Challenges in Sustainability
https://www.acadlore.com/journals/CIS

A Decision-Making Model for Prioritizing Low-Carbon Policies in Climate Change Mitigation

Yanjun Qiu[1,2], Mouhamed Bayane Bouraima[3], Ibrahim Badi[4], Željko Stević[5,6*], Vladimir Simic[7]

[1] School of Civil Engineering, Southwest Jiaotong University, 610031 Chengdu, China
[2] Highway Engineering Key Laboratory of Sichuan Province, Southwest Jiaotong University, 610031 Chengdu, China
[3] Department of Civil Engineering, Sichuan College of Architectural Technology, 618000 Deyang, China
[4] Mechanical Engineering Department, Libyan Academy, 2429 Misurata, Libya
[5] Faculty of Transport and Traffic Engineering, University of East Sarajevo, 74000 Doboj, Bosnia and Herzegovina
[6] School of Industrial Management Engineering, Korea University, 02841 Seoul, Korea
[7] Faculty of Transport and Traffic Engineering, University of Belgrade, 11010 Belgrade, Serbia

[*] Correspondence: Željko Stević (zeljkostevic88@yahoo.com)

Received: 02-11-2024 **Revised:** 04-10-2024 **Accepted:** 04-18-2024

Citation: Qiu, Y. J., Bouraima, M. B., Badi, I., Stević, Ž., & Simic, V. (2024). A decision-making model for prioritizing low-carbon policies in climate change mitigation. *Chall. Sustain.*, *12*(1), 1-17. https://doi.org/10.56578/cis120101.

Abstract: Climate change (CC) represents a paramount environmental challenge, necessitating the deployment of sustainable, low-carbon strategies particularly in developing regions such as Africa. This study introduces a novel decision-making framework aimed at enhancing the prioritization of policies to combat the adverse effects of CC. The proposed two-stage model employs the integration of Step-Wise Weight Assessment Ratio Analysis (SWARA) and Weighted Aggregated Sum Product Assessment (WASPAS) under spherical fuzzy (SF) conditions to address the strategic sequencing of sustainable policies. Initially, SF-SWARA is utilized to ascertain the relative significance of diverse criteria. Subsequently, the SF-WASPAS method ranks these policies, facilitating informed decision-making. The primary obstacles identified include limited institutional capacity, insufficient financial resources, and technological constraints, for which strategic alternatives are proposed. Moreover, rigorous sensitivity and comparative analyses affirm the model's applicability. By systematically delineating and prioritizing necessary policies, this study contributes significantly to the scholarly discourse on climate mitigation (CM) in an African context.

Keywords: Decision-making model; Multiple criteria; Climate change; Step-wise weight assessment ratio analysis; Weighted aggregated sum product assessment; Spherical fuzzy sets

1. Introduction

Collaborative efforts between advanced and emerging nations are crucial for achieving global climate change mitigation (CCM) goals (Seyboth, 2013; Villi, 2023), especially in addressing the enduring impacts in Africa. These impacts include altered rainfall patterns influencing agriculture and food security, heightened water scarcity, diminished fish resources in great lakes due to overfishing and rising temperatures, elevated sea levels impacting densely populated coastal areas, and increased water stress.

Initiatives such as low-carbon development pathways (LCDPs) play a crucial role in the stabilization of the global climate (Tyler et al., 2013). The realization of climate policy goals, particularly in the emerging world, hinges on the effective implementation of LCDPs (Seyboth, 2013). To meet international CCM targets, it is imperative to formulate nationally appropriate mitigation actions (NAMAs) across Africa (Linnér & Pahuja, 2012). In developing nations, such as those in Africa, CM entails steering development away from the traditional link of carbon emissions with income. The objective is to achieve emissions below a business-as-usual baseline without necessarily reducing them below current levels.

African nations frequently emphasize adaptation over mitigation endeavors (Adenle et al., 2017b). Although this approach enhances the resilience of developing economies against escalating weather and climate uncertainties, the integration of mitigation activities can often synergize with adaptation efforts (Duguma et al., 2014). Additionally, numerous African nations have pledged to decrease emissions as part of the Paris Agreement (PA), generating a need for institutions capable of mobilizing funds and executing CM initiatives continent-wide.

As African nations experience income growth, obtaining external funding is crucial for achieving CM goals. Despite dedicating resources to the issue, securing funding from bilateral and multilateral donors remains challenging (Gujba et al., 2012). Key barriers include restricted capacity, fragile institutions, and the absence of a transparent framework for accessing climate financing in Africa (Timilsina et al., 2010).

Strong research and development (R&D) programs, exemplified by China, significantly drive the rapid expansion of renewable energy (RE) in developing nations (Amatayakul & Berndes, 2012). Rong (2010) argued that effective institutionalization, crucial for project implementation, facilitated the effective adoption of the clean development mechanism (CDM). Nevertheless, numerous African nations encountered difficulties in attracting or executing these projects.

Research on CCM in Africa has been conducted in countries like South Africa (Elum et al., 2017), Nigeria (Elum & Momodu, 2017), Kenya (Reppin et al., 2020), Ethiopia (Zegeye, 2018), and Tanzania (Shemdoe et al., 2015), as well as through a broader literature review across regions (Adenuga et al., 2021; Dagnachew et al., 2018; Tschora & Cherubini, 2020). However, only a few researchers have proposed specific strategies for low-carbon development and CCM (LCDCCM) in Africa (Adenle et al., 2015; Adenle et al., 2017a; Adenle et al., 2017b). Notably, Adenle et al. (2017a) are among the few who have addressed such strategies, although their work did not prioritize them. Recognizing the limitations of previous research, addressing LCDCCM necessitates an approach offering a comprehensive managerial perspective and explicitly considering multiple criteria to enhance decision outcomes. Multi-criteria decision-making (MCDM) techniques are well-suited for this purpose (Bouraima et al., 2024a).

1.1 Objectives

The objectives of this study are: (i) to introduce an approach via MCDM to address LCDCCM in Africa; (ii) to identify the most critical challenge to LCDCCM and provide the strategy to overcome the challenge; and (iii) to propose a decision-making model for LCDCCM.

Therefore, the following questions are raised: (i) What is the approach to addressing LCDCCM in Africa? (ii) What are the most critical challenges to LCDCCM? (iii) What is the most appropriate strategy to promote LCDCCM?

1.2 Contributions

This study makes contributions as follows:

Firsthand information was collected by distributing SWARA and WASPAS surveys to seasoned experts with significant policymaking expertise.

Unlike Bouraima et al. (2024b), who presented a framework to manage CC risks (CC adaptation) in Africa, this study identified and proposed solutions to the key challenges in LCDCCM from an MCDM perspective, thereby adeptly addressing a significant gap in CCM literature in Africa.

In addition, this study provides decision-makers with experimental data and leverages a unique MCDM feature for comprehensive guidance. Grounded in spherical fuzzy set (SFS) theory, this method proves suitable for addressing intricate issues, especially in the realm of CC programs, where criteria may not be adequately expressed through mathematical formulations.

This study distinguishes itself from existing literature by utilizing an integrated SF-SWARA-WASPAS methodology to evaluate alternatives in LCDCCM in Africa. The results have potential advantages for African governments, aiding in the selection of effective strategies to promote LCDCCM.

1.3 Motivation for Using the SF-SWARA-WASPAS Approach

SFS was developed for the effective handling of uncertainty in expert judgments (Kutlu Gündoğdu & Kahraman, 2019a). In SFS, although the sum of its three elements can surpass 1, their squared sum must still be within [0, 1], creating a nonlinear function. Additionally, SFS offers decision-makers flexibility by enabling independent definition of the degree of these three elements, improving the formulation of decision-making issues. Its integration enhances the intelligence of the decision-making procedure, closely resembling human judgment and leading to increased accuracy in assessing alternatives.

The determination of criteria weights relies on assessments made by decision-makers and involves subjective opinions. Several methods have recently emerged to calculate subjective weights for criteria. Notably, approaches such as the Best-Worst Method (BWM) and the Full Consistency Method (FUCOM) have found application across various domains of life. BWM, a comparison-based approach (Rezaei, 2016), ensures consistency and reliability with a reduced amount of comparison data, leading to quicker implementation (Rezaei, 2016). Despite these advantages, BWM may be considered less suitable for complex non-linear models due to the extensive pairwise comparisons it requires. FUCOM addresses redundancy in pairwise comparisons for determining criteria weights (Prentkovskis et al., 2018), requiring only less pairwise comparison (Badi & Kridish, 2020). It outperforms BWM in criteria number and stability (Badi & Abdulshahed, 2019), but it lacks more validation approaches. Unlike the analytical hierarchy process (AHP) (Hashemkhani Zolfani et al., 2018), SWARA evaluated subjective criteria weights (Keršuliene et al., 2010) without using predefined scales. This made it more stable, easier to use, and less complicated to compute. As it eliminates pairwise comparisons, SWARA is a suitable choice for this study.

The widely-used multi-attributive border approximation area comparison (MABAC) is known for its consistent outcomes, stable solutions, and a simplified algorithm for huge issues (Pamučar & Ćirović, 2015; Torkayesh et al., 2023). But it has a normalization technique issue, which may introduce biased solutions. Conversely, the WASPAS method, incorporating two different models (Zavadskas et al., 2012), is recognized for its computational simplicity, accuracy, and resistance to rank reversal (Bouraima et al., 2024b), making it well-suited for ranking alternatives for CCM strategies.

The remainder of this study is structured as follows: Section 2 presents a comprehensive review of the literature. Section 3 describes the methodology employed. The application of this model is demonstrated in Section 4. Section 5 conducts a sensitivity analysis. Comparative analysis is undertaken in Section 6. Section 7 discusses the findings. Managerial implications are elaborated in Section 8. The study concludes in Section 9.

2. Literature Review

2.1 Abbreviations

The abbreviations in the study are shown in Table 1.

Table 1. Abbreviations

ARAS	Additive Ratio Assessment	IVN	Interval-Valued Neutrosophic
BCFS	Bipolar Complex Fuzzy Set	MACBETH	Measuring Attractiveness by a Categorical Based Evaluation Technique
CODAS	Combinative Distance-based Assessment	MARCOS	Measurement of Alternatives and Ranking according to Compromise Solution
COPRAS	Complex Proportional Assessment	MEREC	Method based on the Removal Effects of Criteria
CRITIC	Criteria Importance Through Intercriteria Correlation	MULTIMOORA	Multi-Objective Optimization Ratio Analysis plus Full Multiplicative Form
DNMA	Double Normalization-Based Multi-Aggregation	PIPRECIA	Pivot Pairwise Relative Criteria Importance Assessment
EM	Entropy Measure	RS	Rank Sum
FRN	Fuzzy Rough Number	SF	Spherical Fuzzy
IF	Intuitionistic Fuzzy	T2NN	Type-2 Neutrosophic Number
IVFF	Interval Valued Fermatean Fuzzy		
IVIF	Interval Valued Intuitionistic Fuzzy		
IVPFS	Interval Valued Pythagorean Fuzzy Set		

2.2 Overview of CCM Approaches

The global CC denotes the shift in long-term weather patterns worldwide. Scientists absolutely confirm the earth's warming, prompting extensive studies. For instance, Elum et al. (2017) analyzed climate parameters, farmers' perceptions, production constraints, and coping strategies. Reppin et al. (2020) checked agroforestry's potential to improve livelihoods and mitigate CC on smallholder farms. Zegeye (2018) focused on CM drivers, impacts, and mitigation options. Adenuga et al. (2021) explored CM impacts in sub-Saharan Africa and mitigation strategies. Dagnachew et al. (2018) examined the CCM synergies. Adenle et al. (2015) evaluated the impact of R&D on CCM and adaptation technologies.

2.3 Applications of MCDM to CCM Studies

Recent years have seen a significant focus on researching CCM, leading to the development of decision support tools that reduce sources. For instance, Simic et al. (2022) tackled and resolved the challenge of selecting sustainable policies for CCM in urban transport. Deveci et al. (2022) investigated the need for considering societal dynamics in an optimal action plan and explored how implemented actions can impact and reshape CCM strategies. Pamucar et al. (2022) addressed a literature gap by examining the selection procedure for the most effective green approach to CC. Deveci et al. (2023) enhanced studies on the flexibility of transportation networks in the face of CC. Mishra et al. (2023) outlined strategies to decrease greenhouse gas emissions from transportation, aiding urban CC policies. Table 2 contains field-related studies.

Table 2. Decision-making techniques in CCM studies

Source	Focus	GDM	SA	Method
Simic et al. (2022)	CCM effects on urban transportation	Yes	Yes	T2NN, MEREC, MARCOS
Deveci et al. (2022)	Socio-economic dynamics of CCM strategies	Yes	Yes	Fuzzy Einstein WASPAS
Pamucar et al. (2022)	Green strategies in mobility schemes	Yes	Yes	Fuzzy D PRIPRECIA
Deveci et al. (2023)	CCM-flexible transport alternative assessment	Yes	Yes	IVIF, MEREC, RS, MULTIMOORA
Mishra et al. (2023)	Urban CC policy for transport affairs	Yes	Yes	IVFF, DNMA, CRITIC, RS
This study	LCDCCM	Yes	Yes	SF-SWARA-WASPAS

2.4 Overview of Studies Related to SWARA and WASPAS Methods

The SWARA and WASPAS approaches have demonstrated their ability in many studies (Ghoushchi et al., 2022). For the SWARA method, Patel et al. (2023) evaluated the sustainability criteria of a medical waste treatment method. Alkan (2024) assessed the orientation of RE systems toward sustainable development and utilization. Tripathi et al. (2023) evaluated an alternative food waste treatment technology (FWTT) under conditions of uncertainty. Alrasheedi et al. (2023) applied an approach to the RE source issue, considering multiple aspects of sustainability. Cakmak (2023) assessed and chose suppliers for its durable supplier park. Chen et al. (2023) applied a method in a case study related to the production of environmentally friendly materials. Liu et al. (2023) applied the WASPAS method to address the issue of selecting green suppliers. Singh (2024) optimized a solar water heating system to increase its efficiency. Menekşe & Akdağ (2023) evaluated alternative methods for medical waste disposal. Görçün et al. (2023) addressed vehicle fleets appropriately for urban transportation. Hashemkhani Zolfani et al. (2023) chose turret trucks that effectively minimize idle costs and enhance the economic efficiency of logistics. Studies related to both approaches are shown in Table 3.

Table 3. Studies related to the application of SWARA and WASPAS methods

Authors	Aims	Env.	Methods
Patel et al. (2023)	Assessment of medical waste treatment techniques	IF	EM-SWARA-TOPSIS
Alkan (2024)	RE systems assessment	IVPFS	CRITIC-SWARA-CODAS
Tripathi et al. (2023)	FWTT choice	IF	SWARA, COPRAS
Alrasheedi et al. (2023)	Renewable energy choice issues	IF	SWARA, WASPAS
Cakmak (2023)	Supplier selection	IVN	SWARA, CODAS
Chen et al. (2023)	Green supplier choice	FRN	SWARA, ARAS
Liu et al. (2023)	Green supplier choice	BCFS	CRITIC, WASPAS
Singh (2024)	Solar water heat evaluation	-	WASPAS, MACBETH
Menekşe & Akdağ (2023)	Medical waste disposal planning	SF	CRITIC, WASPAS
Görçün et al. (2023)	Tramcar choice for durable transport	-	WASPAS'PH
Hashemkhani Zolfani et al. (2023)	Choice of warehouse handling equipment	IFDAO	FUCOM, WASPAS
This study	LCDCCM	SF	SWARA, WASPAS

3. Methodology

This study proposes an approach to overcome the limitations of previous studies. The goal is to assess critical barriers to LCDCCM in Africa and propose effective strategies to overcome them. The flowchart of the methodology is shown in Figure 1.

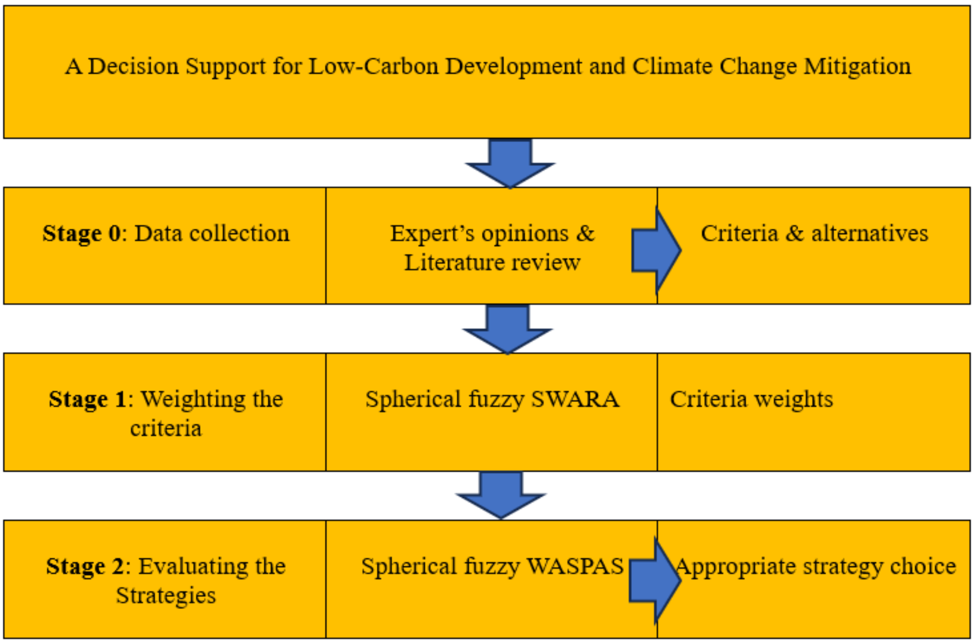

Figure 1. Flowchart of the methodology

3.1 Preliminaries

The imprecision and uncertainty of linguistic expressions can be captured by SFS, which defines three functions that can be implemented more broadly, offering decision-makers greater flexibility in expressing their ideas (Ayyildiz & Taskin, 2022). The definition of these functions is described in [0,1]. Some definitions (Gündoğdu & Kahraman, 2020; Kahraman et al., 2019; Kutlu Gündoğdu & Kahraman, 2019b) indicate conditions that a spherical fuzzy number (SFN) should meet.

Definition 1: A SFN is presented as follows:

$$\tilde{S} \cong \left\{x, \tilde{S}\left(\mu_{\tilde{s}}(x), v_{\tilde{s}}(x), \pi_{\tilde{s}}(x)\right); x \in X\right\} \tag{1}$$

where, $\mu_{\tilde{s}}(x): X \mapsto [0,1]$, $v_{\tilde{s}}(x): X \mapsto [0,1]$ and $\pi_{\tilde{s}}(x): X \mapsto [0,1]$ represent the membership, non-membership, and hesitancy functions of the component $x \in X$ to $\tilde{S}$, respectively, and X is a fixed set. And their sum of squares cannot be greater than 1.

$$0 \le \mu_{\tilde{s}}(x)^2 + v_{\tilde{s}}(x)^2 + \pi_{\tilde{s}}(x)^2 \le 1; x \in U \tag{2}$$

Definition 2: Two SFNs $\tilde{\alpha} = S\,(\mu_\alpha, v_\alpha, \pi_\alpha)$ and $\tilde{\beta} = S\left(\mu_\beta, v_\beta, \pi_\beta\right)$ are summed as follows (Gündoğdu & Kahraman, 2020):

$$\tilde{\alpha} \oplus \tilde{\beta} = \tilde{S}\left(\sqrt{\mu_{\tilde{\alpha}}^2 + \mu_{\tilde{\beta}}^2 - \mu_{\tilde{\alpha}}^2\mu_{\tilde{\beta}}^2}, v_{\tilde{\alpha}}v_{\tilde{\beta}}, \sqrt{\left(1-\mu_{\tilde{\alpha}}^2\right)\pi_{\tilde{\beta}}^2 + \left(1-\mu_{\tilde{\beta}}^2\right)\pi_{\tilde{\alpha}}^2 - \pi_{\tilde{\alpha}}^2\pi_{\tilde{\beta}}^2}\right) \tag{3}$$

Definition 3: Two SFNs $\tilde{\alpha} = S\,(\mu_\alpha, v_\alpha, \pi_\alpha)$ and $\tilde{\beta} = S\left(\mu_\beta, v_\beta, \pi_\beta\right)$ are multiplied as follows:

$$\tilde{\alpha} \otimes \tilde{\beta} = \tilde{S}\left(\mu_{\tilde{\alpha}}\mu_{\tilde{\beta}}, \sqrt{v_{\tilde{\alpha}}^2 + v_{\tilde{\beta}}^2 - v_{\tilde{\alpha}}^2 v_{\tilde{\beta}}^2}, \sqrt{\left(1-v_{\tilde{\alpha}}^2\right)\pi_{\tilde{\beta}}^2 + \left(1-v_{\tilde{\beta}}^2\right)\pi_{\tilde{\alpha}}^2 - \pi_{\tilde{\alpha}}^2\pi_{\tilde{\beta}}^2}\right) \tag{4}$$

Definition 4: A SFN $\tilde{\alpha} = S\,(\mu_\alpha, v_\alpha, \pi_\alpha)$ is multiplied by a positive scalar as follows:

$$\lambda\tilde{\alpha}=\tilde{S}\left(\sqrt{1-\left(1-\mu_{\tilde{\alpha}}^{2}\right)^{\lambda}},v_{\tilde{\alpha}}^{\lambda},\sqrt{\left(1-\mu_{\tilde{\alpha}}^{2}\right)^{\lambda}-\left(1-\mu_{\tilde{\alpha}}^{2}-\pi_{\tilde{\alpha}}^{2}\right)^{\lambda}}\right) \tag{5}$$

Definition 5: The positive power of SFN $\tilde{\alpha} = S\ (\mu_\alpha, v_\alpha, \pi_\alpha)$ is as follows:

$$\tilde{\alpha}^{\lambda}=\tilde{S}\left(\mu_{\tilde{\alpha}}^{\lambda},\sqrt{1-\left(1-v_{\tilde{\alpha}}^{2}\right)^{\lambda}},\sqrt{\left(1-v_{\tilde{\alpha}}^{2}\right)^{\lambda}-\left(1-v_{\tilde{\alpha}}^{2}-\pi_{\tilde{\alpha}}^{2}\right)^{\lambda}}\right) \tag{6}$$

Definition 6: The scoring function for an SFN $\tilde{\alpha} = S\ (\mu_\alpha, v_\alpha, \pi_\alpha)$ is as follows (Ayyildiz & Taskin, 2022):

$$\mathrm{Score}(\tilde{\alpha})=\left(2\mu_{\tilde{\alpha}}-\pi_{\tilde{\alpha}}\right)^{2}-\left(v_{\tilde{\alpha}}-\pi_{\tilde{\alpha}}\right)^{2} \tag{7}$$

Definition 7. Spherical Weighted Arithmetic Mean (SWAM) is given below (Kahraman et al., 2019):

$$SWAM_{w}\left(\tilde{\alpha}_{1},\ldots\ldots,\ \tilde{\alpha}_{n}\right)=w_{1}\ \tilde{\alpha}_{1}+w_{2}\ \tilde{\alpha}_{2}+\ldots\ldots+w_{n}\ \tilde{\alpha}_{n}$$
$$=\left\{\begin{array}{c}\left[1-\prod_{i=1}^{n}\left(1-\mu_{\tilde{\alpha}_{i}}^{2}\right)^{w_{i}}\right]^{1/2},\prod_{i=1}^{n}v_{\tilde{\alpha}_{i}}^{w_{i}},\\ \left[\prod_{i=1}^{n}\left(1-\mu_{\tilde{\alpha}_{i}}^{2}\right)^{w_{i}}-\prod_{i=1}^{n}\left(1-\mu_{\tilde{\alpha}_{i}}^{2}-\pi_{\tilde{\alpha}_{i}}^{2}\right)^{w_{i}}\right]^{1/2}\end{array}\right\}$$

where, $w = (w_1, w_2 \ldots \ldots, w_n)$, $w_i \in [0,1]$, and $\sum_{i=1}^{n} w_i = 1$.

3.2 SF-SWARA

In this investigation, the criteria weighting was carried out using the SF-SWARA methodology with the following steps (Bouraima et al., 2023; Jafarzadeh Ghoushchi et al., 2023).

Step 1. Experts proposed a matrix decision, employing linguistic variables from the study by Jafarzadeh Ghoushchi et al. (2023) to assess the importance of criteria. Let $\tilde{A}_{jk} = (\mu_{jk}, v_{jk}, \pi_{jk})$ be a SFN for criterion j assessment by decision-maker k.

Step 2. Experts' judgments were aggregated via a SWAM operator.

$$SWAM_{\omega_k}(\tilde{A}_{jk}, \ldots \ldots, \tilde{A}_{jt}) = \omega_1 A\tilde{A}_{j1} + \omega_2 \tilde{A}_{j2} + \cdots \ldots + \omega_t \tilde{A}_{jt}$$
$$\tilde{z}_j = (\mu_j, v_j, \pi_j) = \left\{\begin{array}{c}\left[1-\prod_{k=1}^{t}\left(1-\mu_{\tilde{A}_{jk}}^{2}\right)^{\omega_k}\right]^{1/2},\prod_{k=1}^{t} v_{\tilde{A}_{jk}}^{\omega_k},\\ \left[\prod_{k=1}^{t}\left(1-\mu_{\tilde{A}_{jk}}^{2}\right)^{\omega_k}-\prod_{k=1}^{t}\left(1-\mu_{\tilde{A}_{jk}}^{2}-\pi_{\tilde{A}_{jk}}^{2}\right)^{\omega_k}\right]^{1/2}\end{array}\right\} \tag{8}$$

where, ω_k is the expert value k, t is the expert number, and z_j is the aggregate value of j criteria.

Step 3. Each criterion score was calculated as follows:

$$\mathrm{Score}\left(\tilde{z}_{j}\right)=\left(2\mu_{j}-\pi_{j}\right)^{2}-\left(v_{j}-\pi_{j}\right)^{2} \tag{9}$$

Step 4. The score values for criteria were ranked in decreasing order.

Step 5. The calculation of comparative significance (c_j) was established by distinguishing the score rate of j and j-1 criteria, respectively.

Step 6. Comparative coefficient (k_j) was established for each criterion.

$$k_j = \begin{cases} 1, & j = 1 \\ c_j + 1, & j > 1 \end{cases} \tag{10}$$

Step 7. Criterion weight (q_j) was calculated as follows:

$$q_j = \begin{cases} 1, & j = 1 \\ \dfrac{q_{j-1}}{k_j}, & j > 1 \end{cases} \tag{11}$$

Step 8. Recomputed weights were normalized as follows:

$$w_j = \frac{q_j}{\sum_{j=1}^{n} q_j} \tag{12}$$

3.3 SF-WASPAS

This section describes the following nine steps:
Step 1. A decision matrix was established for the evaluation of alternatives.
Step 2. A SWAM operator was applied to aggregating expert judgments as follows:

$$SWAM_{\omega_k}(\tilde{X}_{ijk}, \dots \dots, \tilde{X}_{ijt}) = \omega_1 \tilde{X}_{ij1} + \omega_2 \tilde{X}_{ij2} + \cdots \dots + \omega_t \tilde{X}_{ijt}$$
$$\tilde{R}_{ij} = (\mu_{ij}, \nu_{ij}, \pi_{ij}) = \left\{ \begin{array}{c} \left[1 - \prod_{k=1}^{t} \left(1 - \mu_{\tilde{X}_{ijk}}^2\right)^{\omega_k}\right]^{1/2}, \prod_{k=1}^{t} \nu_{\tilde{X}_{ijk}}^{\omega_k}, \\ \left[\prod_{k=1}^{t} \left(1 - \mu_{\tilde{X}_{ijk}}^2\right)^{\omega_k} - \prod_{k=1}^{t} \left(1 - \mu_{\tilde{X}_{ijk}}^2 - \pi_{\tilde{X}_{ijk}}^2\right)^{\omega_k}\right]^{1/2} \end{array} \right\} \tag{13}$$

Step 3. A weighted decision matrix regarding criteria weights was established.
Step 4. The weight sum model (WSM) ($\tilde{Q}^1$) was calculated for alternatives:

$$\tilde{Q}_i^1 = \sum_{j=1}^{n} \tilde{S}_{ijw}$$
$$\tilde{S}_{ijw} = \tilde{S}_{ij} w_j = \left(\sqrt{1 - (1 - \mu_{\tilde{R}_{ij}}^2)^{w_j}}, \nu_{\tilde{R}_{ij}}^{w_j}, \sqrt{(1 - \mu_{\tilde{R}_{ij}}^2)^{w_j} - (1 - \mu_{\tilde{R}_{ij}}^2 - \pi_{\tilde{R}_{ij}}^2)^{w_j}} \right) \tag{14}$$

Step 5. Weight product model (WPM) ($\tilde{Q}^2$) was calculated as follows:

$$\tilde{Q}_i^2 = \prod_{j=1}^{n} \tilde{R}_{ij}^{w_j} \tag{15}$$

$$\tilde{R}_{ij}^{w_j} = \left(\mu_{\tilde{R}_{ij}}^{w_j} \sqrt{1 - \left(1 - \nu_{\tilde{R}_{ij}}^2\right)^{w_j}}, \sqrt{\left(1 - \nu_{\tilde{R}_{ij}}^2\right)^{w_j} - \left(1 - \nu_{\tilde{R}_{ij}}^2 - \pi_{\tilde{R}_{ij}}^2\right)^{w_j}} \right) \tag{16}$$

Step 6. WSM and WPM were combined with the threshold value $(\lambda) \in [0, 1]$.

$$\lambda \tilde{Q}_i^1 = \left(\sqrt{1 - \left(1 - \mu_{\tilde{Q}_i^1}^2\right)^{\lambda}}, \nu_{\tilde{Q}_i^1}^{\lambda}, \sqrt{\left(1 - \mu_{\tilde{Q}_i^1}^2\right)^{\lambda} - \left(1 - \mu_{\tilde{Q}_i^1}^2 - \pi_{\tilde{Q}_i^1}^2\right)^{\lambda}} \right) \tag{17}$$

$$(1-\lambda)\tilde{Q}_i^2=\left(\sqrt{1-\left(1-\mu_{\tilde{Q}_i^2}^2\right)^{(1-\lambda)}}, v_{\tilde{Q}_i^2}^{1-\lambda}, \sqrt{\left(1-\mu_{\tilde{Q}_i^2}^2\right)^{(1-\lambda)}-\left(1-\mu_{\tilde{Q}_i^2}^2-\pi_{\tilde{Q}_i^2}^2\right)^{(1-\lambda)}}\right) \tag{18}$$

Step 7. The performance of the alternatives was analyzed via the relative weight.

$$\tilde{Q}_i=\lambda\ \tilde{Q}_i^1+(1-\lambda)\ \tilde{Q}_i^2 \tag{19}$$

Step 8. The final scores were determined.
Step 9. The alternatives were ranked based on final scores.

4. Application

This section involves identifying critical challenges and determining appropriate alternatives for promoting LCDCCM. It comprises three sub-sections. To ensure reliability, interviews were conducted with three experts selected based on criteria such as proficiency and extensive experience in policymaking.

4.1 Definitions of Criteria and Alternatives

Six challenges and four alternatives are defined in Table 4.

Table 4. Definitions for criteria and alternatives

Criteria and Alternatives	Definitions	References
Limited institutional capacity (**C1**)	It encompasses shortcomings related to technical competence (expertise or skills), legal frameworks, experience, and regulation.	Bouraima et al. (2024b)
Lack of funds (**C2**)	The climate finance deficit is a pressing challenge for Africa, limiting its ability to handle key climate-related issues, adapt to changing conditions, mitigate CC impacts, and build resilience against adverse effects.	Adenle et al. (2017b)
Technological limitations (**C3**)	Limited infrastructure hampers the widespread adoption of vital advanced technologies for sustainability, while financial constraints restrict many African countries from acquiring and implementing costly technologies necessary for effective CCM.	Francisco Ribeiro & Camargo Rodriguez (2020)
Lack of awareness (**C4**)	A significant challenge persists due to a lack of awareness among the public and policymakers regarding the benefits of transitioning to a low-carbon economy. This hinders effective advocacy for mitigation action at the national level.	Expert opinion
Unfavorable politics (**C5**)	It emphasizes that adverse politics pose a substantial barrier in Africa. Their survey brings attention to concerns about inadequate R&D in RE technologies, particularly when governments derive benefits from fossil fuel rents. This suggests a lack of political will among resource-dependent governments to shift away from dependence on fossil fuels.	Adenle et al. (2017b)
Poor physical infrastructure (**C6**)	Improving public transportation infrastructure can reduce greenhouse gas emissions, ease congestion, and enhance urban life. However, in Africa, weak institutions, compounded by barriers like inadequate infrastructure, hinder project implementation. According to a study, poor road infrastructure limits the distribution of emission-reducing cooking stove technologies in remote rural areas, isolating them from markets.	Clough (2012)
Strategic partnership development (**S1**)	Current regional partnerships are disintegrated among institutions, resulting in overlapping projects for sustainable development and CCM. Many African universities have limited or no commitment to existing regional development institutions. Therefore, there is a critical necessity to establish powerful partnerships to provide funds and enhance collaboration within the continent and globally. Strategic partnerships should also include research collaborations with researchers from advanced countries to build sustainable research abilities, particularly in planning and evaluating mitigation priorities, knowledge transfer, technology and market-based mechanisms.	Cloete et al. (2012)
R&D (**S2**)	The Climate Change Mitigation Institution (CCMI) should support African researchers in universities and institutes to engage in R&D for developing context-appropriate mitigation technologies. This could involve incentivizing	Tawney et al. (2011)

	subsidies for the creation of low-emission technologies, leading to reduced costs over time.	
Financial coordination (**S3**)	Finance ministries can collaborate with the CCMI to align international and domestic funding sources, facilitating support for LCDPs. The CCMI's role extends to helping national governments and private sectors access existing financing for LCDPs, and it can also contribute to establishing an organization dedicated to collecting and distributing CM funds, complementing institutional strengthening efforts.	Expert opinion
Institutional capacity building (**S4**)	A successful CCMI in Africa should empower individual governments to establish local institutions for implementing the mitigation projects outlined in the NAMA. The CCMI can also assist existing institutions in addressing CM and provide support as countries enhance their own capacity beyond policy and institutional development.	Expert opinion

Figure 2 shows the four potential strategies/alternatives, which are used to address the most critical challenges that impede LCDCCM in Africa.

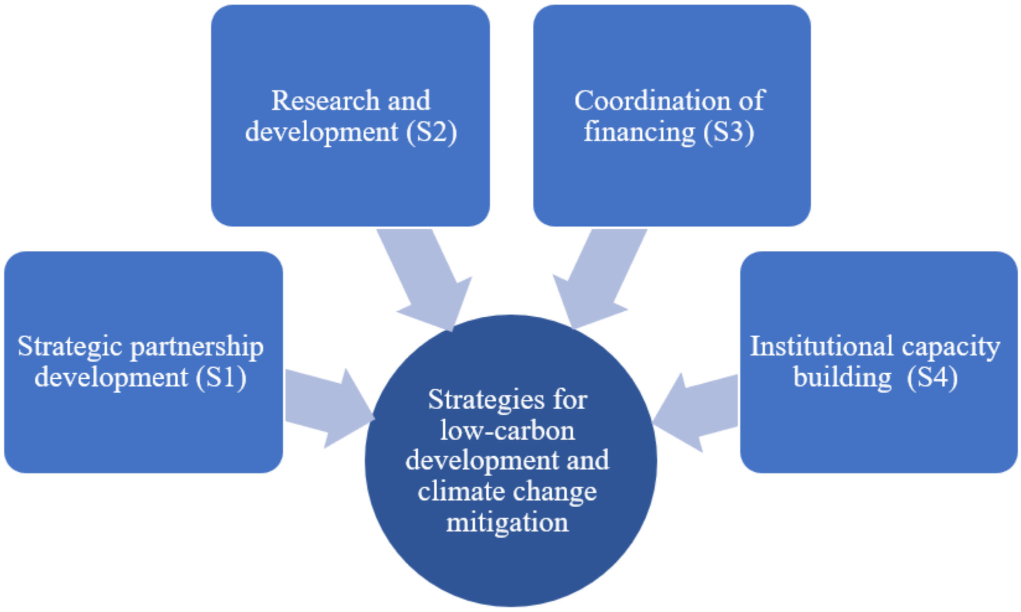

Figure 2. Adopted strategies for LCDCCM in Africa

4.2 Weighting of Criteria

Expert teams were tasked with completing a questionnaire to contribute their insights on the importance of each criterion. The linguistic indicators in Table 5 show the weights assigned to these criteria by experts. Following the collection of expert opinions, SWAM operators were utilized in the integration process by considering the experts' weights outlined in Table 6. Through interviews with the experts, weights were assigned accordingly, with E1 and E3 having the same weight of 0.35 and E2 having a weight of 0.30. After defining the scoring function, the criterion weight was established using the SF-SWARA method in Table 7.

In Figure 3, limited institutional capacity is identified as the most crucial challenge by experts, followed by lack of funds, technological limitations, poor physical infrastructure, unfavorable politics, and lack of awareness. The normalized weight for criterion C1 (limited institutional capacity) is 0.212, while that of criterion C4 (lack of awareness) is 0.133.

Table 5. Importance of criterion weights

Criteria	E1	E2	E3
C1	H	VH	MH
C2	VH	MH	MH
C3	H	M	MH
C4	EL	EL	VL
C5	VL	VL	ML
C6	MH	M	M

Table 6. Weights of criteria according to SWAM operators

Criteria	Criterion Weight		
	μ	v	π
C1	0.719	0.284	0.636
C2	0.690	0.314	0.642
C3	0.612	0.391	0.702
C4	0.138	0.869	0.801
C5	0.279	0.734	0.789
C6	0.539	0.462	0.753

Table 7. Results of SF-SWARA

Criteria	Score Value	s_j	k_j	q_j
C1	0.518		1	1
C2	0.439	0.079	1.079	0.926
C3	0.270	0.169	1.169	0.793
C6	0.177	0.093	1.093	0.725
C5	0.051	0.127	1.127	0.644
C4	0.022	0.029	1.029	0.626

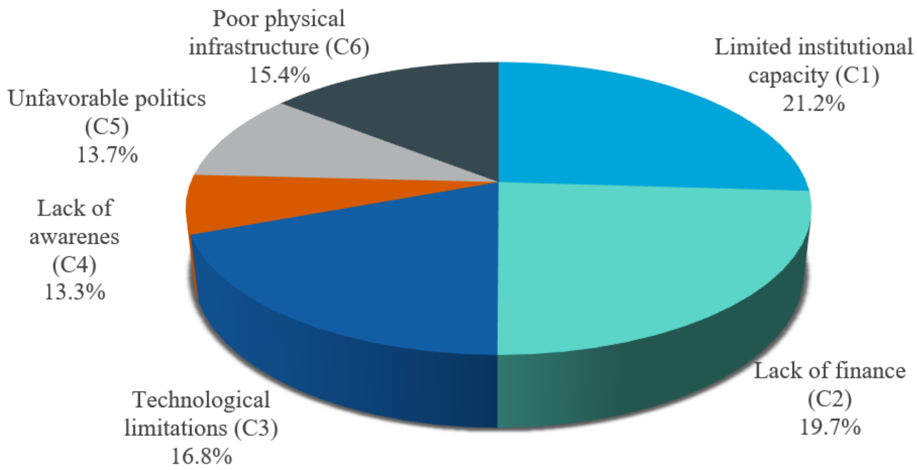

Figure 3. Weights of challenges to LCDCCM

4.3 Rank of Strategies

Following the assessment of criteria importance, the experts constructed a grid, which is instrumental in determining the most appropriate strategy through the SF-WASPAS approach. In the initial phase, linguistic variables were translated into the SFN, employing the scale outlined in reference (Francisco Ribeiro & Camargo Rodriguez, 2020). Following this, expert opinions were combined using the SWAM operator to establish expert weights. An SF decision matrix was generated in this procedure, as shown in Table 8. After establishing the weights for each criterion, the strategies were ranked through the WSM and WPM constituents shown in Table 9.

The two constituents of the WASPAS method were combined with λ= 0.5. Table 10 shows the final scores and the ranking of strategies based on them. The obtained ranking is S4> S3>S1>S2. "S4: institutional capacity building" emerges as the most appropriate strategy since it has the highest evaluation score.

Table 8. SF decision grid

	Criteria	μ	ϑ	π
S1	C1	0.838	0.162	0.076
	C2	0.416	0.590	0.326
	C3	0.485	0.526	0.322
	C4	0.539	0.462	0.366
	C5	0.218	0.796	0.133
	C6	0.369	0.633	0.272

S2	C1	0.469	0.533	0.372
	C2	0.376	0.633	0.291
	C3	0.735	0.266	0.171
	C4	0.304	0.715	0.221
	C5	0.300	0.700	0.200
	C6	0.444	0.562	0.356
S3	C1	0.600	0.400	0.300
	C2	0.873	0.127	0.048
	C3	0.669	0.332	0.236
	C4	0.376	0.663	0.291
	C5	0.300	0.700	0.200
	C6	0.569	0.432	0.336
S4	C1	0.639	0.362	0.266
	C2	0.900	0.100	0.000
	C3	0.669	0.332	0.236
	C4	0.469	0.533	0.372
	C5	0.674	0.327	0.231
	C6	0.700	0.300	0.200

Table 9. WSM and WPM models

	WSM			**WPM**		
	μ	v	π	μ	v	π
S1	0.996	0.008	0.037	0.366	0.730	0.215
S2	0.995	0.012	0.046	0.301	0.776	0.216
S3	0.998	0.004	0.024	0.420	0.682	0.201
S4	0.999	0.002	0.015	0.504	0.598	0.218

Table 10. Ranking of alternatives

Ranking	**Strategy**	**Final Score**
3	S1	3.950
4	S2	3.929
2	S3	3.980
1	S4	3.993

5. Sensitivity Analysis

The sensitivity analysis involves two phases. In the first phase, the stability of the methodology was evaluated by the varying threshold value (λ) within the [0, 1] range, as shown in Figure 4. The figure displays the relative ranking of the alternatives based on the variation of coefficient λ, indicating that changes in λ do not alter the ranking but preserve their original order.

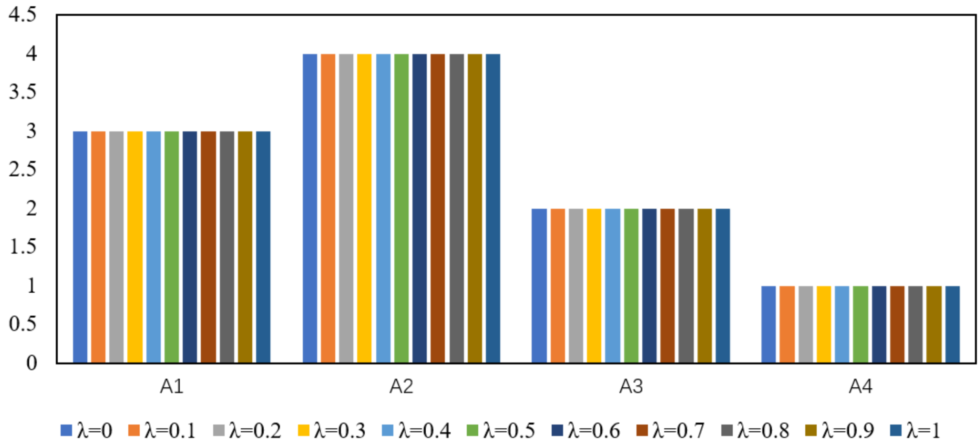

Figure 4. Sensitivity analysis outcomes related to coefficient λ

The next phase entails examining the influence of variation on the criterion weights across 60 scenarios. In each scenario, the values of C1-C6 were diminished using Eq. (20). Each of the ten scenarios involved changes to the criteria, with their value decreasing between 5% and 95%, while the other criteria values remained constant.

$$\bar{W}_{n\beta} = \left(1-\bar{W}_{n\alpha}\right)\frac{\bar{W}_{n=\beta}}{\left(1-\bar{W}_{n}\right)} \tag{20}$$

where, $\overline{W}_{n\beta}$ is the criterion's new value for these scenarios, $\overline{W}_{n\alpha}$ is the diminished value of the significant criteria by scenario categories, and $\overline{W}_{n}$ is the original value of the criterion with diminished value.

Following the scenario setup, calculations were rerun using the SF-WASPAS approach, resulting in a new ranking for every scenario displayed in Figure 5. Despite changes in the values of criteria and the diminished importance of key criteria, all alternatives maintained their original ranking.

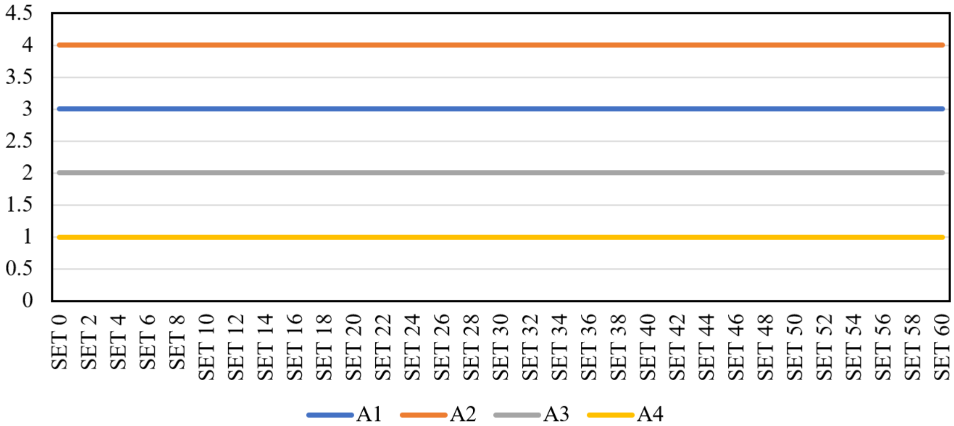

Figure 5. Initial outcome comparison across all scenarios

6. Comparative Analysis

This section compares the stability of the findings of this study with other methods, including the Aczel Alsina Weighted Assessment (ALWAS) (Pamucar et al., 2023), the alternative ranking technique based on adaptive standardized intervals (ARTASI) (Pamucar et al., 2024), and the alternative ranking order method accounting for two-step normalization (AROMAN) (Bošković et al., 2023). Figure 6 displays the ultimate classification, revealing variations compared to the original ranking. These differences may be due to the distinct steps and scoring functions used in each method. For example, it was observed that the strategy initially ranked first (S1) was relegated to the third position in the alternative methods, while the strategy previously in third place (S3) ascended to the top rank. Such shifts in ranking underscore the significance of strategy S3 for LCDCCM in the African context.

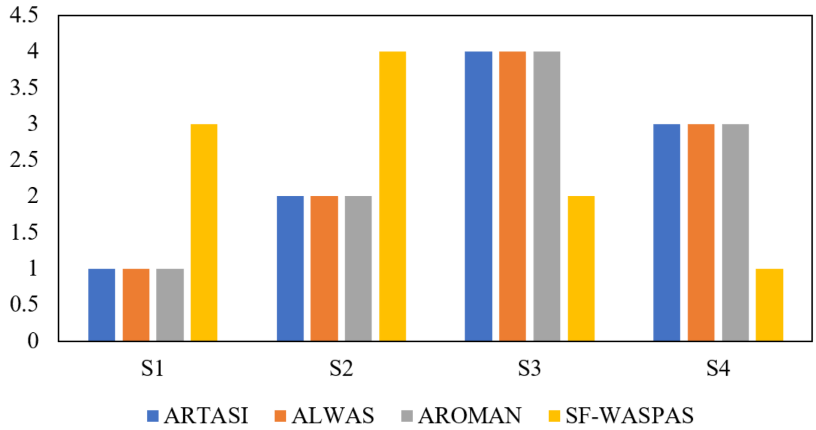

Figure 6. Comparative analysis outcomes

7. Findings and Discussion

After extensively reviewing existing literature and consulting with experts, it was found that several challenges hindered CCM efforts. Three primary obstacles were identified, each with the potential to impede the mitigation process. To assess their significance, the SF-SWARA approach was employed to establish criterion values.

Experts emphasized that the primary challenge lied in limited institutional capacity, a perspective supported by Adenle et al. (2017b), indicating that weak institutional capacity impedes African nations from taking part in previous CCM programs. Additional data concerning institutional capacity also supports these conclusions. It is indicated that robust public institutions are essential for mitigating the impacts of CC effectively. Moreover, deficiencies in skills and regulatory frameworks are highlighted as factors that weaken the institutionalization process. It is important to enhance human capacity and establish effective institutions to make the CDM projects successful at the national level. At the same time, adequate policies, human resource accessibility, and a strong legal framework are also necessary for global participation in CDM investments.

Following the challenge of limited institutional capacity, the next significant obstacle is a lack of funds. These conclusions are consistent with the previous research of Chirambo (Chirambo, 2016), emphasizing that insufficient financial resources hinder Africa's ability to effectively mitigate climate change. Additionally, there is a lack of efficient financial mechanism distribution at the sub-country level, especially in meeting the needs of economically disadvantaged communities, which are often the most susceptible to the CC impacts. As a result, ministries of finance should collaborate with the CCMI to coordinate international funding and tap into local sources of finance.

The third most significant issue pertains to technology limitations, consistent with the findings of Adenle et al. (2015). Their research reveals that climate-friendly technology often faces deficiencies and low adoption rates, primarily attributed to inadequate public investment in R&D and incompetent personnel for advanced technology maintenance (Karakosta & Psarras, 2013). To overcome technology limitations, a comprehensive strategy is needed. This involves investing in R&D to create and adapt cost-effective and region-specific technologies. International collaboration is crucial for sharing expertise and securing financial support. Capacity building through education and training programs is essential to ensuring local proficiency in adopting and managing climate-friendly technologies. Supportive policies and regulations, including tax incentives and subsidies, encourage businesses to invest in sustainable practices. Public-private partnerships can leverage innovation and resources, while technology transfer initiatives facilitate the adoption of existing technologies. Promoting off-grid solutions, engaging local communities, and incentivizing innovation contribute to a holistic approach. Continuous monitoring and evaluation ensure the effectiveness of technology implementation, guiding future decisions and strategies.

The findings of this study underscore pivotal factors influencing CCM in Africa, with a strong emphasis on the crucial role of robust institutional capacity and strategic partnership. These findings underscore the significance of an effective CCMI in Africa. A major hurdle identified is the deficiencies in local capacity building, impeding project implementation. The establishment of institutional capacity should be primarily led by national and regional institutions, complemented by donors' partnerships. A successful CCMI must align with country-level goals set in the PA. This involves engaging diverse stakeholders, ranging from local communities to federal governments. Additionally, assistance should be provided to existing institutions in addressing CM across various sectors. In addition to institutional growth, nations should receive assistance from the CCMI to build their capacity, such as building trust in efficient mitigation financing and familiarizing local actors with the essential elements of successful project implementation as a starting point.

8. Managerial Implications

The study provides various managerial insights.

The findings of the study serve to raise awareness among the public and policymakers regarding the significance of transitioning to a low-carbon economy. This awareness facilitates advocacy for mitigation measures at both national and continental levels. Additionally, the study offers practical guidance on prioritizing four distinct aspects, contributing to a more effective integration of African nations into global CM endeavors.

Government authorities overseeing African CCM can benefit from the study's insights. Policymakers can use this information to define institutional elements for building capacity and accessing mitigation funds. Integrating all African nations into global CM efforts is crucial for cost-effective mitigation and the successful implementation of LCDPs across the continent.

9. Conclusion

This study presents the merging of SWARA and WASPAS in an SF setting to address LCDCCM challenges. A case study in Africa validates this model. Findings show key issues, such as limited institutional capacity, lack of funds, and technological problems, with institutional capacity building and strategic partnership strategies outlined to address them. The study contributes by providing a framework for LCDCCM in Africa, offering strategies for rational implementation (professional contribution), and applying the SF-SWARA-WASPAS approach to achieving this framework (scientific contribution).

While some insights have been gained from this study, some limitations have been noticed. Initially, the study focused on the African continent as a whole for LCDCCM, overlooking the diverse conditions across its multiple countries. Future research should consider separate investigations in different countries under similar conditions. Second, only a few experts participated in the data collection process, which may be insufficient for accurate results. The inclusion of more experts should be considered in the future. Thirdly, the methodology was used in a fuzzy environment. Future studies should encompass a rough or interval-rough environment. Additionally, it is suggested to apply a linear programming scheme under uncertainty to establish new integrated approaches. Moreover, the proposed methodology can be utilized to evaluate sustainability issues and circular economy topics. The methodology and findings presented in this study are of significant importance for policymakers in the context of CCM. They offer a framework for assessing current challenges in CCM programs. The findings indicate that policymakers should enhance human capacity and establish effective institutions. Furthermore, they should coordinate international funding, leverage domestic financing sources across various sectors and ministries, and invest in R&D to create and adapt cost-effective and region-specific technologies.

Author Contributions

Conceptualization, M.B.B. and Y.Q.; methodology, Z.S. and I.B; software, Z.S. and I.B; validation, M.B.B, I.B, and Z.S.; formal analysis, Z.S and V.S.; investigation, Z.S and V.S.; resources, Z.S and Y.Q.; data curation, M.B.B, I.B, and Z.S.; writing—original draft preparation, M.B.B. and I. B; writing—review and editing, Z.S and V.S.; visualization, Z.S and V.S; supervision, Z.S and V.S; project administration, Z.S and V.S.; funding acquisition, Z.S. All authors have read and agreed to the published version of the manuscript.

Data Availability

The data supporting our research results are included within the article or supplementary material.

Conflicts of Interest

The authors declare no conflict of interest.

References

Adenle, A. A., Azadi, H., & Arbiol, J. (2015). Global assessment of technological innovation for climate change adaptation and mitigation in developing world. *J. Environ. Manage., 161,* 261-275. https://doi.org/10.1016/j.jenvman.2015.05.040.

Adenle, A. A., Ford, J. D., Morton, J., Twomlow, S., Alverson, K., & Cattaneo, A. (2017a). Managing climate change risks in Africa-A global perspective. *Ecol. Econ., 141,* 190-201. https://doi.org/10.1016/j.ecolecon.2017.06.004.

Adenle, A. A., Manning, D. T., & Arbiol, J. (2017b). Mitigating climate change in Africa: Barriers to financing low-carbon development. *World Dev., 100,* 123-132. https://doi.org/10.1016/j.worlddev.2017.07.033.

Adenuga, K. I., Mahmoud, A. S., Dodo, Y. A., Albert, M., Kori, S. A., & Danlami, N. J. (2021). Climate change adaptation and mitigation in sub-Saharan African countries. *Energy Environ. Secur. Dev. Ctries.,* 393-409. https://doi.org/10.1007/978-3-030-63654-8_16.

Alkan, N. (2024). Evaluation of sustainable development and utilization-oriented renewable energy systems based on CRITIC-SWARA-CODAS method using interval valued picture fuzzy sets. *SEGAN., 38,* 101263. https://doi.org/10.1016/j.segan.2023.101263.

Alrasheedi, A. F., Mishra, A. R., Rani, P., Zavadskas, E., & Cavallaro, F. (2023). Multicriteria group decision making approach based on an improved distance measure, the SWARA method and the WASPAS method. *Granul. Comput., 8,* 1867-1885. https://doi.org/10.1007/s41066-023-00413-x.

Amatayakul, W. & Berndes, G. (2012). Determining factor for the development of CDM biomass power projects. *Energy Sustain. Dev., 16*(2), 197-203. https://doi.org/10.1016/j.esd.2012.01.004.

Ayyildiz, E. & Taskin, A. (2022). A novel spherical fuzzy AHP-VIKOR methodology to determine serving petrol station selection during COVID-19 lockdown: A pilot study for İstanbul. *Socio-Econ. Plan. Sci., 83,* 101345. https://doi.org/10.1016/j.seps.2022.101345.

Badi, I. & Abdulshahed, A. (2019). Ranking the Libyan airlines by using full consistency method (FUCOM) and analytical hierarchy process (AHP). *Oper. Res. Eng. Sci. Theor. Appl., 2*(1),1-14. https://doi.org/10.31181/oresta1901001b.

Badi, I. & Kridish, M. (2020). Landfill site selection using a novel FUCOM-CODAS model: A case study in Libya. *Sci. Afr., 9*, e00537. https://doi.org/10.1016/j.sciaf.2020.e00537.

Bošković, S., Švadlenka, L., Jovčić, S., Dobrodolac, M., Simić, V., & Bacanin, N. (2023). An alternative ranking order method accounting for two-step normalization (AROMAN)—A case study of the electric vehicle selection problem. *IEEE Access, 11,* 39496-39507. https://doi.org/10.1109/ACCESS.2023.3265818.

Bouraima, M. B., Ayyildiz, E., Özçelik, G., Tengecha, N. A., & Stević, Ž. (2024a). Alternative prioritization for mitigating urban transportation challenges using a Fermatean fuzzy-based intelligent decision support model. *Neural Comput. Appl., 36,* 7343-7357. https://doi.org/10.1007/s00521-024-09463-x.

Bouraima, M. B., Ibrahim, B., Qiu, Y., Kridish, M., & Dantonka, M. (2024b). Integrated spherical decision-making model for managing climate change risks in Africa. *J. Soft. Comput. Decis. Anal., 2*(1), 71-85. https://doi.org/10.31181/jscda21202435.

Bouraima, M. B., Qiu, Y., Ayyildiz, E., & Yildiz, A. (2023). Prioritization of strategies for a sustainable regional transportation infrastructure by hybrid spherical fuzzy group decision-making approach. *Neural Comput. Appl., 35*(24), 17967-17986. https://doi.org/10.1007/s00521-023-08660-4.

Cakmak, E. (2023). Supplier selection for a power generator sustainable supplier park: Interval-valued neutrosophic SWARA and EDAS application. *Sustainability, 15*(18), 13973. https://doi.org/10.3390/su151813973.

Chen, X., Zhou, B., Štilić, A., Stević, Ž., & Puška, A. (2023). A fuzzy-rough MCDM approach for selecting green suppliers in the furniture manufacturing industry: A case study of eco-friendly material production. *Sustainability, 15*(13), 10745. https://doi.org/10.3390/su151310745.

Chirambo, D. (2016). Integrating microfinance, climate finance and climate change adaptation: A Sub-Saharan Africa perspective. *Clim. Change Adapt. Resil. Hazards,* 195-207. https://doi.org/10.1007/978-3-319-39880-8_12.

Cloete, N., Bailey, T., & Maassen, P. (2012). *Universities and Economic Development in Africa: Pact, Academic Core and Coordination.* African Minds. https://doi.org/10.47622/9781920355807.

Clough, L. (2012). The Improved Cookstove Sector in East Africa: Experience from the Developing Energy Enterprise Programme (DEEP). London, UK: GVEP-Global Village Energy Partnership International, 108.

Dagnachew, A. G., Lucas, P. L., Hof, A. F., & van Vuuren, D. P. (2018). Trade-offs and synergies between universal electricity access and climate change mitigation in Sub-Saharan Africa. *Energy Policy, 114,* 355-366. https://doi.org/10.1016/j.enpol.2017.12.023.

Deveci, M., Gokasar, I., Mishra, A. R., Rani, P., & Ye, Z. (2023). Evaluation of climate change-resilient transportation alternatives using fuzzy Hamacher aggregation operators based group decision-making model. *Eng. Appl. Artif. Intell., 119,* 105824. https://doi.org/10.1016/j.engappai.2023.105824.

Deveci, M., Pamucar, D., Gokasar, I., Isik, M., & Coffman, D. M. (2022). Fuzzy Einstein WASPAS approach for the economic and societal dynamics of the climate change mitigation strategies in urban mobility planning. *SCED., 61,* 1-17. https://doi.org/10.1016/j.strueco.2022.01.009.

Duguma, L. A., Minang, P. A., & van Noordwijk, M. (2014). Climate change mitigation and adaptation in the land use sector: From complementarity to synergy. *Environ. Manage., 54*, 420-432. https://doi.org/10.1007/s00267-014-0331-x.

Elum, Z. A., Modise, D. M., & Marr, A. (2017). Farmer's perception of climate change and responsive strategies in three selected provinces of South Africa. *Clim. Risk Manag., 16*, 246-257. https://doi.org/10.1016/j.crm.2016.11.001.

Elum, Z. A. & Momodu, A. S. (2017). Climate change mitigation and renewable energy for sustainable development in Nigeria: A discourse approach. *Renew. Sustain. Energy Rev., 76*, 72-80. https://doi.org/10.1016/j.rser.2017.03.040.

Francisco Ribeiro, P., & Camargo Rodriguez, A. V. (2020). Emerging advanced technologies to mitigate the impact of climate change in Africa. *Plants, 9*(3), 381. https://doi.org/10.3390/plants9030381

Ghoushchi, S. J., Jalalat, S. M., Bonab, S. R., Ghiaci, A. M., Haseli, G., & Tomaskova, H. (2022). Evaluation of wind turbine failure modes using the developed SWARA-CoCoSo methods based on the spherical fuzzy environment. *IEEE Access, 10,* 86750-86764. https://doi.org/10.1109/ACCESS.2022.3199359.

Görçün, Ö. F., Pamucar, D., & Küçükönder, H. (2023). Selection of tramcars for sustainable urban transportation by using the modified WASPAS approach based on Heronian operators. *Appl. Soft Comput., 151,* 111127. https://doi.org/10.1016/j.asoc.2023.111127.

Gujba, H., Thorne, S., Mulugetta, Y., Rai, K., & Sokona, Y. (2012). Financing low carbon energy access in Africa. *Energy Policy, 47*, 71-78. https://doi.org/10.1016/j.enpol.2012.03.071.

Gündoğdu, F. K. & Kahraman, C. (2020). A novel spherical fuzzy analytic hierarchy process and its renewable energy application. *Soft Comput., 24,* 4607-4621. https://doi.org/10.1007/s00500-019-04222-w.

Hashemkhani Zolfani, S., Görçün, Ö. F., & Küçükönder, H. (2023). Evaluation of the special warehouse handling equipment (Turret Trucks) using integrated FUCOM and WASPAS techniques based on intuitionistic fuzzy Dombi aggregation operators. *Arab. J. Sci. Eng., 48*, 15561-15595. https://doi.org/10.1007/s13369-023-

07615-0.
Hashemkhani Zolfani, S., Yazdani, M., & Zavadskas, E. K. (2018). An extended stepwise weight assessment ratio analysis (SWARA) method for improving criteria prioritization process. *Soft Comput., 22,* 7399-7405. https://doi.org/10.1007/s00500-018-3092-2.
Jafarzadeh Ghoushchi, S., Shaffiee Haghshenas, S., Memarpour Ghiaci, A., Guido, G., & Vitale, A. (2023). Road safety assessment and risks prioritization using an integrated SWARA and MARCOS approach under spherical fuzzy environment. *Neural Comput. Appl., 35*(6), 4549-4567. https://doi.org/10.1007/s00521-022-07929-4.
Kahraman, C., Gundogdu, F. K., Onar, S. C., & Oztaysi, B. (2019). Hospital location selection using spherical fuzzy TOPSIS. *In 11th Conference of the European Society for Fuzzy Logic and Technology (EUSFLAT 2019),* pp. 77-82. https://doi.org/10.2991/eusflat-19.2019.12.
Karakosta, C., & Psarras, J. (2013). Understanding CDM potential in the Mediterranean basin: A country assessment of Egypt and Morocco. *Energy Policy, 60,* 827-839. https://doi.org/10.1016/j.enpol.2013.05.078.
Keršuliene, V., Zavadskas, E. K., & Turskis, Z. (2010). Selection of rational dispute resolution method by applying new step-wise weight assessment ratio analysis (SWARA). *J. Bus. Econ. Manag., 11*(2), 243-258. https://doi.org/10.3846/jbem.2010.12.
Kutlu Gündoğdu, F. & Kahraman, C. (2019a). A novel VIKOR method using spherical fuzzy sets and its application to warehouse site selection. *J. Intell. Fuzzy Syst., 37*(1), 1197-1211. https://doi.org/10.3233/JIFS-182651.
Kutlu Gündoğdu, F. & Kahraman, C. (2019b). Spherical fuzzy sets and spherical fuzzy TOPSIS method. *J. Intell. Fuzzy Syst., 36*(1), 337-352. https://doi.org/10.3233/JIFS-181401.
Linnér, B. O. & Pahuja, N. (2012). A registry of nationally appropriate mitigation actions: Goals, outcomes, and institutional requisites. *Ambio., 41,* 56-67. https://doi.org/10.1007/s13280-011-0241-6.
Liu, P., Saha, A., Mishra, A. R., Rani, P., Dutta, D., & Baidya, J. (2023). A BCF-CRITIC-WASPAS method for green supplier selection with cross-entropy and Archimedean aggregation operators. *J. Ambient Intell. Humaniz. Comput., 14,* 11909-11933. https://doi.org/10.1007/s12652-022-03745-9.
Menekşe, A. & Akdağ, H. C. (2023). Medical waste disposal planning for healthcare units using spherical fuzzy CRITIC-WASPAS. *Appl. Soft Comput., 144,* 110480. https://doi.org/10.1016/j.asoc.2023.110480.
Mishra, A. R., Rani, P., Deveci, M., Gokasar, I., Pamucar, D., & Govindan, K. (2023). Interval-valued Fermatean fuzzy heronian mean operator-based decision-making method for urban climate change policy for transportation activities. *Eng. Appl. Artif. Intell., 124,* 106603. https://doi.org/10.1016/j.engappai.2023.106603.
Pamučar, D. & Ćirović, G. (2015). The selection of transport and handling resources in logistics centers using Multi-Attributive Border Approximation area Comparison (MABAC). *Expert Syst. Appl., 42*(6), 3016-3028. https://doi.org/10.1016/j.eswa.2014.11.057.
Pamucar, D., Deveci, M., Stević, Ž., Gokasar, I., Isik, M., & Coffman, D. M. (2022). Green strategies in mobility planning towards climate change adaption of urban areas using fuzzy 2D algorithm. *SCS., 87,* 104159. https://doi.org/10.1016/j.scs.2022.104159.
Pamucar, D., Ecer, F., Gligorić, Z., Gligorić, M., Deveci, M. (2023). A novel WENSLO and ALWAS multicriteria methodology and its application to green growth performance evaluation. *IEEE Trans. Eng. Manag.,* 1-16, 2023. https://doi.org/10.1109/TEM.2023.3321697.
Pamucar, D., Simic, V., Görçün, Ö. F., & Küçükönder, H. (2024). Selection of the best Big Data platform using COBRAC-ARTASI methodology with adaptive standardized intervals. *Expert Syst. Appl., 239,* 122312. https://doi.org/10.1016/j.eswa.2023.122312.
Patel, A., Jana, S., & Mahanta, J. (2023). Intuitionistic fuzzy EM-SWARA-TOPSIS approach based on new distance measure to assess the medical waste treatment techniques. *Appl. Soft Comput., 114,* 110521. https://doi.org/10.1016/j.asoc.2023.110521.
Prentkovskis, O., Erceg, Ž., Stević, Ž., Tanackov, I., Vasiljević, M., & Gavranović, M. (2018). A new methodology for improving service quality measurement: Delphi-FUCOM-SERVQUAL model. *Symmetry, 10(12),* 757. https://doi.org/10.3390/sym10120757.
Reppin, S., Kuyah, S., de Neergaard, A., Oelofse, M., & Rosenstock, T. S. (2020). Contribution of agroforestry to climate change mitigation and livelihoods in Western Kenya. *Agrofor. Syst., 94,* 203-220. https://doi.org/10.1007/s10457-019-00383-7.
Rezaei, J. (2016). Best-worst multi-criteria decision-making method: Some properties and a linear model. *Omega, 64,* 126-130. https://doi.org/10.1016/j.omega.2015.12.001.
Rong, F. (2010). Understanding developing country stances on post-2012 climate change negotiations: Comparative analysis of Brazil, China, India, Mexico, and South Africa. *Energy Policy, 38*(8), 4582-4591. https://doi.org/10.1016/j.enpol.2010.04.014.
Seyboth, K. (2013). *Intergovernmental panel on climate change (IPCC).* Encycl Energy Nat Res Environ Econ.
Shemdoe, R., Kassenga, G., & Mbuligwe, S. (2015). Implementing climate change adaptation and mitigation

interventions at the local government levels in Tanzania: Where do we start? *COSUST.*, *13*, 32-41. https://doi.org/10.1016/j.cosust.2015.01.002.

Simic, V., Gokasar, I., Deveci, M., & Švadlenka, L. (2022). Mitigating climate change effects of urban transportation using a type-2 neutrosophic MEREC-MARCOS model. *IEEE-TEM., 71*, 3233-3249. https://doi.org/10.1109/TEM.2022.3207375.

Singh, T. (2024). Entropy weighted WASPAS and MACBETH approaches for optimizing the performance of solar water heating system. *Case Stud. Therm. Eng.*, *53*, 103922. https://doi.org/10.1016/j.csite.2023.103922.

Tawney, L., Almendra, F., Torres, P., & Weischer, L. (2011). *Two Degrees of Innovation-How to Seize the Opportunities in Low-Carbon Power.* Washington, DC: World Resources Institute.

Timilsina, G. R., de Gouvello, C., Thioye, M., & Dayo, F. B. (2010) Clean development mechanism potential and challenges in Sub-Saharan Africa. *Mitig. Adapt. Strateg. Glob. Change, 15,* 93-111. https://doi.org/10.1007/s11027-009-9206-5.

Torkayesh, A. E., Tirkolaee, E. B., Bahrini, A., Pamucar, D., & Khakbaz, A. (2023). A systematic literature review of MABAC method and applications: An outlook for sustainability and circularity. *Informatica, 34*(2), 415-448. https://doi.org/10.15388/23-INFOR511.

Tripathi, D., Nigam, S. K., Mishra, A. R., & Shah, A. R. (2023). A novel intuitionistic fuzzy distance measure-SWARA-COPRAS method for multi-criteria food waste treatment technology selection. *Oper. Res. Eng. Sci. Theor. Appl., 6*(1). https://doi.org/10.31181/oresta111022106t.

Tschora, H. & Cherubini, F. (2020). Co-benefits and trade-offs of agroforestry for climate change mitigation and other sustainability goals in West Africa. *Glob. Ecol. Conserv., 22,* e00919. https://doi.org/10.1016/j.gecco.2020.e00919.

Tyler, E., Boyd, A., Coetzee, K., Torres Gunfaus, M., & Winkler, H. (2013). Developing country perspectives on 'mitigation actions', 'NAMAs', and 'LCDS'. *Clim. Policy, 13*(6), 770-776. https://doi.org/10.1080/14693062.2013.823334.

Villi, B. (2023). An empirical analysis of the nexus between climate change anxiety and sustainable consumption patterns among Turkish individuals. *J. Green Econ. Low-Carbon Dev., 2*(3), 110-121. https://doi.org/10.56578/jgelcd020301.

Zavadskas, E. K., Turskis, Z., Antucheviciene, J., & Zakarevicius, A. (2012). Optimization of weighted aggregated sum product assessment. *Elektronika Ir Elektrotechnika, 122*(6), 3-6. https://doi.org/10.5755/j01.eee.122.6.1810.

Zegeye, H. (2018). Climate change in Ethiopia: Impacts, mitigation and adaptation. *Int. J. Res. Environ. Stud., 5*(1), 18-35.