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Game-theoretic DEA optimization for sustainable agricultural carbon trading: Evidence from Türkiye's maize production

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A R T I C L E   I N F O

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A B S T R A C T

Effective agricultural carbon policy requires reliable monitoring and frameworks that consider efficiency, welfare, and adoption. Although monitoring systems are typically stronger in developed countries, they are costly to maintain, whereas in developing countries they are often limited or insufficient. We hypothesize that a performance-based carbon policy integrated with welfare and farm decision behavior improves suitability for heterogeneous agricultural settings under limited emissions data. This paper proposes a Forward-Looking Cooperative Cap-and-Trade Carbon Pricing (FCTCP), policy that assesses farms' carbon performance using carbon-equivalent resource, operational, and agrochemical inputs instead of direct carbon emission data, while integrating farm-level decision-making, cooperative carbon trading, and a welfare indicator aligned with emission performance. In this framework, farms are classified using Data Envelopment Analysis into efficient, near-efficient, and inefficient categories, and their policy participation is modeled through a cooperative Nash game. Nonlinear strategic interactions are solved using a hybrid optimization scheme consisting of four metaheuristic algorithms, including Particle Swarm Optimization, Artificial Bee Colony, Grey Wolf Optimizer, and Genetic Algorithm, and a nonlinear quasi-Newton optimization method, L-BFGS-B, to identify robust Nash equilibria. A case study of 104 maize farms in Türkiye shows green welfare improvements of 9.65 % for near-efficient farms and 15.23 % for inefficient farms while achieving the low-carbon benchmark. Key determinants of adoption include efficiency-based caps, asymmetric trading rules, and carbon exchange without discounting. The results demonstrate that FCTCP is a practical, welfare-linked, and forward-looking policy mechanism capable of guiding early-stage carbon transitions in agricultural systems lacking mature carbon monitoring infrastructure.

1. Introduction

1.1. Motivation and background

Agriculture is highly sensitive to climate change and significantly contributes to greenhouse gas (GHG) emissions through agricultural practices (IPCC, 2019). In developed economies, monitoring, reporting, and verification (MRV) systems provide an effective way to measure carbon emissions in the farmlands. For example, the European Union focused on emissions trading systems (ETSs) integrated with extensive MRV protocols (OECD, 2024b). In addition, Canada has launched a $4 million MRV soil-carbon initiative to improve its monitoring systems in farmlands (RealAgriculture News Team, 2025). On the other hand, Türkiye and many developing countries lack sufficiently mature farm-level MRV systems to help measure carbon emissions (OECD, 2024a). This gap makes it difficult for governments to implement their carbon tax policies on farmlands effectively and successfully. Furthermore, numerous traditional carbon trading policies primarily focus on economic implications, and there is an absence of a cohesive integration of policy outcomes with welfare metrics in agricultural lands (Cariappa & Krishna, 2025; Harrison et al., 2021). Hence, it is essential to design a carbon tax policy that not only enhances the carbon market among

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agricultural enterprises but also serves as a metric for assessing each entity's contribution to low-carbon transitions, particularly in developing countries such as Türkiye.

Motivated by these gaps, we introduce a Forward-Looking Cooperative Cap-and-Trade Carbon Pricing (FCTCP) framework, a novel, performance-based carbon trading policy designed to assist emerging economies in implementing carbon tax policies in the absence of MRV systems, while also incorporating a new green welfare metric to facilitate low-carbon transitions in agricultural areas. The FCTCP offers a premonitoring, preparatory policy tool, a step aligned with forward-looking carbon governance in countries where MRV protocols are emerging rather than established. In the background, the FCTCP framework integrates farm-level resource, operational, and agrochemical data with group-based benchmarking and green welfare metrics while assessing farms' behavioral responses to the carbon market to evaluate cooperative stakeholder policy adoption. Data Envelopment Analysis (DEA) is applied to measure the production efficiency of farms, where group-based benchmarking is established both in green welfare and carbon trade. A novel cooperative game is proposed to understand each group's reaction to the FCTCP under different carbon cap and trade scenarios. An empirical analysis of maize production in Türkiye shows micro-level data from 104 farms and illustrates how DEA classification affects FCTCP participation and emission-based welfare implications in both conventional and cooperative carbon pricing frameworks.

1.2. Literature review

In recent years, the environmental impacts of agricultural production have become a central concern in sustainability research, as quantitative evidence increasingly shows that modern farming practices contribute significantly to biodiversity loss, soil degradation, water contamination, and greenhouse gas (GHG) emissions (Pereira et al., 2025). Conventional agricultural practices mostly rely on agrochemicals, machinery, irrigation, and energy, and their overuse or misuse can cause climate instability (Columbia University's Mailman School of Public Health, 2024). To effectively fight climate change, various carbon tax instruments are introduced. For example, in 2023 alone, 75 carbon-pricing instruments worldwide generated 104 billion USD in revenues, over half of which were allocated to climate and nature programs (World Bank, 2024). Central to these market-based instruments is the quantitative classification of agricultural enterprises according to emission efficiency (Kumar et al., 2024). In this regard, DEA has emerged as a data-driven technique to classify diverse farms into efficiency groups based on their agricultural practices (Kaur et al., 2024). Here, farm classification enables policymakers to allocate emission allowances or set tax rates in a performance-sensitive manner for equity and cleaner production (Kyrgiakos et al., 2023).

In a cap-and-trade setting, caps put limitations on emissions and make it possible for agricultural enterprises to trade allowances in the market (Xi et al., 2025). Hence, such frameworks lead to measurable improvements for enterprises to lower their emissions level as well as be an active part in the carbon trade. Globally, agricultural cap-and-trade systems show diverse designs and adoption levels. For example, The European Union integrates cap-and-trade with sustainability objectives (Mohammed et al., 2025), while New Zealand includes biological emissions from livestock and fertilizers (Zhang et al., 2025a). On the other hand, California's program uses agricultural offset protocols integrated with methane reduction policies (Lazenby, 2024), while China has piloted agricultural carbon trading via digital carbon monitoring (Zhao et al., 2025). MRV protocols play important role in ensuring accurate carbon emissions measurement. Recent studies on MRV systems indicate that carbon markets and cap-and-trade systems are quickly moving toward more standardized and digital frameworks (Ecklu & Thomas, 2025; Körner et al., 2025; Li & Zhang, 2024). The World Bank indicates that numerous low-income and developing countries exhibit deficiencies in the implementation of MRV in their carbon markets (Bank, 2025). Additionally, the financial costs associated with MRV protocols present a significant barrier to their implementation in agriculture. Countries such as Brazil, Mexico, India, and South Africa frequently experience budget constraints and weak institutional capacity, leading to inadequate infrastructure for carbon emissions data collection (Secretariat, 2021). In the context of Türkiye, agricultural enterprises currently lack mature, farm-level MRV systems, which creates an urgent need for a policy framework that enables the government to perform its carbon-reduction commitments under the Paris Agreement (First Biennial Transparency Report of Türkiye, 2024).

Collaboration in the cap-and-trade market can be challenging to manage, particularly when faced with varying carbon regulations and the feasibility of climate policy. For instance, the cases of the US and China illustrate that emissions trading can reduce methane emissions; however, regulatory differences between the two nations complicate climate cooperation (Zhu et al., 2025). Conversely, the Australian case demonstrates that carbon farming initiatives can effectively align with cap-and-trade policies, potentially encouraging stakeholder participation in broader climate cooperation (Milne et al., 2024). Digital platforms in agriculture and enhanced carbon monitoring systems similarly enhance stakeholder collaboration in the carbon market, as demonstrated by Chinese pilot programs (Zhang et al., 2024). The South African case illustrates that smallholder farmers are inclined to adopt climate-smart agricultural practices when government support and viable market opportunities are present in cap-and-trade systems (Funke & Munyaradzi, 2025).

Farm classification for carbon market participation relies heavily on frontier efficiency and performance measurement methods (Bazyli & Kryszak, 2025). DEA remains the dominant tool, capturing multi-input, multi-output production typical of agriculture, while stochastic frontier analysis (Zhu et al., 2024) and network DEA (Chen & Wang, 2025) provide extensions that account for production risk and value-chain interactions. Carbon emission intensity serves as a key metric for classification, although it can oversimplify complex environmental performance profiles. These methods underpin both initial allocation of emission allowances and continuous benchmarking for regulatory oversight (Díaz et al., 2025), yet integrating dynamic, temporal performance metrics remains a methodological challenge (Zheng, 2024).

Game-theoretic modeling provides a robust framework to capture strategic interactions among agricultural firms under carbon regulation (Hamidoğlu, 2024). Both non-cooperative (Hamidoğlu et al., 2024) and cooperative approaches (Hamidoğlu & Weber, 2024) analyze permit trading, coalition formation, and regulator negotiation, while recent literature extends these models to stochastic, dynamic, discrete, and evolutionary games (Cheng et al., 2025; Hamidoğlu et al., 2025), capturing uncertainty, adaptation, and temporal change in agricultural supply chains.

1.3. Paper contribution

This paper presents a novel cap-and-trade policy, FCTCP, which includes four key achievements and unique aspects that address existing gaps in the literature.

First, the FCTCP policy presents a new interpretation of carbon emissions in agricultural enterprises, independent of carbon monitoring systems. It employs carbon-equivalent metrics for resources, operations, and agrochemicals, translating these into GHG emission equivalents. This approach measures performance-based efficiency for group-based benchmarking to establish carbon cap and trade regulations. The proposed policy's forward-looking nature is innovative in the literature and holds potential for developing or emerging economies such as Türkiye, where MRV systems are either lacking or insufficient for assessing carbon emission data in agricultural lands.

Second, the FCTCP policy incorporates DEA-derived farm heterogeneity into its policy framework. The proposed work includes a DEA classification framework for benchmarking farms and establishes three

Table 1
Parameters of average total carbon emissions of each enterprise group.

Parameters	Descriptions
Γ_1	Average total carbon emissions of the technically efficient group
Γ_2	Average total carbon emissions of the near efficient group
Γ_3	Average total carbon emissions of the inefficient group

categories based on their unique production efficiency frontier. This framework defines carbon allocation and trading regulations within the farm network by identifying sellers and buyers, as well as uniform and asymmetric trading options. This approach expands the applications of DEA in the literature, not solely for ranking purposes but also for the design of carbon markets.

Third, the FCTCP policy employs collective policy adoption through a novel cooperative Nash game, integrating the decision-making processes of various farms to improve green welfare as a policy acceptance outcome. This methodological perspective is unique in the carbon trading literature, which primarily relies on independent stakeholder adaptation and carbon pricing.

Finally, the paper implements five optimization techniques, including ABC, PSO, GWO, GA, and L-BFGS-B, to develop a hybrid solver for a non-linear optimization problem emerged from the Nash game. Here, the hybrid optimization scheme integrates global metaheuristic search with local gradient-based refinement to identify equilibrium strategies and confirm their robustness. In literature, this hybrid scheme represents a novel integration, particularly in achieving climate policy outcomes more effectively and robustly.

1.4. Organization

The rest of the paper is organized as follows. Section 2 provides the system description of the FCTCP. The methodology of the paper is presented in Section 3. The Türkiye case and comparative analysis of the work are given in Section 4. Finally, the paper concludes in Section 5 with further remarks, policy implications, limitations, and future directions.

2. System description

This section introduces a system description of the FCTCP, including its workflow, DEA-based farm classification according to production efficiency, and cooperative decision-making among farms. The FCTCP framework evaluates farms across three fundamental dimensions of agricultural practice: resource-based inputs (such as seeds, irrigation water, and energy use), operation-based inputs (including machinery deployment and labor requirements), and agrochemical-based inputs (such as fertilizers and pesticides). The policy establishes its forward-looking perspective by measuring farm-level technical efficiency in contexts where MRV systems are insufficient or still under development. Hence, the FCTCP does not take true carbon emissions as an undesirable output but rather employs a carbon-equivalent representation of key inputs, allowing farms to be benchmarked using production data. This approach ensures that efficiency classification is consistent across farms while enabling the policy to serve as a preparatory mechanism for emerging economies transitioning toward full MRV-capable, measurement-based carbon markets.

According to the DEA, we classify farms into three different efficiency groups. The first group is the technically efficient group, which operates at lower input-based carbon intensity, achieves high relative green efficiency, and serves as the benchmark for the sector. The second group is the near-efficient group, which demonstrates moderate input-based carbon intensity and partial green efficiency. The third group is the inefficient group, which exhibits high input-based carbon intensity and low green efficiency. This categorization is essential to establish the structural basis for the cooperative cap and trade mechanism, where allowance allocation, trading opportunities, and tax liabilities are differentiated according to group classification.

In real-world applications, we observe common practices for identifying benchmark enterprises and their ability to sell carbon allowances, rather than treating it as an arbitrary privilege. In this regard, the free allocation or benchmarking is based on the performance frontier, which means benchmarks are determined according to the emissions intensity, and if firms outperform those benchmarks, then they are allowed to trade and do discounts accordingly. For example, the EU ETS uses output-based benchmarks (EU ETS European Commission, 2025), while China's national ETS likewise applies output-based benchmarking for the power sector, allocating allowances according to firm performance (ICAP, 2024a). On the other hand, cap-and-trade programs in Japan similarly use benchmarking and staged allocation rules during early phases to align participants with best practice and to create tradable surplus only when firms outperform the benchmark (ICAP, 2024b). Hence, the FCTCP allows only technically efficient farms to sell unused allowances to other low-performing groups to upgrade their practices and motivate them to join the benchmark group and access the trading benefits for themselves.

The FCTCP policy defines a benchmark-based seller-buyer structure, where only the technically efficient group (Group 1) can provide tradable allowances, while the others (Group 2 and Group 3) are allowed to buy carbon allowances. This structure parallels established cap-and-trade systems including China's national ETS, where only benchmark or top-performing units can supply tradable credits, while lower-performing units rely on allowance purchases to improve compliance and transition toward more sustainable input use (Ruan et al., 2025).

Table 2 presents the key parameters for two government policy frameworks: the FCTCP and the traditional uniform carbon tax.

Cap policy of the FCTCP, is formulated as follows: The government determine the carbon cab based on firms collectively demonstrating the lowest emission intensities per unit of output are classified as technically efficient (first), with their average total carbon emissions, denoted as Γ_1 (see Table 1), serving as the benchmark standard. These firms receive full exemption from carbon taxation, contingent upon maintaining their efficient emission status in subsequent years. Any firm within the first group whose total carbon emissions, X_1, exceed the benchmark Γ_1 must pay a carbon tax proportional to the excess emissions:

$$T(X_1 - \Gamma_1).$$

Firms that do not meet the efficiency benchmark are categorized into near-efficient (second) and inefficient (third) groups based on their aggregate emission levels. The carbon tax is applied in a tiered structure accordingly:

$$T(X_2 - \Gamma_1) \quad \text{and} \quad T(X_3 - \Gamma_1),$$

where X_2 and X_3 denote the total carbon emissions of the second (near efficient) and third (inefficient) groups, respectively. This tiered approach incentivizes continuous emission reductions across all efficiency levels by linking tax liabilities directly to deviations from the benchmark.

Trade policy of the FCTCP is formulated as follows: The trade of carbon-emission allowances is allowed for the first group as the seller and the second and third groups as the buyers. Here, the second-group and third-group enterprises are not allowed to sell their carbon allowances to other groups; only first-group members are allowed.

Table 2
Government policy parameters under the FCTCP for the first (technically efficient), second (near efficient), and third (inefficient) groups, compared to a uniform traditional carbon tax scheme.

Parameters	Descriptions
λ_1	Trading rate of unused allowances within the first group
λ_2	Trading rate of unused allowances within the second group
λ_3	Trading rate of unused allowances within the third group
τ	Trading power determined by the first group for carbon trade
T	Government's uniform levy per unit of carbon equivalent emissions.

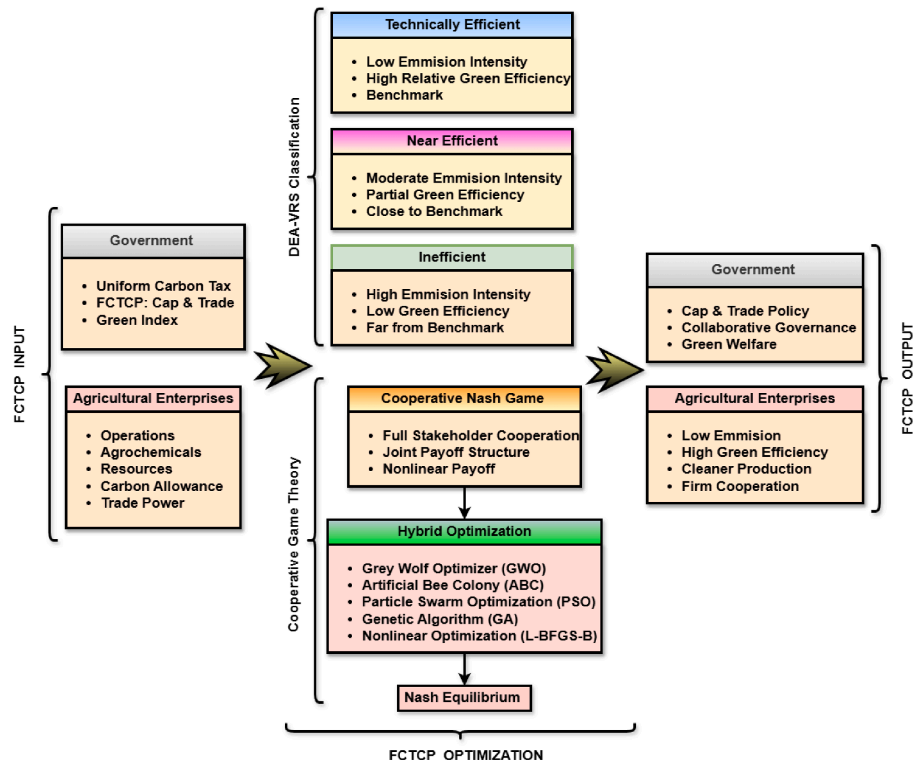

Fig. 1. A comprehensive flowchart of the FCTCP framework that integrates DEA-based efficiency classification, cooperative Nash game theory, and metaheuristic optimization to achieve equilibrium adoption outcomes for agricultural carbon policy.

More precisely, any firm within the first group whose total emissions, Π_1, are lower than the benchmark, Γ_1, has the right to sell the unused allowance to other groups:

$\lambda_1(\Gamma_1 - \Pi_1)$ to the first; $\lambda_2(\Gamma_1 - \Pi_1)$ to the second;
$\lambda_3(\Gamma_1 - \Pi_1)$ to the third;

keeping the inequality

$$\lambda_1 \leq \lambda_2 \leq \lambda_3 \quad \text{and} \quad \lambda_1 + \lambda_2 + \lambda_3 \leq 1. \tag{1}$$

This asymmetric trading arrangement is designed to preserve fairness while incentivizing higher-emission groups, particularly the inefficient tier, to improve their performance toward the benchmark. By granting these groups a larger share of potential allowance purchases from the technically efficient group, the scheme strengthens inter-group cooperation and accelerates convergence toward lower emission intensities.

Fig. 1 shows the complete FCTCP framework, which links government regulation, farm-level decisions, and computational optimization into a unified carbon policy model. Here, we assume that the government initially had a uniform carbon tax, and the FCTCP framework is proposed as an alternative carbon tax mechanism. In the game model, groups that choose to adopt FCTCP operate under its benchmark-based quota and trading rules, while groups that reject it remain under the standard carbon tax regime. In this context, this mixed configuration does not imply two parallel monitoring systems, but rather it measures how different stakeholders respond and how payoffs are shaped with and without the FCTCP. Thus, the mixed perspective serves purely as a game-theoretic device to model strategic heterogeneity in stakeholder adoption without increasing real-world administrative complexity.

3. Methods

This section outlines the methods employed in this work and is structured as follows. Section 3.1 presents the field data of 104 maize producers in Türkiye and conducts input-oriented DEA to establish efficiency frontiers to categorize farms. Section 3.2 presents a novel cooperative Nash game involving three groups and formulates a nonlinear optimization problem for Nash cooperation regarding the acceptance of the FCTCP policy within the carbon market. Section 3.3 examines a hybrid optimization scheme that integrates four distinct metaheuristics with one gradient-based optimization method to address the optimization problem arising from the Nash game. Finally, Section 3.4 introduces a green welfare metric designed to evaluate the policy outcomes of the FCTCP, using the efficiency frontier as a benchmark.

3.1. Data collection and classification

This study is based on a field survey conducted with 104 maize producers operating in Konya, one of Türkiye's major grain-producing regions, as shown in Fig. 2. The region is characterized by a semi-arid

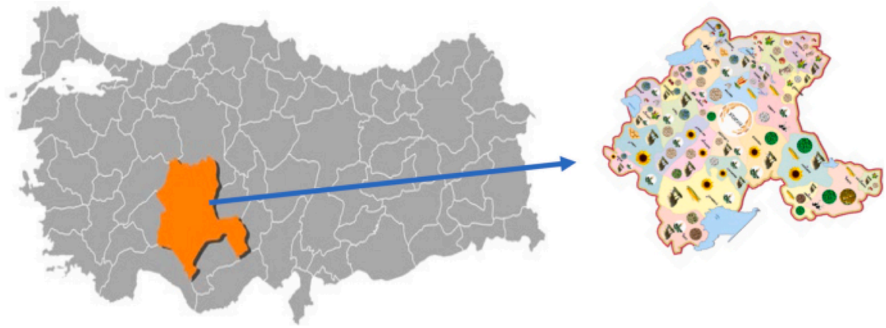

Fig. 2. Map showing the geographical location of the study area in Türkiye (Candemir et al., 2024).

climate and intensive, irrigation-based production systems. The data were collected through face-to-face interviews using a structured questionnaire between April and July 2021. The questionnaire was designed to quantify the physical amounts of major agricultural inputs used per hectare.

The collected dataset includes information on inputs such as seed, nitrogen, phosphorus fertilizers, diesel fuel, electricity, irrigation water, pesticides, machinery usage, and labor. The responses were based on farmers' self-reports and operational routines, and were standardized on a per-hectare basis to enable comparisons across farms. The dataset covers only in-field production activities; post-harvest processes such as transportation, storage, or processing are excluded.

This study measures technical efficiency for maize farms using an input-oriented DEA under VRS. For each farm, the central object is the proportional input contraction $\theta \in (0,1]$ that preserves current output; $\theta = 1$ denotes best practice, and smaller values imply larger proportional savings. The farm population of size N is partitioned into H strata of sizes N_h with $\sum_{h=1}^{H} N_h = N$. Representativeness is achieved by proportionate stratified simple random sampling without replacement, allocating a total sample n as

$$n_h = n\frac{N_h}{N} \quad (h = 1, \dots, H).$$

When n is determined from precision requirements on a finite-population proportion,

$$n = \frac{N\,p(1-p)}{(N-1)D^2 + p(1-p)}, \qquad D = \frac{d}{t},$$

where p is the target proportion, d is the absolute margin of error, and t is the relevant critical value (Bayramoglu & Gundogmus, 2009). Primary data are collected on-farm and normalized per unit of cultivated area; inputs comprise seed, nutrients, chemical control, irrigation, labor, and machine power, and the output is maize grain yield.

Let x_{ij} and y_{rj} denote, respectively, input $i = 1, \dots, m$ and output $r = 1, \dots, s$ for sampled farm $j = 1, \dots, n$. For a given farm α, the input-oriented VRS model solves

$$\begin{aligned} \min_{\theta,\lambda,s^-,s^+} \quad & \theta \\ \text{s.t.} \quad & \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{i\alpha}, \quad i = 1, \dots, m, \\ & \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{r\alpha}, \quad r = 1, \dots, s, \\ & \sum_{j=1}^{n} \lambda_j = 1, \quad \lambda_j \ge 0, \quad s_i^- \ge 0, \quad s_r^+ \ge 0. \end{aligned}$$

The convexity constraint implements VRS and allows for scale heterogeneity. The optimal value $\hat{\theta}$ is farm α's technical efficiency (TE). Positive input slacks $\hat{s}_i^-$ indicate input-specific savings beyond the common contraction, and farms with $\hat{\lambda}_j > 0$ form the peer set.

Solving the problem for all farms yields $\hat{\theta}_j$, which are then grouped into predefined TE score bands, as shown in Table 3. In this context, farms are classified as "technically efficient", "near efficient", or "inefficient" (Banker et al., 1984; Seiford & Thrall, 1990; Latruffe et al., 2012).

Since we have no direct emission data from each farm, we translate each input into its CO_2-equivalent version to understand each farm's emission performance in its agricultural practices. In addition, this perspective allows us to establish a common unit for the inputs of diverse farms and provides a deeper understanding of FCTCP policy outcomes based on emission performance and their collaborative decision-making on a unified scale. In this context, emissions are quantified using the following formula:

$$GHG_{Total} = \sum_{i=1}^{n} (Q_i \times EF_i), \tag{2}$$

where Q_i indicates input i used per hectare and EF_i represents emission factor corresponding to input i. These calculations are performed separately for each farm in the sample.

Table 4 presents a structured breakdown of the three major categories of inputs and the primary output in maize production: operational inputs, agrochemical inputs, and resource inputs, alongside the harvested maize output. For each category, both the energy-equivalent values and the greenhouse gas (GHG) emission coefficients are provided in Table 4.

3.2. Game description

This section presents the complete game construction of a cooperative Nash game, including emerging efficient enterprises coming together and cooperating on whether to accept the FCTCP in their respective markets.

Now, we present the following playability conditions for the game models:

1. The players in this game are three rational groups of agricultural enterprises: technically efficient, near efficient, and inefficient.
2. The technically efficient group comprises only members whose total emissions exceed the benchmark, and their decision ultimately determines whether the policy is fully accepted or rejected.
3. Each group chooses whether to adopt the FCTCP in their respective market. Their respective probabilities of adoption are denoted by x (technically efficient), y (near efficient), and z (inefficient).
4. The government implements either the FCTCP or a traditional uniform carbon tax scheme regarding the decisions of players.
5. If none of the three groups adopt the FCTCP, all groups are subject to taxation under the traditional uniform carbon tax policy.
6. If at least one group adopts the FCTCP, that group complies with its regulations, while the remaining groups are taxed under the uniform carbon tax scheme.
7. If all three groups adopt the FCTCP, the technically efficient group determines a trading power parameter $\tau \in (0,1]$, which enables it to set a more favorable price for carbon allowance trading.

Table 3
Farm characteristics by technical efficiency classification.

Efficiency Group	TE Score Range	Description
Technically efficient	$0.95 \leq \text{TE} \leq 1.00$	These farms form the reference group that uses the minimum amount of input to achieve a given output level under existing technology.
Near efficient	$0.90 \leq \text{TE} < 0.95$	This group includes farms with observable inefficiencies in production techniques.
Inefficient	$\text{TE} < 0.90$	These farms are furthest from the efficiency frontier, operating with high input redundancy and carbon intensity.

Table 4
Energy equivalents and GHG emission coefficients of farms in maize production.

Category	Input	Unit	GHG Emission Coefficient (kg CO_2-eq/unit)
Operational Input	Human labor	H	0.360 (Houshyar et al., 2015)
	Machinery	H	0.071 (Khoshnevisan et al., 2013)
Agrochemicals	Nitrogen	kg	1.300 (Lal, 2004)
	Phosphorus	kg	0.200 (Lal, 2004)
	Pesticides	kg	5.100 (Ozkan et al., 2004; Lal, 2004
Resource Input	Seed	kg	0.270 (Houshyar et al., 2015)
	Diesel fuel	L	2.760 (Dyer & Desjardins, 2006)
	Irrigation water	m^3	0.170 (Yaldiz et al., 1993; Houshyar et al., 2015)
	Electricity	kWh	0.608 (Rezvani Moghaddam et al., 2011; Lal, 2004)
Output	Maize	kg	(Ozkan et al., 2004; Mandal et al., 2002)

Based on the above rules, we determine the payoffs of all groups as follows. First of all, we define Γ_1 as the benchmark and Π, be the median of all first group members whose total emission levels are lower than the benchmark. Based on the parameter values given in Section 2, we define

$$\phi_1 = T(\Psi_1 - \Gamma_1); \quad \phi_2 = T(\Psi_2 - \Gamma_1); \quad \phi_3 = T(\Psi_3 - \Gamma_1);$$
$$\rho_1 = \lambda_1 T(\Gamma_1 - \Pi); \quad \rho_2 = \lambda_2 T(\Gamma_1 - \Pi); \quad \rho_3 = \lambda_3 T(\Gamma_1 - \Pi);$$

where Ψ_1, Ψ_2, Ψ_3 denote the average total emissions of the technically efficient, near efficient, and inefficient groups, respectively. In this framework, ϕ_1, ϕ_2, ϕ_3 denote the carbon tax generated under the cap component of the FCTCP, whereas ρ_1, ρ_2, ρ_3 represent the financial gains arising from its trade component. Here, the players' payoffs are formulated within a minimization framework that seeks to reduce the collective carbon tax burden while simultaneously maximizing the aggregate gains from allowance trading under the FCTCP.

To begin, when the technically efficient group accepts the FCTCP, its resulting payoff is determined by the combined cap and trade components, as outlined below.

$$G_1^Y = (\phi_1 - \tau\rho_1)yz + (\phi_1 - \rho_1)(1-y)z + (\phi_1 - \rho_1)y(1-z) + (\phi_1 - \rho_1)(1-y)(1-z) = \phi_1 - \rho_1 - \rho_1 yz(\tau - 1).$$

If the technically efficient group declines the FCTCP, the resulting payoff will consist of a uniform tax framework as outlined below:

$$G_1^N = \xi T \Psi_1.$$

where ξ is a sensitivity parameter on the uniform tax scheme. The expected payoff of the near efficient group becomes

$$G_1^E = xG_1^Y + (1-x)G_1^N.$$

Similarly, we establish the payoff of the near-efficient group based on its decision regarding participation in the FCTCP. If the near efficient group approves the FCTCP, the payoff contains a cap and trade framework as shown below:

$$G_2^Y = (\phi_2 - \tau\rho_2)xz + \phi_2(1-x)z + (\phi_2 - \rho_2)x(1-z) + \phi_2(1-x)(1-z) = \phi_2 - x\rho_2 - xz\rho_2(\tau - 1).$$

Here, compared to G_1^Y, the near-efficient group benefits from the government's carbon cap; however, in the absence of the technically efficient group, it is excluded from participating in the trading mechanism of the FCTCP. If the near-efficient group rejects the FCTCP, then the resulting payoff will be the following:

$$G_2^N = \xi T \Psi_2.$$

The expected payoff of the near efficient group becomes

$$G_2^E = yG_2^Y + (1-y)G_2^N.$$

Finally, we present the payoff structure for the inefficient group based on its decision regarding the FCTCP. If the inefficient group adopts the policy, then we have

$$G_3^Y = (\phi_3 - \tau\rho_3)xy + \phi_3(1-x)y + (\phi_3 - \rho_3)x(1-y) + \phi_3(1-x)(1-y) = \phi_3 - x\rho_3 - xy\rho_3(\tau - 1).$$

If the near-efficient group rejects the FCTCP, then the resulting payoff will be the following:

$$G_3^N = \xi T \Psi_3.$$

The expected payoff of the near efficient group becomes

$$G_3^E = zG_3^Y + (1-z)G_3^N.$$

Table 5 presents the eight potential payoff outcomes for the three groups based upon the acceptance or rejection of the FCTCP policy.

Now, we define the Nash equilibrium as the set of mixed strategy probabilities (x_N, y_N, z_N) for the three enterprise groups to minimize the incentive for unilateral deviation from their strategic choice under the FCTCP. Here, we construct the net utility as

$$F(x, y, z) = x(G_1^Y - G_1^E) + y(G_2^Y - G_2^E) + z(G_3^Y - G_3^E).$$

In this construction, the difference of each $(G_i^Y - G_i^E)$ shows the net gain of player i from adopting the FCTCP relative to its expected outcome. This formulation presents three different scenarios: the case when the payoff from participation exceeds the expected payoff, the case when the difference is zero, and the case when the participation payoff is below the expectation. In the literature, this type of difference-based formulation is mathematically and economically equivalent to standard expected-utility optimization under mild regularity conditions (Hamidoğlu, 2024; Hamidoğlu et al., 2024; Hamidoğlu & Weber, 2024).

Now, we are ready to propose our equilibrium problem as follows:

$$(x_N, y_N, z_N) = \arg\left(\min_{0 \leq x,y,z \leq 1} F(x, y, z)\right) \tag{3}$$

Table 5
Payoff outcomes for each enterprise group under different strategic combinations of FCTCP adoption. (Y: Yes = Adopts FCTCP, N: No = Rejects FCTCP).

Strategic Profile (Y/N)	Technically efficient Group	Near efficient Group	Inefficient Group
$\{Y, Y, Y\}$	$\phi_1 - \tau\rho_1$	$\phi_2 - \tau\rho_2$	$\phi_3 - \tau\rho_3$
$\{Y, N, Y\}$	$\phi_1 - \rho_1$	$\xi T\Psi_2$	$\phi_3 - \rho_3$
$\{Y, N, N\}$	$\phi_1 - \rho_1$	$\xi T\Psi_2$	$\xi T\Psi_3$
$\{Y, Y, N\}$	$\phi_1 - \rho_1$	$\phi_2 - \rho_2$	$\xi T\Psi_3$
$\{N, Y, Y\}$	$\xi T\Psi_1$	ϕ_2	ϕ_3
$\{N, N, Y\}$	$\xi T\Psi_1$	$\xi T\Psi_2$	ϕ_3
$\{N, Y, N\}$	$\xi T\Psi_1$	ϕ_2	$\xi T\Psi_3$
$\{N, N, N\}$	$\xi T\Psi_1$	$\xi T\Psi_2$	$\xi T\Psi_3$

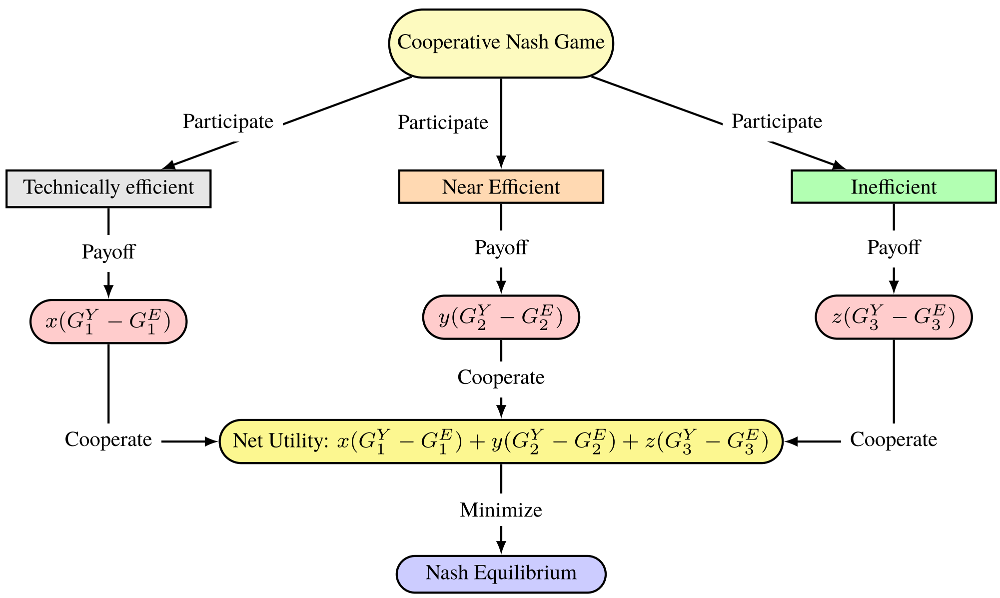

Fig. 3. A Nash game framework involving agricultural enterprises for cooperative acceptance of the FCTCP.

where each term in the summation quantifies the extent to which a group's cooperative strategy outperforms its expected average payoff, reflecting the incentive to maintain or adjust its current behavior.

The overall minimization represents the system's progression toward a Nash equilibrium, where no group can improve its outcome through unilateral deviation. Fig. 3 shows the game flow of all participants towards cooperative FCTCP policy acceptance and achieving Nash equilibrium at the end.

3.3. Hybrid optimization

This section considers a hybrid optimization scheme consisting of four different metaheuristics and one gradient-based optimization to solve the proposed nonlinear optimization problem given in (3). The objective function in (3) is inherently non-convex due to the presence of several nonlinear and mixed terms. Because of this non-convex structure, we consider the use of metaheuristic algorithms, including Artificial Bee Colony (ABC) (Karaboga & Basturk, 2007), Grey Wolf Optimizer (GWO) (Mirjalili et al., 2014), Particle Swarm Optimization (PSO) (Kennedy & Eberhart, 1995), and Genetic Algorithm (GA) (Holland, 1992) for global search and nonlinear quasi-Newton optimization method, L-BFGS-B (Zhu et al., 1997) for robust local search. These algorithms are designed to explore complex, rugged search spaces effectively and are capable of escaping local optima, making them particularly suitable for solving this class of equilibrium-based optimization problems.

Fig. 4 shows the key descriptions of the hybrid optimization framework for deriving the Nash equilibrium decision for FCTCP acceptance. Here, each optimization technique provides a distinct search behavior and together affects the robustness of the solution. In this context, the ABC algorithm explores candidate strategies through neighbor-based foraging, probabilistic selection, and scout-driven diversification, while PSO introduces collective learning and velocity-guided movement. On the other hand, GWO adds a leadership-hierarchy structure and exploits it through coordinated pursuit, while GA improves population diversity through selection pressure, crossover mixing, and mutation-driven variation. In the local sense, the L-BFGS-B method uses a gradient-based search with precise boundary data, providing a stable and robust estimation for the equilibria. Hence, together, these methods create a comprehensive hybrid optimization architecture allowing for both wide exploration and strict local refinement. Algorithm 1 provides a brief description of hybrid optimization to derive the Nash equilibrium for the problem. Here, the Algorithm 1 consists of two phases. The first phase is to do a global search by using all four metaheuristics, ABC, PSO, GWO, and GA, with random populations, and the second phase is to perform a local search by using L-BFGS-B with bounded constraints and given initial starting data. Overall, the algorithm compares all five outcomes, picks the best one, and names it Nash equilibrium.

3.4. A green welfare index

In the context of agricultural sustainability and carbon taxation, it is critical to develop a robust metric that can evaluate the environmental performance of heterogeneous producers. For this purpose, we propose a green welfare index that measures the relative environmental efficiency of emerging agricultural enterprises compared to a benchmark technically efficient firm. This approach draws from established methodologies in efficiency analysis and sustainability benchmarking (Addis, 2025; Han et al., 2024).

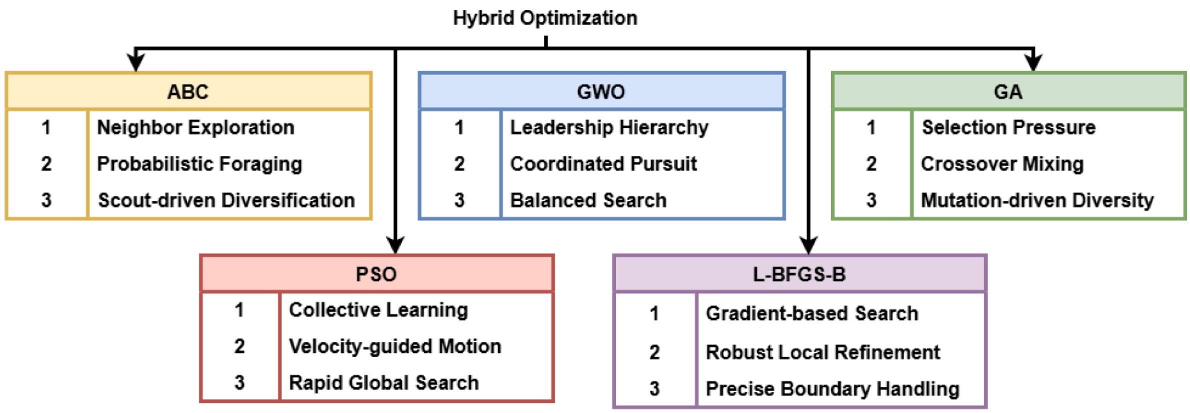

Fig. 4. Short descriptions of hybrid optimization scheme consisting of five different optimization techniques.

Algorithm 1 Hybrid optimization for the Nash equilibrium estimation.

1: **Search Domain:** $\Omega = [0,1]^3$.
2: **Initialize:** Random populations $\mathcal{P}^{ABC}, \mathcal{P}^{PSO}, \mathcal{P}^{GWO}, \mathcal{P}^{GA}$ for metaheuristic; deterministic start (x_0, y_0, z_0) for L-BFGS-B.
3: **Global Metaheuristic Search**
4: **for** $\theta \in \{\mathrm{ABC}, \mathrm{PSO}, \mathrm{GWO}, \mathrm{GA}\}$ **do**
5: Run optimizer θ for T iterations:

$$(x^\theta, y^\theta, z^\theta) = \arg \min_{(x,y,z)\in\Omega} F(x,y,z)$$

6: **end for**
7: **Local Deterministic Search**
8: Apply L-BFGS-B with bound constraints Ω:

$$(x^L, y^L, z^L) = \arg \min_{(x,y,z)\in\Omega} F(x,y,z) \quad \text{starting from } x_0.$$

9: **Selection of Global Minimizer**
10: For hybrid optimization set $\mathcal{H} = \{\mathrm{ABC}, \mathrm{PSO}, \mathrm{GWO}, \mathrm{GA}, L\}$, evaluate:

$$(x^*, y^*, z^*) = \arg \min_{\theta\in\mathcal{H}} F(x^\theta, y^\theta, z^\theta).$$

11: **Output:** Nash equilibrium estimate (x^*, y^*, z^*).

The concept of using a fully efficient producer as a benchmark aligns with best-practice frontier analysis found in DEA and stochastic frontier models. In environmental economics, the use of reference entities has been widely adopted to set attainable targets and evaluate the potential for emission reduction (Ceres, 2025; Dong et al., 2025).

The technically efficient firm, in our case, minimizes greenhouse gas (GHG) emissions per unit of output while maintaining maximum productivity under current operation, agrochemical, and resource constraints. It serves as the green frontier against which all other (emerging efficient) firms are compared (Yılmaz, 2025). As shown in Table 4, GHG-emitting activities are categorized into three primary input types: operation-based inputs (OB), which include emissions from human labor and machinery use; agrochemical-based inputs (AB), encompassing fertilizers and pesticides; and resource-based inputs (RB), which consist of diesel fuel, irrigation water, electricity, and seeds.

For each input category $\Lambda \in \{\mathrm{OB}, \mathrm{AB}, \mathrm{RB}\}$, the emission intensity (EI) per kilogram of maize output for each group i is calculated as follows:

$$EI_{\Lambda,i} = \frac{\sum_{j\in\Lambda} E_{\Lambda,j}}{A_i}, \tag{4}$$

where $E_{\Lambda,j}$ is the CO_2-eq emission from input j in category Λ, and A_i is the output (kg maize) of group i. Here, we consider the technically efficient firm as the benchmark, with its emission intensity in category Λ denoted as EI_Λ. The relative green efficiency (RGE) of each firm in category Λ is then computed with respect to this benchmark as follows:

$$RGE_{\Lambda,i} = \frac{EI_\Lambda}{EI_{\Lambda,i}}, \quad \text{with} \quad RGE_{\Lambda,i} \le 1. \tag{5}$$

Finally, we define the green welfare index (GWI) for each group i as follows:

$$GWI_i = \omega_1 RGE_{OB,i} + \omega_2 RGE_{AB,i} + \omega_3 RGE_{RB,i} \tag{6}$$

where $\omega_1, \omega_2, \omega_3 \in [0,1]$ are weights with $\omega_1 + \omega_2 + \omega_3 = 1$.

Here, if the farm has the GWI score of 1, then it becomes green-efficient, while the score closer to 0 indicates poor environmental performance. Hence, a GWI from a farm serves as an interpretive tool to measure how far the near-efficient and inefficient groups deviate from this technically efficient frontier according to their efficient resource use, operational, and agrochemical inputs. More precisely, GWI scores reveal how much green improvement is needed for each group to reach the benchmark if they choose to adopt the FCTCP policy. As a result, stakeholder cooperative decision-making is indirectly involved within GWI scores, showing not only FCTCP adoption under carbon cap and trade pricing strategies but also how much green effort is needed to achieve the benchmark.

4. Results and discussions

This section presents the results and discussions of the FCTCP and is organized as follows. Section 4.1 presents a case study on maize production in Türkiye, measuring the potential green welfare resulting from policy acceptance and evaluating Nash collaborations among three distinct efficiency groups. This section examines and simulates benchmark-based carbon trade and group-level cap scenarios to establish Nash equilibria within the framework of the FCTCP policy. In simulations, all four metaheuristic algorithms are executed with 30 population sizes and a maximum of 100 iterations to facilitate a fair comparison, while the L-BFGS-B method terminates at the iteration when achieving convergence to the Nash equilibrium. Section 4.2 presents a comparative analysis of the FCTCP policy, supported by results from the Türkiye case study and recent literature, highlighting its advantages and uniqueness.

4.1. A case study

This section presents a Turkish maize case study, considering 104 different farms in Konya, Türkiye. The data was collected by means of face-to-face surveys from April to July 2021, including key inputs in maize production and operational practices. In this context, Table 6 summarizes the mean operational and input-output characteristics of three efficiency groups, classified from DEA-based technical efficiency scores, where each group represents a distinct performance tier under variable returns to scale (see Table A.1 for raw farm input–output data, reported before CO_2-eq conversion).

Table 6
Average CO_2-eq emissions from maize production across efficiency groups in Türkiye's Konya region, with table values reported as mean (Mean) and standard deviation (Std. Dev.).

Variable	Technically efficient		Near efficient		Inefficient	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Labour	18.087	8.020	19.243	5.843	18.104	6.448
Diesel	1228.162	161.149	1205.897	166.977	1280.626	149.878
Seed	12.656	2.319	13.500	2.205	13.693	2.236
Pesticides	11.218	4.748	10.855	4.825	13.340	4.353
Irrigation Water	1059.844	235.504	1190.000	196.299	1213.891	169.308
Nitrogen	340.710	116.410	363.561	116.944	358.333	89.469
Phosphor	35.543	17.238	33.038	11.719	37.818	10.363
Machinery	1.784	0.596	1.939	0.426	1.799	0.509
Electricity	2909.375	511.875	3290.563	552.329	3334.500	555.810
Yield (kg)	18818.125	1835.337	18195.625	1266.875	16873.036	1540.759
Total Emissions (kg CO_2-eq)	5617.377	1057.859	6128.594	1057.567	6272.105	988.374
Emission Intensity (kg CO_2-eq/kg)	0.2985	–	0.3368	–	0.3717	–

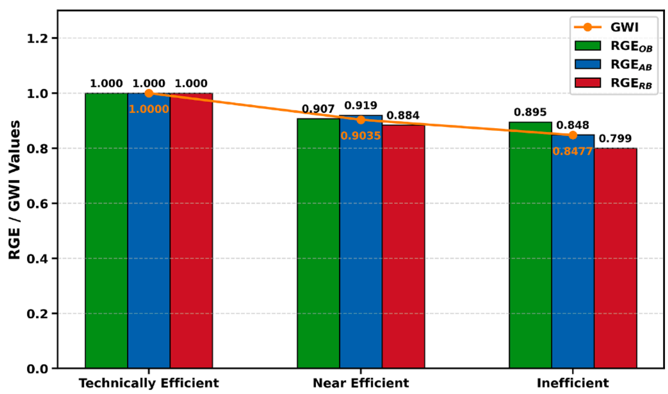

Fig. 5. RGE and GWI measures of near-efficient and inefficient farms relative to the technically efficient benchmark.

From Table 6, we evaluate the green welfare index of the near-efficient and inefficient groups using the technically efficient group as the benchmark. We give equal weight to the three inputs OB, AB, and RB:

$$\omega_1 = \omega_2 = \omega_3 = \tfrac{1}{3}.$$

For each group $i = 1, 2, 3$ (technically efficient, near efficient, and inefficient, respectively), the emission intensities are

$$(EI_{OB,1}, EI_{AB,1}, EI_{RB,1}) = (0.00106, 0.0206, 0.2769),$$
$$(EI_{OB,2}, EI_{AB,2}, EI_{RB,2}) = (0.00116, 0.0224, 0.3132),$$
$$(EI_{OB,3}, EI_{AB,3}, EI_{RB,3}) = (0.00120, 0.0243, 0.3463).$$

As shown in Fig. 5, the near-efficient group is projected to enhance its green welfare performance by 9.65 % to align with the benchmark set by the technically efficient group, whereas the inefficient group requires a 15.23 % improvement under the FCTCP. The improvements indicate enhancements in resource allocation efficiency, the adoption of cleaner production methods, and operational optimization. The FCTCP establishes a systematic approach for reallocating carbon allowances, motivating both near- and low-performing groups to enhance their performance and facilitating an economically sustainable trajectory for the overall system to achieve a low-emission equilibrium.

Now, we implement our tax policy, FCTCP, into this case study and use our proposed Nash cooperative game to measure their equilibrium adoption of the policy. From Table 6, the government sets its cap as $\Gamma_1 = 5617$ based on the average total carbon emissions data of the technically efficient group. By using the complete maize data (see supplementary), we calculate the median of the technically efficient group whose emission scores are below the cap is found as $\Pi = 5052$, while the rest average of this group becomes $\Psi_1 = 6301$. Moreover, we find $\Psi_2 = 6128$ and $\Psi_3 = 6272$.

The timing of Türkiye's ETS development is particularly critical given the European Union's Carbon Border Adjustment Mechanism (CBAM), which will move from its transitional phase into full enforcement in 2026 (European Commission, 2023, 2025). Under CBAM, Turkish exporters of carbon-intensive goods will face an additional levy when accessing EU markets, based on the embedded carbon emissions of their products. Estimates suggest that the CBAM-related fees for Turkish exports will fall within the range of 30-50 EURO per tonne of CO_2-eq (Deutsche Bank Research, 2024). Hence, we set Türkiye's domestic carbon tax benchmark as 40 EURO per tonne of CO_2-eq, which makes $T = 0.04$ (tax per kg CO_2-eq).

For uniform carbon trade, we assume $\lambda_1 = \lambda_2 = \lambda_3 = \frac{1}{3}$, which reflects the principle of fairness, acknowledging that each group, regardless of size or efficiency, is granted an equal opportunity to participate in carbon trading. The next two sections analyze distinct carbon trades: one emphasizes collective carbon trading dynamics, while the other investigates varying levels of cap stringency. In the final section, we examine a scenario where uniform carbon trading is unavailable. Instead, the distribution of carbon allowance rates occurs asymmetrically, specifically with values of $\lambda_1 = 0.1$, $\lambda_2 = 0.35$, and $\lambda_3 = 0.55$, satisfying (1).

4.1.1. Collective carbon trade

This section examines cooperative decision dynamics within the framework of the FCTCP by addressing problem (3) through four metaheuristic algorithms: ABC, PSO, GWO, and GA, under the assumption of equal carbon trade allowances. Three collective carbon trade scenarios are considered, with trading power values $\tau = 1$, $\tau = 0.7$, and $\tau = 0.4$. Here, $\tau = 1$ means full trading power without having any discount applied by the technically efficient group, whereas $\tau = 0.7$, and $\tau = 0.4$ represent 30 % and 60 % discounts applied when selling carbon allowance to the groups under the benchmark, respectively.

Figs. 6–8 show Nash equilibrium acceptance of the FCTCP policy by all groups involved under four different metaheuristics with 100 iterations, and robustness of Nash equilibrium estimations is supported by the L-BFGS-B, as illustrated in Fig. 9.

Furthermore, Fig. 10 shows that both near-efficient and efficient groups exhibit reduced acceptance as τ decreases, with the drop-off being more pronounced in the inefficient group. This suggests that carbon trade-based incentives may disproportionately demotivate the inefficient group, posing a challenge to broad FCTCP adoption.

Comprehensive numerical results for all three scenarios are presented in Figs. B.1–B.3, with optimal Nash equilibrium outcomes listed in Tables B.1–B.3 for $\tau = 1$, $\tau = 0.7$, and $\tau = 0.4$, respectively. In these simulations, we see that ABC and PSO together with L-BFGS-B become more effective in deriving the optimal solution of the cost function (3).

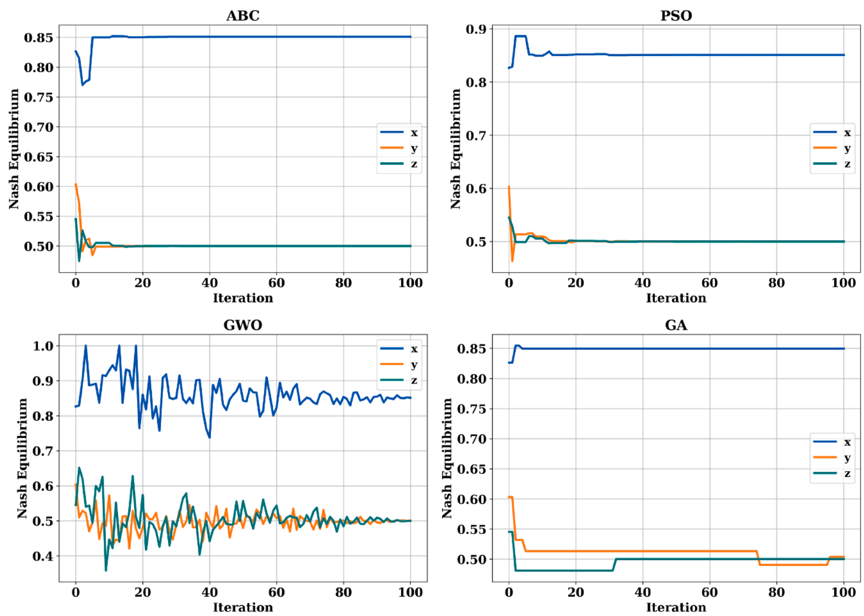

Fig. 6. Nash equilibrium of FCTCP adoption under 100 simulations across four metaheuristic when $\tau = 1$.

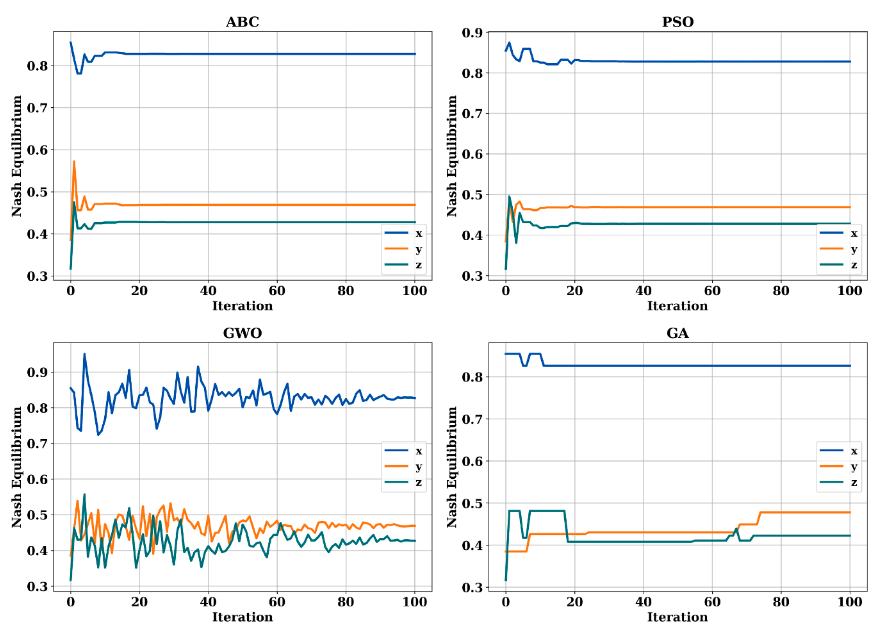

Fig. 7. Nash equilibrium of FCTCP adoption under 100 simulations across four metaheuristic when $\tau = 0.7$.

4.1.2. *Cap stringency*

In this section, we examine government-imposed cap scenarios under the FCTCP. The baseline cap is set at the average technically efficient emission level, $\Gamma_1 = 5617$ (Table 6). Using this as a benchmark, we analyze two alternative caps: $\Gamma_1 = 5500$, which is slightly below the benchmark and $\Gamma_1 = 6500$, which is substantially above it. To assess the policy's effectiveness, we assume a trading power of $\tau = 1$, indicating the absence of a discount option in the carbon market.

As shown in Fig. 11 and Table B.4, when the cap is below the benchmark, the technically efficient group fully accepts the FCTCP. However, Fig. 12 and Table B.5 reveal that when the cap is set far above the benchmark, acceptance within this group drops to 59 %. This indicates that caps close to the efficient benchmark strongly motivate policy adoption among technically efficient participants, whereas overly generous caps diminish support. Fig. 14 summarizes the best Nash decision outcomes, showing that near-efficient and inefficient groups remain evenly split across all scenarios, suggesting that cap adjustments have little influence on their acceptance. Finally, Figs. 13, B.4, and B.5 demonstrate that L-BFGS-B alongside ABC and PSO outperform GWO and GA in converging to the optimal solution.

4.1.3. *Asymmetric carbon trade*

This section examines the asymmetric distribution of carbon trade allowances across all groups, using an unbalanced framework with $\lambda_1 = 0.1$, $\lambda_2 = 0.35$, and $\lambda_3 = 0.55$, satisfying (1). Within this setting, both cooperative carbon trade and cap stringency scenarios, as outlined in Sections 4.1.1 and 4.1.2, are analyzed.

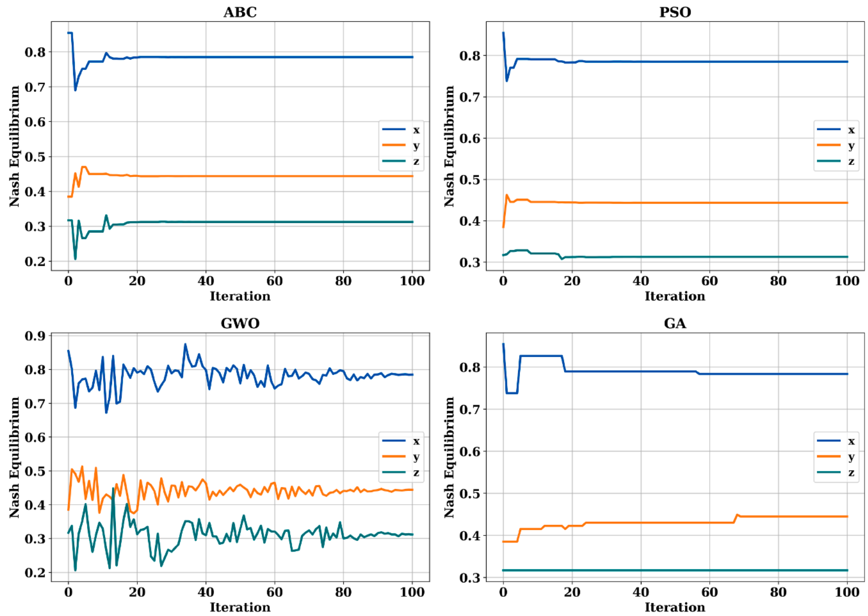

Fig. 8. Nash equilibrium acceptance of the policy derived from 100 simulations across four metaheuristic algorithms when $\tau = 0.4$.

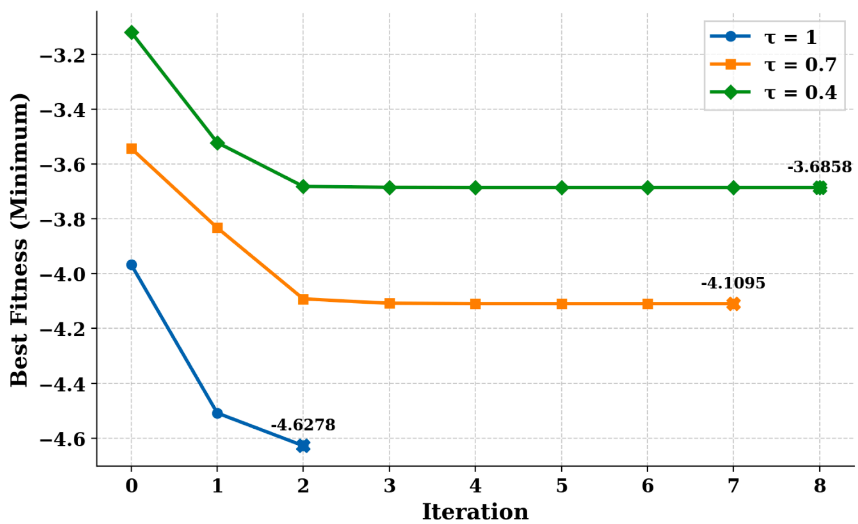

Fig. 9. The minimum values of net utility, along with the convergent iteration numbers, are presented for the cases where $\tau = 1, 0.7, 0.4$ under the L-BFGS-B method.

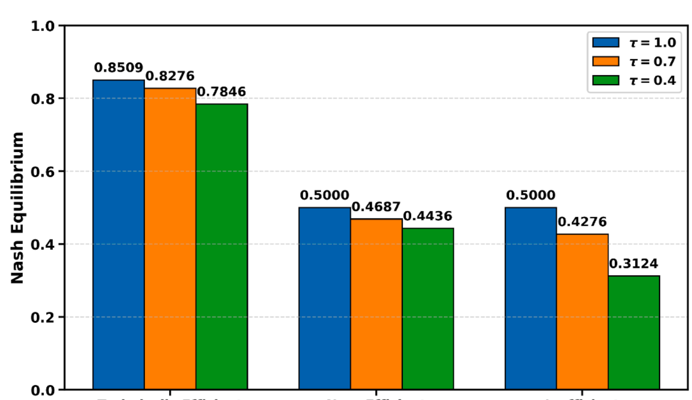

Fig. 10. Best Nash equilibrium outcomes from four metaheuristic optimizations for collective carbon trading under trading power levels of $\tau = 1, 0.7$, and 0.4.

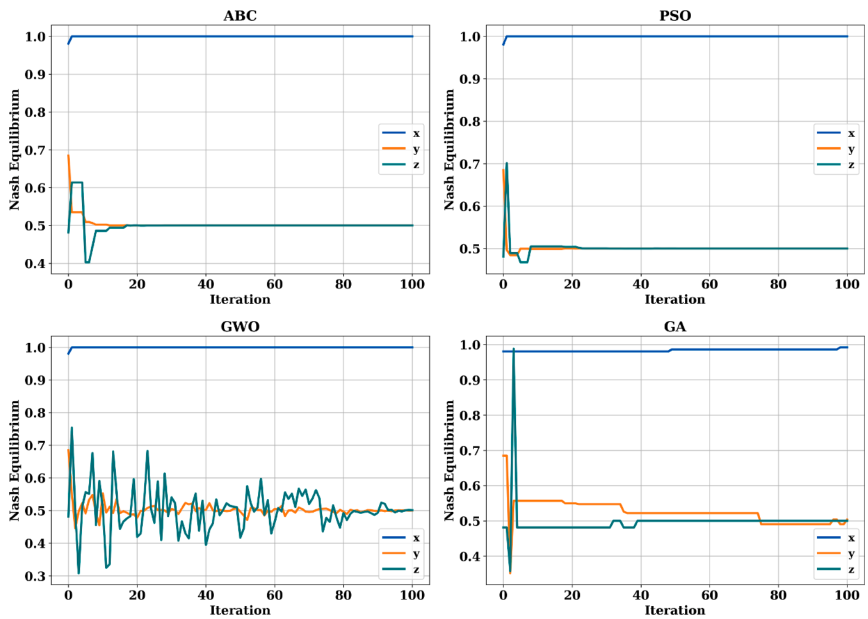

Fig. 11. Nash equilibrium acceptance of the policy under 100 iterations when $\tau = 1$ and $\Gamma_1 = 5500$.

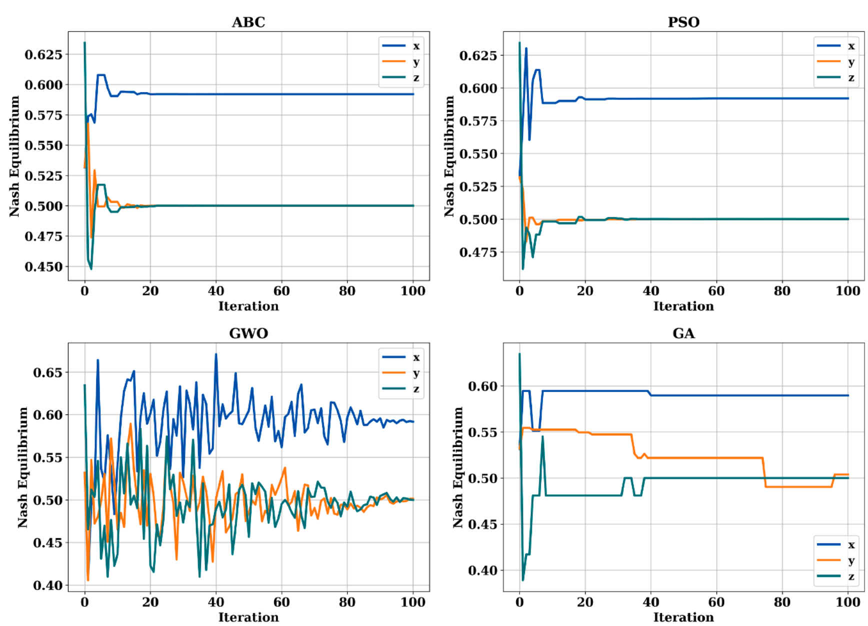

Fig. 12. Nash equilibrium acceptance of the policy under 100 iterations when $\tau = 1$ and $\Gamma_1 = 6500$.

Fig. 15 illustrates the complete trends under different cap-and-trade scenarios, with the best outcomes achieved using the ABC algorithm. An increase in the carbon cap reduces the acceptance rate of the technically efficient group, with the decline being more pronounced under balanced carbon allowance distribution. In contrast, the Nash decisions of the near-efficient and inefficient groups remain at fifty-fifty, mirroring the pattern observed in the balanced case. Moreover, as shown in Fig. 15, an increase in carbon trading power reduces all groups' Nash decisions in favor of FCTCP implementation. However, this decline is slower compared to the balanced case. Therefore, an asymmetric carbon allowance distribution proves more favorable than a balanced one for securing FCTCP acceptance among stakeholders.

4.2. Comparative analysis

This section provides a comparative analysis of the FCTCP policy with other existing carbon tax policies in recent literature, together with its advantages and uniqueness.

First, the FCTCP policy is performed without using MRV protocols or carbon monitoring systems, which makes it a suitable tax policy candidate for developing economies like Türkiye during the initial phase of carbon policy adoption. In MRV systems, governments and agricultural enterprises pay costs together, where governments are responsible for the MRV infrastructure, while agricultural enterprises bear data collection, verification, and compliance costs. Recent literature indicates that

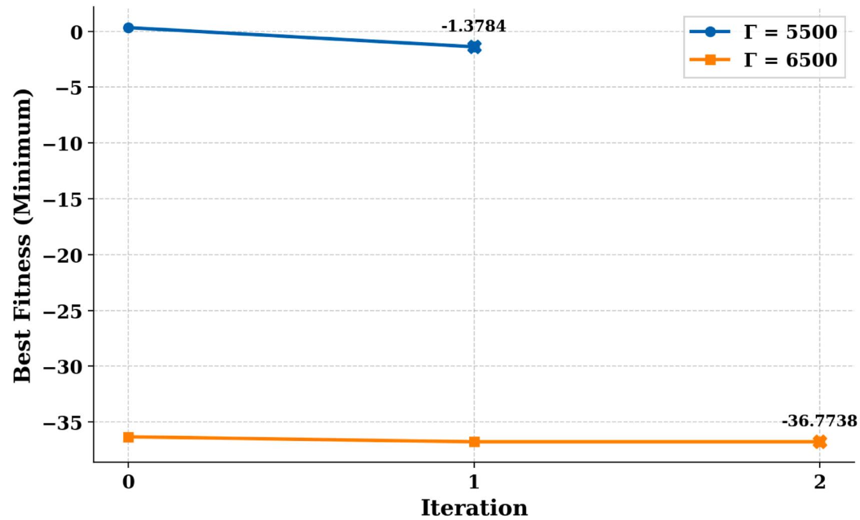

Fig. 13. The minimum values of net utility, along with the convergent iteration numbers, are presented for the cases where $\tau = 1$ and $\Gamma_1 = 5500, 6500$ under the L-BFGS-B method.

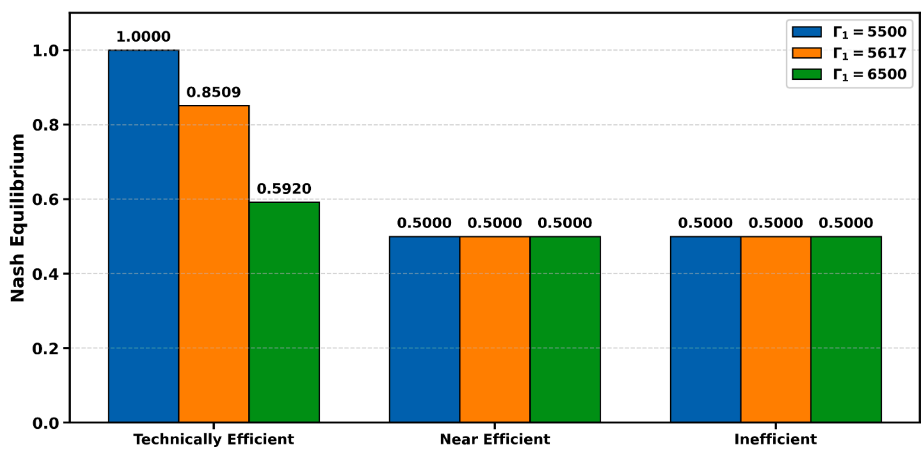

Fig. 14. Optimal Nash equilibrium outcomes obtained from four metaheuristic algorithms under varying cap stringency levels ($\Gamma_1 = 5500, 5617$, and 6500).

MRV systems may result in significant costs (Ho et al., 2023; Mercer et al., 2024), resulting in the exploration of alternative carbon measurement methods to promote effective carbon trading in industry (Ecklu & Thomas, 2025; Heister et al., 2025; Körner et al., 2025). Different from existing literature, the FCTCP introduces a carbon trade policy that assesses each farm's performance based on CO_2-equivalents associated with its agricultural activities, including resources, operations, and agrochemicals, while eliminating reliance on expensive MRV protocols, thus presenting a viable option for developing countries.

Second, the FCTCP policy uses group-level caps, which have potentials to prevent liquidity shortages and price volatility in carbon markets (Ibikunle et al., 2016; Yoon & Karali, 2025). The case study of Türkiye indicates that all three groups exhibit increased motivation to adopt the FCTCP policy when subjected to a group-level cap, while higher caps tend to discourage the most efficient groups from participating in the policy. Empirical evidence from China's pilot ETS shows that markets with limited participants experience thin trading and price instability (Wang et al., 2018), while benchmark-based grouping, like the FCTCP policy, improves liquidity and stabilizes prices (Song et al., 2022).

Third, the FCTCP performs benchmark-based carbon trade where best performers are allowed to sell their extra carbon allowance to the lower performers within the carbon market. Similar setups are widely used in literature. For instance, the European Union's ETS utilizes product-based benchmarks (European Commission, Directorate-General for Climate Action, 2024), whereas China's national ETS employs emission intensity-based benchmarks (Zhang et al., 2025b). In contrast, California's cap-and-trade policy applies output-based allocation rules (Climate, 2024), while Tokyo's cap-and-trade system uses facility-level intensity-based allocations (The Tokyo Metropolitan Environmental Security Ordinance, 2015). The FCTCP policy distinguishes itself from existing benchmarking schemes by employing DEA-derived efficiency frontiers to establish a unique carbon trade market. The case of Türkiye demonstrates that the FCTCP significantly influences farms in achieving efficiency frontiers within an asymmetric carbon trade context.

Finally, policy acceptance of the FCTCP directly impacts the green welfare index; as more farms approach the efficiency frontier, they experience greater improvements in green welfare. Conventional cap and trade schemes in the literature produce prices and compliance data; however, these schemes lack an embedded welfare or sustainability metric that correlates market outcomes with a comprehensive, production-level sustainability score (Colmer et al., 2025; Flori et al., 2024; Jiang et al., 2025; Jung et al., 2021). The FCTCP uniquely translates policy outcomes into a green welfare metric, as demonstrated in Türkiye's

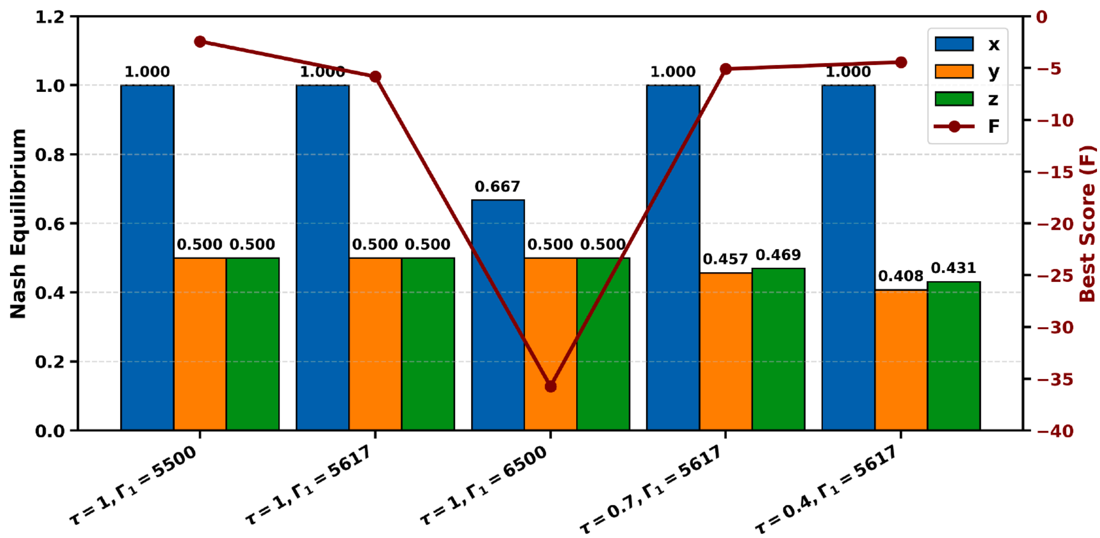

Fig. 15. Nash equilibrium outcomes and optimal scores across carbon trade and cap stringency scenarios under asymmetric carbon allowance distribution, computed using the ABC algorithm.

case study, where near-efficient farms contribute to a 9.65 % increase in green welfare, while inefficient farms lead to a 15.23 % welfare improvement.

5. Conclusion

The study introduces a novel forward-looking cap and trade policy, FCTCP, to serve as a preparatory carbon tax mechanism for emerging economies transitioning toward full MRV-capable, measurement-based carbon markets. In the methodology, we apply DEA and GHG emissions coefficients to evaluate agricultural practices on each farm. A novel cooperative game shows how the cap and trade mechanism should be to reach the overall Nash equilibrium within the FCTCP policy. Evidence from Türkiye's maize production shows the robustness of the policy and improvements in green welfare performance for near-efficient and inefficient farms. In the following subsections, we present policy implications, limitations, and future directions of the FCTCP policy.

5.1. Policy implications

The section outlines the policy implications of applying the FCTCP in agricultural carbon trading. First, we see that asymmetric trade policies are more effective than uniform distributions for encouraging policy adoption. Second, we observe that carbon caps close to the efficiency benchmark would motivate farms to participate in the policy. Third, policymakers should apply no discount on carbon trades to increase the acceptance of the policy. Forth, we see in all cap and trade scenarios that the technically efficient farms show a greater preference for the FCTCP scheme compared to other groups. Here, policymakers should surpass certain thresholds on carbon pricing to get the maximum policy acceptance rate. Finally, reductions in excessive agrochemical use, improvements in machinery and labor efficiency, or improved management of water, energy, and seed resources can directly decrease each farm's distance to the benchmark group, thereby improving farms' GWI scores. In this regard, policymakers should consider a full MRV system not only for measuring the overall carbon emissions of each farm but also for how well it contributes to sustainable resource use when practicing its agricultural activities.

5.2. Limitations

The study identifies several limitations. First, the FCTCP policy relies on farms' resource, operational, and agrochemical data, which sometimes poses challenges to measure or obtain for developing economies. Second, the FCTCP structure is transferable but requires recalibration for application to different crops or regions. Local operational, agrochemical, and resource datasets are necessary for these recalibrations. Third, we assume that farmers should build a cooperative cap and trade mechanism under the policy, but in reality, this assumption may face challenges due to social, cultural, or political barriers in farmlands. Fourth, the FCTCP relies on the true data of all farms involved; there is always a risk of bias or manipulation of reported data to take advantage of the system. For this reason, safeguards, including third-party verification, monitoring of carbon accounts, and strict penalties, are necessary to prevent such actions and provide a fair and safe platform for farms. Finally, the FCTCP framework performs its forward-looking design by evaluating farms according to the carbon-equivalent intensity of their operational, agrochemical, and resource inputs rather than on directly measured GHG emissions. This modeling choice is intentional and reflects the reality of many developing economies, such as Türkiye, and emerging economies, like Vietnam, where carbon pricing mechanisms are in their early stages and farm-level emission monitoring systems remain incomplete or nonexistent.

5.3. Future works

The study provides several future directions. First, the FCTCP policy divides agricultural practices into three categories, which makes it quite applicable to crops other than maize and has the potential to prove its robustness in different regions. Second, the policy can be coupled with government subsidies or incentive scenarios to create accessible pathways for farmers towards low-carbon transitions. Third, the policy can be expended to use more agricultural data sets to broaden carbon efficiency with climate resilience. Finally, the FCTCP policy can integrate direct, farm-level emissions data to evolve its forward-looking nature into a measurement-based cap-and-trade mechanism.

Declaration of use of artificial intelligence

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CRediT authorship contribution statement

Ali Hamidoğlu: Conceptualization, Formal analysis, Investigation, Methodology, Validation, Software, Visualization, Writing – original draft, Writing – review & editing; **Serhan Candemir:** Conceptualization, Methodology, Validation, Resources, Data curation, Writing – original draft; **Zeki Bayramoğlu:** Conceptualization, Validation, Data curation, Writing – review & editing; **Hasan Gökhan Doğan:** Conceptualization, Data curation, Writing – review & editing; **Kemalettin Ağizan:** Resources; **Seifedine Kadry:** Validation, Writing – review & editing.

Data availability

Data will be made available on request.

Declaration of competing interest

The authors declare no competing financial interests or personal relationships that could have influenced the work. There are no conflicts of interest related to the publication of this paper.

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Appendix A. Farm data

Table A.1
Mean and standard deviation (SD) of inputs and outputs for maize farms by efficiency groups.

Variable	Unit	Technically efficient ($0.950 \le TE \le 0.999$)		Near-Efficient ($0.900 \le TE \le 0.949$)		Inefficient ($TE < 0.900$)	
		Mean	SD	Mean	SD	Mean	SD
Labour	H	50.240	22.278	53.452	16.231	50.289	17.911
Diesel	L	444.986	58.387	436.919	60.499	463.995	54.304
Seed	kg	46.875	8.590	50.000	8.165	50.714	8.281
Pesticides	kg	2.200	0.931	2.128	0.946	2.616	0.854
Irrigation Water	m^3	6234.375	1385.317	7000.000	1154.701	7140.536	995.927
Nitrogen	kg	262.084	89.546	279.663	89.957	275.641	68.822
Phosphor	kg	177.713	86.192	165.188	58.594	189.089	51.816
Machinery	H	25.120	8.388	27.304	6.001	25.344	7.164
Electricity	kWh	4785.156	841.900	5412.109	908.436	5484.375	914.161
Yield	kg	18818.125	1835.337	18195.625	1266.875	16873.036	1540.759

Appendix B. Nash game simulation data

Table B.1
Iteration numbers (N), minimum values and corresponding Nash equilibrium (x, y, z) when $\tau = 1$.

Algorithm	Minimum	x	y	z	N
ABC	−4.627807	0.8509	0.5000	0.5000	100
PSO	−4.627807	0.8509	0.5000	0.5000	100
GWO	−4.627798	0.8510	0.5009	0.4998	100
GA	−4.627649	0.8494	0.5037	0.5000	100
L-BFGS-B	−4.627807	0.8509	0.5000	0.5000	2

Table B.2
Iteration numbers (N), minimum values and corresponding Nash equilibrium (x, y, z) when $\tau = 0.7$.

Algorithm	Minimum	x	y	z	N
ABC	−4.109476	0.8276	0.4687	0.4276	100
PSO	−4.109476	0.8276	0.4687	0.4276	100
GWO	−4.109472	0.8270	0.4689	0.4269	100
GA	−4.108590	0.8263	0.4778	0.4223	100
L-BFGS-B	−4.109476	0.8276	0.4687	0.4276	7

Table B.3
Iteration numbers (N), minimum values and corresponding Nash equilibrium (x, y, z) when $\tau = 0.4$.

Algorithm	Minimum	x	y	z	N
ABC	−3.685844	0.7846	0.4436	0.3124	100
PSO	−3.685844	0.7846	0.4436	0.3124	100
GWO	−3.685842	0.7846	0.4440	0.3117	100
GA	−3.685747	0.7835	0.4446	0.3168	100
L-BFGS-B	−3.685844	0.7846	0.4436	0.3124	8

Table B.4
Best fitness (minimum) values and corresponding Nash equilibrium when $\tau = 1$ and $\Gamma_1 = 5500$.

Algorithm	Minimum	x	y	z	N
ABC	−1.378376	1.0000	0.5000	0.5000	100
PSO	−1.378376	1.0000	0.5000	0.5000	100
GWO	−1.378375	1.0000	0.5001	0.5008	100
GA	−1.348324	0.9923	0.5037	0.5000	100
L-BFGS-B	−1.378376	1.0000	0.5000	0.5000	1

Table B.5
Best fitness (minimum) values and corresponding Nash equilibrium when $\tau = 1$ and $\Gamma_1 = 6500$.

Algorithm	Minimum	x	y	z	N
ABC	−36.773800	0.5920	0.5000	0.5000	100
PSO	−36.773800	0.5920	0.5000	0.5000	100
GWO	−36.773705	0.5917	0.5013	0.4999	100
GA	−36.772786	0.5896	0.5037	0.5000	100
L-BFGS-B	−36.773800	0.5920	0.5000	0.5000	2

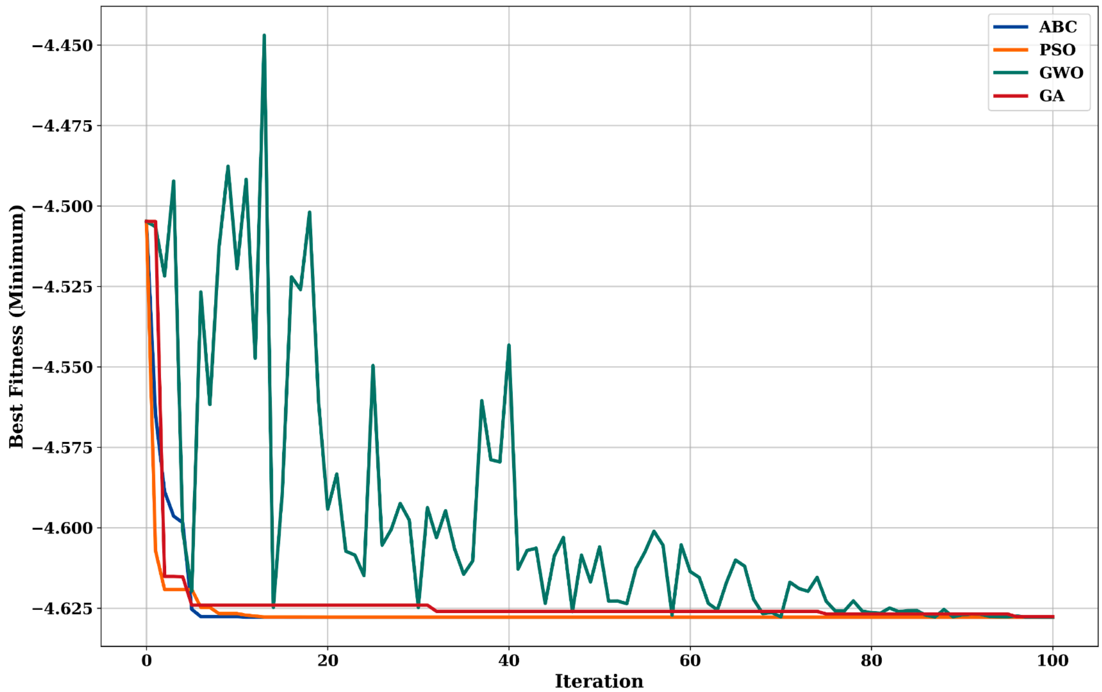

Fig. B.1. Estimated minimum values of problem (3) obtained from 100 simulations using four metaheuristics when $\tau = 1$.

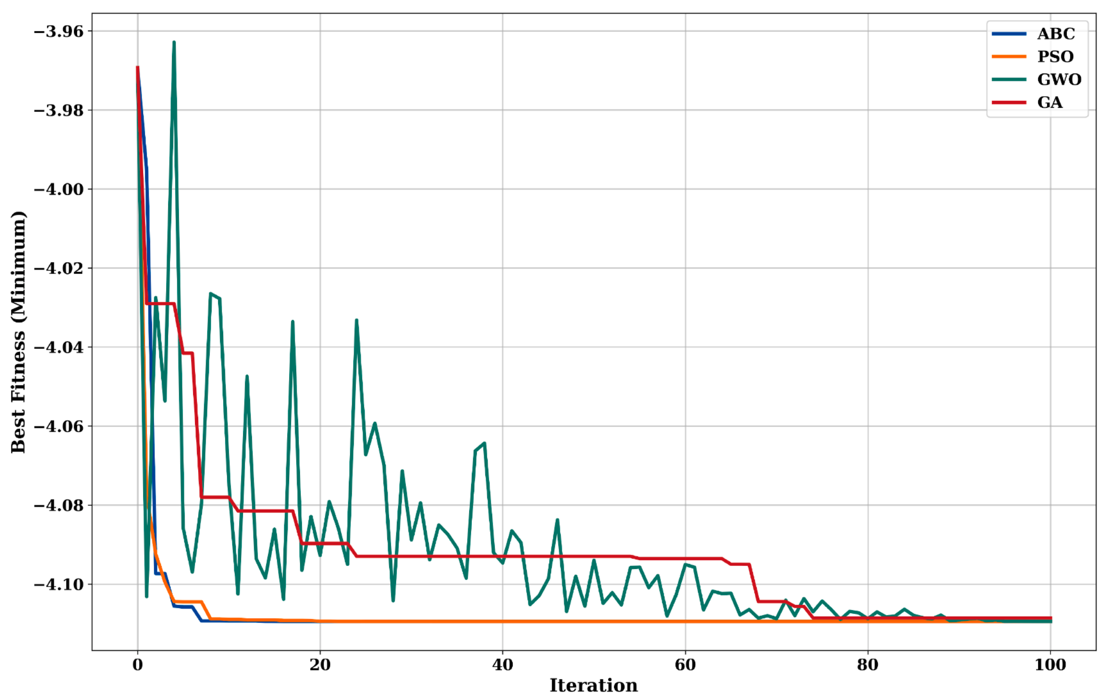

Fig. B.2. Estimated minimum values of problem (3) obtained from 100 simulations using four metaheuristics when $\tau = 0.7$.

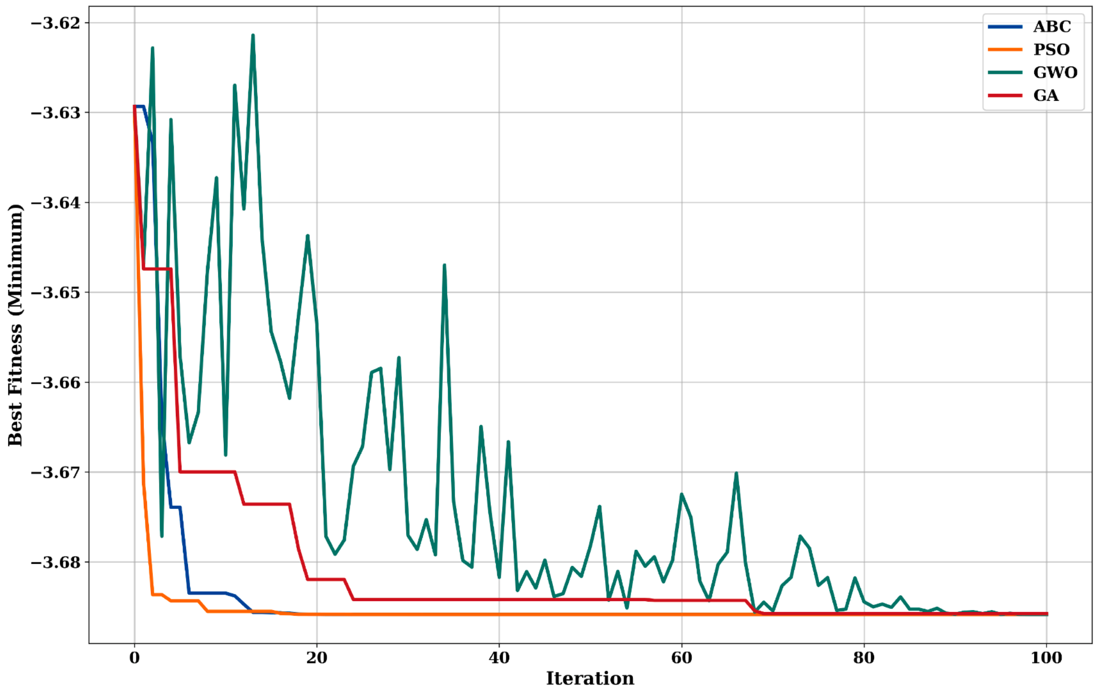

Fig. B.3. Estimated minimum values of problem (3) obtained from 100 simulations using four metaheuristics when $\tau = 0.4$.

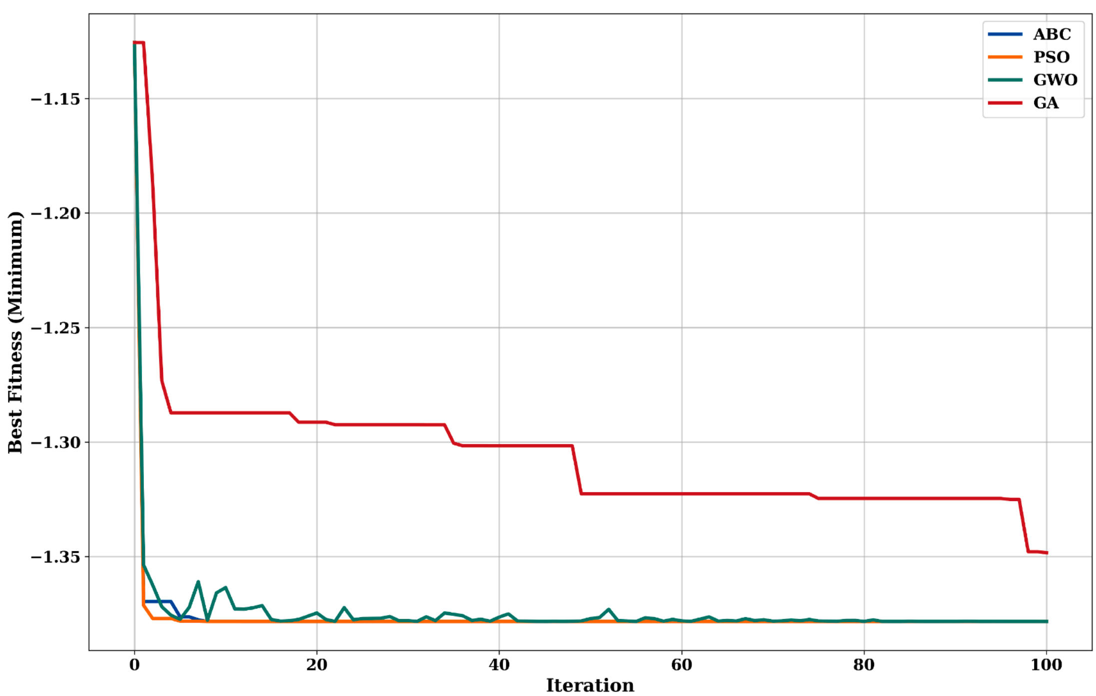

Fig. B.4. Estimated minimum values of problem (3) obtained from 100 simulations using four metaheuristics when $\tau = 1$ and $\Gamma_1 = 5500$.

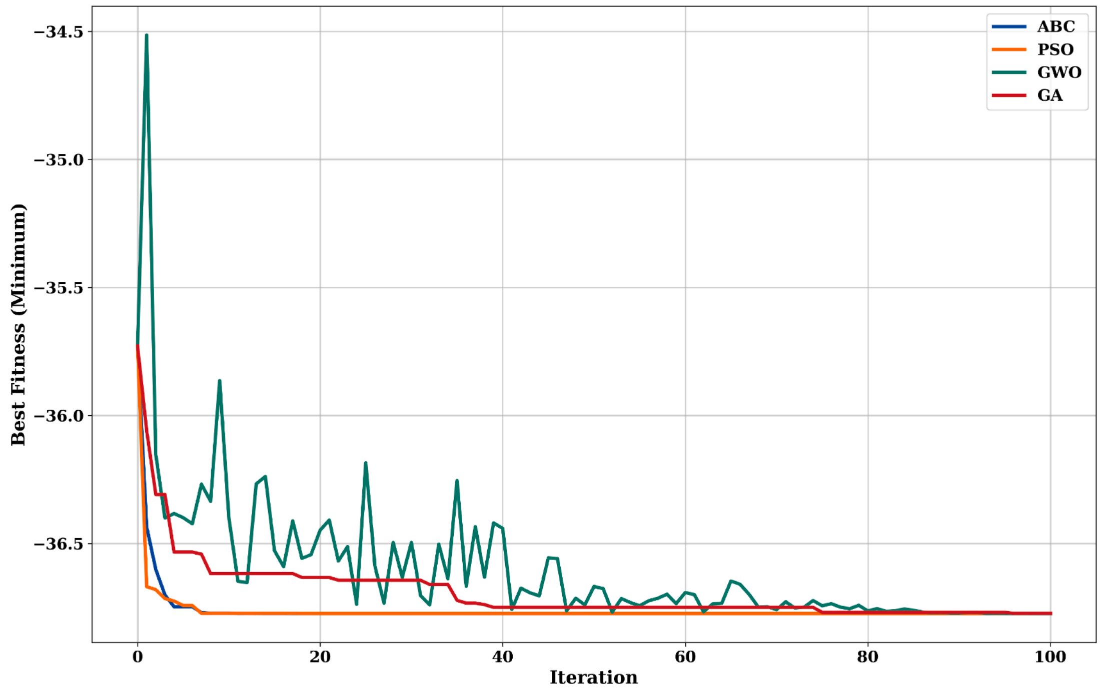

Fig. B.5. Minimum values of problem (3) obtained from 100 simulations using four metaheuristics when $\tau = 1$ and $\Gamma_1 = 6500$.

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