

An Approach Using Border Approximation Area in Bipolar Neutrosophic Settings for Optimal Alternative of Agricultural Sustainability

Lazim Abdullah

Abstract— Earlier studies indicate that the Multi-Attributive Border Approximation Area Comparison (MABAC) method is among the most reliable techniques for ranking alternatives. This method has been combined with various fuzzy set-based decision-making methods. However, the combination of MABAC with the four tuple-memberships of bipolar neutrosophic sets has yet to be explored. This paper proposes the Bipolar Neutrosophic Multi-Attributive Border Approximation Area Comparison (BiN-MABAC) method and applies it to the case of sustainable agriculture practices. Linguistic data was collected from five experts in the agricultural field to evaluate the performance of seven alternatives based on ten criteria. The computational implementation of BiN-MABAC indicates that the alternative agroforestry (A4) is the optimal solution for agricultural sustainability. This study represents the first identifiable application of the BiN-MABAC decision-making approach to agricultural sustainability.

Index Terms— Border approximation, Bipolarity, Decision making, Neutrosophic Sets, Weight coefficient

I. INTRODUCTION

THE Multi-Attributive Border Approximation Area Comparison (MABAC) method is one of the multi-criteria decision-making methods where the concept of distances is prevalently used. The MABAC was originally proposed by Pamucar and Cirovic [1] calculates the distance between alternatives. Besides the distance measures, the MABAC also deals with the Border Approximation Area (BAA) where alternatives could belong to upper approximation area or lower approximation area. With these special features, the MABAC has several advantages such as stability in results and straightforward in computations. Pamucar et al. [2] opined several other advantages which among others are its capacity to evaluate the stability of the derived outcomes in relation to changing weight criteria, inclusion of qualitative and quantitative parameters for solving complex multi-criteria decision making problems and more importantly it tends to be easily combined with other uncertainty based sets such as

neutrosophic sets. For example, Wang et al. [3] combined 2-tuple linguistic neutrosophic sets and MABAC method. Along with comparison assessments, a numerical example was presented to demonstrate how their innovative approach for safety evaluation in a building project may be applied. In another research, Liang et al. [4] attempted to find an effective way to evaluate the risk of rock bursting in difficult decision-making circumstances. Triangular fuzzy numbers were used to represent risk index values, and the MABAC method was applied to determine the ranking results and accurately assess the risk levels of rock bursts in a fuzzy environment. The MABAC method and triangular fuzzy numbers were fused together in suggesting the risk values. The results indicate that the combined triangular fuzzy numbers-MABAC approach is both effective and practical for assessing rock burst risk, providing valuable insights for its prevention and management.

In recent years, an increasing number of researchers have explored MABAC in conjunction with the latest advancements in fuzzy set theory. Wang et al. [5], for example, considered the MABAC model and q-rung orthopair fuzzy set theories in their research. These two entities were combined and attested to a decision making problem. Not only combined with fuzzy set based linguistic variables, the MABAC also has been combined with other well-known multi-criteria decision making methods. For example, Chakraborty et al. [6] undertook a comprehensive assessment of the performance of thirty-two major Indian international airports across eight distinct evaluation criteria. This evaluation amalgamated the Best Worst Method (BWM), as conceptualized by Rezaei [7] and the MABAC method. The BWM, a recognized multi-criteria decision making method, facilitates a meticulous pairwise comparison of decision criteria to elicit essential input data. Employing the perspectives of four decision-makers, they utilized BWM to ascertain criterion weights. Subsequently, the MABAC approach was deployed to rank airports according to their preference, delineating a continuum from superior to inferior performance while delineating their relative strengths and weaknesses. Pamucar and Cirovic [1] proposed an integrated approach combining two multi-criteria decision-making methods, DEMATEL and MABAC, to support investment decisions related to acquiring coercive

Lazim Abdullah is a Professor at Faculty of Computer Science and Mathematics, Universiti Malaysia Terengganu, 21030 Kuala Nerus Malaysia (e-mail: lazim_m@umt.edu.my).

transport for logistics centers. The DEMATEL method was employed to calculate the weight coefficients of the parameters used in evaluating the alternatives. Concurrently, the MABAC method was employed to select transport options. In another study, MABAC and fuzzy rough LMAW were combined and applied to a case of customer requirement and market trends. This approach was applied to rank suppliers and ultimately identify the top-performing one [8]. Recently, Liu et al. [9] combined the MABAC and VIKOR methods to assess urban quality. The MABAC method was utilized to establish weights for indicators, while the VIKOR method was employed to evaluate enhancements in urban quality based on public satisfaction indicators.

The above literature supports the use of a combined MABAC based methods in decision making. The combination could be offered as a stand-alone multi-criteria decision-making process or as linguistic variables. Linguistic variables used in the previous research were defined using membership of fuzzy sets. However, single membership or two-tuple memberships are still not enough to deal with uncertainty in decision making process. Perhaps bipolarity with six-tuple membership of neutrosophic sets may provide a new linguistic variable in decision making. There are no multi-criteria decision-making techniques that take into account bipolar neutrosophic sets to the MABAC, as far as the authors are aware. The bipolar neutrosophic set is a six-tuple membership where three-tuple membership is characterized with positive memberships and negative memberships. As a result, the goal of this study is to introduce an integration of bipolar neutrosophic linguistic variables with the MABAC method. The integration bipolar neutrosophic sets-MABAC (BiN-MABAC) is characterized by six-tuple membership used in defining linguistic variables. Specifically, this research aims to propose BiN-MABAC and its application to agricultural sustainability. Agricultural sustainability assessment frequently involves conflicting and uncertain information, where a particular alternative may simultaneously exhibit both beneficial and unfavourable impacts. For example, agricultural practices may substantially improve soil fertility, biodiversity preservation, and climate resilience while at the same time increasing operational costs or reducing short-term farmer income. Similarly, agroforestry practices may contribute positively to carbon sequestration and ecological stability but may require longer investment periods before economic returns are achieved. Such dual characteristics cannot be adequately represented using conventional single-membership or unipolar evaluation frameworks. In this context, bipolar neutrosophic sets provide a more realistic representation of sustainability-related decision problems because they explicitly accommodate both positive and negative dimensions of evaluation. The positive memberships describe the degree to which an alternative satisfies desirable sustainability attributes, whereas the negative memberships reflect the extent of undesirable effects or limitations associated with the same alternative. Consequently, the bipolar structure enables simultaneous modelling of supportive and adverse assessments under

uncertain environments. This capability is particularly important in agricultural sustainability studies, where environmental, economic, and social considerations are often interrelated and contradictory. Therefore, the integration of bipolar neutrosophic sets into the MABAC framework offers a more comprehensive and flexible approach for evaluating sustainable agriculture alternatives.

II. MATERIAL AND METHOD

This section examines the methodology employed to identify the key criteria and optimal alternatives for agricultural sustainability, utilizing the proposed BiN-MABAC as a computational tool. The approach in this study relies on expert opinions gathered through specified linguistic variables.

A. Experts and Linguistic Variable

Five experts were asked to participate in this study and provide their knowledge about the relative importance of each criterion. This degree of influence is measured using a five-point rating scale, s^1 (no influence), s^2 (very low influence), s^3 (Low influence), s^4 (High influence) and s^5 (Very high influence) as shown in Table 1.

TABLE I
FIVE-POINT RATING SCALE AND THEIR RESPECTIVE
LINGUISTIC TERMS [10]

Rating and Linguistic terms	Single valued-Neutrosophic numbers
s^1	$\langle 0.90, 0.10, 0.10 \rangle$
s^2	$\langle 0.80, 0.25, 0.15 \rangle$
s^3	$\langle 0.50, 0.40, 0.45 \rangle$
s^4	$\langle 0.35, 0.60, 0.70 \rangle$
s^5	$\langle 0.10, 0.80, 0.90 \rangle$

Their evaluations also account for the importance of alternatives concerning the criteria. Table 2 presents a five-point scale used to measure this degree of importance.

TABLE 2 FIVE-POINT RATING SCALE AND THEIR RESPECTIVE
LINGUISTIC TERMS [11]

Rating Scale	Linguistic terms
0	Not Important
1	Low Important
2	Neutral
3	Important
4	Very Important

The expert group includes three men (E1, E2, E3) and two women (E4, E5) from government agricultural agencies. Each expert has over three years of experience in the agricultural sector.

Besides a group of experts and degree of linguistic variables, the approach also must consider alternatives and criteria of agricultural sustainability.

B. Alternatives and Criteria

Seven alternatives and ten criteria of agricultural sustainability are selected in this study. The descriptions of alternatives and criteria are summarized in Table 3.

TABLE 3
CRITERIA AND ALTERNATIVES FOR PROMOTING SUSTAINABLE AGRICULTURE [12]

Criteria		Alternatives	
C_1	source of food	A_1	Integrated pest management
C_2	wood and fibre	A_2	Integrated nutrient management
C_3	water supply and regulation	A_3	Conservation tillage
C_4	nutrient cycling and fixation	A_4	Agroforestry
C_5	soil formation	A_5	Aquaculture
C_6	biological control of pests	A_6	Water harvesting in drylands
C_7	climate regulation	A_7	Integration of livestock
C_8	storm protection and flood control		
C_9	carbon sequestration		
C_{10}	recreation and leisure		

Experts are requested to rate alternatives with respect to criteria. Table 4 presents the E1 ratings of alternatives with respect to criteria.

TABLE 4
RATINGS OF ALTERNATIVES WITH RESPECT TO CRITERIA (E1)

Criteria											
Exp ert	Alternativ es	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
E1	A_1	4	4	3	3	3	4	2	2	3	1
	A_2	4	4	2	4	3	2	1	1	3	1
	A_3	4	4	3	3	3	1	1	1	2	1
	A_4	4	4	3	3	3	2	3	1	3	1
	A_5	4	4	2	3	1	1	1	1	1	1
	A_6	4	4	4	3	3	1	2	1	3	1
	A_7	4	4	1	1	1	1	1	1	2	1

Similar ratings are collected from experts E2, E3, E4, and E5. These ratings serve as the input data for the proposed computational tool.

C. Proposed BiN-MABAC

The proposed BiN-MABAC method is a modification of the MABAC technique, where the linguistic terms are defined using bipolar neutrosophic numbers. Specifically, a six-tuple of bipolar neutrosophic numbers is employed to represent a five-scale linguistic variable of influence. This modification extends the MABAC method without altering its fundamental structure. The details of the proposed method and its computational procedures are elucidated below.

Step 1. Develop the new linguistic variable based on bipolar neutrosophic numbers.

The single-valued neutrosophic numbers serve as the foundation for creating a new linguistic variable. Table 1 presents the linguistic variable 'influence' along with its associated single-valued neutrosophic number.

The linguistic variable of single-valued neutrosophic numbers is converted to the linguistic variable of bipolar neutrosophic numbers through a straightforward arithmetic operation. This is the main modification where single-valued neutrosophic numbers are substituted with bipolar neutrosophic numbers. The linguistic scales used in this study were represented using bipolar neutrosophic numbers to accommodate both positive and negative aspects of expert judgments under uncertain environments. Unlike single-

valued linguistic representations, the bipolar neutrosophic framework simultaneously considers positive truth, indeterminacy, and falsity memberships together with their corresponding negative memberships.

Each linguistic term is represented by a six-tuple membership of the form $(T^+, I^+, F^+, T^-, I^-, F^-)$ where T^+, I^+, F^+ are the memberships of $[0, 1]$ denote the positive truth, indeterminacy, and falsity memberships, respectively, while T^-, I^-, F^- are the memberships of $[-1, 0]$ represent the corresponding negative memberships.

In order to modify the above linguistic variable, a bipolar neutrosophic set is defined. A bipolar neutrosophic set $\tilde{\tilde{B}}$ in P is characterized as an entity of the following form:

$$\tilde{\tilde{B}} = \left\langle x, T_{\tilde{\tilde{B}}}^+(x), I_{\tilde{\tilde{B}}}^+(x), F_{\tilde{\tilde{B}}}^+(x), T_{\tilde{\tilde{B}}}^-(x), I_{\tilde{\tilde{B}}}^-(x), F_{\tilde{\tilde{B}}}^-(x) \right\rangle, x \in P$$

The above definition highlights the bipolar nature of positive and negative membership. The positive membership degree indicates the levels of truth, indeterminate, and false memberships of an element concerning a bipolar neutrosophic set. Likewise, the negative membership degree reflects the levels of truth, indeterminate, and false memberships of an element within a bipolar neutrosophic set [13]. Based on this definition, a new linguistic variable is created as follows.

Let $X = \{x_1, x_2, x_3, x_4, x_5\}$ is linguistic variable, then the six-tuple memberships of bipolar neutrosophic sets for five linguistic terms are defined as Equation (1).

$$\tilde{\tilde{B}} = \left\{ \begin{aligned} &\langle x_1, (0.10, 0.10, 0.90 \in [0, 1]), (-0.10, -0.10, -0.90 \in [-1, 0]) \rangle, \\ &\langle x_2, (0.35, 0.20, 0.70 \in [0, 1]), (-0.35, -0.20, -0.70 \in [-1, 0]) \rangle, \\ &\langle x_3, (0.50, 0.40, 0.45 \in [0, 1]), (-0.50, -0.40, -0.45 \in [-1, 0]) \rangle, \\ &\langle x_4, (0.80, 0.60, 0.15 \in [0, 1]), (-0.80, -0.60, -0.15 \in [-1, 0]) \rangle, \\ &\langle x_5, 0.90, 0.80, 0.10 \in [0, 1], (-0.90, -0.80, -0.10 \in [-1, 0]) \rangle \end{aligned} \right\} \quad (1).$$

$\tilde{\tilde{B}}$ is a bipolar neutrosophic number where $T^+(x), I^+(x), F^+(x), P \in [0, 1]$, and $T^-(x), I^-(x), F^-(x), P \in [-1, 0]$. For example, we define linguistic x_1 as $(0.10, 0.10, 0.90 \in [0, 1])$ and $(-0.10, -0.10, -0.90 \in [-1, 0])$. The new linguistic variables 'influence' are s^1 (no influence), s^2 (very low influence), s^3 (Low influence), s^4 (High influence) and s^5 (High influence) and its respective memberships of bipolar neutrosophic numbers are summarised in Table 5.

TABLE 5
BIPOLAR NEUTROSOPHIC LINGUISTIC VARIABLE

Rating scale and linguistic terms	Bipolar neutrosophic fuzzy numbers
s^1	$\langle 0.10, 0.10, 0.90, -0.10, -0.10, -0.90 \rangle$
s^2	$\langle 0.35, 0.20, 0.70, -0.35, -0.20, -0.70 \rangle$
s^3	$\langle 0.50, 0.40, 0.45, -0.50, -0.40, -0.45 \rangle$
s^4	$\langle 0.80, 0.60, 0.15, -0.80, -0.60, -0.15 \rangle$

Step 2. Create the matrix of aggregated direct relations.

This phase involves combining the bipolar neutrosophic data using the bipolar neutrosophic weighted average operator.

Let $\ddot{E}_e = \langle T_j^+, T_j^-, I_j^+, I_j^-, F_j^+, F_j^- \rangle$ where $(j = 1, 2, \dots, n)$ is used to indicate a BNS that assesses the e -expert. The weight coefficient for the e -th expert can be calculated using Equation (2),

$$w_j = \frac{1 - \sqrt{\frac{(1 - (T_j^+(x) + T_j^-(x))^2 + (I_j^+(x) + I_j^-(x))^2 + (F_j^+(x) + F_j^-(x))^2}{3}}}{\sum_{e=1}^n \left(1 - \sqrt{\frac{(1 - (T_j^+(x) + T_j^-(x))^2 + (I_j^+(x) + I_j^-(x))^2 + (F_j^+(x) + F_j^-(x))^2}{3}} \right)} \quad (2)$$

where

$$\sum_{j=1}^n w_j = 1, (1 \leq j \leq n).$$

then, Bipolar neutrosophic weighted average operator (A_w) is defined as:

$$A_w(\bar{a}_1, \bar{a}_2, \dots, \bar{a}_n) = \sum_{j=1}^n w_j \bar{a}_j = \left\langle \begin{aligned} &(1 - \prod_{j=1}^n (1 - T_j^+)^{w_j}), \prod_{j=1}^n (I_j^+)^{w_j}, \\ &\prod_{j=1}^n (F_j^+)^{w_j}, -\prod_{j=1}^n (-T_j^-)^{w_j}, \\ &-(1 - \prod_{j=1}^n (1 - (-I_j^-)^{w_j}), \\ &-(1 - \prod_{j=1}^n (1 - (-F_j^-)^{w_j}) \end{aligned} \right\rangle \quad (3)$$

where w_j is weights of experts.

Step 3: Reduction of Bipolar Neutrosophic Numbers. Reduction refers to the process of transforming neutrosophic numbers into crisp values. The reduction of a bipolar neutrosophic set in X is defined as mapping the set $\tilde{B}$ into a neutrosophic set. Let $B = (T^+, I^+, F^+, T^-, I^-, F^-)$ be a bipolar neutrosophic number, where T^+, I^+, F^+ are the memberships of $[0, 1]$ and T^-, I^-, F^- are the memberships of $[-1, 0]$. The crisp value is obtained using the following reduction function (see equation (4))

$$\mu_b(x) = \left\{ 1 - \frac{1}{2} \sqrt{\frac{(1 - T^+(x))^2 + I^+(x)^2 + F^+(x)^2}{3}} + \frac{1}{2} \sqrt{\frac{(1 - (-T^-(x))^2 + (-I^-(x))^2 + (-F^-(x))^2}{3}} \right\} \quad (4)$$

This reduction function simultaneously considers the positive and negative memberships of truth, indeterminacy, and falsity while preserving the bipolar characteristics of neutrosophic information. Higher values of $\mu(x)$ indicate stronger preference and greater suitability of the evaluated element.

Step 4. Construct the initial decision matrix.

$$\bar{X} = \begin{bmatrix} \bar{x}_{11} & \bar{x}_{12} & \cdots & \bar{x}_{1n} \\ \bar{x}_{21} & \bar{x}_{22} & \cdots & \bar{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \bar{x}_{m1} & \bar{x}_{m2} & \cdots & \bar{x}_{mn} \end{bmatrix} \quad (5)$$

where $m \times n$ indicates the size of alternative and criteria.

Step 5. Normalize the initial decision matrix

The normalised matrix is presented in equation (6)

$$\bar{N} = \begin{bmatrix} \bar{n}_{11} & \bar{n}_{12} & \cdots & \bar{n}_{1n} \\ \bar{n}_{21} & \bar{n}_{22} & \cdots & \bar{n}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \bar{n}_{m1} & \bar{n}_{m2} & \cdots & \bar{n}_{mn} \end{bmatrix} \quad (6)$$

$$\text{where } \bar{n}_{ij} = \frac{\bar{x}_{ij} - \bar{x}_i^-}{\bar{x}_i^+ - \bar{x}_i^-} \quad (7)$$

for benefit criteria.

$$\text{and } \bar{n}_{ij} = \frac{\bar{x}_{ij} - \bar{x}_i^+}{\bar{x}_i^- - \bar{x}_i^+} \quad (8)$$

for cost criteria

Step 6. Find weighted matrix.

$$\bar{v}_{ij} = \bar{w}_i (\bar{n}_{ij} + 1) \quad (9)$$

where $\bar{n}_{ij}$ are the elements of the normalized matrix, $\bar{w}_i$ is the weight coefficients of the criteria.

We can obtain the weighted matrix,

$$\bar{V} = \begin{bmatrix} \bar{v}_{11} & \bar{v}_{12} & \cdots & \bar{v}_{1n} \\ \bar{v}_{21} & \bar{v}_{22} & \cdots & \bar{v}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \bar{v}_{m1} & \bar{v}_{m2} & \cdots & \bar{v}_{mn} \end{bmatrix} \quad (10)$$

Step 7. Determine BAA matrix.

$$\bar{g}_i = \left(\prod_{j=1}^m \bar{v}_{ij} \right)^{\frac{1}{m}} \lim_{m \rightarrow \infty} \quad (11)$$

where $\bar{v}_{ij}$ are the elements of the matrix in Step 6. The BAA matrix is arranged in matrix $n \times 1$:

$$\bar{G} = [\bar{g}_1 \quad \bar{g}_2 \quad \cdots \quad \bar{g}_n] \quad (12)$$

Step 8. Find the distance of alternatives.

$$\bar{Q} = \begin{bmatrix} \bar{q}_{11} & \bar{q}_{12} & \cdots & \bar{q}_{1n} \\ \bar{q}_{21} & \bar{q}_{22} & \cdots & \bar{q}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \bar{q}_{m1} & \bar{q}_{m2} & \cdots & \bar{q}_{mn} \end{bmatrix} \quad (13)$$

Step 9. Rank the alternatives

The criterion function values for each alternative are determined by summing the distances of the alternative from the BAA. The final criterion function values for the alternatives are computed by summing the elements of the matrix across each row.

$$\bar{S}_i = \sum_{j=1}^n \bar{q}_{ij}, (i = 1, 2, \dots, m; j = 1, 2, \dots, n) \quad (14)$$

These nine-step computational procedures are implemented to the case study of criteria and alternatives of agricultural sustainability.

III. RESULTS AND DISCUSSION

This section provides a detailed explanation of the computations involved in the BiN-MABAC method. The computations are implemented in accordance with the proposed method.

Step 1. Construct the linguistic variable of BNNs.

The linguistic variable 'influence' and its BNNs are proposed based on the work of Rahim et al.[11]. With some modifications to this work, the linguistic variable is constructed (see Table 5).

Step 2. Construct Bipolar Neutrosophic Aggregated Direct Relation Decision Matrix. by applying equation (2) and equation (3). Table 6 presents the Bipolar Neutrosophic Aggregated Direct Relation Decision Matrix. (see Appendix 1).

Step 3. Reduction of bipolar neutrosophic.

Reduction is implemented using equation (8).

The aggregated relation-matrix after implementing reduction is presented in Table 7.

TABLE 7 REDUCED AGGREGATED RELATION MATRIX

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
A ₁	0.7339	0.6982	0.7447	0.7446	0.7325	0.7411	0.6837	0.6604	0.6940	0.6316
A ₂	0.7339	0.7337	0.6932	0.7339	0.7446	0.7196	0.6316	0.6462	0.7183	0.6462
A ₃	0.7409	0.7338	0.7194	0.7330	0.7447	0.7112	0.6552	0.6462	0.6741	0.6316
A ₄	0.7290	0.7290	0.7325	0.7325	0.7313	0.6630	0.7322	0.6982	0.7325	0.6982
A ₅	0.7339	0.7088	0.6932	0.7199	0.6316	0.6316	0.6462	0.6316	0.6462	0.6713
A ₆	0.7088	0.7005	0.7339	0.7191	0.6892	0.6316	0.6837	0.6552	0.6892	0.6567
A ₇	0.7339	0.7088	0.6536	0.6680	0.6417	0.6462	0.6316	0.6462	0.6510	0.6552

The narrow range of these crisp values suggests a high degree of consensus and homogeneity among the expert assessments regarding the overall influence of criteria within the model. This minimal spread of values in the initial crisp matrix indicates consistency in the data input.

Step 4. Construct initial decision matrix.

Using Equation (5), the initial decision matrix is obtained as

$$\bar{X} = \begin{bmatrix} 0.7409 & 0.7338 & \cdots & 0.6316 \\ 0.7290 & 0.7290 & \cdots & 0.6982 \\ \vdots & \vdots & \ddots & \vdots \\ 0.7339 & 0.7088 & \cdots & 0.6552 \end{bmatrix}$$

Step 5. Normalize the matrix

Table 8 displays the components of the normalised initial decision matrix using Equation (11).

TABLE 8
NORMALIZED INITIAL DECISION MATRIX

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
A ₁	0.7808	0.0000	1.0000	1.0000	0.8923	1.0000	0.5184	0.4317	0.5540	0.0000
A ₂	0.7808	0.9974	0.4356	0.8594	0.9999	0.8034	0.0000	0.2186	0.8354	0.2186
A ₃	1.0000	1.0000	0.7226	0.8484	1.0000	0.7267	0.2351	0.2186	0.3237	0.0000
A ₄	0.6301	0.8647	0.8661	0.8413	0.8817	0.2872	1.0000	1.0000	1.0000	1.0000
A ₅	0.7808	0.2960	0.4356	0.6775	0.0000	0.0000	0.1448	0.0000	0.0000	0.5957
A ₆	0.0000	0.0637	0.8814	0.6676	0.5092	0.0000	0.5184	0.3543	0.4982	0.3764
A ₇	0.7808	0.2960	0.0000	0.0000	0.0892	0.1330	0.0000	0.2186	0.0563	0.3543

Step 6. Find the weighted elements of the normalized initial decision matrix.

To find weighted normalized decision matrix, equation (9) and equation (10) are utilized. The determination of criteria weights plays an important role in the implementation of the proposed BiN-MABAC framework, as the weights reflect the

relative importance of the sustainability criteria in the decision-making process. In this study, the weights of the criteria were determined based on the evaluations provided by the participating agricultural experts. Initially, the experts assessed the importance of each criterion using the predefined

bipolar neutrosophic linguistic scale. The linguistic evaluations were then converted into bipolar neutrosophic numbers and aggregated using the bipolar neutrosophic weighted averaging operator. Subsequently, the aggregated bipolar neutrosophic values were transformed into crisp values through the reduction procedure. Finally, normalization was performed to obtain the criteria weight vector.

The resulting criteria weight vector is presented as $w_i = (0.0306, 0.0304, 0.0305, 0.0249, 0.0329, 0.0293, 0.0287, 0.0280, 0.0278, 0.0265)$. The obtained weights indicate the relative contribution of each sustainability criterion in the evaluation of agricultural alternatives. These

weights were subsequently utilized in the construction of the weighted normalized decision matrix and the computation of the border approximation areas within the proposed BiN-MABAC framework. Table 9 displays the weighted components of the normalized initial decision matrix.

TABLE 9
WEIGHTED NORMALIZED DECISION MATRIX WITH WEIGHTS

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
A ₁	0.0545	0.0304	0.0609	0.0497	0.0572	0.0586	0.0435	0.0401	0.0433	0.0265
A ₂	0.0545	0.0608	0.0437	0.0462	0.0604	0.0529	0.0287	0.0341	0.0511	0.0323
A ₃	0.0613	0.0608	0.0525	0.0459	0.0604	0.0506	0.0354	0.0341	0.0368	0.0265
A ₄	0.0499	0.0567	0.0568	0.0458	0.0569	0.0377	0.0573	0.0560	0.0557	0.0531
A ₅	0.0545	0.0394	0.0437	0.0417	0.0302	0.0293	0.0328	0.0280	0.0278	0.0424
A ₆	0.0306	0.0323	0.0573	0.0414	0.0456	0.0293	0.0435	0.0379	0.0417	0.0365
A ₇	0.0545	0.0394	0.0305	0.0249	0.0329	0.0332	0.0287	0.0341	0.0294	0.0359

Step 7. Determine the BAA matrix (G Values).

BAA matrix is obtained using equation (15). Table 10 shows the BAA for each criterion.

TABLE 10
ELEMENT OF BAA MATRIX ACCORDING TO CRITERIA (G VALUES).

Criteria	BAA (G values)
C_1	0.05043
C_2	0.04403
C_3	0.04822
C_4	0.04136
C_5	0.04740
C_6	0.04018
C_7	0.03748
C_8	0.03699
C_9	0.03967
C_{10}	0.03522

Step 8. Find distances of alternatives from BAA matrix

Equation (17) is used to calculate the distances between the choices and the BAA matrix's entries.

Step 9. Find a sum of distances

The final sum of distances of alternatives can be obtained using Equation (18).

The sum of distances for other alternatives is computed accordingly. The final sum of distances of alternatives are eventually indicates the ranking of alternatives. The uncertainty analysis was performed based on the variations in expert assessments and the resulting computational outputs. The inclusion of statistical indicators such as standard deviations provides further insight into the consistency and

reliability of the obtained rankings and enables a clearer interpretation of the differences among alternatives. Table 11 presents the final sums of distances together with their corresponding standard deviation values and ranking.

TABLE 11
SUM OF DISTANCES OF ALTERNATIVES AND THEIR RANKING

Alternatives	Sum, $\bar{S}$	Standard Deviations	Ranking
A ₁	0.04382	0.0043	2
A ₂	0.04377	0.0048	3
A ₃	0.04348	0.0051	4
A ₄	0.10494	0.0032	1
A ₅	-0.05107	0.0064	6
A ₆	-0.02465	0.0059	5
A ₇	-0.07744	0.0071	7

The standard deviation values indicate the variability of the ranking scores derived from expert evaluations. Among all alternatives, agroforestry (A₄) achieved the highest final sum of distances with the lowest variability, demonstrating strong consistency and robustness under uncertain decision-making conditions. In contrast, alternatives with lower ranking positions exhibited relatively larger variability, reflecting greater sensitivity to variations in expert assessments.

The alternatives are ranked as

$A_4 \succ A_1 \succ A_2 \succ A_3 \succ A_6 \succ A_5 \succ A_7$, based on the sum of their distances from the BAA. Therefore, A₄ is the most important alternative of agricultural sustainability. Figure 1 illustrates the distances and rankings of the alternatives.

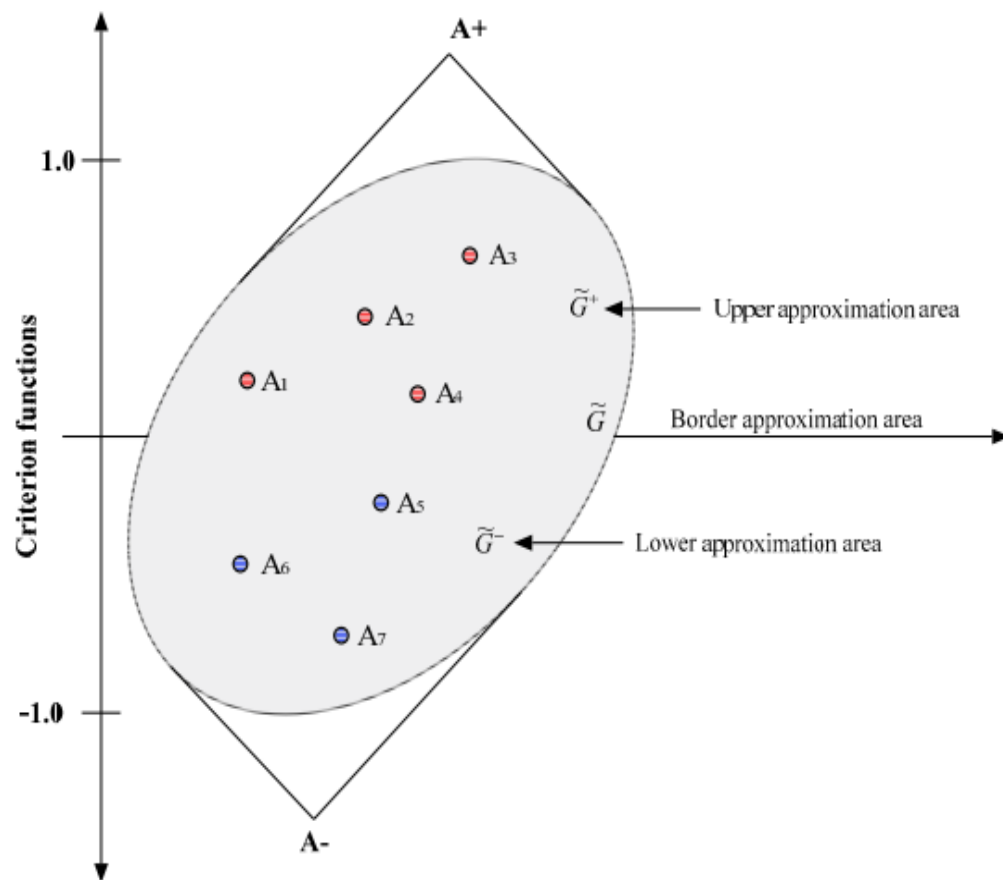


FIG 1. DISTANCES OF ALTERNATIVES IN BORDER APPROXIMATION AREAS

Figure 1 illustrates the distribution of alternatives within the upper and lower approximation areas of the proposed BiN-MABAC framework. The Border Approximation Area $\tilde{G}$ (horizontal axis) represents the reference boundary computed for each criterion. An alternative is located in the upper approximation area when the sum of its distances from the border is positive, indicating that the overall performance of the alternative is better than the border approximation area. Conversely, a negative sum of distances places the alternative in the lower approximation area, indicating relatively weaker performance. Larger positive distances indicate stronger superiority of an alternative, whereas larger negative distances reflect weaker overall performance relative to the evaluated sustainability criteria.

It can be observed that the border divides the alternatives into an upper approximation area and a lower approximation area. The alternative with the highest rank in the upper approximation area is A_4 , while the lowest-ranked alternative is A_7 . This result suggests that agroforestry (A_4) is the most important alternative, while integration of livestock (A_7) is the least important alternative for sustainable agriculture practices. Though integration of livestock is the least important alternative of agricultural sustainability, it is a very important field in investigating the association of flu of livestock to certain zoonotic diseases [14]. Computational results show

that the proposed method has the ability to identify agroforestry as the optimal solution of agricultural sustainability. It is a practice in agriculture that integrates multifunctional trees and collective management of nearby forest resources into agricultural systems. The ranking results obtained from the proposed BiN-MABAC framework identified agroforestry as the highest-performing alternative, indicating its superior contribution toward sustainable agricultural development. This finding is consistent with existing agricultural sustainability literature, which widely recognizes agroforestry as an effective strategy for balancing environmental conservation, economic productivity, and social sustainability. According to agroforestry research by Pleninger et al. [15], agroforestry systems play a significant role in sustainable landscape management by supporting biodiversity conservation, improving ecosystem resilience, enhancing soil quality, and contributing to multiple Sustainable Development Goals. Similarly, Singh and Singh [16] emphasized that agroforestry represents a highly sustainable agricultural model due to its integrated economic, environmental, social, and human sustainability benefits. Their study further demonstrated the suitability of multi-criteria decision-making approaches in evaluating sustainable agroforestry systems. The highest ranking achieved by the agroforestry alternative in the present study is not only supported by the computational results of the proposed BiN-MABAC model but is also strongly aligned with established findings in the agricultural sustainability literature.

IV. SENSITIVITY AND COMPARATIVE ANALYSIS

To evaluate the robustness and stability of the proposed BiN-MABAC framework, a sensitivity analysis was conducted based on variations in the criteria weight vector while employing the concept of the distance from the BAA, which constitutes the fundamental principle of the MABAC method. Unlike conventional aggregation approaches, the BiN-MABAC method determines the final assessment value by measuring the distance between each alternative and the BAA for every criterion. Positive distance values indicate that an alternative performs above the BAA, whereas negative values indicate performance below the BAA. Three sensitivity scenarios were considered to investigate the effect of criteria weight variations on the final ranking results. Scenario S1 represents the baseline condition using the original criteria weights, while Scenario S2 and Scenario S3 represent +20% and +40% increases in the criteria weights, respectively. In the baseline scenario (S1), Alternative A4 achieved the highest distance value from the BAA ($\text{Sum}, \bar{s} = 0.10494$), indicating the strongest overall performance among all alternatives (see Table 11). Alternatives A1, A2, and A3 also produced positive distance values, suggesting that these alternatives performed above the BAA. Conversely, Alternatives A5, A6, and A7 obtained negative values, indicating relatively weaker performance compared with the BAA. After increasing the criteria weights by 20% in Scenario S2, the magnitude of the distances from the BAA increased proportionally. However, the ranking positions of the alternatives remained unchanged, with A4 consistently maintaining the highest-ranking position. Table 12 presents the ranking positions of alternatives in Scenario 2.

Table 12. Scenario S2 – +20% Criteria Weight Variation

Alternative	Sum, $\bar{s}$	Rank
A ₁	0.05258	2
A ₂	0.05252	3
A ₃	0.05218	4
A ₄	0.12593	1
A ₅	-0.06128	6
A ₆	-0.02958	5
A ₇	-0.09293	7

Similarly, in Scenario S3, where the criteria weights were increased by 40%, all sum values increased further in magnitude while preserving the same ranking structure observed in the previous scenarios. Table 13 presents the ranking results in Scenario S3.

Table 13 Scenario S3 – +40% Criteria Weight Variation

Alternative	Sum, $\bar{s}$	Rank
A ₁	0.06135	2
A ₂	0.06128	3
A ₃	0.06087	4
A ₄	0.14692	1
A ₅	-0.07150	6
A ₆	-0.03451	5
A ₇	-0.10842	7

The sensitivity analysis demonstrates that the proposed BiN-MABAC framework exhibits strong robustness and stability under variations in criteria weights. Although the magnitudes of the distances from the BAA changed proportionally across the scenarios, the ranking order of the alternatives remained unchanged. In all scenarios, Alternative A4 consistently emerged as the best-performing alternative, while Alternative A7 remained the lowest-ranked alternative. These findings confirm the reliability and consistency of the proposed decision-making model.

To further check the reliability and consistency of the proposed method, another sensitivity analysis was conducted to examine the robustness of the proposed BiN-MABAC framework under variations in criterion weights and expert preferences. Several scenarios were generated by modifying the weights of the economic-related criteria and altering the influence of selected experts while maintaining the normalization condition. In particular, the weights of the economic-related criteria increased by 20% and 40%, respectively, followed by recalculation of the ranking results. The findings indicate that agroforestry (A₄) consistently retained the highest-ranking position across all sensitivity scenarios. Although slight variations were observed among the intermediate alternatives, especially between A₁ and A₂ as well as A₅ and A₆, the overall ranking structure remained relatively stable. Additional experiments involving changes in expert weights also produced consistent results, where the optimal alternative remained unchanged. Figure 2 presents the ranking behaviour of the alternatives under different sensitivity scenarios.

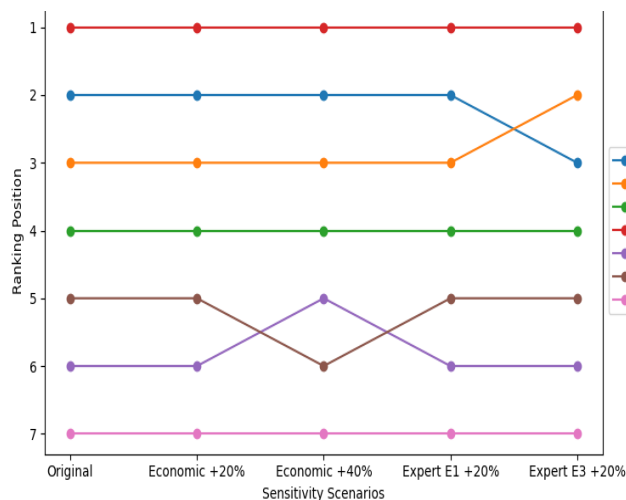


Figure 2 Sensitivity Analysis of the BiN-MABAC

The outcomes of ranking positions demonstrate that the proposed BiN-MABAC method is robust against moderate variations in both criterion importance and expert judgments.

A comparative analysis was also performed to evaluate the consistency of the proposed BiN-MABAC method against Neutrosophic TOPSIS and Neutrosophic VIKOR methods. The same decision matrix and criterion weights were utilized to ensure a fair comparison. Table 14 summarizes the ranking positions of all alternatives obtained from the three methods.

Table 14 Ranking Positions of Alternatives under different Methods

Alternative	BiN-MABAC	Neutrosophic TOPSIS	Neutrosophic VIKOR
A1	2	3	2
A2	3	2	3
A3	4	4	4
A4	1	1	1
A5	6	5	5
A6	5	6	6
A7	7	7	7

The comparative results indicate that all three methods consistently identified agroforestry (A₄) as the best alternative for sustainable agriculture practices, while integration of livestock (A₇) remained the lowest-ranked alternative. Minor differences were observed among the intermediate alternatives, particularly between A₁ and A₂ as well as A₅ and A₆. Despite these slight variations, the overall ranking structure remained highly consistent across the evaluated methods. Figure 3 illustrates the ranking performance of the alternatives under different decision-making methods.

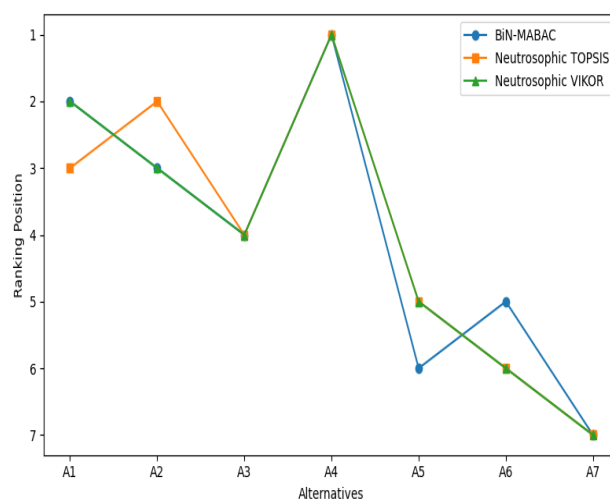


Figure 3 Performance of Alternatives Under Different Methods

The close similarity of the ranking trends demonstrates that the proposed BiN-MABAC framework produces stable and reliable results while maintaining effective discrimination among alternatives.

V. CONCLUSION

In this research, the BiN-MABAC method was proposed as a novel combination of the MABAC method and bipolar neutrosophic sets. A five-scale linguistic term with bipolar neutrosophic numbers was created to facilitate linguistic data collection. Five agricultural specialists were asked to offer linguistic assessments of the relative importance of seven options in relation to ten agricultural sustainability criteria. The sum of distances of the alternatives was computed, and these values were used to rank the alternatives in terms of their importance for agricultural sustainability. The results identified agroforestry (A₄) as the optimal solution for agricultural sustainability. However, the proposed method requires further investigation. The aggregation process used in the method is based on the weighted arithmetic averaging operator. Future research could explore other aggregation processes, such as those based on the weighted geometric averaging operator [17] and optimization techniques [18]. The outcomes of the computational application of the suggested approach are based on an analysis that considers several factors, such as expert weights, criterion weights, the language used, and the degree of uncertainty in expert opinions. Further analysis can be conducted to evaluate the robustness of the proposed method. It is recommended that the criteria weights be used as input parameters for a sensitivity analysis, and this aspect could be explored further in future research.

ACKNOWLEDGMENT

The author would like to thank the research student N.Amani for conducting linguistic data collection and computations of this research.

AUTHOR CONTRIBUTIONS

The author, Lazim Abdullah, was solely responsible for the

conceptualization, methodology, formal analysis, investigation, resources, data curation, writing original draft preparation, and writing review and editing of the manuscript.

AI TOOL USAGE ACKNOWLEDGMENT

The author declares that no AI technologies tools were utilised during the preparation and writing of this article. AI-assisted tool was used solely for the purpose of checking English grammar and refining sentence structures.

CONFLICT OF INTEREST

The author declares that there is no conflict of interest regarding the publication of this article.

DECLARATION OF FUNDING

The author declares that no financial support was received for the research, authorship and/or publication of this article.

REFERENCES

- [1] D. Pamučar, and G. Ćirović. "The selection of transport and handling resources in logistics centers using Multi-Attributive Border Approximation Area Comparison (MABAC)". *Expert Syst. Appl.* vol. 42, no. 6, pp. 3016-3028. 2015.
- [2] D. Pamučar, I. Petrović, and G. Ćirović, "Modification of the Best–Worst and MABAC methods: A novel approach based on interval-valued fuzzy-rough numbers" *Expert Syst. Appl.* 2018; vol.91, pp. 89-106. 2018.
- [3] P. Wang, J. Wang, G. Wei, C. Wei, and Y. Wei, "The multi-attributive border approximation area comparison (MABAC) for multiple attribute group decision making under 2-tuple linguistic neutrosophic environment", *Informatica*, vol. 30, no. 4, pp. 799-818. 2019.
- [4] W. Liang, G. Zhao, H. Wu and B. Dai, "Risk assessment of rock burst via an extended MABAC method under fuzzy environment". *Tunn. Undergr. Space Tech.* vol.283, pp. 533-544. 2019.
- [5] J. Wang, G. Wei, C. Wei, and Y. Wei, "MABAC method for multiple attribute group decision making under q-rung orthopair fuzzy environment." *Def Tech.* 2020; vol. 16, no. 1, pp. 208-216. 2020.
- [6] S. Chakraborty, S. Ghosh, B. Sarker and S. Chakraborty, "An integrated performance evaluation approach for the Indian international airports", *J. Air Transp Manag.* vol.88, pp. 101876. 2020.
- [7] J. Rezaei, "Best-worst multi-criteria decision-making method: Some properties and a linear model" *Omega.* vol. 4, pp. 126–130. 2016.
- [8] A. Puška, A. Štilić M. Nedeljković M, Božanić D, S. Biswas," Integrating fuzzy rough sets with LMAW and MABAC for green supplier selection in agribusiness", *Axioms.* Vol. 12, no.8, pp. 746. 2023.
- [9] D. Liu, L. Qiao, C. Liu, B. Liu, and S. Liu, "Evaluation of Urban Quality Improvement Based on the MABAC Method and VIKOR Method: A Case Study of Shandong Province, China." *Sustainability*, vol.16, no.8, pp. 3308. 2024.
- [10] L. Abdullah, and S.N. Rahim, "Bipolar neutrosophic DEMATEL for urban sustainable development", *J. Intell. Fuzzy Syst.* vol. 39, no. 5, pp. 6109-6119. 2020.
- [11] N. Rahim, L. Abdullah, and B. Yusoff. "A Border Approximation Area Approach Considering Bipolar Neutrosophic Linguistic Variable for Sustainable Energy Selection". *Sustainability*, 12(10):3971. 2020.

- [12] J. Pretty, "Agricultural sustainability: concepts, principles and evidence". *Philos Trans R Soc Lond B Biol Sci.* vol. 363, no. 1491, pp. 447-465. 2008.
- [13] I. Deli, M. Ali, and F. Smarandache, "Bipolar neutrosophic sets and their application based on multi-criteria decision-making problems". In 2015 International Conference on Advanced Mechatronic Systems (ICAMEchS) 2015; pp.249-254. DOI: 10.1109/ICAMEchS.2015.7287068.
- [14] Q.M. Koyee, R.A. Khailany, M.L.Rahman and L.N. Nassraddin "Histopathologic Changes and Molecular Characterization of Fascioliasis (a Zoonotic Disease) among Slaughtered Livestock in Erbil and Halabja Abattoirs, Kurdistan Region-Iraq". *Baghdad Sci. J.*, vol.21, no. 7, pp. 2191-.2209, 2024.
- [15] T. Plieninger, J., Muñoz-Rojas, L. E.Buck, & S. J. Scherr, "Agroforestry for sustainable landscape management". *Sust Sci*, 15(5), pp. 1255–1266 (2020).
- [16] S. Singh, G. Singh, G. "Agroforestry for sustainable development: Assessing frameworks to drive agricultural sector growth". *Environ Dev Sustain* 26(9), pp. 22281-22317. . (2024).
- [17] J.C. Alcantud, "Multi-attribute group decision-making based on intuitionistic fuzzy aggregation operators defined by weighted geometric means". *Granul. Comput.* vol. 8, no. 6, pp. 1857-1866. 2023.
- [18] M. Jalasari, S. Manikandan, A.D. Nicholas, S. Gobimohan, N.S. Rao. "Hybrid optimized data aggregation for fog computing devices in internet of things". *Baghdad Sci. J.* vol. 21, no. 5 (S1)), pp. 1811-. 2024.

Author Biography

Lazim Abdullah is a professor of computational mathematics, Faculty of Computer Science and Mathematics, Universiti Malaysia Terengganu, Malaysia. He received his B.Sc in Mathematics from University of Malaya and Ph.D in Information Technology from the Universiti Malaysia Terengganu. He has authored over 350 publications that are published in refereed journals, proceedings, books and monographs. His research focuses on the mathematical theory of fuzzy sets, decision making methods and their applications.



Appendix 1

Table 6 Bipolar Neutrosophic Aggregated Direct Relation Decision Matrix

Criteria/ Alternatives	C ₁	C ₂	C ₃	C ₄	C ₅	...	C ₁₀
A ₁	<0.9000,	<0.7451,	<0.8254,	<0.8000,	<0.7913,		<0.4190,
	0.8000,	0.3546,	0.6348,	0.6000,	0.5867,		0.1927,
	0.1000,	0.2410,	0.1386,	0.1500,	0.1715,	...	0.5675,
	0.9000,	0.3951,	0.8186,	0.8000,	0.7472,		0.2607,
	2.87E-05,	5.4E-07,	1.1E-05,	8.8E-06,	7.9E-06,		4.8E-08,
	2.51E-09>	1.9E-07>	1.2E-08>	1.7E-08>	3.2E-08>		6.3E-06>
A ₂	<0.9000,	<0.8146,	<0.6110,	<0.9000,	<0.8000,		<0.4927,
	0.8000,	0.5501,	0.3623,	0.8000,	0.6000,		0.2038,
	0.1000,	0.1693,	0.3489,	0.1000,	0.1500,	...	0.5242,
	0.9000,	0.7175,	0.5245,	0.9000,	0.8000,		0.2668,
	2.87E-05,	5.3E-06,	8.9E-07,	2.9E-05,	8.8E-06,		6.1E-08,
	2.51E-09>	3.2E-08>	7.4E-07>	2.5E-09>	1.7E-08>		4.3E-06>
A ₃	<0.8713,	<0.8382,	<0.7318,	<0.7663,	<0.8254,		<0.4190,
	0.7204,	0.5820,	0.4254,	0.5601,	0.6348,		0.1927,
	0.1160,	0.1564,	0.2428,	0.1808,	0.1386,		0.5675,
	0.8622,	0.7343,	0.6058,	0.7386,	0.8186,	...	0.2607,
	1.79E-05,	6.8E-06,	1.6E-06,	6.2E-06,	1.1E-05,		4.8E-08,
	5.43E-09>	2.1E-08>	1.8E-07>	4.7E-08>	1.2E-08>		6.3E-06>
A ₄	<0.8630,	<0.8630,	<0.8141,	<0.8141,	<0.7607,		<0.6713,
	0.6985,	0.6985,	0.6155,	0.6155,	0.5542,		0.3314,
	0.1342,	0.1342,	0.1605,	0.1605,	0.1860,		0.3446,
	0.8022,	0.8022,	0.7617,	0.7617,	0.7297,	...	0.4937,
	1.60E-05,	1.6E-05,	1E-05,	1E-05,	6.2E-06,		7.5E-07,
	1.00E-08>	1E-08>	2.2E-08>	2.2E-08>	4.7E-08>		5E-07>
A ₅	<0.9000,	<0.7894,	<0.6110,	<0.7208,	<0.4190,		<0.5309,
	0.8000,	0.42202,	0.3623,	0.5176,	0.1927,		0.3192,
	0.1000,	0.2133,	0.3489,	0.2238,	0.5675,		0.4409,
	0.9000,	0.5002,	0.5245,	0.6741,	0.2607,	...	0.4685,
	2.87E-05,	1.3E-06,	8.9E-07,	4.4E-06,	4.8E-08,		6.2E-07,
	2.51E-09>	1E-07>	7.4E-07>	1.3E-07>	6.3E-06>		2E-06>

A ₆	<0.7894,	<0.7774,	<0.9000,	<0.7293,	<0.6541,	<0.5238,
	0.4220,	0.3751,	0.8000,	0.4238,	0.3124,	0.2332,
	0.2133,	0.2226,	0.1000,	0.2441,	0.2881,	... 0.4992,
	0.5002,	0.4043,	0.9000,	0.6049,	0.3751,	0.3403,
	1.33E-06,	6.9E-07,	2.9E-05,	1.6E-06,	3.4E-07,	1.2E-07,
	1.03E-07>	1.3E-07>	2.5E-09>	1.8E-07>	4E-07>	3.5E-06>
A ₇	<0.9000,	<0.7894,	<0.5164,	<0.5494,	<0.4502,	<0.4839,
	0.8000,	0.4220,	0.2313,	0.2623,	0.2167,	0.2480,
	0.1000,	0.2133,	0.4836,	0.4783,	0.5437,	... 0.5178,
	0.9000,	0.5002,	0.2847,	0.4210,	0.3225,	0.4114,
	2.8E-05,	1.3E-06,	1.1E-07,	2.3E-07,	9.2E-08,	1.8E-07,
	2.51E-09>	1E-07>	3E-06>	2.9E-06>	5.2E-06>	4.2E-06>