to external dumps and subsequent re-transport during the rehabilitation phase, with spoil dumps being reconstituted either by less precise direct dumping (electric shovel/dragline rehandling) or controlled haulage (waste transport using trucks) (Figure 5). Such multi-stage handling increases the complexity and the duration of reclamation process, ultimately increasing the time and cost associated with reclamation efforts aimed at restoring the site to its original conditions [27, 28].

Regarding energy consumption, clear differences are observed among the mining sites, primarily reflecting variations in overburden thickness, strip ratio, equipment selection, and production scale. At a general level, energy demand in strip mining operations increases with the volume of material handled per unit of extracted ore, particularly through hauling and blasting operations associated with overburden removal. Site 1, characterized by the lowest overburden thickness of 11.6 m and ordinary mining machinery such as shovels, loaders, and dump truck, exhibits the lowest consumption of diesel at 2.71 L/t and explosives at 1.81 kg/t. However, it demonstrates a significant reliance on electricity, consuming 13.96 kWh/t, indicative of its employment of draglines for managing thick overburden layers. In contrast, site 4, with a higher overburden thickness (17.1m) and a 19:1 strip ratio, has the highest total energy input (181.1 MJ/t), probably due to the intensive use of haulage trucks and excavators, leading to elevated diesel consumption. Similarly, site 3 shows higher explosive usage (6.91 kg/t), due especially to the high strip ratio of 22:1 in the site, requiring more blasting to access ore. Site 2, with a relatively thick overburden (27.0 m) and a moderate strip ratio of 13:1, shows relatively reduced diesel and explosive consumption (10.72 L/ton and 4.24 kg/t, respectively), suggesting that efficient equipment deployment and higher productivity can partially mitigate the energy penalties associated with increased stripping intensity. Thus, the results indicate that strip ratio and overburden thickness are the dominant drivers of energy demand, while equipment type and production scale act as moderating factors. This interpretation is consistent with the findings of Westfall et al., where a linear relationship between energy consumption and the volume of overburden and waste material hauled during mineral extraction was reported [29].

Energy source dominance further reflects these operational differences. At site 1, most of the energy demand comes from electricity since its operations rely on large electrically powered machines such as draglines and shovels. In contrast, sites 2, 3, and 4 mainly use smaller diesel-driven equipment to remove overburden, meaning diesel plays a much larger role in their overall energy consumption. Although geological conditions strongly influence absolute energy requirements, larger production scales benefit from economies of scale, distributing energy inputs over higher output volumes. Larger operations tend to use energy more efficiently which can be seen in the gradual decline in potential energy impacts as production scales up from site 4 to site 1. Figure 6 summarizes the effects of overburden thickness on rehabilitation efforts, land use, energy consumption, and climate change impacts.

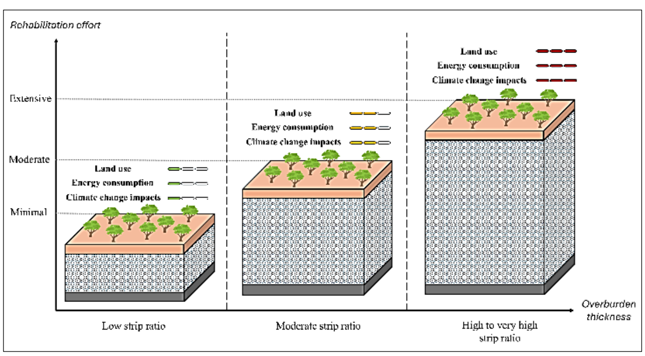

Figure 6. Schematic representation of the impact of overburden thickness on rehabilitation efforts and studied environmental parameters.

Under the analyzed conditions, it is suggested to explore alternative approaches for evaluating the environmental impact per ton of extracted ore considering the major influence of stripping ratios, production scales, machinery types, and operational practices on these impacts. Based on these important criteria, we investigate in the following the viability of using ANN modelling through a conceptual framework to predict these impacts.

4.2. Applicability of ANN for predicting the environmental effects

To mitigate the environmental effects of strip-mining activities in areas with thick and extremely thick overburden layers, it is essential to consider the most influential parameters and their interactions within each specific context. In this sense, new approaches based on advanced methodologies are required. Accordingly, this section proposes the use of artificial intelligence (AI), specifically ANN for a proactive assessment of environmental impacts under varying geological configurations and technical characteristics of extraction methods and equipment.

An ANN is a computational model inspired by the architecture and operation of the human brain's neural system [30]. It comprises layers of interconnected processing units, commonly known as neurons. These networks can learn from real-world data and are extensively utilized in scientific and engineering fields for predictive tasks [31–33]. As a branch of AI, ANN are specifically engineered to identify and represent complex, nonlinear relationships between input and output variables within datasets. It is suggested that each one of the discussed environmental impacts can be predicted using an ANN model. The geological and technical attributes of the mining site will function as input parameters in the conceptual framework to suggest. The resultant outputs would represent the diverse environmental impact indicators of interest. This conception will subsequently allow for the proposal of an initial architecture model for the network.

4.3. Input parameters for ANN model and network architecture

The choice of pertinent and high-quality input parameters determines mostly the accuracy and predictive ability of an ANN model. To guarantee the accuracy and generalizability of a model, these inputs must effectively reflect the technical, operational, and environmental elements associated with each mining context. The inputs required for each specific category of environmental impact are presented as follows: Table 5 presents the inputs for the model of climate change impact; Tables 6 and 7 respectively show the input parameters for the models of land use and energy consumption impact.

It is worth mentioning that data regarding equipment efficiency, explosives utilization, and diesel and electricity consumption can be acquired through benchmarking or alternative estimation techniques, leading to realistic values suitable for developing a reliable model and allowing prediction even before site preparation and starting mining activities which represents the central objective that drives the development of such strategies.

A proposed architectural design for the conceptual predictive models illustrates the interactions between the three evaluated aspects and their respective inputs. The network architectures are organized as follows: the climate change impact model comprises relevant input parameters and a singular output, the land use model integrates specific inputs and generates two outputs, and the energy consumption model is configured with three distinct outputs, as illustrated in Figure 7. Additional details on the neuron structure and the associated ANN components are provided in Figure 8.

Best practices and insights from previous studies were followed to define the optimal architecture of the conceptual framework that ensures the best performance in future prediction processes. It has been widely suggested in the literature that a single hidden layer is generally sufficient for most predictive modeling problems, with little to no benefit observed from adding additional layers [34]. Therefore, this study adopted a network structure with a single hidden layer for the suggested architectures. However, the determination of the optimal number of neurons remains a critical aspect of ANN design [35], and only further practical case studies, supported by systematic error analysis, can validate the optimal number of neurons, their respective activation functions (f_1, f_2, $f_3 ... f_n$), and the reliability of each proposed model architecture.

In order to mitigate the negative environmental effects of strip mining at various phases of the mining process, the suggested conceptual model supports the optimization of excavation techniques. With further development, its predictions can be used to modify mining practices and planification (reallocating machinery, switching to different blasting techniques, or altering overburden removal and handling techniques) until achieving the optimal configuration that ensures compliance with regulations and the economic profitability of operation. Verifying the model's viability could enable more efficient machine deployment based on anticipated impacts, thereby improving the selection of equipment and materials throughout the whole mining project life.

4.4. Challenges of the ANN model and perspectives

The wide spectrum of research in AI applications makes it difficult to determine a conclusive dataset size for evaluating the environmental impact of strip-mining using ANN. The limited implementation of ANN-based methods in the specific context of environmental impact assessment for strip mining compounds this difficulty even more. Nonetheless, the literature shows some overall tendencies [36]. Usually,

Table 5. Input parameters for climate change impact model.

Model output	Related input parameters	Description	Unit
Climate change impact (kg CO_2 eq./ton ore)	Overburden/interburden thickness	Total thickness of the overburden/interburden above ore layer(s)	m
	Ore layer thickness	Total thickness of ore layer(s)	m
	Efficiency of used equipment and machinery	Parameters to use for the estimation of work hours for preparation, drilling, overburden removal, ore transportation and reclamation	hrs/m^2; hrs/m^3
	Quantity of GHG generated by each stage of extraction activity	the estimated quantity of each of the greenhouse gases (CO_2, CH_4, N_2O)	g/ton of extracted ore

Table 6. Input parameters for land use model.

Model output	Related input parameters	Description	Unit
Direct land area impacted by strip mining (m²/ton)	Overburden/ interburden thickness	Total thickness of the overburden/ interburden above ore layer(s)	m
	Ore layer thickness	Total thickness of ore layer(s)	m
	Annual production	amount of ore extracted by strip mining operations each year	ton/year
Annual land use (m² year/ton)	Mine life	number of years expected for strip mining operation	year

Table 7. Input parameters for energy consumption model.

Model output	Related parameters	Description	Unit
Energy consumption per ton of extracted ore:	Overburden/interburden thickness	Total thickness of the overburden/interburden above ore layer(s)	m
	Ore layer thickness	Total thickness of ore layer(s)	m
	Efficiency of used equipment and machinery	Parameters to use for the estimation of work hours for preparation, drilling, overburden removal, ore transportation and reclamation	hrs/m^2; hrs/m^3
Electricity consumption (KWh/ton)	Electricity consumption for dragline	The average electricity consumption of dragline per hour of work	KWh
	Electricity consumption for blast hole drill	The average electricity consumption of blast hole drill per hour of work	KWh
Diesel fuel consumption for on-site equipment (L/ton)	Diesel consumption for dozer	The average fuel consumption of dozer per hour of work	L/hr
	Diesel consumption for truck	The average fuel consumption of truck per hour of work	L/hr
	Diesel consumption for loader	The average fuel consumption of loader per hour of work	L/hr
	Diesel consumption for shovel	The average fuel consumption of shovel per hour of work	L/hr
Explosives used in blasting (Kg/ton)	Explosives consumption	The average quantity of explosives required to blast 1m^3 of overburden/interburden	kg/m^3

influenced by the complexity of the mining scenario, the number of data points falls between several hundred and several thousand. More complicated systems or the inclusion of extra input variables usually needs bigger datasets to fairly depict system behaviors. Furthermore, a constraint is data availability since gathering high-quality field data can be expensive and time-consuming. The accuracy of model predictions influences data quantity as well; generally, higher accuracy goals call for more training data [37].

This variation also goes through the distribution of data among training, validation, and testing processes (Figure 9). The ability of the model to generalize depends on proper dataset partitioning. While the remaining data is split between validation (usually 10–20%) used to adjust model parameters and testing (commonly 10–20%) to objectively evaluate performance, a standard practice consists of allocating 60–80% of the data for training [38, 39]. However, these ratios might change based on the validation technique used and quality of dataset. Furthermore, uncertainties in predictions may arise from factors such as data completeness, relevance, accuracy, and underlying assumptions. Further studies should aim to identify and address potential sources of uncertainty qualitatively to ensure the model's accuracy and validity for different strip mining contexts.

As highlighted previously, understanding the specific challenges of each mining context within the mining operation allows for the identification of key areas for improvement [28, 40–43]. Modeling the potential impact of operational adjustments allows for the optimization of practices to reduce local strip-mining effects, including land use and disruption [28, 44], as well as greenhouse gas emissions and climate change [28]. However, adopting standardized practices for optimization efforts presents considerable challenges. A complicating factor in this adoption is the lack of regulatory agreements that may take into account the unique aspects of extractive industry activities [45]. Such a framework, if combined with novel approaches like AI prediction techniques, could objectively quantify environmental performance, provide tailored guidelines, and differentiate between sustainable and less environmentally friendly practices. The absence of reliable data and transparency concerns regarding certain mining operators further complicates this task [46]. Further opportunities for efficiency are present in countries exhibiting limited governance capacities and mining companies in need of supplementary resources for environmental management practices [47]. This shift towards eco-efficient methods, despite the inherent challenges, is essential to achieve more sustainable strip mining practices in challenging contexts.

5. Conclusions

Strip mining for deep deposits, though economically favorable, presents substantial environmental challenges. The purpose of this study is to demonstrate how increasing climate change impacts and other negative effects are inherent to this mining method if associated with thicker overburden. Taken together, the results suggest that thicker overburden and higher strip ratios tend to increase climate change, land use, and energy-related impacts, mainly because larger volumes of material per unit of extracted ore must be handled and mining activities are sustained over longer periods. At the same time, the analysis shows that production scale plays an important moderating role, as larger operations are generally able to distribute energy use and land occupation more efficiently. From a practical point of view, this highlights how mine design choices, equipment, and production scale

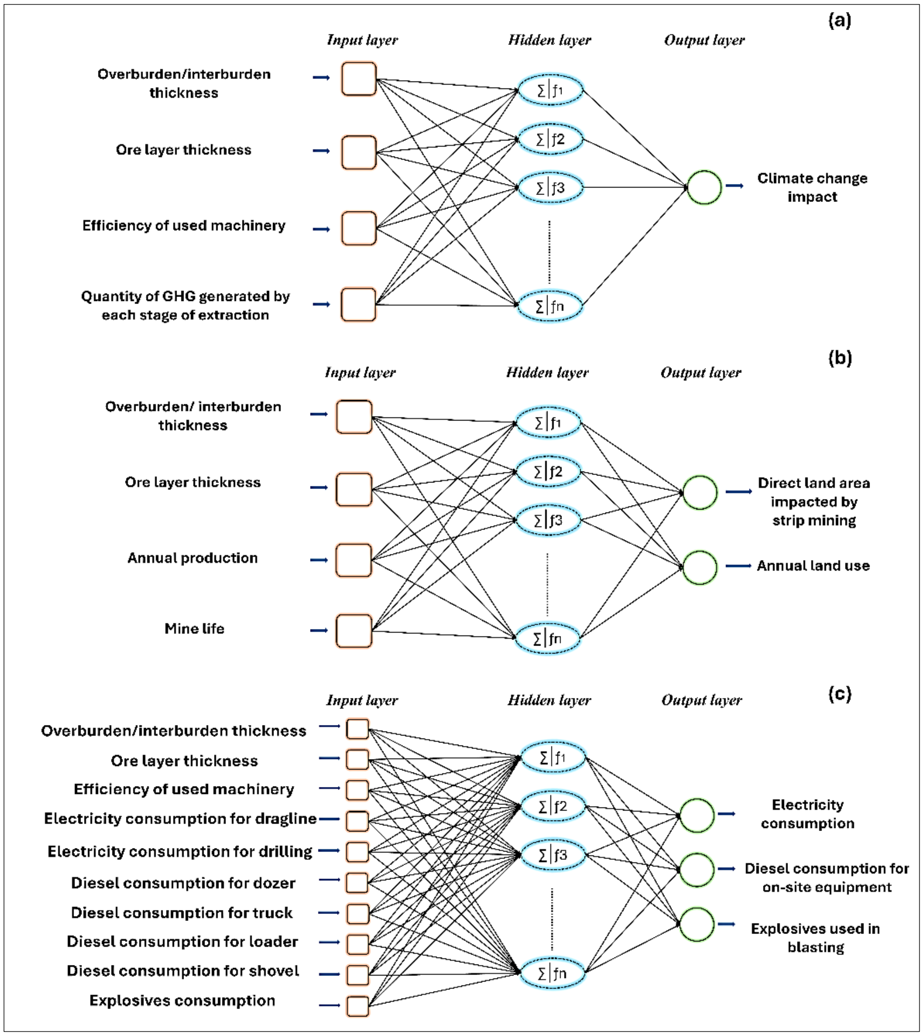

Figure 7. Proposed network architecture for predicting strip mining environmental impact: (a) climate change impact; (b) land use; (c) energy consumption.

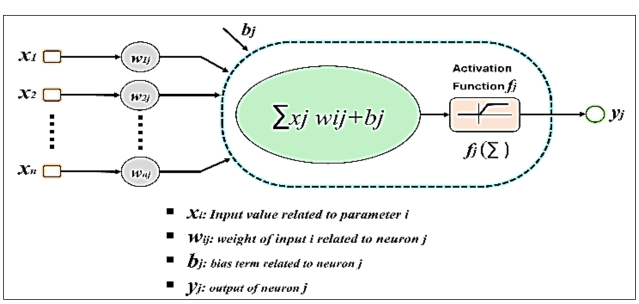

Figure 8. Schematic representation of a neuron with inputs, weighted summation, and activation function.

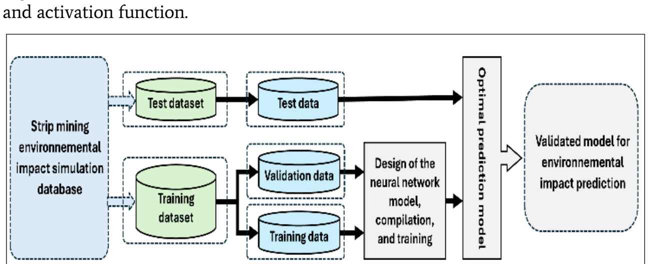

Figure 9. Dataset distribution and validation process of the ANN model proposed for environmental impact prediction.

together influence the environmental performance of these operations. In this context, the conceptual ANN framework proposed in this study may serve as a basis for future developments aiming to predict and manage these impacts under such mining conditions. Policymakers and multinational mining corporations are urged to consider these frameworks to improve the sustainability of their activities and facilitate rehabilitation efforts in the affected regions. Nonetheless, the advancement of these initiatives encounters challenges due to the lack of a standardized regulatory framework for surface mining and limited reliable data from most mining operators. It can therefore be concluded that addressing these concerns requires a multifaceted approach that combines innovative techniques, regulatory frameworks, and sustainable practices to mitigate the environmental impact of this method in the quest for viable mining of deeper deposits.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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