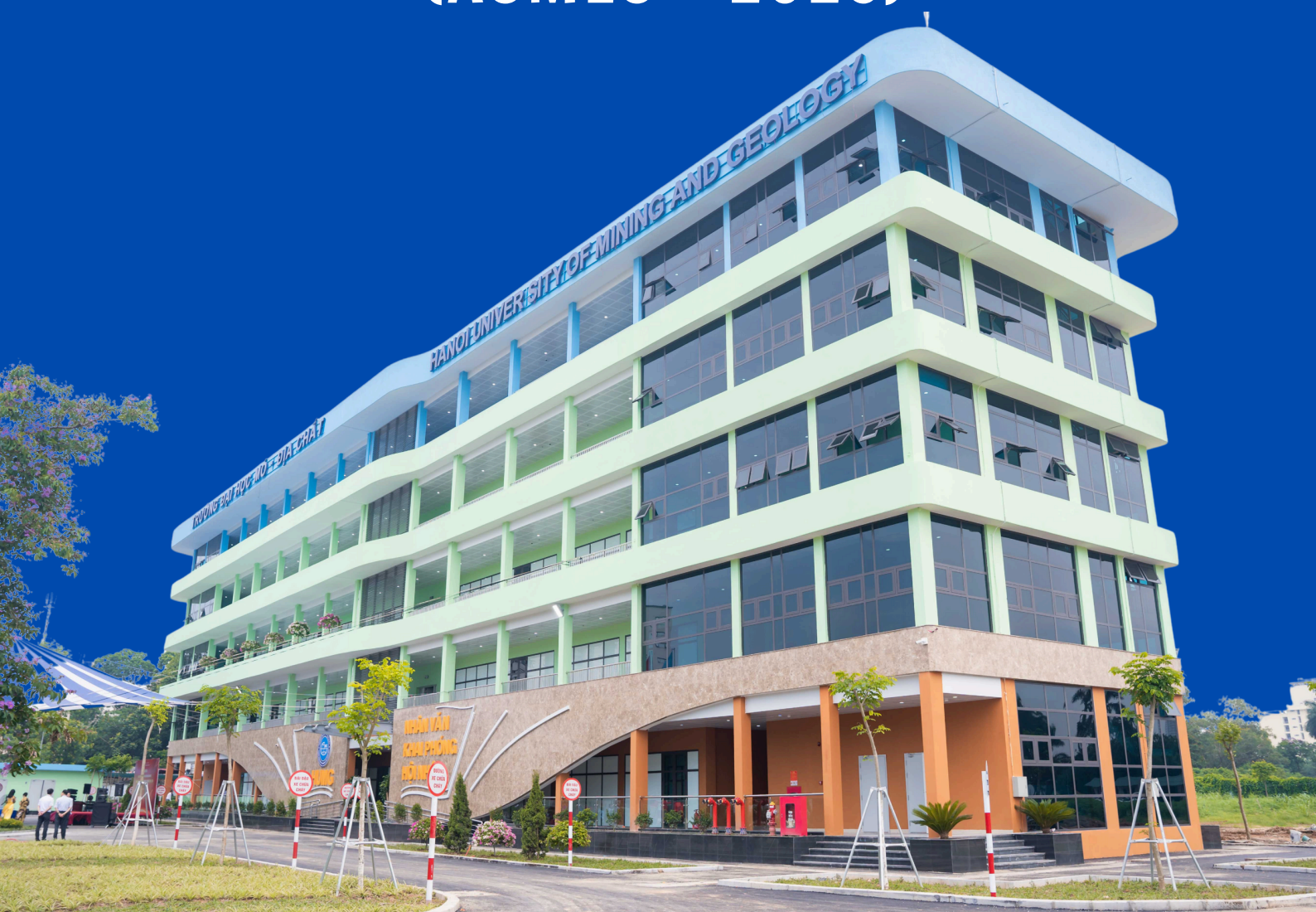


PROCEEDINGS OF THE INTERNATIONAL WORKSHOP ON ADVANCES IN
SURFACE MINING FOR ENVIRONMENTAL PROTECTION AND SUSTAINABLE
DEVELOPMENT 17 OCTOBER 2025, HA NOI, VIET NAM



ADVANCES IN SURFACE MINING FOR ENVIRONMENTAL PROTECTION AND SUSTAINABLE DEVELOPMENT-2025 (ASMES - 2025)



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MỤC LỤC

TT	TẬP THỂ TÁC GIẢ	TÊN BÀI BÁO	TRANG
1.	Bùi Xuân Nam, Trần Quang Hiếu, Nguyễn Anh Tuấn, Đỗ Ngọc Hoàn, Nguyễn Phú Vụ, Lê Văn Quyển	Định hướng đào tạo và nghiên cứu khoa học ngành Khai thác mỏ Lộ thiên: Vững bước hội nhập, vươn tầm kỷ nguyên mới	1-14
2.	Nguyen Anh Tuan, Pham Van Viet, Pham Van Hoa, Do Ngoc Hoan, Tran Dinh Bao,	Stone in Vietnam: Building stone, rock fill and armourstone in construction for Sustainable Development	15-23
3.	Xuan-Nam Bui, Carsten Drebenstedt, Nguyen Hoang, Nguyen Van Duc, Tran Quang Hieu, Nguyen Quoc Long, Le Ngoc Ninh	Smart Mining - Opportunities and Challenges for Vietnam's Mining Industry	24-41
4.	Lai Hong Thanh, Mai The Toan, Le Ngoc Ninh, Xuan-Nam Bui	Vietnam's 2024 Law on Geology and Minerals: Opportunities and Challenges for the Mining Industry	42-55
5.	Le Thi Thu Hoa, Nguyen Hoang, Tran Quang Hieu, Tran Dinh Bao, Le Qui Thao, Nguyen Truc Anh, Atrushkevich Victor, Xuan-Nam Bui	Some Technological Approaches, Optimization Strategies, and Sustainable Development Directions for Selective Mining in Vietnam's Open-Pit Coal Mines	56-66
6.	Le Qui Thao, Do Ngoc Le Dung, Nguyen Thi Thuc Anh, Do Ngoc Hoan, Xuan-Nam Bui	Some Technological Orientations for Safe and Environmentally Friendly Mining Technology of Coastal Placer Titanium Deposits in Vietnam	67-83
7.	Tran Quang Hieu, Nguyen Van Duc, Xuan-Nam Bui, Trinh Hai Son ² , Bui Hoang Bac	Sustainable Rare Earth Mining Technologies: Global Trends and a Tailored Model for Vietnam's Development	84-98
8.	Tran Quang Hieu, Bui Xuan Nam, Le Ngoc Ninh, Tran Van Dung, Do Duc Khoa	The management and utilization of industrial explosives in Vietnam: Achievements, opportunities, challenges, and future development orientations.	99-110
9.	Thang Dam Trong, Duc Ngo The	Experimental investigation on the influence of water saturation on the propagation velocity of blasting stress waves	111-123
10.	Nguyen Dinh An , Tran Dinh Bao	Controlling Harmful Impacts of Rock Blasting for Construction Site Preparation in Ha Giang Province, Vietnam	124-136
11.	Ngô Ngọc Thủy, Đàm Trọng Thắng	A Study on Mitigating Air Shock Wave Intensity in Surface Blasting for Rock Fragmentation Using Sand Cover Layers	137-148

12.	Van-Viet Pham, Pirat Jaroopattanapong, Nguyen Anh Tuan, Van -Hoa Pham	Prediction of an appropriated powder factor used for blasting under the consideration of blast direction and rock mass quality	149-163
13.	Vũ Tùng Lâm, Trần Quang Hiếu, Vũ Trọng Hiếu	Nghiên cứu phân tích, lựa chọn phương pháp hợp lý để xác định mức độ đập vỡ đất đá từ số liệu thực nghiệm	164-175
14.	Do Ngoc Hoan, Tran Quang Hieu, Tran Dinh Bao	Achievements and Challenges in Occupational Safety and Health Management in the Mineral Mining industry in Vietnam	176-189
15.	Lam Kieu Anh, Tran Quang Hieu, Do Ngoc Hoan	Assessment of Fire and Explosion Risks at Industrial Explosives Storage Facilities in Vietnam	190-209
16.	Do Van Trieu, Tran Dinh Bao, Dang Tien Anh, Dinh Ba Lam, Nguyen Van Hoang	Overview of Carbon Storage Technologies in Mine Waste Rock: Opportunities and Challenges for TKV Open-Pit Mines	210-223
17.	Đỗ Thị Lan Chi Vũ Văn Thú	Safety Culture In Enterprises: An Assessment And Intervention Framework Based On A Multi-Model Approach	224-233
18.	Xuan-Nam Bui, Thi-Tam Nguyen, Ngoc-Ninh Le, Duc-Tin Quach, Quang-Hieu Tran, Chang-Woo Lee, Van-Trieu Do, Van-Duc Nguyen	Decarbonizing Vietnam's Open-Pit Coal Mining: A Life Cycle Case Study of Emissions and Mitigation Pathways	234-248
19.	Tuan-Ngoc Le, Hoang Nguyen	Predicting PM2.5 Concentrations in an Open-Pit Copper Mine Using Advanced AI Techniques: Insights from the Sin Quyen Copper Mine, Vietnam	249-268
20.	Léopold Dupuy, Hoang Nguyen	Assessment and Prediction of Carbon Sequestration in Rehabilitated Open-Pit Mining Areas Using Remote Sensing and AI Techniques: A Case Study from Northern Vietnam	269-290
21.	Tran Dinh Bao, Vu Van Thu	Analysis, evaluation, and proposal of solutions to enhance the effectiveness of occupational safety and health practices in Vietnam in the current period	291-312
22.	Do Duc Thanh, Ngo Thanh Tuan	Impact of large capacity solar power sources when connected near high-voltage power system supplying electricity to mining areas	313-320
23.	Nguyen Hoang Long, Bui Xuan Nam, Tran Thi Hai Van, Dinh Bao Ngoc, Tran Truong Giang,	Development of a Management and Monitoring System for Production Activities in Open-Pit Quarries in Vietnam	321-328
24.	Nguyễn Mạnh Thường, Đàm Trọng Thắng, Tạ Quang Yên	Исследования, изготовление и испытание сборной плавучей рабочей платформы для подводного бурения	329-342

		шахтных скважин подводных взрывных работ в морских условиях в провинции Куангнинь	
25.	Nguyễn Văn Tính, Đàm Trọng Thắng, Lê Sỹ Thượng, Trần Quang Hiếu	Исследование расчета, проектирования и изготовления разумных малых зарядов взрывчатых веществ (ВВ) для экспериментальных работ по взрыву грунта и горных пород на миниатюрных моделях	343-358
26.	Нгуен В.Х, Дам Ч.ТХ, Нгуен В.И, Татаринов В.В, Чан В.Л	Экспериментальное исследование решений по снижению шума в модели электрического взрывного устройства	359-374
27.	Нгуен Мань Тхыонг, Дам Чонг Тханг, Та Куанг Йен	Исследования, изготовление и испытание сборной плавучей рабочей платформы для подводного бурения шахтных скважин подводных взрывных работ в морских условиях в провинции Куангнинь.	375-385
28.	Nguyễn Anh Tuấn, Phạm Văn Việt, Đỗ Ngọc Hoàn, Trần Quang Hiếu	Đề xuất bộ tiêu chí trong khai thác lộ thiên khoáng sản rắn đảm bảo hiệu quả, bền vững và tích ứng với biến đổi khí hậu ở Việt Nam	386-395
29.	Trần Quang Hiếu, Nguyễn Anh Tuấn, Đỗ Ngọc Hoàn, Bùi Xuân Nam, Lê Ngọc Ninh, Nguyễn Văn Đức, Lại Hồng Thanh	Tương lai ngành khai thác mỏ lộ thiên tại Việt Nam: Cơ hội, thách thức và các định hướng phát triển bền vững	396-412
30.	Lê Đức Phương, Đỗ Ngọc Hoàn	Phương pháp xác định biên giới kết thúc khai thác lộ thiên hợp lý cho các mỏ quặng đơn và đa khoáng thuộc TKV	413-422
31.	Nguyễn Anh Tuan, Pham Van Viet, Tran Trung Anh, Nguyen Van Tinh, Tran Dinh Bao, Pham Minh Tu, Noelie Escutenaire	Trung hòa chất lượng quặng nguyên khai: Áp dụng điều kiện khai thác khối 24-122, mỏ Tây Tân Rai, Tây Nguyên	423-431
32.	Nguyễn Anh Tuấn, Phạm Văn Việt, Trần Trung Anh, Trần Đình Bảo, Trần Đăng Hòa, Phạm Minh Tú, Noelie Escutenaire	Mô hình hàm lượng quặng bauxite: xây dựng bản đồ phân bố trữ lượng và hàm lượng quặng bauxite cho khối 24-122, mỏ Tây Tân Rai	432-440
33.	Khuong The Hung, Bui Hoang Bac, Vu The Thu	Sustainable development of apatite ore at the Coc mine, Lao Cai province based on a comprehensive assessment of geological conditions and mining status	441-447
34.	Lê Bá Phúc, Đỗ Văn Triều, Đặng Tiến Anh, Trần Đình Bảo	Nghiên cứu xây dựng phương pháp giám sát mô hình chất tải trên các ô tô vận chuyển đất đá tại các mỏ lộ thiên phục vụ chuyển đổi số	449-460
35.	Đỗ Ngọc Tước, Nhữ Việt Tuấn, Trịnh thị Phượng	Đánh giá tiềm năng khí hóa than ngầm bằng vi sinh tại bể than Đồng bằng Sông Hồng	461-470

36.	Đàm Quang Sang, Nguyễn Văn Tính, Hoàng Trung Hữu, Nguyễn Ngàn, Trần Văn Dũng, Trần Quang Hiếu	Phương pháp xác định các thông số của môi nổ dùng cho nổ mìn trên các mỏ lộ thiên ở Việt Nam	471-480
37.	Phạm Văn Hòa, Trần Văn Dũng, Hoàng Anh Phong, Trịnh Quang Trung, Lê Văn Quyển, Dương Thành Trung, Trần Đình Bảo, Trần Quang Hiếu, Nguyễn Anh Tuấn, Nguyễn Đình An, Phạm Văn Việt	Hệ thống quản lý công tác khoan nổ mìn – đáp ứng yêu cầu chuyển đổi số và phù hợp điều kiện thực tế cho các mỏ than lộ thiên vùng Quảng Ninh	481-491
38.	Đoàn Văn Thanh, Đỗ Văn Triều, Đinh Bá Lâm, Trần Đình Bảo	Nghiên cứu mô phỏng lan truyền sóng ứng suất nổ mìn trong điều kiện đất đá ngậm nước tại các mỏ than thuộc TKV	492-501
39.	Hoàng Mạnh Thắng, Đoàn Văn Thanh, Đinh Bá Lâm, Đặng Tiến Anh	Nghiên cứu một số phương pháp phá vỡ đất đá không sử dụng thuốc nổ cho các mỏ lộ thiên tại Việt Nam	502-511
40.	Lưu Văn Thực, Đỗ Văn Triều, Lê Bá Phúc, Lê Thị Thu Hoa	Nghiên cứu xây dựng cơ sở dữ liệu quan trắc dịch động và chương trình cảnh báo ổn định bờ mỏ, bãi thải bằng mô hình số kết hợp trí tuệ nhân tạo (AI) cho các mỏ lộ thiên thuộc TKV	512-521
41.	Đào Văn Chi, Vũ Thái Tiến Dũng, Phan Mai Linh	Kinh nghiệm quốc tế về lồng ghép bảo vệ môi trường trong các hoạt động khoáng sản và bài học cho Việt Nam	522-528
42.	Phạm Hải Anh, Nguyễn Anh Tuấn, Trịnh Văn Hiệp, Phạm Hồng Thái, Đặng Anh Đức	Tiềm năng ứng dụng công nghệ thu hồi, sử dụng và lưu trữ Carbon (CCUS) tại các nhà máy nhiệt điện thuộc TKV (Kỳ I)	529-539
43.	Nguyễn Anh Tuấn, Nguyễn Xuân Tú, Phạm Văn Việt, Đỗ Anh Sơn, Ngô Thanh Tuấn, Nguyễn Tiến Hưng.	Nghiên cứu đánh giá sự ảnh hưởng của moong khai thác lộ thiên đến các công trình hầm mỏ: Khai thác than mỡ khu Bắc Làng Cẩm, Thái Nguyên	540-557
44.	Nguyễn Đình An, Nhữ Văn Bách, Trần Đình Bảo	Ứng dụng trí tuệ nhân tạo lập hộ chiếu nổ mìn theo thời gian thực nhằm nâng cao hiệu quả và đảm bảo an toàn nổ mìn trong khai thác mỏ	558-565



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Soil Organic Carbon Assessment and Prediction in Rehabilitated Open-Pit Mining Areas Using GIS and Machine Learning: Insights from France

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ABSTRACT

Post-mining rehabilitation plays a vital role in restoring ecosystem services and enhancing carbon sequestration. This study assessed soil organic carbon (SOC) stocks in former open-pit mining areas in France and proposed a transferable framework for application to rehabilitated mines in northern Vietnam. SOC was quantified using the Walkley–Black method and calibrated Near-Infrared (NIR) spectroscopy, while above-ground biomass was briefly estimated through allometric equations to situate SOC within the broader carbon accounting context. Geographic Information System (GIS) tools were used to georeference soil samples and map the spatial distribution of SOC. Machine learning models, particularly Extreme Gradient Boosting (XGBoost), were trained using soil physical properties such as bulk density, moisture content, gravel fraction, and stone fraction. Results revealed that forests and natural environments stored the highest SOC, while cultivated or disturbed lands contained substantially lower stocks. Single-variable models performed weakly ($R^2 < 0.25$), confirming the limited explanatory power of individual predictors but highlighting the potential of integrated machine learning approaches to capture non-linear dynamics. The study advances understanding of SOC drivers in post-mining landscapes and provides a reproducible framework combining field measurements, GIS-based mapping, and machine learning. This framework can be directly adapted to rehabilitation planning, sustainable land management, and participation in carbon credit schemes in tropical and subtropical mining regions such as Vietnam.

Keywords: Soil organic carbon, Post-mining rehabilitation, Carbon sequestration, GIS mapping, XGBoost model

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1. Introduction

Open-pit mining has historically caused severe land degradation, biodiversity loss, and depletion of ecosystem carbon pools through the removal of vegetation and topsoil (Xu et al., 2023). Post-mining rehabilitation is therefore a critical environmental management strategy to restore soil functions, promote vegetation recovery, and enhance carbon sequestration (Zhu et al., 2024). Among ecosystem services regained through rehabilitation, soil organic carbon (SOC) is particularly important, as it contributes to soil fertility, long-term carbon storage, and climate change mitigation.

While above-ground biomass has often been emphasized in carbon accounting, SOC dynamics in post-mining landscapes remain comparatively underexplored, despite their central role in ecosystem recovery (Fox et al., 2020). Previous studies have typically assessed biomass or SOC in isolation, with limited integration of field measurements, Geographic Information Systems (GIS), and advanced machine learning (ML) approaches for spatial prediction (Khanal et al., 2018; Issa et al., 2020; Mishra et al., 2020; Li et al., 2024; De Caires et al., 2025; El Bouanani et al., 2025). Research combining these components is especially scarce in tropical and subtropical mining regions, including northern Vietnam, where rehabilitation strategies range from plantation forestry to natural regeneration.

A further challenge is the limited availability of site-specific datasets in Vietnam, which constrains direct assessment of rehabilitation outcomes. To overcome this limitation, this study leverages extensive soil datasets collected in post-mining areas of France as a robust testing ground for an integrated methodological framework. SOC was quantified using the Walkley–Black laboratory method and complemented by Near-Infrared (NIR) spectroscopy, while GIS tools were employed to link soil measurements with mining areas and visualize SOC distribution. Extreme Gradient Boosting (XGBoost) was selected as the primary ML model to evaluate the predictive capacity of soil physical properties such as bulk density, moisture content, and coarse fragment fractions.

The objectives of this study are to:

- (i) quantify SOC in post-mining soils using combined laboratory and spectroscopic methods;
- (ii) apply GIS for spatial representation of SOC stocks;
- (iii) evaluate the potential of machine learning models to predict SOC from soil and environmental variables.

By situating SOC within the broader carbon cycle, this work provides methodological advances that can be directly adapted to rehabilitated mining sites in Vietnam, supporting sustainable land management and integration into carbon credit schemes.

2. Literature review

2.1. Carbon sequestration in post-mining landscapes

Open-pit mining leads to major depletion of carbon pools through the removal of vegetation and topsoil (LEI et al., 2023). Rehabilitation efforts aim to restore these pools via natural regeneration, reforestation, or mixed strategies (Di Sacco et al., 2021). Studies have consistently shown that tree species exert a strong influence on SOC recovery and overall carbon sequestration. For example, a study in post-mining sites of Upper Silesia reported that birch (*Betula pendula*) stands accumulated up to 59.6 tC/ha in biomass and 120.5 tC/ha in soil organic carbon after 25 years of reclamation, substantially higher than pine (*Pinus sylvestris*) stands, which stored 41.2 tC/ha in biomass and 86.9 tC/ha in soil carbon (Sloan 2016). Similarly,

research in Budapest's urban forests revealed notable interspecific differences: on the Buda side, sessile oak (*Quercus petraea*) and Turkey oak (*Quercus cerris*) showed the highest net carbon uptake, whereas pedunculate oak (*Q. robur*) and linden (*Tilia* spp.) acted as net carbon sources during the 2010–2020 monitoring period. In contrast, on the Pest side, pedunculate oak, Turkey oak, and black locust (*Robinia pseudoacacia*) contributed positively to sequestration, while Scots pine (*Pinus sylvestris*) represented a net carbon emitter (Király et al., 2025).

These findings confirm that species selection is critical in rehabilitation strategies, as differences in growth dynamics, root systems, and litter quality directly affect SOC accumulation and long-term carbon balance. Pioneer broadleaf species generally enhance carbon accumulation more effectively than conifers due to their interactions with soil fauna and improved soil structure.

Meta-analyses confirm that recultivation type, climate, and soil conditions are key determinants of SOC recovery (Baier et al., 2022). Topsoil replacement plays a critical role: on brown-coal dumpsites in the Czech Republic, areas covered with natural topsoil had a mean topsoil organic carbon of 1.92% (0–20 cm), compared with 0.92% on adjacent areas without natural topsoil (loess cover), evidencing roughly a two-fold increase attributable to topsoiling (Penizek 2013). In these reclamation projects, the natural topsoil cover was applied at ~2,500–3,000 t ha⁻¹, illustrating the scale typically required to restore initial fertility and SOC inputs (Gholizadeh et al., 2015). Overall, SOC restoration is driven not only by time but also by vegetation type, soil biological activity, and management practices.

2.2. Estimating biomass and SOC

Reliable carbon accounting requires integrating both biomass and SOC pools (Petrokofsky et al., 2012; Baral and Malins 2014). Above-ground biomass (AGB) is commonly estimated with allometric equations linking DBH, tree height, and species identity, while SOC is calculated from carbon concentration, bulk density, horizon thickness, and coarse fragment fractions (Feyisa et al., 2018; Wola 2023). Laboratory methods such as the Walkley–Black oxidation remain standard, while Near-Infrared (NIR) and Mid-Infrared (MIR) spectroscopy offer faster, scalable alternatives once calibrated (Bellon-Maurel and McBratney 2011; Hutengs et al., 2019). In practice, combining direct laboratory measurements with calibrated spectroscopy ensures both accuracy and efficiency, which is particularly important in heterogeneous post-mining landscapes (Benndorf et al., 2022; Koerting et al., 2024; O'Donnell et al., 2024).

2.3. Use of GIS in environmental mapping

Geographic Information Systems (GIS) allow the integration of field-based carbon measurements with spatial data (Issa et al., 2020). Techniques such as kriging and inverse distance weighting are used to interpolate SOC values from sampling points (Bhunia et al., 2018; Qiao et al., 2018). Remote sensing indices (e.g., NDVI, EVI) further improve carbon mapping at landscape scales (Noumonvi et al., 2019). GIS provides critical tools to visualize heterogeneity across restoration strategies and to link carbon distribution to land-use trajectories, thereby supporting carbon monitoring and participation in credit schemes (Liang et al., 2025).

2.4. Application of machine learning in environmental prediction

Machine learning (ML) methods such as Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Artificial Neural Networks (ANN) have been increasingly applied to predict SOC

and biomass in complex ecological systems (Ding 2024; Palansooriya et al., 2025; Zhao et al., 2025). These approaches are capable of capturing non-linear interactions between vegetation, soil, and environmental drivers. In particular, RF is valued for its robustness to noise, while ANN can model highly non-linear dynamics but often requires large datasets. XGBoost has consistently demonstrated superior predictive accuracy in tabular environmental datasets due to its regularization and boosting strategy.

In this study, XGBoost was selected as the primary modelling approach, given its balance between predictive performance and data requirements. Integrating ML with GIS and field data enhances the accuracy of spatial prediction and strengthens decision-making for post-mining rehabilitation planning.

2.5. Research gap summary

Despite substantial progress, most studies assess biomass and SOC separately, often relying on conventional field methods or simple statistics. Research integrating SOC and biomass estimation with GIS mapping and ML prediction remains scarce—particularly in tropical and subtropical mining regions such as northern Vietnam. The limited availability of site-specific data further constrains direct application of advanced approaches. This study addresses the gap by using extensive French datasets to test and validate an integrated framework that can later be transferred to Vietnam, ensuring methodological readiness for data-scarce contexts.

Table 1. Summary of previous studies on carbon sequestration in post-mining landscapes

Study	Site & treatment	Metric (unit)	Reported value(s)
Das and Maiti (2016)	Jharia Coalfields, India; 4-yr plantation (<i>Albizia</i> , <i>Dalbergia</i> , <i>Bambusa</i>) on reclaimed mine soil	Biomass C; Soil C; Total ecosystem C	13.0 Mg C ha ⁻¹ (biomass); 16.3 Mg C ha ⁻¹ (soil); 30.3 Mg C ha ⁻¹ total $\approx$ 111 Mg CO ₂ , ha ⁻¹
Juwarkar et al., (2010)	Gumgaon, India; manganese spoil dump reclaimed via integrated biotechnological approach	SOC concentration (%) at 0-15 cm	Increased from 0.104% to 0.69% after 20 yrs; forest 1.11%; agriculture 0.40%
Ussiri and Lal (2005)	Review of reclaimed minesoils (USA & global)	SOC sequestration rate (Mg C ha ⁻¹ yr ⁻¹)	0.3-1.85 (pastures/rangelands); 0.2-1.64 (forest)
Bowen et al., (2005)	Surface coal mine, Wyoming (USA); topsoil depth replacement treatments	Organic C mass to 75 cm (Mg C ha ⁻¹)	60 cm topsoil: 18.7; 0 cm topsoil: 11.3 (20 cm also lower than 60 cm)
Matos et al., (2012)	Reclaimed lignite mine soils	C sequestration rate (Mg C ha ⁻¹ yr ⁻¹)	4.0
Yuan et al., (2017)	Pingshuo opencast mine, China; forests 22-25 years after reclamation	SOC pool (Mg C ha ⁻¹)	11.66-69.10 across forest RMSs
Ahirwal and	Revegetated coal mine (India)	C sequestration rate (Mg C ha ⁻¹ yr ⁻¹)	1.9 after 14 years of revegetation

Study	Site & treatment	Metric (unit)	Reported value(s)
Maiti (2017)			
Ahirwal et al., (2017)	Reclaimed coal mine (India)	SOC sequestration rate ($\text{Mg C ha}^{-1} \text{ yr}^{-1}$)	1.71; SOC & N stocks doubled after 7-11 yrs
Ussiri et al., (2014)	Method paper summarizing reclaimed minesoils	SOC sequestration rate ($\text{Mg C ha}^{-1} \text{ yr}^{-1}$)	0.45-3.0 during first two decades after reclamation
Woś et al., (2024)	Upper Silesia (Poland) coal-mine heaps; topsoiling (TS) vs. bare rock (BR) succession	Total C storage (Mg C ha^{-1})	TS: 68.13-121.08 (soil 52.20-102.89; biomass 12.09-20.15); BR: 523.14 (soil 507.66) due to geogenic C
Ghosh and Maiti (2021)	Jharia Coalfield, India; 8-yr reclaimed spoil with biochar treatments	Total C stock (Mg C ha^{-1}); change vs. control (%)	RMS: 30.98; BC30: +31%; BC60: +45% (soil total C: $36.3\text{-}40 \text{ g kg}^{-1}$ vs. 21 g kg^{-1})

3. Study area and data collection

3.1. Study site description

This study focuses on metropolitan France ($\approx 551,000 \text{ km}^2$, $41\text{--}51^\circ\text{N}$), a region characterized by high climatic and pedological diversity, ranging from Atlantic oceanic to continental and Mediterranean zones. France also has a long mining history, including coal, iron, bauxite, uranium, and polymetallic ores, most of which ceased between the 1960s and 2000s. These activities left extensive degraded lands that have undergone various rehabilitation pathways such as natural regeneration, reforestation, or agricultural conversion.

To capture post-mining soil conditions, sampling points were selected from the French Soil Quality Monitoring Network (Réseau de Mesures de la Qualité des Sols – RMQS) located within or near documented mining areas. These sites provide a unique opportunity to examine carbon sequestration under contrasting environmental and management contexts.

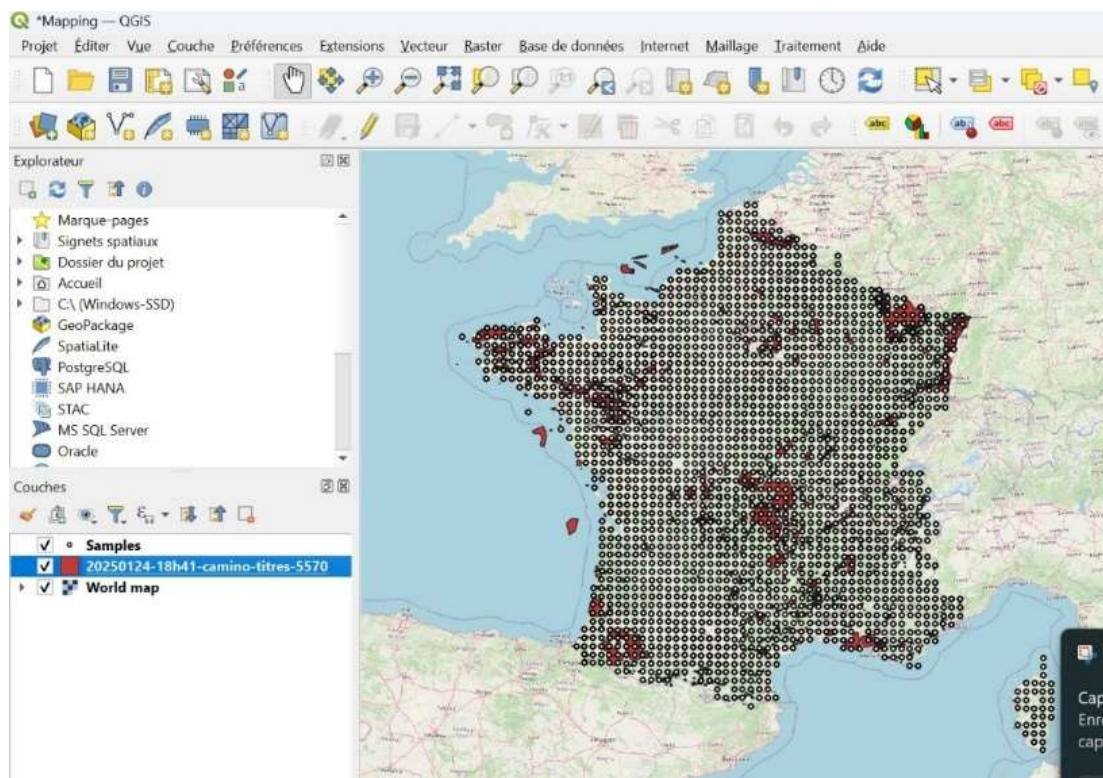


Figure 1. Distribution of the first sampling points overlaid on French mining areas.

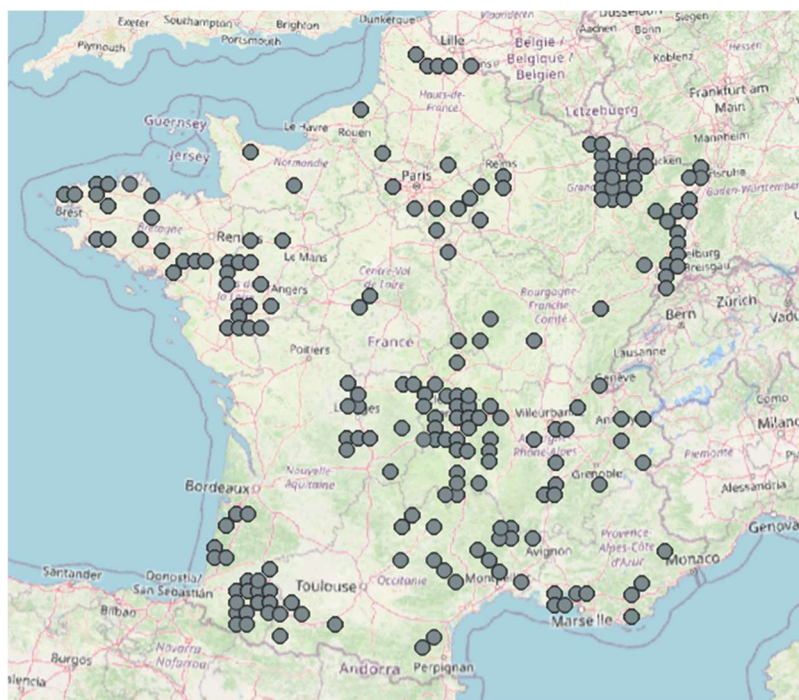


Figure 2. Intersection between the first sampling points and mining areas

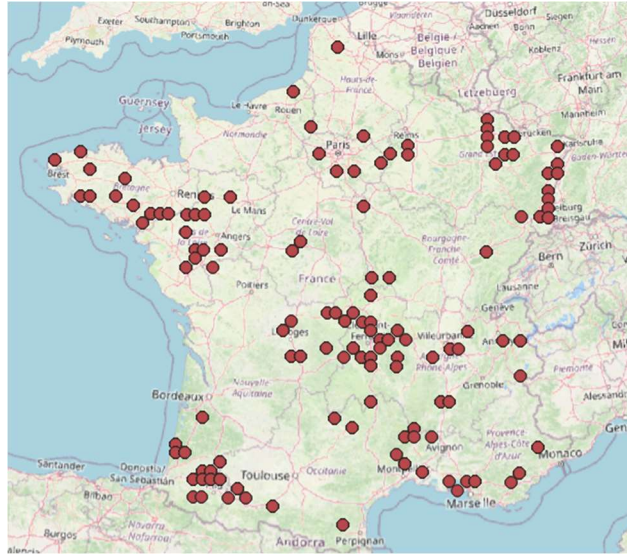


Figure 3. Intersection between the second sampling points and mining areas.

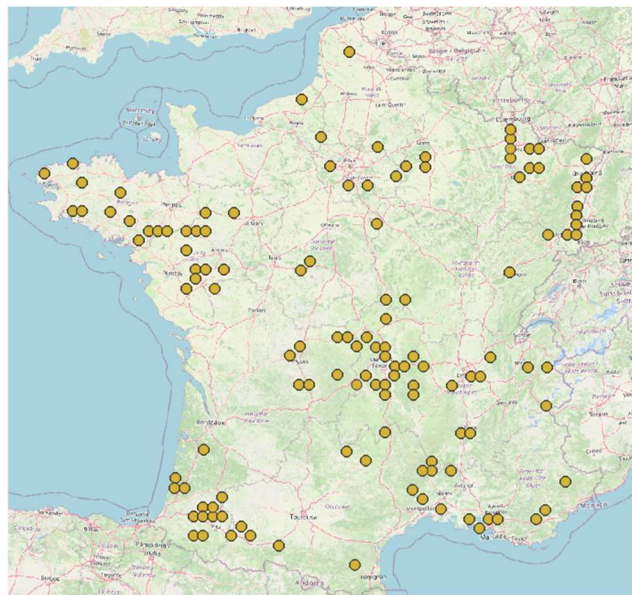


Figure 4. Common sampling points within mining areas from both campaigns.

3.2. Soil measurements

SOC-related parameters were extracted from RMQS profiles, including:

- Organic carbon concentration (C),
- Bulk density (ρ),
- Horizon thickness (e), and
- Coarse fragment fraction (CF).

These inputs enabled SOC stock calculation using the standard formula Eq. (1):

$$SOC = C \times \rho \times e \times (1 - CF) \quad (1)$$

SOC values were determined through laboratory analyses, with Walkley–Black wet oxidation as the reference method and Near-Infrared (NIR) spectroscopy applied for scalable prediction after calibration

3.3. Environmental and site variables

In addition to soil profile data, several environmental and contextual variables were considered to explain the spatial variability of carbon stocks:

- Topographic attributes: slope and elevation were extracted from digital elevation models, as they influence water redistribution, erosion, and organic matter dynamics.
- Soil type: soil classification was obtained from profile descriptions, allowing us to assess the role of intrinsic soil properties (texture, depth, drainage) in carbon sequestration.
- Land cover: land use and vegetation cover (forest, grassland, bare soil, etc.) were identified to distinguish natural conditions from anthropogenic surfaces.
- Revegetation type: rehabilitated mine sites display contrasting restoration approaches, such as forest plantations and natural regeneration. This variable is crucial for comparing carbon storage trajectories under different post-mining management strategies.

Together with SOC measurements, these variables provide insights into the main environmental and anthropogenic drivers that shape soil carbon sequestration in post-mining landscapes.

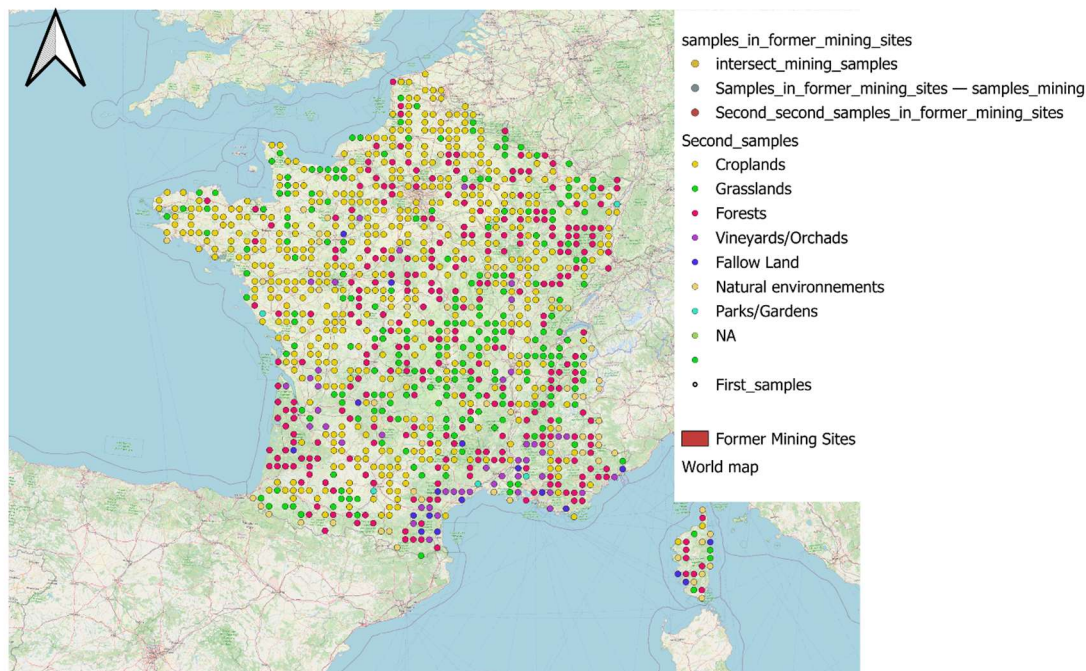


Figure 5. Example of land cover classes within mining areas, derived from CORINE Land Cover data, overlaid with soil sampling points

4. Methodology

4.1. Carbon quantification

Carbon stocks were assessed in two pools:

- Above-ground biomass (AGB): estimated non-destructively using species-specific allometric equations relating DBH, tree height, and wood density. Biomass values were converted to carbon using a 0.47–0.50 factor.
- Soil organic carbon (SOC): quantified with the Walkley–Black wet oxidation method as reference, complemented by calibrated Near-Infrared (NIR) spectroscopy for efficient large-scale estimation. SOC stocks were calculated as mentioned in Eq. (1).

4.2. Spatial mapping with GIS

Soil samples were georeferenced and overlaid with former mining areas using national cartographic layers. GIS techniques were applied to:

- Link SOC measurements to mining sites.
- Perform spatial interpolation (kriging, IDW) to generate continuous SOC maps.
- Integrate land cover and topographic attributes for further analysis.

This approach allowed both spatial representation and temporal comparison of SOC stocks across different rehabilitation strategies.

4.3. Machine learning modelling

Model selection: Among various algorithms applied in environmental prediction, Random Forest (RF), Artificial Neural Networks (ANN), and Extreme Gradient Boosting (XGBoost) are often considered. In this study, XGBoost was selected as the sole model due to its strong predictive performance, ability to capture non-linear relationships, and robustness against overfitting with tabular datasets. RF and ANN were not implemented because of dataset size limitations and the risk of overfitting with more complex models.

Input variables: Five predictors were used: mean soil depth, gravel content, stone content, bulk density, and moisture content. These variables represent soil physical properties that directly influence SOC dynamics.

Training and validation:

- A 5-fold cross-validation was applied to ensure robustness.
- Hyperparameters (number of trees, max depth, learning rate, subsample) were tuned to balance accuracy and generalization.
- Model performance was evaluated using R^2 , RMSE, MAE, and bias.

4.4. Workflow diagram

The overall workflow of this study integrates field measurements, GIS analysis, and machine learning into a reproducible framework (Figure 6). The process includes the following steps:

1. Data acquisition

- Soil profile data from the RMQS network (organic carbon, bulk density, horizon thickness, coarse fragments).
- Auxiliary variables: slope, elevation (DEM), land cover, and revegetation type.

2. Data preprocessing

- Cleaning and harmonization of datasets.
- Standardization of variables and georeferencing of soil samples.

3. Carbon quantification

- SOC quantified using Walkley–Black laboratory analysis, calibrated with NIR spectroscopy.
- Above-ground biomass estimated via allometric equations for contextual reference.

4. Spatial integration with GIS

- Overlay of sampling points with mining areas.
- Spatial interpolation (kriging, IDW) to produce continuous SOC distribution maps.

5. Machine learning modelling (XGBoost)

- Input variables: mean soil depth, bulk density, moisture content, gravel and stone fractions.
- Training with 5-fold cross-validation.
- Hyperparameter tuning and evaluation with R^2 , RMSE, MAE, and bias.

6. Predictive mapping and interpretation

- Application of the trained XGBoost model to generate SOC prediction surfaces.
- Comparison of SOC storage across land-use and rehabilitation types.

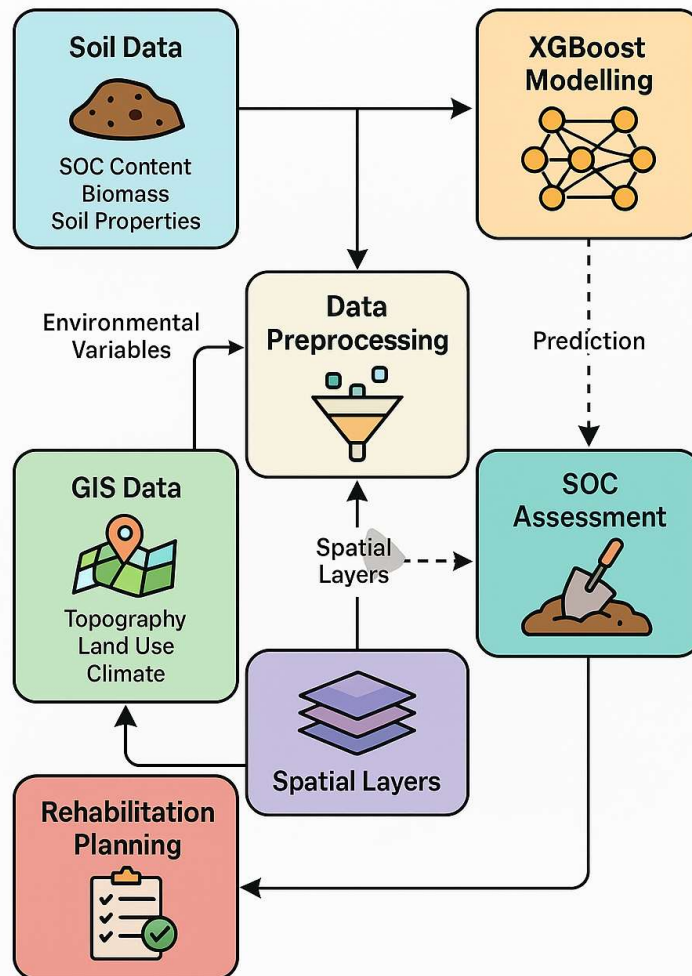


Figure 6. Workflow of the integrated approach combining soil data, GIS, and XGBoost modelling for SOC assessment in post-mining areas

5. Results

5.1. Descriptive statistics

Soil physical properties displayed wide variability across the study sites (Table 2). Moisture content ranged from 2.2% to 136.1% (mean 23.4%), while bulk density varied from 0.28 to 2.26 g/cm³ (mean 1.34). Coarse fragments were heterogeneous: gravel content averaged 11.9% (max 71.7%), and stone content 4.3% (max 75%). SOC values showed substantial variation across land-use categories, reflecting the diversity of rehabilitation strategies.

Table 2. Descriptive statistics of soil and environmental variables

Land Use	Mean	SD	Min	Max
Grasslands	3.13	0.94	0.43	5.53
Forests	2.99	0.97	0.9	5.13
Vineyards/Orchads	3.34	1.1	0.96	5.98
Fallow land	2.87	1.03	0.83	4.8
Natural environnements	3.78	0.16	3.62	3.98
Parks/Gardens	3.42	0.86	2.12	5.13

5.2. Relationships between SOC and soil properties

Correlation and XGBoost exploratory analyses revealed distinct patterns:

- **Moisture content:** weak negative correlation ($r = -0.15$). XGBoost indicated a non-linear decline at higher moisture levels (Figure 7).
- **Bulk density:** weak positive correlation ($r = 0.17$). SOC slightly increased in denser soils (Figure 8).
- **Gravel content:** stronger negative correlation ($r = -0.44$). SOC decreased markedly as gravel fraction increased (Figure 9).
- **Stone content:** negative correlation ($r = -0.30$). Soils with higher stone fractions stored less SOC (Figure 10).

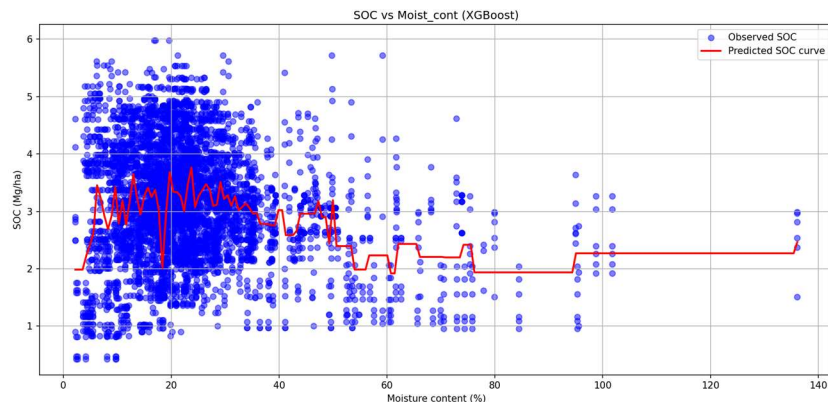


Figure 7. Relationship between soil moisture content and SOC stocks (XGBoost regression curve)

Bulk density values ranged from 0.28 to 2.26 g/cm³, with an average of 1.34 g/cm³. The dataset showed moderate variability (standard deviation of 0.28 g/cm³), with most samples concentrated between 1.18 and 1.50 g/cm³. The median (1.37 g/cm³) was close to the mean, indicating a relatively balanced distribution without strong skewness. A weak positive Pearson correlation was found between bulk density and SOC ($r = 0.17$, $p < 0.001$), suggesting only a slight tendency for SOC to increase with denser soils. To further examine this relationship, an exploratory XGBoost regression curve was fitted. While not aimed at predictive accuracy, this curve highlights the non-linear interactions between BD and SOC, offering a complementary perspective beyond the linear correlation.

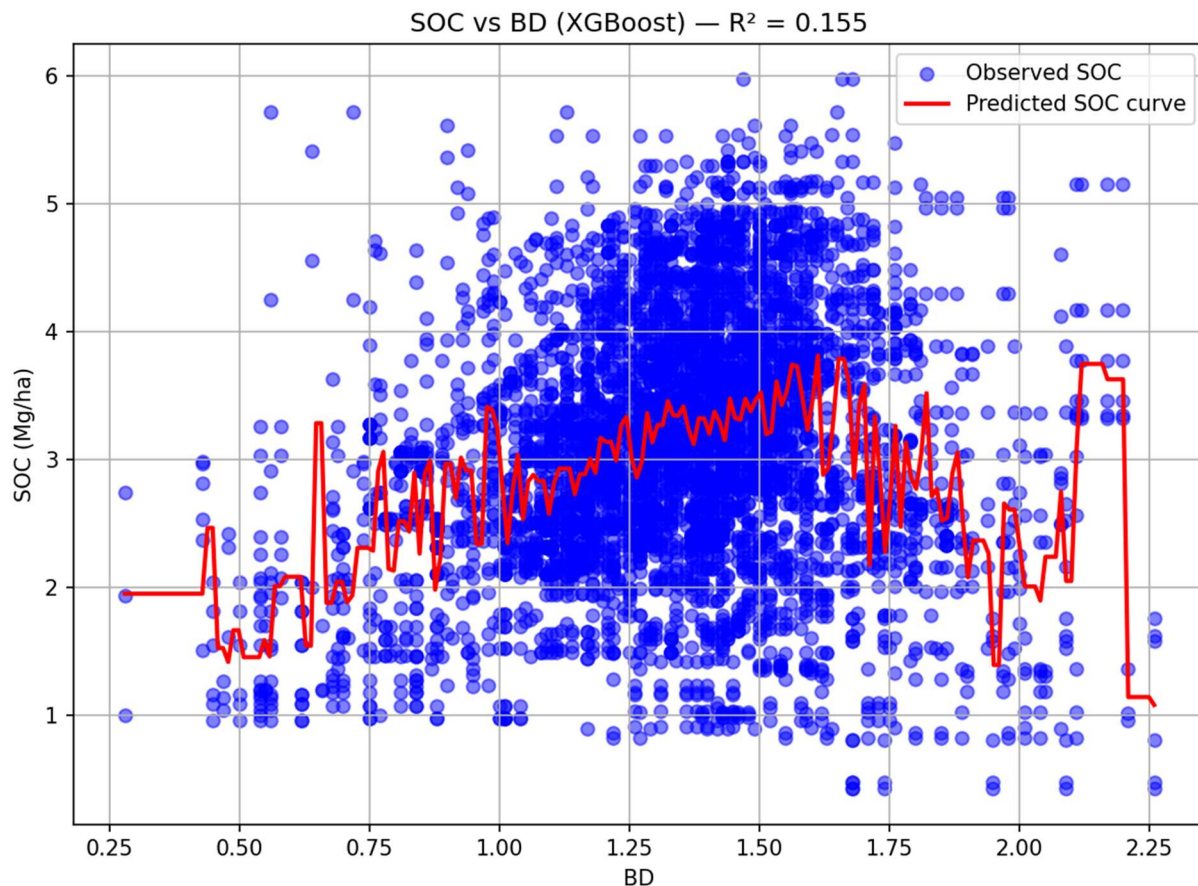


Figure 8. Relationship between bulk density and SOC stocks (XGBoost regression curve)

Gravel content exhibited substantial variability across the samples, with values ranging from 0% to 71.7% and an average of 11.9%. The distribution was right-skewed, as reflected by a relatively large standard deviation (12.9%) compared to the mean. A moderately strong negative Pearson correlation with SOC was observed ($r = -0.44$), indicating that higher gravel content is generally associated with lower SOC. The XGBoost regression curve further highlighted this trend, capturing the non-linear decline in SOC as gravel fractions increased.

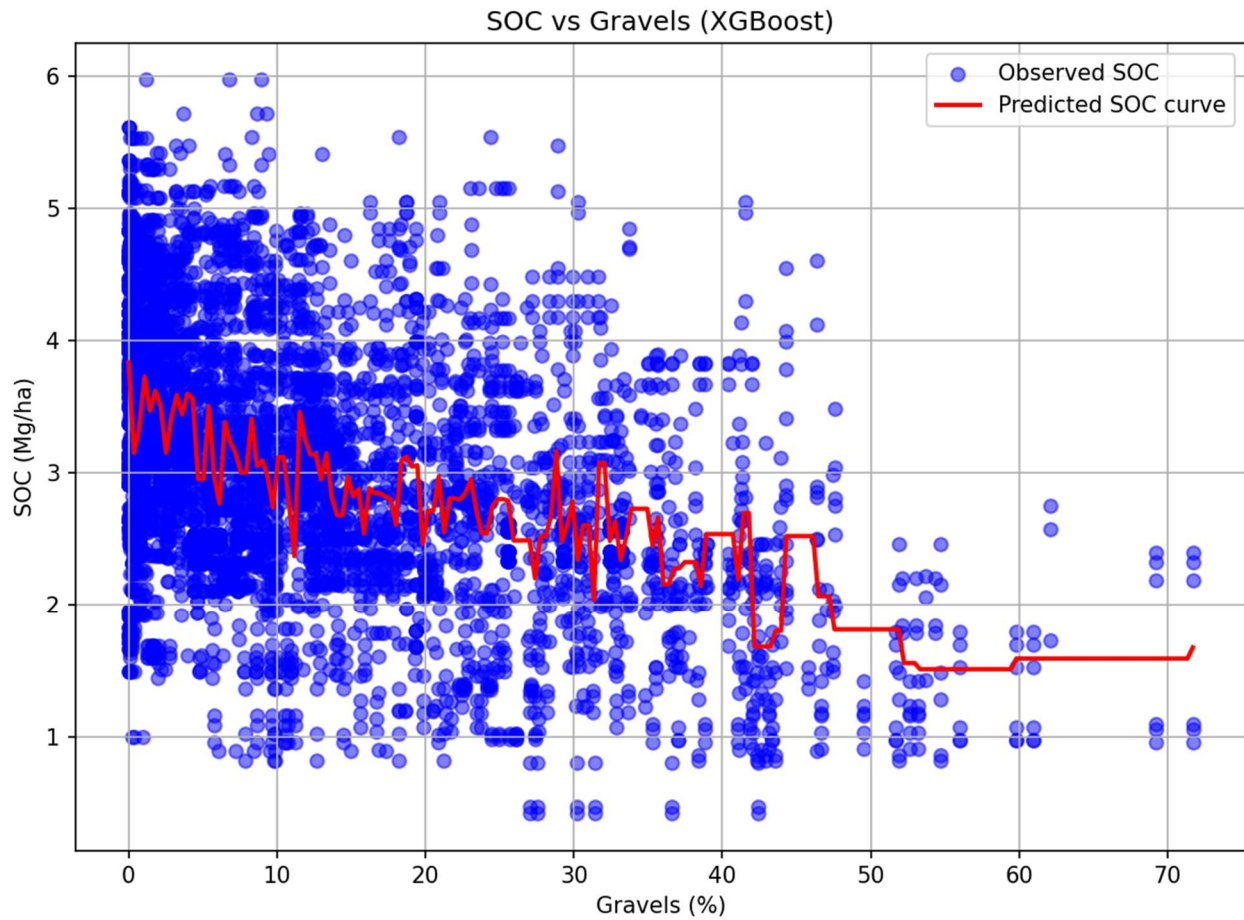


Figure 9. Relationship between SOC and gravel content (XGBoost regression curve)

Stone content was on average much lower, with a mean of 4.3% and most values concentrated near zero. The median was 0%, while the maximum reached nearly 75%, pointing to a highly skewed distribution where only a subset of samples contained substantial stone fractions. A negative correlation was also observed with SOC ($r = -0.30$), though weaker than that of gravels, suggesting that stonier soils also tend to store less SOC. The XGBoost curve revealed a non-linear relationship, emphasizing the sharp reduction in SOC in soils with higher stone content.

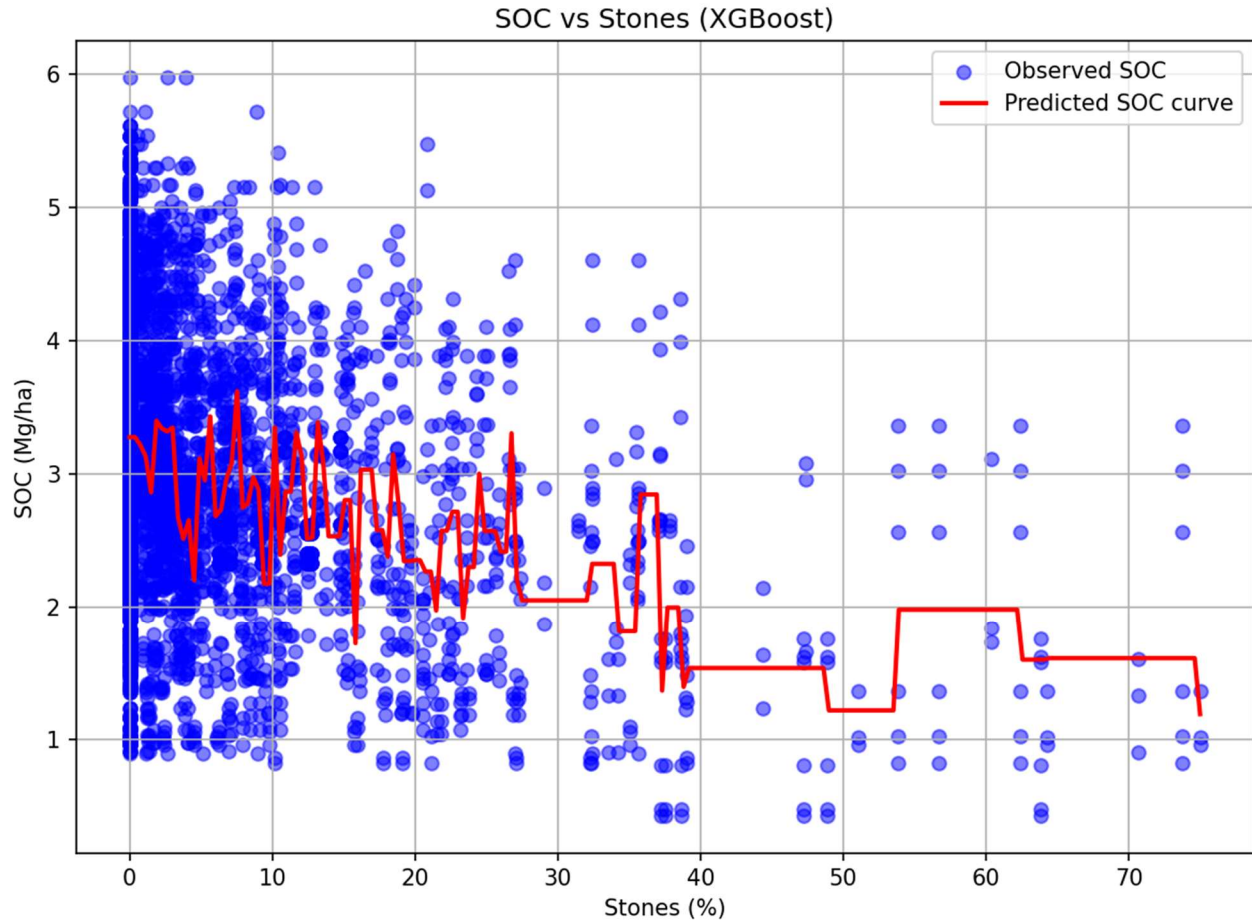


Figure 10. Relationship between SOC and stone content (XGBoost regression curve)

5.3. SOC across land-use and rehabilitation types

SOC stocks differed significantly by land cover (Figure 11).

- **Forests and natural areas** stored the highest SOC, reflecting dense vegetation and minimal disturbance.
- **Grasslands** maintained moderate stocks with narrow variability.
- **Vineyards and orchards** showed slightly lower SOC, likely due to soil management practices.
- **Fallow land** displayed highly variable SOC, indicating inconsistent recovery.
- **Parks and gardens** showed intermediate values, influenced by both organic inputs and human disturbance.

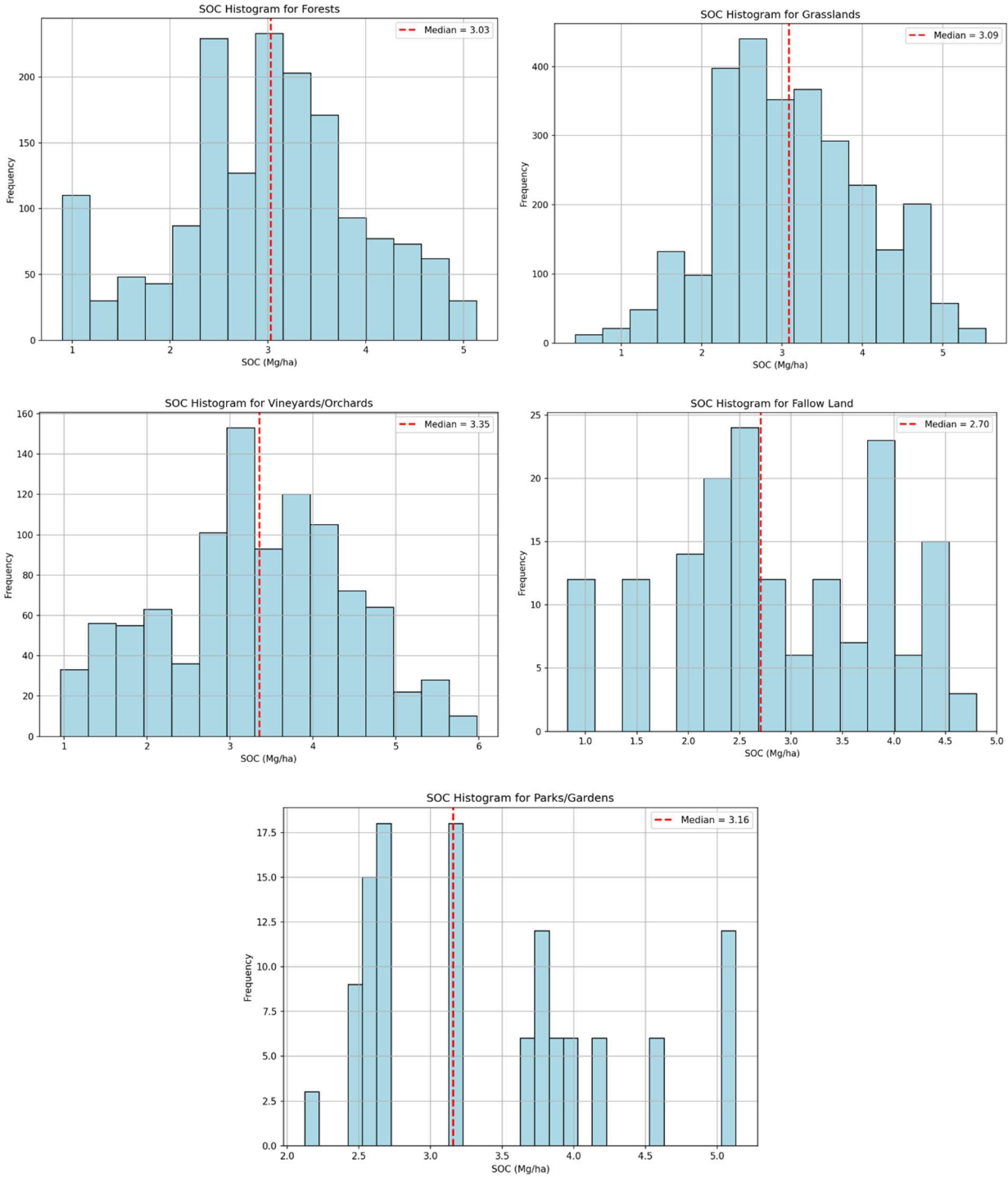


Figure 11. Histogram of SOC stocks across land-use categories

5.4. XGBoost model performance

SOC prediction using single-variable XGBoost models confirmed the limited explanatory power of individual predictors ($R^2 < 0.25$).

- Moisture: $R^2 = 0.13$, RMSE = 0.92 Mg/ha.

- Bulk density: $R^2 = 0.16$, RMSE = 0.90 Mg/ha.
- Gravel: $R^2 = 0.21$, RMSE = 0.88 Mg/ha.
- Stone: $R^2 = 0.13$, RMSE = 0.92 Mg/ha.

Although predictive accuracy was weak at the single-variable level, gravel and stone fractions showed the strongest influence. These findings highlight the importance of combining multiple variables in future multivariate models.

Table 3. Performance metrics (R^2 , RMSE, MAE, bias) of single-variable XGBoost models

Predictor	R^2	RMSE (Mg/ha)	MAE (Mg/ha)	Bias (Mg/ha)
Moisture content	0.128	0.917	0.732	−0.037
Bulk density	0.155	0.903	0.710	−0.065
Gravel content	0.213	0.877	0.694	+0.035
Stone content	0.130	0.922	0.748	+0.022

5.5. Machine learning model performance

The analysis of soil physical properties indicates that both moisture content and bulk density have a limited ability to predict SOC when modeled independently with XGBoost. For moisture content, the model achieved an R^2 of 0.128 with a small negative bias (−0.037 Mg/ha), an RMSE of 0.917 Mg/ha, and an MAE of 0.732 Mg/ha. Similarly, bulk density produced a slightly higher R^2 of 0.155, with a comparable error structure (bias −0.065 Mg/ha, RMSE 0.903 Mg/ha, MAE 0.710 Mg/ha). In both cases, the low R^2 values highlight that these single-variable models explain only a small fraction of the variance in SOC, while the moderate error magnitudes suggest that predictions remain uncertain at the plot scale. This confirms that although soil moisture and bulk density are relevant indicators of SOC dynamics, they cannot capture the complexity of carbon storage on their own and should be integrated with additional variables to improve model robustness.

The predictive performance of the models using gravel and stone contents as single predictors of SOC was generally weak, although slightly higher than for moisture content and bulk density. The XGBoost model based on gravel content achieved an R^2 of 0.213, with a low bias of 0.035 Mg/ha and moderate errors (RMSE = 0.877 Mg/ha, MAE = 0.694 Mg/ha). This suggests that gravel proportion provides some explanatory power for SOC variability, but remains insufficient to capture the complexity of soil carbon dynamics. In contrast, the model relying on stone content displayed a lower explanatory capacity ($R^2 = 0.130$), with a similarly small bias (0.022 Mg/ha) but slightly higher errors (RMSE = 0.922 Mg/ha, MAE = 0.748 Mg/ha). Overall, while both features exhibit a weak but non-negligible correlation with SOC, they cannot be considered reliable standalone predictors and should be integrated within multivariate approaches to improve accuracy.

6. Discussion

6.1. Drivers of SOC variation

The results confirm that soil physical properties play an important role in shaping SOC stocks in post-mining environments. Bulk density showed a weak positive correlation with

SOC, suggesting that moderately compacted soils may promote stabilization of organic matter through reduced aeration. In contrast, gravel and stone fractions displayed stronger negative effects, as coarse fragments reduce the fine soil matrix available for organic matter incorporation. Moisture content was only weakly correlated with SOC, likely reflecting the wide climatic heterogeneity across French mining sites. Overall, these findings emphasize that soil structure—particularly the proportion of coarse fragments—is a stronger determinant of SOC recovery than moisture alone, consistent with previous reports from South Africa and Central Europe.

6.2 Applicability and transferability of the XGBoost model

Using XGBoost allowed non-linear interactions between soil variables and SOC to be captured more effectively than linear methods. However, when applied to single predictors, performance remained limited ($R^2 < 0.25$), underscoring the need for multivariate approaches. The model, trained on French post-mining soils, provides a transferable framework for data-scarce regions such as Vietnam, provided that input variables are measured consistently. Transferability can be enhanced through site-specific calibration or partial retraining with local datasets. Similar approaches have been used successfully in China and India, where combining soil and land cover variables improved predictive accuracy.

6.3 Implications for rehabilitation planning

From a management perspective, forests and natural vegetation clearly offer the highest SOC sequestration potential, while cultivated or disturbed lands maintain lower stocks. This aligns with evidence that broadleaf plantations and natural regeneration enhance carbon storage more effectively than monocultures. The ability of XGBoost to generate predictive SOC maps offers practical value for mine operators and policymakers:

- guiding the selection of vegetation types in rehabilitation,
- prioritizing areas with low SOC recovery for targeted interventions, and
- supporting transparent reporting in carbon credit schemes such as Verra or the Gold Standard.

Integrating this framework into national rehabilitation programs could strengthen both ecological restoration and economic incentives for sustainable land use.

6.4 Limitations and directions for future work

Several limitations must be acknowledged. First, the analysis was restricted to French datasets, which may not fully represent tropical or subtropical conditions in Vietnam. Second, the explanatory variables were limited to soil physical properties, without including vegetation indices or remote sensing data that could enhance prediction. Third, the model evaluated only single-variable XGBoost regressions; future research should test multivariate approaches to better capture the drivers of SOC dynamics.

Future improvements could involve:

- integrating high-resolution remote sensing (UAV, LiDAR) to account for vegetation structure,
- expanding datasets across diverse climates to improve generalization, and
- including socio-economic and policy dimensions to ensure rehabilitation strategies are both ecologically and socially sustainable.

7. Conclusions and future work

This study highlights the variability of soil organic carbon (SOC) stocks in post-mining landscapes and the factors influencing their recovery. SOC levels were found to differ markedly across land-use types, with forests and natural areas exhibiting the highest values, while cultivated and disturbed lands maintained substantially lower stocks. Soil structure emerged as a decisive driver: gravel and stone fractions were negatively associated with SOC, whereas bulk density showed a weak positive effect and moisture content exerted only a limited influence. Importantly, single-variable XGBoost models accounted for only a small portion of SOC variance ($R^2 < 0.25$), underscoring the necessity of multivariate approaches for improved predictive performance.

Beyond empirical findings, this study makes several scientific and practical contributions. It introduces a reproducible framework that integrates field-based SOC quantification, GIS-based spatial mapping, and machine learning into a unified approach for post-mining carbon assessment. The use of XGBoost demonstrated its capacity to capture non-linear SOC–soil relationships in heterogeneous environments, thereby offering methodological advances over conventional approaches. Comparative analysis across rehabilitation strategies provided new insights into SOC recovery potential, delivering evidence-based guidance for mine closure planning and highlighting opportunities for integration into emerging carbon credit schemes. Furthermore, by grounding the analysis in French datasets, the study establishes a methodological foundation that can be readily adapted to rehabilitation projects in Vietnam and other tropical mining regions where empirical data remain limited.

At the same time, several limitations point to promising avenues for future work. Expanding datasets to encompass tropical and subtropical post-mining environments will be critical for enhancing model calibration and transferability. The integration of high-resolution remote sensing tools such as UAV or LiDAR, together with vegetation indices, could substantially improve SOC and biomass spatial prediction. Finally, incorporating socio-economic considerations into rehabilitation planning will help ensure that ecological restoration strategies are not only scientifically sound but also socially inclusive and aligned with national policy frameworks.

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Contributions of authors

Léopold Dupuy: Conducted data collection, performed data analysis, and prepared the initial draft of the manuscript.

Nguyen Mai Anh: Assisted with data processing, literature review, and contributed to the preparation of figures and tables.

Hoang Nguyen: Conceived and supervised the study, provided methodological guidance, and critically revised and finalized the manuscript.

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