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Original article

Conceptual framework to assist in the decision-making process when planning for post-mining land-uses

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ABSTRACT

To avoid a climate crisis, major industrial economies are being urged to reduce their dependence on coal-fired power generation. Given decarbonisation pressures, many coal mining regions worldwide are facing the prospect of mine closures. However, few viable planning mechanisms are available to assess potential post-mining alternatives and enhance regional transition. To optimise transition outcomes and maximise stakeholder acceptance, mechanisms that incorporate input from a diverse range of stakeholders and disciplinary perspectives are needed at a regional scale. These mechanisms need to compute seemingly disparate types of multi-disciplinary and multi-scale data in a robust, coherent, and transparent fashion. This paper presents a conceptual mixed-method framework for post-mining land-use planning that integrates stakeholders' involvement, GIS, multi-criteria decision-making and fuzzy logic. The framework utilise environmental and socio-technical data to support the decision-making process. This work is driven by the urgency to offer mining regions in transition a tool for planning their post-mining future. The proposed framework builds on previous literature and has the ability to support a wide variety of institutions and professionals in their efforts to facilitate the post-mining planning process in mining-dependent regions toward a low-carbon future.

Abbreviations

AHP	Analytic Hierarchy Process
ANP	Analytic Network Process
CO_2	Carbon dioxide
CP	Compromise Programming
ELECTRE	ELimination Et Choix Traduisant la REalité
FCM	Fuzzy Cognitive Map
FIS	Fuzzy Inference System
GIS	Geographic Information System
IAHP	Improved Analytic Hierarchy Process
ICMM	International Council on Mining and Metals
LP	Linear Programming
MCDM	Multi-Criteria Decision-Making
MDA	Multi-Dimensional Analysis
PROMETHEE	Preference Ranking Organization METHod for Enrichment of Evaluations
PMLU	Post-mining land-use
RWA	Relative Weights of Attributes
SAW	Simple Additive Weighting
SMART	Simple Multi-Attribute Ranking Technique
TFN	Triangular Fuzzy Number
TrFN	Trapezoidal Fuzzy Number
PFN	Pentagonal Fuzzy Number
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution

Parameters and constants

$\mu_{(x)}$	Fuzzy membership function
N	Pair-wise matrix dimension
A_{nxn}	Pair-wise matrix that contains a_{ij} PMLU attributes preferences
a_{ij}	Stakeholders expressed preference of PMLU attribute i over PMLU attribute j
P_{nxn}	Normalise pair-wise matrix that contains p_{ij} PMLU attributes preferences
p_{ij}	Normalised value of the preference of PMLU attribute i over PMLU attribute j
W_{nx1}	Matrix that contains w_i PMLU attributes weights

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w_i Is the weight of PMLU attribute i

$p_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}}$ Equation to normalise pair-wise matrix A_{nxn}

$w_i = (\prod_{j=1}^{n} p_{ij})^{\frac{1}{n}}$ Equation to calculate weight matrix W_{nx1}

1. Introduction

Climate change mitigation has become a global normative priority. Consequently, efforts to reduce CO_2 emissions are projected to place unprecedented downward pressure on the acceptability of thermal coal use as a source of energy (Arratia-Solar, 2019). At scale, this implies a progressive phasing-out of thermal coal, which has consequences for both coal mines and the regions that host them (Fleming-Muñoz et al., 2019). Decarbonisation policies are likely to drive the closure of many of the world's thermal coal mines in coming decades (Svobodova et al., 2020), which brings an urgency for viable post-mining solutions for many regions. To respond to this urgency, planning alternatives that can meaningfully represent and process complex and multiple possibilities are required.

There is an array of constraints when planning for a post-mining transition. For example, how planners can incorporate input from a diverse range of disciplines and stakeholders (Strambo et al., 2019). Mine closure represents one of the most challenging and understudied phases of the resource development lifecycle (Bainton & Holcombe, 2018). Deciding how land will be used in the aftermath of mining is still largely overlooked by mining companies and governments, who generally prioritise the productive phases of mining projects (Everingham et al., 2018). Coal mining regions worldwide are facing the prospect of multiple mine closures while having few viable planning mechanisms available to assess potential post-mining alternatives (Snyder, 2018). Jurisdictions where coal mines are major contributors to the economic prosperity of regions and even the whole nation, are looking for options to minimise the implications of a transition to low-carbon alternatives (e.g. Goverment of Canada, 2018).

Advanced post-mining land-use (PMLU) planning approaches are urgently needed. This is critical for coal mining-dependent regions, where changes will be substantial, driven by large-scale land-use changes to post-mining alternatives. If coal is to be successfully phased-out in these regions, robust and centrally coordinated closure planning is required. This paper addresses this urgency by proposing a conceptual framework that facilitates multi-stakeholder PMLU decision-making. The framework is able to process complex multi-disciplinary data for use in planning of post-mining alternatives, considering the context of thermal coal mining –although the approach can be generalised to any mining context.

The framework aims to develop an efficient, inclusive, and transparent tool capable of optimising PLMU planning process. Development of the framework took into account how to: (1) efficiently involve stakeholders in different aspects of the planning process, (2) understand, and work towards, stakeholder consensus, (3) successfully account for the uncertainty that PMLU decision processes imply, and (4) efficiently integrate a wide range of relevant qualitative and quantitative data in a coherent manner.

The framework incorporates three key features. First, it uses a multi-disciplinary, mixed-method approach to analyse environmental and socio-technical characteristics of mining-dependent regions. Second, it provides guidance for engaging stakeholders and collecting their different views about the value of future PMLU alternatives. Third, it considers the embedded uncertainty that a coal transition brings. These three aspects are critical if PMLU planning is to be effective and accepted by a broad base of stakeholders. The objective of the framework is to support a wide variety of institutions and professionals in their efforts to facilitate the process of PMLU planning in mining-dependent regions toward a low-carbon future.

The paper is structured as follows. Section 2 reviews existing literature that links PMLU planning and multi-criteria decision-making methods. The section includes a brief background on fuzzy set theory, which is used in this approach. Section 3 presents the conceptual framework, along with its analytical components. The key advantages of the framework are discussed in Section 4. The section also discusses the importance of adaptable, transparent and evidence-based tools for planning at scale, in the global context of the low-carbon energy transition. Finally, Section 5 offers a conclusion and identifies future work and research opportunities.

2. Literature review

This section is presented in four subsections. Subsection 1 introduces the recent literature on PMLU planning. Subsection 2 reviews studies that use spatial multi-criteria decision-making (SMDM), which is a combination of multi-criteria decision-making methods (MCDM) and geographic information systems (GIS) capabilities. Subsection 3 provides an overview of the use of fuzzy set theory within the MCDM context. The fourth part presents a systematic literature review of PMLU studies that have applied MCDM methods.

2.1. Post-mining land-use planning

Regardless of the industry and the country, decommissioning and closure decision-making processes are complex and often driven by technocratic processes (Vivoda et al., 2019). In the mining context, this complexity comes from a diversity of stakeholder expectations, involvement, and competing interests. Individual preferences and needs of stakeholders, landowners, and potential future land users make PMLU decision-making processes site-specific and difficult to re-apply elsewhere (Everingham et al., 2018; Svobodova et al., 2021). The unique complexity of each mine closure implies that different technical, socio-economic, environmental and governance conditions for each site need to be defined, characterised and evaluated (Kivinen, 2017; Svobodova et al., 2019).

One key component of PMLU planning is to identify and define potential land uses that can be pursued in the land where a mine operates. However, defining a land-use classification to address PMLU planning processes has not been straightforward as evidenced by the variety of different land-use classifications that exist in the literature. For instance, Hendrychová et al. (2020) expand these categories by classifying 30 types of post-mining habitats as part of PMLU planning, while Masoumi et al. use only eight. The process to identify land categories also vary across studies. For example, Larondelle and Haase (2012) use an ecosystem services approach to evaluate different PMLUs, while Doley and Audet (2013) highlight the importance of preserving original ecosystems in PMLU planning.

PMLU planning also brings a range of uncertainties given the complexity of such decision-making process. Lechner et al. (2017) provide a five-step framework for planning in mining regions that incorporates sensitivity analyses to capture the uncertainties in PMLU planning. One of the many complexities of this planning process is how to include stakeholder's perspectives. Kivinen et al. (2018) propose using a public participatory GIS approach to enable residents of mining regions to map their PMLU preferences. One way to address uncertainties within PMLU planning process is to perform the analysis of alternatives under a fuzzy environment as a part of a participatory process with relevant stakeholders (Kaya et al., 2019). Fuzzy set theory is explained in Subsection 2.3.

2.2. Spatial multi-criteria decision-making

MCDM is a branch of *Operation Research* that aims to find the best alternative among a set of feasible alternatives in complex scenarios, including conflicting objectives and criteria (Kumar et al., 2017). This discipline offers different ways of disaggregating complex problems, measuring the extent to which options achieve required objectives, weighting the achievements, and reassembling the outcomes (Beinat et al., 1998). Eshun et al. (2018) highlight that MCDM does not aim to reach an optimal and final decision; however, MCDM optimises the decision-making process by supporting decision makers throughout the process.

Spatial Multi-criteria Decision Making (SMDM) is the combination of MCDM methods and GIS (Greene et al., 2011). Malczewski (1999b) argues that the combination of GIS and MCDM is of critical importance, as GIS provides the capabilities of data acquisition, storage, retrieval, manipulation, visualisation and analysis, while MCDM techniques add the tools for integrating both the geographic information and the decision maker's preferences into the decision-making process.

MCDM and GIS methods have been applied in diverse sectors such as environment, transport, education, health care, defence, investment, agriculture, immigration, mining and energy (Bilbao-Terol et al., 2015; Jain et al., 2014; Lipuščěk et al., 2010; Liu et al., 2015; Mondal & Pramanik, 2014; Mrówczyńska et al., 2021; Papathanasiou et al., 2016; Rashid, 2019; Sánchez-Lozano et al., 2015; Sitorus et al., 2019). The way that GIS and MCDM are combined across studies vary according to the context and disciplines. Their synergistic capabilities combined in a SMDM analysis enables the development of policy recommendations in a systematic, efficient and transparent way (Malczewski, 1999a, 2006; Sánchez-Lozano et al., 2013).

2.3. Fuzzy set theory

Fuzzy set theory was introduced by Zadeh (1965), who proposed a way to model the uncertainty and imprecision that often prevails in social situations. The essence of the concept when applied to MCDM is that the fuzzy environment introduces a buffer around expressed stakeholder preferences, which accounts for potentially ambiguity, subjectivity and imprecision. The following paragraphs present the necessary details of the approach.

A set is understood as a collection of distinct elements. This might include, for example, the first six positive integer numbers, prime numbers that are less or equal to 19, or a list of countries that have green and yellow colours on their flags. Sets are commonly represented by italicised capital letters: e.g. let F be the set whose elements are the first six prime numbers: F = (2, 3, 5, 7, 11, 13). In this example, element 7 belongs to F ($7 \in F$) but element 17 does not ($17 \notin F$). This belonging within a set is referred as membership function, which can also assist in defining a specific set.

The classical set is defined as $B \rightarrow B = [b, b']$; with b, $b' \in R$; with membership function $\mu_{(x)}$ (see Equation (1) below). As with any classical set, the membership function $\mu_{(x)}$ follows a binary pattern, where the membership function $\mu_{(x)}$ for any element x is equal to 1, if and only if $b \leq x \leq b'$, otherwise the membership function $\mu_{(x)}$ takes value 0 implying that any other element x that sits outside that specific range does not have a membership in set B. The blue area in Fig. 1a shows a full membership, implying that $\mu_{(x)} = 1$. The full membership boundaries are set by b and b'. Outside that specific boundary the value of the membership function $\mu_{(x)} = 0$, implying that any value of x that is larger than b' or smaller than b does not belong to set B.

$$\mu_{(x)} = \begin{cases} 0, x < b \\ 1, b \leq x \leq b', \text{ if } b = b', \text{ then } B = [b, b] = b, \text{ indicating only point } b \\ 0, x > b', \end{cases} \tag{1}$$

Classical sets fit the classification of objects that have a defined criterion of membership ($\mu_{(x)} = 0$ or $\mu_{(x)} = 1$), such as taxonomic ranks, where all living organisms either belong or do not belong to a certain domain, kingdom, phylum, class and so on. However, there are classes of objects that do not have defined or agreed criteria of membership, such as "class of tall people", "approximately eight" or "in the region of eight". Consequently, these classes or sets of objects do not fulfil the classical definition of sets. But, as Zadeh argues, those "*imprecisely defined 'classes' play an important role in human thinking*" (Zadeh, 1965, p. 338). In this way, fuzzy sets provide a quantifiable way of dealing with those uncertain and imprecise situations as part of the MCDM method.

Fuzzy set membership functions have a continuum grade of membership between 0 and 1 instead of the binary membership (only 0 or 1) that classical sets have. Hence the name fuzzy sets (Zadeh, 1965). Therefore, any value x that belongs to a fuzzy set has a membership function $\mu_{(x)}$ with values in the range $0 < \mu_{(x)} \leq 1$. Fig. 1b shows fuzzy set C represented by a bell shape function where a fuzzy membership function of set C can be appreciated. The nearer the value of $\mu_{(x)}$ to 1, the higher the grade of membership of element x in set C, such as the case for c_2 in Fig. 1b.

Since Zadeh (1965) developed the concept of the fuzzy set, different types of fuzzy numbers have been defined such as triangular, trapezoidal, pentagonal, hexagonal, and heptagonal fuzzy number (Chakraborty et al., 2020; Karsak, 2002; Maity et al., 2020; Mateos & Jiménez, 2009; Nagar & Surana, 2015). Fig. 2 shows the three most used fuzzy numbers.

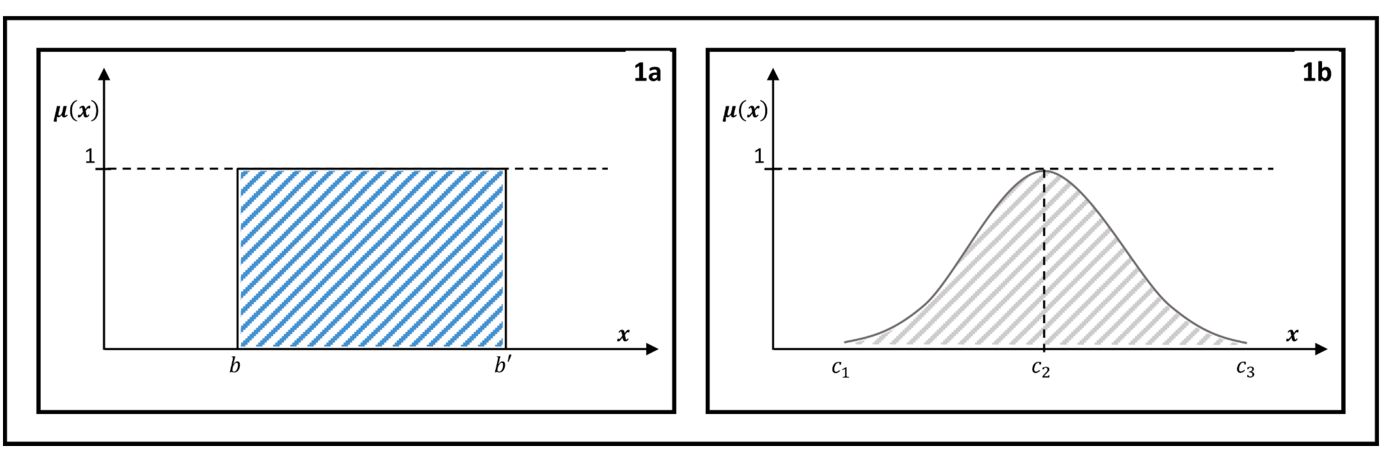

Fig. 1. Membership Function **1(a)** classical set ***B*** displayed as a membership function that follows a binary pattern**.** Blue area represents full membership ($\mu_{(x)} = 1$) for any element x that is larger or equal to b and smaller or equal than b'. **(1b)** bell shape function representing fuzzy set ***C***. The grey area represents the continuum membership function $\mu_{(x)}$ of fuzzy set ***C***.
Source: Authors, adapted from (Zadeh, 1965)

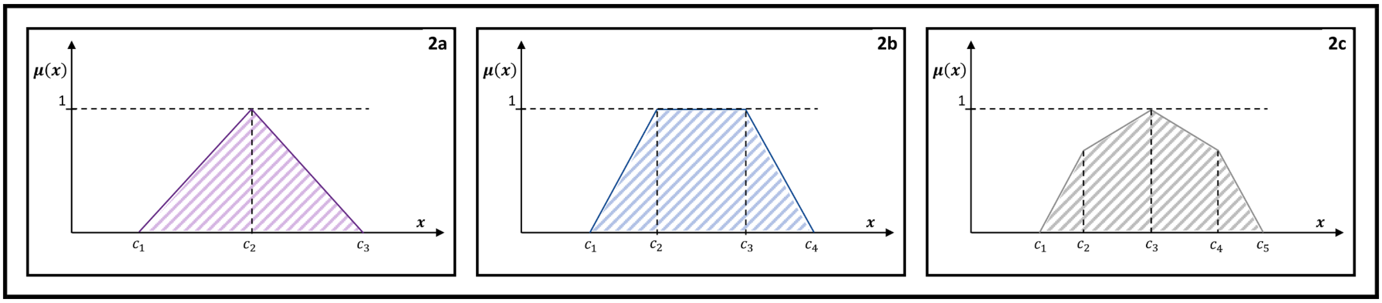

Fig. 2. Examples of fuzzy numbers. **2a** Triangular Fuzzy Number (TFN). **2b** Trapezoidal Fuzzy Number (TrFN). **2c** Pentagonal Fuzzy Number (PFN).
Note: All fuzzy numbers displayed are two-dimensional fuzzy sets, also known as Type-1 fuzzy sets (Karmakar et al., 2021). Source: Authors, adapted from (Panda & Pal, 2015)

Triangular fuzzy numbers (TFN) are widely used to represent the range of opinions held by decision-makers. Sitorus and Brito-Parada argue that TFN is popular due to its ease of application and relatively straightforward calculations (Sitorus & Brito-Parada, 2020). Following the definition of an interval, TFN can be represented by three points as follows: $D = [d_1, d_2, d_3]$; where d_1 = lower bound, d_2 = middle bound, and d_3 = upper bound. An interpretation of C as a membership function $\mu_{(x)}$ is defined in Equation (2) and graphically display in Fig. 2a.

$$\mu_{(x)} = \begin{cases} 0, \; x < d_1 \\ \dfrac{x - d_1}{d_2 - d_1}, \quad d_1 \le x \le d_2 \\ 1, \; x = d_2 \\ \dfrac{d_3 - x}{d_3 - d_2}, \quad d_2 \le x \le d_3 \\ 0, \; x > d_3 \end{cases} \tag{2}$$

Given its characteristics and practical use, TFN was selected for this study to inform the MCDM part of the conceptual framework. Its implementation is explained in section 3.

2.4. PMLU planning through the lens of MCDM

This subsection presents a systematic literature review on PMLU planning approaches that have utilised MCDM methods. The literature review was conducted using Scopus. Only peer-reviewed literature was included. Table 1 presents the specific search combinations that was applied. From this search a total of 170 potentially relevant documents were obtained. Documents that were not accessible online, presented in a language other than English and duplicated documents were removed from the pool, leaving a total of 81 documents. In the next step, the 81 papers were reviewed. Papers that did not related to PMLU were eliminated, leaving a total of 22 documents. These documents are listed in Table 2.

MCDM has been widely used in the productive stages of mining (see Sitorus et al., 2019), but applications to closure and PMLU decisions are scarce. Table 2 shows 22 studies that have applied MCDM to PMLU planning and have advanced the PMLU literature. From the systematic literature review, Bascetin (2007) appears as the first study proposing a support system to optimise PMLU decision-making planning processes using a multi-criteria approach, which the author applies using Analytical Hierarchy Process (AHP) method to rank PMLUs. Following this approach, Soltanmohammadi team published three studies where three different hybrid multi-criteria approaches are proposed to facilitate the PMLU decision-making process (Soltanmohammadi et al., 2009, 2010; Soltanmohammadi et al., 2008). These approaches apply a Mined Land Suitability Analysis (MLSA) framework that consists of 50 attributes based on economic, social, technical, and mine site factors (Soltanmohammadi et al., 2008).

From Table 2 it is possible to see that stakeholders' participation has

Table 1
Literature review keywords combination utilised for the advance search conducted in Scopus.

Scopus advance key search
(TITLE-ABS-KEY (pmlu OR {post-mining land-use} OR {post-mining} OR {mine closure} OR {Mined land suitability} OR mlsa OR {mined land rehabilitation} OR {mined land reclamation} OR {Reclamation methods}) AND TITLE-ABS-KEY ("multi attribute decision-making" OR "multi-criteria decision-making" OR "multi attribute decision analysis" OR "Multi-criteria decision analysis" OR {GIS-based} OR "AHP" OR "TOPSIS" OR "ELECTRE" OR "PROMETHEE" OR "SMART")) AND PUBYEAR > 1999 AND PUBYEAR < 2021
(TITLE-ABS-KEY (pmlu OR {post-mining land-use} OR {post-mining} OR {mine closure} OR {Mined land suitability} OR mlsa OR {mined land rehabilitation} OR {mined land reclamation} OR {Reclamation methods}) AND TITLE-ABS-KEY (madm OR mcdm OR mada OR mcda OR "multi-criteria" OR "decision-making" OR "multicriteria" OR {GIS-based} OR "AHP" OR "TOPSIS" OR "ELECTRE" OR "PROMETHEE" OR "SMART")) AND PUBYEAR > 1999 AND PUBYEAR < 2021
(TITLE-ABS-KEY (pmlu OR {post-mining land-use} OR {post-mining} OR {mine closure} OR {Mined land suitability} OR mlsa OR {mined land rehabilitation} OR {mined land reclamation} OR {Reclamation methods}) AND TITLE-ABS-KEY ("multi attribute decision-making" OR "multi-criteria decision-making" OR "multi attribute decision analysis" OR "Multi-criteria decision analysis" OR {GIS-based} OR "AHP" OR "TOPSIS" OR "ELECTRE" OR "PROMETHEE" OR "SMART") AND TITLE-ABS-KEY (fuzzy)) AND PUBYEAR > 1999 AND PUBYEAR < 2021
(TITLE-ABS-KEY (pmlu OR {post-mining land-use} OR {post-mining} OR {mine closure} OR {Mined land suitability} OR mlsa OR {mined land rehabilitation} OR {mined land reclamation} OR {Reclamation methods}) AND TITLE-ABS-KEY (madm OR mcdm OR mada OR mcda OR "multi-criteria" OR "decision-making" OR "multicriteria" OR {GIS-based} OR "AHP" OR "TOPSIS" OR "ELECTRE" OR "PROMETHEE" OR "SMART") AND TITLE-ABS-KEY (fuzzy)) AND PUBYEAR > 1999 AND PUBYEAR < 2021

been frequently included across cases (e.g., ÇInar & ÖCalir, 2019; Cui et al., 2020; Hartono et al., 2020). However, Hartono et al. (2020) manage to capture the whole diversity of stakeholder groups, by for example, including 200 surveyees from which 150 belong to the local community. As seen, AHP is the most common MCDM method used, either by itself or included in a hybrid approach. Interestingly, Adibee et al. (2013) and Kaźmierczak et al. (2019) use AHP to evaluate tailings characteristics to determine possible post-mining options addressing environmental and socio-economic risks that tailings could present.

PMLU planning has inherent complexities, such as (1) the need to integrate qualitative and quantitative types of data (Bielecka & Król-Korczak, 2010), (2) the inclusion of stakeholders from different sectors and backgrounds, who usually have different expectations for post-mining alternatives (Everingham et al., 2018), (3) the uniqueness of each site and its host environment (Kivinen, 2017), (4) the volatility of commodities prices creating a highly variable business environment (Lèbre et al., 2021), (5) the information that is either subjective or difficult to obtain implies uncertainty to the process as well (Masoumi et al., 2014).

The proposed framework builds from previous studies and is driven by the need for efficiency, dynamism, inclusiveness and transparency in

Table 2
Studies focusing on determining PMLU using decision-making approaches.

Study	Method	Fuzzy	GIS	Stakeholders Non	Go	Co	Min	Uni	Oth	Study description
Bascetin (2007)	AHP	-	-	-	-	-	✓	-	-	This paper uses AHP for the selection of an optimal reclamation method for an open-pit coal mine located at Seyitomer region in Turkey.
Soltanmohammadi et al. (2008)	AHP-ELECTRE	-	-	✓	-	-	-	-	-	In this study a framework for MLSA including economic, social, technical and mine site factors was developed as a foundation for decision-making problems.
(Soltanmohammadi et al. (2009)	AHP-PROMETHEE	-	-	✓	-	-	-	-	-	This paper utilised AHP-PROMETHEE and the MLSA developed by (Soltanmohammadi et al., 2008) to achieve a set of feasible PMLU.
(Pavloudakis et al. (2009)	LP	-	✓	✓	-	-	-	-	-	This work proposes a spatial decision-support system to select the optimal PMLU for a lignite mine located at West Macedonia Lignite Centre in Greece.
Bielecka and Król-Korczak (2010)	FIS	✓	-	✓	-	-	-	-	-	This paper proposed a FIS for post-mining regions. The system was applied in an opencast mine located at Zator region, Poland.
Soltanmohammadi et al. (2010)	AHP-TOPSIS	-	-	-	-	-	-	-	✓	This paper developed a hybrid AHP-TOPSIS approach along with MLSA to determine a preference ranking list for possible PMLUs.
Bangian et al. (2011)	AHP	✓	-	-	-	-	-	-	✓	This study proposed AHP to find the Optimal PMLU specifically for the pit area of Sungun copper mine in Iran.
Narrei and Osanloo (2011)	Entropy; AHP; RWA TOPSIS; SAW; CP	-	-	✓	-	-	-	-	-	This study proposed a combined MCDM to obtain the optimum alternative that has the highest degree of satisfaction among all possible PMLUs.
Bangian et al. (2012)	AHP	✓	-	✓	-	-	-	-	-	This work developed a model to attain the optimum PMLU for pit area through Fuzzy-AHP.
Adibee et al. (2013)	AHP	-	-							This paper determined PMLU for tailings based on the characteristic and impacts those tailings have on the environment.
Dimitrijevic et al. (2014)	PROMETHEE and ELECTRE	-	-							This work determines PMLU by comparing scenario ranking equivalence between PROMETHEE and ELECTRE.
Masoumi et al. (2014)	AHP-TOPSIS	✓	-	-	-	-	✓	✓	-	This study aimed to use the hybrid fuzzy AHP-TOPSIS method to a surface coal mine to influence the decision-making process of PMLU.
Yavuz and Altay (2015)	Yager and AHP	✓	-	-	-	-	✓	-	-	This paper utilised two different fuzzy methods (Yager's and F-AHP) to compared result in determining PMLU for the Magnesite Mine Company in Turkey.
Anis et al. (2017)	AHP	✓	✓	✓	-	-	-	-	-	This research used a GIS-based Fuzzy method for coal remaining resources and PMLU planning for Adaro mine in Indonesia.
Amirshenava and Osanloo (2018)	AHP-TOPSIS AHP-PROMETHEE	-	-	-	-	-	✓	-	-	This study developed a procedure for mine closure risk management along a hybrid MCDM approach to determine optimal PMLU in Choghart iron ore mine in Iran.
ÇInar and ÖCalir (2019)	ANP	✓	✓		✓		✓	✓	✓	This study used GIS-based fuzzy method to create a land use suitability model as a decision support tool in marble mining regions in Turkey.
Kaźmierczak et al. (2019)	AHP	-	-	-	-	-	-	-	✓	This work proposed to use AHP to determine the suitability of mining waste sites for PMLU in Lower Silesia region in Poland.
Król-Korczak and Brzychczy (2019)	FIS	✓	-	✓	-	-	-	-	-	This paper proposed a FIS for open pit mines of natural gravel and sand aggregates and was applied in Małopolska in Poland.
Bakhtavar et al. (2019)	Multi goal FCM-ANP	✓	-	-	-	-	✓	✓	-	This study developed an approach that integrates intelligent multi-goal FCM and a fuzzy ANP to evaluate and prioritize PMLU in a limestone mine area.
Cui et al. (2020)	TOPSIS-IAHP	-	-	-	✓	✓	✓	-	✓	This study combined IAHP and TOPSIS methods to provide a quantitative and transparent process for optimal ordering of the reutilization patterns.
Hartono et al. (2020)	AHP	-	-	-	✓	✓	✓	✓	✓	This paper investigated the absence of reclamation activities for post-mining area in mining companies in North Kolaka District, Indonesia.
Spanidis et al. (2020)	AHP-TOPSIS	-	-	-	-	-	-	✓	-	This work proposed AHP-TOPSIS method for the ranking of restoration alternatives based on a low-risk approach applied to two lignite mines in Greece.

Notes 1: **ANP** = Analytic Network Process; **AHP** = Analytic Hierarchy Process; **IAHP** = Improved Analytic Hierarchy Process; **ELECTRE** = ELimination Et Choix Traduisant la REalité; **PROMETHEE** = Preference Ranking Organization METHod for Enrichment of Evaluations; **SMART** = Simple Multi-Attribute Ranking Technique; **TOPSIS** = Technique for Order of Preference by Similarity to Ideal Solution; **FIS** = Fuzzy Inference System; **LP** = Linear Programming; **FCM** = Fuzzy Cognitive Map; **RWA** = Relative Weights of Attributes; **SAW** = Simple Additive Weighting; **CP** = Compromise Programming; **Non** = the work does not mention stakeholder participation; **Go** = stakeholders from government organisations; **Co** = community related stakeholders; **Min** = mining industry stakeholders; **Uni** = researchers and academia related stakeholders; **Oth** = other stakeholders

PMLU planning processes. The qualitative and quantitative nature of the data requires using mixed methods, which is achieved here by integrating GIS and MCDM into what is known as Spatial Multi-criteria Decision Making. A wide number of studies argue that multi-criteria decision-making (MCDM) analysis facilitates participation by aggregating views from different stakeholders into decision-making processes while allowing stakeholders to be involved in these processes (Martins et al., 2020; Soltani et al., 2015). However, one of the main issues of MCDM is that stakeholders' participation brings uncertainty and ambiguity to both the process and the outcome. According to Sun (2010), MCDM does not handle the uncertainty associated when human judgment is involved. One way to address this issue is to use fuzzy set theory, as prescribed by Masoumi et al. (2014) and Mrówczyńska et al. (2021). The next section describes the proposed conceptual PMLU planning framework.

3. A conceptual mixed-methods framework to guide PMLU decision-making process

This section outlines the proposed conceptual framework that aims to capture and integrate the complexities of PMLU planning. The framework has five stages as shown in Fig. 3. Stage 1 establishes land-use classification and PMLU attributes lists. The two lists are generic and exhaustive and serve as basis for the application of the framework to any context. Stage 2 imposes a Multi-Dimensional Analysis (MDA) that filters the land-use types and PMLU attributes from Stage 1 based on the specific conditions of the study area. In Stage 2, stakeholders are involved in identifying a feasible set of PMLU alternatives and key PMLU attributes Stage 3 collects stakeholder preferences in order to determine a ranking of both PMLU attributes and alternatives. In this stage, data collection takes place through two online questionnaires administered to a stakeholder panel. Stage 4 applies the MCDM model using data collected in Stage 3. The outcome is a ranked set of PMLU alternatives that are suitable for the study area and stakeholder preferences. Both Stage 3 and Stage 4 are conducted applying fuzzy set theory. Finally, Stage 5 delivers the rank of suitable PMLU alternatives derived in Stage 4 to the relevant decision makers of the region, who decide the timing and considerations for the PMLU implementation.

The next subsections describe in detail each stage of the framework. For the description of Stage 2, examples of data outcomes are laid out so the potential outcomes of the stage can be observed, and their implications discussed.

Stage 1 – Land-use classification and PMLU attribute's definition

Stage 1 defines the initial lists of land-use classifications and PMLU attributes. This provides a baseline to identify and assess PMLU alternatives. The land-use classification designed for this framework follows Anderson et al. (1976) as is shown in Table 3. The land-use classification has a wide array of land-use options, which are organised into nine land-cover groups.

Table 3
Land-cover and land-use classification system.

Land-cover group	Land-use options
Urban or built-up	Residential; Commercial and services; Industrial; Transportation, communications, and utilities; and Recreational
Agriculture	Cropland and pastureland; Orchards, groves, vineyards, nurseries, and ornamental horticultural areas; Farms; and Other agriculture
Rangeland	Herbaceous rangeland; and Shrub and brush rangeland
Forest land	Deciduous forest land; Evergreen forest land; Mixed forest land; and Forest plantation
Water	Streams and canals; Lakes, Reservoirs; and Bays and estuaries
Wetlands	Forest wetlands; and Non-forest wetlands
Barren land	Dry salt flats; Beaches; Sandy areas other than beaches; Bare exposed rock; Strip mines, quarries, and gravel pits; and Transitional land
Tundra	Shrub and brush tundra; Herbaceous tundra; Bare ground tundra; and Wet tundra
Others	Others

Notes: Land-use options for the purpose of 'Ecosystems and habitats conservation', and 'Research and innovation' can be included in any of the nine land-cover groups.
Source: Authors, adapted from (Anderson et al., 1976)

Table 4 displays the list of PMLU attributes. Attributes are organised into five criteria: economic, technical, environmental, social, and governance. PMLU attributes of each criterion were selected after a review of previous studies including Amirshenava and Osanloo (2018); Bangian et al. (2012); Eshun et al. (2018); Masoumi and Rashidinejad (2011); Soltanmohammadi et al. (2010). From the multiple attributes used in these studies, Table 4 provides a generic PMLU attribute list that aims to cover all mining contexts and scales.

Stage 1 is common to any context where the framework would be applied. Whereas the next section of the framework narrows the scope of the analysis based on the characteristics of the study area.

Stage 2 – Multi-dimensional analysis of the study area

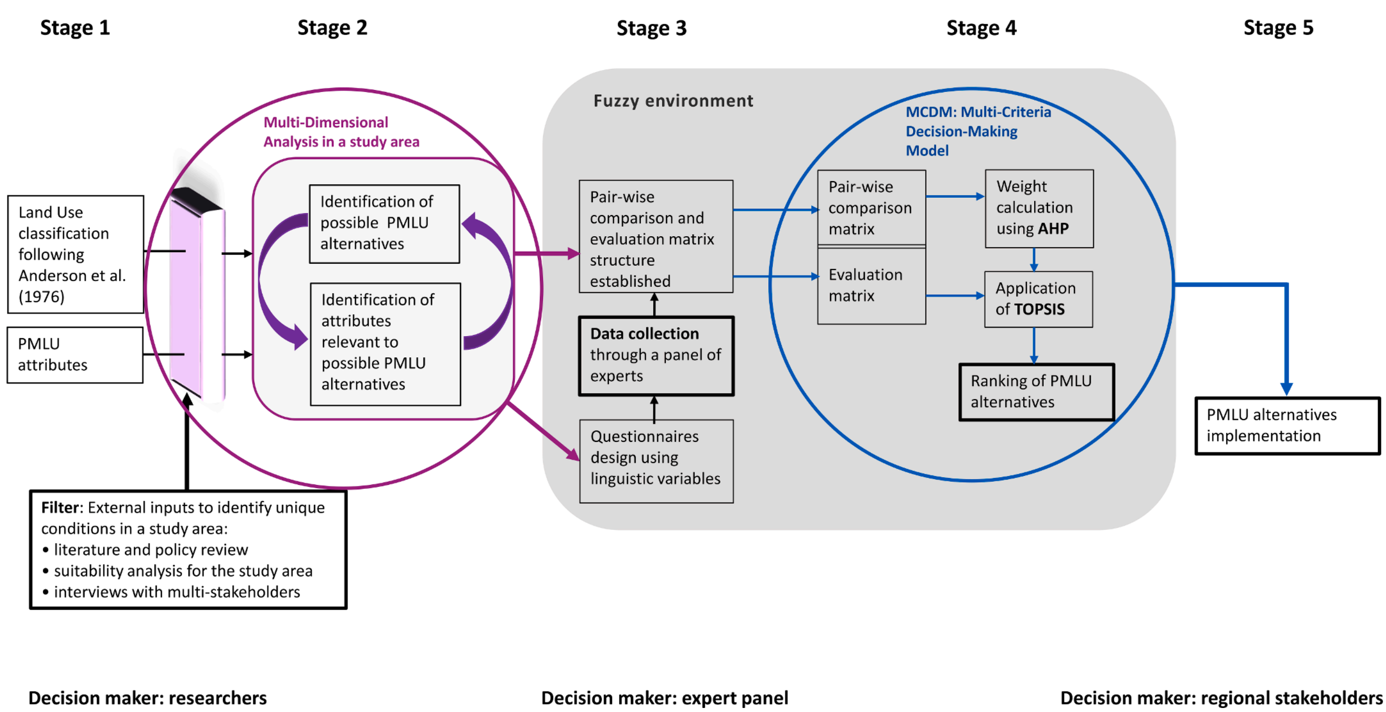

Fig. 3. A conceptual framework to address decision-making planning processes for post-mining land-use.
Source: Authors

Table 4
List of PMLU attributes grouped by criteria.

Criterion	Attribute
Economic: This criterion considers the economic (financial, employment and development) characteristics of PMLU alternatives	Net present value Potential changes in real estate values Land ownership type Regional economic growth potential Market profile of the region Employment opportunities Tourism
Technical: This criterion considers aspects that could impose technical constraints at the selection of PMLU alternatives	Shape and size of mined land Environmental contaminations Access to reclamation techniques Accessibility Traffic frequency of mined land Distance to communities
Environmental: This criterion includes key environmental features to consider for a suitability analysis of each PMLU alternative	Soil properties Climate Topography Pit geometry Geology structure
Social: This criterion includes measurable attributes to quantify the impacts of PMLU alternatives on communities and region	Effects on in-migration and out-migration to the region Aligned (consistency) with local needs (requirements) Region demographic characteristics Social and cultural identification (backgrounds, profile) Positive changes in welfare Diversification of skills and technical knowledge
Governance: This criterion includes political characteristics that could influence or facilitate PMLU alternatives	Current and potential future land-use in surrounding areas (zoning laws, planning schemes) Regional safety condition Regional political condition Legislation and regulation requirements

Source: Authors

Stage 2 aims to scale the framework according to the specific characteristics of the study region. This stage applies an analytical filter to refine the lists provided in Stage 1. As each mine site and its surroundings have unique conditions (Lima et al., 2016; Kivinen, 2017), Stage 2 performs a Multi-Dimensional Analysis (MDA) of the study area. This analysis includes (1) a comprehensive literature and policy review, including any available documentation that provides information on the social, environmental and economic conditions in the study region or related to the mine itself (e.g. closure plans and social and environmental impact assessments), (2) a GIS-based data analysis that collects relevant spatial information that will help evaluate the suitability of PMLU alternatives (e.g. climate condition, the location of settlements and existing businesses etc.), and (3) a data analysis from multi-stakeholder knowledge and expertise obtained via interviews.

This last component gathers the perceptions, expectations and preferences of different stakeholders and stakeholder groups. Relevant stakeholder groups include mining communities at large (distinguishing potential vulnerable groups such as indigenous communities, agrarian communities, or artisanal miners), mining employees, contractors, government representatives (including industry regulators and local councils), and members of academia with relevant knowledge and expertise (Svobodova et al., 2019). Transparency and inclusiveness are critical for this component. Thus, the interviews should target a diverse cohort of participants and follow a clear and transparent process. Because the process is exploratory, a semi-structured interview format is preferable. Participants would have a wide range of technical knowledge and expertise, as well as local representation—including minority and vulnerable groups—to successfully represent perspectives across multiple disciplines and stakeholders, always aiming to incorporate the collective vision regarding the future PMLU that could be achieved in the study region.

Table 5
Stage 2 outcome example.

Land-cover	Suitable land-use	PMLU alternatives	PMLU attributes
Urban	Commercial and services Industrial Recreational	Outdoor stores, cafes and restaurants Brick factory Multipurpose recreational park including mountain biking trails, road bike circuit, cross country running tracks, equestrian trails and picnic facilities	**Economic:** -market profile of the region -employment opportunities -tourism **Technical:** -mined land accessibility -distance to communities -traffic frequency of mined land **Social:** -positive change in welfare **Governance:** -regional safety condition
Agricultural	Cropland and pastureland Farms	Crops including sorghum, barley, wheat and chickpeas Cattle farms	
Forest land	Forest Plantation	Quercus plantation	

Source: Authors

Table 6
Linguistic variables to be used in questionnaire A and their respective crisp numbers and triangular fuzzy numbers, to be used in the AHP method.

Linguistic variables	Crisp numbers	Triangular Fuzzy Numbers (TFN)	Inverted (TFN)
Absolute preference	9	(8, 9, 9)	(1/9, 1/9, 1/8)
Strong preference	7	(6, 7, 8)	(1/8, 1/7, 1/6)
Moderate preference	5	(4, 5, 6)	(1/6, 1/5, 1/4)
Slight preference	3	(2, 3, 4)	(1/4, 1/3, 1/2)
Equal preference	1	(1, 1, 1)	(1, 1, 1)
Intermediate values	2, 4, 6, 8	(1, 1, 2); (3, 4, 5) (5, 6, 7); (7, 8, 9)	(1/2, 1, 1); (1/5, 1/4, 1/3) (1/7, 1/6, 1/5); (1/9, 1/8, 1/7)

The functionality of Stage 2 - the filtering process - is depicted in Table 5, where an example of potential data is shown. For this example, from a total of nine land-cover options (listed in Table 3) only three are identified as feasible, and only six land-uses are suitable. Considering the suitable land-uses, in this example, the MDA identifies that the region has suitable soils and climate characteristics to grow six PMLU alternatives: sorghum, barley, wheat, chickpeas, cattle farms, and *Quercus suber* plantation. For this example-region, it is assumed that the mine is near to two tourist towns and has an established road connectivity to a main city, therefore the MDA also identified 'Recreational', and 'Commercial and services' land-uses as suitable. From these suitable land-uses, the PMLU alternatives that could be proposed are a multipurpose recreational park with hospitality facilities. An additional PMLU alternative that the MDA could identify is a brick factory (Industrial land-use) as the example-region is assumed to have a strong connection to this industry. Each of these alternatives are then linked to specific attributes that will be used to evaluate the alternatives following a consultation with experts in Stage 3.

Table 5 offers an example of a potential data outcome for Stage 2. The output of this stage becomes a direct input for Stage 3 and Stage 4 as the PMLU alternatives and attributes guide the structure of the MCDM that is performed following fuzzy set theory.[1]

Stage 3 – Matrixes design and data collection

The purpose of Stage 3 is to collect data from a panel of experts. This panel would be, at least partially, composed of stakeholders that have already participated in the initial interviews conducted in Stage 2. To collect the data, this stage firstly designs and then applies two questionnaires (A and B) to the panel of experts. Questionnaire A focuses on the Stage 2 defined PMLU attributes by comparing them in pairs, so to judge which PMLU attributes are preferred. Questionnaire B collects PMLU alternatives preferences. The questionnaires are presented as an online survey to experts. The questionnaires are designed using linguistics variables utilising a scale of 1 to 9 following Saaty (1988). The linguistic variables that questionnaires A and B use are displayed in the first columns of Table 6 and Table 7, respectively. Following the example of potential data logic describe in Stage 2, example questions for questionnaire A and B would be structure as follow, questionnaire A: “Please, express your preference between the following two PMLU attributes: employment opportunities and mined land accessibility”. To answer, the person taking the questionnaire would use the linguistic variables in Table 6 (first column). An example question in questionnaire B would be "Please, evaluate Brick factory (as a potential PMLU alternative) based on employment opportunities (PMLU attribute)”, for which the person taking the questionnaire would use the linguistic variables in Table 7 (first column).

Later in Stage 4, all data collected through the questionnaires will be translated from linguistic variables into fuzzy number—third and fourth columns of Table 6 and Table 7 respectively—to compute the MCDM model.

The configuration of the expert panel and responses to the questionnaires are key considerations to ensure the robustness of the framework. Ideally, the panel of experts should include technical disciplines such as urban and demographic planning, environmental management, renewable energy, anthropology and sociology, economics, and engineering (including structural, hydrological, transport and chemical engineers among others). Representatives from these disciplines with local knowledge, if available, should be prioritised. Local groups, including minority groups, should complement the expert panel to provide clear and practical knowledge of the study case. Consistent with the initial interviews, the expert panel should be diverse, and its recruitment done in a transparent way. Both diversity and recruitment transparency are critical aspects to establishing trust in the process and ensuring that a wide variety of possibilities are well captured and considered (Mercer-Mapstone et al., 2018).

With respect to the panel size, Campagne et al. (2017) found that the variability of the final results between samples is flattened when the panel gathers 15 experts, while the variability reaches a stable mean when 30 experts are involved in the panel. Therefore, Stage 3 would rely on a panel of experts with a minimum composition of between 15 and 30 experts to avoid disparities in the results.

Stage 4 – Multi-criteria decision-making fuzzy AHP-TOPSIS

Stage 4 runs the MCDM model under a fuzzy environment using the data obtained from experts in Stage 3. The MCDM model includes AHP and TOPSIS methods, following a hybrid approach. The hybrid AHP-TOPSIS approach has been widely applied in mining research and its strength has been demonstrated in complex problems (Masoumi et al., 2014). To calculate the weights of each PMLU attribute to run the MCDM, the AHP method is used.

Table 7
Linguistic variables to be used in questionnaire B and their respective crisp numbers and triangular fuzzy numbers, to be used in the TOPSIS method.

Linguistic variables	Crisp numbers	Triangular Fuzzy Numbers (TFN)	Inverted (TFN)
Excellent	9	(8, 9, 9)	(1/9, 1/9, 1/8)
Good	7	(6, 7, 8)	(1/8, 1/7, 1/6)
Average	5	(4, 5, 6)	(1/6, 1/5, 1/4)
Low	3	(2, 3, 4)	(1/4, 1/3, 1/2)
Lowest	1	(1, 1, 2)	(1/2, 1, 1)
Intermediate values	2, 4, 6, 8	(1, 2, 3); (3, 4, 5) (5, 6, 7); (7, 8, 9)	(1/3, 1/2, 1); (1/5, 1/4, 1/3) (1/7, 1/6, 1/5); (1/9, 1/8, 1/7)

The AHP, first developed by Saaty (1988), is a mathematical method that measures importance using ratio scales to calculate criteria weights. AHP is a powerful tool used for the hierarchical decomposition of complex problem (Adibee et al., 2013) and is the most commonly applied method to calculate the weight of criteria by itself or when integrated with another MCDM method (Kaya et al., 2019). An empirical issue that arises when applying AHP is the consistency of the pairwise matrix. To avoid this issue, Krejčí and Stoklasa (2018) recommend that a geometric mean is used to calculate the PMLU attributes weights. The data to calculate the weights are obtained from questionnaire A. The questionnaire compares PMLU attributes in pairs, which translates into a pair-wise matrix.

The steps and explanations to calculate the weights of the PMLU attributes using AHP are described in Equation (3) as follows:

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix}, a_{ij} = \frac{1}{a_{ji}}, a_{ii} = 1 i, j, = 1, 2, \ldots, n \quad (3)$$

Where A_{nxn} is the pair-wise matrix that contains all a_{ij} preferences.

Where a_{ij} is the preference of PMLU attribute i over PMLU attribute j and vice versa for ji.

Following fuzzy set theory $a_{ij} = (l_{ij}, m_{ij}, u_{ij})$; $\frac{1}{a_{ij}} = \left(\frac{1}{u_{ij}}, \frac{1}{m_{ij}}, \frac{1}{l_{ij}}\right)$ and $a_{ii} = (1, 1, 1)$ respectively.

Then matrix A_{nxn} is normalised following Equation (4).

$$p_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \quad (4)$$

Where p_{ij} is the normalised value of the preference of PMLU attribute i over PMLU attribute j and vice versa for ji.

The normalised matrix P_{nxn} composition is displayed in Equation (5) as follows:

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{bmatrix} \quad (5)$$

The next step is to calculate the AHP weights for each PMLU attribute i, following Equation (6).

$$w_i = \left(\prod_{j=1}^{n} p_{ij}\right)^{\frac{1}{n}} \quad (6)$$

So that $\sum_{i=1}^{n} w_i = 1$, where w_i is the weight of PMLU attribute i,

The weight matrix W_{nx1} composition follows Equation (7):

[1] The derivation of land-use suitability, PMLU alternatives and PMLU attributes are the results of the Multi-Dimensional Analysis (MDA) that includes literature and policy reviews, GIS analysis and stakeholder consultation. The (MDA) is by itself a complex and detailed work that requires research and resources. The scope of this paper does not intent to cover the details of such complex research.

$$W = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix} \quad (7)$$

TOPSIS is a distance method proposed by Hwang and Yoon (1981). Following Guarini et al. (2018) recommendation to identify suitable mathematical approaches when using MCDM models, TOPSIS was selected as it empirically fits with a PMLU decision-making planning process.[2] This method is based on the concept that the best alternative should have the shortest Euclidean distance from the positive ideal solution and the largest Euclidean distance from the negative solution and is commonly used to rank a set of alternatives. In the framework, TOPSIS uses the data obtained from questionnaire B, which contains the expert's PMLU alternative preferences with respect to PMLU attributes. This process translates into an evaluation matrix, that determines the PMLU alternative ranking from the most suitable to the less suitable alternative.

Stage 5 – Delivery of PMLU alternatives ranking

Finally, Stage 5 delivers the ranking of the full set of PMLU alternatives. This full set is derived using the data collected and analysed in the previous stages of the framework. In this last stage, the full set of alternatives could be shortlisted by relevant stakeholders (e.g., state government, local government, city councils), who can later decide, in an informed way, the implementation of the ranked PMLU alternatives. In other words, with the support of the framework and the product delivered in this final stage, the post-mining planning process can be finalised by deciding the timeframes and the circumstances to implement the proposed PMLU alternatives for the study region.

4. Discussion

To avoid an irreversible climate crisis, major industrial economies are being urged to drastically reduce, if not entirely phase out their dependency on coal power. This fundamental change in the composition of the global energy system will have profound consequences. Debates emerging over the past two decades about a "just transition" highlight the likely effects of a switch from coal-based power to renewable alternatives. Re-adjusting coal markets will not only have an impact on trade and supply relations between nations but will alter the basic economic character within nations. Countries like the United States, South Africa, Australia and China will need to confront and evaluate their coal situation, keeping in mind the regional dependencies, including the economies of major cities that have formed around coal mining over decades, and in some cases centuries. Phasing out coal will not be a one-step or simple task in these countries, and any effort at meeting global targets will require a well-planned and evidence-based approach that can be appropriately scaled to coal mining-dependant region's characteristics.

The literature has identified important gaps in knowledge. Firstly, most studies have a site-level focus, while encompassing regional dynamics is crucial. ÇInar and ÖCalir (2019) and Cui et al. (2020) are examples studies that have a regional perspective. Secondly, views from all stakeholder groups need to be captured and integrated to the determination of PMLU alternatives. Of the studies reviewed, only Hartono et al. (2020) considers the full variety of stakeholders. The proposed framework enables a regional perspective, as attributes identified in Stage 2 are both site-related and regional attributes, and regional stakeholders can participate in the process in stages 2 and 3. In applying the framework, particular emphasis will need to be placed on including participants across all stakeholder groups.

With the political signals about the undesirability of coal, plus the volatility of commodity prices creating a highly variable business environment, planners will require tools that can support both the qualitative dimensions of stakeholders participation and the setting of political goals, alongside vast quantitative data on the geography, demography and economic impact on coal mining-dependant towns and regions. Should markets move quickly, planning tools will need to be dynamically adaptive, with the capability to reconcile high levels of uncertainty? The framework that is proposed in this document, moves research and future planning into this area.

5. Conclusion

The ultimate goal of the framework is to support stakeholders in their quest for viable alternatives for a post-mining future. The integrated use of GIS, MCDM, and stakeholder consultation introduces novel efficiencies into the process of PMLU planning. The framework enables planners to have a systematic process for collecting data and evaluating PMLU alternatives. The use of MCDM techniques offers robustness in apprehending the complexity associated the close of mining operations. More importantly, the framework ensures views from all relevant stakeholder groups are appropriately captured and identifies specific areas and ways stakeholders should be engaged in the planning process. This is an important aspect that will govern the level of trust stakeholders are likely to have in the planning process and the outcomes that follow. This aspect has often been overlooked in most other studies.

The contribution of this paper is the presentation of a framework that has the potential to handle disparate forms of data across a range of disciplines and scales. However, challenges remain for the planners and other users of the framework to determine the amount of data necessary to obtain a clear view of the regional and local settings (i.e. the data required to filter the options in Stage 2) and how and where to source the data. In its current state, the proposed framework is largely conceptual and requires further development and testing to establish optimal points for integration between stages, as well as to confirm how the final output of the PMLU process can most practically guide end-users. The next step in this research project is to apply the framework to case studies, and refine it through an iterative process, using lessons learned from the case studies.

More generally, further work in this space is greatly needed. The levels of complexity associated with the closure of mining operations have been noted at several points throughout the paper. This complexity is the result of historical factors related to the operating of the mine itself, the geophysical characteristics of the project, market dynamics, together with other socio-economic and political variables. It is essential that mine closure is considered from a regional perspective, as opposed to previous studies that have mainly focused on the local, site-level perspective. The current context of coal phase out reinforces the need to a regional perspective in coal mining regions. The demands placed on planners in terms of participation and for the need to incorporate geographically relevant and diverse data is likely to rise exponentially in such context.

Declaration of competing interest

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

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[2] TOPSIS empirically fits PMLU decision-making planning process as this process presents a large number of criteria and alternatives, qualitative and quantitative data needs to be considered, active participatory stakeholder process is sought, and lastly the framework is aiming for a set of ideal alternatives that meet diverse criteria.

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