ECONOMIC VIABILITY OF BIOCHAR APPLICATION FOR PRIVATE LANDOWNERS: EVIDENCE FROM EXTENDED REGRESSION AND LINEAR PROGRAMMING OPTIMIZATION

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Abstract. This study re-analyzes the dataset of Kadam (2025) to evaluate the economic viability of biochar application for private landowners in the southeastern United States. Moving beyond stochastic simulations, the analysis combines extended econometric regression with linear programming optimization to capture both marginal elasticities and operational constraints. The regression results demonstrate that manufacturing costs have the most significant negative impact on profitability, with federal support and carbon credit revenues serving as key positive contributors. Reformatting carbon-related variables into a combined metric indicates that higher carbon prices, alongside lower transaction fees, substantially boost net returns. The optimization model reveals that total profits increase proportionally with treated areas but are limited by transportation and manufacturing capacities. Scenario analysis suggests that minor policy changes, such as a \$10 reduction in manufacturing costs, a \$500 increase in federal support, or a \$100 rise in carbon credit prices, produce notable gains in both per-hectare and total profits. Overall, the findings imply that resilient and profitable biochar markets depend on reducing production costs, increasing subsidies, and creating stronger incentives in carbon markets. By applying econometric and optimization methods, this research offers both methodological improvements and practical guidance for policymakers, aggregators, and landowners aiming to align climate mitigation with economic feasibility.
Keywords: *biochar economics, profitability analysis, carbon markets, federal incentives (EQIP), regression with elasticities, linear programming optimization, scenario analysis, private landowners, cost–benefit analysis, sustainable agriculture*

Introduction

Biochar has gained increasing attention as both a soil amendment and a carbon sequestration strategy, with significant potential to improve soil fertility, boost crop productivity, and help mitigate climate change (Shyam et al., 2025). However, the adoption of biochar by private landowners remains critically dependent on its economic feasibility. The foundational work of Kadam et al. (2025) laid the groundwork for such assessments by creating a cost–benefit framework for biochar projects in the southeastern United States. Their analysis included manufacturing, loading, hauling, and on-farm application costs, along with income from federal Environmental Quality Incentives Program (EQIP) subsidies and carbon credit revenues. Using Monte Carlo simulations across 10,000 scenarios, they showed that 95% of cases resulted in positive profits, though outcomes were sensitive to production costs, subsidies, and carbon prices. The related dataset (Kadam, 2025) provides detailed operational cost data and income structures, serving as a helpful resource for further research.

The present study extends this line of inquiry by re-analyzing the Kadam (2025) dataset with alternative methodological tools. Specifically, we apply extended regression

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models, including interaction terms and logarithmic transformations, to capture nonlinear cost–revenue dynamics. In parallel, we implement linear programming optimization to identify profit-maximizing adoption strategies under transportation and manufacturing capacity constraints. This dual-optimization framework moves beyond average-scenario analysis, providing both statistical interpretation and operational optimization.

A substantial body of literature underscores the importance of combining economic, policy, and agronomic perspectives when evaluating biochar feasibility. From an economic standpoint, Zhao et al. (2016) advanced the techno-economic analysis (TEA) framework by incorporating stochastic modeling, while Campbell et al. (2018) confirmed that investment viability in biofuel and biochar systems is highly sensitive to market fluctuations. Regional studies, such as Ahmed et al. (2025) in Michigan and Nematian et al. (2024) in California, highlighted that profitability depends on feedstock availability, carbon pricing, and transport logistics. These findings are reinforced by systemic analyses in the IEA Bioenergy (2022) BioHub report. Earlier contributions, including Roberts et al. (2010) and Shackley et al. (2011), emphasized the central role of coproduct revenues and carbon credit pricing in determining profitability.

Complementary agronomic research has provided essential insights into the biological and soil-related mechanisms underpinning biochar adoption. For example, Biala et al. (2021) and Busscher et al. (2010) documented improvements in soil carbon and physical soil properties. Reviews and field studies by Lehmann et al. (2011), Enders et al. (2012), Sadowska et al. (2020), and Głąb et al. (2020) highlighted that biochar's agronomic impacts are strongly conditioned by feedstock, soil type, and pyrolysis parameters. More recent assessments, such as Owsianiak et al. (2021) and Robb et al. (2023), demonstrated that financial viability varies significantly across regions and scales, reinforcing the need for flexible modeling that integrates agronomic variability with economic feasibility.

Further methodological advancements also support this study's approach. Field et al. (2013) modeled trade-offs between biochar and bioenergy, showing how carbon pricing influences long-term returns. Nematian et al. (2024) used scenario-based methods to evaluate the impacts of subsidies and prices on profitability. Similarly, Yadav et al. (2021) reviewed recent progress in lignocellulosic biomass pyrolysis, stressing the importance of process parameters. Yoder et al. (2009) and El Hanandeh (2011) developed conceptual and applied models linking pyrolysis conditions to product yields and profitability, while Byun and Han (2019) employed stochastic TEA to capture volatility in coproduction systems. Collectively, these studies emphasize the value of non-linear econometric specifications and probabilistic extensions.

Recent policy-oriented contributions further highlight the systemic importance of subsidies, markets, and logistics. For example, Elias et al. (2024) analyzed wildfire-derived biochar coupled with carbon credits in the western USA, estimating potential investment values above $20 billion. Nosenzo (2024) assessed sugarcane bagasse biochar in Brazil, confirming profitability at high carbon prices. Haddad et al. (2024) reviewed the agronomic potential of biochar in Jordan. Huang et al. (2023) detailed optimization trade-offs between biochar and biofuel, and Lehmann and Joseph (2015) provided a seminal review of biochar's environmental management potential.

Taken together, these studies show that the economics of biochar adoption are complex, affected by cost structures, agronomic performance, policy incentives, and carbon market design all at once. The present study adds to this body of work by filling an important gap: while Kadam et al. (2025) quantified profitability distributions using

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Monte Carlo simulation, they did not explicitly model elasticities, nonlinearities, or logistical constraints. By combining econometric regression with optimization, we offer a more detailed and practical analysis of profitability, providing useful insights for policymakers, aggregators, and landowners. To account for uncertainty, Kadam et al. (2025) conducted a Monte Carlo simulation of 10,000 scenarios, varying eight key parameters of manufacturing cost, loading, hauling, application, federal support, carbon credit price, transaction fee, and landowner share, by ±20% around their mean values. Profitability outcomes were then summarized as probability distributions, and sensitivity was assessed using Pearson correlation coefficients. Results showed that manufacturing costs (−0.64), federal support (0.68), carbon price (0.32), and transportation costs (−0.10) were the most influential factors. Their analysis concluded that 95% of scenarios yielded positive profits, with 73.8% and 38.29% exceeding \$500/ha and \$1000/ha, respectively.

In contrast, our study re-analyzes this dataset using an alternative methodological approach. Instead of relying solely on stochastic simulations, we employ econometric regression with interaction and log-transformed variables to better capture nonlinearities. Additionally, we utilize linear programming optimization to identify profit-maximizing adoption strategies within realistic capacity constraints. This combined method offers a complementary perspective to the probabilistic analysis of Kadam et al. (2025), enabling both statistical interpretation and operational optimization.

It is important to note that the dataset does not involve direct observations from private landowners. The 10,000 observations represent simulated economic scenarios generated by Kadam et al. (2025) using Monte Carlo methods rather than real-world survey data.

Materials and methods

Data and study context

This study builds directly on the dataset developed by Kadam et al. (2025), which evaluated the economic viability of biochar application for private landowners in the southeastern United States. Their baseline framework integrated costs of manufacturing, transportation, loading, and on-farm application with revenues from federal EQIP payments and voluntary carbon markets.

Additionally, we utilize linear programming optimization to identify profit-maximizing adoption strategies within realistic capacity constraints. This combined method offers a complementary perspective to the probabilistic analysis of Kadam et al. (2025), enabling both statistical interpretation and operational optimization.

This study builds upon the dataset of biochar production and application costs, federal support payments, and carbon credit revenues developed initially for private landowners in the southeastern United States. The dataset includes parameters such as manufacturing cost per ton, loading and transportation expenses, farm-level application costs, federal incentive payments under the EQIP, and revenues from voluntary carbon credit transactions. The required application rate of biochar is fixed at 20.17 tons per hectare, consistent with agronomic recommendations. The data also incorporate landowner shares of carbon revenues and transaction fees, reflecting realistic market conditions.

For analysis, data were categorized into two broad groups:

Cost components:

- C_{manuf}: Manufacturing cost per wet ton of biochar (USD/ton)
- C_{load}: Loading cost at the production site (USD/ton)

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- C_{haul}: Hauling cost per truckload (USD/truckload)
- C_{farm}: On-farm unloading and spreading cost (USD/ha)

Income components:

- $I_{federal}$: Federal support per hectare (USD/ha)
- $I_{carbon:}$ Carbon credit revenues, adjusted for landowner share and transaction fees (tCO_2e/ha)
- The application rate was fixed at q = 20.17 tons per hectare, consistent with agronomic recommendations

Baseline profitability equations

The total cost per hectare is expressed as:

$$C_{total} = C_{manuf}.\,\mathrm{q} + \frac{C_{load}}{r_{load}}.\,\mathrm{q} + \frac{C_{haul}}{r_{haul}}.\,\mathrm{q} + \frac{C_{farm}}{r_{farm}}.\,\mathrm{q} \quad \text{(Eq.1)}$$

where r_{load}, r_{haul}, and r_{farm} denote the respective processing or transportation rates (tons per unit).

The income per hectare is given by:

$$I_{total} = I_{federal}.\,(1 - \delta) + P_{carbon}.\,Q_{carbon}.\,\mathrm{S}.\,(1 - f) \quad \text{(Eq.2)}$$

$I_{federal}$ = federal incentive payment, δ = proportion deducted for the administrative cost of federal support (5%), P_{carbon} = carbon price per ton CO_2e, Q_{carbon} = credits generated per hectare (=12.17 tCO_2e/ha from regression), s = landowner’s share of carbon revenues, f = transaction fee rate.

Thus, net profit per hectare is

$$\pi_{ha} = I_{total} - C_{total} \quad \text{(Eq.3)}$$

and the profit margin is

$$\mathrm{M} = \frac{\pi_{ha}}{C_{total}} \quad \text{(Eq.4)}$$

Extended regression analysis

To evaluate the determinants of profitability, we estimated multiple regression models where the dependent variables were net profit per hectare and profit margin. Independent variables included manufacturing, loading, hauling, and farm application costs, as well as federal support, carbon credit prices, landowner share of revenues, and transaction fees.

We estimated multiple regression models to explain variation in π_{ha} and M:

$$\mathrm{Y} = \alpha + \beta_1 C_{manuf} + \beta_2 C_{load} + \beta_3 C_{haul} + \beta_4 C_{farm} + \beta_5 I_{fedral} + \beta_6 P_{carbon} + \beta_7 \mathrm{f} + \beta_8 \mathrm{s} + \varepsilon \quad \text{(Eq.5)}$$

where Y represents either Net Profit or Profit Margin.

Because net profit and margin are accounting identities of cost and income components, the regressions should be interpreted as decompositions of sensitivity and elasticities rather than strict causal effects. The exceptionally high levels of statistical

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significance observed are a direct reflection of the deterministic structure of the Kadam (2025) dataset, which was generated from fixed cost–revenue formulas.

Extensions included

Interaction terms

$$P_{carbon} \times s,\ P_{carbon} \times (1-f),\ C_{manuf} \times I_{federal} \quad \text{(Eq.6)}$$

to capture multiplicative relationships.

Logarithmic transformations ($lnC_{manuf},\ lnI_{federal}, lnP_{carbon}$) to estimate elasticities:

$$\beta_i = \frac{lny\partial}{lny\partial_i} \quad \text{(Eq.7)}$$

Dependent variable transformation margin using the inverse hyperbolic sine:

$$Y^* = \sinh^{-1}(M) \quad = \ln\left(M + \sqrt{M^2 + 1}\right) \quad \text{(Eq.8)}$$

All models were estimated using Ordinary Least Squares (OLS) with HC1 robust standard errors to correct for heteroskedasticity. It is important to clarify that net profit (πha) in this dataset is itself a derived accounting identity of costs and revenues. As a result, regression models using net profit as the dependent variable tend to reproduce deterministic relationships, often yielding substantial standardized coefficients with near-zero standard errors. These coefficients should not be interpreted as literal dollar-for-dollar effects. Instead, they reflect the mechanical construction of the dataset. For meaningful economic interpretation, standardized coefficients for the profit margin (M) are more reliable, since M normalizes profit relative to costs and better captures elasticities under variability. Note that while reverse causality (for example, profit-maximizing landowners reducing costs) is theoretically possible, this dataset specifies costs and revenues exogenously from Kadam et al. (2025). Thus, endogeneity concerns are mitigated, and the regression analysis serves primarily to quantify elasticities and sensitivities rather than causal effects.

Unlike prior studies that applied only linear models, we extended the specification to include:

- Interaction terms, such as manufacturing cost × federal support, hauling × farm application, and carbon price × landowner share, are used in order to capture the multiplicative nature of costs and revenues.
- Logarithmic transformations of key variables (for example, log of manufacturing cost, log of federal support, log of carbon price) to estimate elasticities. This allowed us to interpret coefficients as percentage changes, providing insights into how 1% variations in costs or revenues affect profitability.
- Nonlinear dependent variable transformation, using the inverse hyperbolic sine (asinh) of profit margin to account for potential negative values and stabilize variance.

All models were estimated using Ordinary Least Squares (OLS) with heteroskedasticity-consistent robust standard errors (HC1). Model diagnostics included R^2, adjusted R^2, RMSE, and Breusch–Pagan tests for heteroskedasticity.

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Linear programming optimization

In addition to regression analysis, we developed a Linear Programming (LP) model to determine the optimal scale of biochar application under resource constraints. The decision variables were:
h: the number of hectares treated with biochar.
t: the total quantity of biochar transported (tons).
The objective function maximizes total profit:

$$max\ \Pi = \pi_{ha} \cdot h \quad \text{(Eq.9)}$$

Subject to:

$$t = q \cdot h \quad \text{(Eq.10)}$$
$$t \leq Captransport, t \leq Capmanufacturing, h, t \geq 0$$

where π_{ha} is the profit per hectare, computed as:

π_{ha}=Net Federal Support +Carbon Revenue −Total Cost per Hectare

This formulation ensures that landowners cannot apply more biochar than permitted by logistical and manufacturing limits.

Scenario analysis

To evaluate the sensitivity of profitability to policy and market interventions, we conducted scenario analyses by adjusting key parameters around baseline averages:

- Carbon price increase: $P_{carbon} + 100$ (per ton CO_2e)
- Manufacturing cost reduction: $C_{manuf} - 10$ (per ton of biochar)
- Federal support increase: $I_{federal} + 500$ (per hectare)

For each scenario, both per-hectare profits π_{ha} and total profits Π were recalculated under transport and manufacturing capacity constraints of 500 tons and 1000 tons. This enabled comparison of baseline and policy-adjusted outcomes and the identification of marginal contributions of each intervention.

It is important to emphasize that these scenarios are designed as policy experiments rather than causal predictions. The adjustments to carbon price, manufacturing cost, and federal support are exogenous shocks applied to the deterministic framework of Kadam et al. (2025). As such, the results illustrate how profitability responds mechanically to parameter shifts under specified constraints, rather than forecasting actual behavioral or market dynamics.

By integrating extended regression models, used to capture elasticities and nonlinear relationships, with linear programming optimization, applied to determine profit-maximizing adoption strategies under logistical constraints, this approach provides a robust framework for assessing biochar’s economic viability. The combined methodology ensures that both statistical sensitivities and operational feasibility are considered, yielding insights relevant to policymakers, market developers, and landowners.

It is important to note that the minimal robust standard errors observed in the regression outputs are not the result of multicollinearity. Variance Inflation Factors

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(VIFs) for all explanatory variables were approximately equal to 1, indicating no problematic correlation among regressors. Instead, this outcome reflects the mechanical structure of the dataset, which was generated from deterministic accounting relationships in the original Kadam et al. (2025) biochar economic model. Because costs and revenues were computed through fixed formulas (for example, cost = rate × quantity), the regression essentially re-estimates identities already embedded in the dataset, yielding coefficients with near-zero estimation uncertainty. While statistically valid, such precision does not necessarily capture the variability expected in real-world applications. This limitation underscores the need for incorporating nonlinear transformations, interaction terms, and optimization-based extensions to introduce realistic variability and provide more policy-relevant elasticity estimates.

The combined methodological approach employed in this study, extending the Monte Carlo framework of Kadam et al. (2025) with econometric regression and linear programming, is chosen to provide a multi-faceted economic assessment. The regression analysis, while applied to a deterministic dataset, is specified with interaction and log-transformed terms to decompose sensitivities and estimate elasticities, following standard econometric practices for sensitivity analysis (Wooldridge, 2016). This offers standardized metrics for policy analysis. Subsequently, the linear programming model translates the per-hectare profitability into an operational plan by identifying the profit-maximizing scale of adoption under explicit capacity constraints, a well-established technique in agricultural and resource economics (Hazell and Norton, 1986; McCarl and Spreen, 2011). This integration moves beyond a probabilistic assessment of viability to address both the statistical influence of key parameters and the practical optimization of deployment. The framework thereby aligns with and extends the analytical approaches used in prior biochar feasibility and valuation studies (Roberts et al., 2010; Galinato et al., 2011), contributing to the literature on integrated assessment for agricultural technology adoption.

Results

The analysis draws on a simulated dataset of 10,000 Monte Carlo scenarios developed by Kadam et al. (2025) to evaluate the economics of biochar application for private landowners in the southeastern United States. The dataset integrates variation in both cost and revenue components, including manufacturing, loading, hauling, and on-farm application costs, alongside federal EQIP support payments and carbon credit revenues adjusted for landowner shares and transaction fees. Descriptive statistics confirm realistic ranges and variability: manufacturing costs average $143/ton (SD = 16.6; range = 115–172), loading costs $65/ton (SD = 7.5; range = 52–78), hauling costs $1,201/truckload (SD = 138; range = 960–1440), and farm application costs $125/ha (SD = 14.4; range = 100–150). The breadth of this simulated sample provides a statistically representative foundation for regression and optimization modeling, ensuring robust evaluation of landowner-level profitability under realistic market conditions.

While Kadam et al. (2025) analyzed profitability through a stochastic framework, randomly varying eight key parameters (±20%) across 10,000 iterations and summarizing outcomes via probability distributions and correlation coefficients (for example, −0.64 for manufacturing cost, 0.68 for federal support), the present study advances the analysis by adopting a regression-based approach. Unlike correlation analysis, which only captures associations under simulated uncertainty, regression

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modeling quantifies the marginal effects of each cost and income component on profitability while controlling for other factors. This methodological shift explains why the coefficients reported in *Table 1* differ from the correlation values in Kadam et al. (2025). In addition, the regression framework enables the use of interaction terms, logarithmic transformations, and nonlinear adjustments, thereby providing a richer elasticity-based interpretation and creating direct linkages with the subsequent optimization analysis.

Extended regression results

Before presenting the regression outcomes, it is helpful to contrast the methodological framework of Kadam et al. (2025) with the present re-analysis. *Table* 1 provides a comparative summary of data sources, methods, and policy insights.

Table 1. *Methodological comparison between Kadam et al. (2025) and the current study*

Aspect	Kadam et al. (2025) – original study	Current study – re-analysis
Data source	Expert estimates, literature, EQIP payments, and carbon credit prices	Re-analyzed dataset from Kadam (2025)
Core method	Monte Carlo Simulation (10,000 scenarios, ±20% variation)	Econometric regression (interactions + logs) and linear programming
Uncertainty treatment	Randomized parameter variation	Elasticities and nonlinear terms are explicitly modeled
Output metrics	Profitability distributions, sensitivity via Pearson correlations	Coefficient estimates, elasticities, profit optimization
Key results	95% profitable scenarios; most influential factors: manufacturing cost (−0.64), federal support (0.68), carbon price (0.32), transportation cost (−0.10)	Manufacturing cost elasticity (−1.31); federal support elasticity (0.18); the effective carbon price is significant; logistics constrain optimal adoption area
Policy insight	Near thresholds profitability; dependent on incentives and costs	Clear guidance on reducing costs, strengthening subsidies, and optimizing under constraints

The standardized regression results (*Table 2*) confirm that manufacturing cost is the dominant constraint on profitability ($\beta = -0.118$, $p < 0.001$ for Profit Margin). In contrast, federal EQIP support ($\beta = 0.099$, $p < 0.001$) and carbon credit price ($\beta = 0.045$, $p < 0.001$) significantly enhance net returns. Transaction fees and revenue-sharing terms were not statistically significant, suggesting that their effects are primarily absorbed in the effective carbon revenue measure.

These findings are consistent with Kadam et al. (2025), who reported strong negative correlations for manufacturing costs (−0.64) and positive associations for federal support (0.68) and carbon pricing (0.32). However, by employing regression with standardized coefficients, the current study extends the analysis beyond correlations, providing elasticity-based interpretations that quantify the marginal effects of each determinant on landowner profitability.

It is worth noting that the standardized coefficient for manufacturing cost in the Net Profit model ($\beta = -335$) appears disproportionately large and may be misinterpreted if read literally. This is a statistical artifact of using net profit, which is itself a composite of the independent variables, as the dependent variable in a deterministic dataset.

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Because the variance of some cost components is very small relative to net profit, standardized coefficients are inflated. The more appropriate indicator for interpretation is the Profit Margin model, where the effect of manufacturing cost is $\beta = -0.118$ ($p < 0.001$). This result is economically consistent and aligns with Kadam et al. (2025), who reported a strong negative correlation (−0.64) between manufacturing costs and profitability.

Table 2. *Standardized regression results for profitability determinants*

Model	Variable	Coefficient (β)	Robust std. error	t-Value	p-Value
Net profit (Std.)	Manufacturing Cost	−334.9***	>0.001	−8.39E+15	>0.001
	Loading Cost	−2.78***	1.85E−14	−1.50E+14	>0.001
	Hauling Cost	−56.7***	3.36E−14	−1.69E+15	>0.001
	Farm Load & Spread	−17.8***	4.64E−14	−3.84E+14	>0.001
	NRCS Support	348.2***	1.53E−14	2.28E+16	>0.001
	Carbon Price	158.2***	6.04E−14	2.62E+15	>0.001
	Carbon Transaction	9.53E-15	1.02E-14	9.35E-01	0.35
	Share of Carbon	-1.61E-14	1.76E-14	-9.14E-01	0.36
Profit margin (Std.)	Manufacturing Cost	−0.118***	1.96E−04	−603	>0.001
	Loading Cost	−0.001***	1.48E−04	−6.54	>0.001
	Hauling Cost	−0.020***	1.56E−04	−130	>0.001
	Farm Load & Spread	−0.006***	1.48E−04	−43.1	>0.001
	NRCS Support	0.099***	1.74E−04	568	>0.001
	Carbon Price	0.045***	1.57E−04	287	>0.001
	Carbon Transaction	3.08E-05	1.49E-04	2.06E-01	0.84
	Share of Carbon	6.59E-05	1.49E-04	4.43E-01	0.66

***$p < 0.01$; HC1 robust standard errors reported

As shown in *Figure 1,* reformulating carbon-related variables into a composite measure (Eff_{Carbon}) substantially improved explanatory power. The coefficient of 12.17 ($p < 0.001$) confirms that adequate carbon revenues, accounting for price, landowner share, and transaction costs, represent a critical income stream for landowners. Interestingly, while loading costs were significant in earlier models, they became statistically insignificant once Eff_{Carbon} was introduced, suggesting that carbon-related revenues dominate the marginal contribution of smaller logistical costs. These findings extend the insights of Kadam et al. (2025), moving beyond correlation-based sensitivity analysis to reveal how carbon market participation directly enhances profitability under econometric specification.

A comparison between the individual-variable specification (*Table* 2) and the composite carbon specification (*Table* 3) reveals important differences in the determinants of profitability. In *Table 1,* while manufacturing cost (−20.18), federal support (0.95), and carbon price (10.1) were significant drivers of net profit, the effects of carbon transaction fees and landowner share were weak and statistically insignificant. This suggested that the carbon-related variables, when modeled separately, diluted each other's influence due to their interactive nature.

By contrast, *Table* 3 and *Figure 2* reformulated these components into a composite carbon variable ($Eff_{Carbon} = \text{Price} \times \text{Share} \times (1 - \text{Fee})$), yielding a highly significant and

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economically meaningful coefficient (12.17). Under this specification, the loading cost lost its significance, indicating that adequate carbon revenue dominates the marginal contribution of smaller logistical costs. Manufacturing cost and hauling cost remained strongly negative, while federal support continued to play a central positive role.

Taken together, these results demonstrate that profitability is best explained not by individual carbon parameters in isolation, but by their combined effect through adequate carbon revenues. This aligns with the findings of Kadam et al. (2025), who highlighted carbon income as a key revenue source, but extends their analysis by quantifying its direct impact in a regression framework.

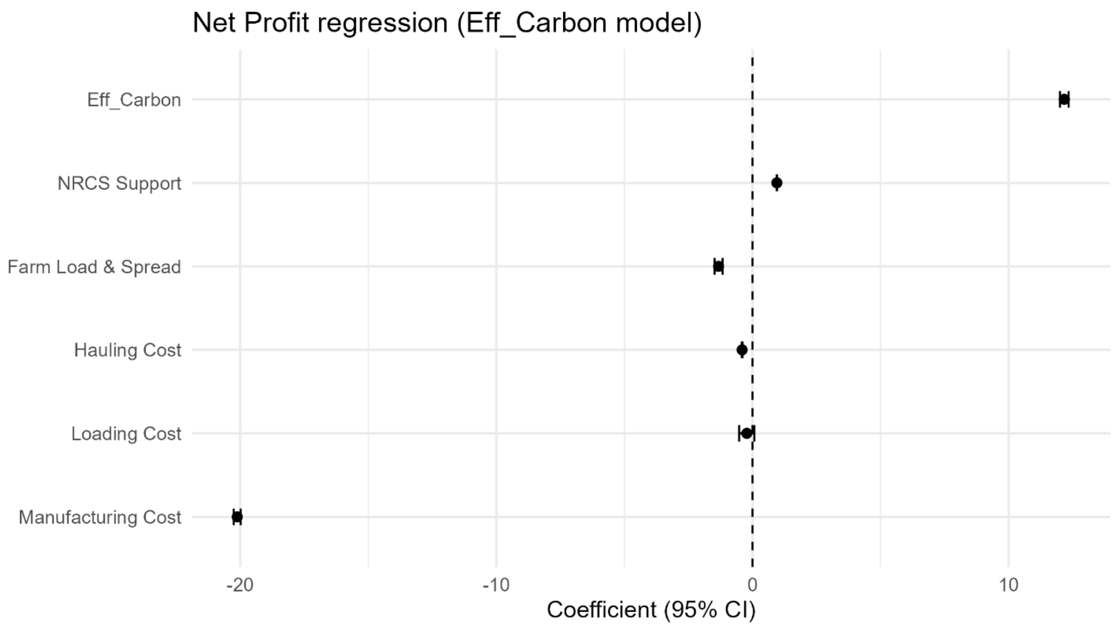

Figure 1. *Regression coefficients with composite carbon variable (Eff_{Carbon})*

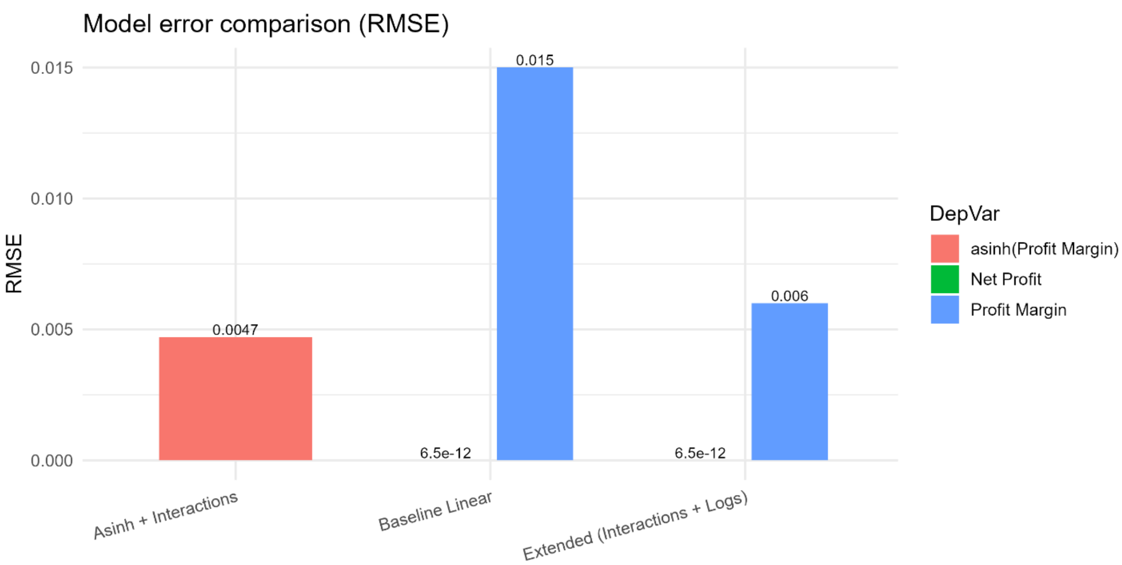

Figure 2. *Model comparison of residual errors (RMSE) across specifications*

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Table 3. *Regression results with composite carbon variable*

Variable (dependent variable: net profit per ha)	Coefficient	Robust std. error	t-Value	p-Value
Manufacturing Cost	−20.12***	0.069	−292.06	0
Loading Cost	−0.22	0.151	−1.46	0.143
Hauling Cost	−0.40***	0.008	−48.29	0
Farm Load & Spread	−1.32***	0.079	−16.73	0
NRCS Support	0.95***	0.003	307.48	0
Eff_{Carbon}	12.17***	0.085	142.64	0

*** $p < 0.01$; HC1 robust standard errors reported

Linear programming optimization

The linear programming (LP) optimization results are presented in *Figure 3* and *Tables 4* and *5*. Under the baseline scenario (*Table 4*), the optimal treated area is determined entirely by the transport and manufacturing capacity constraints. At a 500-ton capacity, approximately 24.8 ha can be treated, generating total profits of about $23,100. Doubling capacity to 1000 tons increases the treated area to 49.6 ha and total profits to $46,100. These results confirm that aggregate profits scale linearly with treated area when per-hectare margins remain constant.

Table 4. *Linear programming (LP) baseline optimization results*

Capacity (tons)	Optimal area (ha)	Total tons transported	Profit per ha ($)	Total profit ($)
500	24.8	500	930	23054
1000	49.6	1000	930	46108

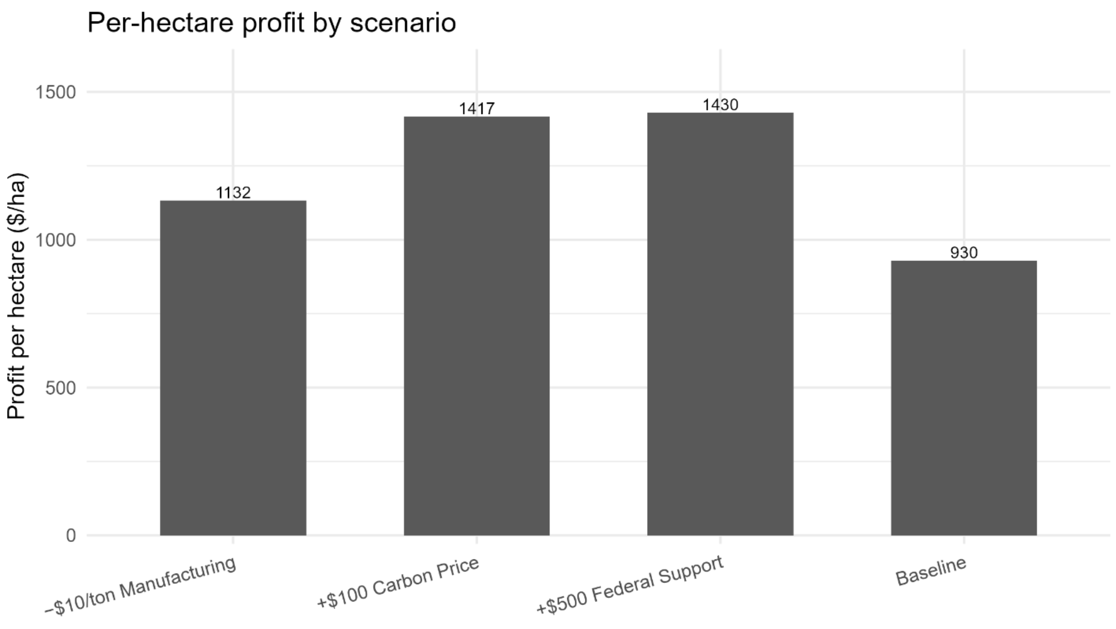

Figure 3. *Baseline LP optimization results at 500-ton and 1000-ton capacities*

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Policy and market intervention scenarios (*Fig. 4; Table 5*) illustrate the sensitivity of profitability to changes in carbon price, manufacturing costs, and federal subsidies. For a 500-ton limit, increasing the carbon price by $100 boosts total profit to $35,100, while reducing manufacturing costs by $10 per ton or raising federal support by $500 per hectare increases profits to $28,100 and $35,500, respectively. At a 1000-ton limit, aggregate profits nearly double, reaching $70,300 and $70,900 under the carbon price and subsidy scenarios, respectively. These results demonstrate that modest adjustments in market or policy parameters translate into significant gains when scaled across constrained capacities.

Table 5. *LP scenario results (500-ton and 1000-ton capacities)*

Scenario	Capacity	Optimal Area ha	Total Tons	Profit per ha	Total Profit
Baseline	500	24.8	500	930	23100
Baseline	1000	49.6	1000	930	46100
+$100 Carbon Price	500	24.8	500	1417	35100
+$100 Carbon Price	1000	49.6	1000	1417	70300
-$10/ton Manufacturing	500	24.8	500	1132	28100
-$10/ton Manufacturing	1000	49.6	1000	1132	56100
+$500 Federal Support	500	24.8	500	1430	35500
+$500 Federal Support	1000	49.6	1000	1430	70900

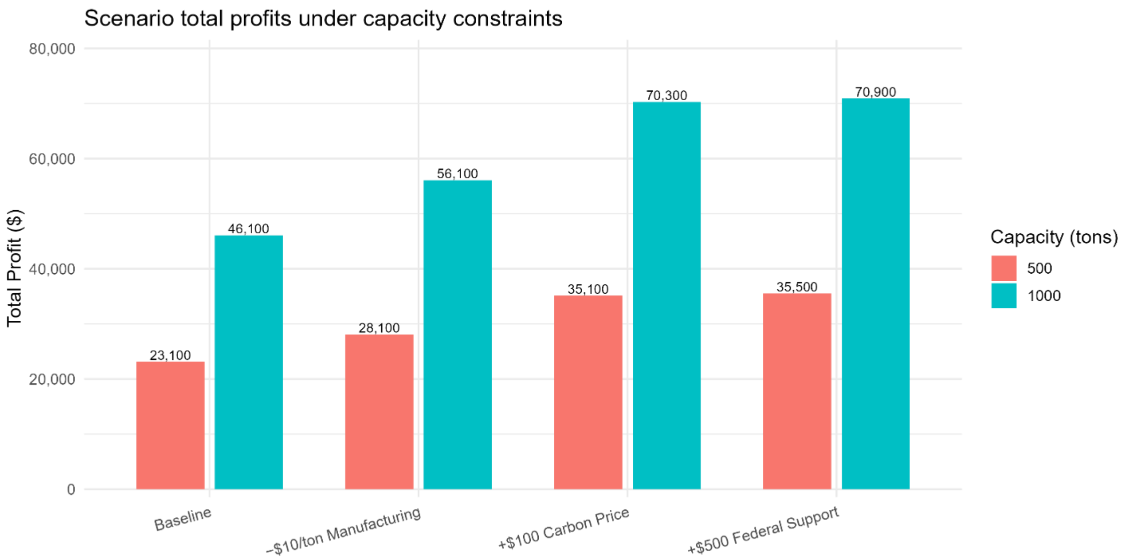

Figure 4. *LP scenario results comparing baseline with carbon price, subsidy, and manufacturing interventions*

Together, these LP results highlight that landowner profitability depends not only on per-hectare margins but also on operational capacity. While net profit per hectare is a helpful indicator, aggregate gains are ultimately constrained by logistics and scale. Therefore, policies that both enhance per-hectare margins (through subsidies and carbon pricing) and relax logistical bottlenecks (for example, transport, manufacturing limits) will be essential for expanding the economic viability of biochar adoption.

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Policy and market implications

This study confirms that biochar application profitability heavily depends on three key factors: reducing manufacturing costs, increasing federal subsidies, and raising carbon credit prices. Without improvements in at least one of these areas, landowners are at risk of barely breaking even in biochar markets. This aligns with previous research that identified production efficiency, policy support, and market incentives as the main drivers of biochar adoption.

From a methodological perspective, the integration of extended regression models with linear programming optimization provides a more robust evaluation of economic feasibility compared to baseline stochastic approaches. Regression analysis clarifies marginal effects and elasticities, revealing how cost and revenue variables interact to shape profitability. At the same time, the LP framework translates these per-hectare margins into maximum aggregate profits under realistic transport and manufacturing constraints. Together, these complementary tools offer both strategic and operational insights for policymakers, aggregators, and private landowners. By linking econometric evidence with optimization-based decision rules, the study supports the design of targeted policies and market mechanisms that can foster resilient and profitable biochar markets.

Discussion

This study re-examined the economics of biochar application for private landowners using the Monte Carlo dataset of Kadam et al. (2025), extending the analysis through econometric modeling and linear programming optimization. The results consistently show that profitability is shaped by a small number of dominant factors, most notably manufacturing cost, federal EQIP support, and carbon credit revenues. These findings align with Kadam et al. (2025), who identified manufacturing cost (−0.64), federal support (0.68), and carbon price (0.32) as the strongest correlates of profitability. However, the present study advances this evidence by estimating marginal effects and elasticities, thereby quantifying the scale of impact while controlling for interactions among variables.

Regression results demonstrate that manufacturing cost remains the principal constraint, with a standardized elasticity of −0.118 for profit margin, indicating that profitability is highly sensitive to production efficiency. This is consistent with techno-economic studies (for example, Zhao et al., 2016; Campbell et al., 2018; Ahmed et al., 2025), which similarly highlight cost-sensitive thresholds in biomass conversion systems. Federal EQIP support emerges as a robust positive determinant, reinforcing the role of subsidies in offsetting high operational costs, a conclusion echoed in previous economic assessments of biochar and biomass systems (Roberts et al., 2010; Shackley et al., 2011).

A key contribution of this study is the reformulation of carbon-related variables into a composite measure (Eff_{Carbon}), which significantly improved explanatory power. This result underscores that carbon revenues should be modeled holistically rather than through fragmented parameters such as landowner share, price, and fees. The strong coefficient associated with Eff_{Carbon} is consistent with recent work emphasizing the importance of carbon market participation and transaction structures in shaping landowner incentives (Owsianiak et al., 2021; Robb et al., 2023).

Linear programming results complement the regression findings by illustrating how logistical constraints, transport and manufacturing capacity, limit aggregate profitability, regardless of per-hectare margins. Doubling capacity from 500 to 1000 tons nearly

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doubled profits, confirming the linear scaling relationship when margins remain unchanged. Scenario analyses further show that relatively modest policy shifts, such as increasing carbon price by $100 or raising EQIP subsidies by $500 per hectare, produce large gains when applied across constrained operational scales.

Overall, the discussion demonstrates that cost reductions, subsidy enhancements, and strengthened carbon market mechanisms are essential for expanding the economic feasibility of biochar adoption. By integrating regression-derived elasticities with operational optimization, the study provides a more actionable and policy-relevant understanding of biochar profitability than earlier simulation-only approaches.

Conclusion

This study re-analyzed the dataset of Kadam (2025) to evaluate the economic feasibility of biochar application for private landowners by combining extended regression models with linear programming optimization. The analysis confirmed that manufacturing cost is the most significant constraint on profitability, exerting a substantial adverse effect. At the same time, federal support and carbon credit revenues play a crucial role in enhancing net returns. Reformulating carbon-related parameters into a composite variable further demonstrated that higher carbon prices, alongside reduced transaction costs, can substantially increase landowner profitability.

The optimization framework highlighted that the scale of land treated is ultimately limited by transport and manufacturing capacities, emphasizing the importance of operational constraints in determining aggregate profit potential. Scenario analyses showed that even modest policy interventions, such as a $10 reduction in manufacturing cost, a $500 increase in federal support, or a $100 rise in carbon credit price, translate into significant improvements in both per-hectare margins and total profits.

It should be emphasized that these scenario results represent structured policy experiments within a deterministic economic framework, not causal forecasts of landowner behavior. The models illustrate how profitability outcomes respond mechanically to exogenous parameter shifts under defined constraints, thereby providing insight into system sensitivities and policy leverage points rather than predicting actual farmer decision-making. Overall, the results indicate that resilient and profitable biochar markets require a balanced combination of lower production costs, more substantial subsidies, and more reliable carbon market incentives. By moving beyond stochastic simulations and incorporating elasticity-based regression and optimization under realistic constraints, this research provides both theoretical refinement and practical guidance. The findings deliver actionable insights for policymakers, aggregators, and landowners aiming to align climate mitigation goals with economic viability.

While the dataset analyzed in this study originates from the southeastern United States, the results provide important insights for Saudi Arabia, where biochar adoption is increasingly discussed as part of the National Agriculture Strategy 2030 and the Saudi Green Initiative. The findings highlight two critical lessons for the Saudi context. First, the dominance of manufacturing costs as a negative determinant of profitability underscores the need for technological innovation and cost-reduction strategies in pyrolysis systems, which remain relatively expensive in Saudi Arabia due to reliance on imported equipment. Second, the positive role of subsidies and carbon credit revenues mirrors policy instruments already under development in the Kingdom, such as carbon market frameworks and targeted agricultural subsidies. In particular, the LP results

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demonstrate that profitability is constrained not only by per-hectare margins but also by logistical capacity, a point highly relevant for Saudi Arabia's geographically dispersed agricultural regions. Without investment in decentralized biomass processing hubs and efficient transport systems, profitability gains will remain limited. Thus, policy measures that combine financial incentives (carbon credits, subsidies) with infrastructure development (biochar hubs, transport networks) are likely to be most effective in enabling Saudi farmers and landowners to benefit from biochar adoption.

Data availability statement. The authors confirm that all data generated or analyzed during this study are included in this article.

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