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Planning Negative Emissions Technologies Portfolios Under Neutrosophic Environment

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Abstract: The deployment of large-scale Negative Emission Technologies (NETs) is now considered a key strategy in climate change mitigation due to their capability to counteract emissions biophysically and economically. However, large-scale NETs will require resources such as land, water, and energy that are limited and uncertainties are present in such technologies. Managing such uncertainties is critical in NET portfolio modeling because they significantly impact the resulting optimized solutions. Existing studies often fail to adequately address these uncertainties, particularly in portfolio optimization, as traditional models often rely on post-optimization sensitivity analysis that does not fully capture the inherent uncertainties in NET performance. This work addresses the research gaps by developing a neutrosophic linear programming (NeLP) model that incorporates membership, non-membership, and indeterminacy components to represent the uncertainties in resource availability, CDR capacities, and synergistic interactions. Unlike previous models, the current novel NeLP model applies different models of uncertainty as neutrosophic sets and adjust expert's risk tolerance levels providing a more flexible and realistic approach to NET portfolio optimization . The model is demonstrated in two case studies. The results suggest that the carbon dioxide removal (CDR) levels of various options have different behaviors across different risk settings, as illustrated by the two case studies. The changing optimal solutions in response to shifts in risk appetite provide decision-makers with valuable insight into selecting NETs with significant CDR potential for reducing large-scale greenhouse gas emissions.

Keywords: optimization; carbon dioxide removal; fuzzy sets, intuitionistic fuzzy sets; risk management; synergistic interactions; uncertainty.

1. Introduction

The search for effective and economical strategies for mitigating climate change (Minx et al., 2018) has led to the emergence of Negative Emissions Technologies (NETs) in the climate change discourse. Today, NETs play an indispensable role in reaching net-zero emissions by 2050, which is a necessary step to achieve the Paris Agreement goals (IPCC, 2022). NETs operate by removing carbon dioxide directly from the atmosphere for storage in a different medium such as in biomass, geological reservoirs, in the soil, etc. (The Royal Society, 2018). Examples of NETs include afforestation/reforestation (AR), biochar (BC) application to soil, soil carbon sequestration (SCS), bioenergy with carbon capture and storage (BECCS), enhanced weathering (EW), and direct air carbon capture and storage (DACCS). Aside from their biophysical capability to sequester carbon dioxide from the atmosphere, NETs are recognized strategies to help economically reach net-zero emissions (Fuss et al., 2018), especially considering sectors that are difficult to decarbonize (IPCC, 2022). However, the large-scale deployment of NETs is faced with multiple challenges that need to be systematically investigated using computational techniques to manage the risks associated with their deployment (Tan et al., 2022).

Such challenges include the large-scale NETs' environmental and societal impacts (Iyer et al., 2021). NETs have multiple environmental footprints (P. Smith et al., 2016) and costs (Fuss et al., 2018) that may compete with societal priorities. Studies have also reported that large-scale implementation of biomass-based NETs such as BECCS will negatively impact the water supply for agriculture (Ai et al., 2021), and may even violate the planetary boundaries (Heck et al., 2018) or the earth's recommended safe operating limits (Steffen et al., 2015). One approach to addressing the sustainability concerns of large-scale NETs is to implement the technologies in portfolio solutions consisting of multiple NETs at smaller individual scales (Minx et al., 2018). In this way, the risks and negative resource impacts in implementing individual, large-scale NETs, may be averted. NET portfolios also open the possibility for synergistic resource interactions between NETs, where synergistic technologies consume fewer resources when implemented together as opposed to their individual deployment (Migo-Sumagang et al., 2022). To address the concerns and to exploit the opportunities, various approaches for the systematic deployment of NETs have been presented in the literature.

Mathematical modeling and optimization can be used for the systematic deployment of NETs. The optimization model consists of an objective function that maximizes the profit or carbon dioxide efficiency or minimizes the cost and resource consumption, subject to constraints such as supply balances. Example works include the modeling of a BECCS supply chain for importing biomass to the UK while minimizing land and water use (Fajardy et al., 2018). The same BECCS supply chain model was also implemented in the UK using indigenous biomass materials (Bui et al., 2021). A study investigated the energy, water, and food nexus in Qatar with BECCS in the energy mix (Namany et al., 2019). The deployment of other NETs has also been investigated using optimization models. A multi-period source-sink model that maximizes the carbon sequestration of a BC-based system has been developed (Tan, 2016). EW networks that minimize carbon dioxide emissions while considering the available rocks and sink capacity have also been investigated (Tan & Aviso, 2019). Negative emissions polygeneration systems have been illustrated in the literature (Belmonte et al., 2019). The BC-based carbon sequestration systems have been improved by considering multiple resource savings (Ong et al., 2021). Similarly, resource conservation networks that generate carbon-negative designs have also been studied (Abraham et al., 2021). These studies have used mathematical programming to optimize the deployment of individual NETs. However, only a few studies have investigated the deployment of NET portfolios. Such studies include a multi-period model that optimizes the net present value of a NET portfolio while considering resources, carbon value, and discount rates have also been developed (Migo-Sumagang et al., 2023).

One important consideration in NET portfolio modeling is the presence of uncertainties due to the lack of knowledge of the system and because some of the NETs are emerging technologies with uncertain performance and cost. In Rickels et al. (2019), it is revealed that various experts utilizing integrated assessment models (IAM) and Earth Systems Model (ESM) have different perceptions in the development of greenhouse gas (GHG) emissions mitigation strategies that involve NETs in their portfolio. Uncertainties are largely present in carbon sinks, especially in land sinks, and should be reduced for effective NETs deployment (Le Quéré et al., 2009). Underground CO_2 storage for capturing CO_2 involved in NETs such as BECCS and DAC also posed risks due to uncertainties in its capacity, flow rate limit, and seismic integrity (Middleton & Yaw, 2018). Such uncertainties must be analyzed since they significantly impact the resulting optimal portfolio. An example approach that deals with the uncertain performance and costs of technologies is using a target-oriented robust optimization technique, that generates a range of solutions and subjects them to Monte Carlo simulation to evaluate the tradeoffs between the performance and robustness of the system (Aviso et al., 2017). Aside from NET performance and cost, the availability of resources is also an uncertain parameter that needs to be considered in the large-scale deployment of NETs. Previous studies on NET portfolios have used the traditional post-optimization sensitivity analysis to manage these uncertainties. A study improved this approach by implementing a global sensitivity analysis using a space-filling design of experiments (Tan et al., 2015). The method enables the investigation of interactions and higher-order effects of the parameters on the responses using regression analysis.

Optimizing NET portfolios with uncertain parameters can also be addressed using fuzzy mathematical programming (FMP). Originally based on the fuzzy set theory (Bellman & Zadeh, 1970), the FMP formulation (Zimmermann, 1978) addresses both uncertainty and multi-objectivity in the model. In the FMP formulation, each fuzzy objective and constraint's degree of membership increases linearly from zero to one, and the solution with the highest aggregate membership is the optimal solution (Zimmermann, 1978). The use of FMP in investigating NETs has been illustrated in the literature. Negative emissions BC polygeneration systems with uncertain performance and cost were modeled using FMP (Ubando et al., 2014). A study implemented FMP in BC networks using direct and indirect biomass co-firing while considering uncertain sink capacities (Aviso et al., 2020). EW networks were also modeled using FMP with uncertain source and sink capacities (Aviso & Tan, 2020). The FMP approach has been demonstrated in NET portfolios with uncertain resource constraints, where the model is able to identify a compromising NET portfolio that maximizes a negative emission target while minimizing the resource consumption within the fuzzy intervals (Migo-Sumagang et al., 2022). Neutrosophic data envelopment analysis (NDEA), which is related to FMP, is another approach for evaluating uncertain parameters in NET selection and evaluation. Neutrosophic sets are built on the concepts of fuzzy sets (Zadeh, 1965) and intuitionistic fuzzy sets (Atanassov, 1986). The advantage of NDEA over the fuzzy and intuitionistic fuzzy sets is that NDEA accounts for membership, non-membership, and indeterminacy in uncertain parameter values. In this way, NDEA is able to represent the human perception of risks due to uncertain information (Tapia, 2021). NDEA has been demonstrated to identify suitable NETs while considering the trade-off between its benefits and risks (Tapia, 2021). Recent work by Kandemir et al. (2024) demonstrates the effectiveness of neutrosophic methods in environmental data analysis, particularly in analyzing temperature data across cities in Turkey. Smarandache (2024) introduced the appurtenance and inclusion equations which resemble solving equations with set-valued coefficients, enhancing the understanding of neutrosophic statistics. Except for the study by Tapia (2021), no study has been found applying neutrosophic sets for decision-making and optimization of NETs.

This work addresses the research gaps by developing a novel neutrosophic linear programming (NeLP) model for NET portfolio optimization. The model considers uncertainties in the parameters, specifically, in the removal capacity, resource availability limits, and reduction target. This study contributes to modeling uncertain NET portfolios while managing their risks. The perception of uncertainty such as resource availability, removal capacity, reduction goal, and geological characteristics are modelled based on neutrosophic input for preference on lower parameter levels and neutrosophic output for preference on higher preference levels (Tapia, 2021). The insights derived from this study support the identification and selection of NETs with significant carbon dioxide removal (CDR) potential for reducing large-scale greenhouse gas emissions. The rest of the paper is as follows. Section 2 presents the problem statement. Section 3 showcases the optimization model. Sections 4 and 5 illustrate the model in two case studies. The first case study demonstrates the model on a BECCS portfolio using different biomass feedstocks while the second case study involves a portfolio of various land-based NETs. Finally, section 6 presents the conclusions and recommendations of this work.

2. Problem Statement

The formal problem statement to be addressed in this paper is as follows:

- The system consists of m resources and n CDR options.

- Each CDR option is characterized by its resource requirements or impact per year. Each option has a removal capacity given by a lower limit and an upper limit. The removal capacity is neutrosophic in nature with components of membership, non-membership, and indeterminacy. Figure 1a shows the representation of these neutrosophic components. The membership function represents the degree of satisfaction towards achieving CDR levels of each technology while the non-membership function represents the degree of dissatisfaction towards opportunity loss from lower CDR levels. The indeterminacy function represents the degree of uncertainty at which the levels of CDR can be attained. This neutrosophic model is adapted from the neutrosophic output in the NDEA model by Tapia (2021).
- Each resource is characterized by a lower limit and an upper limit availability and is neutrosophic in nature. Figure 1b shows the membership, non-membership, and indeterminacy functions of the input and output parameters. The membership function provides a degree of satisfaction towards minimizing the impact or resource utilization to achieve a higher CDR target. Consequently, the non-membership component models the degree of dissatisfaction towards higher resource utilization. The indeterminacy component represents the degree of uncertainty in achieving lower resource utilization. This neutrosophic model is adapted from the neutrosophic input in the NDEA model by Tapia (2021).
- The synergistic interaction between CDR options is considered in this study. The resource consumption of two interacting options is less than their impact when considered individually.
- For the NET portfolio that utilizes geological storage as a resource, the use of CO_2 storage is modeled as a neutrosophic set adapted from Tapia (2023). The storage capacity is given as a triplet of the lower bound of the estimate, the best estimate as the middle value, and the upper bound. Figure 1c shows the neutrosophic components of storage utilization. Both the membership and non-membership components are based on minimizing the risk associated with over-estimation of storage capacity while the indeterminacy components are based on the inaccuracy of the storage estimates.
- The overall CDR target is treated as a neutrosophic objective where the total reduction is set between an upper and a lower bound. The same model as a neutrosophic output from the NDEA model from Tapia (2021) is adopted. The analogy adopted here is based on the neutrosophic nature of the performance of the whole NET portfolio. Figure 1d shows the neutrosophic nature of the overall CDR target.
- The neutrosophic nature of resource availability can be adjusted based on the risk appetite of the model user. Figure 1 shows two parameters that are set by the user depending on how uncertainty is perceived. The falsity tolerance (TE) represents the tolerance by which the user is willing to accept higher resource utilization but is more satisfied with lower impacts. The indeterminacy tolerance (TI) represents the tolerance that depends on the user's capability to attain the lower impact levels.

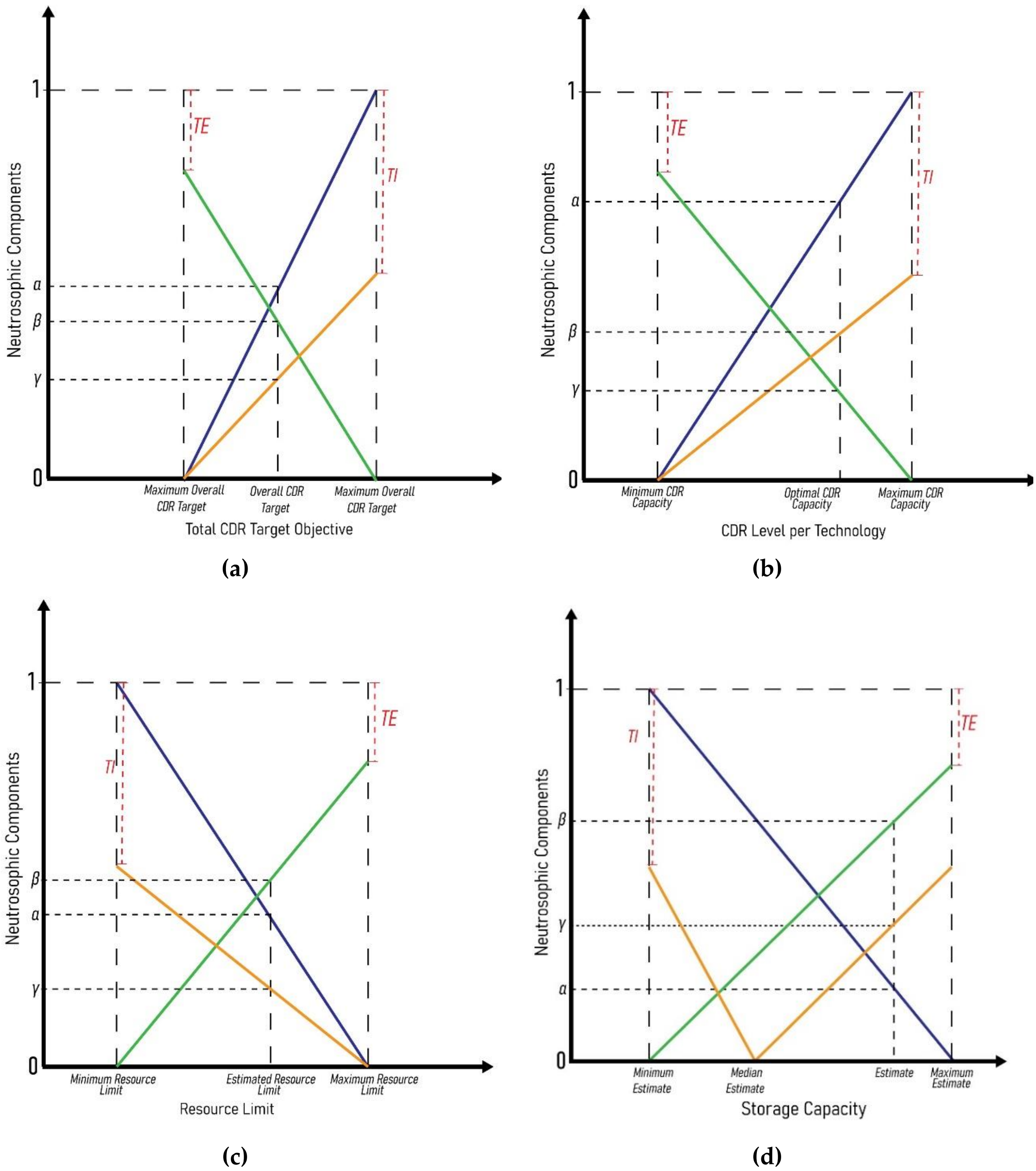


Figure 1. Graphical representation of the membership, non-membership, and indeterminacy functions of the (a) total CDR target for the NET portfolio, (b) individual CDR level per technology, (c) limits for the resources used by the NET options and (d) geological storage capacity as a resource. The graph illustrates the degree of satisfaction (α), dissatisfaction (β), and uncertainty (γ) for an expert-defined risk aversion of TE for performance dissatisfaction and TI for uncertainty.

3. Optimization Model

The objective function is to maximize the aggregation of the degrees of satisfaction, dissatisfaction, and uncertainty:

$$\max \alpha - \beta - \gamma + \frac{1}{M}(R) \tag{1}$$

where α is the overall degree of satisfaction, β is the overall degree of dissatisfaction, and γ is the overall degree of uncertainty. Eq (1) maximizes α and minimizes both β and γ in equal weights. The fourth term in the objective function ensures the optimality of the overall CDR target while giving priority to the aggregated overall neutrosophic components of α, β, and γ.

The overall CDR target is neutrosophic in nature:

$$R - R^L \geq \alpha(R^{\mathrm{U}} - R^{\mathrm{L}}) \tag{2}$$

$$(1 - TE)(R^U - R) \leq \beta(R^{\mathrm{U}} - R^{\mathrm{L}}) \tag{3}$$

$$(1 - TI)(R - R^L) \leq \gamma(R^{\mathrm{U}} - R^{\mathrm{L}}) \tag{4}$$

where R is the total CDR target bounded between R^{L} and R^{U}. The maximum degree of satisfaction is attained at the lower bound, R^L of the CDR target while the minimum degree of satisfaction is attained at the upper bound R^{U}, TE and TI are the falsity and indeterminacy tolerances, β is the overall degree of dissatisfaction and γ is the overall degree of uncertainty. For neutrosophic optimization, β represents the maximum degree of dissatisfaction among individual degrees from all resource types while γ represents the maximum degree of uncertainty.

Planning for a NETs portfolio requires the selection of a set of CDR options to achieve the target. The capacity of the selected CDR option is bounded between an upper and a lower limit:

$$b_i X_i^{\mathrm{L}} \leq x_i \leq b_i X_i^{\mathrm{U}} \qquad \forall i \tag{5}$$

where x_i is the capacity of option i in terms of the target reduction assigned to that option. The binary variable b_i represents the variable whether the CDR option i is selected ($b_i = 1$) or not ($b_i = 0$). If it is selected, the reduction is bounded between the lower limit, X_i^{L} and the upper limit, X_i^{U}.

The neutrosophic nature of the CDR levels is also considered for modeling:

$$x_i - X_i^{\mathrm{L}} \geq \alpha(X_i^{\mathrm{U}} - X_i^{\mathrm{L}}) \qquad \forall i \tag{6}$$

$$(1 - TE)\left(X_i^{\mathrm{U}} - x_i\right) \leq \beta(X_i^{\mathrm{U}} - X_i^{\mathrm{L}}) \quad \forall i \tag{7}$$

$$(1 - TI)(x_i - X_i^L) \leq \gamma(X_i^{\mathrm{U}} - X_i^{\mathrm{L}}) \qquad \forall i \tag{8}$$

The degree of satisfaction for the CDR of option i increases with the increasing value of x_i to represent the increasing satisfaction for investment in a CDR option. A decreasing trend is modeled for the degree of dissatisfaction where the maximum dissatisfaction is assigned to the lower bound of the option should it be decided on that technology. For the indeterminacy component, the uncertainty in achieving the level of CDR in the optimal solution increases as the value increases due to the complexity of the interaction between factors contributing to its attainment.

The total CDR is calculated as a sum of individual reductions from all technologies:

$$\textstyle\sum_i x_i = R \tag{9}$$

To account for the activation of two simultaneous NET options, a binary variable set in which its relationship with the individual binary decision variables is as follows:

$$b_i \geq c_{ik} \qquad \forall i, k \tag{10}$$

$$b_k \geq c_{ik} \qquad \forall i, k \tag{11}$$

$$b_i + b_k - 1 \leq c_{ik} \qquad \forall i, k \tag{12}$$

where b_i and b_k are binary variables for the selection of option i and k, respectively and c_{ik} is the binary variable that denotes whether option i and k are both selected for the portfolio. Eq (10) and (11) represent the constraint that the selection of individual options must be independent of each, however, c_{ik} will have a value of 1 when both binary variables b_i and b_k are equal to 1 based on

Eq (12). The interaction between two CDR options is considered for setting the resource availability limitation of the different impacts and resources:

$$\sum_i x_i M_{ij} \leq D_j + 0.5 \sum_i \sum_k Z_{ijk} c_{ik} \qquad \forall j \tag{13}$$

where M_{ij} is the utilization of resource j by option i, Z_{ijk} is the discount for resource j if options i and k are activated at the same time, and D_j is the availability of resource j. The second term relaxes the upper limit of the resource available by considering the reduction of resource consumption or impact caused by the synergistic relationship between options i and k.

A special type of interaction in NETs is land use. Eq (14) may be used for considering land use interaction, however, the shared land must be known beforehand. In this case, a topological parameter, E_i is a binary parameter that takes a value of 1 if option j can be implemented in the same land with other options. The synergistic interaction can then be accounted for:

$$E_i x_i M_{ij} + \sum_k (1 - E_k) x_i M_{ij} \leq F_j \qquad \forall j \in S \tag{14}$$

Where S is the set of synergistic resource where the resource can be shared (i.e., land use). The second term in Eq (14) denotes that all other options that synergize with option i will not be accounted for in the resource consumption or impact if they both share the same resource.

The resource availability is neutrosophic in nature with linear membership, non-membership, and indeterminacy functions:

$$D_j^{\mathrm{U}} - D_j \geq \alpha (D_j^{\mathrm{U}} - D_j^{\mathrm{L}}) \qquad \forall j \tag{15}$$

$$(1 - TE)(D_j - D_j^{\mathrm{L}}) \leq \beta (D_j^{\mathrm{U}} - D_j^{\mathrm{L}}) \quad \forall j \tag{16}$$

$$(1 - TI)\left(D_j^{\mathrm{U}} - D_j\right) \leq \gamma (D_j^{\mathrm{U}} - D_j^{\mathrm{L}}) \quad \forall j \tag{17}$$

Where D_j^{U} and D_j^{L} are the upper and lower limits of the resource availability. Eq (10) means that the maximum degree of satisfaction for resource utilization and impact can be achieved at the lower limit. Eq (15) shows that the maximum degree of dissatisfaction can be attained at the upper limit while Eq (16) shows that the maximum degree of uncertainty can be attained at the lower limit.

Some NETs utilize geological storage to fully realize the net negative emissions impact of these technologies. The total reduction from all NETs that utilize geological storage should be less than the estimated geological storage capacity:

$$\sum_i x_i S_i = E \qquad \forall j \tag{18}$$

where E is the geological storage capacity utilized in the system and S_i is the binary parameter that denotes that option i requires a geological storage resource. The estimated geological storage capacity can be modeled with neutrosophic uncertainties with linear membership, non-membership, and indeterminacy functions:

$$E^U - E \geq \alpha (E^U - E^L) \qquad \forall j \tag{19}$$

$$(1 - TE)(E - E^L) \leq \beta (E^U - E^L) \qquad \forall j \tag{20}$$

$$(1 - TI)(E^M - E) \leq \gamma (E^M - E^L) \qquad \forall j \tag{21}$$

$$(1 - TI)(E - E^M) \leq \gamma (E^U - E^M) \qquad \forall j \tag{22}$$

where $[E^L, E^M, E^U]$ represents the neutrosophic triplet of the geological storage consisting of the lower bound, modal value, and the upper bound of the storage capacity. Eqn. (19) represents the constraint for linear membership in which the degree of satisfaction increases with less storage utilization to minimize the risk of over-storing beyond actual storage capacity. Eqn. (20) represents the constraint for non-membership that increases with increasing storage utilization to model the dissatisfaction with the increasing risk of over-storage. Eqn (20) and (21) represent the degree of indeterminacy associated with the accuracy and vagueness of the estimate of the storage capacity, being the modal value representing the best storage capacity estimate. Considering all neutrosophic components, Eq (1) aims to minimize the maximum degrees of dissatisfaction and indeterminacy through the negative sign in the second and third terms respectively.

The decision variables in this model are continuous for the reduction of individual options and binary of other decision variables:

$$x_i \geq 0 \qquad \forall i \tag{23}$$

$$b_i, b_k, c_{ik} \in \{0,1\} \qquad \forall k \tag{24}$$

The model has an objective function in Eq (1) subject to constraints in Eq (2) to Eq (24). The model is implemented in AIMMS 4.95 in a PC with 3.59 GHz of processor and 16 GB of RAM. The case studies used to illustrate the model have a negligible computational time.

4. Case Studies

Case Study 1: BECCS Feedstock Selection

Case Study 1 focuses on a portfolio of BECCS using dedicated energy crops. The selected scenario for implementation is in the Association of Southeast Asian Nations (ASEAN) region in 2050 with some of the presented data used for this case study slightly modified. The ASEAN region, comprising Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Singapore, Thailand, and Vietnam, has a of population 661 million, a total land area of 4.49 x 106 km^2, and a GDP of USD 3 trillion in 2020 (ASEAN, 2021). The rapidly advancing nations in this region will significantly benefit from NETs, given their anticipated increase in fossil energy consumption and emissions in the forthcoming years (Asian Development Bank, 2013). The year 2050 is selected since it is forecasted to have an increased utilization of advanced technology NETs like BECCS, DACCS, and EW (Rueda et al., 2021). Using the region's Intended Nationally Determined Contributions (INDCs) (Fulton et al., 2017), a carbon dioxide removal target between 0.375 to 0.725 Gt CO_2/y can be expected. For this case study, a more conservative estimate of 0.3 to 0.7 Gt CO_2/y is used.

The capacity and impact of BECCS using various feedstock is presented in Table 1. The upper limit of the capacities of different feedstock are estimated at a more conservative value ranging from 0.325 to 0.475 Gt CO_2/y. These values illustrate the uncertainty in attaining higher CDR levels beyond the 0.375 Gt CO_2/y minimum limit in the INDCs from ASEAN countries. The lower capacity limit is set to zero, allowing the model to incorporate or exclude NETs from the portfolio as required. The data on Switchgrass and Miscanthus are obtained from the study of (Fajardy & Mac Dowell, 2017). Due to limited data availability, the impact of Eucalyptus is adopted from the study of (L. J. Smith & Torn, 2013), where the plantation was originally intended for AR. The energy impact of BECCS using Eucalyptus is estimated from the study of Cavalett et al. (2018) assuming an energy penalty of 40-60%. The cost of BECCS is assumed to be between USD 100-200/t CO_2 (Fuss et al., 2018).

The resource and storage limits of the ASEAN region are presented in Table 2 as first implemented in the study of (Migo-Sumagang et al., 2022). The available land is calculated using the original forest cover in the ASEAN region (Estoque et al., 2019) and the limit recommended by the planetary boundary framework (Steffen et al., 2015). A revised constraint on water usage of 990 km^3 for green water supplied by rainfall (Rosa et al., 2021) is implemented. The renewable energy supply is based on the surplus projections (IRENA, 2019). The nutrient limits are based on the regional constraints imposed by the planetary boundary framework. The budget constraint is based on 15% of the global budget for climate change adaptation as recommended by (UNEP, 2016). It is assumed that the available rock for EW is not limiting. Lastly, the geological storage capacity is set at 0.62-0.67 Gt CO_2/y. This value is based on the total storage of 49.7-54 Gt CO_2, representing the combined reported capacity of four ASEAN countries (Indonesia, Philippines, Thailand, and Vietnam), primarily situated within saline aquifers (Asian Development Bank, 2013). It was assumed that no synergistic interactions exist among the various BECCS options.

Table 1. Capacity and impact of BECCS using various feedstock for Case Study 1

Feedstock	Upper capacity limit in 2050 (Gt CO_2/y)	Land use (Mha/Gt CO_2)	Water use (km^3/Gt CO_2)	Energy (EJ/Gt CO_2)	Nitrogen (Mt/Gt CO_2)	Phosphorus (Mt/Gt CO_2 eq.)	Cost (B USD/ Gt CO_2)
Switchgrass	0.455	150.3	971.05	-0.885	11.22	6.65	150
Miscanthus	0.475	53.965	549.6	0.9	4.67	4.38	175
Eucalyptus*	0.325	2.95	1575	-5.85	0.1125	0.1325	190

*Data from afforestation using Eucalyptus (L. J. Smith & Torn, 2013). Energy impact is estimated using the results of (Cavalett et al., 2018), assuming a 40% energy penalty.

Table 2. Resource and storage limits

Resource	Limit
Land use (Mha)	0 - 45.7
Water use (km^3/y)	495-990
Energy input (EJ/y)	7.38 - 19.5
Nitrogen (Mt/y)	0 - 6.2
Phosphorous (Mt/y)	0 - 6.2
Cost (B USD/y)	42-75
Geological storage (Gt CO_2/y)	[0.40, 0.60, 0.70]

The optimal solution for three decision environments, namely, fuzzy $(TE = 1, TI = 1)$, intuitionistic fuzzy $(TE = 0, TI = 1)$ and completely neutrosophic $(TE = 0, TI = 0)$ is summarized in Table 3 for the CDR levels of each option. The resource limits estimated for each decision environment are shown in Table 4. In this case, the optimal CDR levels do not change when the decision environment is changed from fuzzy to intuitionistic fuzzy, signifying that when the decision is made where the indeterminacy is not considered, (i.e. $TI = 1$) switching the highest tolerance to dissatisfaction to the lowest does not affect the CDR levels of all technologies. In both cases, using Switchgrass as feedstock for BECCS will potentially provide the highest CDR level in comparison to Miscanthus and Eucalyptus. This insight can be attributed to its lower cost, higher upper limit of CDR capacity, and its net positive energy generation. On the other hand, Eucalyptus yields the lowest CDR potential, mainly due to its high water footprint. The optimal CDR changes when the decision environment changes to completely neutrosophic. Here, all three components of membership, non-membership, and indeterminacy are considered. As shown in Table 4, the estimates for resource limit drive the optimal CDR reduction being the adjustment of the water footprint limit to a more conservative value than in the optimal estimate in a fuzzy decision environment. It leads to the choice of feedstock for BECCS, being limited to only Switchgrass and Miscanthus. However, the costs for this portfolio are increasing due to the higher contributions of both options. The optimal energy consumption generated from setting the decision environment into completely neutrosophic provides a trade-off between low- and high-energy consumption scenarios in the other two decision environments. This case study provides important insights as to how the CDR levels of NETs can be optimized in different conditions. In the case where parametric uncertainty is present in the available data of CDR, the NeLP model for NETs portfolio optimization generates the CDR level considering the consequences of attaining different levels of uncertain resource availability. By determining which resource is affected by the change in risk appetite, policymakers can prioritize which resources need to be scaled up.

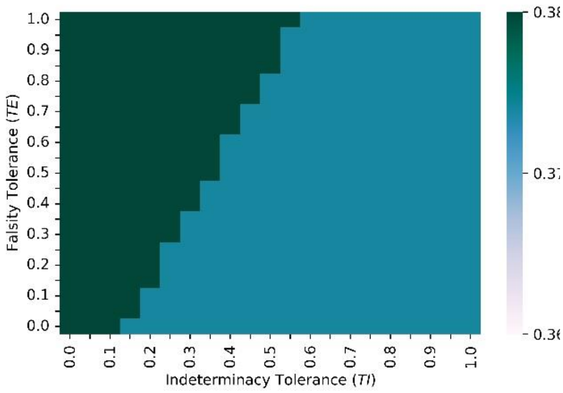
Table 3. Optimal CDR levels (in Gt/y) for different BECCS feedstock options in different decision environments

Technology	CDR Level (Gt CO_2/y)		
	Fuzzy ($TE = 1, TI = 1$)	Intuitionistic Fuzzy ($TE = 0, TI = 1$)	Completely Neutrosophic ($TE = 0, TI = 0$)
Switchgrass	0.209	0.209	0.217
Miscanthus	0.105	0.105	0.243
Eucalyptus	0.060	0.060	0.000
Total	0.374	0.374	0.460

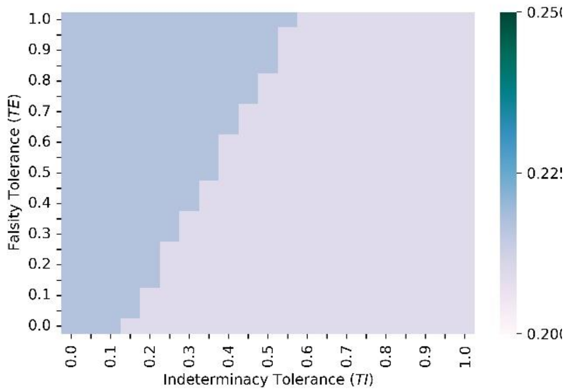
Table 4. Optimal resource limit estimates (in Gt/y) for different BECCS feedstock options in different decision environments

Technology	Resource Limit Estimates		
	Fuzzy ($TE = 1, TI = 1$),	Intuitionistic Fuzzy ($TE = 0, TI = 1$)	Completely Neutrosophic ($TE = 0, TI = 0$)
Land Use (Mha/Gt CO_2)	37.25	37.25	45.70
Water Use (km^3/Gt CO_2)	898.43	659.21	659.21
Energy (EJ/Gt CO_2)	17.26	7.38	11.40
Nitrogen (Mt/ Gt CO_2)	5.05	2.84	3.57
Phosphorus (Mt/ Gt CO_2)	5.05	1.86	2.51
Cost (billion USD/Gt CO_2)	61.13	61.13	75.00
Storage (Gt CO_2/y)	0.374	0.374	0.460

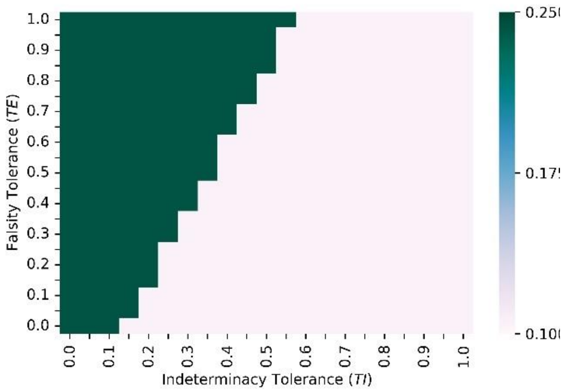
A sensitivity analysis is performed to determine the effect of varying the expert risk parameters TE and TI to the optimal CDR of the BECCS feedstock option. Figure 2 shows the heat maps of the CDR levels at different combinations of the risk parameters. The changes in the total CDR from all three feedstock can be observed when the indeterminacy tolerance changes at 0.15 when $TE = 0$ to 0.55 when $TE = 1$. The same behavior is observed in individual options. For instance. Miscanthus and Switchgrass can achieve higher CDR levels at lower indeterminacy levels. The trend reveals that as the policymaker becomes more adaptable to indeterminacy changes, the optimal decision is going towards putting more investment into Eucalyptus as feedstock. It also indicates that, at intermediate tolerance towards indeterminacy (i.e., $TI = 0.1$ to $TI = 0.5$), the model suggests investing to a higher CDR level as the tolerance towards dissatisfaction increases. The main factor that drives this change is the cost and land footprint to maximize their CDR. However, between them, Miscanthus has a potentially higher optimal CDR level due to lower water requirements. Eucalyptus has a higher CDR level at higher indeterminacy tolerance. This insight reveals that the use of both Switchgrass and Miscanthus for BECCS feedstock must be selected where a more efficient process is available to meet the upper limit provided. The heatmap provides a more comprehensive map of risk behavior that can be considered for feedstock selection in BECCS.



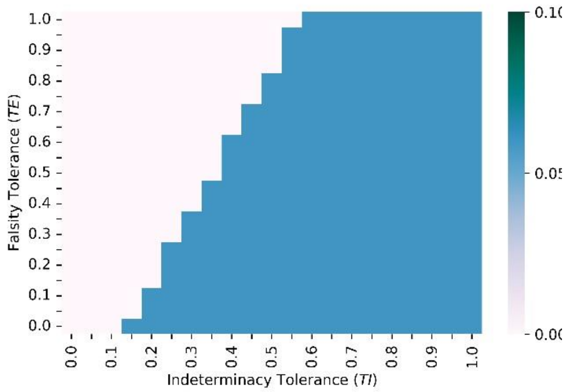
(a) Total CDR



(b) CDR for Switchgrass



(c) CDR for Miscanthus



(d) CDR for Eucalyptus

Figure 2. Sensitivity analysis results for CDR levels of feedstock options for BECCS.

Case Study 2: NET Portfolio Optimization

Case Study 2 involves the optimization of a NET portfolio with varying technologies. As with Case Study 1, the selected scenario is the ASEAN region in 2050. The study focuses on land-based NETs including BECCS, AR, SCS, BC, EW, and DACCS. As opposed to the ocean-based NETs, research and data availability are more extensive for land-based NETs, thus the former are excluded from the study. The annual capacity and impact of NETs per unit of carbon sequestration are presented in Table 5 from various references. The upper capacity limit of each NET is obtained by projecting the ASEAN NET capacities in 2050 (Migo-Sumagang et al., 2023). As with the previous case study, the lower capacity limit is set to zero, enabling the model to include or exclude NETs from the portfolio as needed. The data on BECCS is from the study using Switchgrass and Miscanthus (Fajardy & Mac Dowell, 2017) as first presented in the previous case study. AR land, water, and nutrient use are based on the study on tropical Eucalyptus plantations (L. J. Smith & Torn, 2013) as previously cited. Overall, SCS has insignificant water and energy impact (Brack & King, 2021) and it can be implemented without changing the land use (Sykes et al., 2020). The data on BC is based on the study of (P. Smith et al., 2016). Land use for DACCS assumes that land use from the energy source (photovoltaics) is excluded (Fajardy & Mac Dowell, 2017). The data on EW is based on the study using basalt and dunite rocks (Strefler et al., 2018). The water footprints of DACCS are based on the study of (Rosa et al., 2021). The costs of the NETs are obtained from the study of (Fuss et al., 2018)).

It was assumed that no synergistic interactions exist among the NET options. For this case, the overall target CDR is set from 0.6 to 0.9 Gt CO_2/y.

Table 5. Capacity and impact of NETs for Case Study 2

NET	Upper capacity limit in 2050 (Gt CO_2/y)	Land use (Mha/Gt CO_2)	Water use (km^3/Gt CO_2)	Energy (EJ/Gt CO_2)	Nitrogen (Mt/Gt CO_2)	Phosphorus (Mt/Gt CO_2 eq.)	Cost (B USD/Gt CO_2)
BECCS	0.375	113.85	574	0.605	9.574	6.65	150
AR	0.12	2.95	1575	-	0.1125	0.1325	27.5
SCS	0.15	-	-	-	22	5.5	50
BC	0.12	58		-35	8.2	2.7	75
DACCS	0.225	0.1365	4.415	14.65	-	-	200
EW	0.49	84.65	1.5	6.35	-	-	125

The optimal solution for three decision environments, namely, fuzzy ($TE = 1, TI = 1$), intuitionistic fuzzy ($TE = 0, TI = 1$) and completely neutrosophic ($TE = 0, TI = 0$) is summarized in Table 6 for the CDR levels of each option. The resource limits estimated for each decision environment are shown in Table 7. Like Case Study 1, both the CDR levels under fuzzy and intuitionistic fuzzy decision environments are the same, however, the resource limits are estimated at different values. Here, it is estimated more conservatively, especially for phosphorus use, water footprint, and energy consumption. A compromise between the optimal limits obtained in fuzzy and intuitionistic fuzzy decision environments is generated for a completely neutrosophic decision setting. A decrease in CDR level is observed for all technologies except for EW where the CDR level increases by 86%. This may be attributed to its higher upper limit capacity, lower cost, and negligible requirements for phosphorus and nitrogen nutrients. From the optimal solutions, CDR levels to different NET options are suggested to be ranging from 0.10 to 0.12 Gt/y except for DAC where the optimal investment is 0.061 Gt/y at the maximum. It can be attributed to its high cost and high energy requirements. AR, SCS, and BC are viable options in the portfolio as the suggested levels of CDR are at their maximum or near their maximum level.

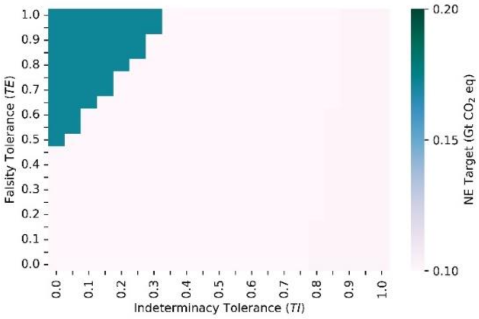
Table 6. Optimal CDR levels (in Gt/y) for different NET options in different decision environments

Technology	CDR Level (Gt CO_2/y)		
	Fuzzy ($TE = 1, TI = 1$)	Intuitionistic Fuzzy ($TE = 0, TI = 1$)	Completely Neutrosophic ($TE = 0, TI = 0$)
BECCS	0.102	0.102	0.066
AR	0.120	0.120	0.073
SCS	0.115	0.115	0.092
BC	0.120	0.120	0.073
DAC	0.061	0.061	0.047
EW	0.163	0.163	0.302
Total	0.682	0.682	0.653

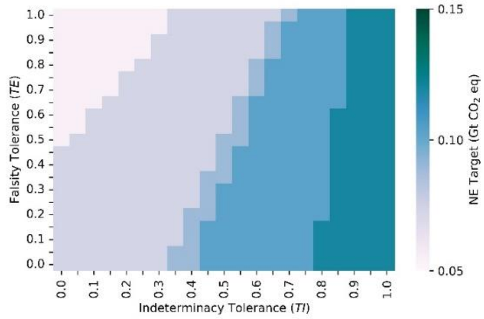
Table 7. Optimal resource limit estimates (in Gt/y) for different NET options in different decision environments

Technology	Resource Limit Estimates		
	Fuzzy ($TE = 1, TI = 1$),	Intuitionistic Fuzzy ($TE = 0, TI = 1$)	Completely Neutrosophic ($TE = 0, TI = 0$)
Land Use (Mha/Gt CO_2)	33.26	32.75	37.60
Water Use (km^3/Gt CO_2)	855.20	495.00	687.99
Energy (EJ/Gt CO_2)	16.20	7.38	12.11
Nitrogen (Mt/ Gt CO_2)	4.51	4.51	3.26
Phosphorus (Mt/ Gt CO_2)	4.51	1.65	2.42
Cost (billion USD/Gt CO_2)	66.01	66.01	69.15

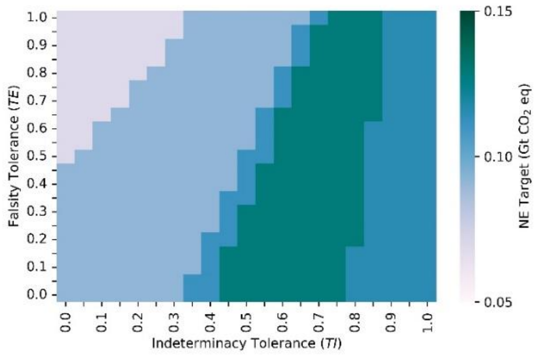
A sensitivity analysis is performed to determine the effect of varying the expert risk parameters TE and TI to the optimal CDR of different NET options. Figure 3 shows the heat maps of the CDR levels at different combinations of the risk parameters. The plots indicate that the changes in CDR levels for each option are attributed more to the changes in the tolerance level to indeterminacy rather than to falsity. The highest total CDR levels are attained at high values of indeterminacy tolerance. This insight means that scaling up the CDR level of the portfolio can be achieved better when more information is provided to achieve the upper limits of the target CDR. The target levels of different options are maximized at different sets of tolerance levels. For BECCS, the maximum CDR levels can be achieved for low indeterminacy tolerance and high falsity tolerance levels. For SCS, the highest CDR level is achieved at an indeterminacy tolerance of 0.45 to 0.75 and for EW, it is achieved between 0 to 0.45. The differences in optimal CDR at different tolerance levels suggest how different NETs can be optimized depending on the confidence of the decision-makers in the available information to achieve higher levels of CDR. The insights provided in the case study can be used by decision-makers for the selection of NETs and the target CDR levels for their portfolio. In addition, the varying levels of sensitivity of technologies to expert's perceptions can aid in specific policies based on available economic resources, and regional or state conditions to deploy the NETs.



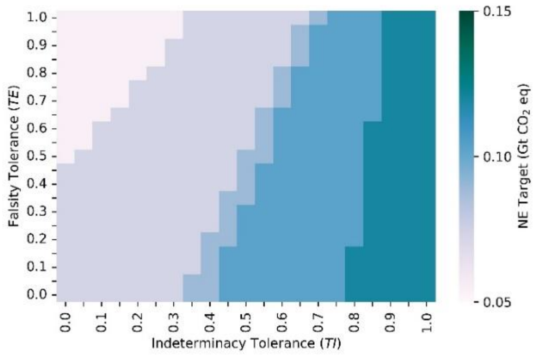
(a) CDR level for BECCS



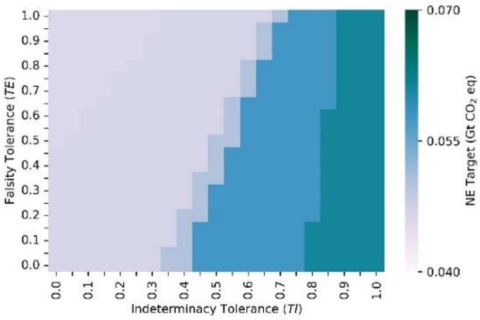
(b) CDR level for AR



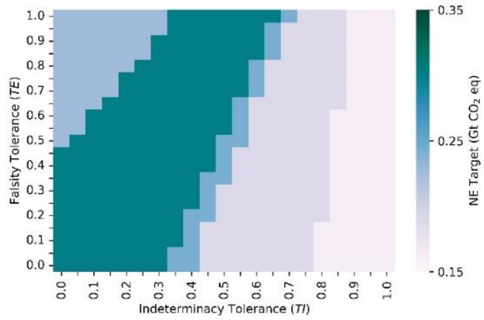
(c) CDR level for SCS



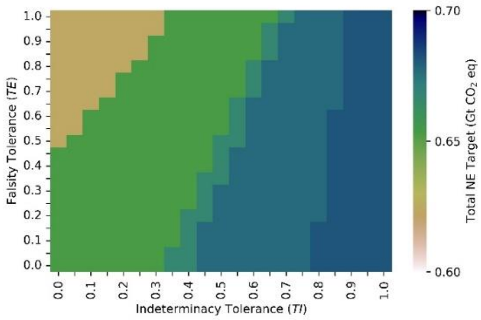
(d) CDR level for BC



(e) CDR level for DACCS



(f) CDR level for EW



(h) Total CDR

Figure 3. Sensitivity analysis results for CDR levels of feedstock options for all NET options.

5. Discussion

Traditional optimization models for NET deployment often rely on deterministic assumptions or post-optimization sensitivity analyses, which do not fully capture the inherent uncertainties in resource availability, technological performance, and decision-makers' risk perceptions (Migo-Sumagang et al., 2022). In contrast, the proposed NeLP model explicitly incorporates membership, non-membership, and indeterminacy components to represent uncertainties, providing a more comprehensive framework for risk management. Existing studies on NET portfolio optimization, such as those by Migo-Sumagang et al. (2023) and Fajardy et al. (2018), have primarily focused on deterministic or fuzzy optimization frameworks. While these approaches provide valuable insights, they often fail to account for risk perceptions. The NeLP model addresses this gap by generating optimal CDR levels tailored to different risk behaviors, as demonstrated in the case studies. For example, in the BECCS feedstock selection case study, the model identifies Switchgrass and Miscanthus as optimal choices, while excluding Eucalyptus due to its high resource uncertainties. This result contrasts with traditional models, which may not adequately capture the trade-offs between resource utilization and risk tolerance. The insights derived from the NeLP model have significant practical implications for policymakers and stakeholders. For instance, the sensitivity analysis reveals that the optimal CDR levels of different NET options vary significantly across risk settings. In the land-based NET portfolio case study, Enhanced Weathering (EW) shows higher CDR potential under low indeterminacy tolerance, while Direct Air Carbon Capture and Storage (DACCS) performs better under higher indeterminacy tolerance. These findings provide decision-makers with a range of solutions that align with their risk appetite, enabling more informed and adaptive strategies for NET deployment.

6. Conclusions

A neutrosophic linear programming model is developed for optimizing NET portfolios considering the environmental impacts of the NETs such as costs, energy consumption, water use, land footprint, and nitrogen and phosphorus requirements. The model considers the total CDR target, optimal CDR levels of each option, and the resource limits as neutrosophic sets with components of membership, non-membership, and indeterminacy. The consideration of neutrosophic sets allows the management of risks associated with uncertainties in different parameters. The model can generate the optimal CDR levels at different risk behaviors generated from different levels of dissatisfaction towards the sub-optimality of neutrosophic factors and indeterminacy of attaining optimality of these factors. From the two case studies presented, the behavior of the CDR levels of different options varies from one risk setting to another. The CDR levels generated from all risk settings are numerous optimal solutions that can be adopted at a given range of indeterminacy and dissatisfaction tolerance. The insights gathered from the changing optimal solutions based on changes in risk appetite allow the decision-makers to see which NET has the potential for large-scale greenhouse gas emission reduction. For instance, the optimal level of reduction from DAC is higher when the decision environment calls for a high tolerance to indeterminacy where the indeterminacy of attaining high levels of CDR is lower. The case is different for EW, where the CDR level gets smaller with a higher tolerance of indeterminacy. In terms of the choice of feedstock for BECCS, potential candidates include Switchgrass and Miscanthus based on the data presented. Future work includes extending the model to incorporate multi-period and multi-regional settings where resources can be allocated between regions and integrating with other uncertainty frameworks, such as stochastic programming to enhance its robustness. Additionally, the mathematical programming model developed can be extended to consider different set structures such as plithogenic sets, and neutrosophic statistics. This future work may incorporate socio-economic factors, and development into decision support tools will broaden its applicability and practical impact in climate change mitigation and beyond.

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Conflicts of Interest: "The authors declare no conflict of interest.

Nomenclature

Abbreviations

AR	Afforestation/Reforestation
BC	Biochar Application to Soil
BECCS	Bioenergy with Carbon Capture and Storage
CDR	Carbon Dioxide Removal
DACCS	Direct Air Carbon Capture and Storage
EW	Enhanced Weathering
FMP	Fuzzy Mathematical Programming
NDEA	Neutrosophic Data Envelopment Analysis
NETs	Negative Emissions Technologies
SCS	Soil Carbon Sequestration

Index

i and k	Index of NET option
j	Index of resource

Parameters

D_j	Availability of resource j
D_j^{L}	Lower resource availability limit
D_j^{U}	Upper resource availability limit
E	Estimated geological storage capacity
E^L	Lower geological storage capacity limit
E^U	Upper geological storage capacity limit
E^M	Modal geological storage capacity limit
M_{ij}	Utilization of resource j by option i
R	Total CDR
R^{L}	Lower bound of total CDR
R^{U}	Upper bound of total CDR
S_i	Binary parameter that denotes that the option i requires a geological storage resource
TE	Falsity tolerance
TI	Indeterminacy tolerance
X_i^{L}	Lower capacity limit of NET i
X_i^{U}	Upper capacity limit of NET i
Z_{ijk}	Discount for resource j if options i and k are activated at the same time

Variables

α	Overall degree of satisfaction
β	Overall degree of dissatisfaction
b_i	Represents whether the CDR option i is selected
c_{ik}	Denotes whether option i and k are both selected
γ	Overall degree of uncertainty
x_i	Capacity of NET option i in terms of the target reduction

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