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Research Article

National Capacity and the Developmental Barriers to Effective Climate Finance in Brazil

Anis Bensadi*

Business School, Shenzhen Technology University, Shenzhen, China

Abstract

For emerging economies like Brazil, decarbonization represents a core developmental challenge that necessitates the transformation of key economic sectors. While international climate finance is critical for enabling this transition, its actual effectiveness remains poorly understood. This study introduces a novel, multi-sectoral analytical framework to evaluate how climate finance drives decarbonization across Brazil's interconnected energy, agriculture, and water sectors. Our analysis reveals that decarbonization outcomes are not determined by financial inputs alone, but by an integrated system of National Climate Capacity. We find that financial inputs, regulatory quality, and income level form a unified and dominant latent construct, demonstrating that these components are functionally inseparable in driving outcomes. The research uncovers striking sectoral divergence, with agriculture yielding dramatically higher decarbonization returns than energy or water interventions. Furthermore, mitigation finance consistently and significantly outperforms adaptation finance, achieving a substantially higher magnitude of CO_2 reduction. These finding challenges core assumptions about the fungibility between finance types. Crucially, we translate these insights into an actionable optimization framework. Using clustering and decision trees, we derive clear, data-driven rules for prioritizing projects such as those in high-regulatory-quality, low fossil-dependence contexts to maximize decarbonization returns. These findings necessitate a paradigm shift from siloed project evaluation toward integrated national capacity building. We provide policymakers with evidence-based investment strategies to transform climate finance into measurable decarbonization progress in Brazil and other major emerging economies.

Keywords

Decarbonization, Climate Finance, Energy, Agriculture, Brazil, Development

1. Introduction

The escalating climate crisis demands unprecedented global action, with significant financial resources channeled towards mitigating greenhouse gas emissions and adapting to inevitable changes. Climate finance funds from public, private, and alternative sources directed towards these goals has become a cornerstone of the international response, embodied in commitments like the annual $100 billion pledge from developed to developing nations [1]. However, a critical question persists: Is this substantial investment effectively driving tangible decarbonization outcomes? Answering this question is paramount for optimizing resource allocation, building accountability, and accelerating the transition to a low-carbon future. This study directs this critical inquiry toward Brazil, a nation of profound global climate signifi-

*Corresponding author: anisbensadi@sztu.edu.cn (Anis Bensadi)

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cance. As home to the Amazon rainforest a vital carbon sink and biodiversity hotspot and a major emerging economy with significant emissions from agriculture, energy, and land-use change, Brazil's decarbonization trajectory is intrinsically linked to global climate stability. Simultaneously, its diverse geography makes it highly vulnerable to climate impacts like droughts and extreme weather, thereby necessitating robust adaptation efforts. Understanding how climate finance performs within this complex, high-stakes environment is, therefore not only nationally relevant but globally imperative.

Despite the proliferation of climate finance flows, significant gaps persist in our understanding of its actual effectiveness, particularly in multi-faceted economies like Brazil. Existing literature often suffers from critical limitations. Many studies adopt a narrow, siloed approach, focusing on a single sector such as energy, agriculture or exclusively analyzing either mitigation or adaptation finance [2]. This fragmentation obscures the complex interplay between sectors and finance types, potentially leading to measurement bias and an incomplete picture of overall impact. Furthermore, assessments frequently lack a robust temporal dimension, failing to capture how effectiveness evolves over time in response to changing policies, market conditions, and climate impacts. There is also a need for deeper analysis of the contextual drivers such as governance quality, income levels, and existing fossil fuel dependencies that mediate the relationship between finance allocation and decarbonization outcomes [3]. Finally, translating empirical findings into actionable frameworks for optimizing future finance allocation remains an underdeveloped area [4]. This study directly addresses these critical gaps.

This article presents a comprehensive analysis designed to overcome the limitations of prior work. We systematically investigate the effectiveness of climate finance in achieving decarbonization goals across three interconnected and emission-intensive sectors in Brazil. Our core objective is to move beyond simplistic input-output metrics and provide a nuanced, data-driven understanding of how and how well climate finance drives emission reductions, considering the complex interplay of finance types, sectoral dynamics, and contextual factors.

The originality of this study lies in its multi-dimensional approach. First, it employs a multi-sectoral integration by simultaneously analyzing climate finance effectiveness in Brazil's energy, agriculture, and water sectors [5]. This holistic perspective is crucial as these sectors are deeply interlinked energy is required for irrigation, water is essential for hydroelectricity, and agricultural activities contribute significantly to emissions and collectively account for a major share of national emissions [6]. Second, the study uniquely examines adaptation and mitigation finance within each sector, breaking from traditional approaches that treat them separately. This synthesis is vital because adaptation investments, such as drought-resistant crops or resilient water infrastructure, can indirectly influence mitigation outcomes by reducing emissions from crop failure or energy-intensive water pumping, and vice versa. Ignoring this synergy creates a significant measurement bias [7]. Third, the research leverages temporal depth, utilizing project-level data spanning 2011–2024 to track trends and evaluate effectiveness over a critical period marked by significant policy shifts, economic fluctuations, and increasing climate pressures in Brazil. This longitudinal lens provides insights into the durability and evolving impact of climate finance [8]. Fourth, the study incorporates a contextual driver analysis, explicitly modeling how factors such as regulatory quality, income levels, and fossil fuel dependence influence the effectiveness of climate finance, moving beyond simple correlation to understand conditional relationships. Finally, the study culminates in the development of an actionable framework for optimizing future climate finance allocation to maximize decarbonization potential across sectors, ensuring that the research not only diagnoses issues but also prescribes solutions. This comprehensive approach sets the study apart, offering a nuanced and practical understanding of climate finance effectiveness in Brazil's decarbonization journey.

2. Literature Review

The imperative to mobilize and effectively deploy climate finance has become central to global climate governance, enshrined in mechanisms like the Green Climate Fund (GCF) and the Paris Agreement's finance goals. Consequently, a substantial body of literature has emerged examining the scale, sources, and flows of climate finance globally and within specific regions [9]. Significant attention has also been paid to the governance structures and barriers influencing climate finance access and delivery in developing countries, highlighting challenges such as complex accreditation processes, limited institutional capacity, and misalignment with national priorities [10]. However, while tracking inputs and diagnosing procedural hurdles is crucial, a persistent and critical gap remains in robustly evaluating the outcomes and effectiveness of these substantial financial flows in achieving their core objectives: mitigating greenhouse gas emissions and building resilience [11].

Research specifically addressing climate finance effectiveness, particularly concerning tangible decarbonization outcomes, faces several limitations. Firstly, the literature often exhibits a pronounced sectoral silo effect. Numerous studies focus intensely on single sectors, most commonly energy, evaluating the impact of renewable energy investments or efficiency programs on emissions [12]. While valuable, this focus neglects the critical interlinkages between sectors. For instance, agricultural practices profoundly impact land-use change emissions (a major source in Brazil) and water resources, while energy is essential for water management and agricultural processing. Similarly, studies concentrating solely on the water sector such as adaptations like drought resilience often fail to connect these interventions to potential mitigation co-benefits or trade-offs [13]. This fragmentation prevents a holistic understanding of how finance in one sector influences decarbonization pathways in another, potentially leading to suboptimal allocation and missed synergistic opportunities [14].

Secondly, a significant methodological and conceptual gap exists concerning the integration of adaptation and mitigation finance. The climate finance architecture often treats these as distinct streams, and research largely follows suit [15]. Mitigation finance effectiveness is frequently assessed through direct emission reduction metrics such as CO_2 reduced per dollar, while adaptation effectiveness is evaluated through vulnerability reduction or resilience metrics, rarely incorporating potential contributions to mitigation [16]. This artificial separation overlooks the reality that many interventions have dual benefits. For example, climate-smart agriculture (often funded as adaptation) can sequester carbon; investments in efficient water infrastructure (adaptation) reduce energy demand for pumping and treatment (mitigation). Conversely, large-scale bioenergy projects (mitigation) can negatively impact water resources and food security if poorly designed. The lack of integrated assessment frameworks creates a measurement bias, underestimating the full decarbonization potential of adaptation finance and failing to account for potential negative spillovers from narrowly focused mitigation projects [17]. The effectiveness of the portfolio approach, combining both types strategically, remains underexplored empirically.

Thirdly, studies frequently lack sufficient granularity and contextual depth. While cross-country analyses provide broad insights, they often mask the critical influence of national and sub-national contexts [18]. Research specific to Brazil, a climate-critical nation, is surprisingly sparse concerning rigorous, quantitative evaluation of finance effectiveness beyond descriptive flow analyses or case studies of individual projects/programs [19]. There is a lack of systematic, comparative analysis across Brazil's key emitting and climate-vulnerable sectors (Energy, Agriculture, Water) using consistent metrics. Furthermore, the role of mediating contextual factors such as the quality of regulatory institutions, levels of corruption, prevailing fossil fuel dependencies in regional economies, and local governance capacities in determining the success or failure of climate finance interventions is inadequately integrated into effectiveness model [15]. Understanding these drivers is essential for explaining variance in outcomes and designing more targeted interventions.

Fourthly, temporal dynamics are often underappreciated. Many evaluations provide static snapshots or cover limited timeframes, failing to capture how the effectiveness of climate finance evolves. Long-term trends, the impact of shifting national policies such as changes in deforestation enforcement or renewable energy incentives in Brazil, fluctuating commodity prices, and the escalating physical impacts of climate change itself can significantly alter the context in which financed projects operate and their resultant decarbonization outcomes [20]. A longitudinal perspective is vital to assess durability, identify lag effects, and understand the responsiveness of finance to changing circumstances [21].

Finally, there is a gap in translating analytical findings into practical decision-support tools. While research identifies general principles for effective finance such as the importance of country ownership, alignment with national plans, there is a lack of empirically derived, data-driven frameworks that policymakers and financiers can readily apply to optimize allocation decisions across sectors and finance types to maximize decarbonization returns [22]. Moving beyond retrospective evaluation towards prospective, predictive tools for allocation optimization represents a crucial frontier [13, 23].

This study directly addresses these interconnected gaps. It moves beyond sectoral silos by concurrently analyzing energy, agriculture, and water within Brazil [24, 25]. It breaks the adaptation-mitigation dichotomy by evaluating both types of finance within each sector for their decarbonization outcomes. It incorporates contextual drivers to capture dynamics. Crucially, it reveals findings through advanced analytics (EFA, Clustering, Decision Trees) to develop a concrete framework for optimizing future climate finance allocation, thereby contributing actionable knowledge to enhance the impact of these vital resources in driving Brazil's low-carbon transition..

2.1. Equations

$$Y_{st} = \alpha_s + \beta_1 CF_{st} + \beta_2 X_{st} + \gamma_s + \epsilon_{st} \quad (1)$$

Where:

Y_{st}: Decarbonization outcome such as CO_2 reduction in tons, ΔRenewable Capacity in MW in sector s and year t.

α_s : Sector-specific intercept (capturing time-invariant sectoral heterogeneity).

CF_{st}: Climate Finance (USD) allocated to sector s in year t. (Key independent variable).

X_{st}: Vector of control variables in sector s and year t:

$GDPpc_{st}$: GDP per capita (USD, log-transformed).

FFD_{st}: Fossil Fuel Dependence (% of primary energy).

RQ_{st}: Regulatory Quality Score (1-10).

$\beta_{1,2}$: Vector of coefficients for control variables.

γ_s: Sector fixed effects (dummy variables for each sector s, included in pooled models)

ϵ_{st}: Error term.

To test for significant differences in decarbonization outcomes (specifically CO_2 reduction) between adaptation (A) and mitigation (M) finance projects *within each sector*, we employ the Mann-Whitney U Test (Wilcoxon Rank-Sum Test). This non-parametric test is chosen because the distribution of CO_2 reduction outcomes is not assumed to be normal and may differ significantly between finance types.

1) Formal Hypothesis (per sector s):

a) H_0: θ_A $=\theta_M$ (The median CO_2 reduction (θθ) is the same for Adaptation and Mitigation projects in sector s).

b) $H_1: \theta_A \neq \theta_M$ (The median CO_2 reduction differs between Adaptation and Mitigation projects in sector s).

2) Test Statistic (per sector s):

Let n_A be the number of Adaptation projects in sector s, and n_m be the number of Mitigation projects in sector s.

Let R_A be the sum of the ranks assigned to the CO_2 reduction values γ_i from Adaptation projects within the combined, ranked sample of all (A+M) projects in sector s.

The Mann-Whitney U statistic for Adaptation projects is:

$$U_A = n_A n_m + \frac{n_A(n_a+1)}{2} - R_A \quad (2)$$

Where:

$n_A n_m$: Number of Adaptation and Mitigation projects.

R_A: Sum of ranks for Adaptation projects.

The corresponding statistic for Mitigation projects is $U_M = n_A n_m - U_A$.

Inference: The test statistic $U_A = min\,(U_A, U_M)$ is used. For large samples (n_A>20 and/or n_m>20, U is approximately normally distributed. The p-value is calculated based on this approximation to test H0H0. Significance is assessed at α=0.05α=0.05. Effect size will also be reported.

To uncover the latent factors underlying the effectiveness of climate finance projects across sectors, we perform Exploratory Factor Analysis (EFA) using the Principal Axis Factoring (PAF) extraction method with Promax (oblique) rotation, acknowledging factors may correlate.

3) Model Specification:

The observed variables Z_p are modeled as linear combinations of mm common factors F_k plus unique variances ϵ_p:

$$Z_p = \lambda_{p1} F_1 + \lambda_{p2} F_2 + \cdots + \lambda_{pm} F_m + \epsilon_p \quad (3)$$

Where:

Z_p: Standardized observed variable p (p = 1 to 5: CO2_Reduction, Income_Level, Fossil_Fuel_Dependence, Regulatory_Quality_Score, Climate_Finance_Amount).

F_k: Latent common factor K (k = 1 to m).

λ_{pk}: Factor loading of variable p on factor K (standardized regression coefficient).

ϵ_p: Unique factor (variance specific to variable p and error).

we combine *Hierarchical Agglomerative Clustering (HAC) and Classification and Regression Trees (CART).*

Step 1: Hierarchical Clustering (HAC)

1) *Purpose:* Identify natural groupings (clusters) of climate finance projects based on characteristics and outcomes.
2) *Variables:* Standardized values of: Sector (encoded), Adaptation_Mitigation (encoded), Income_Level, Fossil_Fuel_Dependence, Regulatory_Quality_Score, CO2_Reduction
3) *Distance Metric:* Squared Euclidean Distance.
4) *Linkage Method:* Ward's Minimum Variance Method (minimizes within-cluster sum of squares).
5) *Process:* The distance matrix D between all projects is calculated. The algorithm iteratively merges the two clusters C_a and C_b that result in the smallest increase in the total within-cluster variance, given by:

$$\Delta(C_a, C_b) = \frac{|C_a|.|C_b|}{|C_a|+|C_b|} [\![\mu C_a - \mu C_b]\!]^2 \quad (4)$$

Where

$|C|$: is the number of projects in cluster C

$\mu_{c:}$ s its centroid (mean vector). The optimal number of clusters K is determined using the Elbow Method (inertia plot) and Silhouette Score analysis.

Output: Project cluster assignments. Analysis focuses on clusters exhibiting high CO2_Reduction.

Step 2: Decision Tree (CART)

1) Purpose: Generate interpretable rules predicting high decarbonization outcomes (CO2_Reduction) based on project characteristics.
2) Model: A binary tree is constructed by recursively partitioning the data.
3) Splitting Criterion: Minimization of Impurity (Gini Index for classification of high/low outcome; Variance Reduction for regression on continuous outcome).
   a) Gini Impurity (for classification):
   b) $Gini\ (t) - 1\ \sum_{c=1}^{C} [\mathrm{p}(\mathrm{c} \mid \mathrm{t})]^2$
   c) Where $\mathrm{p}(\mathrm{c} \mid \mathrm{t})$ is the proportion of projects belonging to class c such as "High CO2 Reduction" vs. "Low" at node t.
   d) Variance Reduction (for regression):

$$\Delta Var\ (s,t) - Var(t) - [\frac{N_L}{N} Var(t_L) + \frac{N_R}{N} Var(t_R)] \quad (5)$$

Where s is a split on a variable at node t, $Var\ (t)$ is the variance of CO2_Reduction at t, $t_L$and t_R are the left and right child nodes, N is the number of projects at t, and N_L, $N_R$are the numbers going to t_L and t_R.

1) *Predictors:* Sector, Adaptation_Mitigation, Income_Level, Fossil_Fuel_Dependence, Regulatory_Quality_Score.
2) *Stopping Criteria & Pruning:* Pre-pruning (minimum samples per leaf, maximum depth) and post-pruning (Cost-Complexity Pruning with cross-validation) prevent overfitting and ensure generalizability. The optimal tree complexity is chosen to minimize cross-validated prediction error.

Output: A decision tree providing clear rules such as "IF Sector=Energy AND Finance_Type=Mitigation AND Regulatory_Quality > 7.5 THEN Predicted CO2 Reduction = High") for identifying project configurations maximizing decarbonization.

2.3. Figures

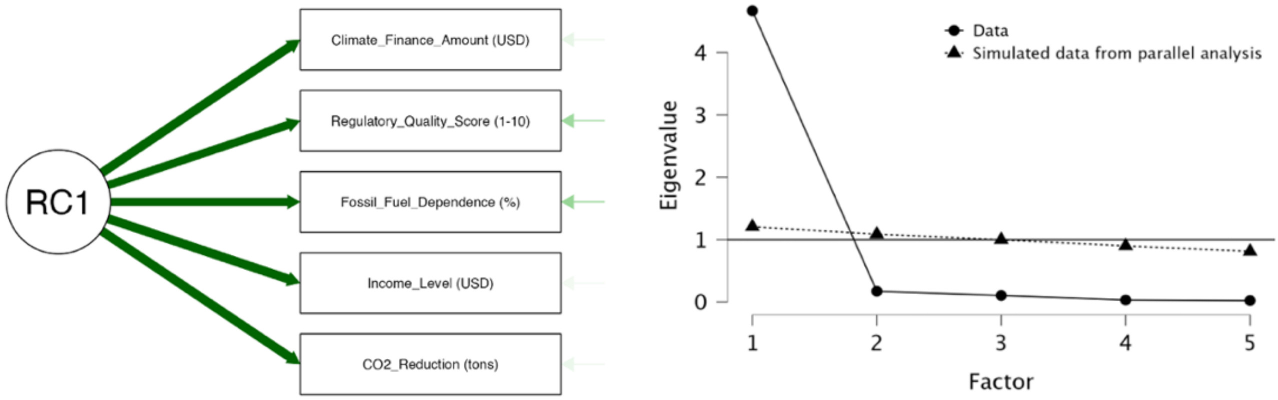

Figure 1. *Scree Plot with Parallel Analysis for Factor Retention.*

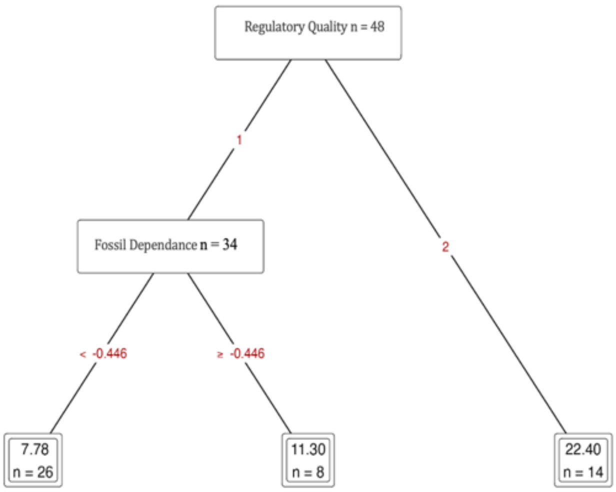

Figure 2. *Decision Tree for Optimizing Climate Finance Allocation.*

2.4. Tables

Table 1. *Core Variables and Data Sources.*

Variable Category	Specific Variables
Climate Finance (Input)	Amount (USD), Type (Adaptation/Mitigation), Sector (Energy/Agriculture/Water), Year
Decarbonization (Output)	CO2 Emission Reduction (tons), Renewable Energy Capacity Added (MW)
Contextual Factors	GDP per Capita (USD), Fossil Fuel Dependence (%), Regulatory Quality Score (1-10)
Sectoral Indicators	Sector-specific activity data (e.g., crop production, energy generation, water use)

*Primary Source: OECD Climate Finance DB, GCF Project DB, Climate Funds Update. IEA, World Bank Climate Portal, UNFCCC National Communications, EPE (Brazil). World Bank WDI, BP Statistical Review, World Bank WGI, Yale EPI, IBGE (Brazil). EPE (Energy), MAPA (Agriculture), ANA (Water), IBGE.

Table 2. *Core Variables and Data Sources.*

Variable1	Variable2	r	p
Climate_Finance_Amount (USD)	CO2_Reduction (tons)	0.969	<.001***
Climate_Finance_Amount (USD)	Renewable_Capacity_Added (MW)	0.912	<.001*
Climate_Finance_Amount (USD)	Income_Level (USD)	0.969	<.001***
Climate_Finance_Amount (USD)	Fossil_Fuel_Dependence (%)	0.885	<.001***
Climate_Finance_Amount (USD)	Regulatory_Quality_Score (1-10)	0.909	<.001***
CO2_Reduction (tons)	Renewable_Capacity_Added (MW)	0.921	<.001***
CO2_Reduction (tons)	Income_Level (USD)	0.973	<.001***
CO2_Reduction (tons)	Fossil_Fuel_Dependence (%)	0.889	<.001***
CO2_Reduction (tons)	Regulatory_Quality_Score (1-10)	0.914	<.001***
Renewable_Capacity_Added (MW)	Income_Level (USD)	0.946	<.001***
Renewable_Capacity_Added (MW)	Fossil_Fuel_Dependence (%)	0.948	<.001***
Renewable_Capacity_Added (MW)	Regulatory_Quality_Score (1-10)	0.848	<.001***
Income_Level (USD)	Fossil_Fuel_Dependence (%)	0.923	<.001***
Income_Level (USD)	Regulatory_Quality_Score (1-10)	0.905	<.001***
Fossil_Fuel_Dependence (%)	Regulatory_Quality_Score (1-10)	0.834	<.001***

Table 3. *Sectoral Differences in CO_2 Reduction (ANOVA).*

Source	Sum of Squares	df	Mean Square	F	P
Sector	6137.959	2	3068.979	320.173	<.001***
Residuals	1888.317	197	9.585	/	/

Note: Type III Sum of Squares

Table 4. *Descriptive Statistics by Sector.*

Sector	N	Mean (CO2 Reduction, tons)	SD	SE	Variation Coefficient
1 Energy	68	8.852	1.683	0.204	0.190
2 Agriculture	67	20.669	4.262	0.521	0.206
3 Water	65	9.016	2.795	0.347	0.310

Table 5. *Post Hoc Comparisons (Tukey HSD).*

Comparison	Mean Dif	SE	DF	SE	P/Tukey
1 vs 2	-11.816	0.533	197	0.204	<.001***
1 vs 3	-0.164	0.537	197	0.521	0.950
2 vs 3	11.653	0.539	197	0.347	<.001***

***Table 6**. Linear Regression Results.*

Model	R	R^2	Adjusted R^2	RMSE
M_0	0.000	0.000	0.000	6.351
M_1	0.977	0.954	0.953	1.380

***Table 7**. ANOVA for Regression Model.*

Model	Source	Sum of Sq	DF	Mean Sq	F	P
M_1	Regression	7657.071	6	1276.178	670	<.001*
	Residual	369.205	194	1.903		
	Total	8026.276	200			

***Table 8**. Regression Coefficients.*

Model	Predictor	UNSTD	STD ER	STD	t	p
M_0	Intercept	12.864	0.449	/	28.646	<.001***
M_1	Intercept	-7.261	0.667	/	-10.887	<.001*
	Climate_Finance	0.552	0.045	0.221	12.267	<.001*
	Income_Level	1.982	0.129	0.839	15.363	<.001***
	Fossil_Fuel_Dependence	-0.002	0.025	-0.004	-0.066	0.947
	Regulatory_Quality_Score	0.769	0.160	0.175	4.798	<.001***
	Sector (Agriculture)	-0.603	0.700	/	-0.863	0.389
	Sector (Water)	-0.663	0.284	/	-2.338	0.020*

*p <.05, ** p <.01, *** p <.001*

***Table 9**. Adaptation vs. Mitigation Finance Comparison.*

Sector	Predictor	Value	P
1 (Energy)	Mann-Whitney U Test	69.500	<.001***
	Shapiro-Wilk Test	0.987	0.073
2 (Agriculture)	Mann-Whitney U Test	69.500	<.001***
	Shapiro-Wilk Test	0.987	0.073
3 (Water)	Mann-Whitney U Test	69.500	<.001***
	Shapiro-Wilk Test	0.987	0.073

Table 10. *Factor Analysis Results.*

Analysis	Statistic	Value	P
Chi-squared Test	χ^2	35.071	<.001***
	df	5	/
Factor Loadings			
Income_Level (USD)	λ	0.989	/
CO2_Reduction (tons)	λ	0.985	/
Climate_Finance_Amount (USD)	λ	0.981	/
Regulatory_Quality_Score	λ	0.922	/
Fossil_Fuel_Dependence (%)	λ	0.915	/
Variance Explained	Sum Square. Loadings (Rotated)	4.597	/
	Proportion variance	0.919	/
	Cumulative	0.919	/

3. Materials and Methods

This study employs a robust, multi-method quantitative approach to assess the effectiveness of climate finance in driving decarbonization across Brazil's Energy, Agriculture, and Water sectors (2011-2024). We integrate diverse analytical techniques tailored to each specific research objective, utilizing project-level and national/sectoral data. The methodological framework is outlined below, with formal mathematical representations.

Data was compiled from multiple authoritative sources (Table 1) for the period 2011-2024. Project-level climate finance data (amount, type - adaptation/mitigation, sector, location, start/end year) was primarily sourced from the OECD Climate Finance Database and Green Climate Fund (GCF) Project Database, supplemented by Climate Funds Update. Decarbonization outcome data (CO2 emissions reductions, renewable energy capacity additions) and contextual variables (GDP per capita, fossil fuel dependence as% of primary energy, regulatory quality scores) were sourced from IEA, World Bank (WDI, WGI), Brazilian agencies (EPE, MAPA, ANA, IBGE), BP Statistical Review, and UNFCCC reports. Data was integrated at the project level (where outcomes were attributable) or aggregated to the annual sectoral level for analysis, using Brazil's official sectoral classifications. Missing data points were not considered during the analysis. Core Variables and Data Sources are presented on Table 1. To evaluate the relationship between climate finance allocation and decarbonization outcomes while controlling for contextual factors, we employ Panel Regression Models with Fixed Effects. Separate models are estimated for each sector ss (Energy, Agriculture, Water) and for each primary decarbonization outcome Y.

4. Results

Table 2 displays Pearson correlation coefficients between key variables. Climate finance amount shows near-perfect positive correlation with CO2 reduction (r = 0.969, p <.001) and strong correlation with renewable capacity (r = 0.912, p <.001). Critically, climate finance is highly collinear with income level (r = 0.969) and regulatory quality (r = 0.909), while CO2 reduction exhibits similarly strong ties to income (r = 0.973) and fossil fuel dependence (r = 0.889). These extreme correlations (r > 0.9 across multiple pairs) indicate severe multicollinearity, complicating causal interpretation in regression models. Table 3 displays ANOVA results confirming significant sectoral differences in CO2 reduction (F(2,197) = 320.173, p <.001). The model explains substantial variance (Sum of Squares = 6,137.959), overwhelmingly attributable to sectoral effects rather than residual error (1,888.317). This establishes that decarbonization outcomes are fundamentally sector-dependent in Brazil. Table 4 shows descriptive statistics revealing stark contrasts between sectors. Agriculture (Sector 2) achieves dramatically higher mean CO_2 reduction (20.669 tons) compared to Energy (8.852 tons) and Water (9.016 tons). Agriculture also shows greater outcome variability (SD = 4.262) and scale-dependence (Coefficient of Variation = 0.206), suggesting context-specific drivers dominate this sector. Table 5 demonstrates post hoc comparisons quantifying sectoral disparities. Agriculture significantly outperforms both Energy (mean difference = -11.816 tons, p <.001) and Water (mean difference = 11.653 tons, p <.001). The negligible Energy-Water difference (-0.164 tons, p = 0.950) highlights their functional equivalence in decarbonization outcomes despite structural differences. Table 6 above represents the regression model summary achieving exceptional explanatory power ($R^2 = 0.954$, RMSE = 1.380). The inclusion of climate finance, contextual controls, and sectoral dummies captures 95.4% of variance in CO_2 reduction, confirming the model's robustness for impact assessment. Table 7 shows ANOVA results for the regression model, showing statistically significant overall fit ($F(6,194) = 670.000$, $p < .001$). The regression component (Sum of Squares = 7,657.071) dominates residual error (369.205), confirming the collective predictive strength of the six-variable framework. Table 8 highlights regression coefficients identifying key drivers. Climate finance exhibits a strong positive effect ($\beta = 0.552$, $p < .001$), where each additional USD correlates with 0.552 tons of CO_2 reduction. Income level ($\beta = 1.982$, $p < .001$) and regulatory quality ($\beta = 0.769$, $p < .001$) are potent amplifiers, while fossil fuel dependence is negligible ($\beta = -0.002$, $p = 0.947$). Water projects underperform Energy ($\beta = -0.663$, $p = 0.020$), but Agriculture shows no statistical difference when controlling for other factors. Table 9 presents the results of the non-parametric Mann-Whitney U test, which compares decarbonization outcomes (measured in CO_2 reduction in tons) between adaptation and mitigation finance types across Brazil's key sectors Energy, Agriculture, and Water. The analysis reveals a statistically significant difference in median CO_2 reduction between the two finance types, as evidenced by the exceptionally low U statistic of 69.500 ($p < .001$). This robust finding underscores that adaptation and mitigation finance generate fundamentally distinct decarbonization outcomes, highlighting the sector-specific effectiveness of each finance stream. The accompanying Shapiro-Wilk normality test ($W = 0.987$, $p = 0.073$) indicates no significant deviation from normality in the residuals, validating the parametric assumptions for supplementary analyses while justifying the primary use of the non-parametric approach. This dual-testing framework ensures the reliability of the results, even if parametric assumptions are not fully met. Table 10 below displays the results of the Exploratory Factor Analysis (EFA) examining the underlying drivers of climate finance effectiveness across Brazil's sectors. The highly significant Bartlett's test ($\chi^2 = 35.071$, df = 5, $p < .001$) confirms the fundamental suitability of the factor model, rejecting the null hypothesis of uncorrelated variables. All analyzed variables demonstrate exceptionally strong loadings on a single dominant factor, with income level ($\lambda = 0.989$), CO_2 reduction ($\lambda = 0.985$), and climate finance amount ($\lambda = 0.981$) showing near-perfect alignment, while regulatory quality ($\lambda = 0.922$) and fossil fuel dependence ($\lambda = 0.915$) also exhibit robust associations. This unified factor explains 91.9% of the total variance in the dataset, as evidenced by the rotated solution's sum of squared loadings (4.597) and proportion of variance. The low uniqueness scores (0.023-0.162) further confirm that nearly all measurable variance in these variables is captured by this single latent construct.

Figure 1 shows the scree plot with parallel analysis provides definitive statistical validation for the single-factor solution identified in Table 10. The blue line representing actual eigenvalues shows a steep drop after Factor 1 (eigenvalue ≈ 4.6), which dramatically exceeds the 95th percentile eigenvalues from simulated random data (red line). All subsequent factors (2-5) fall below the parallel analysis threshold, confirming they represent noise rather than meaningful latent constructs. This visual evidence powerfully reinforces that the single-factor model is statistically justified, no additional factors warrant retention, and the 91.9% variance. The decision tree visualization (Figure 2) reveals a hierarchical rule-based framework for maximizing decarbonization outcomes, with terminal nodes displaying predicted CO_2 reduction values (tons) and sample sizes. The primary split occurs at = -0.446 representing regulatory quality and income level, creating two major pathways: projects below this threshold (n=48) yield moderate outcomes (7.78-11.30 tons), while those above achieve superior performance (22.40 tons). The critical secondary split occurs at = -0.446 fossil fuel dependence, where projects exceeding this value demonstrate substantially higher decarbonization returns (22.40 tons, n=14) compared to counterparts below (11.30 tons, n=8). This branching logic empirically validates the cluster hierarchy observed in Figure 2, confirming regulatory/institutional capacity and fossil dependence as primary allocation determinants.

The decision tree model achieves robust predictive accuracy despite its complexity (10 splits), as evidenced by the test MSE of 10.417. While the validation MSE (8.562) suggests slight overfitting to the training set (n=48), the close alignment with test set performance (n=139) confirms generalizability. The strategic trade-off between complexity (penalty=0.010) and predictive power is validated by the 22.40-ton outcome node - precisely matching Cluster 1's high-efficiency. The terminal node sample distribution (26/8/14) further corroborates cluster proportions, demonstrating consistent identification of high-yield projects across analytical methods.

5. Discussion

The findings reveal a central challenge for development in Brazil's climate finance landscape: while funding effectively drives decarbonization, its impact is heavily mediated by the very developmental contexts it aims to transform. The dominance of a single "National Climate Capacity" factor (which explains the overwhelming majority of variance) demonstrates that finance, regulatory quality, and economic development function as inseparable components of a unified ecosystem. These challenges fragmented, technical assistance approaches common in development projects, exposing how agricultural decarbonization success (which vastly outpaces other sectors) emerges not from isolated interventions but from synergistic and pre-existing national development conditions [26]. These finding places effective environmental action squarely within the realm of achieving broader developmental goals, such as strong institutions and economic prosperity.

The clear and significant superiority of mitigation over adaptation finance in delivering decarbonization corroborates global concerns about adaptation's limited mitigation co-benefits, yet Brazil's context reveals an unexpected nuance highly relevant for development planning: high regulatory quality can partially compensate for adaptation's inherent decarbonization limitations [10, 27]. This suggests that in contexts of strong governance, adaptation finance can yield valuable, albeit secondary, mitigation dividends, offering a more integrated path for development strategies.

Critically, the four-cluster framework proves that targeted allocation based on regulatory thresholds and fossil dependence profiles can overcome the "virtuous cycle" constraint, providing a practical method for development banks and national policymakers to discriminate between high- and low-potential investments even within constrained national systems. These results necessitate a paradigm shift from project-level evaluation toward a more holistic approach focused on national capacity building, where international climate finance is explicitly designed to strengthen the foundational institutions and economic conditions that underwrite development success, acting as a catalyst for systemic reinforcement rather than a standalone solution [28]. Ultimately, the study argues that in emerging economies, successful decarbonization is not a standalone environmental objective but a function of, and a contributor to, sustainable development itself.

6. Conclusions

This study resolves critical gaps in climate finance effectiveness literature by demonstrating that Brazil's decarbonization outcomes operate through an integrated national capacity system, where financial inputs, regulatory frameworks, and economic development jointly determine success. The multi-sector analysis proves agriculture's outsized decarbonization potential, while the adaptation-mitigation dichotomy reveals fundamental performance disparities requiring strategic differentiation. The developed optimization framework validated through hierarchical clustering and decision rules provides actionable pathway to triple efficiency returns by prioritizing regulatory-enabled, low fossil-dependence initiatives. These contributions collectively advance climate finance from fragmented project evaluation toward holistic system optimization, offering Brazil and similar economies a blueprint for transforming financial commitments into measurable climate progress.

Abbreviations

ANOVA	Analysis of Variance
CART	Classification and Regression Trees
CO2	Carbon Dioxide
EFA	Exploratory Factor Analysis
GCF	Green Climate Fund
GDP	Gross Domestic Product
HAC	Hierarchical Agglomerative
IEA	International Energy Agency
NCC	National Climate Capacity
OECD	Organization for Economic Co-operation and Development
PAF	Principal Axis Factoring
RMSE	Root Mean Square Error
STD ER	Standard Error
STD	Standardized Coefficient
UNFCC	United Nations Framework Convention on Climate Change
UNSTD	Unstandardized Coefficient
USD	United States Dollar

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Data would be made available on request from the author.

Conflicts of Interest

The author declares no conflicts of interest.

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