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Research article

Ranking negative emissions technologies under uncertainty

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ABSTRACT

Existing mitigation strategies to reduce greenhouse gas (GHG) emissions are inadequate to reach the target emission reductions set in the Paris Agreement. Hence, the deployment of negative emission technologies (NETs) is imperative. Given that there are multiple available NETs that need to be evaluated based on multiple criteria, there is a need for a systematic method for ranking and prioritizing them. Furthermore, the uncertainty in estimating the techno-economic performance levels of NETs is a major challenge. In this work, an integrated model of fuzzy analytical hierarchy process (AHP) and interval-extended Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is proposed to address the multiple criteria, together with data uncertainties. The potential of NETs is assessed through the application of this hybrid decision model. Sensitivity analysis is also conducted to evaluate the robustness of the ranking generated. The result shows Bioenergy with Carbon Capture and Storage (BECCS) as the most optimal alternative for achieving negative emission goals since it performed robustly in the different criteria considered. Meanwhile, energy requirement emerged as the most preferred or critical criterion in the deployment of NETs based on the decision-maker. This paper renders a new research perspective for evaluating the viability of NETs and extends the domains of the fuzzy AHP and interval-extended TOPSIS hybrid model.

1. Introduction

The 2015 Paris Agreement has set the goal to limit global average temperature increase to "well below 2 °C above pre-industrial level" [1]. The target is based on the global carbon budget of one tetraton (Tt) of CO_2-eq. until 2100. The tight carbon budget estimated implies the imperative need for the deployment of Negative Emission Technologies (NETs), which create a net removal of CO_2 from the atmosphere by relocating it to carbon sinks such as plants, soil and the ocean, or by storing CO_2 in geological formations. Most of the promising technologies are in fact still in small scale, while some are likely to be limited by their specific practical limitations such as storage, bio-productivity, or energy supply [2]. The significance of soil as carbon sink has been recognized by the European Commission [3, 4], whereby the present increase in atmospheric CO_2 can be mitigated through a 4% annual growth rate of the soil carbon stock. To help achieving this, a sustainable use and soil-water management system has to be prioritized as well as exploring nature-based solutions [4]. According to the Emission Gap Report 2013, existing clean technologies, which primarily focus on improving process efficiency gain and increasing renewable inputs used, are inadequate to deliver the scale and emission reduction required to meet the 2 °C and 1.5 °C targets [5]. Moreover, climate model simulations have identified that NETs, particularly Bioenergy with Carbon Capture and Storage (BECCS), are essential to achieving the GHG emission reductions [6]. This implies the need for a massive industrial shift to NETs. The prospect of NETs as mitigation strategy to climate change have recently gained interest and can be seen in the growth of the scientific literature on this topic – to date, searching the Scopus database using the keyword "negative emissions technologies" results in 229 publications, of which 177 were published from 2018 to the present.

Currently, there are many activities around the world fighting climate change through afforestation and reforestation (AR) [7]. Zomer et. al. [7] has identified globally that about 750 Mha is suitable for this project. They are mostly found in South America and Sub-Saharan Africa. However, for this project to be successful, further implications on local to regional food security and local community livelihoods have to be considered [7]. Biochar (BC), produced from the pyrolysis of biomass, has been identified as another option to store carbon provided it has the suitable compositions and properties [8]. The way it works is through improving soil fertility, leading to higher crop yields, potentially

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impacting agricultural activities and food security [9, 10]. In response to the climate changes as well as to stabilize or increase crop yields, supplemental irrigation and shifting sowing dates are considered as viable options [10]. Since BC is relatively stable, its application to soil indirectly acts as a mechanism of carbon capture from the atmosphere. On the other hand, bioenergy systems combined with carbon capture and storage (BECCS), which are biomass utilization technologies (such as liquid biofuels production) combined with carbon capture and storage technologies, is expected to have significant impact in bringing down CO_2 emissions [11, 12]. However, a critical factor for implementing BECCS is biomass availability and lack of policy incentives. Direct air capture (DAC) technology is still in its infancy, although there has been a study assessing the viability of this option as one climate change mitigation solution [13]. It has been reported that massive implementation of this technology is necessary to see its significant impact. Nonetheless, low temperature (LT) DAC system is more favourable then the high temperature (HT) DAC due to its lower heat supply costs and the possibility of using lower grade heat systems. Enhanced weathering (EW) is accelerating the natural process of weathering which involves the breakdown of minerals, such as olivine, due to its reaction with atmospheric CO_2 [14]. This process then traps the CO_2 into water soluble bicarbonates. The weathering reactions involves alkalization, which is beneficial in combating ocean acidification. Some studies concluded that Mg-rich olivine has shown to be the technically feasible option. Nonetheless, huge amounts of olivine is required to have a significant impact [14]. However, most experts agree that it has the potential of sequestering gigatons of CO_2 annually. Ocean fertilization (OF) works by supplying more nutrients to surface waters to enhance the growth of microscopic marine plants and increase the uptake of atmospheric CO_2 by the ocean [15]. In this regard, an enormous amount of nutrients is required to see the impact, while it has also been shown that the Southern Ocean has the most potential.

Today, various literatures on NETs provide an estimation of the potential of each NET in quantitative and qualitative terms. Fuss et. al. [16] summarized the prospects of the above-mentioned NETs with respect to carbon capture potential, cost, socio-economic, environmental and biophysical impact. McLaren [2] has looked into the technical status and limiting factors above the potential capacity and cost estimation of NETs. Apart from these aspects, Smith et. al. [17] assessed the biogeochemical, energy and economic resource implications of NETs for large-scale implementation. However, there is no literature that conducts the multi-criteria comparison among the NETs. A study by Gurnani et. al. [18] examines the viability of carbon storage sites in Turkey using MADM method, but does not assess the viability of carbon capture and storage (CCS) technologies.

This paper aims to provide a new research perspective in evaluating the viability of NETs. Using MADM methods offers a more systematic procedure for the ranking and selection of NETs. The ranking generated from the study provides information that can serve as a guideline in mapping future research work and advancement of NETs. An alternative which is prioritized in the ranking process indicates less risk involved in deployment and hence, should be emphasized in research and development efforts. This promotes the early deployment of prospective NETs to curb global temperature increase. On the other hand, the ranking generated could aid technology investment decision-making. This helps reduce project risks, which might result in additional operating and maintenance cost and other unforeseeable impacts.

The prioritization of NETs is immensely complex, due to two factors: the presence of multiple criteria (e.g., cost, energy demand, capacity, and technological maturity), and the inherent uncertainty associated with NETs assessment of novel technologies. To address the multiple and often conflicting criteria involved in the prioritization of NETs, Multiple Attribute Decision Making (MADM) techniques can be utilized to provide a systematic approach to the problem. There is extensive literature on various MADM techniques and their applications. The Analytic Hierarchy Process (AHP) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) are two popular and versatile MADM tools; the Scopus database currently lists about 14,000 publications on AHP and about 8,000 on TOPSIS, including approximately 1,700 papers on both methods (including hybrid AHP and TOPSIS methods). Mardani *et al.* [19] highlighted that AHP and TOPSIS are among the most employed MADM methods in environmental and energy problems. Initially developed by Saaty [20], AHP reduces a complex decision-making problem to a decision hierarchy which reflects the decision structure of a decision-maker. The procedure is followed by the generation of a pairwise comparison matrix to compare elements in each hierarchy. Finally, a mathematical procedure is implemented to synthesize the result scores. The pairwise comparison in AHP allows the incorporation of both subjective and objective aspects of the decision problem [20]. However, the abovementioned methodology is often prone to uncertainty in information and vagueness in human judgement, thus making it difficult for decision-makers to come up with exact assessment and recognition [21]. Fuzzy set theory provides a mathematical framework for representing uncertainty that is not associated with randomness or stochastic processes [19]. It can be further integrated into fuzzy AHP (FAHP) to incorporate the ambiguity of decision makers in providing judgement [20]. A wide range of FAHP applications has been reported in the area of process engineering, for example to select electrolytic cells and wastewater treatment processes [21], and to rank heat exchanger network (HEN) designs [22]. Accounting for uncertainty means that FAHP may give different results from conventional AHP [23]. On the other hand TOPSIS was originally proposed by Hwang and Yoon [24], and allows for the prioritization of alternatives by integrating the attribute scores into a single comparable value. TOPSIS computes the final score of an alternative by evaluating its proximity to the ideal reference point [25]. Unlike AHP, TOPSIS does not have a specific procedure for determining criteria weights; instead, the weights are assumed to be known a priori.

One benefit of AHP is the involvement of subjective judgement, which forces the decision-maker to articulate his mental decision-making process. However, AHP may become tedious for large problems. TOPSIS on the other hand, does not allow for weight elicitation and consistency analysis. However, it facilitates computation of larger sets of alternatives [25]. These relative strengths lead to the development of a hybrid MADM model which possesses the complementary benefits of both AHP and TOPSIS. Hybrid models of AHP and TOPSIS have been used for customer-driven product design process [26], machine evaluation and selection [18, 27], education websites [28], 3D printer selection [29], and supplier selection in the textile industry [30], to name a few. Despite extensive use of this hybrid technique, to date, no publications have reported its application to the current problem of evaluating and ranking NETs for carbon management. The closest prior work makes use of an MADM tool known as simple additive weighting (SAW) coupled with a procedure for performing sensitivity analysis with respect to criteria weights [31].

In this paper, this research gap is addressed by developing a novel MADM technique and applying it to the problem of ranking NETs despite the presence of data uncertainties. This is an important contribution due to the urgent need to prioritize alternative NETs as carbon management strategies which will have to be scaled up rapidly in the coming decades [32]. Due to the diverse sources of information, interval data is used in this study to address the inherent uncertainty from the computation of estimates and the aggregation of information from different literature. Furthermore, the interval data considers the fact that the ideal performance of each alternative may change depending on the situation, resulting in a range. This gives a more comprehensive mapping of the possibilities of the alternatives with respect to each criterion. The interval-extended TOPSIS allows the input of interval data as alternative information. The priority weights of the criteria are first derived through fuzzy AHP. Then, the criteria weights are used as input to TOPSIS to generate the ranking of NETs based on interval-value-data from scientific literature.

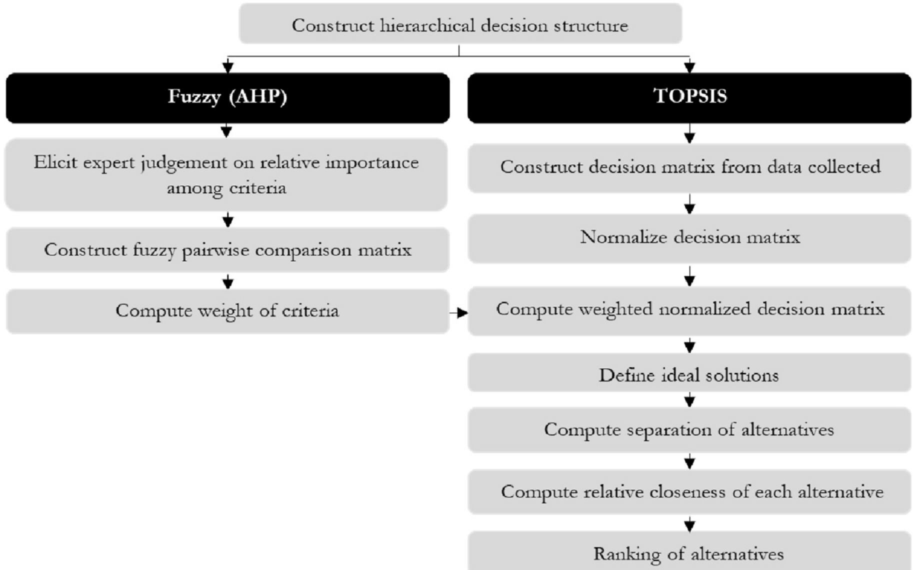

Figure 1. The framework for hybrid model of fuzzy AHP and TOPSIS for MADM problems.

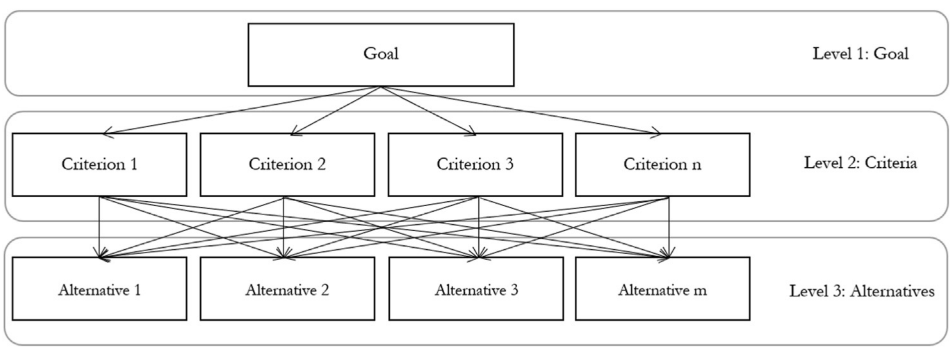

Figure 2. Generic hierarchical decision structure.

The rest of this paper is further organized as follows. The next section gives a description of the proposed integrated MADM methodology. Next, a case study on prioritization of the viability of NETs is considered to demonstrate the capabilities of the method. Finally, conclusions and recommendations for future work are discussed.

2. Problem statement

The formal problem statement can be given as follows:

- Given a set of negative emission technology alternatives, I (e.g. $I = \{1, 2, 3, \cdots M\}$), which are characterized by a set of criteria, J (e.g. $J = \{1, 2, 3, \cdots N\}$)
- An expert or decision-maker provides his or her preference between the criteria and between criteria and alternatives using pairwise comparisons. Furthermore, the expert provides his or her level of confidence for each pairwise comparison made.
- Criterion weights, w_i, can then be derived from the pairwise comparisons.

Table 1. Numerical values associated with linguistic scales (Saaty, 1980).

Numerical Value	Linguistic Term for comparison of criteria	Linguistic terms for comparison of preferences
1	Equally important	Equally preferred
3	Moderately more important	Moderately preferred
5	Strongly more important	Strongly preferred
7	Very strongly more important	Very strongly preferred
9	Extremely more important	Extremely preferred

3. Methodology

Figure 1 illustrates the procedures for the integrated MADM methodology using fuzzy AHP and interval-extended TOPSIS. Suppose the prioritization problem is composed of M alternatives and N criteria (C_1, C_2, …C_n). Initially, the problem is decomposed into a linear hierarchical structure as shown in Figure 2. The line connecting different levels in the hierarchy denote the priority weights of the elements in the lower level (i.e. criteria) with respect to elements in the higher level (i.e. goal) [33]. Pairwise judgment is solicited from a domain expert using a linguistic scale and compiled into a pairwise comparison matrix $\boldsymbol{A}$, shown in Eq. (1). The conventional linguistic scale can be found in Table 1. Each element of the matrix represents the expert's preference between the objects being compared relative to the goal in the upper level of the decision hierarchy. For example, the element a_{21} represents the preference of object 2 with respect to object 1 and is equivalent to the ratio between the weight of object 2 and object 1 or $\frac{w_2}{w_1}$. In the same way, the element a_{12} is equal to $a_{12} = \frac{w_1}{w_2} = \frac{1}{a_{21}}$. Furthermore, to account for uncertainty in the judgement, the linguistic scale can be translated into Triangular Fuzzy Numbers (TFNs).

Table 2. Triangular fuzzy numbers and the linguistic scale [33].

Triangular Fuzzy Number	Linguistic Term for comparison of criteria	Linguistic terms for comparison of preferences
$\langle \frac{1}{1+\delta}, 1, 1+\delta \rangle$	More or less equally important	More or less equally preferred
$\langle 3-\delta,\ 3,\ 3+\delta \rangle$	Moderately more important	Moderately preferred
$\langle 5-\delta,\ 5,\ 5+\delta \rangle$	Strongly more important	Strongly preferred
$\langle 7-\delta,\ 7,\ 7+\delta \rangle$	Very strongly more important	Very strongly preferred
$\langle 9-\delta, 9,\ 9+\delta \rangle$	Extremely more important	Extremely preferred

$$A = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1m} \\ a_{21} & 1 & \cdots & a_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \vdots & 1 \end{bmatrix} \tag{1}$$

A TFN can be characterized by the lower bound, modal value and upper bound of the judgement and the span between lower and upper bound signifies the experts' level of confidence [34]. TFNs are typically represented by the scales shown in Table 2 where the value of δ may be derived by calibrating the fuzzy scales. The fuzzy judgements are thus represented by $\widehat{a_{ij}}$ and the pairwise comparison matrix, $\boldsymbol{A}$, is translated to $\widehat{A}$ as shown in Eq. (2).

$$\widehat{A} = \begin{bmatrix} <1,1,1> & \widehat{a_{12}} & \cdots & \widehat{a_{1n}} \\ \widehat{a_{21}} & 1,1,1 & \cdots & \widehat{a_{2n}} \\ \vdots & \vdots & \ddots & \vdots \\ \widehat{a_{m1}} & \widehat{a_{m2}} & \cdots & <1,1,1> \end{bmatrix} \; where \; \widehat{a_{ij}} = a_{ij}^L, a_{ij}^M a_{ij}^U; \widehat{a_{ji}} = \frac{1}{\widehat{a_{ij}}} = \frac{1}{a_{ij}^U}, \frac{1}{a_{ij}^M}, \frac{1}{a_{ij}^L} \tag{2}$$

The criteria weights (w_j) are then deduced through the non-linear programming model proposed in [33], following Eqs. (3), (4), (5), and (6). This model approximates the criteria weights by constraining the consistency index, $\lambda \in [0,1]$, within the fuzzy bound.

$$\text{maximize} \;\; \lambda \tag{3}$$

Subject to:

$$\lambda\left(a_{ij}^M - a_{ij}^L\right) w_j - w_i + a_{ij}^L w_j \le 0 \;,\; i = 1, \ldots, m-1,\; j = 2, \; \ldots, \; n \tag{4}$$

$$\lambda\left(a_{ij}^U - a_{ij}^M\right) w_j + w_i - a_{ij}^U w_j \le 0 \;,\; i = 1, \ldots, m-1,\; j = 2, \; \ldots, \; n \tag{5}$$

$$\sum_{j=1}^{n} w_j = 1, \;\; \text{where} \;\; w_j > 0 \tag{6}$$

In the context of TOPSIS, the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS) represent the best and worst performance values respectively. The PIS maximizes benefit criteria and minimizes cost criteria, whereas the NIS minimizes benefit criteria and maximizes cost criteria. Hence, an ideal alternative would have the shortest distance from the PIS and is the furthest away from NIS [35]. This paper applies a direct interval extension of TOPSIS proposed by Dymova *et al.* [35]. The interval data elicited from literature is assigned to the alternatives and presented in the interval-valued decision matrix of size $m \times n$. The decision matrix is then normalized using the linear scale transformation (max-min), which considers both the maximum and minimum performance ratings of attributes [36] and indicated in Eqs. (7) and (8).

For criteria j which need to be maximized (e.g. benefit):

$$r_{ij} = \frac{x_{ij} - \min_i\{x_{ij}\}}{\max_i\{x_{ij}\} - \min_i\{x_{ij}\}} \tag{7}$$

For criteria j which need to be minimized (e.g. cost):

$$r_{ij} = \frac{\max_i\{x_{ij}\} - x_{ij}}{\max_i\{x_{ij}\} - \min_i\{x_{ij}\}} \tag{8}$$

Subsequently, the weighted normalized decision matrix is computed by multiplying the priority weights of criteria derived from fuzzy AHP. The PIS (A^+) and NIS (A^-), represented in interval form as shown in Eqs. (9) and (10), are defined from the weighted normalized decision matrix, $D[(v_{ij}^L, v_{ij}^U)]_{m\times n}$. The separation of each alternative *i*, (S_i^+) and (S_i^-) from the PIS (A^+) and NIS (A^-) are calculated following Eqs. (11) and (12), in which the distance between an alternative to the ideal solutions is obtained through midpoint subtraction. The midpoint refers to the middle point of the lower and upper bound in the decision matrix. K_b and K_c are benefit and cost criteria respectively. Finally, the relative closeness (RC_i) is computed following Eq. (13), which represents the final scores of alternatives.

$$A^+ = \left\{ \left(max_i\left[v_{ij}^L, v_{ij}^U\right] \middle| j \in K_b \right), \left(min_i\left[v_{ij}^L, v_{ij}^U\right] \middle| j \in K_c \right) \right\} \qquad j = 1, \; \ldots, \; n \tag{9}$$

$$A^- = \left\{ \left(min_i\left[v_{ij}^L, v_{ij}^U\right] \middle| j \in K_b \right), \left(max_i\left[v_{ij}^L, v_{ij}^U\right] \middle| j \in K_c \right) \right\} \qquad j = 1, \; \ldots, \; n \tag{10}$$

$$S_i^+ = \frac{1}{2}\sum_{j\in K_b}\left(\left(v_j^{+L} + v_j^{+U}\right) - \left(v_{ij}^L + v_{ij}^U\right)\right) + \frac{1}{2}\sum_{j\in K_c}\left(\left(v_{ij}^L + v_{ij}^U\right) - \left(v_j^{+L} + v_j^{+U}\right)\right) \qquad i = 1, \ldots, m \tag{11}$$

$$S_i^- = \frac{1}{2}\sum_{j\in K_b}\left(\left(v_{ij}^L + v_{ij}^U\right) - \left(v_j^{-L} + v_j^{-U}\right)\right) + \frac{1}{2}\sum_{j\in K_c}\left(\left(v_j^{-L} + v_j^{-U}\right) - \left(v_{ij}^L + v_{ij}^U\right)\right) \qquad i = 1, \ldots, m \tag{12}$$

Table 3. Description of NETs [2, 16, 17].

Alternative	Description
Enhanced Weathering (EW)	Artificially accelerate the carbonate or silicate weathering reactions to increase absorption of CO_2 from the atmosphere [2].
Biochar (BC)	Thermochemically convert biomass into carbon-rich charcoal and store in soils [39].
Direct Air Capture (DAC)- Artificial Tree (AT)	Sequester CO_2 form the atmosphere through amine-based absorbent with large area of absorption [39].
Direct Air Capture (DAC) – Soda-lime Process (SLP)	Use aqueous sodium hydroxide to sequester CO_2 from the air through a scrubbing tower and Carbon Capture and Storage (CCS) technology [39].
Bioenergy with Carbon Capture and Storage (BECCS)	Create negative emission using biomass for energy generation, followed by capturing and storing CO_2 released [8].
Ocean Liming (OL)	Release calcium oxide (lime) into the ocean to increase absorption of CO_2 from the atmosphere [5].
Soil Carbon Sequestration (SCS)	Increase organic carbon content in soil through land management [5].

Table 4. Interval data of the NETs [2, 16, 17].

Alternatives	Technical Status (TRL)	Potential Capacity ($GtCO_2$-pa)	Costs Estimates ($/$tCO_2$)	Energy Requirement (GJ/tCO_2)
EW	1–5	1	20–40	0.9 to 12.60
BC	4–6	0.9–3	8–300	-5.45 to -13.64
DAC – Artificial Tree	3–5	10	40–300	1.14
DAC – Soda-lime Process	4–6	10	165–600	8.86
BECCS	4–6	2.4–10	70–250	-0.82 to -10.91
OL	3–4	0.99	51–64	0.7–6.9
SCS	2–7	2.3	0–100	0

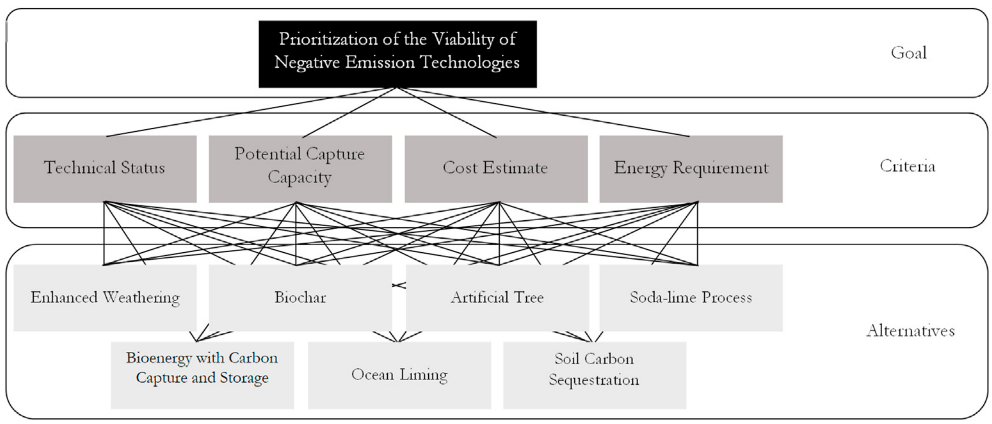

Figure 3. Hierarchical decision structure of the prioritization of NETs.

Table 5. Calibrated linguistic scale for relative importance [34].

Linguistic Term	Symbol	Fuzzy Number	Triangular Fuzzy Numbers (TFNs)
Equally	EQ	1	(1.0, 1, 1.0)
Slightly More	SM	2	(1.2, 2, 3.2)
Moderately More	MM	3	(1.5, 3, 5.6)
Strongly More	ST	5	(3.0, 5, 7.9)
Very Strongly More	VS	8	(6.0, 8, 9.5)

$$RC_i = \frac{S_i^-}{S_i^+ + S_i^-}\ , \quad \text{where} \ \ 0 \le RC_i \le 1. \qquad i = 1, \ldots, m \tag{13}$$

Sensitivity analysis is then employed to assess the robustness of the derived solution by varying the criteria weight from 0 to 1 using intervals of 0.1, while maintaining the weight ratio of other criteria. This step is conducted for all criteria considered. The deviation in the ranking of the alternatives from the optimal ranking is then analysed.

4. Case study

This case study evaluates the viability of NETs for deployment. Various climate model simulations envisioned the potential of NETs through three vital features - biophysical potential for CO_2 sequestration, economic and social costs, and economic and environmental effects [16]. On the other hand, Nemet et. al. [37] discussed the significance of innovation and upscaling of NETs in delivering the climate benefits and achieving the climate goal. Hence, a total of four criteria are included in this study, namely technical status, potential capture capacity, cost estimate and energy requirement. The technical status is measured via the Technology Readiness Level (TRL) scale with levels from 1 to 9 [2]. The potential capture capacity measures the ability of NETs to remove CO_2 from the atmosphere. Material inputs, equipment and implementation costs are all included in the cost estimate. Finally, the energy requirement indicates the required external energy supply or carbon offset for the deployment and operation of NETs.

Following a set of parameters which include capture process, technology cluster and various implementation options, Minx *et al.* [38] categorised NETs into seven clusters, namely a) afforestation and reforestation (AR), b) soil carbon sequestration (SCS), c) biochar (BC), d) BECCS, e) Direct Air Capture (DAC), f) enhanced weathering and ocean alkalinisation (EW) and g) ocean fertilisation (OF). In this paper, the NETs cluster of Enhanced Weathering and Ocean Alkalinisation is further segregated into Enhanced Weathering (EW) and Ocean Liming (OL) due to the variation in the mineral application and difference in carbon storage (i.e. soil and ocean). AR and OF are excluded in this study due to insufficient information from scientific literature, which signifies high data uncertainties. In addition, OF possesses immense risk to the

Table 6. Fuzzy pairwise comparison judgement of criteria.

	Technical Status (C1)	Potential Capture Capacity (C2)	Cost Estimate (C3)	Energy Requirement (C4)
Technical Status	(1, 1, 1)	(0.313, 0.5, 0.833)	(1, 1, 1)	(0.179, 0.333, 0.667)
Potential Capture Capacity	(1.2, 2, 3.2)	(1, 1, 1)	(1.2, 2, 3.2)	(0.313, 0.5, 0.833)
Cost Estimate	(1, 1, 1)	(0.313, 0.5, 0.833)	(1, 1, 1)	(0.179, 0.333, 0.667)
Energy Requirement	(1.5, 3, 5.6)	(1.2, 2, 3.2)	(1.5, 3, 5.6)	(1, 1, 1)

Table 7. Separation, relative closeness and ranking of NETs alternatives.

Alternatives	S_i^+	S_i^-	RC_i	Ranking
EW	0.6020	0.1659	0.2160	7
BC	0.2684	0.4994	0.6505	3
DAC – Artificial Tree	0.2594	0.5084	0.6621	2
DAC – Soda-lime Process	0.4227	0.3451	0.4495	5
BECCS	0.2161	0.5518	0.7186	1
OL	0.5447	0.2232	0.2907	6
SCS	0.4155	0.3524	0.4589	4

environment that offsets its carbon sequestration benefits [15]. The description of the NETs applied in this study as defined in the previous section is presented in Table 3 while the corresponding interval data used is listed in Table 4. Note that negative values in Table 4 denote energy production from the NETs. The information in the table can be read; for example as, Enhanced Weathering (EW) is in TRL 1–5, its potential is about 1 gigatons of CO_2 per year, its cost is estimated to be in the range of $ 20 to $ 40 per ton of CO_2, and it requires 0.9–12.6 GJ of energy per ton of CO_2. In this regard, if there is only one value for a criterion, then that particular value becomes the minimum and maximum values. In this case, EW has the minimum and maximum potential capacity of 1 gigaton of CO_2 per year. Following the identification of the NETs alternatives and evaluating criteria, the hierarchy structure of the decision-making problem can be mapped as shown in Figure 3.

This study utilizes the calibrated fuzzy scale proposed by Promentilla *et al.* [34], as shown in Table 5. The calibrated scale provides a more accurate mapping of the extent of ambiguity in the decision maker's evaluation. The priority weights of the criteria are computed based on the linguistic judgement from an expert in sustainable and negative emission studies. The judgement is elicited through a survey questionnaire, as illustrated in [40], which allows the pairwise comparison from the expert. Table 6 shows the fuzzy pairwise comparison of the criteria. Each entry in Table 6 signifies the relative importance of a criterion with respect to another. Applying the non-linear programming model proposed by Promentilla *et al.* [33], λ is obtained to be 0.783 and the computed criteria weights (in descending order) for energy requirement, potential capture capacity, cost estimate and technical status are 0.466, 0.255, 0.140 and 0.140 respectively. The result shows that the expert prioritizes energy requirement for deployment and operation when evaluating the potential of NETs. The value of 0.783 obtained for λ is within the interval [0,1] and thus indicates that the judgement provided by the expert is consistent. Hence, the priority weights computed are acceptable for this study.

TOPSIS is then performed using interval data for NETs in Table 4. The relative closeness (RC) of each alternative indicates the corresponding potential of NETs for deployment. The result computed from TOPSIS using Eqs. (11), (12), and (13) are shown in Table 7. A higher value of RC indicates that the corresponding alternative is more viable or more desirable. Results show that BECCS is the most viable alternative, followed by DAC-AT. Since the energy requirement criterion (C4) is prioritized by the expert in evaluating the viability of NETs, BECCS and BC, a negative energy requirement will result in a relatively small value of positive separation measure, hence, results in larger value of relative closeness (RC).

Both BECCS and DAC-AT rely on Carbon Capture and Storage (CCS) for enactment, hence in line with Haszeldine *et al.* [41], which identified CCS as significant in achieving negative emission. There is also much emphasis on BECCS in various climate model simulations to reach the 2 °C climate target [6]. Despite CCS-based, DAC-SLP ranked 5th due to its high associated cost and comparably high energy requirement. EW is ranked last among all NETs due to its technology immaturity, low capture capacity and relatively high energy requirement.

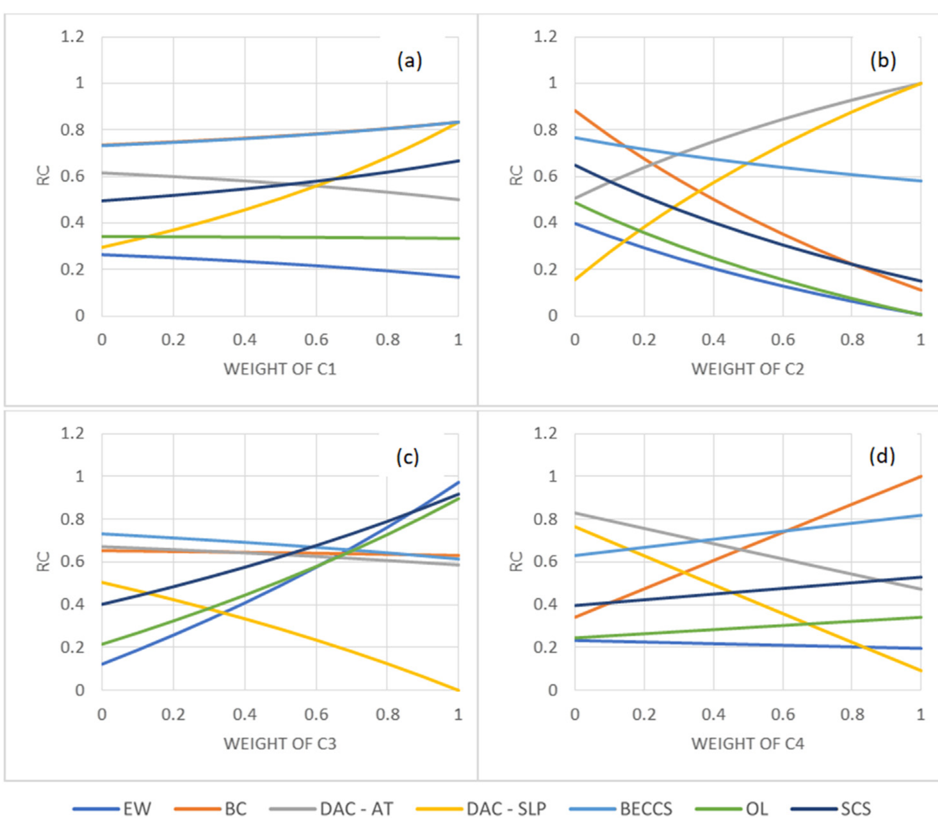

Figure 4. Sensitivity analysis on the impact of criteria weights on NETs ranking: (a) C1 – Technical Status, (b) C2 – Potential Capture Capacity, (c) C3 – Cost Estimate, (d) C4 – Energy Requirement.

Table 8. Sensitivity index, α with respect to criteria.

Alternatives	α			
	C1	C2	C3	C4
EW	-0.0966	-0.3915	0.8498	-0.0371
BC	0.0986	-0.7715	-0.0226	0.6580
DAC – AT	-0.1150	0.4938	-0.0853	-0.3557
DAC – SLP	0.5382	0.8435	-0.5049	-0.6724
BECCS	0.1012	-0.1859	-0.1178	0.1879
OL	-0.0085	-0.4822	0.6807	0.0962
SCS	0.1718	-0.4984	0.5149	0.1323

5. Sensitivity analysis

To test the robustness of the NETs prioritization, a sensitivity analysis is conducted to elicit the effect of criteria weighs alteration on the eventual NETs ranking. In the context of multi-attribute problems, 'robust' indicates insensitivity of preferred alternatives to a set of feasible weights [18]. Figure 4 illustrates how the variation in weight alters the ranking of alternatives. Sensitivity index, α (tabulated in Table 8) is the total change in the relative closeness of an alternative with respect to the criteria weight variation from 0 to 1. A positive value of α indicates that the alternative exhibits a positive trend line gradient (increasing relative closeness), while a negative α denotes a negative trend line gradient (decreasing relative closeness). Since sensitivity analysis evaluates the stability of the ranking, a minimal change in the relative closeness of the alternative with respect to weight variation is desired to avoid rank reversal. α serves as a measure of the sensitivity of an alternative with respect to weight change. A smaller absolute value of α indicates less sensitivity and vice versa.

The result from Figure 4 suggests that varying the weight of C1 has no effect on the ranking of BECCS, BC and EW. Note that the trend line for BECCS and BC are overlapping, indicating both alternatives have the same rank throughout the variation of C1. Since both BECCS and BC are of the same technological development stage, they result in the same ranking when C1 is set as the sensitivity criterion.

Relatively larger values of α indicate higher sensitivity. It can be concluded that the alternatives are most sensitive to C2, followed by C3. On the other hand, BECCS, SCS, OL and EW kept a relatively stable relative closeness against the variation in C4 as shown by α of value 0.1879, 0.1323, 0.0962, -0.0371 respectively. These are summarized in Table 8. BECCS is relatively insensitive to change in all criteria weights, as shown by its α value of 0.1012, -0.1859, -0.1178 and -0.1876 for C1, C2, C3 and C4 respectively. Since BECCS is the most viable alternative (notable in Table 7), the relative stability of BECCS is important in determining the overall stability of the ranking. DAC-SLP, on the other hand, was the most sensitive in all criteria weight variations, which is indicated by the comparably large α computed for all criteria.

6. Conclusion

An integrated decision model consisting of fuzzy AHP and interval-extended TOPSIS was developed and applied to the problem of ranking of NETs under uncertainty. This model can account for qualitative and quantitative criteria in the decision structure, capture uncertainties and vagueness inherent in human judgement and consider more realistic performance of technology alternatives in decision-making. The prioritization of NETs is essential for mapping the future research work and advancement of NETs as important carbon management strategies. It also serves as a guideline for deciding on technology investments. The set of criteria considered in this work includes technical feasibility or status, potential capture capacity, cost estimate and energy requirement. The set of NET alternatives included in this assessment are BECCS, DAC-AT, BC, SCS, DAC-SPL, OL and EW. The NETs were identified based on scientific literature. The criteria weights are computed from the fuzzy pairwise judgement of an expert, with verified consistent judgement. The results show that the expert perceives energy requirement as the most crucial criterion in evaluating NETs, and that BECCS, is the most viable alternative. The robustness of the result is assessed through sensitivity analysis. The result from the study is crucial for R&D efforts, and technology investment decision-making. Furthermore, results can be used to identify key areas for improvement in the identified NETs. It is acknowledged that there are some limitations in the research. The assessment of NETs involves not only the four criteria mentioned here, but also scalability, socio-economic influence, biophysical impact and an evaluation of the most suitable NET within existing plant facilities. The integration of these qualitative criteria into the decision-making framework may be the focus of future work. Other areas which may be explored may consider the inclusion of multiple decision-makers or stakeholders who may potentially have conflicting objectives. It is also worth noting that most scenarios of Integrated Assessment Models (IAM) are conducted within the time frame of first and half century, hence, future work can also look into considering both short- and long-term perspective in the planning horizon of NETs prioritization.

Declarations

Author contribution statement

Zulfan Adi Putra: Analyzed and interpreted the data; Wrote the paper.

Weng Yan Ng, Chia Xin Low: Performed the experiments; Wrote the paper.

Michael Angelo Promentilla, Kathleen Aviso: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Raymond Tan: Conceived and designed the experiments; Analyzed and interpreted the data; Wrote the paper.

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Data availability statement

Data included in article/supplementary material/referenced in article.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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