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A Machine Learning-Driven Framework for Evaluating and Clustering City-Level Carbon Trading Strategies

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Abstract
The global urgency to combat climate change has led to the widespread adoption of carbon emission trading schemes as market-based instruments. This study introduces a scalable and interpretable machine learning-based framework for evaluating, clustering, and predicting city-level carbon trading strategies. This study fills a gap in localized policy evaluation by combining economic, social, environmental, and political factors to make carbon regulation more adaptive and based on evidence. The hybrid framework that was suggested combines Multi-Objective Optimization (MOO), Multi-Criteria Decision Making (MCDM), Particle Swarm Optimization—Self-Organizing Maps (PSOM), and Random Forest classification. Criteria are weighted using a combination of Fuzzy Delphi Method (FDM) and Stepwise Weight Assessment Ratio Analysis (SWARA), with prioritization executed via MABAC. Cities are clustered through PSOM based on weighted indicators, and policy predictions are generated using Random Forest trained on these clusters. The framework effectively demonstrated regional differences and putting cities into separate policy groups based on their social, economic, environmental, and institutional characteristics. It also demonstrated strong predictive accuracy in recommending feasible carbon trading strategies using the Random Forest classifier. Combining fuzzy logic and machine learning made it possible to deal with the unpredictability and non-linearity that are common in city-level statistics. This study introduces a new and adaptable decision support system based on machine learning that improves the accuracy and responsiveness of evaluations in the carbon market. The integrated methodology furnishes policymakers with an all-encompassing instrument to evaluate and project localized strategies, thereby promoting more equitable and effective carbon governance across heterogeneous urban environments.

Keywords- Carbon trading, Multi-objective optimization (MOO), Multi-criteria decision making (MCDM), Particle swarm optimization – Self-organizing maps (PSOM), Machine learning.

Abbreviations

MCDM	Multi-Criteria Decision Making
MOO	Multi-Objective Optimization
PSOM	Particle Swarm Optimization - Self-Organizing Maps
FDM	Fuzzy Delphi Method
SWARA	Stepwise Weight Assessment Ratio Analysis
MABAC	Multi-Attributive Border Approximation Area Comparison
NSGA	Non-Dominated Sorting Genetic Algorithm
TFN	Triangular Fuzzy Number
GDP	Gross Domestic Product
IC	Industrial Composition
EE	Energy Efficiency
ICA	Innovation Capabilities
IQ	Infrastructure Quality
PD	Population Density
EI	Equity and Inclusion
PTQ	Public Transport Quality
UP	Urban Planning
PCE	Per Capita Emissions
IMR	Energy Mix Renewable
W2E	Waste to Energy
LUP	Land Use Planning
CRP	Climate Resilience Plans
GI	Green Infrastructure
RS	Regulatory Support

1. Introduction

Dealing with climate change has become a global priority, which has led governments to pass stricter environmental rules (Adetama et al., 2022; Cui et al., 2024). Cities are central to these efforts, as they are major consumers of energy and significant sources of carbon dioxide emissions. But many cities still don't have plans that are specific to their needs for being carbon neutral (Zhang et al., 2024). Moving toward a low-carbon economy is now a necessary step to make sure that economic growth and environmental protection go hand in hand (Wang et al., 2024a).

Trade openness and foreign direct investment make growth cleaner by making it easier to use technology that are good for the environment (Wang et al., 2023b). This shows how important it is to have good carbon market mechanisms that cut emissions by giving people price incentives and letting them trade freely (Zhang and Lin, 2023). Government-led carbon trading programs have proven effective in prompting cleaner production, strengthening monitoring, and fostering innovation (Nasir et al., 2021; Wang et al., 2021). For instance, regulatory frameworks in Indonesia emphasize the importance of enforcing sanctions to enhance corporate compliance (Torodji et al., 2023). In the energy sector, carbon trading policies have improved productivity and resource use efficiency through mechanisms such as cost compensation and innovation stimulation (An and Whitcomb, 2024; Chen et al., 2024).

At the regional level, these programs advance sustainability by strengthening environmental governance and enhancing carbon productivity (Shen et al., 2021). In the international trade context, they reduce risk and create opportunities in green sectors (Mao, 2024). However, in numerous developing nations, reliance on fossil fuels remains substantial, and unregulated expansion persists as a source of environmental concern (Han et al., 2023). To counteract these trends, carbon trading has also been shown to improve energy efficiency and enhance the impact of policy assessments (Hu et al., 2023). As economies expand, energy consumption increases in tandem, bringing with it heightened environmental impacts (Wang et al., 2024b). However, evidence of declining emissions intensity suggests that low-carbon development is achievable (Du et al., 2022). Differentiated regional regulations and tailored emissions trading strategies are essential for aligning environmental goals with local development needs (Kang and Zhao, 2022).

New developments in data science have facilitated these transitions. In particular, machine learning especially explainable approaches is being applied more frequently to reveal complex, non-linear linkages among emissions, economic performance, and urban structure (Zhu et al., 2021). Unsupervised and guided learning approaches have enhanced model accuracy and interpretability for emissions forecasting and policy evaluation (Du et al., 2023; Liu & Xu, 2024). Nevertheless, the integration of machine learning into carbon trading research is still largely limited and insufficiently explored Owing to the economic, social, and environmental complexities of carbon markets, decision-support approaches like Multi-Criteria Decision Making (MCDM) have emerged as vital tools (Wu and Niu, 2024). Researchers have emphasized the importance of accounting for spatial and temporal policy effects (Chang and Zhao, 2024) and utilizing causal inference techniques to evaluate policy impacts (Wang et al., 2023c; Liu et al., 2024a). Carbon emission trading systems are some of the most scalable and useful market-based tools. China's national market, initiated in 2021 after a decade of pilot projects, has rapidly become a global leader (Zhang and Deng, 2025). Yet, pronounced spatial and temporal disparities in pricing, enforcement, trading practices, technological capacity, ecological constraints, and land use continue to undermine equity and efficiency in carbon governance (Mandal et al., 2025).

Moreover, the cascading transformation of urban, cropland, and ecological landscapes directly influences carbon storage and crop production, reinforcing the need for integrated, spatially aware policy design using Multi-Objective Optimization framework integrated with interpretable machine learning (Chen et al., 2025). Addressing these complexities calls for machine learning-based frameworks to evaluate carbon trading performance, identify regional trade-offs, and cluster strategies in a manner that supports informed, adaptive, and data-driven climate decision-making (Rochd et al., 2025).

Machine learning and artificial intelligence have been applied in forecasting carbon prices, identifying key policy levers, and supporting the design of dynamic trading strategies (Wu et al., 2024; Zhao et al., 2025). The interpretability of these models has been further improved through techniques like Shapley Additive Explanations, enabling more informed, evidence-driven policymaking. Moreover, adaptive strategy models, such as deep reinforcement learning and federated learning, have enabled the real-time optimization of trading decisions, even in decentralized and heterogeneous environments (Singh and Singh, 2025). Complementary policy tools, such as energy quota trading, have also proven effective in reducing regional carbon inequality and promoting social equity (Wang et al., 2025).

By integrating supervised evaluation, unsupervised clustering, and MCDM, the model addresses the following objectives:

- Determine carbon policy priorities using an MOO and MCDM approach.
- Identify regional carbon policy patterns through mapping and clustering using a hybrid PSOM.
- Predict feasible carbon trading policies for cities using the Random Forest classification model.

This study proposes a novel hybrid framework that integrates the MOO, MCDM, PSOM, and Random Forest algorithms that can be used in the evaluation, grouping, and adaptive prediction process in a single integrated system of city-level carbon trading strategies. Further, the framework offers scalable, context-sensitive decision support in addressing spatial heterogeneity, and enables data-driven policy planning.

The comprehensive study is depicted in **Figure 1**, delineating the sequential methodological procedures and the integration of key analytical components within the study framework.

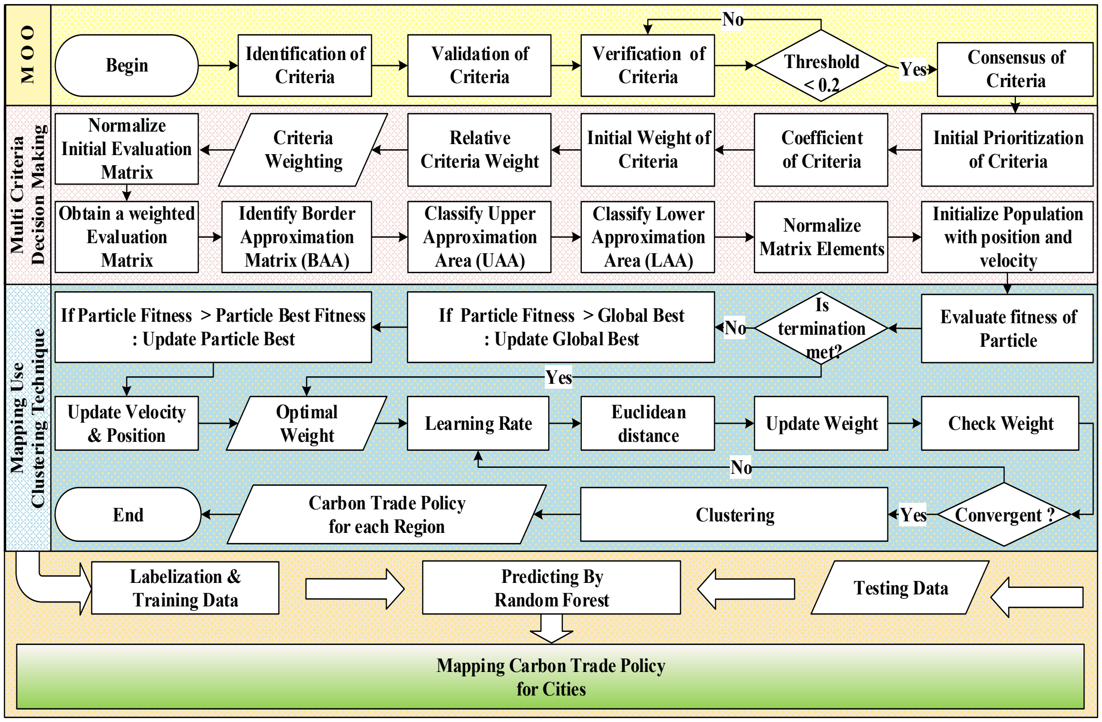


Figure 1. Proposed framework.

The remainder of this paper is organized as follows: Section 2 reviews related works on carbon trading policies and frameworks; Section 3 presents the materials and methods used in this study, including the development of the proposed hybrid model; Section 4 discusses the experimental results and analysis; and Section 5 concludes the paper while outlining potential directions for future research.

2. Related Works

2.1 Carbon Trade Policy

Both governments and investors need to devise an effective carbon asset trading strategy if they want to reach their long-term economic and environmental goals (Zhang and Chen, 2024). By allowing the exchange of emission credits, carbon trading systems provide a market-based way to lower emissions (Xu et al., 2024). Bekkers and Cariola (2022) came up with the carbon club structure, which encourages regulatory harmonization and more people to get involved in global climate governance.

Cities are the most essential sites to work on climate change because they are responsible for more than 70% of carbon emissions. Most policy research, on the other hand, is still focused on the national level and often doesn't take into account how emissions change in different localities (Liu et al., 2024b). Research by Ma (2023) revealed that employing both taxes and carbon trading systems together can isolate emissions from economic growth. But most assessments still rely primarily on historical data and don't have the methodological flexibility to account for changes in space and time at the city level (Wu et al., 2022). Wong (2022) called for clear and open policy frameworks that take into account the needs of cities, given these restrictions. Even though there have been some big improvements, creating adaptive, real-time city-level models that show how policies change and emissions change in specific areas is still a problem.

2.2 MOO and MCDM in Urban Policy

MCDM and MOO frameworks are increasingly used to guide sustainability assessments in complex urban systems. Ferdous et al. (2024) introduced a decision-tree model that integrates MOO optimization under uncertainty, offering a structured analysis despite data gaps. Gallo and Maheut (2023) showed how MCDM approaches can be used in many different ways in urban logistics and policy evaluation. Reyes-Norambuena et al. (2024) came up with a Grey MCDM framework to make pedestrian infrastructure better. This app shows how MCDM can help with city planning. Keshavarz-Ghorabaee et al. (2022) also talked about how MCDM may help with city transportation planning. But MOO and MCDM are not fully integrated into urban carbon policy yet, and there aren't many studies that offer a unified framework for optimization, assessment, and prediction.

2.3 Applications in Energy and Emission Reduction

In response to global climate issues, there is an international consensus that carbon emissions must be reduced (Cao et al., 2024a), with several studies focusing on carbon trading policies and emission reductions. Xia et al. (2021) provided empirical evidence of carbon trading's role in emission reductions within construction and land use, highlighting the necessity of multi-criteria evaluation frameworks like MOO and MCDM. Zinatizadeh et al. (2017) underscored the importance of MCDM in evaluating trade-offs across environmental, economic, and social dimensions in urban sustainability.

Kokkinos et al. (2020) built a tool to help people make decisions about decarbonization strategies in the optimization of energy systems. However, they noted a need to further explore social and behavioral impacts on household-level energy choices. Esmat et al. (2023) have built a model to help people choose decentralized heating sources. This proves that MCDM helps city planners establish a balance between their economic and environmental goals. Even while these kinds of apps are helpful, most research are still focused on descriptive analysis and haven't made any headway on building tools that can anticipate how well carbon trading would work at the municipal level. These studies reveal a gap in understanding how carbon trading policies influence individual decision-making.

2.4 Advances in Hybrid Models and Future Directions

Recent studies show that hybrid models could help with the problems that come up in carbon trading. Bian et al. (2024) looked at bidding techniques in energy storage markets, and Qin et al. (2024) stressed the need for systems that can handle several objectives quickly. Baars et al. (2023) made progress on integrated evaluations for the sustainability of electric vehicles and suggested that MOO should be improved even more. Cao et al. (2024b) came up with an optimization model that uses a chaotic artificial hummingbird method for regional dispatch. However, their method is not clear about how prioritizing techniques are put into action in optimization algorithms.

Zhang et al. (2022) stated that quasi-natural experiments and synthetic controls are also good ways to find out how well carbon trading works. Most hybrid models are only useful in few areas, and they have trouble scaling, adapting, and being used in real time in cities.

2.5 Advantages of the Hybrid MOO-MCDM-PSOM-Random Forest Methods

Recent progress in machine learning has made it even more important to choose the right features and fine-tune hyperparameters when creating predictive models (Alahmari et al., 2025). Shang et al. (2025) indicated that hybrid deep learning models might be helpful, but they also brought out issues with multivariate analysis. These limits highlight how crucial it is to create frameworks that can adapt to many different parts of a city.

Xu and Zhang (2023) research showed how hard it is to find a compromise between accuracy and usefulness when measuring emissions in cities. The suggested system combines the Fuzzy Delphi Method (FDM), Stepwise Weight Assessment Ratio Analysis (SWARA), Multi-Attributive Border Approximation Area Comparison (MABAC), PSOM, and Random Forest algorithms to overcome these challenges. This integration allows for dynamic criterion weighting, strong clustering, and accurate prediction, which makes it possible to do scaled, context-aware evaluations of carbon trading policies. The use of machine learning for urban classification (Xing et al., 2024) and predictive carbon mapping has showed potential, although it is still not fully developed in integrated frameworks. The proposed approach solves this problem by connecting clustering with machine learning to help optimize carbon trading in each city.

2.6 Research Gap

The growing need to do something about climate change has led to more academic writing about carbon trading frameworks, optimization methods, and sustainability evaluations. Dynamic policy studies (Xu et al., 2024) and global cooperation frameworks like the carbon club (Bekkers and Cariola, 2022) are useful, but they usually only look at national-level situations and don't take into account differences between cities. In the same way, hybrid models and optimization methods like carbon tax (Ma, 2023), volatility modeling in carbon pricing (Wu et al., 2022), and MOO-MCDM integration (Ferdous et al., 2024) generally focus on theoretical frameworks without putting them into practice in specific cities.

Many current approaches rely primarily on historical or static datasets (Li et al., 2020), which makes it hard for them to adjust to quickly changing urban settings. Also, decision-making tools often don't take into account social and behavioral factors, like in energy policy models (Kokkinos et al., 2020). Also, even while multi-agent and hybrid optimization models (Cao et al., 2024b) have made certain areas of business run more smoothly, they frequently can't be scaled up, respond in real time, or be used in a variety of urban contexts.

3. Materials and Methods

3.1 Identification of Aspect and Criteria

Based on a review of several previous studies, several aspects are summarized, including economic aspects (Chen et al., 2021) involving Gross Domestic Product (GDP), Industrial Composition (IC), Energy Efficiency (EE), Innovation Capabilities (ICA), and Infrastructure Quality (IQ) as criteria. Moreover, the social aspects (Yao et al., 2023) involve Population Density (PD), Equity and Inclusion (EI), Public Transport Quality (PTQ), and Urban Planning (UP). The environmental aspects (Li et al., 2022; Yu and Luo, 2022) involve Per Capita Emissions (PCE), Energy Mix Renewable (IMR), Waste to Energy (W2E), Land Use Planning (LUP), Climate Resilience Plans (CRP), and Green Infrastructure (GI) as criteria. Finally, the political aspect (Wang et al., 2023a) involves the Regulatory Support (RS) criterion, which relates to implementing carbon trade policies for a city.

3.2 Design of Hybrid MOO-MCDM-PSOM

MOO and MCDM are operations research disciplines that aim to help make the best decisions in complex problems (Neira-Rodado et al., 2023). The process of assigning weights to criteria employs the reciprocal methodology, which computes the magnitude of the weight values, taking into account the varying significance of the order of indices (Faisal and Rahman, 2023a). The Fuzzy Delphi offers a resilient framework adept at managing uncertainties and ambiguities, acknowledging that decision-making processes are often hindered by incomplete or imprecise information (Shen et al., 2021).

The approach of FDM-SWARA is particularly relevant for organizations and policymakers who want to strategize based on uncertain data while still obtaining reliable results (Thompson et al., 2024). The

SWARA method is an efficient approach to evaluating criteria by prioritizing criteria in ascending order based on expected meaning through consultation with experts (Sarvari et al., 2024; Faisal et al., 2025). Furthermore, Torrey et al. (2024) support it, stating that the FDM enables comprehensive analysis without additional computational load and steep learning curves compared to more complex methods. The explanation of decision-making using the hybrid approach of MOO-MCDM-PSOM based on the flowchart is as follows:

Step 1. The threshold value is determined using the Equation (1).

$$d(\bar{m},\bar{n}) = \sqrt{\frac{1}{3} * [\,(M_1 + M_2 + M_3)]} \tag{1}$$

The dataset utilizes triangular fuzzy numbers to determine a threshold value (d).

Step 2. Defining fuzzy score value using Equation (2).

$$\tilde{A} = \left(\frac{1}{n}\sum_{i=1}^{n} l_i\,, \frac{1}{n}\sum_{i=1}^{n} m_i\,, \frac{1}{n}\sum_{i=1}^{n} u_i\right) \tag{2}$$

where, n is the number of authorities. Inconstant l, m, and u are the combined bounds of lower, middle, and upper, respectively.

MCDM makes it easier for participants to voice their opinions and helps them find the best computational solution (Carneiro et al., 2021). The SWARA method is an efficient approach to evaluating criteria based on knowledge, experience, and implicit information, as well as the opinions of experts or group interests on the importance of the weighting process (Lorenzoni et al., 2024).

Step 3. Summarize the expert assessments for each criterion and calculate the average value for each opinion (Soltani and Aliabadi, 2023), as detailed in Equation (3).

$$\bar{t}_j = \frac{\sum_{k=1}^{r} t_{jk}}{r} \tag{3}$$

Step 4. Finding the comparative value (S_j) and value of the coefficient (K_j) using Equation (4).

$$K_j = \begin{cases} \frac{1}{S_j}, & \text{if } j = 1 \\ 1, & \text{if } j > 1 \end{cases} \tag{4}$$

Step 5. Recalculate the weight of q_j using the Equation (5).

$$q_j = \begin{cases} \frac{k_j - 1}{k_j}, & \text{if } j = 1 \\ 1, & \text{if } j > 1 \end{cases} \tag{5}$$

Step 6. Determine the weight using Equation (6).

$$w_j = \frac{q_j}{\sum_{j=1}^{n} q_j} \tag{6}$$

After assigning weights to each criterion, the next step is to apply the procedure to the MABAC method as follows (Dai et al., 2024):

Step 7. Construct the evaluation matrix (X) by assessing m alternatives against n criteria, where each alternative is represented as a vector $A_i = (x_{i1}, x_{i2},..., x_{in})$. Here, x_{ij} denotes the evaluation value of the i alternative under the j criterion (for i = 1, 2,.., m and j = 1, 2,.., n), and is determined using Equation (7).

$$X = \begin{array}{c} \\ A_1 \\ A_2 \\ \cdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \end{array} \tag{7}$$

Step 8. The elements in the original matrix are normalized using Equation (8).

$$N = \begin{array}{c} \\ A_1 \\ A_2 \\ \cdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} t_{11} & t_{12} & \cdots & t_{1n} \\ t_{21} & t_{22} & \cdots & t_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ t_{m1} & t_{m2} & \cdots & t_{mn} \end{bmatrix} \end{array} \tag{8}$$

Step 9. The normalized matrix *(N)* elements are calculated using Equation (9).

for the benefit type is written: $t_{ij} = \frac{x_{ij} - x_i^-}{x_i^+ - x_i^-}$,

for the cost type is written: $t_{ij} = \frac{x_{ij} - x_i^+}{x_i^- - x_i^+}$ (9)

Step 10. Compute the weighted matrix (V) elements using Equation (10).

$$v_{ij} = fw_i t_{ij} \tag{10}$$

where, t_{ij} represents the elements of the normalized matrix (N), and fw_i denotes the weight coefficients assigned to the factors and criteria.

Step 11. Determine the border approximation area matrix G for each criterion by applying Equation (11).

$$g_i = \left(\prod_{j=1}^{m} v_{ij}\right)^{1/m} \tag{11}$$

Step 12. Calculate the distance of each alternative from the border approximation area to obtain the matrix elements (Q), using Equation (12).

$$Q = V - G \tag{12}$$

A Self-Organizing Map (SOM) neural network is a type of competitive and unsupervised learning that can learn and regulate itself (Qu et al., 2020). This study uses the Particle Swarm Optimization (PSO) approach to find the best starting weights to use in the Self-Organizing Map (SOM) clustering model. The reason for this pick is that PSO is said to be very adaptable and flexible, which makes it a good choice for solving a wide range of optimization problems (Peng et al., 2023). The PSO method helps to improve the process of finding the best parameters by making it easier to explore different weight combinations. This leads to faster convergence and more accurate neural network topologies.

Step 13. Evaluate the SOM clustering by calculating the quantization error using Equation (13).

$$QE = \frac{1}{N}\sum_{i=1}^{N} {}^{Min}_{j} \|xi - wj\| \tag{13}$$

This error quantifies the extent to which the SOM has mapped the data, with lower values indicating better clustering performance.

Step 14. Based on the training data, adjust the SOM weights using Equation (14).

$$\theta_j(x) = exp\left(-\frac{\|x - w_j(t)\|^2}{2\sigma^2(t)}\right) \tag{14}$$

This Equation adjusts the weights of neurons in the SOM based on their proximity to the input data point, with closer neurons having a larger influence.

Step 15. Update particle position and velocity using Equation (15).

$$Vi^{(t+1)} = w\,.Vi^{(t)} + c1.rand()\,.\left(pBest^{(i)} - xi^{(t)}\right) + c2\,.rand()\,.\left(gBest - xi^{(t)}\right) \tag{15}$$

The values of w, $c1$, and $c2$ are constants controlling the influence of previous velocity and the attraction to the best-known positions. The update process ensures particles move toward promising regions in the solution space based on personal and collective experiences.

Step 16. Update the position of the particle based on its new velocity using Equation (16).

$$xi^{(t+1)} = xi^{(t)} + Vi^{(t+1)} \tag{16}$$

The Equation moves particles through the solution space toward optimal solutions.

Step 17. Determine the shortest distance between each output neuron and the input data by applying Equation (17).

$$D_i = \sum_i (w_i - x_i)^2 \tag{17}$$

where, D_i is the distance from the input data point x_i to the weight vector w_i .

This Equation helps identify the best-matching neuron for each input point, a core process in SOM.

Step 18. Update the neighbouring for each weight (w_{ij}) using Equation (18).

$$W_{ij}(t+1) = W_{ij}(t) + \alpha(t)\,.h(t)\,.\left(X_i(t) - w_{ij}(t)\right) \tag{18}$$

This Equation adjusts the weights of neurons in the BMU to help the SOM map the data more accurately.

Step 19. Each cluster's centroid is the final weight of the neurons, as written in Equation (19).

$$Centroid_k = Weight_{jk} \tag{19}$$

where, W_{jk} is the weight vector of neuron j in cluster k.

Step 20. Construct the dataset for the Random Forest using SOM clustering results.
Each data point x_i is labelled according to its corresponding cluster identified by SOM. Formulate the training set written using Equation (20):

$$X_{RF}=\{(x_i, ClusterLabel_i)\}, \quad i=1,2,\ldots,N \tag{20}$$

This dataset will be utilized as the training set for classification and prediction.

Step 21. Training data using Equation (21).

$$RF_{model} = RandomForest(X_{RF}, Y_{RF}) \tag{21}$$

where, X_{RF} are data points, and Y_{RF} are the corresponding cluster labels.

Step 22. Calculate the importance of the feature's impact on the clustering using Equation (22).

$$FI_j = \frac{1}{T}\sum_{t=1}^{T}\left(I_j(t)\right) \tag{22}$$

where, FI_j is the importance of feature j, T is the number of trees, and $I_j(t)$ is the importance of feature j in tree t.

Step 23. Utilize the trained Random Forest for prediction and decision support using Equation (23).

$$ClusterLabel_{new} = RF_{model}(X_{new}) \tag{23}$$

The proposed framework employs a sequential approach to improve clustering accuracy and predictive performance.

3.3 Data Collection

The dataset included information from multiple dimensions that came from a number of reputable organizations. This study got economic, environmental, and regional indicators from the accessible data from the Organisation for Economic Co-operation and Development and the World Bank. The Indonesian Ministry of Environment and Forestry and the Central Bureau of Statistics of Indonesia gathered city-specific data from Indonesia, which was then augmented by reports from local governments. This study got further information on the context and policies from peer-reviewed scholarly journals. This study chose 15 cities, which included a mix of big cities, medium-sized cities, and up-and-coming cities. This made sure that this study covered a wide range of socio-economic and geographic circumstances. Cross-checking with other sources of information makes sure that the data is strong and that the multifunctional model keeps the dataset's trustworthiness.

3.4 Data Preprocessing

The collected city-level carbon trading dataset underwent several preprocessing steps to ensure consistency, completeness, and model compatibility:

- Handling Missing Data
  Any missing entries in numerical criteria were imputed using the mean value of their respective features. For categorical or ordinal fields, the mode value was used for imputation.
- Normalization
  Since the data included features with different scales, min-max normalization was applied to scale all values into the [0, 1] range, facilitating convergence in clustering and prediction models.
- Data Consistency Verification
  Cross-validation against multiple sources was performed to confirm the integrity and consistency of each city's indicators.

3.5 Rationale for Machine Learning Method Selection

The selection of the PSOM and Random Forest algorithms in the proposed framework is guided by their complementary strengths. PSOM enhances clustering precision by dynamically optimizing the weight initialization of the SOM, thereby improving the ability to reveal topological relationships and enhancing the quality of data grouping. As Bensaoud and Kalita (2025) stated, in the context of urban carbon trading data, which is often high-dimensional and heterogeneous, requiring scalable and adaptive methods.

The Random Forest approach, on the other hand, is used because it can classify data well and works better with complicated, non-linear datasets. It serves as a core analytical component for model benchmarking and classification, offering interpretability and reliability in predictive modelling tasks (Ziakopoulos et al., 2023). Its proven effectiveness across similar domains makes it well-suited for analyzing city-level readiness and variability in carbon trading strategies (Herawati et al., 2024). By combining supervised and unsupervised learning approaches, the hybrid framework fixes the difficulties with standard single-paradigm models. This synergy enhances detection accuracy, adaptability to data complexity, and resilience in predictive performance, thereby providing a comprehensive and context-sensitive decision-support tool for evaluating urban carbon policy.

4. Result and Discussion

4.1 Application of hybrid MOO-MCDM-PSOM

MOO significantly enhances decision-making in engineering contexts, demonstrating its potential to address complex and conflicting decision scenarios with conflicting objectives in production environments (Faisal et al., 2024). This study engages experts to determine the priority index scale for each criterion, using the FDM with a fuzzy-scale evaluation system by a Triangular Fuzzy Number (TFN) to capture subjective judgments more effectively, as follows:

- Totally Agree (T) = 5{1.0;0.8;0.6}
- Agree (A) = 4{0.8;0.6;0.4}
- Simply Agree (S) = 3{0.6;0.4;0.2}
- Less Agree (L) = 2{0.4;0.2;0.0}
- Disagree (D) = 1{0.2;0.0;0.0}

This fuzzy linguistic scale enables a more nuanced evaluation of qualitative data, supporting improved decision-making under uncertainty. The scoring results and calculations are displayed in **Table 1**.

Table 1. Scoring data and consensus values.

Expert	PCE	GDP	IC	IMR	EE	PD	EI	RS	ICA	IQ	PTQ	UP	W2E	LUP	CRP	GI
1	T	A	T	T	T	T	T	T	A	T	A	S	A	T	A	T
2	S	A	T	T	T	T	T	T	A	T	A	S	A	S	A	T
3	T	T	A	T	T	T	A	T	A	A	A	A	A	S	T	T
4	T	T	T	T	T	T	A	S	A	T	A	T	S	S	T	S
5	T	T	T	A	A	T	A	S	A	T	A	S	T	T	T	A
6	A	T	T	T	A	T	T	T	A	T	S	S	T	T	T	T
7	T	T	T	T	T	T	T	T	A	T	T	A	A	A	T	A
8	T	T	T	T	A	T	T	T	A	T	S	A	A	A	A	A
9	A	T	A	T	T	T	T	A	A	T	A	A	T	A	A	A
10	T	T	T	T	T	A	T	A	A	T	A	A	A	A	A	T
11	T	T	T	A	T	A	T	T	A	A	A	A	T	T	A	T
12	T	T	T	A	T	A	T	T	A	T	A	A	A	A	T	A
13	T	T	T	A	A	A	A	A	A	A	T	T	A	T	T	S
14	T	T	A	T	T	T	T	T	S	T	A	A	A	A	T	T
15	T	T	A	T	A	A	A	A	A	A	T	T	S	A	A	A
16	A	T	T	T	A	A	A	A	A	A	S	T	A	T	A	A
Threshold	0.09	0.04	0.07	0.08	0.09	0.09	0.09	0.10	0.02	0.08	0.07	0.10	0.08	0.12	0.10	0.11
F-Evaluation	11.8	12.4	12	12	11.6	11.6	11.6	11.6	9.4	11.8	9.6	9.6	10	10.2	11.2	10.8
F-Number	0.74	0.78	0.75	0.75	0.72	0.72	0.72	0.72	0.58	0.75	0.6	0.6	0.62	0.63	0.70	0.67
Construction	0.086															
Consensus	0.960															

The optimization results for each criterion, as presented in **Figure 2**, demonstrate that the FDM method achieves more comprehensive and balanced optimization across a broader spectrum of criteria. In collocation, the NSGA-II algorithm demonstrates a more limited optimization efficacy, concentrating predominantly on a more specific range of criteria. Consequently, the decision indices for the evaluated criteria are established as EE, PCE, GDP, IC, EI, PD, ICA, RS, GI, IMR, LUP, CRP, W2E, UP, IQ, and PTQ.

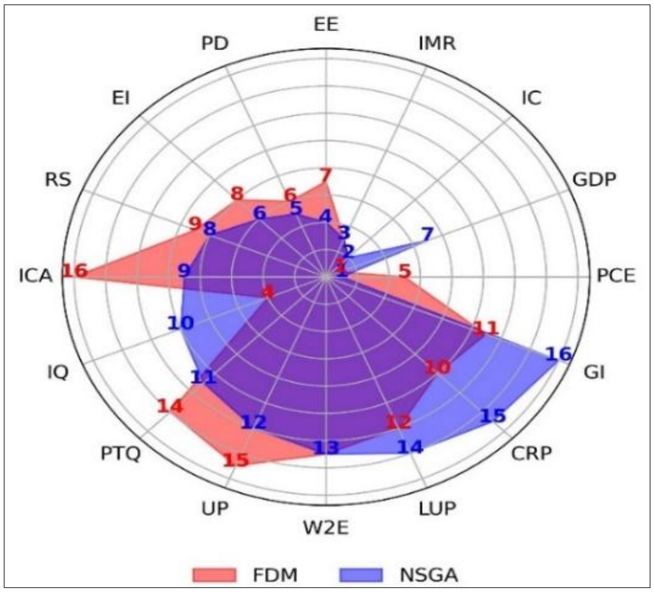


Figure 2. The MOO results for each criterion based on NSGA-II and FDM.

The first step in implementing MCDM is to determine the weight of each criterion using the SWARA, where an index between 1 and 16 influences the weight value of each criterion, as shown in **Table 2**.

Table 2. Criteria weight based on SWARA.

Criteria	Index	Comparative value (S_j)	Coefficient value (K_j)	Relative weight (q_i)	Criteria Weights (W_j)
EE	1	0	0	1	0.18753
PCE	2	0.30	1.30	0.7692	0.14425
GDP	3	0.25	1.25	0.6154	0.11540
IC	4	0.20	1.20	0.5128	0.09617
EI	5	0.15	1.15	0.4459	0.08362
PD	6	0.10	1.10	0.4054	0.07602
ICA	7	0.05	1.05	0.3861	0.07240
RS	8	0.40	1.40	0.2758	0.05172
GI	9	0.35	1.35	0.2043	0.03831
IMR	10	0.30	1.30	0.1571	0.02947
LUP	11	0.25	1.25	0.1257	0.02357
CRP	12	0.20	1.20	0.1048	0.01964
W2E	13	0.15	1.15	0.0911	0.01708
UP	14	0.10	1.10	0.0828	0.01553
IQ	15	0.05	1.05	0.0789	0.01479
PTQ	16	0.02	1.02	0.0773	0.01450

Table 3. Subcriterion weights based on SWARA.

Subcriterion ([Benefit] ; [Cost])	Comparative value (S_j)	Coefficient value (K_j)	Relative weight (q_i)	Result
[Extremely High] ; [Low]	0	1	1	0.3966
[High] ; [Average]	0.3333	1.3333	0.75	0.2974
Moderate	0.6666	1.6666	0.45	0.1784
[Average] ; [High]	1	2	0.225	0.0892
[Low] ; [Extremely High]	1.3333	2.3333	0.0964	0.0382

Based on the data in **Table 3**, it is stated that each subcriterion consists of a benefit or cost category, where the value is determined based on the character of a criterion (Jufri, 2024), as shown in **Table 4**.

Table 4. Potential scoring levels for each criterion.

Criteria	Low	Average	Moderate	High	Extremely High
EE	< 0.50	0.50 - 0.60	0.60 - 0.70	0.70 - 0.80	> 0.80
PCE	< 1 ton	1 - 4 ton	4 - 7 ton	7 - 10 ton	> 10 ton
GDP	< $5000	$5000 - $10000	$10000 - $20000	$20000 - $30000	> $30000
IC	< 0.10	0.10 - 0.20	0.20 - 0.35	0.35 - 0.50	> 0.50
EI	< 0.30	0.30 - 0.50	0. 50 - 0.70	0.70 - 0.90	> 0.90
PD	< 2000	2000 - 4000	4000 - 7000	7000 - 10000	> 10000
ICA	< 0.10	0.10 - 0.30	0.30 - 0.50	0.50 – 0.70	> 0.70
RS	0 - 0.10	0.10 - 0.30	0.30 - 0.50	0.50 - 0.70	> 0.70
GI	< 0.05	0.05 - 0.15	0.15 - 0.30	0.30 - 0.50	> 0.50
IMR	< 0.05	0.05 - 0.15	0.15 - 0.30	0.30 - 0.50	> 0.50
LUP	< 0.10	0.10 - 0.20	0.20 - 0.30	0.30 - 0.40	> 0.40
CRP	< 0.05	0.05 - 0.15	0.15 - 0.30	0.30 - 0.50	> 0.50
W2E	< 0.10	0.10 - 0.30	0.30 - 0.50	0.50 - 0.70	> 0.70
UP	< 0.05	0.05 - 0.15	0.15 - 0.30	0.30 - 0.50	> 0.50
IQ	< 0.10	0.10 - 0.30	0.30 - 0.50	0.50 - 0.70	> 0.70
PTQ	< 0.10	0.10 - 0.30	0.30 - 0.50	0.50 - 0.70	> 0.70

After determining the weight and scale of the assessment based on the criteria and subcriteria, the test data of each city were calculated using the MABAC method. The score data for each city is shown in **Table 5**.

Table 5. Criterion scores for each city based on the carbon trading policy.

City	EE	PCE	GDP	IC	EI	PD	ICA	RS	GI	IMR	LUP	CRP	W2E	UP	IQ	PTQ
Jakarta	0.75	6.0	40000	0.50	0.80	15000	0.70	0.85	0.80	0.25	0.70	0.85	0.30	0.80	0.80	0.07
Surabaya	0.80	4.5	30000	0.40	0.75	12000	0.65	0.80	0.75	0.30	0.65	0.80	0.35	0.75	0.75	0.65
Bandung	0.85	3.5	25000	0.30	0.85	14000	0.80	0.75	0.85	0.35	0.80	0.75	0.40	0.85	0.85	0.80
Medan	0.70	4.0	20000	0.35	0.70	10000	0.60	0.70	0.70	0.20	0.60	0.70	0.25	0.70	0.70	0.60
Semarang	0.90	3.0	15000	0.25	0.90	11000	0.75	0.90	0.90	0.40	0.75	0.90	0.45	0.90	0.90	0.75
Makassar	0.82	3.2	16000	0.30	0.82	10500	0.68	0.78	0.82	0.32	0.68	0.78	0.32	0.82	0.82	0.68
Palembang	0.84	3.7	18000	0.33	0.84	10800	0.72	0.82	0.84	0.34	0.72	0.82	0.37	0.84	0.84	0.72
Denpasar	0.78	2.8	14000	0.28	0.78	9500	0.66	0.76	0.78	0.28	0.66	0.76	0.28	0.78	0.78	0.66
Balikpapan	0.80	2.9	14500	0.29	0.80	9800	0.70	0.80	0.80	0.30	0.70	0.80	0.30	0.80	0.80	0.70
Yogyakarta	0.75	2.6	13000	0.26	0.75	8600	0.65	0.75	0.75	0.25	0.65	0.75	0.25	0.75	0.75	0.65
Malang	0.77	3.1	15500	0.31	0.77	10200	0.69	0.77	0.77	0.27	0.69	0.77	0.27	0.77	0.77	0.69
Batam	0.80	3.3	16500	0.35	0.80	10700	0.70	0.80	0.80	0.30	0.70	0.80	0.30	0.80	0.80	0.70
Pekanbaru	0.83	3.4	17000	0.32	0.83	10900	0.73	0.83	0.83	0.33	0.73	0.83	0.33	0.83	0.83	0.73
Banjarmasin	0.79	3.0	15000	0.30	0.79	9000	0.67	0.79	0.79	0.29	0.67	0.79	0.29	0.79	0.79	0.67
Pontianak	0.81	2.7	13500	0.27	0.81	9300	0.71	0.81	0.81	0.31	0.71	0.81	0.31	0.81	0.81	0.71

Next, the decision matrix for each city is determined based on the criteria, as shown in **Table 6.**

Table 6. Decision matrix calculation results.

City	EE	PCE	GDP	IC	EI	PD	ICA	RS	GI	IMR	LUP	CRP	W2E	UP	IQ	PTQ
Jakarta	0.290	0.289	0.231	0.192	0.167	0.152	0.072	0.103	0.038	0.029	0.024	0.020	0.017	0.016	0.030	0.015
Surabaya	0.290	0.289	0.178	0.192	0.167	0.152	0.072	0.103	0.038	0.029	0.024	0.020	0.034	0.016	0.030	0.025
Bandung	0.375	0.144	0.178	0.096	0.167	0.152	0.145	0.103	0.038	0.059	0.024	0.020	0.034	0.016	0.030	0.029
Medan	0.188	0.144	0.115	0.096	0.084	0.076	0.072	0.052	0.038	0.029	0.024	0.020	0.017	0.016	0.015	0.025
Semarang	0.375	0.144	0.115	0.096	0.167	0.152	0.145	0.103	0.038	0.059	0.024	0.020	0.034	0.016	0.030	0.029
Makassar	0.375	0.144	0.115	0.096	0.167	0.152	0.072	0.103	0.038	0.059	0.024	0.020	0.034	0.016	0.030	0.025
Palembang	0.375	0.144	0.115	0.096	0.167	0.152	0.145	0.103	0.038	0.059	0.024	0.020	0.034	0.016	0.030	0.029
Denpasar	0.290	0.144	0.115	0.096	0.167	0.076	0.072	0.103	0.038	0.029	0.024	0.020	0.017	0.016	0.030	0.025
Balikpapan	0.290	0.144	0.115	0.096	0.167	0.076	0.072	0.103	0.038	0.029	0.024	0.020	0.017	0.016	0.030	0.025
Yogyakarta	0.290	0.144	0.115	0.096	0.167	0.076	0.072	0.103	0.038	0.029	0.024	0.020	0.017	0.016	0.030	0.025
Malang	0.290	0.144	0.115	0.096	0.167	0.152	0.072	0.103	0.038	0.029	0.024	0.020	0.017	0.016	0.030	0.025
Batam	0.290	0.144	0.115	0.096	0.167	0.152	0.072	0.103	0.038	0.029	0.024	0.020	0.017	0.016	0.030	0.025
Pekanbaru	0.375	0.144	0.115	0.096	0.167	0.152	0.145	0.103	0.038	0.059	0.024	0.020	0.034	0.016	0.030	0.029
Banjarmasin	0.290	0.144	0.115	0.096	0.167	0.076	0.072	0.103	0.038	0.029	0.024	0.020	0.017	0.016	0.030	0.025
Pontianak	0.375	0.144	0.115	0.096	0.167	0.076	0.145	0.103	0.038	0.059	0.024	0.020	0.034	0.016	0.030	0.029

The next stage is to calculate estimated the border area matrix (G) against 16 criteria (1/16), where the results are as follows:

G = [{EE: 0.336};{PCE: 0.178};{GDP: 0.146};
{IC: 0.121};{EI: 0.179};{PD: 0.132};
{ICA: 0.106};{RS: 0.114};{GI: 0.047};
{IMR: 0.048};{LUP: 0.030};{CRP:0.025};
{W2E: 0.030};{UP: 0.020};{IQ: 0.035};{PTQ: 0.032}].

The border area matrix is used to determine the values of the alternative distance matrix elements of the approximate border area (Q) as shown in **Figure 3.**

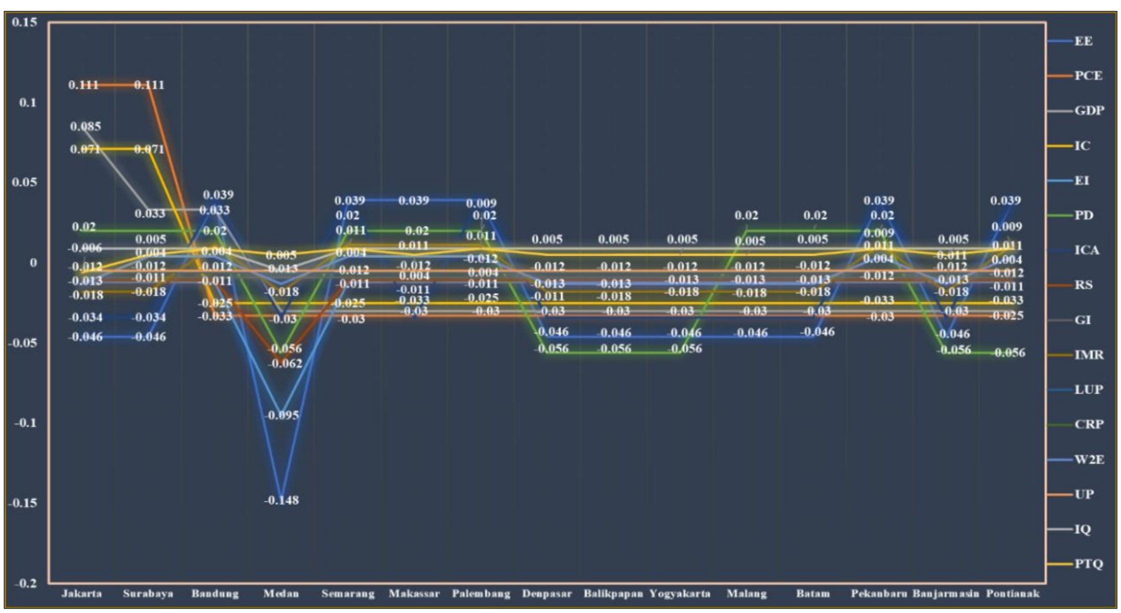


Figure 3. Visualization of the value of the approximate border area (Q).

The MABAC technique can put the cities into three rough border areas based on their economic, social, political, and environmental performance:

- Positive Border Area.
  Jakarta, Surabaya, Bandung, and Semarang are all cities that are known for being good places for development and resources. These cities get a lot of investment and people moving there because they have good infrastructure and stable governments.

- Intermediate Border Area.
  This comprises Yogyakarta, Makassar, and Palembang, which are located between areas with moderate growth and stability. These cities connect core and periphery areas and have the potential to flourish thanks to spillover effects and focused initiatives.

- Negative Border Area.
  This includes Medan, Pontianak, Denpasar, and Banjarmasin, which have lower economic and social metrics, usually because they don't have enough resources or are cut off from other places. These cities have more problems with development and need help with infrastructure, governance, and economic prospects in specific areas.

Next, the values generated by grouping cities based on indicators serve as the input for the clustering process of each city's carbon trade policy using PSOM. Carbon trading policies are categorized into distinct clusters, each representing a specific regulatory and incentive strategy: Policy-A (C1) promotes carbon trading through fiscal incentives for green industries; Policy-B (C2) enforces carbon trading with strict regulations and penalties for non-compliance; and Policy-C (C3) adopts a flexible cap-and-trade scheme to accommodate carbon trading dynamics.

The distance matrix data in **Tables 7** and **8** serve as inputs for the PSOM clustering process, which iterates until convergence. Upon completion, the global best position, which represents the lowest quantization error, determines the optimal SOM weights. These weights are reshaped into a 1x3 SOM grid, yielding the final configuration [0.592; 0.688; 0.781], [0.640; 0.270; 0.288], [0.428; 0.689; 0.641], which minimizes quantization errors and ensures optimal data. The final centroid cluster values are shown in **Table 9**.

Table 7. Input data for the application of PSOM.

City	EE	PCE	GDP	IC	EI	PD	ICA	RS
Jakarta	-0.046	0.111	0.085	0.071	-0.012	0.020	-0.034	-0.011
Surabaya	-0.046	0.111	0.033	0.071	-0.012	0.020	-0.034	-0.011
Bandung	0.039	-0.033	0.033	-0.025	-0.012	0.020	0.039	-0.011
Medan	-0.148	-0.033	-0.030	-0.025	-0.095	-0.056	-0.034	-0.062
Semarang	0.039	-0.033	-0.030	-0.025	-0.012	0.020	0.039	-0.011
Makassar	0.039	-0.033	-0.030	-0.025	-0.012	0.020	-0.034	-0.011
Palembang	0.039	-0.033	-0.030	-0.025	-0.012	0.020	0.039	-0.011
Denpasar	-0.046	-0.033	-0.030	-0.025	-0.012	-0.056	-0.034	-0.011
Balikpapan	-0.046	-0.033	-0.030	-0.025	-0.012	-0.056	-0.034	-0.011
Yogyakarta	-0.046	-0.033	-0.030	-0.025	-0.012	-0.056	-0.034	-0.011
Malang	-0.046	-0.033	-0.030	-0.025	-0.012	0.020	-0.034	-0.011
Batam	-0.046	-0.033	-0.030	-0.025	-0.012	0.020	-0.034	-0.011
Pekanbaru	0.039	-0.033	-0.030	-0.025	-0.012	0.020	0.039	-0.011
Banjarmasin	-0.046	-0.033	-0.030	-0.025	-0.012	-0.056	-0.034	-0.011
Pontianak	0.039	-0.033	-0.030	-0.025	-0.012	-0.056	0.039	-0.011

Table 8. Input data for the application of PSOM (Continued).

City	GI	IMR	LUP	CRP	W2E	UP	IQ	PTQ
Jakarta	-0.009	-0.018	-0.006	-0.005	-0.013	-0.005	0.009	-0.006
Surabaya	-0.009	-0.018	-0.006	-0.005	0.004	-0.005	0.009	0.005
Bandung	-0.009	0.011	-0.006	-0.005	0.004	-0.005	0.009	0.009
Medan	-0.009	-0.018	-0.006	-0.005	-0.013	-0.005	-0.005	0.005
Semarang	-0.009	0.011	-0.006	-0.005	0.004	-0.005	0.009	0.009
Makassar	-0.009	0.011	-0.006	-0.005	0.004	-0.005	0.009	0.005
Palembang	-0.009	0.011	-0.006	-0.005	0.004	-0.005	0.009	0.009
Denpasar	-0.009	-0.018	-0.006	-0.005	-0.013	-0.005	0.009	0.005
Balikpapan	-0.009	-0.018	-0.006	-0.005	-0.013	-0.005	0.009	0.005
Yogyakarta	-0.009	-0.018	-0.006	-0.005	-0.013	-0.005	0.009	0.005
Malang	-0.009	-0.018	-0.006	-0.005	-0.013	-0.005	0.009	0.005
Batam	-0.009	-0.018	-0.006	-0.005	-0.013	-0.005	0.009	0.005
Pekanbaru	-0.009	0.011	-0.006	-0.005	0.004	-0.005	0.009	0.009
Banjarmasin	-0.009	-0.018	-0.006	-0.005	-0.013	-0.005	0.009	0.005
Pontianak	-0.009	0.011	-0.006	-0.005	0.004	-0.005	0.009	0.009

Table 9. Clustering results using PSOM.

City	C1	C2	C3	Cluster	Policy
Jakarta	2.5791	2.3419	0.7960	3	C
Surabaya	1.0409	1.7120	2.6131	1	A
Bandung	0.6810	1.3807	2.1166	1	A
Medan	0.5233	1.1751	2.0222	1	A
Semarang	1.1352	0.6548	1.8289	2	B
Makassar	1.8333	1.8541	1.4470	3	C
Palembang	1.9556	1.7045	1.0995	3	C
Denpasar	1.0735	0.3752	1.7772	2	B
Balikpapan	1.0996	0.1237	1.8631	2	B
Yogyakarta	1.4825	0.7092	1.4648	2	B
Malang	1.1821	0.1242	1.8760	2	B
Batam	1.2125	0.1593	1.8829	2	B
Pekanbaru	1.2075	0.4581	1.5841	2	B
Banjarmasin	1.2125	0.1593	1.8829	2	B
Pontianak	1.7270	0.8534	2.1285	2	B

Based on the testing results in **Table 9**, the analysis aligns each city's characteristics with its cluster and corresponding policy, emphasizing a tailored approach to carbon trading strategies:

- Policy-A, with Fiscal Incentives. This policy targets cities with high sustainability potential yet developing economic and infrastructure indicators by encouraging green industry growth through targeted incentives.
- Policy-B, with Strict Regulations. This policy, applied to cities with balanced development, relies on penalties to uphold sustainable practices and prevent non-compliance.
- Policy-C, with Flexible Cap-and-Trade. This policy supports economically strong cities with limited sustainability infrastructure in their gradual adaptation to carbon targets.

4.2 Sensitivity Test

In evaluating the effectiveness of carbon trade policies, sensitivity tests can help identify sensitive changes in the weight of criteria. Changes in the weight of the criteria based on 4 aspects are shown in **Table 10**.

The sensitivity test is conducted by incrementally increasing each criterion's weight by 0.5 within its respective aspect. Given an example:

Input = [EE;0.75], [PCE;6], [GDP;40000], [IC;0.5], [EI;0.8], [PD;15000], [ICA;0.7],[RS; 0.85], [GI;0.8], [IMR;0.25], [LUP;0.7], [CRP;0.85], [W2E;0.3], [UP;0.8], [IQ;0.8], [PTQ;0.07].

Decision Matrix (X):

EE (0.5) = ((0.297-0.3966) / (0.178-0.3966)), PCE (0) = ((0.389-0.3966) / (0.389-0.3966))

Weighted matrix Border (V): EE (1.063) = (1.063 * 0.68753) + 1.063.

Element Border (Q):

EE (-0.072) = 1.063 – 1.135.

Score (S) = (-0.072) +(0.111) + (0.531) + (0.521) + (-0.012) + 0.020 + (-0.164) + (-0.011) + (-0.009) + (-0.018) + (-0.006) + (-0.005) + (-0.013) + (-0.005) + (1.009) + (-0.006)
= 1.8728 (Positive Area).

Table 10. Aspect and criterion weights for sensitivity test.

Aspect	Criteria	Initial Weight	Type	Sensitivity Weight
Economics	GDP	0.11540	Benefit	0.61540
	IC	0.09617	Cost	0.59617
	EE	0.18753	Benefit	0.68753
	ICA	0.07240	Benefit	0.57240
	IQ	0.01479	Benefit	0.51479
Social	PD	0.07602	Cost	0.57602
	EI	0.08362	Benefit	0.58362
	PTQ	0.01450	Benefit	0.51450
	UP	0.01553	Benefit	0.51553
Environment	PCE	0.14425	Cost	0.64425
	IMR	0.02947	Benefit	0.52947
	W2E	0.01708	Benefit	0.51708
	LUP	0.02357	Benefit	0.52357
	CRP	0.01964	Benefit	0.51964
	GI	0.03831	Benefit	0.53831
Politics	RS	0.05172	Benefit	0.55172

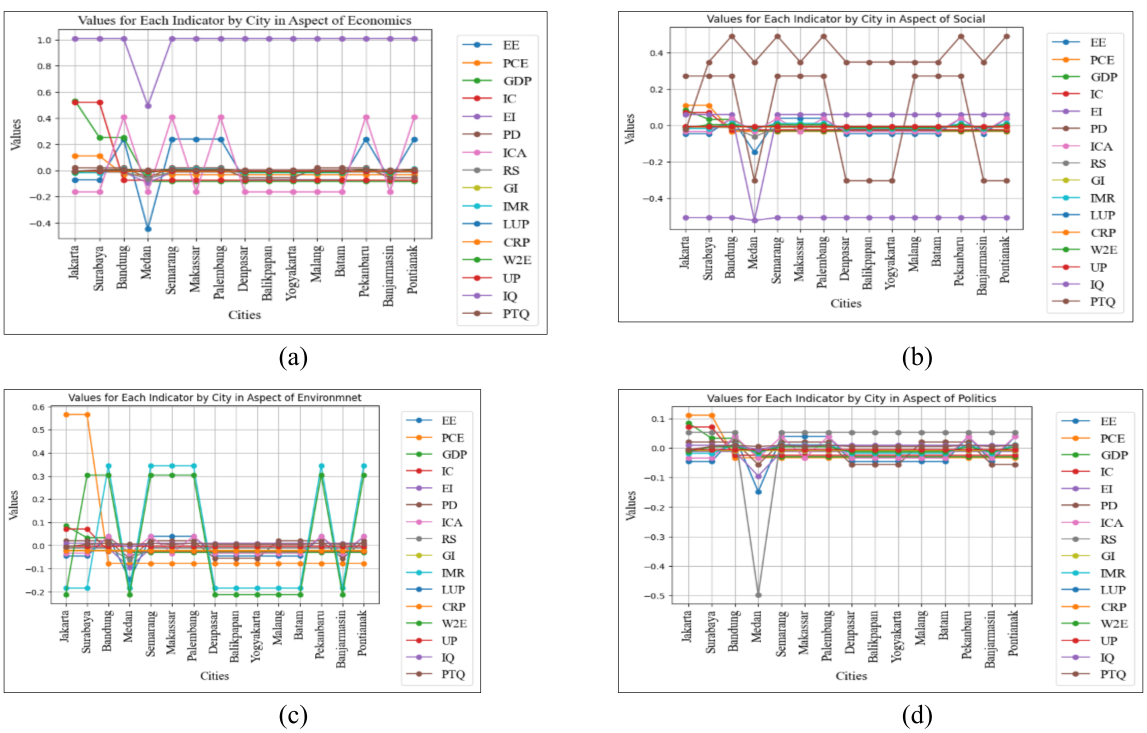


Figure 4. The result of the sensitivity test for each aspect and criterion.

Table 11. MCDM accumulation results based on aspects.

City	Normal	Economics	Social	Environment	Politics
Jakarta	0.1332	1.8728	-0.0949	0.1776	0.1971
Surabaya	0.1083	1.6207	0.2419	0.6527	0.1722
Bandung	0.0590	1.7986	0.3309	0.6034	0.1229
Medan	-0.5406	-0.5737	-1.4070	-0.9961	-0.9766
Semarang	-0.0040	1.4630	0.2679	0.5405	0.0600
Makassar	-0.0804	0.8865	0.0532	0.4641	-0.0164
Palembang	-0.0040	1.4630	0.2679	0.5405	0.0600
Denpasar	-0.2882	0.4515	-0.6546	-0.7437	-0.2242
Balikpapan	-0.2882	0.4515	-0.6546	-0.7437	-0.2242
Yogyakarta	-0.2882	0.4515	-0.6546	-0.7437	-0.2242
Malang	-0.2122	0.5275	-0.0786	-0.6677	-0.1482
Batam	-0.2122	0.5275	-0.0786	-0.6677	-0.1482
Pekanbaru	-0.0040	1.4630	0.2679	0.5405	0.0600
Banjarmasin	-0.2882	0.4515	-0.6546	-0.7437	-0.2242
Pontianak	-0.0800	1.3869	-0.3081	0.4645	-0.0160

As shown in **Table 10**, weight adjustments were analyzed across several cities, indicating that an enhanced hybrid approach with SWARA's adaptive weighting mechanism can effectively respond to different priorities. This outcome affirms the robustness of the proposed methodology in capturing the diverse characteristics of urban environments within the evaluation framework.

Based on the calculation results, it is evident that economic criteria influence the carbon trade policy in the city of Medan. Furthermore, the social aspect affects carbon trade policies in Jakarta, Medan, Denpasar, Balikpapan, Yogyakarta, Malang, Batam, Banjarmasin, and Pontianak. The results of the calculation of each aspect and criterion are illustrated in **Figure 4**.

The cities that were not affected by changes in criterion weights are Surabaya and Bandung. The accumulation result is shown in **Table 11**.

Overall, the data in **Table 11** indicate that economic performance is strong; however, social, environmental, and political issues require attention to achieve balanced development.

4.3 Identification of Patterns in Policy Effectiveness Using PSOM

Changes in the results of carbon trade policy mapping are influenced by the input value of the criterion that describes the city's condition from the perspective of implementing carbon trade policy. The PSOM methodology encompasses data preparation and normalization, weight optimization using the PSO algorithm, training data, identifying centroids, and analyzing cities in clusters with SOM, as outlined in **Figure 5** and **Table 12**.

Based on the results of calculating the centroid of PSOM for cities across various aspects, it is evident that cities have diverse economic, social, environmental, and political profiles.

Analysis of fifteen cities shows significant variations in readiness based on economic, social, environmental, and political dimensions. The results provide an idea that the implementation of carbon trading needs to be tailored to the characteristics and readiness of each city. A gradual, local strength-based approach is key to the success of effective and sustainable carbon trading policies at the city level.

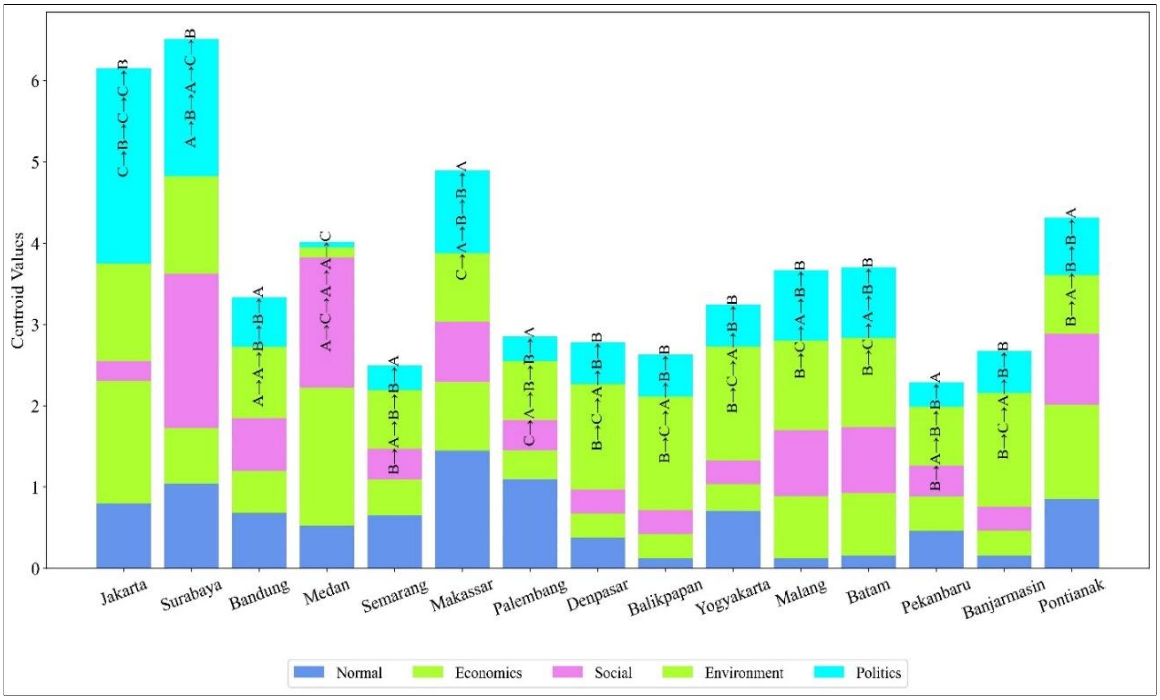


Figure 5. Results of mapping carbon trade policies in each city based on specific aspects.

Table 12. Determination of carbon trading policy in each city based on multiple aspects.

City	Normal	Economics	Social	Environment	Politics
Jakarta	0.7960	1.5100	0.2442	1.2000	2.4000
Surabaya	1.4090	0.6824	1.9000	1.2000	1.6900
Bandung	0.6810	0.5176	0.6479	0.8781	0.6105
Medan	0.5233	1.7000	1.6000	0.1233	0.0663
Semarang	0.6548	0.4382	0.3777	0.7237	0.3020
Makassar	1.4470	0.8460	0.7389	0.8418	1.0200
Palembang	1.0995	0.3502	0.3777	0.7237	0.3020
Denpasar	0.3752	0.3013	0.2912	1.3000	0.5154
Balikpapan	0.1237	0.3002	0.2912	1.4000	0.5154
Yogyakarta	0.7092	0.3286	0.2912	1.4000	0.5154
Malang	0.1242	0.7651	0.8118	1.1000	0.8657
Batam	0.1593	0.7663	0.8118	1.1000	0.8657
Pekanbaru	0.4581	0.4288	0.3777	0.7237	0.3020
Banjarmasin	0.1593	0.3074	0.2912	1.4000	0.5154
Pontianak	0.8534	1.1600	0.8710	0.7237	0.7065

4.4 Comparative Analysis

This study compared the suggested method to three different clustering algorithms that are extensively used: Self-Organizing Maps (SOM), K-Medoids, and K-Means. This was done to see how well it worked. The stage calculation process in each method utilizes the data in **Tables 7** to **8** as input, as shown in **Table 13**.

Table 13. Comparison results of SOM, PSOM, K-means, and K-medoid methods.

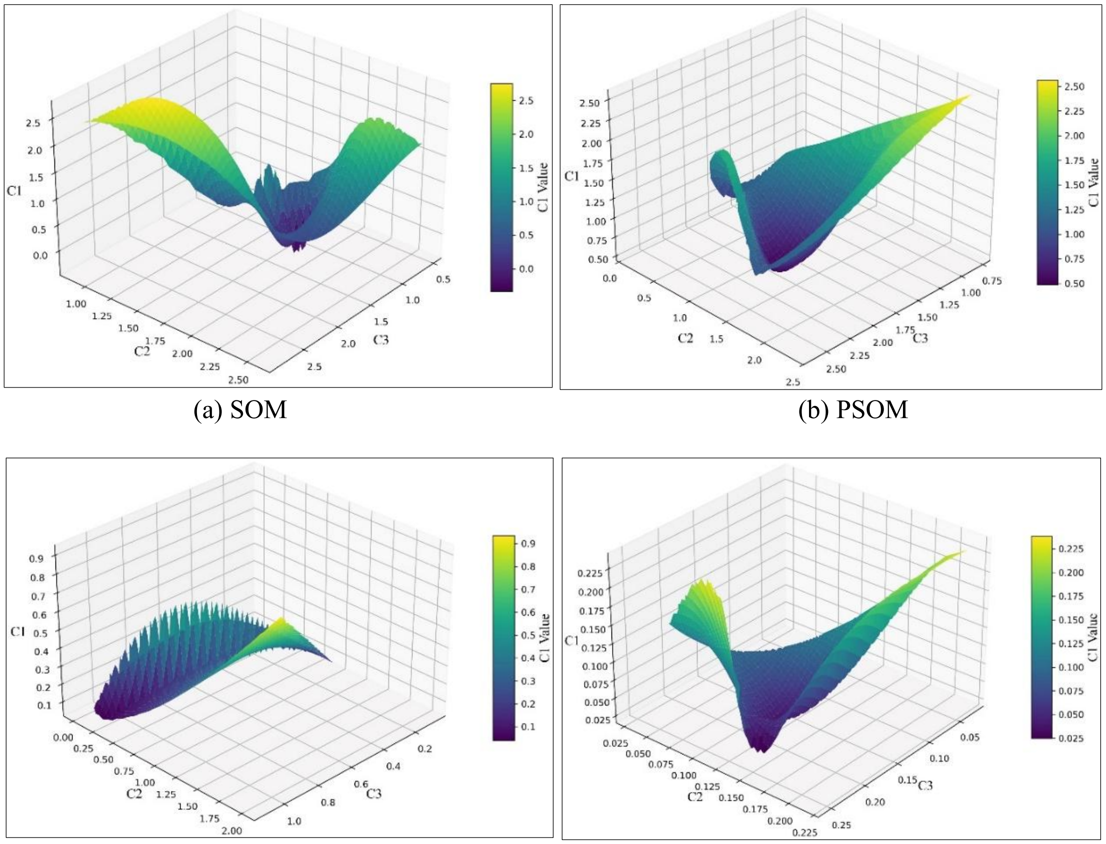
City	SOM			PSOM			K-Means			K-Medoid		
	C1	C2	C3	C1	C2	C3	C1	C2	C3	C1	C2	C3
Jakarta	2.3919	0.8807	2.8223	2.5791	2.3419	0.7960	0.2308	0.2159	0.0279	6.4981	7.8268	0.0000
Surabaya	1.7616	2.5742	0.5397	1.0409	1.7120	2.6131	0.2112	0.1938	0.0279	5.3791	5.7606	3.9550
Bandung	1.4402	2.0665	0.9104	0.6810	1.3807	2.1166	0.0553	0.1533	0.2102	4.9053	1.8555	7.2203
Medan	1.2318	1.9759	0.7694	0.5233	1.1751	2.0222	0.2315	0.1234	0.2526	7.2022	8.8650	9.7004
Semarang	0.6973	1.7835	1.3176	1.1352	0.6548	1.8289	0.0204	0.1397	0.2267	4.5407	4.2146	7.8268
Makassar	1.8821	1.4217	1.9202	1.8333	1.8541	1.4470	0.0631	0.1191	0.2145	3.8589	2.3931	6.9846
Palembang	1.7276	1.0121	2.2628	1.9556	1.7045	1.0995	0.0204	0.1397	0.2267	4.5407	4.2146	7.8268
Denpasar	0.4525	1.7330	1.2620	1.0735	0.3752	1.7772	0.1272	0.0296	0.2091	0.0000	4.5407	6.4981
Balikpapan	0.2157	1.8113	1.2971	1.0996	0.1237	1.8631	0.1272	0.0296	0.2091	0.0000	4.5407	6.4981
Yogyakarta	0.7200	1.4155	1.7496	1.4825	0.7092	1.4648	0.1272	0.0296	0.2091	0.0000	4.5407	6.4981
Malang	0.1033	1.8238	1.3784	1.1821	0.1242	1.8760	0.1110	0.0579	0.1948	2.0412	4.0561	6.1692
Banjarmasin	0.0930	1.8307	1.4079	1.2125	0.1593	1.8829	0.1272	0.0296	0.2091	0.0000	4.5407	6.4981
Pontianak	0.4426	1.5233	1.4640	1.7270	0.8534	2.1285	0.0653	0.1306	0.2391	4.0561	2.0412	8.0886

The clustering comparison result indicates that a substantial proportion of cities (84.9%) are categorized within Cluster C3. This predominance suggests that the implementation of a Flexible Cap-and-Trade policy may constitute the most context-appropriate regulatory mechanism for these municipalities. The clustering analysis is illustrated in **Figure 6**.

The results of the visualization reveal that PSOM makes a considerably superior three-dimensional data surface that is coherent and continuous than K-Means, K-Medoids, and SOM. The surface made by PSOM is smoother and holds its shape better. This cuts down on noise and makes it easier to analyze complex data distributions. The clustering results using K-Means, K-Medoids, and SOM, on the other hand, display more uneven surfaces, which could mask patterns in the data. These findings confirm the robustness of PSOM in handling non-linear data structures and its effectiveness in improving the visualization and interpretability of clustering outcomes (Faisal and Rahman, 2023b).

Based on the enhanced clustering outputs, the created system uses machine learning to forecast the effects of low-carbon policies based on the improved clustering results, using both past data and new trends. Specifically, the Random Forest method is used for prediction, utilizing the clustering outputs (**Table 5**) as input data and the policy categories (**Table 9**) as labels. This predictive model is validated using test data from other cities, as shown in **Table 14**, to support the formulation of effective and responsive low-carbon policies that adapt to environmental and economic dynamics.

The integration of the Random Forest algorithm within the MOO-MCDM framework enables a more nuanced assessment of policy alternatives by classifying and prioritizing criteria according to their relative importance, thereby enhancing the rigour of the decision-making process. Within the domain of carbon trading, Random Forest supports the prediction of policy impacts at the city level, informing optimal strategic pathways facilitated through the PSOM method. As noted by Sipper and Moore (2021), Random Forest constructs an ensemble of decision trees derived from random samples and feature subsets, aggregating their predictions through majority voting to enhance classification accuracy and mitigate the risks of overfitting.



(a) SOM (b) PSOM

(c) K-Medoids (d) K-Means

Figure 6. Visualization of clustering using SOM, PSOM, K-medoid, and K-means.

Table 14. Testing data for predicting and mapping carbon trade policy.

City	EE	PCE	GDP	IC	EI	PD	ICA	RS	GI	IMR	LUP	CRP	W2E	UP	IQ	PTQ
Bogor	0.63	1.8	12000	0.45	0.52	14000	0.50	0.52	0.53	0.12	0.58	0.54	0.18	0.53	0.49	0.56
Manado	0.67	2.1	11500	0.43	0.55	10500	0.52	0.56	0.51	0.13	0.59	0.51	0.22	0.58	0.55	0.60
Samarinda	0.71	2.3	13500	0.39	0.60	12000	0.60	0.61	0.65	0.22	0.65	0.61	0.30	0.63	0.62	0.66
Jambi	0.62	1.7	12500	0.35	0.48	11000	0.49	0.54	0.50	0.10	0.57	0.49	0.16	0.52	0.50	0.51
Padang	0.69	2.5	16000	0.47	0.63	15000	0.58	0.63	0.61	0.21	0.69	0.60	0.27	0.68	0.64	0.62
Kupang	0.55	1.9	11000	0.33	0.47	9800	0.44	0.5	0.42	0.09	0.50	0.47	0.14	0.49	0.44	0.49
Mataram	0.68	2.4	14500	0.48	0.64	16000	0.59	0.64	0.67	0.24	0.70	0.65	0.28	0.71	0.69	0.72
T.Pinang	0.66	2.1	13000	0.38	0.54	12500	0.53	0.58	0.54	0.12	0.63	0.54	0.20	0.57	0.56	0.60
Kendari	0.72	2.0	14000	0.44	0.61	9000	0.62	0.66	0.68	0.20	0.66	0.64	0.25	0.66	0.62	0.64
Palu	0.74	2.6	16000	0.46	0.66	11000	0.65	0.67	0.70	0.23	0.72	0.68	0.30	0.70	0.71	0.68
Ambon	0.59	1.5	3000	0.37	0.51	10500	0.49	0.53	0.47	0.11	0.55	0.51	0.17	0.54	0.51	0.55
Bengkulu	0.65	2.3	14500	0.42	0.57	9500	0.56	0.61	0.61	0.18	0.63	0.59	0.26	0.61	0.60	0.61

The result of the calculation process is shown in **Figure 7**, where machine learning predicts and maps each city's carbon trade policy.

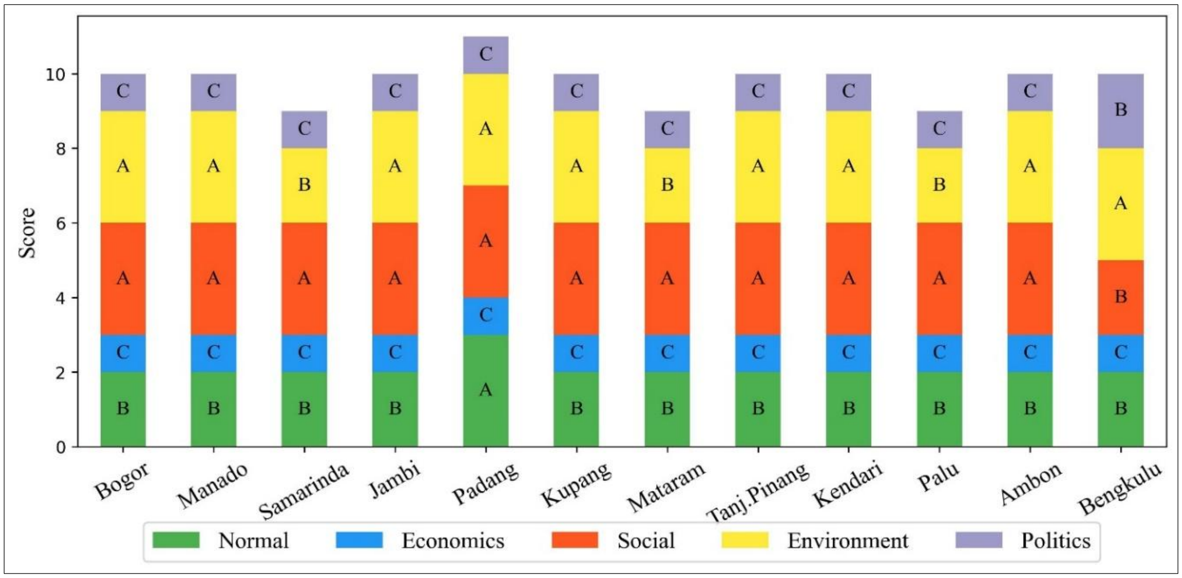


Figure 7. Prediction and mapping carbon trade policy using random forest.

Based on the predictions generated by the integrated model, a system of adaptive, data-informed policy recommendations was established. The results show that Policy-A, which supports tax breaks for green industry growth, works best in cities like Bogor and Ambon that don't do as well economically. Policy-B, on the other hand, is better for places like Samarinda and Kendari that are seeking to fix the environment because it contains rigorous guidelines. Policy-C is the greatest choice for cities like Padang and Kupang that have a variety of diverse development needs because it lets them make progress in both cutting emissions and making the economy more sustainable.

This customized policy framework lets each community work toward its particular social, economic, and environmental goals in the way that works best for them. This is excellent for the bigger purpose of fighting climate change, as well as good for the greater goal of combatting climate change. The multidimensional evaluation of selected cities across economic, social, environmental, and political dimensions demonstrates the effectiveness of the proposed machine learning-driven framework in mapping urban carbon profiles, informing targeted policy interventions, and highlighting the strong predictive potential to guide carbon trading strategies and support IoT-based smart decision-making.

4.5 Baseline Method Comparison for Evaluation

A comparative analysis was conducted against baseline clustering and predictive methods further to validate the effectiveness of the proposed hybrid framework. The result is shown in **Tables 15** and **16**.

Table 15. Clustering accuracy comparison.

Methods	Adjusted rand index	Quantization error
SOM	0.92	0.24
K-Medoids	0.91	0.27
K-Means	0.90	0.30
PSOM	0.96	0.18

Based on the evaluation results, it is evident that PSOM demonstrated the best overall performance, with the highest Adjusted Rand Index value (0.96) and the lowest value (0.18). This signifies that PSOM is the most accurate in mimicking the original label structure and the most precise in data representation.

Table 16. Predictive accuracy comparison.

Predictive model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Decision Trees	90.36 %	90.50	91.00	90.75
Support Vector Machine	92.10 %	91.80	92.00	91.90
PSOM + Random Forest	95.57 %	95.40	95.50	95.45

Based on the confusion matrix evaluation results, it is evident that the combined PSOM and Random Forest algorithm achieved higher prediction accuracy (95.57%) than simpler baselines, thereby reinforcing the superiority of the proposed hybrid framework.

4.6 Computational Efficiency

All computational testing was conducted using Google Colab, a cloud-based development platform with a runtime environment on Intel Xeon CPU 2.20GHz, 12GB RAM, and Python 3.10. This environment allows for scalable and reproducible analysis across urban datasets. Although the PSOM framework incurs a slightly longer runtime, its superior clustering precision, topological preservation, and predictive power justify the trade-off, making it well-suited for complex city-level carbon policy evaluation tasks.

5. Conclusions

5.1 Summary of Contributions

This study introduced a novel hybrid analytical framework that integrates MOO, MCDM, PSOM, and Random Forest methods to support the evaluation and clustering of city-level carbon trading strategies. The framework demonstrates strong potential in capturing the spatial heterogeneity of urban emissions, thereby enhancing the interpretability of carbon readiness classifications and supporting predictive policy modelling. Empirical results confirm that the PSOM-based clustering improves initialization and stability over conventional methods, while Random Forest enables accurate classification of cities. Collectively, these components form a scalable and context-aware decision support system for policymakers.

5.2 Key Results

The critical results of this study include:

- Dynamic Multidimensional Evaluation
  The integration of MOO and MCDM enables simultaneous consideration of multiple, often conflicting, policy criteria, offering a holistic assessment of urban carbon trading strategies.
- Improved Clustering by PSOM
  Using PSOM makes city clustering far more accurate and stable than older methods like SOM, K-Means, and K-Medoids.
- Predictive Modelling with Random Forest
  Leveraging the Random Forest trained on PSOM-derived clusters extends the model from static evaluation to dynamic prediction, facilitating anticipatory carbon policy planning based on evolving urban datasets.
- Tailored Policy Recommendations
  The framework does a good job of putting cities into groups based on how ready they are for carbon trading, which helps with targeted and stage-appropriate policy changes.

5.3 Practical Implications

The proposed framework contributes theoretically by advancing the integration of MCDM and machine learning into a cohesive model for multidimensional policy evaluation. Practically, it offers policymakers a scalable and context-aware decision-support tool for assessing the performance of carbon trading initiatives, identifying priority areas, and tailoring interventions to specific urban conditions.

5.4 Limitations and Future Work

The study has several interesting ideas, however it is limited because it only analyzes cross-sectional and historical data. This could make it less able to adapt to changes in policy. It also did not include variables linked to behaviour, institutions, and governance, which could have left out critical things that determine how well carbon trading works in a given area.

Adding Internet of Things (IoT) data, spatial-temporal analytics, and agent-based modeling to the framework will make it more helpful in real time. This is what future research should focus on. It will also be important to look into policy simulations, stakeholder dynamics, and behavioral incentives to make the model better at predicting and adapting to different urban settings.

Conflict of Interest

We declare that there is no conflict of interest regarding the study presented in this paper.

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AI Disclosure

During the preparation of this work the author(s) used generative AI in order to improve the language of the article. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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