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**System dynamics model driven by process parameters for
carbon emission prediction and mitigation scenario
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Abstract

Carbon emissions from open-pit metal mines vary with production plans, haulage distances, energy use, energy mix, and emission factors, but conventional inventories provide limited support for planning. This study developed a process parameter driven system dynamics model that links mine plans to monthly emissions from drilling, blasting, loading, haulage, crushing, beneficiation, tailings handling, and land disturbance carbon sink loss. The model was validated using 2024 data and applied to the 2027 production plan of a case study mine. Relative errors in electricity use, diesel use, explosive consumption, and whole-mine emissions were below 3%, with a mean absolute percentage error of 0.99%. The 2027 baseline emissions were 1762.53 kt CO₂ eq; beneficiation and tailings handling accounted for 91%, and monthly emissions were strongly correlated with mining stripping quantity ($r = 0.9993$). Beneficiation energy efficiency improvement, electricity decarbonization, and haulage electrification reduced whole mine emissions by 7.83%, 14.06%, and 0.85%, respectively. Combined implementation reduced emissions to 1381.05 kt CO₂ eq and potential carbon cost from 176.67 to 138.42 million CNY. Haulage electrification reduced haulage emissions by 18.74%, but its whole mine effect was limited by haulage's small baseline contribution. The model supports identification of key sources and comparison of mitigation pathways during mine design and production planning.

Keywords: Open-pit mining; Carbon emission prediction; System dynamics modeling; Mine production planning; Mining decarbonization; Carbon cost

1 Introduction

The global low-carbon energy transition is increasing demand for mineral resources that underpin electrification, renewable power generation, grid expansion and energy storage [1,2]. Metal resources such as copper, nickel, cobalt, lithium, and rare-earth elements are widely used in electric vehicles, renewable energy infrastructure, and energy storage systems, and their global mine production has reached a substantial scale [3]. The expansion of energy transition mineral supply also has substantial land-use implications, particularly where mining projects intersect with land-connected peoples [4]. At the same time, mineral resource development remains energy and carbon intensive, and mining activities contribute substantially to global greenhouse gas emissions [5,6]. Previous studies have also noted that greenhouse gas emissions from mining are often underreported,

and emissions accounting lacks transparency. As carbon trading mechanisms continue to develop, mining enterprises will face increasing pressure to quantify not only historical emissions but also future emission trajectories and carbon costs. Therefore, historical emission accounting alone is insufficient to support low-carbon investment, production planning and operational optimization.

Open-pit mining is a major method for extracting metallic minerals, characterized by large mining and stripping volumes, long haulage distances, high-power equipment and concentrated energy consumption [7]. Carbon emissions from open-pit mines mainly arise from drilling, blasting, loading, haulage, crushing, mineral processing, tailings handling and purchased electricity use, with diesel and electricity consumption usually dominating. Life cycle assessment studies have provided important insights into emission sources in mining and mineral processing. Norgate and Haque [8] showed that the dominant emission sources differ among mineral types, with loading and haulage contributing substantially to iron ore and bauxite production, whereas crushing and grinding are more important for copper concentrate production. Memary et al. [9] further demonstrated that ore grade, production technology and regional energy structure can significantly affect the carbon footprint of copper products. These studies provide a foundation for mining carbon emission accounting, but they mainly focus on life cycle inventory construction, historical emission assessment or product carbon footprint comparison. Less attention has been paid to the dynamic emission mechanisms associated with changes in production parameters during open-pit mines development.

Carbon emissions from open-pit mines are not determined simply by production output and fixed emission factors. Instead, they evolve with spatial pit development and production organization. As mining progresses deeper and expands outward, the stripping ratio, haulage distance, vertical haulage height, road conditions, equipment load and unit energy consumption may all change, thereby affecting diesel consumption, electricity consumption and carbon emission intensity. Wang et al. [10] developed a fuel consumption prediction model based on truck haulage cycle data from open-pit mines and identified vertical haulage height, payload, haulage distance and cycle time as key factors affecting truck fuel consumption. Bodziony and Patyk [11] further showed that operating conditions in surface mine haulage influence energy consumption and equipment availability. These studies clarify the relationship between haulage conditions and energy use, but most focus on the haulage system or individual production processes. They therefore do not fully explain the system level coupling among production planning, multi-process energy consumption, emission factors and carbon cost.

Existing methods for carbon emission assessment and prediction include emission factor accounting, life cycle assessment, scenario analysis, regression models, grey prediction models, machine learning models and system dynamics models. Emission factor methods and life cycle assessment can clearly define accounting boundaries and emission sources, but they are less effective in representing time varying production parameters, technological substitution and policy related feedback. Data driven prediction models have strong fitting capabilities, but they often

provide limited interpretability of causal relationships and feedback mechanisms within complex production systems. System dynamics, originally proposed by Forrester, is suitable for analyzing complex systems characterized by nonlinearity, feedback, time delays and long term evolution [12]. For open-pit mines, pit development changes haulage distance, vertical haulage height and mining stripping intensity, which in turn affect diesel consumption. Changes in production scale and crushing grinding load affect electricity consumption, while equipment renewal and energy substitution alter the emission intensity per unit operation. These interactions have clear temporal and cumulative characteristics, making system dynamics suitable for modeling dynamic carbon emissions in open-pit mining systems. System dynamics has been applied to electrification and emission reduction scenario analysis in open-pit copper haulage [13], while dynamic simulation has been used to represent uncertain and time varying operating conditions and support proactive scenario evaluation in open-pit production planning [14]. These studies demonstrate the value of dynamic modeling for prospective mine planning; however, a process level framework integrating the major production stages, emission sources, time varying production parameters, and carbon price scenarios remains lacking.

In summary, three research gaps remain. First, mining carbon emission studies are still dominated by static accounting and life cycle assessment, with limited representation of temporal changes in production conditions and energy consumption. Second, studies on open-pit mine energy consumption often focus on haulage systems or single production processes, and have not fully revealed the coupling relationships among emissions from multiple production stages. Third, carbon emission prediction results are rarely linked with carbon price scenarios, limiting their direct usefulness for carbon cost assessment and low-carbon investment decisions [15]. To address these gaps, this study develops a process parameter driven system dynamics model for dynamic carbon emission prediction and mitigation scenario analysis in open-pit metal mines. The model brings together major production processes, time varying production parameters and carbon price scenarios within a unified framework, enabling coordinated estimation of carbon emissions and carbon cost. Specifically, this study defines the carbon emission accounting boundary for open-pit mine production activities, identifies major emission sources such as diesel, electricity and blasting materials, characterizes the causal relationships among mining stripping scale, haulage conditions, energy-consumption intensity, equipment efficiency, energy structure and carbon emissions, and evaluates emission trends and potential carbon cost under different mitigation scenarios. The results can support the identification of key emission processes, optimization of production organization, and comparison of equipment renewal and energy substitution pathways in open-pit mines.

2 Materials and Methods

2.1 Model framework

Conventional carbon emission accounting for mines is mainly based on actual energy

consumption, material consumption and production statistics, and is therefore suitable for historical emission accounting and reporting. The Chinese standard GB/T 32151.28-2024, Requirements of greenhouse gas emissions accounting and reporting-Part 28: Mining enterprise, specifies the accounting boundary, accounting procedures and data quality requirements for greenhouse gas emissions from mining enterprises [16]. However, for new mining projects, mine design stages and medium to long term production planning, actual operating data are usually incomplete. Ex post accounting methods alone are therefore insufficient for predicting emission changes across future production stages or for analyzing how production parameter adjustments affect emission pathways.

Carbon emissions from open-pit mines are jointly affected by mining and stripping scale, stripping ratio, haulage distance, vertical haulage height, equipment efficiency, energy consumption intensity, energy structure, emission factors and land disturbance area. These variables change continuously with pit development and production organization. Therefore, carbon emission prediction in open-pit mines requires a dynamic modelling method that can represent temporal variation, causal relationships and cumulative effects. System dynamics represents temporal variation, causal relationships, and cumulative effects through linked stock and flow structures and was therefore selected as the modeling approach in this study[12,13].

In this study, Vensim PLE was used to develop a dynamic assessment and prediction model for carbon emissions from open-pit metal mines. In the model, total mine carbon emissions and process level carbon emissions were defined as stock variables, monthly carbon emissions from each production process were defined as flow variables, and mining stripping plans, blast hole pattern parameters, haulage distance, equipment energy consumption intensity, energy structure, emission factors, land disturbance area and carbon price were defined as auxiliary variables. The model describes the relationships among open-pit mine production activities, energy and material consumption, carbon emissions, carbon sink loss caused by land disturbance and potential carbon cost.

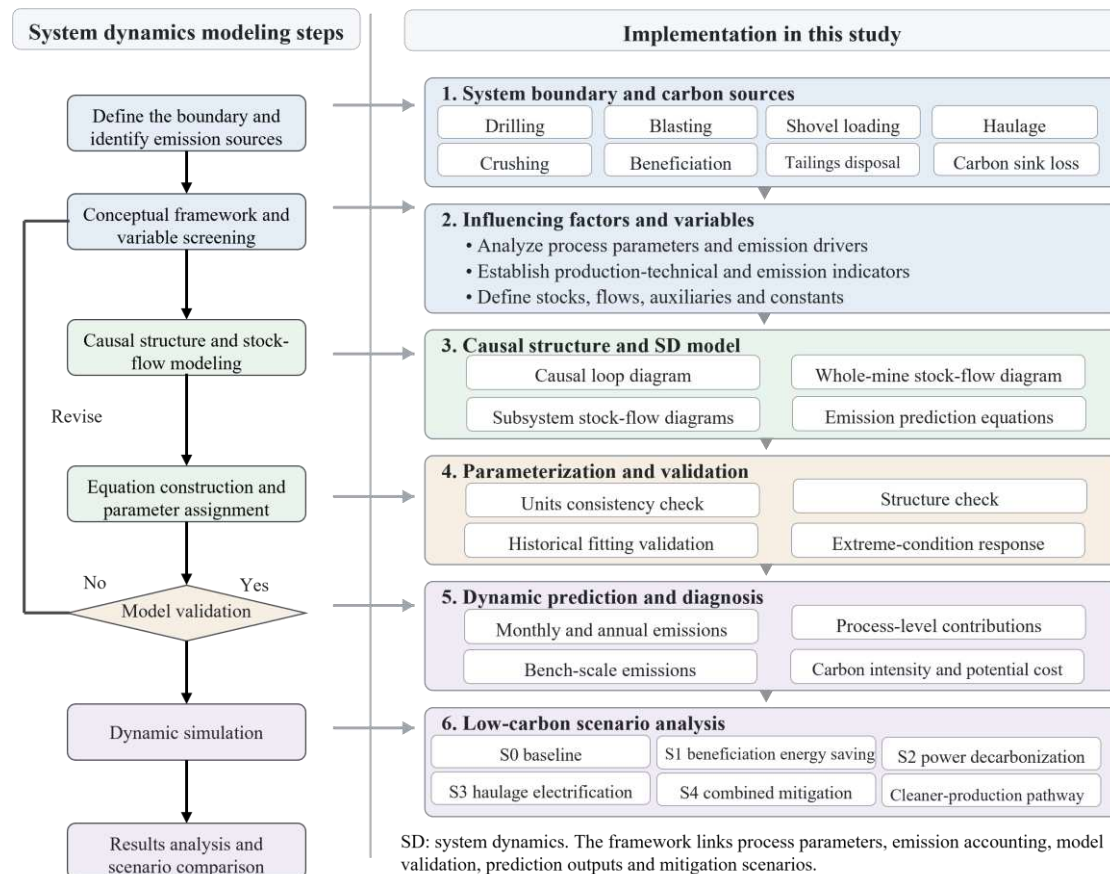


Fig.1. System dynamics modeling workflow and research framework.

Fig. 1 shows the modelling workflow and research framework. First, the system boundary for carbon emissions from open-pit mining was defined, and the main emission sources were identified. Second, the causal structure of the model was constructed based on mine design parameters and production technology indicators. Third, stock-flow diagrams and system dynamics equations were established in Vensim PLE. The model parameters were then assigned using mine design documents, historical production data, energy consumption data and emission factors. Model validity was examined through dimensional consistency checks, structural checks and historical fitting validation. Finally, scenario simulations were conducted to analyze emission changes, process level contributions and potential carbon cost under different production conditions and low-carbon measures.

2.2 System boundary and classification of carbon emission sources

The model boundary covers the process from open-pit extraction to concentrate production and tailings handling, as shown in Fig. 2. Smelting, refining, downstream manufacturing, transportation outside the mine production system and end-use stages were excluded. This boundary is consistent

with the objective of this study, which is to analyze dynamic carbon emission prediction and mitigation scenarios during the mine production stage rather than to conduct a full product life-cycle assessment.

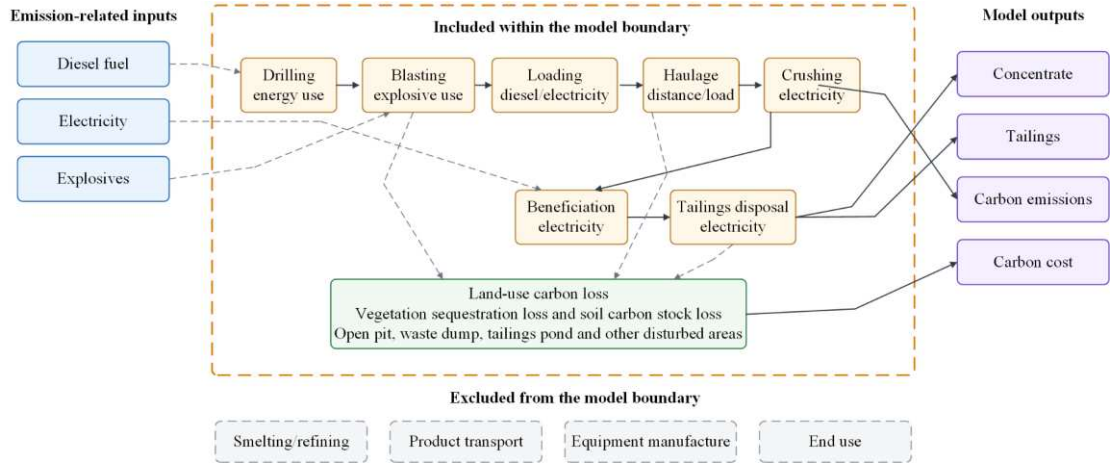


Fig.2. System boundary for carbon emissions in an open-pit metal mine.

Based on the IPCC emission factor method and the greenhouse gas accounting requirements for mining enterprises, a bottom up process decomposition approach was used to identify carbon emission sources[17]. The production system of an open-pit metal mine was divided into eight modules: drilling, blasting, loading, haulage, crushing, beneficiation, tailings handling and carbon sink loss caused by land disturbance. The first seven modules represent production process emissions caused by energy or material consumption. The land disturbance module represents the loss of vegetation carbon uptake capacity and soil carbon storage caused by open-pit excavation, waste dump occupation, tailings storage construction and other disturbed areas[18,19].

Within this system boundary, carbon emission sources were classified into two categories: production process emissions and land disturbance carbon loss, as shown in Fig. 3. Production process emissions mainly arise from electricity, diesel, gasoline and explosive consumption. Drilling, loading, haulage, crushing, beneficiation and tailings handling are mainly associated with diesel or electricity consumption, whereas blasting is mainly associated with explosive consumption. Land disturbance carbon sink loss was estimated using newly disturbed area and unit area carbon parameters. Vegetation and soil carbon sink recovery during subsequent reclamation was not considered in this study.

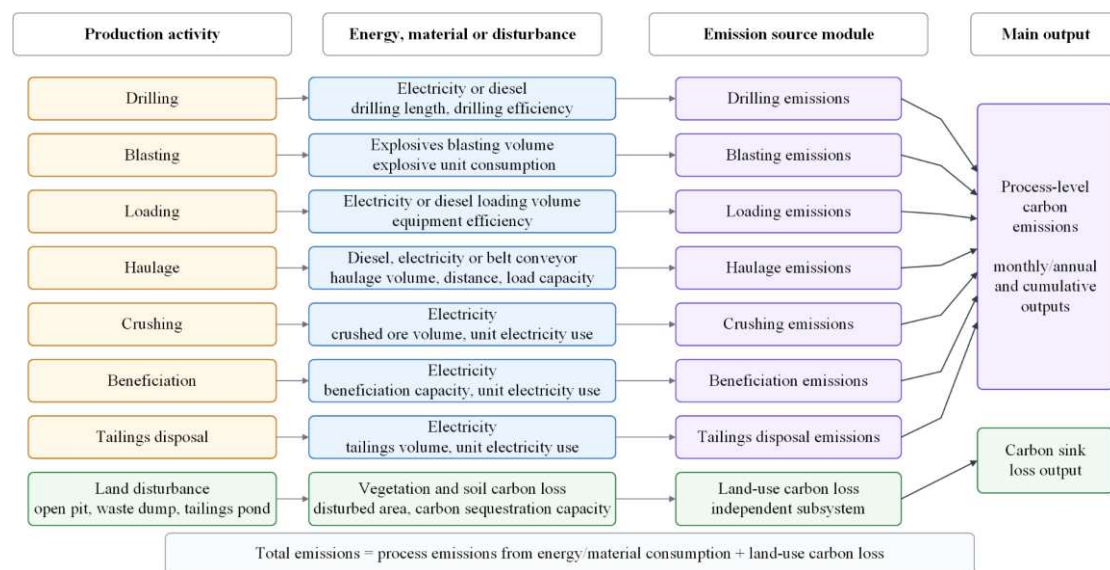


Fig.3. Decomposition of carbon emission sources in an open-pit metal mine.

Carbon emissions in each module were characterized by activity data and emission factors. Drilling emissions were mainly affected by total blast hole length and unit energy consumption of drilling equipment. Blasting emissions depended on blasting volume, explosive consumption intensity and the explosive emission factor. Loading emissions were related to loading volume, equipment type and unit energy consumption. Haulage emissions were jointly affected by haulage volume, haulage distance, haulage equipment type and unit haulage energy consumption. Crushing, beneficiation and tailings handling emissions were mainly determined by processing volume and unit electricity consumption. Land disturbance carbon sink loss was determined by disturbed area, unit area vegetation carbon uptake capacity and unit area soil carbon storage.

2.3 Indicator system and causal structure

Based on the factors affecting carbon emissions in open-pit metal mines, an indicator system was established following the principles of relevance, hierarchy and data availability. The structure of the carbon emission prediction indicator system is shown in Supplementary Fig. S1. The indicators were divided into two categories: production technology indicators and carbon emission indicators, as listed in Supplementary Tables S1 and S2. Production technology indicators describe production conditions that determine operation volume, energy consumption and material consumption, including mining stripping plans, blast hole pattern parameters, explosive consumption intensity, loading equipment parameters, haulage volume, haulage distance, crushing throughput, beneficiation feed, tailings volume, land disturbance area and carbon price assumptions.

Carbon emission indicators describe monthly and cumulative carbon emissions, process level carbon emissions, carbon emission intensity and emission factors.

The mining stripping plan is the upstream driving variable in the model. Annual, monthly and bench scale mining stripping volumes directly determine the operation volumes of drilling, blasting, loading, haulage, crushing, beneficiation and tailings handling. As mining advances deeper or outward, haulage distance, vertical haulage height, stripping ratio and land disturbance area may also change, further affecting energy consumption, material consumption, carbon emissions and carbon emission intensity.

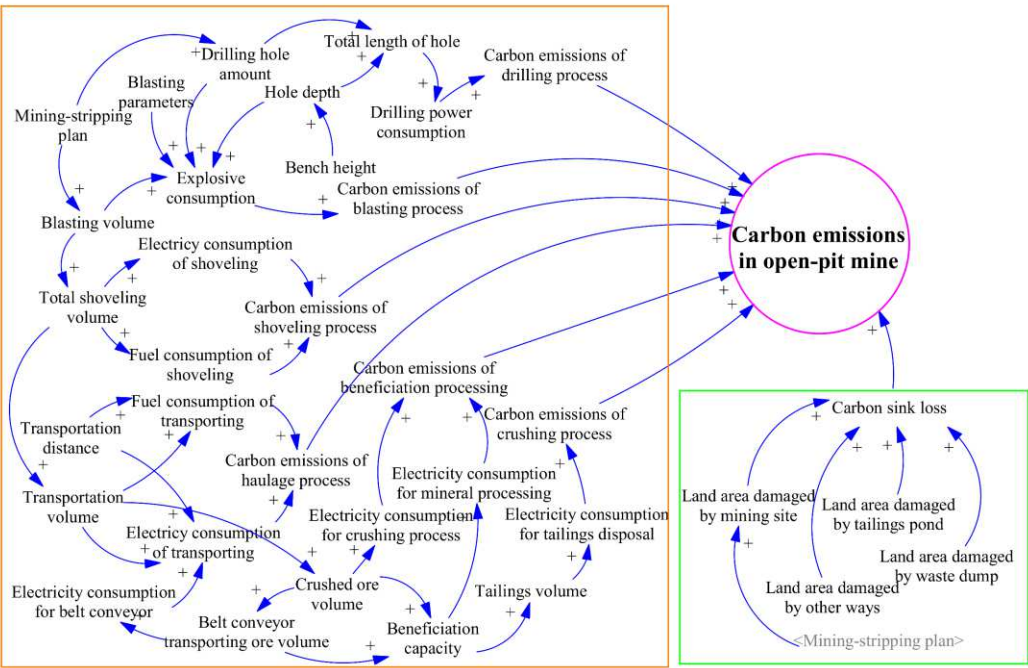


Fig.4. Causal structure diagram of the open-pit mine carbon emission model.

Figure 4 presents the causal structure of the model. Time varying mining stripping plans and key process parameters determine process activity levels, which in turn determine energy and material consumption, process level carbon emissions, and whole mine carbon emissions. The diagram also represents the pathway from land disturbance to carbon sink loss and the estimation of potential carbon cost under specified carbon price scenarios. These directional linkages define the information flow among the subsystem modules and provide the conceptual basis for the stock and flow formulations and governing equations presented in Section 2.4.

2.4 Stock flow structure and accounting equations

The model was implemented as a stock and flow simulation with a monthly time step. Monthly

mining stripping plans and scenario parameters serve as time varying exogenous drivers, whereas process activity levels, energy and material consumption, and process specific carbon emission rates are calculated endogenously through the linked subsystem equations. The detailed stock and flow diagrams for the subsystem modules are provided in Supplementary Figs. S2-S9. A potential carbon cost assessment module applies an assumed carbon price to the modeled whole mine carbon emission rate at each time step and accumulates the resulting monthly costs.

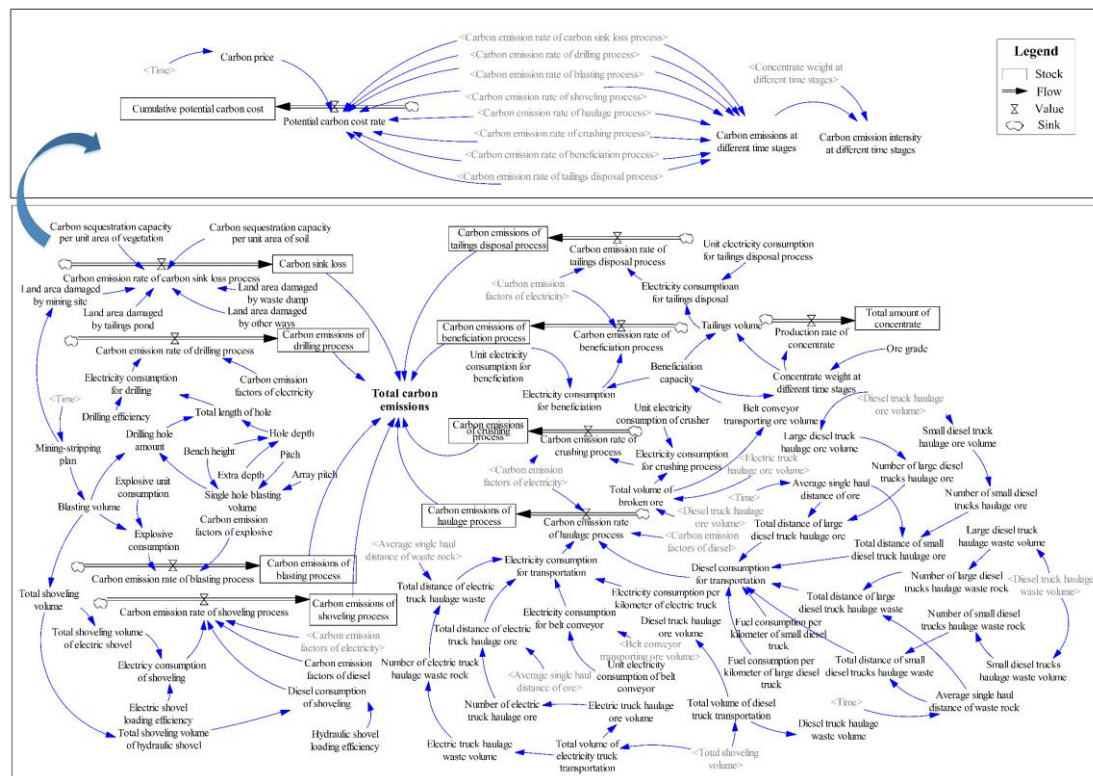


Fig.5. Overall stock and flow structure of the open-pit mine carbon emission model.

In the stock and flow structure, cumulative process level carbon emissions and cumulative potential carbon cost are represented as stock variables, whereas process specific carbon emission rates and the potential carbon cost rate are represented as flow variables. Cumulative whole mine carbon emissions are obtained by summing the process level emission stocks. Mining stripping plans, blast hole pattern parameters, equipment efficiencies, haulage distances, unit energy consumption, energy mix, emission factors, and carbon price are represented as auxiliary variables. By linking these variables, the model translates changes in production plans and operating conditions into process activity levels and energy or material requirements, and subsequently into process level and whole mine carbon emissions, carbon emission intensity, and potential carbon cost. This formulation captures both monthly variations and the cumulative effects of emissions and potential carbon cost

over the simulation horizon.

The basic emission calculation follows the emission factor method, in which stage level carbon emissions are calculated as the product of activity data and the corresponding emission factor:

$$E_{CO_2}(t) = AD(t) \times EF \quad (1)$$

where $E_{CO_2}(t)$ is the carbon emission in stage t , t CO₂ eq. $AD(t)$ is the activity data causing greenhouse gas emissions in stage t mainly referring to energy or material consumption in each production process. EF is the greenhouse gas emission factor corresponding to the activity data.

The carbon emissions of the mine in stage t consist of emissions from drilling, blasting, loading, haulage, crushing, beneficiation, tailings handling and land disturbance carbon loss:

$$EM_i(t) = F_{dr}(t) + F_{ex}(t) + F_{sl}(t) + F_{tc}(t) + F_{cr}(t) + F_m(t) + F_t(t) + F_{cs}(t) \quad (2)$$

where $EM_i(t)$ is the total carbon emission of the mine in stage t , t CO₂ eq. F_{dr} , F_{ex} , F_{sl} , F_{tc} , F_m , F_{cr} , F_t and F_{cs} are the carbon emissions from drilling, blasting, loading, haulage, crushing, beneficiation, tailings handling and land disturbance carbon loss, respectively, t CO₂ eq.

The cumulative carbon emissions of the mine up to stage t are calculated as:

$$EM(t) = EM(t-1) + EM_i(t) \quad (3)$$

The stage level carbon emission intensity is calculated as:

$$CI_i(t) = \frac{EM_i(t)}{M_c(t)} \quad (4)$$

where $EM(t)$ is the cumulative carbon emission up to stage t , t CO₂ eq. $CI_i(t)$ is the carbon emission intensity in stage t , t CO₂ eq/t. $M_c(t)$ is the concentrate output in stage t , t.

2.5 Subsystem prediction modules and potential carbon cost

2.5.1 Drilling subsystem

The drilling module was used to estimate carbon emissions caused by electricity consumption by drilling equipment. Drilling activity data were represented by the total blast hole length, which was jointly determined by blasting volume and blast pattern parameters, including hole spacing, burden, bench height, subdrilling depth and blast hole depth. An increase in blasting volume increases the required number of blast holes and the total blast hole length. Within a reasonable design range, increasing hole spacing, burden or blast hole depth can increase the rock volume broken by a single hole, thereby reducing the number of blast holes and the drilling electricity consumption required per unit rock volume. The equations for the drilling module are given in Eq.

267 (5).

$$\left\{ \begin{array}{l} F_{dr} = INTEG(F'_{dr}, 0, unit: t CO_2eq) \\ F'_{dr} = F_{dr_elec} \times EF_{elec} \times 10^{-3} \\ F_{dr_elec} = D_{dr} \times L_{dr} \\ L_{dr} = \frac{(h + \Delta H)V}{v} \\ v = h \times a \times b \\ V = P \end{array} \right. \quad (5)$$

268 2.5.2 Blasting subsystem

269 The blasting module was used to estimate carbon emissions caused by explosive consumption.
270 Explosive consumption was determined by blasting volume and explosive consumption intensity,
271 and blasting emissions were calculated using explosive consumption and the corresponding
272 explosive emission factor. The equations for the blasting module are given in Eq. (6).

$$\left\{ \begin{array}{l} F_{ex} = INTEG(F'_{ex}, 0, unit: t CO_2eq) \\ F'_{ex} = F_{ex_epe} \times EF_{epe} \times 10^{-3} \\ F_{ex_epe} = q \times V \end{array} \right. \quad (6)$$

273 2.5.3 Loading subsystem

274 The loading module was used to estimate carbon emissions caused by diesel or electricity
275 consumption by loading equipment. Energy consumption in this process was determined by loading
276 volume, equipment type, operating efficiency and unit energy consumption. The equations for the
277 loading module are given in Eq. (7).

$$\left\{ \begin{array}{l} F_{sl} = INTEG(F'_{sl}, 0, unit: t CO_2eq) \\ F'_{sl} = F_{sl_elec} \times EF_{elec} \times 10^{-3} + F_{sl_fuel} \times EF_{dsl} \times 10^{-3} \\ F_{sl_elec} = Q_{sl_elec} \times S_{elec} \\ F_{sl_fuel} = Q_{hy} \times S_{hy} \\ Q_{sl} = Q_{sl_elec} + Q_{hy} \\ V = Q_{sl} \end{array} \right. \quad (7)$$

278 2.5.4 Haulage subsystem

279 The haulage module was used to convert ore and waste rock haulage activities into diesel and
280 electricity consumption. This module considered haulage volume, haulage distance, vehicle type,
281 rated load and unit energy consumption, and was used to compare emission changes under diesel
282 truck, electric truck and other haulage configurations. Haulage emissions were calculated from the
283 fuel or electricity consumption of different haulage modes and the corresponding emission factors.
284 The equations for the haulage module are given in Eq. (8).

$$\left\{ \begin{array}{l} F_{tc} = INTEG(F'_{tc}, 0, \text{unit: } t CO_2eq) \\ F'_{tc} = F_{tc_elec} \times EF_{elec} \times 10^{-3} + F_{tc_fuel} \times EF_{fuel} \times 10^{-3} \\ F_{tc_elec} = T'_{tc_elec} \times (L_{to_elec} + L_{tw_elec}) + F_{bc_elec} \\ F_{tc_fuel} = T_{l_fuel} \times (L_{lto_fuel} + L_{ltw_fuel}) + T_{s_fuel} \times (L_{sto_fuel} + L_{stw_fuel}) \\ F_{bc_elec} = T_{bc_elec} \times (Q_{to_elec} + Q_{to_fuel}) \\ L_{to_elec} = l_{to} \times N_{to_elec} \\ L_{tw_elec} = l_{tw} \times N_{tw_elec} \\ L_{lto_fuel} = l_{to} \times N_{lto_fuel} \\ L_{ltw_fuel} = l_{tw} \times N_{ltw_fuel} \\ L_{sto_fuel} = l_{tc} \times N_{sto_fuel} \\ L_{stw_fuel} = l_{tc} \times N_{stw_fuel} \end{array} \right. \quad (8)$$

285 2.5.5 Crushing subsystem

286 The crushing module estimated electricity related emissions based on crushing throughput and
 287 the unit electricity consumption of crushers. The equations for the crushing module are given in Eq.
 288 (9).

$$\left\{ \begin{array}{l} F_{cr} = INTEG(F'_{cr}, 0, \text{unit: } t CO_2eq) \\ F'_{cr} = F_{cr_elec} \times EF_{elec} \times 10^{-3} \\ F_{cr_elec} = Q_{cr} \times C_{elec} \\ Q_{cr} = Q_{tc_elec} + Q_{tc_fuel} \end{array} \right. \quad (9)$$

289 2.5.6 Beneficiation and tailings handling subsystem

290 The beneficiation and tailings handling modules estimated electricity related emissions based
 291 on beneficiation feed, concentrate output, tailings volume and unit electricity consumption. The
 292 equations for the beneficiation and tailings handling modules are given in Eqs. (10) and (11),
 293 respectively.

$$\left\{ \begin{array}{l} F_m = INTEG(F'_m, 0, \text{unit: } t CO_2eq) \\ F'_m = F_{m_elec} \times EF_{elec} \times 10^{-3} \\ F_{m_elec} = Q_h \times M_{m_elec} \\ Q_h = Q_{bc} \end{array} \right. \quad (10)$$

$$\left\{ \begin{array}{l} F_t = INTEG(F'_t, 0, \text{unit: } t CO_2eq) \\ F'_t = F_{t_elec} \times EF_{elec} \times 10^{-3} \\ F_{t_elec} = Q_t \times M_{t_elec} \\ Q_t = Q_h - M_{c_i} \\ M_{c_i} = Q_h \times g_h \end{array} \right. \quad (11)$$

294 2.5.7 Land disturbance carbon sink loss subsystem

295 The land disturbance carbon sink loss module was used to estimate the loss of carbon sink
 296 function caused by newly disturbed areas. The activity data included the disturbed areas of the open
 297 pit, waste dump, tailings storage facility and other mine engineering areas. Carbon loss was
 298 calculated using unit area vegetation carbon uptake capacity and unit area soil carbon storage
 299 parameters. This module represents the effects of land disturbance on vegetation and soil carbon

pools, but does not include vegetation or soil carbon sink recovery during subsequent reclamation and ecological restoration. The equations for this module are given in Eq. (12).

$$\begin{cases} F_{cs} = INTEG(F'_{cs}, 0, unit: t CO_2eq) \\ F'_{cs} = V_{cs} \times (S_m + S_t + S_w) + S_{cs} \times (S_m + S_t + S_w) \\ S_m = \frac{S_u}{Q_u} \times P \\ S_t = \frac{S}{V_t} \times Q_t \\ S_w = \frac{S}{V_w} \times (Q'_{tc_elec} + Q'_{tc_fuel}) \end{cases} \quad (12)$$

2.5.8 Potential carbon cost

The potential carbon cost module was used to convert predicted carbon emissions into cost exposure under a given carbon price scenario. It does not represent an additional source of carbon emissions. Potential carbon cost was calculated by multiplying stage level carbon emissions by the corresponding carbon price, as shown in Eq. (13).

$$\begin{cases} PC(t) = INTEG(PC'(t), 0) \\ P'_c(t) = P_c(t) \times EM_r(t) \end{cases} \quad (13)$$

where $PC(t)$ is the cumulative potential carbon cost up to time t , in CNY month⁻¹, $PC'(t)$ is the potential carbon cost rate at time t , in CNY, $P_c(t)$ is the assumed carbon price at time t , in CNY/t CO₂ eq; and $EM_r(t)$ is the whole mine carbon emission rate defined in Eq. (2), in t CO₂ eq month⁻¹.

Because carbon allowances, free allocation ratios and offset mechanisms were not included in this study, the result represents only potential cost under the assumed carbon price scenario and does not correspond to the actual carbon market compliance cost of the enterprise.

3 Case study and Data Sources

3.1 Overview of the case-study mine

A large open-pit metal mine in China was selected as the case study mine for model parameterization and simulation. The mine is a restricted industrial site not open to the public and is one of the designated pilot sites of the National Key R&D Program of China (Project No. 2022YFC2903905). Within the approved project framework, the mine operator granted permission to conduct the study and use the relevant operational data. To protect commercially sensitive information, only aggregated and anonymized data are reported, and the identity and precise location of the mine are withheld. The designed production capacity of the mine is 150 kt·d⁻¹, equivalent to 45,000 kt·a⁻¹ assuming 300 operating days per year, and the designed service life is 21

years. The final open-pit boundary covers a total area of 503.57 hm². The waste dump has a designed capacity of 30 million m³ and a final designed area of 84.37 hm². The maximum mining depth is approximately 420 m, and the bench height is 15 m. A three-dimensional view of the final pit limit is shown in Fig. S10.

The main production processes of the case study mine include drilling, blasting, loading, haulage, crushing, beneficiation and tailings handling. The haulage system adopts a combined scheme consisting of truck haulage, semi mobile or fixed crushing stations, and belt conveyors. The crushing system uses a semi-fixed crushing station. The beneficiation process mainly includes an SABC grinding circuit, flotation, dewatering and drying. Tailings are classified by cyclones and thickened before being discharged to the tailings storage facility or a comprehensive utilization system.

From the perspective of model applicability, the mine has typical production characteristics of large open-pit metal mines. As the pit advances deeper and outward, mining stripping volume, ore and waste rock haulage distances, equipment load and land disturbance area vary across production stages, thereby affecting energy consumption, material consumption, carbon emissions and potential carbon cost. Therefore, selecting this mine as the case study enables the proposed model to be tested for its ability to represent production stage changes and the dynamic evolution of carbon emissions in open-pit mining.

3.2 Model parameterization

Model parameterization followed the principle that production organization in the case study mine should be consistent with the measurement requirements of the model equations. Mining stripping plans, equipment configuration and haulage system layout were assigned to reflect the actual production conditions of the case study mine. Energy consumption, material consumption and emission factors were converted to consistent units before being entered into the model. For parameters without continuous statistical records, values were obtained from mine design documents, equipment manuals or industry guidelines, and their rationality was checked during model validation.

The period from January to December 2024 was used for model operation and validation. The initial simulation time was January, the final simulation time was December, and the time step was

one month. The basic model settings are shown in Fig. S11.

The mining stripping plan was decomposed according to the production organization of the mine and then transferred to the drilling, blasting, loading, haulage, crushing, beneficiation and tailings handling subsystems. Some variables in the model changed dynamically with the time step, including mining stripping volume, ore volume, waste rock volume, haulage distance, beneficiation feed, concentrate output, tailings volume, land disturbance area and carbon price. In the baseline scenario, parameters such as unit energy consumption of equipment, blast hole pattern parameters and emission factors were kept constant. In scenario simulation or sensitivity analysis, haulage distance, energy structure, unit energy consumption, electricity emission factor and carbon price were adjusted according to the research purpose.

The main parameter categories, representative variables, data sources and model roles are summarized in Table 1. The complete parameter list, including parameter names, symbols, units and data sources, is provided in Supplementary Table S1.

Table 1

Compact summary of model parameterization.

Parameter category	Representative variables	Main data sources
Mining stripping plan	P, Q_o, Q_w	Annual and monthly mining stripping plans; production schedule
Drilling and blasting	$a, b, H, \Delta H, D_{dr}, q$	Mine design documents; blasting design documents; equipment manuals; material consumption records
Loading	S_{elec}, S_{hy}	Equipment records; equipment manuals; operating records
Haulage	$l_{to}, l_{tw}, T_{fuel}, T_{elec}, T_{bc}$	Haulage system design; dispatching records; equipment operating records
Crushing and beneficiation	$Q_{cr}, Q_m, M_c, C_{elec}, M_{m_elec}$	Production schedule; crushing station records; beneficiation plant operating records
Tailings handling	Q_t, M_{t_elec}	Beneficiation plant records; tailings storage records; equipment data
Land disturbance	$S_m, S_w, S_t, V_{CS}, SOC$	Mine surveying; design documents; remote sensing interpretation; ecological surveys; literature data
Emission factors and carbon price	$EF_{elec}, EF_{fuel}, EF_{ex}, P_{cL}, P_{cM}, P_{cH}$	Regional grid emission factors; greenhouse gas accounting guidelines; enterprise data; carbon market prices and policy assumptions

Note: The complete parameter list, including parameter definitions, units, input forms, data sources and model uses, is provided in Supplementary Table S3.

For external input variables that vary over time and are difficult to express using fixed analytical equations, table functions in Vensim PLE were used for parameter assignment. A table

function establishes a correspondence between time and variable values, and is suitable for representing time series parameters such as monthly mining stripping plans, ore processing volume, haulage distance, land disturbance area and carbon price. In this study, table functions were used to describe the monthly mining stripping plan and carbon price scenario parameters of the case study mine from January to December 2024, as shown in Figs. S12 and S13.

Through the above parameterization, the model uses the monthly mining stripping plan as the driving input and transfers production operation volumes stepwise to the energy consumption, material consumption, carbon emission and potential carbon cost modules. This provides the parameter basis for subsequent model validation and simulation analysis.

3.3 Model validation

3.3.1 Dimensional consistency check

The dimensional consistency check was used to determine whether the measurement units of variables in the model equations were consistent. In this study, the Units Check function in Vensim PLE was used to examine the variable equations in the drilling, blasting, loading, haulage, crushing, beneficiation, tailings handling, land disturbance carbon loss and potential carbon cost subsystems. The check focused on the unit conversion between electricity consumption and electricity emission factors, the matching relationships between diesel and explosive consumption and their corresponding emission factors, the dimensional relationship between land disturbance area and unit area carbon loss parameters, and the conversion relationship between carbon emissions and carbon cost. The results showed that the dimensional relationships among variables were consistent, and no unit mismatch errors were detected. The dimensional consistency check results are shown in Fig. S14, indicating that the model satisfies the basic computational requirements for system dynamics simulation.

3.3.2 Model structure check

The model structure check was used to determine whether the variable relationships, causal links and module boundaries were consistent with the actual production characteristics of open pit metal mines. The check focused on whether the drilling, blasting, loading, haulage, crushing, beneficiation, tailings handling and land disturbance carbon sink loss modules were complete; whether the transmission relationships among mining stripping plans, operation volumes, energy or

material consumption, emission factors and carbon emissions followed engineering logic; and whether duplicate or missing calculations existed among the modules.

During model development, the causal loop diagram and stock flow diagram were revised iteratively using mine design documents, production statistics and field investigation information. In addition, experts in mining engineering, mine production technology, energy management and environmental management were consulted to examine the system boundary, key variable selection, parameter transmission relationships and structural rationality of the model. The Vensim PLE model structure check showed no apparent structural errors.

3.3.3 Historical fitting validation

Historical fitting validation was used to evaluate the consistency between model simulation results and actual production statistics. The period from January to December 2024 was selected as the validation period. Simulated electricity consumption, diesel consumption, explosive consumption and total carbon emissions were compared with enterprise statistical records or previously calculated emission data. Model fitting performance was evaluated using the mean absolute percentage error (MAPE) and root mean squared percentage error (RMSPE), as shown in Eqs. (14) and (15).

$$MAPE = \frac{1}{n} \sum_{t=1}^n \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right| \times 100\% \quad (14)$$

$$RMSPE = \sqrt{\frac{1}{n} \sum_{t=1}^n (Y_t - \hat{Y}_t)^2} \times 100\% \quad (15)$$

where Y_t is the observed value of validation indicator, $\hat{Y}_t$ is the corresponding simulated value, n is the number of validation indicators. In this study, the validation indicators included electricity consumption, diesel consumption, explosive consumption and total carbon emissions.

Table 2

Historical fitting validation results based on annual cumulative values.

Validation indicator	Observed value	Simulated value	Relative error
Electricity consumption (MWh)	1500976.35	1512282.60	0.75%
Diesel consumption (t)	19603.72	19077.94	2.68%
Explosive consumption (t)	55877.92	56035.08	0.28%
Total carbon emissions (t CO ₂ eq)	1416787.3	1413386.29	0.24%
MAPE (%)			0.99%
RMSPE (%)			1.41%

As shown in Table 2, the relative errors for annual cumulative electricity consumption, diesel

consumption, explosive consumption and total carbon emissions were 0.75%, 2.68%, 0.28% and 0.24%, respectively, all below 3%. The relative error for total carbon emissions was only 0.24%, indicating that the model can represent the overall carbon emission level of the case study mine with reasonable accuracy. The MAPE and RMSPE of the four validation indicators were 0.99% and 1.41%, respectively, suggesting that the model adequately captures the overall transmission relationships among energy consumption, material consumption and carbon emissions.

It should be noted that model validity does not mean that the model can replace enterprise level measured greenhouse gas accounting. Rather, the validation results indicate that, under the defined system boundary, parameter assumptions and time scale, the model can reasonably characterize the dynamic relationships among energy consumption, material consumption and carbon emissions in open-pit metal mines.

4 Results and discussion

4.1 Prediction scenario setup and production plan inputs

After model validation, the future annual production plan of the case study mine was entered into the system dynamics model to simulate carbon emissions during the prediction period. The prediction period was set from January to December 2027, with a time step of one month. A baseline scenario was established as the reference scenario for analysing the dynamic changes in total mine emissions, process level emission contributions and low carbon mitigation scenarios.

In the baseline scenario, monthly mining stripping quantity and average haulage distance were used as input variables, as shown in Table 3 and Fig. 11. Monthly mining stripping quantity represents the production load and determines the operation scale of the drilling, blasting, loading, haulage, crushing, beneficiation and tailings handling subsystems. Average haulage distance reflects the influence of pit development and haulage organization on haulage energy consumption. Ore volume, waste rock volume, beneficiation feed, tailings volume, energy consumption and process level carbon emissions were not externally specified; instead, they were calculated stepwise by the internal model equations according to the production process relationships.

Under the baseline prediction scenario, monthly mining stripping quantity and average haulage distance varied according to the future production plan. Blast hole pattern parameters, unit equipment energy consumption, beneficiation technical parameters, energy emission factors,

explosive emission factors and land carbon loss parameters were kept consistent with those used in the model validation period. Because China's national carbon market is still expanding and its institutional framework is still being refined, future monthly carbon prices may be affected by allowance supply and demand, compliance cycles, sectoral coverage and policy expectations. Therefore, carbon price was treated as a scenario parameter in this study. The baseline scenario used a monthly carbon price sequence of 94.5-105.5 CNY/t CO₂ eq for 2027, with an annual mean of 100 CNY/t CO₂ eq, to represent a possible upward trend in carbon prices as compliance constraints strengthen.

Table 3

Main model input parameters for the prediction period.

Month	Mining stripping quantity (m ³)	Average ore haulage distance(km)	Average waste haulage distance(km)	Carbon price (CNY/t CO ₂ eq)
1	2410000	2.144	2.505	94.5
2	2950000	2.354	2.530	95.5
3	2900000	2.275	2.658	96.5
4	3250000	2.326	2.705	97.5
5	3250000	2.653	3.050	98.5
6	4100000	2.718	2.945	99.5
7	3250000	2.637	3.059	100.5
8	3450000	3.769	3.087	101.5
9	4250000	2.773	3.055	102.5
10	3450000	2.828	2.456	103.5
11	3000000	2.637	3.059	104.5
12	3200000	3.769	3.087	105.5

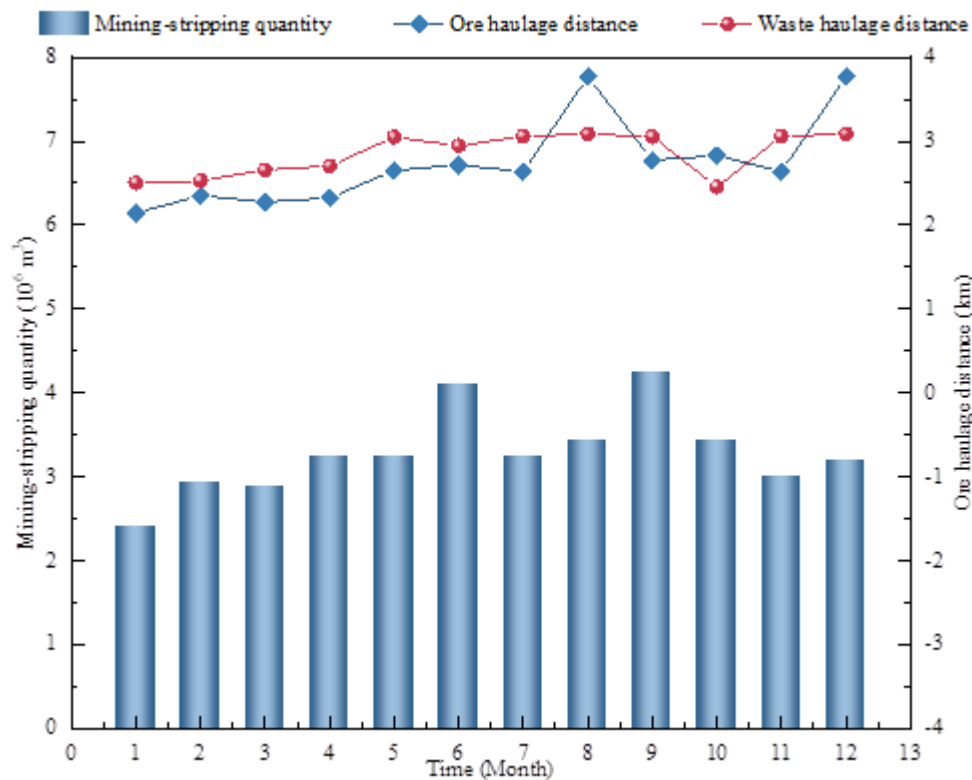


Fig. 6. Monthly mining-stripping quantity and average haulage distance during the prediction period.

Fig. 6 shows how the input variables were transferred through the model to the energy consumption, material consumption and carbon emission modules, generating monthly carbon emission results for the whole mine and for individual production processes during the prediction period. The prediction results represent scenario based simulations under the specified production plan and parameter assumptions. They were used primarily to identify emission peaks, key emission sources and low carbon optimization potential under future production organization conditions.

4.2 Dynamic changes in whole mine carbon emissions during the prediction period

Based on the 2027 production plan inputs, the system dynamics model was used to simulate monthly whole mine carbon emissions during the prediction period. The cumulative annual emissions were 1.763 Mt CO₂ eq, and the monthly average was 146.88 kt CO₂ eq, as shown in Fig. 7(a). Monthly emissions fluctuated substantially. The lowest value occurred in January, at 106.94 kt CO₂ eq, whereas the annual peak occurred in September, at 189.78 kt CO₂ eq, approximately 1.77 times the January value. Emissions in June were also relatively high, reaching 182.90 kt CO₂ eq.

The production plan indicates that monthly production load was the main driver of emission fluctuations. Mining stripping quantities in September and June were 4.25 million m³ and 4.10

million m³, respectively, both substantially higher than the annual monthly average. In contrast, the average ore haulage distance reached 3.769 km in both August and December, but these months did not produce the annual emission peak because their mining stripping quantities were lower. This indicates that, under the baseline scenario, mining stripping scale dominated monthly carbon emission fluctuations, whereas average haulage distance mainly acted as a secondary amplifying factor.

To further identify the influence of production plan parameters on monthly emission fluctuations, mining stripping quantity, average ore haulage distance and average waste rock haulage distance were selected as the main input variables, and their Pearson correlation coefficients with monthly whole mine carbon emissions were calculated as Eq(16).

$$r_{xy} = \frac{\sum_{i=1}^n (x_i - \bar{x}) (y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \quad (16)$$

Where x_i is the model input variable in month i , y_i is the whole mine carbon emission in month i , $\bar{x}$ and $\bar{y}$ are the corresponding monthly mean values, and n is the number of months in the prediction period.

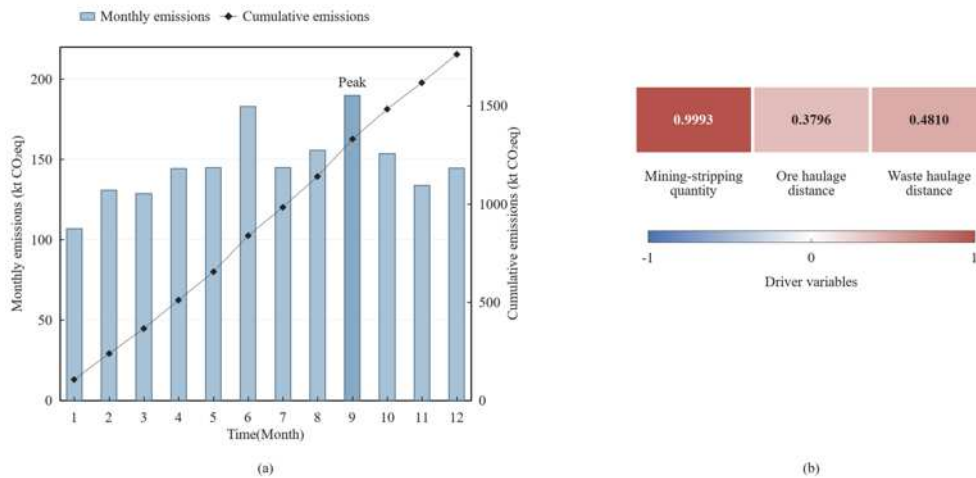


Fig. 7. Dynamic changes in whole mine carbon emissions and correlation analysis of driving variables during the 2027 prediction period: (a) monthly and cumulative carbon emissions, (b) Pearson correlation heatmap.

The correlation analysis in Fig. 7(b) further supports this interpretation. Monthly whole mine carbon emissions were highly correlated with mining stripping quantity, with a correlation coefficient of 0.9993. The correlation coefficients between monthly emissions and average ore and waste rock haulage distances were 0.3796 and 0.4810, respectively, indicating weaker correlations. This result is consistent with the model structure. Under the baseline scenario, in which blast hole

pattern parameters, unit equipment energy consumption and emission factors remain unchanged, changes in mining stripping quantity are directly transmitted to drilling length, explosive consumption, loading volume, haulage volume, crushing throughput, beneficiation feed and tailings handling volume, thereby changing emissions from each production process. Average haulage distance mainly affects the haulage subsystem and has a relatively limited effect on total mine emissions.

4.3 Process level carbon emission contributions and key emission sources

To identify the main sources of whole mine carbon emissions during the prediction period, the cumulative emissions from each production process were analysed, as shown in Fig. 8. In 2027, beneficiation generated 1381.09 kt CO₂ eq, accounting for 78.36% of total mine emissions, and was the dominant emission source in the case study mine. Tailings handling emitted 222.25 kt CO₂ eq, accounting for 12.61%, while haulage emitted 80.41 kt CO₂ eq, accounting for 4.56%. The remaining processes each contributed less than 2%, with loading, carbon sink loss, drilling, blasting and crushing accounting for 1.36%, 1.02%, 0.88%, 0.74% and 0.46%, respectively.

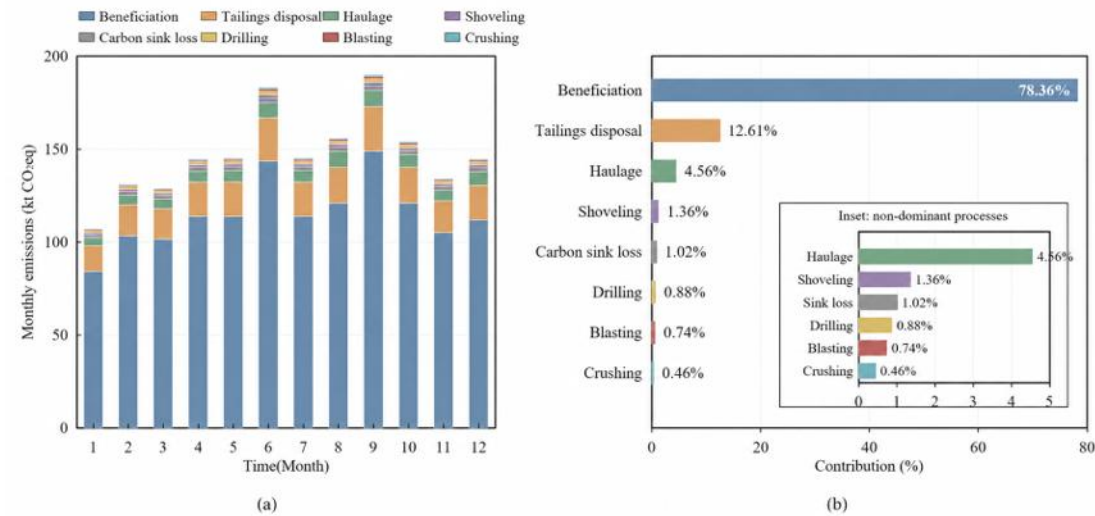


Fig. 8. Carbon emission contributions of different production processes during the prediction period: (a) monthly process level carbon emissions, (b) annual contribution by process.

These results indicate that carbon emissions in the case study mine were mainly controlled by electricity consumption in the beneficiation system. Beneficiation had a large processing volume and long continuous operating time, and electricity consumption was high in grinding, classification and separation processes. Its emission contribution was therefore much greater than that of pit operations. Tailings handling was the second largest emission source, indicating that tailings

thickening, transport and disposal are also important electricity consuming units.

Although haulage contributed less to total mine emissions than beneficiation and tailings handling, it remains an important target for production organization optimization. Haulage emissions are affected not only by haulage volume and average haulage distance, but also by vehicle energy type and the allocation of haulage tasks between diesel and electric trucks. If diesel trucks mainly undertake long distance or high volume haulage tasks, they may still generate substantial haulage emissions even when their share of the fleet is not high. Therefore, the subsequent scenario analysis used the proportion of haulage tasks assigned to different truck types to represent haul truck electrification, rather than using vehicle numbers alone.

4.4 Carbon emission intensity and potential carbon cost exposure

Based on the prediction of total mine emissions, monthly carbon emission intensity and potential carbon cost were calculated to evaluate unit product emissions and cost exposure under the assumed carbon price scenario, as shown in Fig. 9. Carbon emission intensity was defined as the ratio of monthly carbon emissions to concentrate output in the same month. Potential carbon cost was calculated by multiplying monthly carbon emissions by the corresponding carbon price. Because carbon allowances, free allocation ratios and offset mechanisms were not included, potential carbon cost represents only cost exposure under the assumed carbon price scenario and does not correspond to the actual carbon market compliance cost of the enterprise[20].

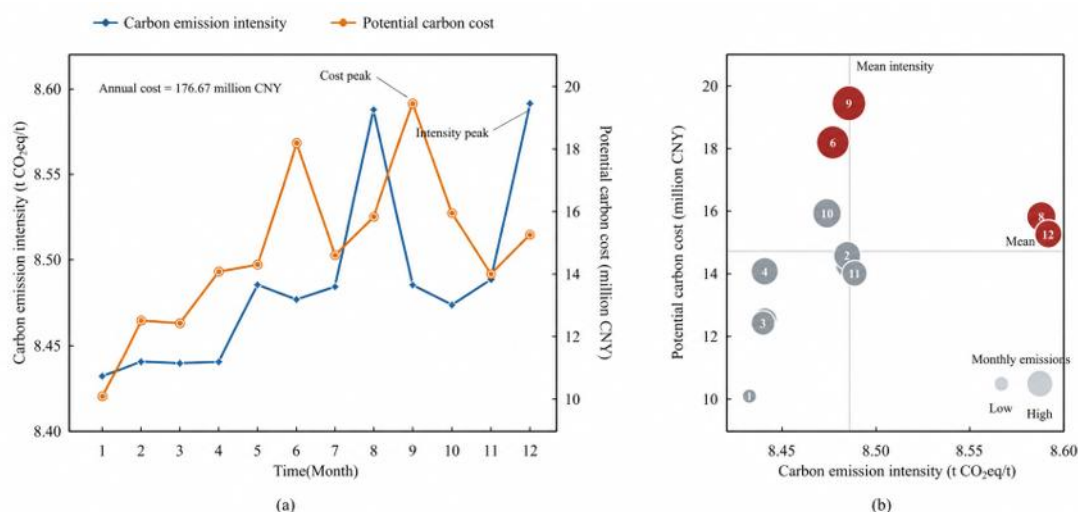


Fig. 9. Carbon emission intensity and potential carbon cost risk during the prediction period: (a) monthly changes in carbon emission intensity and potential carbon cost, (b) exposure distribution based on carbon emission intensity and potential carbon cost.

As shown in Fig. 9(a), monthly carbon emission intensity ranged from 8.432 to 8.592 t CO₂

eq/t during the 2027 prediction period, with an average value of 8.485 t CO₂ eq/t, indicating relatively small fluctuations. The cumulative potential carbon cost was 176.67 million CNY, with a monthly average of 14.72 million CNY. The highest potential carbon cost occurred in September, at 19.45 million CNY, whereas the highest carbon emission intensity occurred in December, at 8.592 t CO₂ eq/t. The peak months of these two indicators were therefore not identical, indicating that potential carbon cost was jointly affected by monthly emission volume and carbon price, whereas carbon emission intensity mainly reflected changes in unit product emissions.

The carbon emission intensity potential carbon cost exposure matrix in Fig. 9(b) further distinguishes high cost months from high intensity months. Using the prediction period averages as references, September and June were located in the high cost region, mainly because high mining stripping quantities increased total emissions. August and December showed relatively high carbon emission intensities; although their potential carbon costs were lower than that in September, they remained above the monthly average. These results indicate that low carbon mine management should not rely only on total emissions, but should also consider unit product emission levels and carbon price variation. Months with high mining stripping quantities are more likely to generate high cost exposure, whereas high intensity months require further tracking of concentrate output, feed grade, beneficiation electricity consumption and tailings handling load. Carbon emission intensity and potential carbon cost can therefore serve as complementary indicators for low carbon operational evaluation and production plan optimization in open pit mines.

4.5 Low carbon scenario simulation and mitigation pathway discussion

Using S0 as the reference, the scenario analysis extended dynamic baseline prediction to mitigation evaluation. At the production planning scale, S0 represented the aggregate effects of changes in stripping ratio, haulage geometry (including distance and vertical height), road conditions, and equipment loading through monthly ore and waste rock volumes, average haulage distances, process throughput, and site calibrated unit energy consumption parameters. Its process level emission profile then guided four mitigation scenarios targeting controllable points in the resulting energy–emission pathways: S1 improved beneficiation energy efficiency, S2 reduced the purchased electricity emission factor across all electricity consuming processes, including tailings handling, and S3 shifted part of the haulage task from diesel to electric trucks; S4 combined the

three measures. All mitigation scenarios retained the same production plan, total haulage demand, and carbon price sequence, enabling consistent comparison of how process efficiency, electricity supply decarbonization, and haulage electrification affect system wide emissions and potential carbon cost under otherwise consistent production conditions.

Table 4

Low-carbon scenario settings.

Scenario	Scenario meaning	Main parameter adjustment
S0	Baseline scenario	The 2027 production plan, unit energy consumption, haulage structure and emission factors remain unchanged
S1	Beneficiation energy saving	Unit electricity consumption of beneficiation is reduced by 10%
S2	Power decarbonization	Purchased electricity emission factor is reduced by 15%
S3	Haulage electrification	30% of the haulage volume undertaken by diesel trucks in the baseline scenario is shifted to electric trucks, while total haulage volume remains unchanged; the haulage volume ratio of electric to diesel trucks changes from 30:70 to 51:49
S4	Combined mitigation	S1, S2 and S3 are implemented simultaneously

In the S3 scenario, the haulage volumes undertaken by different truck types were used to represent the degree of haulage electrification. Under the baseline scenario, the haulage volume ratio of electric trucks to diesel trucks was 30:70. S3 assumes that 30% of the baseline diesel truck haulage volume is shifted to electric trucks, while the total ore and waste rock haulage volume remains unchanged. After adjustment, the haulage volume ratio of electric trucks to diesel trucks becomes 51:49. This scenario changes only the allocation of haulage tasks between the two truck types, and does not affect subsequent crushing, beneficiation or tailings-handling volumes.

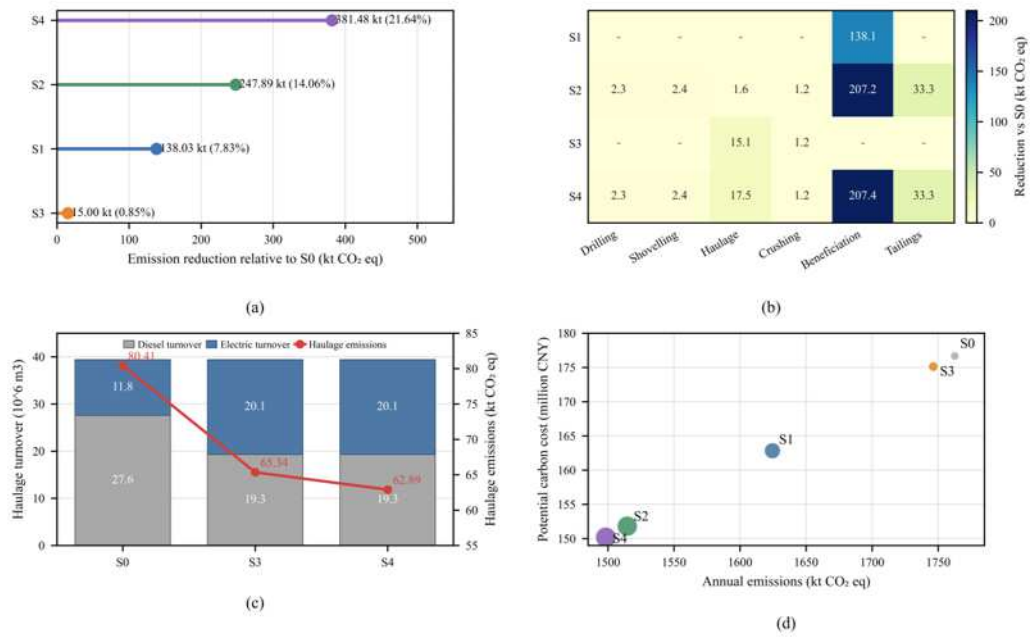


Fig. 10. Mitigation performance, process level emission reductions, and emission cost performance under different low-carbon scenarios: (a) annual emission reductions and reduction rates, (b) process level emission reduction matrix, (c) changes in diesel and electric truck haulage volumes and haulage emissions under the electrification scenarios, (d) relationship between annual emissions and potential carbon cost, with bubble size representing the whole mine emission reduction rate.

As shown in Fig. 10(a), annual whole mine carbon emissions under S1, S2, S3 and S4 were 1624.50, 1514.64, 1747.53 and 1381.05 kt CO₂ eq, respectively. Compared with 1762.53 kt CO₂ eq under S0, the corresponding emission reduction rates were 7.83%, 14.06%, 0.85% and 21.64%. S4 had the greatest mitigation potential, followed by S2, indicating that whole mine emission reduction in the case study mine was mainly driven by electricity related measures. In contrast, adjusting the haulage equipment structure alone had a limited effect on total mine emissions because beneficiation and tailings handling together accounted for approximately 91% of total mine emissions, whereas haulage accounted for only 4.56%.

The process level emission reduction matrix in Fig. 10(b) further reveals the action pathways of different scenarios. Emission reduction under S1 came mainly from the beneficiation process, indicating that reducing unit electricity consumption in beneficiation directly affects the dominant emission source. S2 reduced emissions from multiple electricity consuming processes. Beneficiation and tailings handling decreased by 207.16 and 33.34 kt CO₂ eq, respectively, together contributing approximately 97% of the total reduction under S2. Compared with energy efficiency

improvement targeted only at beneficiation, power decarbonization produced cross process mitigation effects by reducing the emission intensity of electricity use. Therefore, for open pit metal mines dominated by electricity consumption, the carbon intensity of electricity supply may be more decisive for whole mine emissions than the efficiency of a single equipment type.

Haulage electrification showed a clear difference between process level and whole mine effects. As shown in Fig. 10(c), under S3, diesel truck haulage volume decreased from $27.62 \times 10^6 \text{ m}^3$ to $19.34 \times 10^6 \text{ m}^3$, whereas electric truck haulage volume increased from $11.84 \times 10^6 \text{ m}^3$ to $20.12 \times 10^6 \text{ m}^3$. With total haulage volume unchanged, haulage emissions decreased from 80.41 to 65.34 kt CO₂ eq, a reduction of 18.74%. However, whole mine emissions decreased by only 0.85%. This indicates that haul truck electrification has a clear mitigation value within the haulage subsystem, but its whole mine effect is constrained by the relatively small baseline contribution of haulage.

Under S4, emissions from beneficiation, tailings handling and haulage decreased to 1056.30, 188.91 and 62.89 kt CO₂ eq, respectively. Beneficiation contributed approximately 85.14% of the total emission reduction under S4 and remained the decisive source of mitigation in the combined scenario. Compared with S3, haulage emissions under S4 decreased further under the same haulage volume allocation, indicating that a lower electricity emission factor can enhance the mitigation benefit of haul truck electrification. Thus, haulage electrification and power decarbonization are complementary measures.

The emission cost analysis further supports this interpretation. As shown in Fig. 10(d), annual potential carbon costs under S1, S2, S3 and S4 were 162.83, 151.82, 175.12 and 138.42 million CNY, respectively. Compared with 176.67 million CNY under S0, the corresponding reductions were 13.84, 24.85, 1.55 and 38.25 million CNY. S4 performed best in both emissions and potential carbon cost, followed by S2, whereas S3 produced only limited improvement in whole mine cost exposure. Under the specified carbon price scenario, prioritizing mitigation resources for high contribution emission sources is more effective for simultaneously reducing carbon emissions and potential carbon cost.

These results are consistent with and complementary to previous mining carbon emission studies. Norgate and Haque showed that dominant emission sources vary among mineral types and process routes, and that electricity intensive processes such as crushing and grinding can contribute more to copper concentrate production than pit operations. Memary et al. also showed that ore grade,

beneficiation technology and regional energy structure significantly affect the carbon footprint of copper products. In the present case, beneficiation and tailings handling together accounted for approximately 91% of whole mine emissions, further indicating that low carbon electricity supply and beneficiation energy efficiency may deliver greater system level mitigation benefits than haulage equipment substitution alone in electricity dominated open pit metal mines. Meanwhile, Aydogdu et al. showed that mine haulage electrification has clear local mitigation potential. The present results further indicate that when the baseline contribution of haulage to whole mine emissions is low, the whole mine mitigation contribution of haulage electrification is constrained by the emission structure within the system boundary. Therefore, low carbon pathway selection in mines should consider both the emission reduction rate of an individual process and its contribution to the whole mine emission structure.

Overall, the case study mine should prioritize reducing unit electricity consumption in beneficiation and lowering the emission factor of purchased electricity. Haulage electrification can be implemented as a targeted mitigation measure for the pit haulage system and should be coordinated with low carbon electricity supply. This priority order is case dependent. For mines with a higher share of haulage emissions, lower beneficiation electricity consumption or a different electricity mix, the relative benefits of different mitigation measures may change.

4.6 Model applicability and uncertainty

The proposed model is intended mainly for dynamic carbon emission prediction, key emission source identification and low carbon scenario comparison in open-pit metal mines. Its outputs should not be used as a direct substitute for enterprise level measured greenhouse gas accounting. Model prediction accuracy is affected by production plans, average haulage distance, unit equipment energy consumption, unit electricity consumption in beneficiation, emission factors and carbon price assumptions. In practical applications, the model should be updated iteratively using onsite operating data and energy consumption records.

In addition, necessary simplifications were made for land disturbance carbon loss and potential carbon cost. Carbon sink loss was estimated mainly from disturbed area and unit area carbon storage parameters, without further modelling vegetation recovery or long term changes in soil carbon pools. Potential carbon cost did not include carbon allowances, free allocation ratios or offset mechanisms,

and therefore represents only cost exposure under a given carbon price scenario. The model is therefore more suitable as a decision support tool for mine design, production planning and low carbon pathway comparison.

5 Conclusions

This study developed a process parameter driven system dynamics model to support dynamic carbon emission prediction and mitigation scenario comparison during the design and production planning stages of open-pit metal mines. By integrating production plans, process parameters, energy and material consumption, land disturbance carbon loss, carbon emission intensity and potential carbon cost, the model converts monthly mining stripping plans and key process parameters into process level and whole mine emission estimates. Validation against 2024 historical data showed that the relative errors for electricity consumption, diesel consumption, explosive consumption and whole mine carbon emissions were all below 3%, with a MAPE of 0.99%, indicating that the model can reasonably represent the overall relationships among energy use, material consumption and carbon emissions in the case study mine.

Under the 2027 baseline scenario, annual emissions reached 1762.53 kt CO₂ eq. Beneficiation was the dominant source, contributing 78.36% of whole mine emissions, followed by tailings handling and haulage, which contributed 12.61% and 4.56%, respectively. Beneficiation and tailings handling together accounted for approximately 91% of total emissions, indicating that the emission structure of the case study mine was mainly controlled by electricity consumption. Under the baseline parameter assumptions, monthly mining stripping quantity was highly correlated with monthly whole mine emissions, with a Pearson correlation coefficient of 0.9993, and was the main driver of emission fluctuations during the prediction period.

Scenario analysis showed that reducing unit electricity consumption in beneficiation by 10%, reducing the purchased electricity emission factor by 15%, and shifting part of diesel truck haulage to electric trucks reduced whole mine emissions by 7.83%, 14.06% and 0.85%, respectively. Their combined implementation reduced annual emissions to 1381.05 kt CO₂ eq, 21.64% below the baseline, and lowered potential carbon cost from 176.67 million CNY to 138.42 million CNY. Although haulage electrification reduced haulage emissions by 18.74%, its whole mine effect was limited by the small baseline contribution of haulage. For the case study mine, beneficiation energy

saving and low carbon electricity supply should therefore be prioritized, while haulage electrification should be treated as a targeted measure for the pit haulage system and coordinated with electricity decarbonization.

The proposed model provides quantitative support for production planning, key emission source identification and low carbon pathway comparison in open pit metal mines. Its results, however, depend on the defined system boundary, production plan assumptions, unit energy consumption, emission factors and carbon price settings. The current model does not include carbon sink recovery from post mining ecological restoration, carbon allowances, free allocation ratios, offset mechanisms or carbon price uncertainty. Future work should integrate equipment level monitoring data, sensitivity analysis and uncertainty simulation to improve the robustness of dynamic emission prediction and mitigation planning.

Author contributions

B.B. conceived the study, developed the methodology, conducted the investigation, curated and analyzed the data, prepared the visualizations, and wrote the original draft. **G.L.** contributed to the study conception, supervised the work, administered the project, acquired funding, provided resources, and reviewed and edited the manuscript. **J.H.** acquired funding, provided resources, contributed to the investigation and project administration, and reviewed and edited the manuscript. All authors reviewed and approved the final manuscript.

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Declarations

Competing interests

The authors declare no competing interests.

Consent to participate

Not applicable.

Consent for publication

All authors have read and approved the manuscript and consent to its publication.

Data availability statement

All data generated or analyzed during this study are included in this paper and its supplementary information files.

Ethics approval

Ethics approval was not required for this study because it was based exclusively on engineering, operational, and published data and did not involve human participants, personal data, human biological material, or animals.

Appendix A. Supplementary Data

Detailed model equations, parameter definitions, and supporting data for the system dynamics model are provided in Supplementary Materials File.

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