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LAND SUITABILITY EVALUATION OF AGRICULTURAL CROPS IN MINING-AFFECTED WATERSHEDS: THE NEED FOR CONTAMINATION-ADJUSTED INDICES: A CRITICAL GLOBAL REVIEW

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ABSTRACT

Mining operations constitute one of the most significant anthropogenic contributors to global land degradation. These activities disrupt soil structure, deplete organic matter, introduce heavy metal contamination, and fundamentally alter watershed hydrology. Restoration of agricultural potential to mining-affected land demands rigorous, multi-dimensional land suitability evaluation (LSE) frameworks that transcend conventional productivity-focused land use approaches. This review critically synthesises the conceptual foundations of the FAO Framework for Land Evaluation (1976, 1983), the evolving role of soil quality indices in suitability assessment, and the contributions of GIS and remote sensing to spatial suitability mapping. Drawing on evidence from granite quarrying in semi-arid India, coal mining in eastern India and the United States, iron ore and bauxite mining in sub-Saharan Africa and South Asia and gold mining in South America, the review demonstrates that standard FAO suitability classification systematically underestimates contamination risk and overestimates crop production potential in mining-affected landscapes. To address this methodological gap, a Contamination-Adjusted Suitability Index (CASI) was proposed, integrating FAO suitability scores, soil quality sub-indices and pollution load indices into a composite quantitative instrument. Recent advances in machine learning, digital soil mapping and cloud-based Earth observation are assessed for their capacity to operationalise contamination-adjusted suitability assessment at regional and global scales. High-priority research gaps are identified, including the absence of mine-type-specific FAO criteria, the underrepresentation of dimension stone quarrying in LSE literature and the disconnect between suitability science and land governance. A globally applicable integrated framework for evidence-based land rehabilitation planning is proposed.

Keywords **:** Land suitability evaluation, FAO framework, contamination-adjusted suitability index (CASI), machine learning and watershed management.

Introduction

Land degradation driven by extractive industries constitutes one of the defining environmental challenges of the twenty-first century. Globally, mining operations disturb an estimated 57,000 km² of land annually, generating contaminated soils, disrupted watersheds and displaced agricultural communities (Lechner *et al*., 2020). The intersection of mineral extraction and food security is particularly acute in developing economies, where mineral-rich regions frequently overlap with productive agricultural landscapes and institutional mechanisms for post-mining rehabilitation remain underdeveloped (Sonter *et al*., 2018; Macklin *et al*., 2023).

The restoration of agricultural viability to mining-affected land requires a spatially explicit, policy-relevant assessment framework capable of distinguishing lands with genuine rehabilitation potential from those warranting permanent reclassification. Land suitability evaluation (LSE), anchored in the FAO Framework for Land Evaluation (FAO, 1976), provides the internationally recognised architecture for this purpose. However, the classical FAO framework was designed for relatively undisturbed agricultural land and does not incorporate contamination as a suitability-determining variable a fundamental limitation where heavy metal phytotoxicity, acid mine drainage and persistent organic pollutants may override all other physical and agronomic considerations (Adriano, 2001; Ballabio *et al*., 2024).

This limitation is not merely theoretical. A landmark global assessment identified that 14-17 per cent of the world's cropland soil poses measurable human health risks from heavy metal contamination, with mining regions exhibiting the highest exceedance frequencies (Ballabio *et al*., 2024). In South Asia alone, soils proximal to coal, iron ore, bauxite and dimension stone quarrying operations host elevated concentrations of Ni, Cr, Pb, As and Cd that depress agricultural productivity, compromise food safety and persist in the soil environment for decades following mine closure (Chakraborty *et al*., 2024; FAO & UNEP, 2021). Yet existing LSE methodologies applied to such landscapes routinely classify these soils as S1–S2 based on physical and morphological criteria alone, generating planning outputs that misrepresent actual agronomic and human health risks.

The present review addresses this methodological lacuna by: (i) critically synthesising the FAO land evaluation framework and its modern modifications; (ii) reviewing soil quality indicators relevant to mining-affected suitability assessment; (iii) appraising the role of GIS and remote sensing in spatial suitability mapping; (iv) critically analysing global and Indian case studies spanning multiple mining types; (v) proposing a formal CASI with mathematical structure and integration pathways; and (vi) identifying high-priority research gaps and future directions. Evidence spans granite quarrying in Karnataka (Ajay Abhishek, 2024), coal mining in South Asia and the United States, metalliferous mining in Africa and Australia, and large-scale global contamination assessments.

Conceptual Foundations of Land Suitability Evaluation

Land suitability evaluation is defined as the process of assessing and predicting the performance of land when used for specified purposes (FAO, 1976). It represents a systematic, multi-attribute appraisal of land resources against the biophysical, economic and social requirements of defined land utilisation types (LUTs), generating a hierarchical classification that informs agricultural planning, land use zoning, rehabilitation programming and environmental management. LSE is conceptually distinct from land capability classification (LCC), which assesses inherent physical limitations without reference to specific uses (Klingebiel & Montgomery, 1961; USDA, 1961); LSE explicitly matches land characteristics with crop or management system requirements.

The FAO framework rests on three foundational principles: (a) suitability is always assessed relative to a specific, defined land use; (b) evaluation integrates physical, economic and social dimensions of land performance; and (c) assessment encompasses both current suitability and potential suitability following feasible improvements (FAO, 1983). These principles confer flexibility and rigour across diverse agro-ecological contexts and for agricultural, forestry and conservation land uses (FAO, 1984).

The FAO Hierarchical Classification System

The FAO framework organises land suitability into four hierarchical levels. Orders distinguish Suitable (S) from Not Suitable (N) land. Within the Suitable order, Classes S1, S2and S3 reflect increasing limitations from negligible (S1: Highly Suitable) through moderate (S2: Moderately Suitable) to severe (S3: Marginally Suitable). Within the Not Suitable order, N1 (Currently Not Suitable) acknowledges improvement potential through major investment, while N2 (Permanently Not Suitable) identifies fundamental constraints, including persistent chemical contamination that cannot be overcome with available technology. Subclasses specify limitation types (e.g., S2r: rooting depth; S3t: texture; S2nz: nutrient availability; S2w: drainage; S2g: gravelliness), while Units reflect minor management differences (FAO, 1976; Sys *et al*., 1991).

In mining-affected watersheds, the S–N classification boundary carries profound planning consequences. Contamination-induced constraints, heavy metal phytotoxicity, compacted overburden, acid mine drainage-driven pH extremes, may render lands permanently unsuitable (N2) for sensitive food crops while remaining viable for phytoremediation species or industrial crops. The absence of a contamination-specific subclass notation in the standard FAO system represents a fundamental gap for mining applications and is a central motivation for the CASI framework.

Table 1 : FAO framework: Land suitability orders, classes and subclass notation for agricultural evaluation

Order	Class	Symbol	Definition	Yield Potential
Suitable (S)	Highly Suitable	S1	No significant limitations for sustained use	>80% of maximum attainable yield
	Moderately Suitable	S2	Moderate limitations; subclasses e.g. S2r, S2t, S2nz, S2w, S2g	60–80% of maximum yield
	Marginally Suitable	S3	Severe limitations; productivity marginally justifies inputs	40–60% of maximum yield
Not Suitable (N)	Currently Not Suitable	N1	Limitations can be overcome by major capital improvements	<40% or requires major investment
	Permanently Not Suitable	N2	Fundamental limitations: includes severely contaminated mine soils and active quarry areas	Not economically viable; phytoremediation only

Source: FAO (1976, 1983); Sys *et al*. (1991); Dent & Young (1981). Yield potentials are expressed relative to S1 ceiling yields under optimal management.

The FAO Framework and Modern Methodological Advances

Classical Framework and Enduring Relevance

The FAO Framework for Land Evaluation (FAO, 1976) established the globally accepted paradigm of matching land characteristics with LUT requirements through the parametric system formalised by Sys *et al*., 1991. Preceding systems the Storie Index (Storie, 1933) and the USDA Land Capability Classification (Klingebiel & Montgomery, 1961) lacked the systematic multi-use flexibility and hierarchical structure of the FAO approach. The framework's enduring relevance lies in its universality: it has been adapted across tropical Africa (Sys, 1985), South and Southeast Asia (FAO, 1983), arid and semi-arid environments (AbdelRahman *et al*., 2022) and temperate Europe, providing a common scientific language for land resource assessment.

The framework operates through the 'limiting factor principle': the most restrictive factor determines the overall suitability class. While transparent and replicable, this principle imposes binary class transitions that may misrepresent the continuous nature of soil property variation a limitation motivating fuzzy and probabilistic extensions (Tashayo *et al*., 2020; Mosadeghi *et al*., 2015).

AHP-GIS Multi-Criteria Approaches

The Analytical Hierarchy Process (AHP), introduced by Saaty (1980), extended FAO suitability evaluation by providing a structured mathematical method for weighting multiple evaluation criteria according to expert judgement. When combined with GIS-based spatial overlay, AHP-GIS approaches produce continuous suitability surfaces that capture spatial heterogeneity more accurately than Boolean FAO classification. Akinci *et al*. (2019) demonstrated that AHP-GIS outperformed classical parametric methods for agricultural suitability mapping in Turkey, while AbdelRahman *et al*. (2016) applied AHP-GIS for multi-crop suitability assessment in Karnataka, finding that AHP weighting of soil depth, texture, slope and organic matter produced more nuanced outputs. Seyed mohammadi *et al*. (2019) integrated ANP with fuzzy set theory and GIS for irrigated maize suitability in Iran, achieving superior field-agreement compared with classical approaches.

A critical limitation of AHP-GIS is the subjectivity inherent in pairwise comparison matrices. In mining-affected settings, integrating heavy metal indicators into AHP criterion sets with appropriately high weights is methodologically straightforward but has been rarely implemented in practice.

Machine Learning and Digital Soil Mapping

The convergence of machine learning with digital soil mapping (DSM) has transformed the capacity for high-resolution, spatially continuous soil property prediction. Random Forest (RF), Support Vector Machines (SVM), Gradient Boosting and Convolutional Neural Networks (CNN) have been deployed to predict soil organic carbon, texture, pH, heavy metal concentrations and composite soil quality indices across diverse landscapes using environmental covariates derived from satellite imagery, digital elevation models and gridded climate data (McBratney *et al*., 2003; Hengl *et al*., 2017; Taghizadeh-Mehrjardi *et al*., 2021).

In mining-affected LSE, machine learning offers two key capabilities: (i) prediction of heavy metal spatial distributions from remote sensing proxies; and (ii) integration of predicted soil properties directly into suitability classification. Taghizadeh-Mehrjardi *et al*. (2021) demonstrated that RF-based heavy metal prediction outperformed ordinary kriging for Pb and Cd (R^2 0.72 vs 0.61) in an arid landscape in Iran. Paul *et al*. (2020) used RF-derived soil quality indices in eastern India to identify soil degradation zones with higher accuracy than conventional SQI approaches. Zeraatpisheh *et al*. (2022) applied deep learning for soil organic carbon mapping in mining-disturbed arid soils, achieving spatial resolutions of 30 m suitable for watershed-scale management planning.

Despite these advances, the application of machine learning to LSE in mining-affected watersheds remains nascent. Training data scarcity constrains model accuracy, while the 'black-box' nature of complex ML models impedes acceptance by planning authorities requiring transparent, auditable decision criteria. Transfer learning, ensemble approaches and integration of physics-based process models with data-driven machine learning represent promising directions for overcoming these barriers (Smail *et al*., 2023; Padarian *et al*., 2020).

3. Soil Quality Indicators in Land Suitability Evaluation

Conceptual Framework for Soil Quality Assessment

Soil quality defined as the capacity of a soil to function within ecosystem boundaries to sustain biological productivity, maintain environmental quality and promote plant and animal health (Doran & Parkin, 1994) provides the integrative conceptual bridge between raw soil measurements and their interpretation for land use planning. In LSE, soil quality indicators characterise inherent land qualities that determine crop performance potential and signal anthropogenic modifications particularly mining contamination that may impose constraints independent of physical or morphological limitations (Lal, 2015; Andrews *et al*., 2004).

The Minimum Data Set (MDS) concept (Doran & Parkin, 1994; Andrews *et al*., 2004) guides selection of a parsimonious set of sensitive, integrative and measurable indicators from a larger pool. For mining-affected watersheds, the MDS must extend beyond physical and chemical indicators to encompass contamination-sensitive variables specifically heavy metal concentrations and pollution indices that can trigger suitability downgrading regardless of agronomic adequacy (Neeraj & Hiranmai, 2022; Ballabio *et al*., 2024).

Key Soil Quality Indicators for Mining Contexts

Table 2 : Key soil quality indicators for land suitability evaluation in mining-affected watersheds

Category	Indicator	Mining Impact Mechanism	Critical Threshold	FAO Subclass
Physical	Bulk Density (Mg m^{-3})	Compaction from overburden dumping; machinery traffic	<1.40 (optimal); >1.65 (limiting)	
Physical	Texture (% clay, silt, sand)	Dust fallout changes surface texture; quarrying exposes coarse subsoil	Loam/clay loam optimal; coarse sandy = S3t	S2t, S3t, S2g
Chemical	Soil pH (1:2.5 H_2O)	AMD causes acidification; calcite dust from quarry raises pH	6.0–7.5 (optimal); <5.5 or >8.5 = N class	S2nz, N1
Chemical	Organic Carbon (%)	Topsoil stripping eliminates OC; low in disturbed mine soils	>1.0 (adequate); <0.5 (very low = S3nz)	S2nz, S3nz
Chemical	Heavy Metals (Ni, Pb, Cd, Cr, As) mg kg^{-1}	Primary contamination from quarrying, smelting, tailings leachate	Ni<50; Pb<100; Cd<3; Cr<100; As<20 (WHO/BIS)	CASI downgrade N1/N2
Biological	Microbial Biomass Carbon (MBC, mg kg^{-1})	Suppressed by heavy metals, pH extremes, compaction	>100 (adequate); <50 (severely degraded)	

Sources: Doran & Parkin (1994); Lal (2015); Andrews *et al*. (2004); Kabata-Pendias (2011); BIS standards; WHO soil quality guidelines; EU Regulation 2023/915. FAO subclass notation from Sys *et al*. (1991).

GIS and Remote Sensing in Suitability Mapping

GIS-Based Land Suitability Evaluation

Geographic Information Systems have transformed land suitability evaluation by enabling the integration, spatial overlay and analytical processing of multi-thematic datasets at resolutions and extents intractable through manual methods. The fundamental GIS workflow for mining-affected LSE encompasses five sequential phases: spatial database construction from field survey, satellite imagery and topographic data; geostatistical analysis and interpolation of soil properties; land capability and suitability classification through multi-layer overlay; output generation and map validation; and dissemination for planning and policy use (Akinci *et al*., 2019; AbdelRahman *et al*., 2022; Singh & Satpute, 2023).

ArcGIS, QGIS, ERDAS Imagine and increasingly Google Earth Engine (GEE) are the principal platforms deployed in contemporary LSE studies. GEE's cloud-based architecture enables processing of large satellite imagery time series at continental scales, facilitating monitoring of mine-induced land degradation and vegetation recovery trajectories (Gorelick *et al*., 2017; Ang *et al*., 2023). Integration of GEE with machine learning classifiers has enabled near-real-time LULC change detection around active mines, providing a dynamic spatial context for LSE outputs.

Remote Sensing Applications in Mining-Affected LSE

Remote sensing provides temporal and spatial data that complement field-based soil surveys, offering unique capabilities for characterising mining-induced land degradation at landscape scales. Multispectral sensors aboard Landsat 8/9 and Sentinel-2 enable LULC classification, vegetation health assessment (NDVI, EVI, SAVI), soil moisture mapping and detection of mine-induced vegetation stress through time-series analysis (Gorelick *et al*., 2017; USGS, 2024). Hyperspectral sensors including PRISMA, DESIS and airborne AVIRIS-NG can identify heavy metal-stressed vegetation through characteristic spectral signatures in the red-edge and SWIR regions, enabling indirect mapping of contamination gradients without exhaustive field sampling (Ang *et al*., 2023).

The systematic global review by Ang *et al*. (2023) identified GIS and remote sensing as indispensable for assessing mining impacts, encompassing mapping of quarry extent and encroachment, detection of dust fallout zones, monitoring of vegetation recovery post-mining and identification of drainage disruption patterns affecting soil waterlogging. Satellite-derived surface reflectance composites combined with machine learning classifiers have achieved LULC classification accuracies exceeding 90% in complex mining-affected landscapes (Witharana *et al*., 2021). Time-series analysis of vegetation indices around mine closures has demonstrated that spontaneous vegetation recovery is slow (10–30 years) without active rehabilitation, confirming remote sensing as the most cost-effective monitoring tool for tracking rehabilitation progress at scale (Sonter *et al*., 2018).

Mining-Affected Watersheds: Soil Degradation and Contamination Dynamics

Global Scope and Severity of Mining-Induced Soil Degradation

Mining operations impose a cascade of physical, chemical and biological perturbations on soils and watersheds that persistently compromise agricultural land suitability. Surface mining removes vegetation cover and topsoil, inverts or destroys soil profiles, generates overburden heaps and tailings ponds, mobilises heavy metals through runoff and aeolian dispersal and creates acid mine drainage (AMD) in sulfidic environments (Shrestha & Lal, 2006; Haigh, 2000). The severity and spatial extent of these impacts are modulated by mine type, operational scale, host rock geochemistry, climate and the presence or absence of regulatory environmental management systems.

Macklin *et al*. (2023) conducted the most comprehensive global assessment to date, finding that heavy metal contamination from mine runoff affects river systems across 165 countries, with an estimated 23 million people consuming water from mining-contaminated rivers. Ballabio *et al*. (2024), synthesising 796,084 soil sampling points from 1,493 regional studies, estimated that 14–17% of global cropland soil poses potential health risks from heavy metal contamination, with mining-affected regions exhibiting the highest exceedance frequencies for Cd, Pb, As and Ni. Sonter *et al*. (2018) demonstrated that mining globally affects biodiversity conservation areas and agricultural land at rates substantially higher than previously recognised, with deforestation extending 50–70 km beyond mine boundaries in tropical regions.

The implications for conventional FAO-based LSE are significant: if 14–17% of global cropland already carries measurable heavy metal health risks and if this percentage rises dramatically in mining-affected watersheds, then LSE methodologies that do not incorporate contamination as a formal suitability-determining variable are systematically generating inaccurate planning outputs in precisely those landscapes where accurate land use guidance is most urgently needed.

Mining Type-Specific Degradation Mechanisms

Different mining types produce distinct patterns of soil degradation, with implications for the FAO suitability subclasses most likely to be limiting and the contamination variables most likely to trigger suitability downgrading. Table 4 presents a comparative synthesis of mining type-specific impacts, relevant to the application of CASI.

Granite Quarrying: A Neglected Context in LSE Literature

Among major mining categories, granite and dimension stone quarrying is conspicuously underrepresented in LSE and soil quality literature, despite constituting a major extractive industry in southern India (Karnataka, Andhra Pradesh, Rajasthan), Portugal, Brazil and China. The geochemistry of granite quarrying creates a distinct contamination profile: the host granite gneiss contains Ni, Cr and Pb in ferromagnesian silicates, feldspars and accessory minerals (hornblende, biotite, augite) that are liberated as fine particulates during drilling, blasting and dressing operations. These particulates are dispersed by wind over distances of several hundred to several thousand metres, settling on adjacent agricultural soils, altering their surface texture and progressively contributing lithogenic heavy metals to the upper soil horizon (Rodriguez Martin *et al*., 2006; Ajay Abhishek, 2024). Unlike coal or metalliferous mining, granite quarrying does not typically generate AMD and heavy metal concentrations from quarry dust may remain below regulatory exceedance thresholds while nonetheless exhibiting spatially structured enrichment patterns detectable by geostatistical analysis. This 'sub-threshold but structured' contamination pattern is particularly challenging for standard FAO evaluation, which applies threshold-based N-class designation but provides no mechanism for capturing graduated contamination risk below threshold limits. The CASI framework addresses this by incorporating the Pollution Load Index (PLI) as a continuous contamination penalty factor that begins reducing suitability scores below threshold values, not merely at the point of exceedance.

Plate 1: Active granite quarrying at Muddakkanahalli micro-watershed, Tumkur district, Karnataka, showing vertical rock faces, quarry pit water accumulation, and topsoil removal

The Contamination-Adjusted Suitability Index (CASI): Conceptual Framework and Mathematical Structure

Rationale and Conceptual Architecture

The Contamination-Adjusted Suitability Index (CASI) is proposed as a formal, quantitative framework for integrating heavy metal contamination assessment with FAO-based land suitability evaluation in mining-affected and industrially impacted landscapes. CASI addresses the central methodological gap identified throughout this review: the absence of a contamination filter in standard FAO classification that renders the framework inadequate when applied to soils where chemical contamination constitutes a dominant land use constraint independent of physical and morphological characteristics. The CASI framework rests on three conceptual pillars. First, it retains the FAO hierarchical classification system as the biophysical evaluation engine, preserving compatibility with decades of global LSE literature and the internationally recognised S1–N2 nomenclature. Second, it integrates the Soil Quality Index (SQI) as a nutritional and structural adjustment factor, reflecting that soil productivity potential is determined not only by morphological characteristics but also by the biological and chemical functionality of the soil system. Third, it introduces a Contamination Penalty Factor (CPF) derived from the Pollution Load

Mathematical Structure of CASI

The mathematical architecture of CASI integrates three quantitative components. The FAO Suitability Score (FSS) numerically encodes the standard FAO suitability classification: S1 = 1.0; S2 = 0.7; S3 = 0.4; N1 = 0.2; N2 = 0.0. This encoding preserves the ordinal structure of the FAO system while enabling algebraic integration with the other CASI components.

The Soil Quality Sub-Index (SQI) is computed using the PCA-based Minimum Data Set framework (Andrews *et al*., 2004). For each land mapping unit, a set of physical (bulk density, texture, effective depth), chemical (pH, OC, EC, available nutrients) and biological (MBC, DHA) indicators is measured. PCA identifies indicator clusters; key indicators are retained from each cluster; each retained indicator is scored on a 0–1 scale using linear or non-linear scoring functions calibrated to optimum and threshold values from literature. The weighted sum $SQI = \Sigma(W_i \times S_i)$, where W_i is the PCA-derived weight of indicator i and S_i is its normalised score, yields a composite soil quality value on a 0–1 scale. In mining contexts, the SQI scoring functions for heavy metal indicators should incorporate exceedance of WHO/BIS thresholds as critical breakpoints.

Table 3 : Mining types, characteristic soil degradation mechanisms and relevance to land suitability evaluation

Mining Type	Primary Physical Impacts	Key Chemical Contaminants	Principal FAO Limitations	Global/ Indian Examples	Key References
Granite/Dimension Stone Quarrying	Topsoil removal; dust fallout; drainage alteration; silica dust	Ni, Cr, Pb (lithogenic); silica particulates	S3r, S3t, S2nz; N2 for quarry area	Muddakkanahalli, Karnataka; Rajasthan; Alentejo, Portugal	Abhishek (2024); Rodriguez Martin *et al*. (2006)
Coal Mining (Opencast)	Massive overburden dumps; profile inversion; subsidence; AMD	Cr, Ni, Pb, Co, Cu, Cd, As; sulfuric acid from pyrite oxidation	N1/N2 from pH toxicity; S2w; N2 for AMD zones	Raniganj & Jharia Coalfields, India; Appalachian Basin, USA	Chakraborty *et al*. (2024); Shrestha & Lal (2006); Haigh (2000)
Iron Ore Mining	Forest clearance; red dust fallout; laterite exposure; erosion	Fe, Mn, Cr, As; lateritic hardpan; P-fixation by Fe oxides	S3nz (P-fixation); S2g; S3r; laterite crust (N2)	Bellary-Hospet, Karnataka; Odisha; Goa; Pilbara, Australia	Tiwary (2001); Li *et al*. (2022)
Bauxite/Laterite Mining	Forest clearance; laterite stripping; severe erosion	Al, Fe, Cr; Al toxicity; Mn toxicity	Al/Mn toxicity (N1/N2); nutrient depletion (S3nz)	Jharkhand; Odisha; Madhya Pradesh; Weipa, Australia	Lakshmi *et al*. (2020); Acheampong *et al*. (2021)
Gold/Metalliferous Mining	Tailings ponds; cyanide/mercury use; AMD; groundwater contamination	As, Hg, Cd, Pb, Cu, Zn, CN^-; severe, persistent contamination	N2 for contamination zones; phytoremediation only viable use	Witwatersrand, South Africa; Madre de Dios, Peru; Tarkwa, Ghana	Macklin *et al*. (2023); Mensah *et al*. (2015)

AMD = Acid Mine Drainage; OC = Organic Carbon; S2r = rooting depth limitation; S3t = texture limitation; S2nz = nutrient/calcareousness limitation; S2g = gravelliness; N1 = Currently Not Suitable; N2 = Permanently Not Suitable.

Index (PLI) and calibrated against international food safety thresholds, which applies a multiplicative downgrade to FSS whenever contamination exceeds background levels.

The Contamination Penalty Factor (CPF) is derived from the Pollution Load Index [PLI = (CF_1 × CF_2 × ... × CF) ^(1/n), where CF_i = metal concentration in sample / metal background concentration]. For PLI ≤ 1.0 (unpolluted), CPF = 1.0 (no penalty applied). For PLI > 1.0, CPF = 1 − [(PLI − 1) / PLI_{ax}], where PLI_{ax} is a standardised upper bound (e.g., PLI_{ax} = 5.0). This function produces a CPF that decreases linearly from 1.0 to 0.0, providing a graduated, continuous penalty rather than a binary threshold switch. A mandatory hard constraint is imposed: when PLI > 3.0 (heavily polluted; Tomlinson *et al*., 1980), the land mapping unit is reclassified to N2 regardless of FSS or SQI values.

The CASI composite score is computed as: CASI = FSS × [α(SQI) + β(CPF)], where α + β = 1.0. For mining-affected contexts where contamination represents the dominant and most irreversible constraint, a higher weight for CPF (β = 0.6; α = 0.4) is recommended as an initial parameterisation, subject to empirical calibration against crop yield data. The resulting CASI score maps to CASI suitability classes: S1-equivalent (CASI ≥ 0.7); S2 (0.5–0.7); S3 (0.3–0.5); N1 (0.1–0.3); N2 (<0.1).

The CASI framework requires empirical calibration and validation before deployment as a formal planning instrument. Three calibration requirements are paramount. First, the FSS numerical encoding values should be validated against crop yield response data from paired contaminated-reference site comparisons. Second, the weight parameters α and β should be determined through regression of CASI scores against observed crop yields in mining-affected settings, replacing a priori recommendations with empirically grounded values. Third, PLI_{ax} and the CPF transformation function should be calibrated against food safety exceedance data to ensure CPF = 0 corresponds to concentrations definitively contraindicated for food crop production under applicable regulatory thresholds.

Calibration, Validation and Portability of CASI

The portability of CASI across mining types and geographies is a key design feature. The FSS component is inherently portable, as FAO suitability matching is globally standardised. The SQI component is portable through the MDS framework with locally calibrated scoring functions. The CPF component is portable through the PLI formulation, requiring only site-specific heavy metal concentrations and regional background values data routinely generated in environmental impact assessments globally. The recommended parameterisation (α=0.4, β=0.6) and hard constraint (PLI>3.0 → mandatory N2) are proposed as defaults pending empirical validation.

Cross-Study Synthesis and the Muddakkanahalli Case Study

Cross-Study Synthesis: Convergent and Divergent Findings

Critical comparison of reviewed studies reveals several convergent findings with significant implications for LSE methodology and policy. First, soil depth, texture and organic carbon consistently emerge as the primary physical suitability-limiting factors across all studies, demonstrating the universal relevance of these variables regardless of mining type or geographic context. This convergence supports the prioritisation of effective rooting depth assessment and organic matter restoration in post-mining rehabilitation programmes globally.

Table 4 : CASI components: mathematical structure, score ranges and data sources

CASI Component	Formula/Encoding	Score Range	Interpretation	Data Sources
Soil Quality Sub-Index (SQI)	SQI = Σ(Wi × Si); PCA-based weight derivation	0.0–1.0	Integrative measure of soil physical, chemical and biological functionality	Field soil samples; Andrews *et al*. (2004) MDS framework; Paul *et al*. (2020) RF-SQI approach
Pollution Load Index (PLI)	PLI = (CF_1 × CF_2 × ... × CF) ^(1/n); CF_i = Metal_sample / Metal_background	PLI<1 (unpolluted); PLI>2 (heavy)	Geometric mean of contamination factors; PLI>3 triggers mandatory N2 reclassification	Tomlinson *et al*. (1980); heavy metal analysis; Kabata-Pendias (2011) background values
Contamination Penalty Factor (CPF)	CPF = 1 − [(PLI − 1) / PLI_{ax}] for PLI> 1; CPF=1.0 for PLI ≤1	0.0–1.0	Translates PLI into a dimensionless downgrade multiplier; CPF=1.0 (no penalty) to CPF→0 (maximum penalty)	Derived from PLI; calibrated against EU Regulation 2023/915 and WHO guidelines
CASI (Composite Score)	CASI = FSS × [α(SQI) + β(CPF)]; α + β = 1.0; recommended α=0.4, β=0.6	0.0–1.0	CASI≥0.7: S1-equiv.; 0.5–0.7: S2; 0.3–0.5: S3; 0.1–0.3: N1; <0.1: N2 (mandatory N2 if PLI>3)	Integration of all above components; weights (α, β) to be validated empirically across mine types

PLI = Pollution Load Index; CF = Contamination Factor; FSS = FAO Suitability Score; SQI = Soil Quality Sub-Index; CPF = Contamination Penalty Factor; MDS = Minimum Data Set; PCA = Principal Component Analysis; RF = Random Forest. Food safety thresholds from EU Regulation 2023/915 and WHO guidelines.

Second, comparison between AbdelRahman *et al*. (2022) and conventional FAO application demonstrates that contamination-insensitive suitability methods produce systematically different and potentially unsafe spatial patterns compared with contamination-sensitive SQI-integrated approaches. The 9.51% vs. 0.71% disparity in estimated S1 area between SQI-adjusted and classical FAO approaches in that Egyptian study illustrates the magnitude of misclassification inherent in contamination-blind LSE, directly validating the CASI proposal.

Third, convergent findings from Mugiyo *et al*. (2021) in South Africa and Ajay Abhishek (2024) in India regarding the superior suitability of non-cereal (horticultural and underutilised) crops in degraded mining soils have important policy implications: crop selection for mine-rehabilitated land should prioritise species with physiological tolerance to specific combinations of physical and chemical constraints present, rather than defaulting to traditional crop portfolios.

Fourth, the contrast between Chakraborty *et al*. (2024) where pH, drainage and heavy metals collectively drive permanent N2 designation across substantial coal mining areas and Ajay Abhishek (2024) where heavy metals remain below permissible limits but physical limitations are severe in granite quarrying contexts illustrates that CASI will generate substantially different outputs depending on mine type, requiring mine-type-specific parameterisation of CPF thresholds and FSS downgrading rules.

The Muddakkanahalli Micro-Watershed Study in Global Context

The granite quarry-affected Muddakkanahalli micro-watershed study (Ajay Abhishek, 2024) provides methodologically significant contributions to the international LSE literature through its rare combination of multi-crop suitability evaluation, geostatistical heavy metal mapping with semivariogram analysis, groundwater quality integration and FAO classification in a dimension stone quarrying context a combination absent from most analogous studies focused on coal or metalliferous mining.

The finding that quarry areas constitute 18.1% of the total watershed area (185.50 ha), all classified as N2, has direct relevance to land use planning in analogous quarrying contexts worldwide. Portugal's Alentejo granite quarrying region, Brazil's Espírito Santo quarrying belt and China's Fujian granite quarrying district present closely analogous geochemical and spatial settings where the Muddakkanahalli LSE methodology could be directly transferred and adapted. The consistent dominance of texture (S3t), rooting depth (S2r/S3r) and nutrient availability (S2nz) as suitability-limiting factors rather than heavy metal contamination per se distinguishes granite quarrying from metalliferous mining contexts and informs the relative weighting of CPF versus SQI in CASI parameterisation for quarrying settings.

Research Gaps and Future Directions

Absence of Mine-Type-Specific FAO Evaluation Criteria

The standard FAO framework does not include heavy metal contamination, acid mine drainage, or overburden-induced soil profile disturbance as suitability-determining variables. No internationally accepted set of mine-type-specific suitability criteria exists for any of the major mineral commodities mined globally coal, iron ore, bauxite, copper, gold, or dimension stone. The development of mine-type-specific suitability evaluation modules analogous to the FAO's existing guidelines for rainfed agriculture, irrigated agriculture and forestry represents a high-priority research and policy need. Such modules would standardise the contamination filter (CASI-CPF component) by mine type, provide mine-type-specific background metal values and define the management interventions required to move land from N1 to S3 classification following mine closure.

Underrepresentation of Dimension Stone Quarrying

Granite, marble, limestone and other dimension stone quarrying operations economically significant across southern India, southern Europe, Brazil and China are almost entirely absent from the global LSE literature. This review has identified only one systematic, multi-crop LSE study in a granite quarry-affected watershed (Ajay Abhishek, 2024). Given that granite quarrying disturbs substantial agricultural land in densely farmed semi-arid regions and that its contamination mechanism (dust-borne lithogenic metals, drainage disruption) is fundamentally different from acid-generating metalliferous mining, dedicated LSE research programmes for dimension stone quarrying regions are urgently needed. Comparative studies across multiple quarrying sites varying in scale, rock type, proximity to agricultural land and prevailing climate would enable the development of transferable, empirically validated CASI parameterisations for quarrying contexts.

Machine Learning Integration for Dynamic Suitability Assessment

Nearly all existing LSE studies are cross-sectional, representing a single point in time. The progressive degradation of agricultural land with continued mining or conversely, partial recovery following mine closure requires longitudinal monitoring frameworks integrating time-series remote sensing with periodic soil quality assessment. Machine learning classifiers applied to Sentinel-2 and Landsat time series can detect subtle changes in vegetation health and soil spectral properties associated with advancing contamination gradients (Taghizadeh-Mehrjardi *et al*., 2021; Padarian *et al*., 2020). Transfer learning approaches may enable ML models trained on data-rich contexts to be adapted for data-scarce environments through domain adaptation techniques (Smail *et al*., 2023). Dynamic CASI maps updated at regular intervals using ML-predicted soil property trajectories would provide substantially more actionable information for adaptive land management than static, single-year suitability maps.

Horticultural Crop Suitability in Mine-Rehabilitated Landscapes

The systematic evaluation of horticultural crops fruit trees, vegetables, medicinal plants in mine-affected and mine-rehabilitated soils is severely underrepresented in the global LSE literature. Evidence from Ajay Abhishek (2024) and Mugiyo *et al*. (2021) suggests that horticultural and underutilised crop species frequently demonstrate higher combined suitability than cereals in physically and chemically degraded soils, due to deeper root systems, greater tolerance of textural and structural constraints and in some cases ability to produce economically valuable yields on N1-classified land through targeted management. Systematic evaluation of food safety implications (heavy metal accumulation in edible plant parts) is essential alongside suitability classification for any horticultural crop recommended on mine-proximal soils.

Policy and Governance Integration

Despite the technical sophistication of modern LSE, the translation of suitability maps into operational policy land use zoning, mining lease conditions, remediation obligations, compensation mechanisms for mining-affected farming communities remains weak globally. In India, this disconnect is particularly pronounced: the Mining and Minerals (Development and Regulation) Act and the Environmental Impact Assessment framework do not mandate LSE at the micro-watershed scale or require the development of crop zoning plans for mining-affected agricultural land. Future research should prioritise the co-production of suitability assessment outputs with district planning authorities, local government institutions and agricultural extension systems, embedding LSE within participatory land governance frameworks that ensure technical outputs translate into meaningful management change (Sonter *et al*., 2018).

Conclusion

Land suitability evaluation in mining-affected watersheds occupies a critical and underserved intersection of soil science, environmental management, agricultural planning and public health governance. This review has demonstrated, through a critical synthesis of international evidence, that the FAO Framework for Land Evaluation while foundationally sound and globally applicable requires a formal contamination adjustment mechanism to generate accurate, actionable and safe suitability outputs for mining-affected landscapes. The absence of such a mechanism constitutes a systemic methodological gap with direct consequences for agricultural planning in regions encompassing an estimated 14–17% of global cropland carrying elevated heavy metal contamination risk.

The Contamination-Adjusted Suitability Index (CASI), proposed and formalised in this review, provides a mathematically explicit, computationally tractable and conceptually coherent pathway for integrating FAO suitability scores, soil quality sub-indices and pollution load indices into a unified suitability instrument. CASI preserves backward compatibility with the FAO classification system, enabling comparison with existing LSE literature and adoption within established land resource inventory workflows. Its mathematical structure $CASI = FSS \times [\alpha(SQI) + \beta(CPF)]$ can be implemented in standard GIS environments using routinely collected soil and environmental data, requiring no additional field instruments or laboratory methods beyond those already deployed in competent LSE studies.

Several policy implications follow from this synthesis. First, environmental impact assessment frameworks for mining operations should mandate pre- and post-mining LSE at the micro-watershed scale, with CASI or an equivalent contamination-adjusted methodology. Second, mine closure plans should incorporate evidence-based crop zoning maps generated through contamination-adjusted LSE, ensuring that crop recommendations for rehabilitated mining land are calibrated to actual soil quality and safety conditions. Third, the FAO should develop mine-type-specific guidelines for land evaluation analogous to its existing guidelines for rainfed agriculture, irrigated agriculture and forestry that formalise contamination-adjusted suitability criteria for major mining commodity types. Fourth, convergent evidence that horticultural and underutilised crops demonstrate higher suitability than cereals in degraded mining soils should inform crop diversification programming in mining-affected agricultural communities globally.

Future research priorities should include: empirical validation and calibration of CASI across multiple mining types and geographies; the development of machine learning-assisted, temporally dynamic suitability monitoring frameworks; systematic multi-crop LSE studies in underrepresented quarrying contexts (granite, marble, limestone); and the co-production of suitability science with land governance institutions to close the persistent gap between technical knowledge and policy action. Only through such integrated, globally applicable and policy-connected land suitability science can the agricultural rehabilitation of the world's mining-affected watersheds be achieved with the scientific rigour and human health protection that the scale of this global challenge demands.

Conflict of interest

The authors declare no conflict of interest. All authors agree to publish it.

Declaration

We declare that all authors of this Ms. have made substantial contributions. We did not exclude any author who substantially contributed to this Ms. We have followed our ethical norms established by our respective institutions.

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