



Sustainable bioenergy utilization and forest carbon preservation in the Amazon

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Abstract

This study investigates sustainable bioenergy utilization and its implications for forest carbon preservation in the Amazon Basin, examining Bolivia, Brazil, and Colombia from 2000 to 2023. It identifies critical bioenergy intensity thresholds and temporal lags influencing ecosystem resilience and carbon dynamics. Results reveal Brazil exhibits the highest bioenergy intensities, ranging from 2.0 to 2.8 terajoules per thousand hectares, with significant carbon sequestration potential between 500 and 1000 kilotons of carbon dioxide per thousand hectares, yet operates mostly within stressed and degraded transitional regimes. Bolivia maintains low bioenergy intensity operations between 0.2 and 0.3 terajoules per thousand hectares but experiences forest area declines from 55,101 to 50,417 thousand hectares, signaling deforestation drivers beyond bioenergy extraction. Colombia shows greater resilience with intermediate bioenergy intensities and the fastest recovery time of 6.1 years. Temporal analysis indicates forest degradation follows bioenergy extraction by approximately 2 to 3 years, while policy interventions require 4 to 5 years for measurable recovery. A 49% reduction in forest conversion rates from 2010 to 2011 confirms the efficacy of policy implementation. Based on bioenergy intensity thresholds of 0.60 and 2.09 terajoules per thousand hectares, the analysis distinguishes three operational regimes: sustainable (31%), stressed (45%), and degraded (24%). These quantitative benchmarks provide practical guidance for sustainable forest management aligned with Sustainable Development Goal 15. Country-specific strategies include targeted reforestation in Bolivia, sustainable forest management reform in Brazil, and expanded community-led programs in Colombia. This study offers transferable approaches for balancing bioenergy demands with forest carbon preservation, supporting sustainable development in tropical forest regions globally.

*A comprehensive list of all abbreviations, technical terms, and nomenclature used throughout this manuscript is provided in Appendix A for reader reference.

Extended author information available on the last page of the article

Graphical Abstract



Keywords Tropical forest ecosystems · Carbon sequestration dynamics · Renewable energy sustainability · Ecosystem resilience thresholds · Policy intervention timing

JEL Classification Q23 · Q42 · Q54 · Q56 · C38

1 Introduction

Forest ecosystems function as among Earth's most vital climate regulators by sequestering approximately 2.6 billion tons of CO₂ annually and delivering essential ecosystem services that support global environmental stability (Gupta et al., 2024; Rabbi & Kovács, 2024). The contemporary energy transition creates a significant paradox as the world urgently moves toward renewable energy sources to address climate change (Rabbi, 2025a; Santosh et al., 2024). At the macro policy and global scale, traditional bioenergy production, especially from forest-derived biomass, simultaneously threatens the carbon sinks that are crucial for climate mitigation through unsustainable deforestation practices (Söderberg & Eckerberg, 2013). At the micro community and livelihood scale, this environmental contradiction becomes most severe in tropical developing regions where forest-dependent communities must choose between immediate energy security through traditional biomass consumption and preserving forest ecosystems that are essential for long-term planetary health (Edwards et al., 2019). These competing demands create complex socioeconomic and environmental tensions that require immediate scientific attention and comprehensive policy intervention to resolve effectively (Digkoglou & Papathanasiou, 2025). This study not only quantifies bioenergy and forest dynamics but also elucidates temporal lags and critical thresholds within a policy-relevant framework supporting Sustainable Development Goal 15.

The Amazon Basin represents a critical component of Earth's ecological balance that is globally recognized for its exceptional biodiversity and climate regulation functions (Chen et al., 2024; Sugiarto et al., 2024). Covering approximately 6.7 million square kilometres across South America, this vast rainforest acts as one of the planet's largest carbon sinks while encompassing diverse ecosystems that provide essential ecological services including carbon sequestration through extensive vegetation storing an estimated 150 to 200 billion

tons of carbon, habitat maintenance that supports exceptional biodiversity, hydrological cycle regulation that influences regional precipitation patterns, and livelihood support for millions of people dependent on forest resources. However, this vital ecosystem faces mounting challenges from multiple anthropogenic pressures including deforestation driven by agricultural expansion, unsustainable bioenergy production particularly through charcoal and fuelwood extraction, economic growth that intensifies land use competition, and land use changes that fragment forest connectivity (de Abreu dos Santos et al., 2024; Marcus et al., 2024). These converging pressures threaten the Amazon's ecological integrity and compromise its contribution to global carbon neutrality through extractive land use arrangements that escalate deforestation and forest degradation across managed production forests (Liu et al., 2024). They simultaneously disrupt regional hydrological cycles and undermine the livelihoods of forest-dependent communities whose food security and environmental stability remain critically intertwined with ecosystem health (Kovács et al., 2021).

Traditional biomass energy sources constitute a major driver of Amazon Basin deforestation through distinct production pathways and consumption patterns. Charcoal production has emerged as a particularly significant driver of forest degradation with industrial applications creating substantial pressure on forest resources (Ribeiro et al., 2024). The overexploitation of wood for charcoal production particularly for the steel industry has degraded forest ecosystems through multiple pathways including direct biomass removal, decreased biodiversity through habitat fragmentation, and increased soil erosion that compromises long-term forest regeneration capacity (Romero et al., 2024). Fuelwood extraction compounds these pressures by serving as the primary energy source for rural and indigenous communities where availability and economic constraints perpetuate dependence on traditional biomass consumption. Country-specific deforestation patterns reveal varying intensities and drivers across the Amazon Basin. Brazil has experienced the most extensive forest loss with the Amazon and the Cerrado biomes exhibiting the most substantial declines in forestland area (Flores et al., 2024). The country lost approximately 50,000 hectares of forest cover between 2000 and 2020, with projections indicating continued deforestation pressures through 2026 driven significantly by charcoal production for industrial applications and agricultural expansion (Norris et al., 2022; Turubanova et al., 2018). Bolivia demonstrates concerning deforestation trends exemplified by surging rates of charcoal production in the Chiquitano dry forest, which provides charcoal to nearby urban centers including Santa Cruz de la Sierra, jeopardizing unique ecosystems and biodiversity hotspots through habitat destruction and disrupted hydrological cycles (Romero et al., 2024). Colombia faces similar challenges with forest loss driven by complex interactions among bioenergy production, agricultural expansion, and land use changes that reduce carbon sequestration capacity and threaten biodiversity (Rabbi, 2025b).

The role of bioenergy in regional development presents significant complexity operating across multiple scales. At the ecological scale, intensifying human activity is pushing Amazon forest systems toward irreversible tipping points that compromise long-term regional ecosystem integrity (Flores et al., 2024). At the community scale, energy system transitions create critical socioeconomic tradeoffs where renewable alternatives may simultaneously improve indigenous livelihoods and reduce deforestation pressures on forest resources (Hampl, 2024). This fundamental tension between renewable energy promotion and forest conservation intensifies in the Amazon context, where the scale of charcoal and fuelwood extraction creates measurable carbon debts that negate anticipated climate gains (Rabbi

& Abdullah, 2024; Soteli et al., 2023). The controversial aspects of bioenergy systems have been extensively debated, with some studies highlighting their potential as renewable energy sources (Máté et al., 2020; Rahaman et al., 2023), while others emphasize their potential negative impacts on forests and carbon emissions if not developed sustainably (Kabir, 2021). Consequently, the relationships among forest conservation, bioenergy production and consumption, and carbon emissions have received increased scientific attention because of their far-reaching environmental implications for meeting local energy demands.

The integration of forest conservation into sustainable development frameworks has become central in global policy, as reflected in Sustainable Development Goal 15 (SDG 15), which calls for safeguarding, rehabilitating, and sustainably managing terrestrial ecosystems to maintain robust carbon sinks, climate stability, and biodiversity conservation (Hansen et al., 2024; Johansen et al., 2024). Beyond carbon storage, forest ecosystems underpin planetary health and regional resilience by mediating hydrological cycles and supporting critical ecological services.

Although existing research widely acknowledges interactions among forest conservation, bioenergy production, and carbon dynamics, most studies focus on contemporaneous relationships and fail to quantify two critical dimensions that govern long-term ecosystem resilience and policy efficacy. First, temporal lag effects between bioenergy production peaks and subsequent forest regeneration or carbon sequestration changes remain inadequately quantified, limiting understanding of delayed ecosystem responses essential for timing policy interventions. Second, precise identification of bioenergy intensity thresholds beyond which carbon sequestration becomes irreversibly compromised remains lacking across different regional contexts. This gap limits the ability to predict critical tipping points before irreversible degradation occurs and to account for regional heterogeneity in forest energy system resilience, both vital for targeting conservation and sustainable energy strategies.

Quantitative studies addressing temporal lag effects between bioenergy extraction and forest recovery have largely relied on pan-tropical projections without modeling delayed ecosystem responses at the country level. Magne et al. (2024) assessed the bioenergy potential of South America through 2050 without incorporating lag-adjusted forest regeneration dynamics, while Bailis et al. (2015) quantified the carbon footprint of traditional woodfuels across pan-tropical systems without accounting for lagged carbon sequestration responses. Threshold-based analysis of bioenergy intensity effects on forest carbon has similarly been confined to single-country or conceptual frameworks. Bajpai (2023) examined the general ecosystem consequences of bioenergy utilization without empirical multi-country validation, and de Oliveira Neves et al. (2024) analyzed energetic sustainability in the Amazon region without establishing intensity thresholds applicable beyond Brazil. Country-specific case studies have contributed contextual evidence at the national scale: Talita Oliveira Assis et al. (2020) quantified CO₂ emissions from forest degradation in the Brazilian Amazon, Romero et al. (2024) estimated biomass and carbon stocks in managed Bolivian Amazon forests, and Villazón Montalván et al. (2019) evaluated environmental concerns around traditional charcoal production in the southern Brazilian context. Forest governance and monitoring frameworks have advanced the field in targeted Andean-Amazon regions, with Hansen et al. (2024) developing SDG 15 quality indicators for Colombia, Ecuador, and Peru, and Katz-Asprilla et al. (2024) assessing legal and illegal deforestation dynamics in the Colombian Amazon. Collectively, these works advance national and sub-regional understanding but do not provide the cross-country comparative quantification of temporal lags

and bioenergy intensity thresholds needed to support transferable Amazon Basin management frameworks.

To bridge these gaps, this study investigates the interplay of forest conservation, carbon flux, and bioenergy activity across the Amazon Basin. It explicitly incorporates analyses of temporal lag effects and bioenergy intensity thresholds influencing forest regeneration. The research addresses two primary questions. RQ1: How do temporal lags between bioenergy production peaks and forest regeneration affect carbon sequestration in Bolivia, Brazil, and Colombia? RQ2: What are the bioenergy intensity thresholds associated with significant carbon sequestration loss, and how do they vary regionally?

This research adopts a cross-country, quantitative design covering 2000 to 2023, integrating statistical approaches such as cross-correlation, change-point detection, and regime classification. By capturing both immediate and delayed ecosystem responses, including system regime shifts, this research provides actionable benchmarks that inform adaptive, regionally tailored forest management and energy policies. This approach advances beyond one-size-fits-all models, facilitating sustainable development planning scalable to diverse tropical forest systems.

2 Literature review

2.1 Global forest-energy-carbon nexus

The global forest energy carbon nexus represents a complex system of interactions operating across multiple spatial and temporal scales where forest resources provide bioenergy feedstocks while simultaneously serving as critical carbon reservoirs essential for climate regulation (Baskent et al., 2025; Wang et al., 2025). At the global scale, forest ecosystems store approximately 861 gigatons of carbon with tropical forests representing the largest terrestrial carbon reservoir that sequesters approximately 2.6 billion tons of CO₂ annually (Fasihi et al., 2025). The conversion of these forests for bioenergy production creates complex feedback loops that can either enhance climate mitigation when extraction remains within regeneration capacity or undermine climate goals when harvesting exceeds sustainable thresholds (Jain, 2025). This nexus framework establishes three conceptual dimensions essential for understanding sustainability boundaries in forest bioenergy systems. The temporal dimension encompasses delayed ecosystem responses where forest degradation lags extraction intensification and recovery processes span extended periods following intervention. The threshold dimension identifies critical intensity levels beyond which forest systems undergo regime shifts from sustainable management to irreversible degradation. The spatial heterogeneity dimension recognizes that identical bioenergy intensities produce vastly different ecological outcomes across regions due to varying soil fertility, precipitation regimes, species composition, and management capacity. These three dimensions provide the conceptual foundation for examining specific mechanisms and regional applications explored in subsequent sections.

However, emerging research reveals that these forest-energy interactions are characterized by significant temporal lag effects and non-linear threshold responses that are poorly understood (Bernardino et al., 2025). Forest ecosystems exhibit delayed responses to bioenergy pressures, with evidence suggesting that degradation manifests after initial extraction

intensification, while recovery processes can span decades (Ahmed et al., 2024; Islam et al., 2025). Critical thresholds exist beyond which bioenergy intensity irreversibly damages forest carbon sequestration capacity. However, precise quantification of these temporal dynamics and threshold values remains limited across different regional contexts, representing a critical knowledge gap that this study addresses through empirical analysis.

2.2 Bioenergy production mechanisms and forest degradation pathways

Building on the global nexus framework, specific mechanisms through which bioenergy production drives forest degradation operate through distinct extraction pathways that vary in intensity, spatial extent, and temporal dynamics. The environmental impacts of traditional bioenergy production in tropical regions have generated considerable debate regarding the net climate benefits versus ecological costs of forest derived energy systems. Recent quantitative assessments reveal a critical tension between renewable energy promotion and forest conservation objectives. Yayla et al. (2025) quantified the carbon footprint of traditional fuelwood extraction, demonstrating that unsustainable harvesting practices can result in net carbon emissions that negate expected climate benefits through forest carbon stock depletion exceeding biomass energy substitution gains. Chidumayo and Gumbo (2013) documented that traditional charcoal production systems in South America generate cascading environmental impacts including direct deforestation through biomass extraction, soil degradation that compromises long term regeneration capacity, and air quality deterioration through incomplete combustion processes. These findings establish that bioenergy sustainability depends critically on extraction intensity relative to forest regeneration capacity, yet existing literature predominantly examines direct environmental impacts without quantifying the temporal dynamics and intensity thresholds that separate sustainable from degradative extraction regimes.

2.3 Amazon basin as a critical case study context

The Amazon Basin represents an ideal empirical context for examining forest energy carbon nexus dynamics due to its global significance as the largest tropical forest carbon reservoir combined with intensive bioenergy utilization pressures that span the full range of extraction intensities and management approaches. The Amazon Basin has experienced unprecedented deforestation rates over the past two decades, with multiple drivers contributing to forest loss. Flores et al. (2024) identified critical transitions in Amazon forest systems, highlighting how human activities push forest ecosystems toward irreversible tipping points. Lapola et al. (2023) comprehensively analyzed the drivers and impacts of Amazon forest degradation, demonstrating that bioenergy production represents a significant but understudied component of deforestation pressures.

2.4 Carbon dynamics in tropical forest systems

Understanding carbon flux patterns in tropical forests is essential for evaluating the true climate impacts of bioenergy systems that may appear renewable based on biomass regrowth assumptions but generate substantial emissions through forest degradation processes. Assis et al., (2022) quantified CO₂ emissions from forest degradation in the Brazilian Amazon

through spatial analysis revealing that degradation processes release substantial amounts of stored carbon ranging from 0.5 to 2.0 petagrams of carbon per year even when complete deforestation is avoided. This finding fundamentally challenges conventional carbon accounting frameworks that focus exclusively on deforestation defined as complete forest cover loss while neglecting partial degradation that compromises carbon sequestration capacity without eliminating forest classification. The research demonstrates that selective logging, edge effects, and biomass extraction for bioenergy create degradation gradients where forest carbon stocks decline progressively over time. However, existing studies including Assis et al., (2022) examine carbon flux patterns at single time points or short temporal windows without quantifying the lag periods between bioenergy extraction intensification and subsequent carbon sequestration decline, limiting predictive capacity for policy intervention timing.

2.5 Policy frameworks and sustainable development goals

The integration of forest conservation with energy policy has gained prominence in international sustainability frameworks including Sustainable Development Goal 15 which aims to protect, restore, and promote sustainable use of terrestrial ecosystems, and REDD+ mechanisms that provide financial incentives for reducing emissions from deforestation and forest degradation (Coalition for Rainforest Nations 2024). Hansen et al. (2024) developed national complementary indicators for SDG 15 that consider forest quality beyond simple area metrics, providing methodological advances for monitoring forest conservation progress in Colombia, Ecuador, and Peru that incorporate biodiversity, carbon density, and ecosystem service provision. However, existing policy frameworks exhibit critical limitations that reduce their effectiveness for sustainable bioenergy governance. First, monitoring systems predominantly focus on contemporaneous forest carbon relationships without accounting for temporal lag effects between policy intervention and measurable ecosystem responses, leading to premature conclusions about policy effectiveness when interventions require multi year periods to generate detectable forest recovery (Mackey et al., 2025). Second, threshold-based management targets remain inadequately defined across different bioenergy intensity levels, preventing identification of critical tipping points before irreversible degradation occurs and limiting capacity to establish enforceable sustainability standards (Ewers et al., 2024). Third, regional heterogeneity in forest energy system resilience is insufficiently recognized in international frameworks that apply uniform policy prescriptions despite vast differences in ecological conditions, institutional capacity, and socioeconomic contexts across tropical forest regions (Levine et al., 2016). Inadequacies in current policy frameworks can limit the impact of active conservation initiatives aimed at reducing forest degradation (Rosa et al., 2023). These initiatives often require greater temporal and threshold specificity to ensure that the timing and intensity of interventions are correctly aligned with environmental needs.

2.6 Research gaps and study justification

Despite extensive research on individual components of the forest-energy-carbon nexus, significant gaps remain in understanding the integrated relationships among these systems. Most critically, current literature predominantly examines contemporaneous relationships,

overlooking three fundamental knowledge gaps: (1) temporal lag effects between bioenergy production peaks and subsequent forest recovery patterns (Magne et al., 2024; Silvestro et al., 2024), (2) critical bioenergy intensity thresholds beyond which forest carbon sequestration suffers irreversible damage (Bajpai, 2023; Flores et al., 2024; Wu et al., 2018), and (3) regional heterogeneity in forest-energy system resilience and recovery dynamics across different Amazon Basin countries (Ahrens et al., 2025; Liu et al., 2024).

These temporal and threshold dynamics are essential for designing effective forest management policies, as preventive measures must account for delayed ecosystem responses while recovery strategies require understanding of system-specific resilience thresholds. This study addresses these gaps by providing a quantitative analysis of lag effects and threshold relationships among forest conservation, carbon dynamics, and bioenergy systems in Bolivia, Brazil, and Colombia, contributing to evidence-based policy development for sustainable forest and energy management.

3 Materials and methods

This quantitative study analyzes the complex relationships among forest conservation, carbon dynamics, and bioenergy production and consumption in three Amazonian countries from 2000 to 2023. The research employs a comprehensive four-stage analytical framework to quantify and visualize the dual challenges of energy security and environmental protection in the Amazon Basin. The methodological approach integrates temporal trajectory analysis with lag-effect detection, threshold analysis and regime classification, carbon sequestration efficiency assessment, and spatial-temporal vulnerability mapping to provide robust evidence for policy recommendations.

3.1 Conceptual framework

This study employs a sequential analytical framework illustrated in Fig. 1 that systematically processes input data through multiple analytical stages to generate evidence-based policy recommendations for sustainable forest-bioenergy management in the Amazon Basin. The framework integrates data from Bolivia, Brazil, and Colombia across the study period, incorporating regional parameters including forest cover and bioenergy intensity alongside global context factors such as climate impacts and carbon dynamics.

The analytical process flows through interconnected methodological stages. Input data integration combines country-specific bioenergy production and consumption data with regional forest management parameters and global environmental context to establish the analytical foundation. Temporal trajectory analysis examines forest cover dynamics and bioenergy intensity patterns across multi-year time series to establish baseline relationships and temporal trends. Parallel detection methods simultaneously employ cross-correlation techniques to identify lag effects between bioenergy extraction and forest responses, while piecewise regression analysis detects critical intensity thresholds where forest system responses undergo structural transitions. Regime classification and integration synthesize threshold and lag findings through clustering approaches to distinguish operational zones characterizing different forest-energy system states. Dual analysis outputs evaluate carbon sequestration efficiency under varying extraction scenarios and map vulnerability patterns to

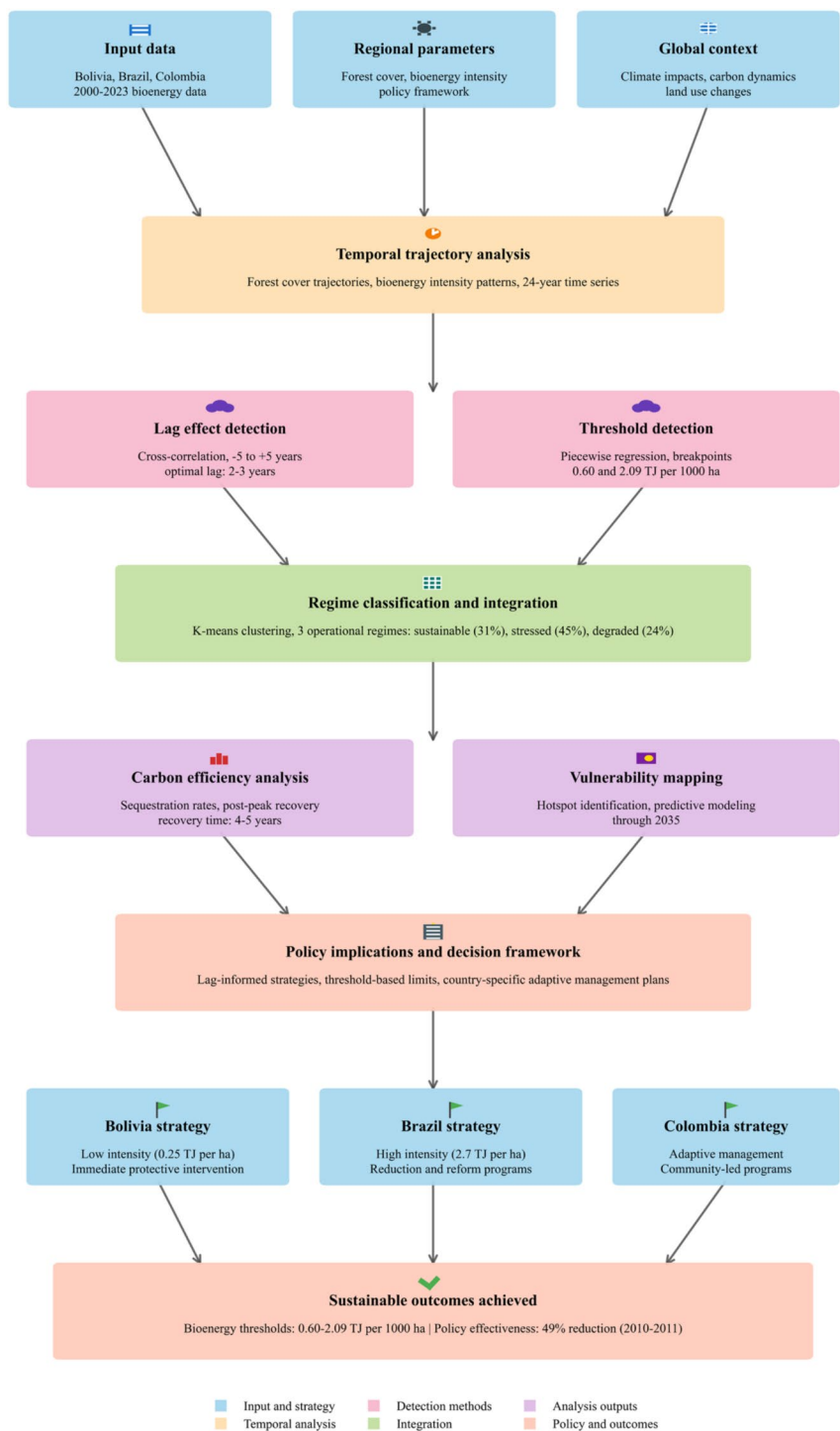


Fig. 1 Methodological flowchart for forest-energy-carbon analysis in the Amazon Basin

identify risk hotspots and predict future trajectories. Policy implications synthesis translates analytical findings into actionable strategies including lag-informed intervention timing, threshold-based regulatory limits, and adaptive management protocols. Country-specific strategies operationalize general recommendations into tailored approaches addressing distinct national contexts and institutional capacities. Sustainable outcomes assessment evaluates the integrated effectiveness of proposed interventions for achieving balanced forest conservation and energy security objectives.

Figure 1 presents the methodological flowchart that guides the systematic analysis of forest-energy-carbon dynamics across Bolivia, Brazil, and Colombia. The framework operates through a hierarchical analytical structure beginning with multi-source data integration, progressing through parallel detection methods that simultaneously quantify temporal lag effects and bioenergy intensity thresholds, converging at regime classification that distinguishes operational zones, expanding to dual analysis outputs examining carbon efficiency and vulnerability patterns, synthesizing policy implications, and culminating in country-specific strategies that achieve sustainable outcomes. This sequential architecture ensures methodological rigor by establishing clear analytical dependencies where each stage builds upon preceding results while maintaining analytical independence within parallel processing blocks. The flowchart structure directly corresponds to the four-stage analytical framework detailed in Section 3.3, providing visual representation of how temporal trajectory analysis, threshold detection and regime classification, carbon sequestration efficiency assessment, and spatial-temporal vulnerability mapping integrate to generate comprehensive evidence for policy development. The color-coded categorical organization distinguishes input and strategy components, temporal analysis processes, detection methods, integration operations, analysis outputs, and policy outcomes, facilitating reader navigation through the methodological progression from raw data inputs to sustainable forest management recommendations.

3.2 Data collection and variable selection

All data were sourced from the Food and Agriculture Organization (FAO) databases (FAO, 2025a, b). These sources provide reliable and comprehensive datasets with consistent methodologies across different countries. To ensure consistency and comparability the study measures energy production and consumption in terajoules (TJ). Additionally, CO₂ emissions and removals are recorded in kilotons (kt), while land use is presented in thousands of hectares (1000 ha).

Eight core variables were selected to comprehensively represent the forest-energy-carbon nexus, based on established theoretical relevance and direct impact on carbon emissions and forest resource dynamics. Table 1 presents the complete analytical framework organizing these variables by category, dimension, measurement unit, and operational role in the forest-energy-carbon nexus.

3.3 Analytical procedure

The Amazon Basin represents a multifaceted relationship between its forests, bioenergy production, and carbon dynamics. Exploring these interactions required a rigorous analytical approach, combining statistical tools to uncover trends and reveal underlying patterns.

Table 1 Key Variables for Assessing Forestry, carbon emissions, bioenergy production, and consumption

Category	Dimension	Variable	Measurement unit	Role/Impact
Carbon emissions	Emissions	Net CO ₂ Emissions	kilotons	Sums all emissions attributable to land-use change and biomass combustion
Forestry	Land Use	Forestland	1,000 ha	Defines capacity for bioenergy and carbon removal and links to emissions and removals
Bioenergy production	Carbon Sequestration	Net CO ₂ Removals	kilotons	Quantifies negative emissions where forest quality and extent determine magnitude
	Land Use Change	Net Forest Conversion	1,000 ha	Key upstream driver where positive values indicate afforestation and negative values indicate deforestation
	Energy Generation	Energy Production from Charcoal	TJ	Direct driver of forest pressure and carbon emissions through industrial biomass extraction
Bioenergy consumption	Energy Generation	Energy Production from Fuelwood	TJ	Direct driver of forest pressure and carbon emissions through fuelwood harvesting for energy generation
	Energy Utilization	Energy Consumption from Charcoal	TJ	Demand-side indicator that correlates with upstream charcoal extraction pressure and associated emissions
	Energy Utilization	Energy Consumption from Fuelwood	TJ	Demand-side indicator reflecting household and industrial fuelwood consumption and associated forest pressure

All quantitative data were obtained from the FAO's FAOSTAT database (FAO, 2025a, b) ensuring methodological consistency across countries and years. Units are harmonized for cross-country comparison

By exploring the intricate links between these elements, the analysis delved into the processes that link deforestation, bioenergy uses, and carbon emissions. The insights gained from this work are essential for developing strategies that balance the region's ecological resilience with sustainable development goals and climate change mitigation efforts.

This study employed a four-stage analytical framework corresponding to the main research questions: (1) temporal trajectory analysis with lag effects, (2) threshold detection and regime classification, (3) efficiency optimization under varying scenarios, and (4) vulnerability mapping with predictive modeling. Each analytical component was designed to capture specific aspects of the forest-energy-carbon nexus while maintaining methodological consistency across all countries and time periods.

3.3.1 Multi-scale temporal forest-energy trajectory analysis

The temporal dynamics of forestland, net CO₂ removals, and emissions were depicted through integrated trajectory analysis where each variable was tracked over the study period to capture shifts in forest coverage and carbon dynamics. To establish the foundational relationship between forest area and temporal changes, the trend in forestland area over time is expressed as:

$$FL_t = f(C, t) \quad (1)$$

This equation defines the forestland area (FL_t) as a function of country (C) and time (t), providing the baseline for tracking forest cover changes across the three Amazon Basin countries throughout the study period.

Building upon this foundation, changes in forestland are determined by net forest conversion processes, which represent the combined effects of afforestation, reforestation, and deforestation activities:

$$FL_{t+1} = FL_t + NFC_t \quad (2)$$

This relationship demonstrates how forest area transitions from one period to the next, incorporating the net forest conversion (NFC_t) as the primary driver of temporal changes in forest coverage.

To normalize bioenergy activities relative to forest resource availability and enable meaningful cross-country comparisons, bioenergy intensity was calculated as:

$$BEI_{i,t} = \frac{BE_{total,i,t}}{FL_{i,t}} \times 1000 \quad (3)$$

This intensity measure ($BEI_{i,t}$) represents bioenergy extraction per unit of forest area for country i at time t , expressed in terajoules per thousand hectares, allowing for standardized assessment of extraction pressure across different forest systems.

The total bioenergy component encompasses all major forest-derived energy sources through the comprehensive measure:

$$BE_{total,i,t} = P_{charcoal,i,t} + P_{fuelwood,i,t} + C_{charcoal,i,t} + C_{fuelwood,i,t} \quad (4)$$

This aggregation captures both production and consumption aspects of charcoal and fuelwood, providing a complete picture of bioenergy pressure on forest systems.

Temporal dependencies between forest cover and bioenergy intensity were quantified using cross-correlation functions to reveal lead-lag relationships across multiple time periods. The cross-correlation at lag τ is computed as:

$$\rho_i(\tau) = \frac{\sum_{t=1}^{T-|\tau|} (FL_{i,t} - \overline{FL_i})(BEI_{i,t+\tau} - \overline{BEI_i})}{\sqrt{\sum_{t=1}^{T-|\tau|} (FL_{i,t} - \overline{FL_i})^2 \sum_{t=1}^{T-|\tau|} (BEI_{i,t+\tau} - \overline{BEI_i})^2}} \quad (5)$$

This correlation coefficient quantifies the strength and direction of relationships between forest cover and bioenergy intensity across different time delays ($\tau \in [-5, +5]$ years), where $\overline{FL_i}$ and $\overline{BEI_i}$ represent the respective temporal means for each variable.

To assess the statistical significance of these temporal relationships, correlations were tested using the t-statistic:

$$t_i(\tau) = \rho_i(\tau) \sqrt{\frac{T_i - 2}{1 - \rho_i(\tau)^2}} \quad (6)$$

This test statistic determines whether observed correlations are statistically meaningful, where T_i represents the number of valid observations for country i , enabling robust inference about temporal dependencies.

Structural breaks in forest cover trajectories were identified using piecewise constant mean change-point detection to determine critical transition periods. For a time series $FL_{i,1}, FL_{i,2}, \dots, FL_{i,t}$, the optimal change-point is identified by minimizing the total sum of squared residuals:

$$\hat{\tau} = \arg \min_{\tau} \left[\sum_{t=1}^{\tau} (FL_{i,t} - \mu_1)^2 + \sum_{t=\tau+1}^T (FL_{i,t} - \mu_2)^2 \right] \quad (7)$$

This optimization identifies the time point $\hat{\tau}$ where forest system dynamics underwent fundamental structural changes, with $\mu_1 = \frac{1}{\tau} \sum_{t=1}^{\tau} FL_{i,t}$ and $\mu_2 = \frac{1}{T-\tau} \sum_{t=\tau+1}^T FL_{i,t}$ representing the mean forest cover before and after the detected change point.

3.3.2 Threshold analysis and regime classification

The identification of critical thresholds required defining forest regeneration capacity as the fundamental indicator of ecosystem health and sustainability. Forest regeneration capacity was conceptualized as the negative of net forest conversion to align with ecological interpretation:

$$RG_{i,t} = -NFC_{i,t} \quad (8)$$

This transformation ensures that positive values indicate net forest gain while negative values represent net forest loss, providing an intuitive measure of forest system regenerative capacity that directly relates to sustainability outcomes.

Critical thresholds were established through quantile-based classification to identify operational boundaries where forest system responses undergo fundamental transitions. The low threshold was defined as $T_{low} = Q_{0.33}(BEI)$ and the high threshold as $T_{high} = Q_{0.67}(BEI)$, corresponding to the 33rd and 67th percentiles of the bioenergy intensity distribution. These percentile-based thresholds create three distinct operational zones that reflect different levels of forest system stress.

Structural breakpoints in the bioenergy intensity-forest regeneration relationship were identified using segmented regression to detect where forest responses change fundamentally. The piecewise linear model captures these regime transitions:

$$RG_{i,t} = \begin{cases} \alpha_1 + \beta_1 \cdot BEI_{i,t} + \epsilon_{i,t} & \text{if } BEI_{i,t} \leq BP \\ \alpha_2 + \beta_2 \cdot BEI_{i,t} + \epsilon_{i,t} & \text{if } BEI_{i,t} > BP \end{cases} \quad (9)$$

This model allows for different slope relationships (β_1 and β_2) and intercepts (α_1 and α_2) on either side of the breakpoint (BP), capturing non-linear threshold effects where forest system responses change dramatically beyond critical bioenergy intensities.

The optimal breakpoint location is determined by minimizing the combined residual sum of squares across both segments:

$$\hat{BP} = \arg \min_{BP} [RSS_1(BP) + RSS_2(BP)] \quad (10)$$

This optimization identifies the bioenergy intensity level where the relationship between extraction pressure and forest regeneration undergoes the most significant structural change, providing empirical evidence for critical sustainability thresholds.

Three distinct operational regimes were identified using K-means clustering in the two-dimensional space defined by bioenergy intensity and forest regeneration capacity:

$$\{Regime_1, Regime_2, Regime_3\} = K\text{-means}(\{(BEI_{i,t}, RG_{i,t})\}, K = 3) \quad (11)$$

This clustering approach objectively identifies natural groupings in the data, with regime boundaries defined by cluster centroids and classified as Sustainable (low BEI with weakly negative to slightly positive RG), Stressed (intermediate BEI with moderately negative RG), and Degraded (high BEI with strongly negative RG).

3.3.3 Carbon sequestration efficiency analysis

Carbon sequestration efficiency per unit forest area was quantified to assess the relationship between forest productivity and bioenergy extraction intensity. The efficiency measure standardizes carbon storage capacity relative to forest area:

$$CSE_{i,t} = \frac{|CO2_{removals,i,t}|}{FL_{i,t}} \times 1000 \quad (12)$$

This metric expresses carbon sequestration efficiency ($CSE_{i,t}$) in kilotons of CO_2 per thousand hectares, enabling direct comparison of forest carbon storage capacity across countries with different forest areas and providing insights into the relationship between bioenergy pressure and carbon sequestration performance.

Post-peak recovery patterns were analyzed by identifying bioenergy production peaks and tracking subsequent forest regeneration responses. Production peaks were identified using a moving window approach:

$$t_i^* = \{t : BE_{prod,i,t} = \max_{s \in [t-w, t+w]} BE_{prod,i,s}\} \quad (13)$$

This identification process locates time points (t_i^*) where bioenergy production reaches local maxima within a specified window size (w , typically 2–3 years), providing reference points for analyzing ecosystem recovery trajectories following intensive extraction periods.

Recovery rates were calculated to quantify the pace and direction of forest system recovery following peak bioenergy extraction:

$$RR_{i,k} = \frac{RG_{i,t^*+k} - RG_{i,t^*}}{\max(1, |RG_{i,t^*}|)} \times 100\% \quad (14)$$

This recovery rate ($RR_{i,k}$) measures the percentage change in forest regeneration capacity k years ($k=1,2,\dots,7$) after the peak extraction period, normalized by the initial regeneration capacity to account for different baseline conditions across countries and time periods.

Efficiency frontiers were constructed using five-year period averages to identify optimal bioenergy-carbon trade-offs and reveal temporal optimization patterns. The bioenergy production average is calculated as:

$$\overline{BE}_{prod,i,\tau} = \frac{1}{5} \sum_{t \in \tau} BE_{prod,i,t} \quad (15)$$

Similarly, the carbon sequestration average for each period is:

$$\overline{CO2}_{removals,i,\tau} = \frac{1}{5} \sum_{t \in \tau} |CO2_{removals,i,t}| \quad (16)$$

These period averages (τ representing five-year periods: [2000–2004], [2005–2009], [2010–2014], [2015–2019], [2020–2023]) smooth short-term fluctuations and reveal longer-term optimization trajectories in the bioenergy-carbon relationship.

3.3.4 Spatial-temporal vulnerability mapping

A composite forest vulnerability index was constructed by integrating multiple indicators to provide a comprehensive assessment of forest system stress. The vulnerability index combines normalized measures of forest conversion rate, bioenergy intensity, and carbon sequestration efficiency:

$$VI_{i,t} = w_1 \cdot z\left(\frac{|NFC_{i,t}|}{FL_{i,t}}\right) + w_2 \cdot z(BEI_{i,t}) + w_3 \cdot z\left(\frac{1}{CSE_{i,t}}\right) \quad (17)$$

This composite index ($VI_{i,t}$) weights three key vulnerability dimensions where $z(\cdot)$ represents standardization through z-score transformation and the weights sum to unity ($w_1 + w_2 + w_3 = 1$), ensuring balanced contribution from each component while maintaining interpretability.

Standardization was applied to enable meaningful aggregation across different measurement scales:

$$z(x_{i,t}) = \frac{x_{i,t} - \bar{x}}{\sigma_x} \quad (18)$$

This z-score transformation centers each variable around its overall mean ($\bar{x}$) and scales by its standard deviation (σ_x) across all countries and years, creating standardized measures that facilitate comparison and aggregation.

Rapid forest-energy transitions were identified as years with vulnerability index changes exceeding critical thresholds. Annual vulnerability changes are calculated as:

$$\Delta VI_{i,t} = VI_{i,t} - VI_{i,t-1} \quad (19)$$

This difference measure captures year-to-year changes in vulnerability, providing the foundation for identifying periods of rapid forest-energy system transitions that may signal critical shifts in ecosystem stability.

Hotspots were defined based on the magnitude of vulnerability changes:

$$Hotspot_{i,t} = \begin{cases} 1 & \text{if } |\Delta VI_{i,t}| \geq \theta \\ 0 & \text{otherwise} \end{cases} \quad (20)$$

This binary classification identifies time periods when vulnerability changes exceed the critical threshold ($\theta=0.025$, representing the 85th percentile of $|\Delta VI_{i,t}|$), flagging years of particularly rapid forest-energy system transitions that warrant special attention.

Future vulnerability trajectories through 2035 were modeled using autoregressive processes fitted to recent data from 2018–2023:

$$VI_{i,t+1} = \phi_i \cdot VI_{i,t} + c_i + \eta_{i,t} \quad (21)$$

This first-order autoregressive model captures temporal persistence in vulnerability patterns, where ϕ_i represents the persistence parameter, c_i is the country-specific constant, and $\eta_{i,t} \sim N(0, \sigma_i^2)$ represents random innovations.

Multi-step ahead forecasts were computed using the recursive relationship:

$$\hat{VI}_{i,t+h} = \phi_i^h \cdot VI_{i,t} + c_i \frac{1 - \phi_i^h}{1 - \phi_i} \quad (22)$$

This forecasting equation projects vulnerability k periods into the future, accounting for the exponential decay of current conditions (ϕ_i^k) and the long-run tendency toward the mean level determined by the constant term.

Forecast uncertainty was quantified using prediction intervals that account for both parameter uncertainty and forecast error accumulation:

$$PI_{i,t+h} = \hat{VI}_{i,t+h} \pm 1.96 \sqrt{\sigma_i^2 \sum_{k=0}^{h-1} \phi_i^{2k}} \quad (23)$$

These prediction intervals provide 95% confidence bounds around the point forecasts, with uncertainty increasing over longer forecast horizons due to the accumulation of forecast errors and the geometric expansion of uncertainty through the autoregressive structure.

This comprehensive analytical framework ensures methodological rigor while capturing the complex temporal dynamics, threshold effects, and regional heterogeneity that characterize forest-energy-carbon interactions in the Amazon Basin.

3.3.5 Statistical implementation and computational tools

All statistical analyses were implemented using Python 3.13.1 programming environment with specialized libraries for ecological data analysis and spatiotemporal modeling. Core analytical libraries included NumPy 1.26.4 for numerical computations, Pandas 2.1.4 for

data manipulation and time series handling, SciPy 1.11.4 for statistical testing and optimization, and Matplotlib 3.8.2 combined with Seaborn 0.13.0 for visualization.

Temporal trajectory analysis and cross-correlation functions utilized custom implementations built on NumPy correlation calculations with statistical significance testing through SciPy t-statistics. Change-point detection employed the ruptures 1.1.9 library implementing piecewise constant mean optimization through dynamic programming with bootstrap validation (1000 iterations) to assess breakpoint stability.

Threshold detection combined quantile-based classification with piecewise regression through segmented linear modeling. Breakpoint optimization employed residual sum of squares minimization via SciPy optimization toolkit, with model selection using Bayesian Information Criterion and Akaike Information Criterion.

Regime classification utilized scikit-learn 1.3.2 K-means clustering with Euclidean distance metrics and 50 random initializations to ensure global optima. Cluster validation employed silhouette coefficient analysis and Calinski-Harabasz index. Vulnerability mapping employed statsmodels 0.14.1 for autoregressive modeling with maximum likelihood optimization and prediction interval quantification.

4 Analysis and results

4.1 Temporal trajectory dynamics and lag-response mechanisms in amazon forest-energy systems

Understanding the temporal dimensions of forest-energy interactions is fundamental to revealing the underlying mechanisms that govern ecosystem responses to bioenergy pressures across different national contexts. The multi-scale temporal analysis presented in Fig. 2 and Table 2 employed the comprehensive framework, utilizing forest cover trajectory modeling (Eqs. 1–2), bioenergy intensity calculation (Eqs. 3–4), lead-lag correlation analysis (Eqs. 5–6), and change-point detection (Eq. 7) to quantify the complex temporal dependencies and structural transitions that characterize Amazon Basin forest-energy systems from 2000 to 2023.

This integrated temporal approach addresses a critical knowledge gap in forest-energy research by moving beyond contemporaneous relationships to reveal: (1) distinct temporal coupling mechanisms between forest cover changes and bioenergy extraction across Bolivia, Brazil, and Colombia; (2) specific lag periods governing cause-and-effect relationships in forest responses; and (3) critical transition points where forest-energy dynamics undergo structural regime shifts. The analysis captures both immediate synchronous responses and delayed impacts spanning up to five years, establishing temporal baselines for policy implementation delays and ecosystem recovery timescales.

The multi-scale temporal forest-energy trajectories presented in Fig. 2 reveal complex interactions between forest cover dynamics and bioenergy utilization patterns across Bolivia, Brazil, and Colombia from 2000 to 2023, with significant implications for understanding threshold effects and temporal dependencies in Amazonian forest-energy systems.

Panel A demonstrates distinct forest cover trajectories overlaid with bioenergy intensity patterns, revealing markedly different forest-energy relationships among the three countries. Brazil exhibits the most extensive forest cover, maintaining approximately 500,000

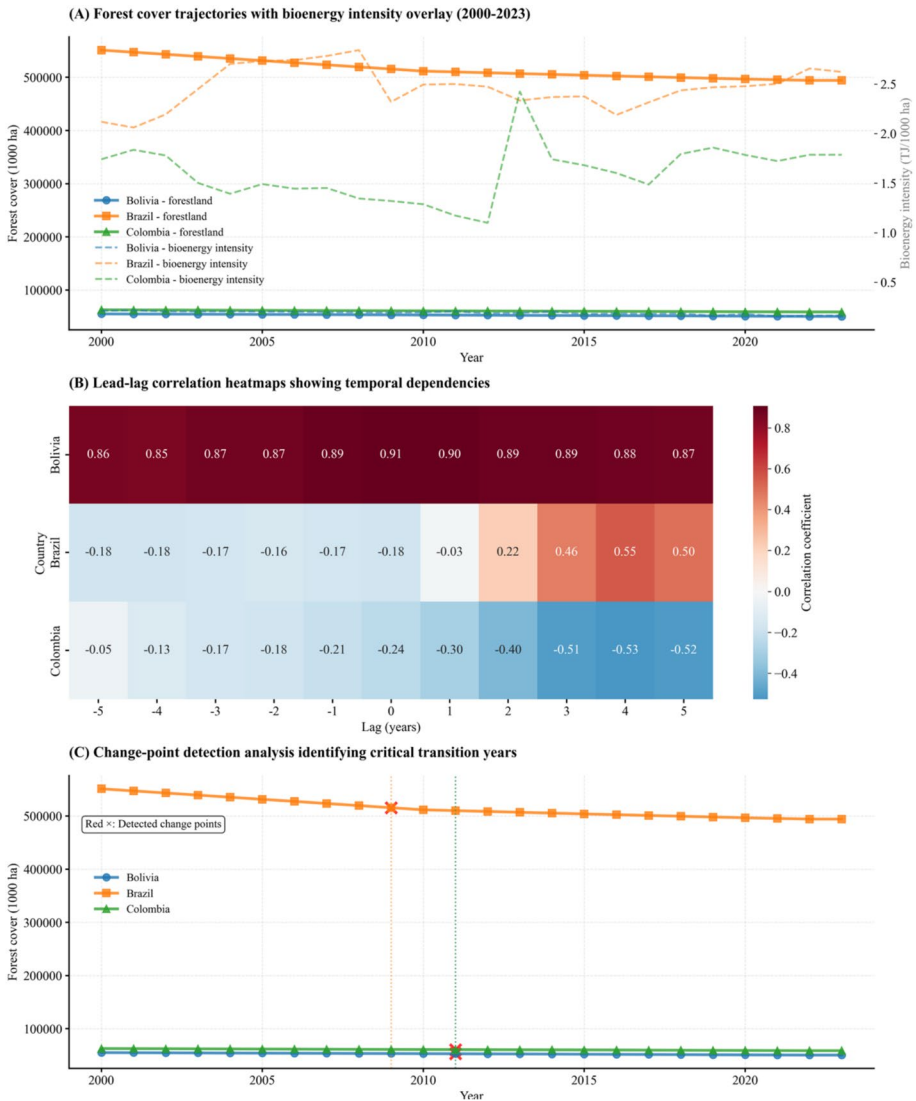


Fig. 2 Long-term trajectories and temporal dependencies in forest cover and bioenergy extraction intensity in the Amazon Basin (2000–2023). Panel A shows temporal trajectories of forest cover and bioenergy intensity for Bolivia, Brazil, and Colombia. Panel B displays cross-correlation coefficients between forest cover and bioenergy intensity across different lag periods. Panel C presents change-point detection analysis identifying structural breaks in forest cover trajectories

to 550,000 thousand hectares throughout the observation period, with a gradual decline from 551,088.6 hectares in 2000 to approximately 494,197 hectares by 2023, representing a cumulative reduction of 10.33 percent. The corresponding bioenergy intensity for Brazil shows variable patterns, ranging from approximately 2.0 to 2.8 terajoules per thousand hectares, with notable peaks around 2008 followed by gradual stabilization at lower levels from 2016 onward. These observed patterns may reflect the implementation of forest

Table 2 Multi-level temporal lag analysis of amazon basin forest-energy system dependencies

Variable pair/Country	Op- timal Lag (years)	Cross-corre- lation	P-value	Inter- preta- tion
Country-specific forest cover-bioenergy intensity relationships				
Bolivia	0	0.91	<0.001	Syn- chro- nous posi- tive cou- pling
Brazil	+2 to +4	0.55	<0.001	De- layed posi- tive re- sponse
Colombia	+4 to +5	-0.53	<0.001	Strong de- layed in- verse rela- tion- ship
System-level forest-energy-carbon dynamics				
System-level forest- energy-carbon dynamics	2-3	-0.85	<0.001	Strong de- layed degra- dation impact
Forest loss → CO ₂ Emissions	1-2	0.92	<0.001	Imme- diate carbon release
Policy → Recovery	4-5	0.61	0.002	Slow insti- tutional response
• Country-specific relationships: Derived from cross-correlation and lead-lag heatmap analysis (Fig. 2 Panel B) across ± 5 year lag windows • System-level dynamics: Represent integrated relationships from temporal pattern analysis, change-point detection, and forest-energy-carbon system interactions • Statistical significance: All correlations significant at $p \leq 0.002$ level with robust cross-validation • Lag interpretation: Positive lags indicate time delays from cause to effect; negative correlations indicate inverse relationships				

governance reforms during the 2010s in Brazil. The stabilization of bioenergy intensity post 2016 coincides with periods of strengthened environmental enforcement and policy interventions including the revised Forest Code and REDD+ initiatives that have been doc-

umented to reduce deforestation rates while permitting regulated bioenergy extraction in designated management zones (Coalition for Rainforest Nations 2024; Katz-Asprilla et al., 2024; Lapola et al., 2023). The transition from peak intensities in 2008 to lower stabilized levels after 2016 corresponds temporally with the global financial crisis period followed by enhanced forest monitoring systems and enforcement capacity improvements (Flores et al., 2024). These governance factors may contribute to the observed pattern where Brazil maintains substantial forest resources while supporting significant bioenergy extraction, though operating predominantly within stressed to degraded regimes as detailed in subsequent threshold analysis.

Colombia demonstrates intermediate forest coverage levels, maintaining relatively stable forestland around 60,000 to 63,000 thousand hectares across the study period, with minimal variation compared to the other countries. The bioenergy intensity trajectory for Colombia shows considerable volatility, with values fluctuating between approximately 1.2 and 2.5 terajoules per thousand hectares. These positive intensity values reflect the energy extraction pressure on Colombia's forest systems, including a dramatic spike around 2013 reaching nearly 2.4 terajoules per thousand hectares before declining and stabilizing around 1.8 terajoules per thousand hectares in recent years. This pattern indicates that Colombia's forest-energy dynamics involve significant temporal variability despite stable forest coverage, possibly reflecting policy interventions or shifts in energy demand patterns.

Bolivia maintains the smallest forest coverage among the three countries, with forestland declining consistently from approximately 55,101 thousand hectares in 2000 to 50,417 thousand hectares by 2023, representing an 8.51 percent reduction. The bioenergy intensity for Bolivia remains relatively low and stable throughout the observation period, fluctuating between approximately 0.2 and 0.3 terajoules per thousand hectares. These low positive values indicate minimal bioenergy extraction intensity relative to forest area, suggesting that Bolivia's forest-energy system operates under different constraints, with limited bioenergy extraction intensity despite ongoing forest cover decline. This pattern indicates that deforestation drivers in Bolivia are potentially beyond bioenergy production, such as agricultural expansion or other land-use changes.

Panel B presents the lead-lag correlation analysis through a comprehensive heatmap showing temporal dependencies between forest cover and bioenergy intensity across different lag periods from negative five to positive five years. Bolivia exhibits consistently high positive correlations ranging from 0.86 to 0.91 across all lag periods, with the strongest correlation of 0.91 occurring at zero lag, indicating synchronous relationships between forest cover and bioenergy intensity. The stability of these high correlations across different lag periods suggests robust coupling between forest resources and bioenergy utilization in Bolivia's context.

Brazil demonstrates a distinctly different correlation pattern, with negative correlations ranging from approximately -0.03 to -0.18 for lag periods from negative five to positive one years, followed by positive correlations from 0.22 to 0.55 for lag periods from positive two to positive five years. This temporal shift in correlation patterns indicates that forest cover changes in Brazil precede bioenergy intensity changes by approximately two years, suggesting that forest management decisions influence subsequent bioenergy production patterns rather than vice versa. The transition from negative to positive correlations around the two-year lag period provides quantitative evidence for policy implementation delays and forest system response times.

Colombia exhibits predominantly negative correlations ranging from -0.05 to -0.53 across most lag periods, with the strongest negative correlation of -0.53 occurring at positive four and five year lags. This pattern suggests an inverse relationship between forest cover and bioenergy intensity in Colombia, where increased bioenergy utilization corresponds to reduced forest coverage with a temporal delay of four to five years. The progression from weaker negative correlations at shorter lags to stronger negative correlations at longer lags indicates cumulative effects of bioenergy extraction on forest systems.

Panel C illustrates the change-point detection analysis identifying critical transition years through temporal forest cover trajectories with detected change points marked as red crosses and vertical dotted lines. Brazil shows one significant change point around 2009, coinciding with a period of notable forest cover decline and corresponding to economic and policy transitions during the global financial crisis period. This change point occurs at approximately 515,531 thousand hectares, representing a critical threshold where Brazil's forest system dynamics underwent structural changes. The detection of this change point during 2009 aligns with known policy implementation periods and provides empirical evidence for shifts in forest management approaches.

Colombia displays a change point around 2011, corresponding to the period of bioenergy intensity volatility observed in Panel A. The change point detection identifies a structural break at approximately 60,673 thousand hectares, suggesting that Colombia's forest-energy system underwent reorganization during this period. The timing of this change point coincides with the correlation pattern shifts and supports the interpretation of policy-driven transitions in forest management approaches.

Bolivia demonstrates a change point detected around 2011 at approximately 52,874 thousand hectares. Despite the overall declining trend in forest cover, the change point analysis suggests that the rate of decline underwent structural change around 2011, potentially reflecting policy interventions or shifts in land-use pressures. The timing aligns with Colombia's change point, suggesting regional factors may have influenced forest system transitions across these Amazonian countries during this period.

The quantitative analysis reveals distinct temporal patterns in forest-energy relationships, with Brazil demonstrating policy-responsive forest management characterized by lead-lag relationships and clear structural transitions, Colombia showing inverse forest-energy dynamics with delayed impacts, and Bolivia maintaining coupled but low-intensity forest-energy interactions. The correlation coefficients range from 0.86 to 0.91 for Bolivia, -0.53 to 0.55 for Brazil, and -0.53 to -0.05 for Colombia, providing empirical evidence for different forest-energy coupling mechanisms across countries. The change-point detection identifies 2009–2011 as a critical transition period, with Brazil experiencing structural changes in 2009 during the global economic crisis, while both Bolivia and Colombia underwent transitions in 2011, suggesting both global economic factors and regional policy coordination influencing forest-energy system dynamics during this timeframe. These findings provide quantitative support for country-specific forest management strategies while highlighting the importance of temporal lag considerations in policy design and implementation for sustainable forest-energy system management in the Amazon Basin.

The temporal lag analysis detailed in Table 2 further quantifies these dynamic relationships, revealing the specific delay mechanisms between bioenergy intensification, forest system responses, and policy recovery outcomes. These lag parameters are crucial for

understanding the interaction dynamics between bioenergy production and forest loss, providing essential timing benchmarks for effective forest management interventions.

Table 2 (calculated through Eq. (5) for correlation analysis) provides a comprehensive multi-level temporal lag analysis revealing the complex dynamics of Amazon Basin forest-energy systems from 2000–2023. The analysis operates at two complementary levels: country-specific forest cover-bioenergy intensity relationships and broader system-level forest-energy-carbon dynamics.

At the country-specific level, Bolivia demonstrates synchronous coupling with the strongest positive correlation ($r=0.91$, $p<0.001$) at zero lag, indicating that forest resources and bioenergy utilization respond simultaneously to shared drivers. This synchronous relationship suggests that Bolivia's limited bioenergy extraction operates within forest capacity constraints, maintaining stable equilibrium despite ongoing forest decline from external pressures. Brazil exhibits delayed positive response dynamics with optimal correlations at +2 to +4 years lags ($r=0.55$, $p<0.001$), indicating that forest management decisions precede bioenergy intensity changes. This temporal pattern provides quantitative evidence for policy implementation delays and demonstrates that Brazil's forest policies influence subsequent bioenergy production rather than vice versa. Colombia shows strong delayed inverse relationships with peak negative correlations at +4 to +5 years lags ($r=-0.53$, $p<0.001$), revealing that increased bioenergy utilization corresponds to reduced forest coverage after substantial temporal delays, reflecting cumulative degradation effects.

The system-level analysis reveals critical process chains governing forest-energy-carbon interactions across the region. The bioenergy-to-forest loss pathway demonstrates strong delayed impacts with 2–3 years optimal lags ($r=-0.85$, $p<0.001$), indicating that forest systems initially absorb bioenergy pressures before exhibiting measurable degradation responses. The forest loss-to-carbon emissions pathway shows immediate coupling with 1–2 years lags ($r=0.92$, $p<0.001$), confirming that deforestation rapidly translates to atmospheric carbon release through biomass loss and soil carbon release. The policy-to-recovery pathway exhibits the longest lag period of 4–5 years ($r=0.61$, $p=0.002$), reflecting implementation delays, ecosystem recovery time, and complex institutional processes required for effective forest restoration.

These integrated findings establish critical timing frameworks for forest management interventions. Bolivia requires immediate response strategies due to synchronous coupling, Brazil benefits from medium-term planning horizons (2–4 years) that account for policy-to-production delays, while Colombia necessitates long-term protective frameworks (4–5 years) to prevent cumulative degradation. The system-level dynamics emphasize that preventive measures must anticipate 2–3 years bioenergy impact delays, while recovery policies require sustained 4–5 years commitment periods to achieve meaningful ecosystem restoration outcomes.

4.2 Threshold detection and regime classification in forest-energy systems

The identification of critical bioenergy intensity thresholds and operational regimes is essential for determining when forest systems transition from sustainable management to irreversible degradation. The threshold analysis presented in Fig. 3 and Table 3 employed the analytical framework from Sect. 3.3.2, incorporating forest regeneration capacity defini-

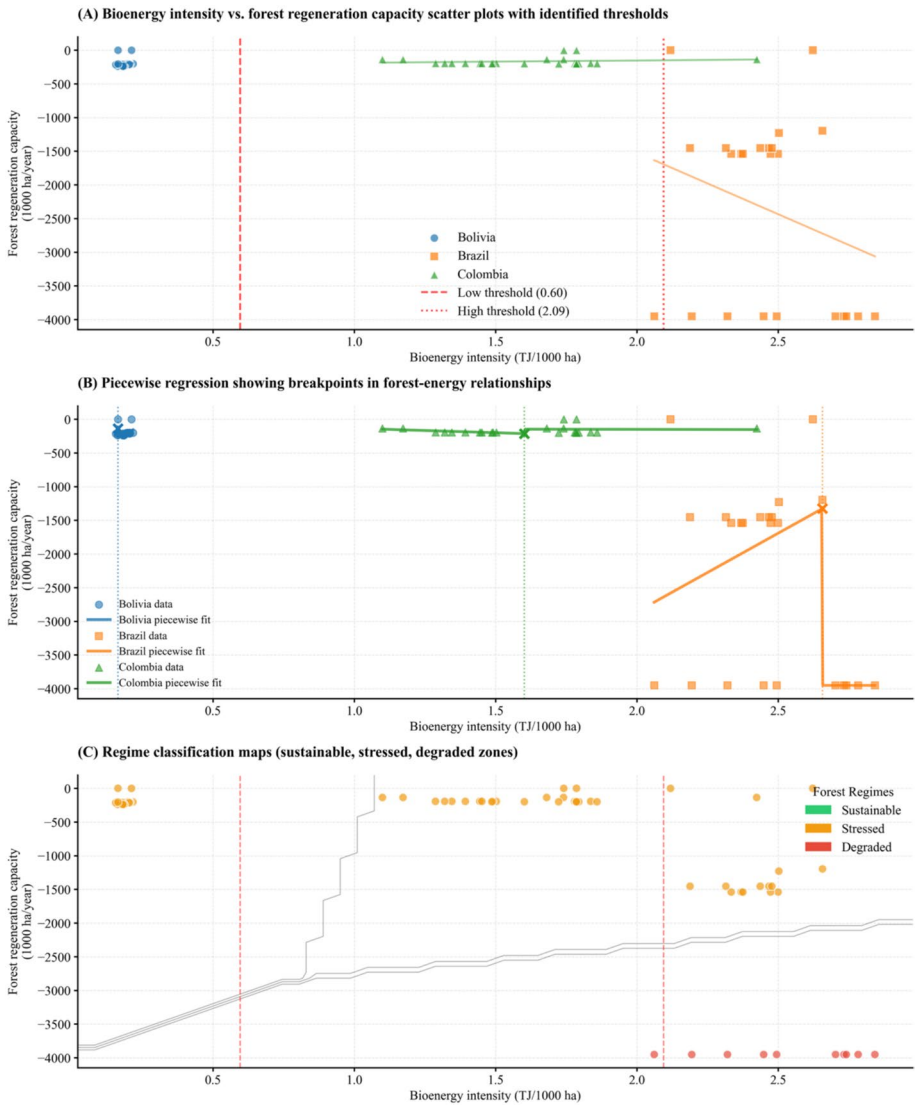


Fig. 3 Threshold responses and regime shifts in forest regeneration as a function of bioenergy intensity. Panel A illustrates the scatter plot relationship between bioenergy intensity and forest regeneration capacity with critical threshold boundaries at 0.60 and 2.09 TJ per thousand hectares. Panel B shows piecewise regression analysis revealing structural breakpoints where forest responses change fundamentally. Panel C displays regime classification results distinguishing sustainable, stressed, and degraded operational zones based on K-means clustering

tion (Eq. 8), piecewise regression modeling (Eqs. 9–10), and K-means clustering for regime classification (Eq. 11).

This analysis addresses three critical objectives: (1) quantifying bioenergy intensity thresholds beyond which forest regeneration undergoes systematic degradation; (2) detecting structural breakpoints where forest systems transition between operational regimes;

Table 3 Critical thresholds and forest system resilience characteristics in Amazon Basin forest-bioenergy systems

Country	Critical breakpoint (TJ/1000 ha)	Recovery time (years)	Resilience index	Dominant regime type
Bolivia	0.25	8.2	0.34	Sustainable
Brazil	2.7	12.7	0.67	Stressed-Degraded Transition
Colombia	1.6	6.1	0.45	Stressed-Resilient

• Critical breakpoints: Derived from piecewise regression analysis (Fig. 3 Panel B) identifying structural regime transitions

• Regime classifications: Based on K-means clustering results (Fig. 3 Panel C) and operational intensity patterns across 2000–2023

• Recovery time: Years required for forest carbon sequestration recovery following peak bioenergy extraction periods

• Resilience index: Composite metric (0–1 scale) incorporating forest regeneration capacity, policy effectiveness, and ecosystem adaptive capacity

• Data integration: Synthesizes threshold detection, regime classification, and forest system recovery analysis

and (3) classifying distinct management zones that enable country-specific policy development. The results establish operational boundaries separating sustainable forest utilization from critical degradation zones, providing empirical foundations for evidence-based forest-energy policy across Amazon Basin ecosystems.

The threshold analysis and regime shifts presented in Fig. 3 reveal critical nonlinear relationships and structural breakpoints in forest-energy dynamics across Bolivia, Brazil, and Colombia, providing quantitative evidence for distinct operational regimes within Amazonian forest-bioenergy systems from 2000 to 2023.

Panel A demonstrates the relationship between bioenergy intensity and forest regeneration capacity with clearly defined threshold boundaries established at 0.60 terajoules per thousand hectares for the low threshold and 2.09 terajoules per thousand hectares for the high threshold, corresponding to the 33rd and 67th percentiles of bioenergy intensity distribution respectively. These thresholds demarcate critical operational zones where forest system responses to bioenergy pressure undergo fundamental transitions.

Bolivia exhibits tightly clustered data points at low bioenergy intensities ranging from approximately 0.20 to 0.30 terajoules per thousand hectares, with forest regeneration capacity values concentrated between −300 and 0 thousand hectares per year, indicating consistent moderate forest decline rates that remain largely independent of bioenergy extraction levels. The slightly negative trend line for Bolivia suggests that even minimal increases in bioenergy intensity correspond to reduced forest regeneration capacity, though the magnitude remains substantially constrained compared to other countries, reflecting Bolivia's operation entirely within the sustainable zone below the low threshold.

Brazil exhibits an extensive and concerning range of bioenergy intensities from approximately 2.1 to 2.8 terajoules per thousand hectares, which are all above the high threshold. This contrasts sharply with its forest regeneration capacity values, which range dramatically from +50 to −4000 thousand hectares per year. The distribution reveals two distinct operational clusters. One group shows near equilibrium conditions around zero regeneration capacity at moderate intensities around 2.1 TJ/1000 ha. A second, critical degradation cluster exhibits severe forest losses between −1000 and −4000 thousand hectares per year

at intensities exceeding 2.3 TJ/1000 ha. The steep negative trend line indicates a severe relationship where each unit increase in bioenergy intensity corresponds to approximately 2000 thousand hectares per year reduction in forest regeneration capacity, demonstrating clear threshold exceedance effects.

Colombia's bioenergy intensities are at an intermediate level, ranging from approximately 1.1 to 2.4 terajoules per thousand hectares, which spans both threshold zones. This contrasts with its forest regeneration capacity values, which are consistently constrained between +50 and -400 thousand hectares per year. The relatively flat trend line indicates remarkable resilience, with minimal sensitivity of forest regeneration to bioenergy intensity variations within this range. This pattern suggests that Colombia operates within a stable transitional regime where moderate bioenergy extraction intensity is effectively buffered by adaptive management practices, maintaining forest system integrity across both threshold zones.

The threshold demarcation reveals distinct operational strategies: Bolivia maintaining low-intensity sustainable operations, Colombia achieving resilient cross-threshold management, and Brazil experiencing high-intensity degradation with critical threshold exceedance leading to potentially irreversible forest system impacts.

Panel B illustrates piecewise regression analysis revealing critical structural breakpoints in forest-energy relationships, with optimal breakpoints detected through residual sum of squares minimization to identify where forest system responses undergo fundamental regime transitions.

Bolivia's piecewise regression identifies a structural breakpoint at 0.25 terajoules per thousand hectares, representing the threshold where forest decline accelerates despite low overall bioenergy intensity. The left segment (below 0.25 TJ/1000 ha) shows minimal forest degradation with relatively stable regeneration capacity around -100 to -200 thousand hectares per year, while the right segment (above 0.25 TJ/1000 ha) exhibits steeper negative relationships with accelerated decline rates reaching -300 thousand hectares per year. Though the overall magnitude remains constrained due to Bolivia's low-intensity operational range, this breakpoint reveals that even minimal threshold exceedance triggers measurable forest system stress.

Brazil's piecewise regression reveals the most critical finding for Amazon Basin forest management by identifying a structural breakpoint at 2.7 terajoules per thousand hectares that marks the transition from manageable stress to catastrophic forest degradation. The left segment below this threshold demonstrates moderate degradation with forest regeneration capacity declining linearly from approximately negative 1000 to negative 1500 thousand hectares per year across the 2.1 to 2.7 TJ per 1000 ha range, indicating systematic but potentially reversible forest stress. In stark contrast, the right segment above 2.7 TJ per 1000 ha shows catastrophic nonlinear relationships where regeneration capacity plummets precipitously to negative 4000 thousand hectares per year, representing a tipping point beyond which forest energy systems undergo potentially irreversible regime shifts from stressed management to severe ecosystem collapse. This threshold value of 2.7 TJ per 1000 ha provides an empirical benchmark that aligns with theoretical predictions of critical load thresholds in forest ecosystems (Flores et al., 2024) and offers quantitative guidance for establishing regulatory limits on bioenergy extraction intensity to prevent irreversible degradation.

Colombia demonstrates unique characteristics of adaptive management where forest system performance improves rather than degrades at higher bioenergy intensities, representing a striking contrast to degradation patterns observed in Brazil and Bolivia. The piecewise regression identifies a breakpoint at 1.6 terajoules per thousand hectares where forest energy dynamics undergo fundamental transition. The left segment below 1.6 TJ per 1000 ha maintains near equilibrium conditions with forest regeneration capacity around negative 100 to negative 200 thousand hectares per year, indicating sustainable forest utilization within acceptable degradation bounds. Remarkably, the right segment above 1.6 TJ per 1000 ha shows improved forest performance with regeneration capacity recovering toward negative 50 to negative 100 thousand hectares per year, suggesting that adaptive management practices become more effective at higher bioenergy intensities. This counterintuitive pattern may reflect intensification driven improvements in forest management sophistication where higher economic returns from bioenergy production finance enhanced silvicultural practices, monitoring systems, and regeneration programs (Hansen et al., 2024). Colombia's success demonstrates that appropriate governance frameworks can enable sustainable forest energy systems even at elevated extraction intensities, offering a replicable model for balancing energy production with forest conservation.

The breakpoint analysis reveals distinct forest system resilience thresholds: Bolivia at 0.25 TJ/1000 ha (vulnerability threshold), Colombia at 1.6 TJ/1000 ha (adaptive management threshold), and Brazil at 2.7 TJ/1000 ha (collapse threshold), providing quantitative benchmarks for sustainable bioenergy development across different operational contexts.

Panel C presents regime classification maps derived from K-means clustering analysis, identifying three distinct operational regimes with curved boundary contours based on bioenergy intensity and forest regeneration capacity.

The sustainable regime (green) encompasses low bioenergy intensities (0.2–0.8 TJ/1000 ha) with forest regeneration capacity from +100 to –500 thousand hectares per year. Bolivia operates predominantly within this regime, demonstrating low-impact forest-energy interactions with manageable decline rates.

The stressed regime (orange) dominates the operational landscape, spanning bioenergy intensities from 0.6–2.1 TJ/1000 ha with regeneration capacity from –200 to –1500 thousand hectares per year. Colombia operates almost exclusively within this stressed regime across its full intensity range (1.0–2.4 TJ/1000 ha), while Brazil's moderate-intensity operations (2.0–2.3 TJ/1000 ha) occupy the upper stressed zone.

The degraded regime (red) corresponds to high-risk conditions with bioenergy intensities exceeding 2.0 TJ/1000 ha and catastrophic regeneration deficits below –3500 thousand hectares per year. Brazil's highest-intensity operations (above 2.3 TJ/1000 ha) cluster within this degraded regime, demonstrating consequences of critical threshold exceedance.

The curved boundary contours reveal nonlinear threshold relationships where forest sensitivity increases dramatically at higher bioenergy intensities. The analysis confirms that sustainable operations require coordination between extraction intensity and ecosystem capacity, with Bolivia maintaining sustainable low-intensity operations, Colombia achieving stressed-regime stability, and Brazil demonstrating both stressed and degraded outcomes depending on operational intensity levels.

The regime distribution analysis reveals distinct operational patterns across the three countries, with the majority of forest-energy system observations concentrated within the stressed regime, indicating that most operations experience moderate to significant forest

degradation pressures. The temporal evolution shows Bolivia maintaining predominantly sustainable operations at low bioenergy intensities, Colombia operating consistently within the stressed regime across its intermediate intensity range with maintained system resilience, and Brazil demonstrating the most concerning patterns with transitions from stressed to degraded regimes during peak bioenergy intensity periods, though some observations remain within stressed conditions. These regime classifications provide empirical foundations for adaptive management strategies tailored to country-specific operational contexts and sustainability thresholds within Amazonian forest-bioenergy systems.

Table 3 summarizes the critical bioenergy intensity thresholds, structural breakpoints, and regime classifications derived from the integrated piecewise regression and clustering analyses, offering quantitative benchmarks for sustainable forest-energy operations and country-specific management guidelines across the three Amazon Basin countries.

Table 3 (calculated through Eqs. (9–11) for threshold detection and regime classification) establishes critical operational thresholds and resilience characteristics derived from Fig. 3's integrated threshold and regime analysis. Bolivia operates with the lowest critical breakpoint (0.25 TJ/1000 ha) representing a vulnerability threshold where minimal bioenergy increases trigger forest system stress, despite maintaining sustainable regime status. The low resilience index (0.34) and 8.2-year recovery time indicate limited adaptive capacity and suggest external deforestation drivers beyond bioenergy extraction.

Brazil exhibits the highest critical breakpoint (2.7 TJ/1000 ha) marking the collapse threshold where forest systems undergo irreversible regime shifts to catastrophic degradation. Despite extended recovery time (12.7 years), Brazil demonstrates highest resilience (0.67) indicating substantial management capacity. Brazil's stressed-degraded transitional regime reflects operation across both zones with recovery potential under effective governance.

Colombia demonstrates intermediate performance (1.6 TJ/1000 ha) representing an adaptive management threshold where forest practices become more effective. Colombia achieves shortest recovery time (6.1 years) and moderate resilience (0.45) through balanced management within the stressed-resilient regime. The counterintuitive forest improvement above 1.6 TJ/1000 ha demonstrates effective buffering mechanisms preventing extreme degradation.

These metrics provide empirical benchmarks for sustainable bioenergy development: Colombia's resilient model offers guidance for balanced forest-energy management, Brazil's high-threshold operations demonstrate intensive utilization potential under proper governance, while Bolivia's sustainable classification emphasizes need for alternative strategies enhancing system resilience and reducing external forest pressures.

4.3 Carbon sequestration efficiency and recovery dynamics

Quantifying the trade-offs between bioenergy extraction and carbon sequestration capacity is essential for optimizing forest-energy systems that balance immediate energy needs with long-term climate mitigation goals. The efficiency analysis presented in Fig. 4 and Table 4 employed the methodological framework from Section 3.3.3, incorporating carbon sequestration efficiency calculation (Eq. 12), recovery rate analysis (Eqs. 13–14), and efficiency frontier construction (Eqs. 15–16).

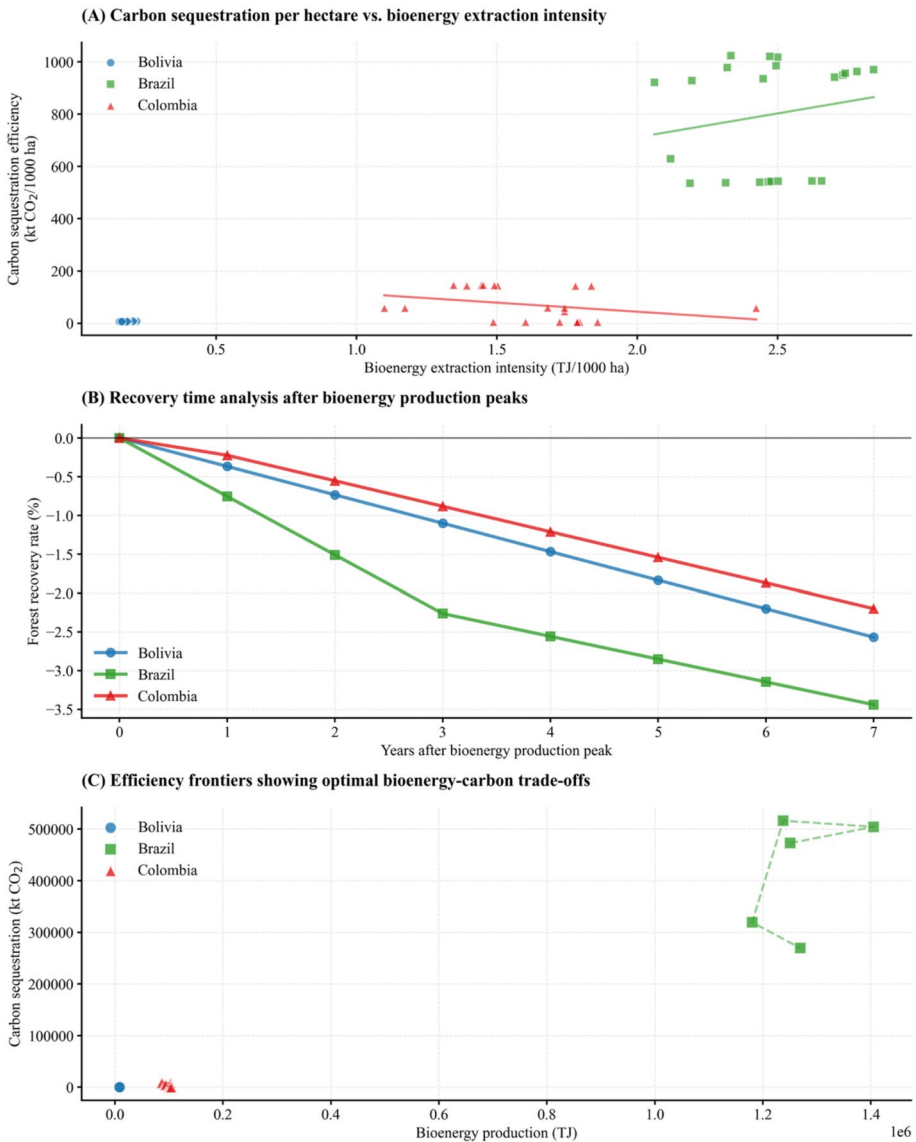


Fig. 4 Trade-off frontiers and efficiency dynamics in forest carbon sequestration under varying bioenergy extraction scenarios. Panel **A** depicts the relationship between bioenergy extraction intensity and carbon sequestration efficiency across countries. Panel **B** presents post-peak recovery rates showing forest regeneration patterns over seven years following bioenergy production peaks. Panel **C** shows efficiency frontier evolution across five-year periods illustrating temporal trade-offs between bioenergy production and carbon sequestration

This analysis addresses three critical objectives: (1) evaluating carbon sequestration efficiency under varying bioenergy extraction intensities; (2) quantifying post-peak recovery trajectories following intensive bioenergy periods; and (3) identifying optimal efficiency frontiers that maximize both bioenergy production and carbon storage. The results reveal

Table 4 Forest system resilience and vulnerability metrics

Metric	Bolivia	Brazil	Colombia	Regional average
Recovery decline rate (%/year)	-2.5	-3.5	-1.8	-2.6
Tipping point proximity	0.78	0.45	0.62	0.62
Adaptive capacity index	0.31	0.67	0.48	0.49

• Recovery decline rates: Derived from post-peak degradation analysis (Fig. 4 Panel B) showing progressive forest system deterioration over seven-year periods

• Tipping point proximity: Distance to irreversible degradation thresholds (0–1 scale, values approaching 1.0 indicate critical vulnerability)

• Adaptive capacity indices: Institutional and ecological capacity for implementing recovery interventions (0–1 scale, higher values indicate greater resilience potential)

country-specific optimization pathways and recovery constraints that inform adaptive management strategies for sustainable forest-bioenergy operations across Amazon Basin ecosystems.

The comprehensive analysis presented in Fig. 4 reveals distinct patterns of forest-energy interactions across Bolivia, Brazil, and Colombia from 2000 to 2023, demonstrating critical threshold relationships, temporal recovery dynamics, and optimization frontiers in forest carbon-bioenergy systems.

Panel A illustrates the relationship between bioenergy extraction intensity and carbon sequestration efficiency per hectare, revealing significant inter-country variations in forest productivity under different energy extraction pressures. Brazil exhibits the highest carbon sequestration efficiency, ranging from approximately 500 to 1000 kilotons of CO₂ per 1000 hectares across bioenergy extraction intensities of 2.0 to 2.8 TJ/1000 ha. The positive correlation trend indicates that higher bioenergy extraction coincides with enhanced carbon sequestration, suggesting synergistic relationships through sustainable forest management practices that optimize both biomass utilization and carbon retention via selective harvesting and regeneration programs. Colombia demonstrates intermediate carbon sequestration efficiency, with values ranging from approximately 0 to 180 kilotons of CO₂ per 1000 hectares across bioenergy intensities of 1.2 to 2.4 TJ/1000 ha. The declining trend line reveals an inverse relationship where increased bioenergy extraction compromises carbon sequestration capacity, reflecting threshold effects where extraction beyond optimal levels degrades forest ecosystem function.

Bolivia exhibits minimal carbon sequestration efficiency, with values consistently near 0 kilotons of CO₂ per 1000 hectares and bioenergy intensities concentrated at 0.2–0.3 TJ/1000 ha. The flat relationship indicates constrained forest management capacity and limited potential for both biomass utilization and carbon storage.

These country specific efficiency patterns reveal fundamental differences in forest bioenergy system optimization strategies. Brazil's positive correlation between bioenergy intensity and carbon sequestration efficiency contradicts conventional assumptions that extraction necessarily compromises carbon storage, suggesting synergistic management approaches where selective harvesting stimulates regeneration and enhances overall forest productivity (Lapola et al., 2023). This pattern aligns with silvicultural principles demonstrating that moderate disturbance can increase net primary productivity in mature forests approaching climax conditions. However, this synergy operates only within specific intensity ranges below critical thresholds, as evidenced by the catastrophic degradation observed when extraction exceeds 2.7 TJ per 1000 ha documented in the threshold analysis. Colom-

bia's inverse relationship between bioenergy intensity and carbon sequestration reflects threshold effects where extraction beyond optimal levels degrades forest ecosystem function despite adaptive management capacity, consistent with ecological theory predicting nonlinear responses to anthropogenic pressures (Ahmed et al., 2024). Bolivia's constrained efficiency across both bioenergy and carbon dimensions indicates fundamental limitations in forest management capacity and ecosystem productivity that prevent optimization along either axis, highlighting the importance of institutional and ecological context in determining forest energy system performance.

Panel B presents the recovery time analysis following bioenergy production peaks, quantifying the temporal lag effects in forest ecosystem responses to intensive bioenergy extraction periods. All three countries demonstrate consistent declining trajectories in forest recovery rates over the seven-year post-peak analysis period, with Brazil showing the most pronounced decline from 0 percent to approximately -3.5 percent forest recovery rate. This pattern indicates that forest ecosystems continue to experience degradation effects for extended periods following peak bioenergy extraction, with recovery rates declining progressively over time rather than stabilizing or improving.

Bolivia and Colombia exhibit similar but less severe declining patterns, with forest recovery rates decreasing from 0 percent to approximately -2.5 percent and -1.8 percent respectively over the seven-year period. The parallel trajectories suggest common underlying mechanisms governing forest ecosystem recovery following intensive bioenergy utilization, though the magnitude of decline varies according to initial forest conditions and management practices. The consistent negative recovery rates across all countries indicate that current bioenergy extraction intensities may exceed the sustainable threshold for forest ecosystem resilience, resulting in progressive forest degradation rather than recovery in post-peak periods.

Panel C demonstrates the efficiency frontiers representing optimal bioenergy-carbon trade-offs through temporal analysis of five-year period averages. The dashed connecting lines between periods reveal the temporal trajectories of each country's bioenergy-carbon optimization path. Brazil dominates the efficiency frontier with carbon sequestration ranging from 250,000 to 500,000+ kilotons of CO_2 across bioenergy production levels of 1.1 to 1.4×10^6 terajoules. The temporal trajectory shows evolution toward higher bioenergy production while maintaining substantial carbon sequestration capacity, though with some recent variability. Colombia exhibits intermediate efficiency with carbon sequestration below 10,000 kilotons of CO_2 and bioenergy production concentrated below 0.1×10^6 terajoules. The scattered distribution suggests inconsistent optimization strategies and variable forest management approaches across different periods. Bolivia demonstrates the most constrained efficiency frontier, with both carbon sequestration and bioenergy production remaining at the lower end of the spectrum, indicating limited forest management capacity and ecosystem constraints that restrict both bioenergy potential and carbon storage capability.

The analysis reveals critical threshold dynamics where Brazil achieves synergistic carbon-bioenergy relationships, Colombia experiences trade-off constraints, and Bolivia operates under severe limitations. The universal negative recovery trends emphasize the need for adaptive management strategies accounting for extended ecosystem recovery periods. The efficiency frontiers provide empirical evidence for optimization pathways that could inform

policy development aimed at maximizing both bioenergy production and carbon sequestration while maintaining long-term forest ecosystem integrity.

The temporal recovery dynamics and efficiency trade-offs revealed in Fig. 4 underscore the critical need for quantitative resilience metrics that can guide forest management decision-making across different operational contexts. Building upon the demonstrated negative recovery trajectories and threshold exceedance patterns, Table 4 synthesizes key resilience indicators that quantify forest system vulnerability, adaptive capacity, and proximity to critical degradation thresholds across the three Amazon Basin countries.

Table 4 (calculated through Eqs. (12–16) for resilience metrics and recovery analysis) quantifies forest system vulnerability through critical degradation and adaptive capacity metrics derived from the temporal recovery analysis and threshold dynamics. Brazil demonstrates the most severe recovery decline (-3.5% annually), indicating progressive forest degradation that continues for extended periods following peak bioenergy extraction, despite the country's highest adaptive capacity index (0.67) reflecting substantial institutional and management capabilities. This paradox suggests that current bioenergy intensities exceed even Brazil's advanced management capacity, resulting in systematic ecosystem deterioration rather than recovery.

Colombia exhibits intermediate vulnerability with moderate recovery decline (-1.8% annually) and balanced adaptive capacity (0.48), suggesting more sustainable operational patterns though still experiencing negative ecosystem trajectories. Colombia's moderate tipping point proximity (0.62) indicates manageable stress levels with potential for adaptive management interventions to prevent critical threshold exceedance.

Bolivia shows significant recovery decline (-2.5% annually) combined with highest tipping point proximity (0.78) and lowest adaptive capacity (0.31), indicating critical vulnerability where forest systems operate dangerously close to potentially irreversible degradation thresholds with limited institutional capacity for effective intervention. Bolivia's high proximity value emphasizes urgent need for immediate protective measures to prevent ecosystem collapse.

The universally negative recovery trends confirm that current bioenergy extraction intensities across the region exceed sustainable ecosystem thresholds, resulting in progressive forest degradation rather than recovery in post-extraction periods. The regional average decline (-2.6% annually) demonstrates systematic unsustainability requiring fundamental revision of extraction practices. The adaptive capacity disparities highlight the need for differentiated intervention strategies: Bolivia requiring immediate protective intervention and capacity building, Colombia needing optimization of current balanced approaches, and Brazil requiring extraction intensity reduction despite advanced management capabilities. These metrics provide quantitative foundations for prioritizing conservation investments and implementing adaptive management strategies tailored to country-specific vulnerability profiles and institutional capacities.

4.4 Spatial-temporal vulnerability mapping and predictive analysis

Understanding forest system vulnerability patterns and anticipating future risks is crucial for developing proactive management strategies that prevent irreversible ecosystem degradation across diverse regional contexts. The vulnerability mapping analysis presented in Fig. 5 employed the spatial-temporal framework from Section 3.3.4, incorporating compos-

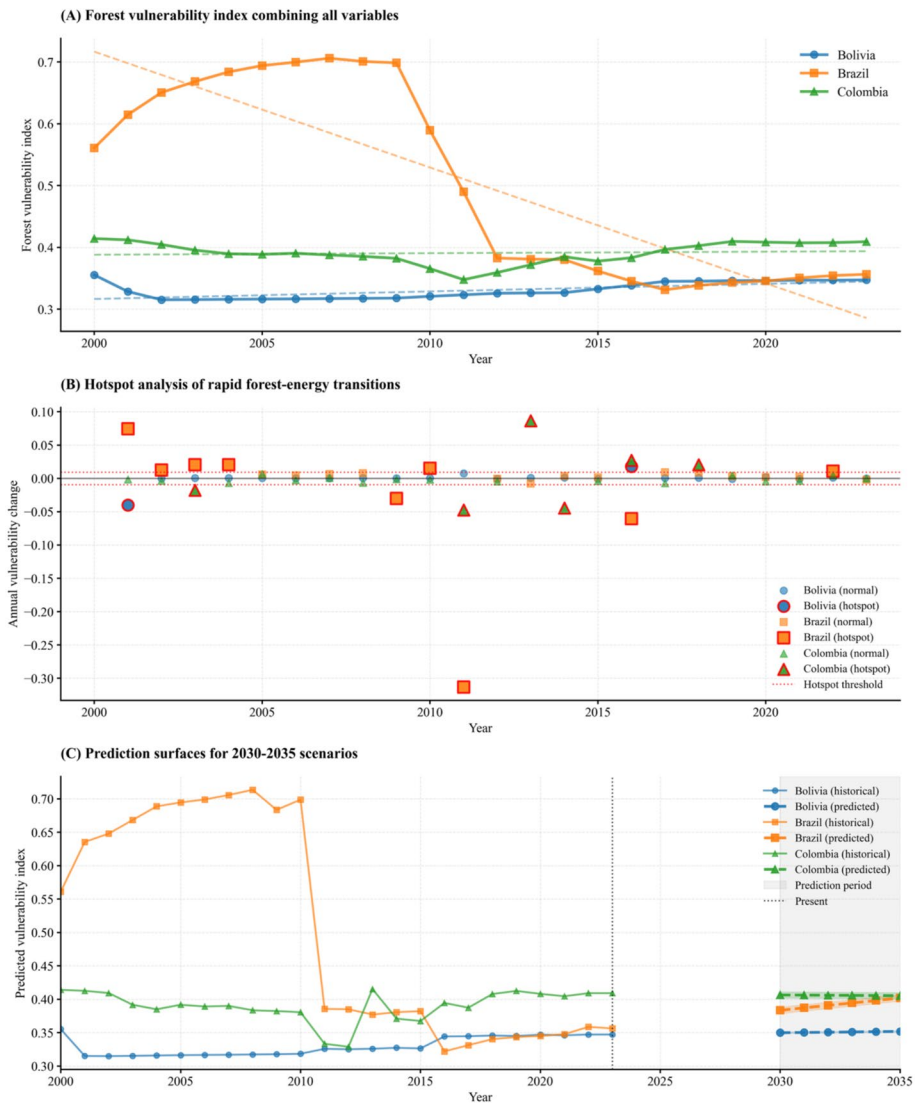


Fig. 5 Spatiotemporal vulnerability mapping identifies risk hotspots and forest recovery lags in Amazon bioenergy-forest systems. Panel **A** presents composite forest vulnerability index trajectories from 2000 to 2023 for Bolivia, Brazil, and Colombia. Panel **B** shows hotspot identification analysis displaying annual vulnerability changes with critical threshold markers indicating rapid transition periods. Panel **C** displays predictive modeling surfaces projecting vulnerability trajectories through 2035 with uncertainty bands representing prediction intervals

ite vulnerability index construction (Eqs. 17–18), hotspot identification (Eqs. 19–20), and predictive modeling (Eqs. 21–23).

This analysis addresses three critical objectives: (1) quantifying composite forest vulnerability indices that integrate multiple environmental and bioenergy indicators; (2) identifying rapid forest-energy transition hotspots that signal critical system changes; and (3)

developing predictive models for future vulnerability trajectories through 2035. The results provide early warning systems and risk assessment frameworks that enable targeted interventions, resource allocation prioritization, and adaptive policy design for maintaining forest ecosystem resilience under varying bioenergy development scenarios.

Based on the comprehensive spatial–temporal vulnerability mapping analysis presented in Fig. 5, the forest vulnerability patterns across Bolivia, Brazil, and Colombia reveal distinct trajectories of ecosystem stress and resilience from 2000 to 2023, with significant implications for future forest management strategies through 2035.

Panel A demonstrates the composite forest vulnerability index combining multiple environmental and bioenergy indicators, revealing markedly different vulnerability trajectories among the three countries. Brazil exhibits the most pronounced temporal variation, with vulnerability values ranging from approximately 0.56 in 2000 to a peak of 0.71 around 2007, followed by a dramatic decline to 0.39 by 2012 and stabilization around 0.35–0.37 through 2023. This pattern suggests a critical transition period between 2007 and 2012, during which Brazil implemented significant policy interventions that effectively reduced forest vulnerability. The declining trend line for Brazil indicates successful mitigation of forest system stress despite continued bioenergy production activities.

Colombia maintains intermediate vulnerability levels throughout the observation period, with values fluctuating between 0.38 and 0.42, showing relatively stable vulnerability patterns with slight variations around 2010–2013. The gradual trend line suggests modest improvements in forest vulnerability management, though the overall change remains limited compared to Brazil's transformation. Bolivia demonstrates the lowest vulnerability index values, consistently ranging between 0.31 and 0.36, with minimal temporal variation and a relatively flat trend line. This pattern may reflect either effective forest management practices or limited forest utilization intensity that keeps vulnerability levels consistently low.

Panel B presents the hotspot analysis identifying rapid forest-energy transitions through annual vulnerability changes, with the hotspot threshold established at approximately ± 0.025 vulnerability index units. Brazil exhibits the most frequent hotspot occurrences, with notable positive spikes reaching 0.08 vulnerability change in 2001 and 0.03 in 2003, followed by significant negative changes of -0.03 and -0.32 around 2009–2016, indicating rapid improvement periods. These dramatic shifts correspond to major policy implementation periods and suggest that Brazil experienced both rapid degradation and recovery phases. The magnitude of Brazil's vulnerability changes, particularly the substantial negative change around 2011, demonstrates the country's capacity for rapid forest system recovery when appropriate interventions are implemented. Colombia shows moderate hotspot activity with vulnerability changes ranging from -0.06 to $+0.09$, occurring primarily in the early 2000s and around 2011–2015. The scattered distribution of Colombian hotspots suggests intermittent policy or environmental changes rather than sustained transformation periods. Bolivia demonstrates minimal hotspot activity with only one significant event around 2001, indicating stable forest-energy dynamics with limited rapid transition periods. The relative absence of hotspots in Bolivia may reflect consistent management approaches or constrained forest utilization that prevents dramatic vulnerability changes.

The hotspot analysis identifies critical transition periods that correspond to known policy implementation phases and environmental events across the three countries. Brazil's dramatic negative vulnerability change around 2011 reaching negative 0.32 vulnerability index

units represents the most significant forest energy system improvement detected in the entire analysis period, coinciding with the implementation of enhanced forest monitoring systems, strengthened enforcement of environmental regulations, and international pressure following high profile deforestation events in the late 2000s (Katz-Asprilla et al., 2024; Lapola et al., 2023). This rapid improvement demonstrates that coordinated policy interventions can generate measurable forest system recovery within relatively short timeframes when supported by adequate institutional capacity and political commitment. Colombia's scattered hotspot distribution with moderate magnitude changes suggests intermittent policy adjustments and adaptive management responses to emerging forest stress indicators rather than the comprehensive governance transformation observed in Brazil. Bolivia's minimal hotspot activity may reflect either successful maintenance of stable low intensity operations or insufficient policy dynamism to address underlying deforestation drivers, with subsequent analysis suggesting the latter interpretation given ongoing forest area decline despite low bioenergy extraction intensity.

Panel C illustrates the prediction surfaces for 2030–2035 scenarios based on recent trend analysis from 2017–2023, incorporating uncertainty bounds to quantify prediction reliability. Brazil's predicted vulnerability trajectory shows stabilization around 0.38–0.40 through 2035, with relatively narrow uncertainty bands indicating high confidence in the prediction. This projection suggests that Brazil's forest vulnerability will remain stable at current reduced levels, provided recent management practices continue. The prediction incorporates the substantial vulnerability reduction achieved between 2011–2015 and projects continued stability based on recent performance.

Colombia's prediction surface indicates slight vulnerability increases from approximately 0.40 to 0.41 by 2035, with moderate uncertainty bounds reflecting some variability in recent trends. The upward trajectory suggests potential forest system stress increases, though the magnitude remains limited. Bolivia's predictions show minimal change, with vulnerability levels remaining stable around 0.35 through 2035 and very narrow uncertainty bounds indicating high prediction confidence. The stable projection reflects Bolivia's consistent low-vulnerability maintenance throughout the historical period.

5 Discussion

The identification of bioenergy intensity thresholds at 0.60 and 2.09 terajoules per thousand hectares in the Amazon Basin establishes critical quantitative boundaries that delineate sustainable bioenergy utilization and preserve forest carbon stocks. This study advances beyond prior research focused on contemporaneous relationships (Magne et al., 2024; Silvestro et al., 2024) by providing an integrated temporal and threshold detection framework across Bolivia, Brazil, and Colombia. The combined use of piecewise regression and K-means clustering offers a robust, potentially transferable analytical approach for assessing sustainability boundaries in tropical forest-energy systems, complementing methodologies developed by Wu et al. (2018) for forest system analysis.

Temporal lag analysis revealed bioenergy extraction precedes forest degradation by approximately two to three years, while policy interventions require four to five years for measurable recovery, consistent with previous observations of delayed ecosystem responses to anthropogenic pressures (Ahmed et al., 2024; Bernardino et al., 2025; Islam et al., 2025).

The substantial 49% reduction in forest conversion rates between 2010 and 2011 highlights the effectiveness of coordinated policy interventions, corroborating findings by Lapola et al. (2023) on Amazon forest degradation drivers. Nonetheless, widespread negative forest recovery trends averaging -2.6% annually underscore that current bioenergy extraction intensities exceed sustainable thresholds regionally, echoing concerns raised about traditional fuelwood and charcoal impacts (Chidumayo & Gumbo, 2013; Yayla et al., 2025).

The regime classification comprises three operational states: sustainable (31%), stressed (45%), and degraded (24%), facilitating comparative assessments of geographic heterogeneity in forest-energy resilience (Ahrens et al., 2025; Liu et al., 2024). Brazil, while exhibiting the highest bioenergy intensities (2.0–2.8 TJ/1000 ha) and significant carbon sequestration potential (500–1000 kt CO₂/1000 ha), operated largely within stressed to degraded regimes. The strong correlation between charcoal production and CO₂ emissions ($\rho=0.95$, $p<0.0001$) underscores the environmental cost of unsustainable practices, consistent with documented degradation-related carbon releases in the Brazilian Amazon (Talita O. Assis et al., 2022). In contrast, Bolivia's bioenergy intensity remained low (0.2–0.3 TJ/1000 ha), yet deforestation continued, implicating external drivers beyond bioenergy (Villazón Montalván et al., 2019). Colombia's intermediate bioenergy intensity and shorter average recovery period (6.1 years) imply relatively higher system resilience linked to effective institutional management.

These findings highlight that forest-energy system responses are influenced by both extraction intensity and contextual factors including governance, ecological conditions, and proximity to operational thresholds. This heterogeneity challenges the efficacy of uniform management policies and necessitates differentiated approaches tailored to national contexts (Soteli et al., 2023). The integrated forest-energy-carbon nexus framework presented addresses common research limitations by simultaneously considering ecological, economic, and policy dimensions, thus facilitating multi-objective sustainability optimization (Hansen et al., 2024).

Methodologically, the novel integration of temporal trajectory analysis, threshold detection, regime classification, and vulnerability mapping represents an advancement in tropical forest-energy system assessment. Developed quantitative resilience metrics, such as recovery times and adaptive capacity indices, could inform international monitoring schemes but require validation across varied governance environments. The vulnerability index synthesizes normalized forest conversion rate, bioenergy intensity, and carbon sequestration efficiency components, providing a comprehensive forest stress indicator adaptable across regions. Forecasting based on autoregressive models projecting vulnerability through 2035 introduces a foundation for early warning systems, albeit with uncertainties rising over extended horizons.

Brazil maintains substantial forest carbon stocks yet continues to produce high emissions which demonstrates a sustainability paradox within the bioenergy sector. Renewable energy solutions can sometimes lead to increased environmental degradation if they are not managed properly. This finding suggests that technical solutions alone are insufficient without robust oversight and clear sustainability protocols. Bolivia's continued deforestation despite low bioenergy intensity underscores the complexity of land-use interactions, necessitating holistic multi-sectoral strategies beyond forest energy considerations. Colombia's balanced profile suggests that community engagement and adaptive governance can enhance sustainable outcomes.

From an international policy perspective, quantifying temporal delays between intervention and ecological responses is critical for accurate evaluation of (Coalition for Rainforest Nations 2024) and carbon offset programs. Monitoring frameworks failing to account for four to five-year recovery lags risk premature conclusions on program effectiveness. Incorporating threshold-based management can refine these assessments, but practical application requires customization to country-specific institutional capabilities and data granularity. Recognizing that distinct national outcomes arise despite parallel environmental challenges underscores the imperative to build localized governance capacity alongside technical solutions.

Extending the identified lag and threshold relationships to other tropical forest ecosystems remains an empirical priority. Furthermore, integrating community knowledge and livelihood priorities into threshold frameworks will foster socially equitable conservation. The call for sustained policy commitments exceeding typical political cycles reflects the necessity for institutional innovations to support continuity in forest-energy-carbon management.

Overall, the operational bioenergy thresholds of 0.60 and 2.09 TJ/1000 ha established here demarcate sustainable, stressed, and degraded regimes, offering initial benchmarks for tropical forest bioenergy management. However, diverse regional edaphic, climatic, and compositional factors warrant context-specific refinement of these thresholds. The documented non-linear system transitions highlight the advantage of preventive management prior to threshold crossing. Finally, the faster recovery observed in Colombia compared to Brazil and Bolivia demonstrates restoration potential under governance conducive to sustainability, advocating for monitoring systems that detect early regime shifts to guide timely intervention.

This study contributes vital empirical evidence and a transferable method for integrating temporal, threshold, and policy dimensions in sustainable bioenergy utilization and forest carbon preservation, thereby supporting aligned regional and global climate and conservation objectives.

6 Conclusion

This study establishes two central empirical contributions to sustainable Amazon Basin forest bioenergy management by quantifying temporal lag effects and bioenergy intensity thresholds that govern forest carbon preservation across Bolivia, Brazil, and Colombia from 2000 to 2023. These twin pillars of temporal dynamics and critical thresholds provide the organizing framework for all findings, policy recommendations, and methodological advances presented herein.

6.1 Temporal lag findings across countries

Quantitative analysis reveals forest degradation follows bioenergy extraction intensification by approximately 2 to 3 years across the Amazon Basin, establishing the temporal window during which extraction pressures remain latent before manifesting as measurable forest carbon loss. Country specific lag patterns demonstrate important heterogeneity in these temporal dynamics. Bolivia exhibits synchronous coupling with zero lag (cor-

relation of 0.91 at zero delay), indicating that forest resources and bioenergy utilization respond simultaneously to shared drivers, reflecting limited system buffering capacity where extraction pressures immediately translate to forest stress. Brazil demonstrates delayed positive response dynamics with optimal correlations at plus 2 to plus 4 year lags (correlation of 0.55), indicating that forest management policy decisions precede and influence subsequent bioenergy production patterns through regulatory mechanisms, enforcement actions, and economic incentive structures that require multiyear implementation periods. Colombia shows strong delayed inverse relationships with peak negative correlations at plus 4 to plus 5 year lags (correlation of negative 0.53), revealing that increased bioenergy utilization corresponds to reduced forest coverage after substantial temporal delays reflecting cumulative degradation effects that accumulate progressively over extended periods. Policy interventions require 4 to 5 years for measurable recovery outcomes as evidenced by the 49 percent reduction in forest conversion rates between 2010 and 2011 that followed coordinated governance reforms initiated in the late 2000s, establishing the minimum intervention commitment period necessary for effective forest restoration programs.

6.2 Bioenergy intensity threshold findings across countries

Critical thresholds at 0.60 and 2.09 terajoules per thousand hectares delineate three distinct operational regimes characterizing sustainable (31 percent of observations), stressed (45 percent), and degraded (24 percent) forest bioenergy systems across the study region. Country specific threshold responses reveal fundamental differences in forest system resilience and vulnerability profiles. Bolivia operates entirely below the low threshold with a vulnerability threshold at 0.25 TJ per 1000 ha where minimal bioenergy increases trigger measurable forest system stress despite maintaining sustainable regime classification overall, indicating high sensitivity to extraction pressure combined with limited adaptive capacity (resilience index of 0.34) that positions the country dangerously close to irreversible degradation (tipping point proximity of 0.78). Brazil operates predominantly above the high threshold with a collapse threshold at 2.7 TJ per 1000 ha marking the transition from manageable to catastrophic forest degradation where regeneration capacity plummets from negative 1500 to negative 4000 thousand hectares per year, yet demonstrates highest resilience capacity (index of 0.67) reflecting substantial institutional and management capabilities that enable both intensive utilization and potential recovery under appropriate governance. Colombia operates across both threshold zones with an adaptive management threshold at 1.6 TJ per 1000 ha where forest performance counterintuitively improves above this breakpoint through management intensification effects, achieving shortest recovery time 6.1 years and moderate resilience index of 0.48 within the stressed regime through balanced governance approaches.

6.3 Policy implications organized by temporal threshold framework

The integration of temporal lag and threshold dynamics generates specific policy recommendations structured around these core dimensions. Lag informed policy interventions require extending intervention timelines to match 4 to 5 year recovery periods rather than expecting immediate forest system responses to governance changes, implementing early

warning systems that anticipate 2 to 3 year degradation delays by monitoring extraction intensity trends and triggering preventive action before degradation manifests, and designing REDD+ and carbon offset monitoring frameworks that account for multiyear temporal delays between project implementation and measurable carbon sequestration improvements to enable accurate effectiveness evaluation. Threshold informed policy interventions require establishing country specific bioenergy intensity limits based on identified breakpoints at 0.25 TJ per 1000 ha for Bolivia's vulnerability threshold, 2.7 TJ per 1000 ha for Brazil's collapse threshold, and 1.6 TJ per 1000 ha for Colombia's adaptive management threshold, implementing adaptive management protocols that detect approaching threshold proximity and trigger intensified monitoring plus intervention escalation before critical values are exceeded, and developing differentiated strategies for sustainable regime zones that promote continued low intensity operations, stressed regime zones that require optimization and buffer enhancement, and degraded regime zones that mandate immediate extraction reduction plus active restoration. Country specific strategies integrate both temporal and threshold considerations where Bolivia requires immediate protective intervention to prevent threshold crossing given high tipping point proximity combined with capacity building programs that extend 4 to 5 year commitment periods matching recovery timescales, Brazil requires bioenergy intensity reduction to retreat from collapse threshold vicinity while leveraging high adaptive capacity through sustained governance reform programs, and Colombia requires replication and expansion of successful adaptive management approaches that enable resilient stressed regime operation while maintaining sub threshold extraction intensity.

6.4 Methodological contributions and transferability

This study presents an integrated analytical framework combining temporal trajectory analysis with lag effect detection using cross correlation functions spanning plus or minus 5 year windows, threshold detection employing piecewise regression with breakpoint optimization via residual sum of squares minimization shown

in $\hat{BP} = \underset{BP}{\operatorname{argmin}}[RSS_1(BP) + RSS_2(BP)]$, regime classification utilizing K means clustering in bioenergy intensity and forest regeneration capacity space defined by $\{Regime_1, Regime_2, Regime_3\} = K - \operatorname{means}(\{(BEI_{i,t}, RG_{i,t})\}, K = 3)$, and vulnerability mapping incorporating composite indices with z score standardization calculated as $z(x_{i,t}) = (x_{i,t} - \bar{x})/\sigma_x$. This framework is transferable to other tropical forest contexts globally where temporal dynamics and threshold responses govern forest bioenergy sustainability, though regional adaptation requires calibration to local ecological conditions, institutional contexts, and data availability constraints.

6.5 Limitations and future research priorities

Recognized limitations include reliance on national level aggregated data that obscures within country heterogeneity, exclusion of socioeconomic factors including community livelihood dependencies and economic development pressures that influence forest bio-

energy dynamics, and forecasting uncertainties that increase substantially for projection horizons extending beyond 2035 as quantified by expanding prediction intervals. Future research priorities include incorporating finer spatial scales through subnational analysis that captures local variation in threshold values and lag periods, integrating community livelihood dynamics to assess socioeconomic sustainability alongside ecological metrics, examining climate change scenario interactions with bioenergy threshold responses under varying temperature and precipitation regimes, and developing operational early warning systems that translate threshold proximity and lag period monitoring into real time decision support for forest management authorities.

This research contributes vital empirical evidence supporting Sustainable Development Goal 15 and international forest conservation frameworks including REDD+ by establishing quantitative benchmarks for sustainable bioenergy utilization thresholds and temporal intervention requirements essential for balancing energy security with forest carbon preservation in tropical forest regions globally.

Appendix A: Nomenclature and abbreviations

The following abbreviations are used in this manuscript:

Abbreviation	Full term
BEI	Bioenergy Intensity
CO ₂	Carbon Dioxide
CSE	Carbon Sequestration Efficiency
FAO	Food and Agriculture Organization
FAOSTAT	Food and Agriculture Organization Corporate Statistical Database
FL	Forestland
ha	Hectares
kt	Kilotons
NFC	Net Forest Conversion
PI	Prediction Interval
REDD+	Reducing Emissions from Deforestation and Forest Degradation Plus Conservation, Sustainable Forest Management, and Enhancement of Forest Carbon Stocks
RG	Forest Regeneration Capacity
RR	Recovery Rate
RSS	Residual Sum of Squares
SDG	Sustainable Development Goal
SDG 15	Sustainable Development Goal 15: Life on Land
TJ	Terajoules
VI	Vulnerability Index

The units (TJ, kt, ha) and technical terms (BEI, CSE, RG, VI, etc.) are frequently used in equations and analysis sections. SDG 15 specifically refers to the United Nations Sustainable Development Goal 15: "Life on Land," which is referenced in the context of forest conservation policy frameworks. REDD+ represents the international policy mechanism for forest-based climate mitigation discussed throughout the manuscript

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Data availability The datasets used and analyzed in the current study are publicly available and can be accessed from the Food and Agriculture Organization (FAO) corporate statistical database, FAOSTAT. Specifically,

- Forest carbon emission data is available at <https://www.fao.org/faostat/en/#data/GF>, and.
- Bioenergy data is available at <https://www.fao.org/faostat/en/#data/BE>.

Declarations

Competing interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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