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Bioclimatic Emission Amplification: A New Paradigm in Climate-Biosphere Feedback Dynamics

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ABSTRACT

This study introduces the Bioclimatic Emission Amplification Theory (BEAT), a novel framework for detecting and forecasting how terrestrial ecosystems, particularly the Amazon Basin, transition from being carbon sinks to becoming carbon sources under compounded bioclimatic stress. BEAT synthesizes satellite-derived data from 2001 to 2022 and integrates temperature anomalies, vapor pressure deficit (VPD), fire activity, and vegetation degradation into a Compound Stress Index (CSI). Methodologically, the study applies piecewise regression, changepoint analysis, and early warning signal (EWS) metrics, including rolling variance and lag-1 autocorrelation, to identify nonlinear emission tipping points and ecological resilience loss. Machine learning models such as XGBoost and SHAP were employed to evaluate the predictive relevance of CSI components and enhance model interpretability. Results reveal a critical CSI threshold (≥ 0.6), beyond which Net Ecosystem Exchange (NEE) exhibits abrupt positive anomalies, indicating carbon emission amplification. EWS metrics significantly increased prior to emission spikes, validating BEAT's predictive capacity for ecological destabilization. In addition, spatial clustering and time-lagged correlation analysis confirmed the alignment between compound stress hotspots and emission anomalies, and when compared to traditional Earth System Models (ESMs), BEAT uniquely captures synergistic stress interactions and nonlinearity. The findings underscore BEAT's potential to improve early warning systems,

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REDD+ monitoring frameworks, and climate adaptation planning. Its scalable design enables application across vulnerable biomes globally and offers a transformative tool for anticipating biosphere-climate tipping points and informing proactive ecosystem governance.

Keywords: Climate Change; Machine Learning; Bioclimatic; Feedback Loops; Greenhouse Gas Emissions; Environment Sustainability

1. Introduction

Climate change is an ever-growing challenge of the century, described by rising global temperatures, extreme weather phenomena, and extensive ecological disruptions. The Amazon Basin, one of the world's significant carbon sinks, plays a pivotal role in regulating Earth's carbon balance. However, the accelerating rate of land-use, deforestation, and climate-induced stresses is putting great pressure on ecosystems such as the Amazon Basin, pushing them towards concerning tipping points. These tipping points could transform these useful carbon sinks into net carbon sources and therefore compound global warming and reduce the effectiveness of current environmental mitigation strategies. Current models often treat biosphere-atmosphere interactions as largely linear processes, with gradual changes in emissions correlated with climatic or anthropogenic drivers [1]. These models (e.g., CLM, LPJmL, CMIP6 ESMs) often assume linear vegetation responses and fail to incorporate compound stressor interactions, tipping point dynamics, and early warning signals. For example, CLM typically separates fire, drought, and vegetation dynamics; LPJmL underrepresents feedback amplification; CMIP6 models rarely include resilience thresholds or machine learning-derived diagnostics. This limits their ability to predict abrupt emissions shifts under compounded stress scenarios. However, this assumption is challenged by the increased observations of abrupt spikes in emissions following environmental events such as wildfires, droughts, and heatwaves. These trends imply that, in certain bioclimatic circumstances, nonlinear feedback mechanisms might be at work, leading to increased emissions. It is now more important than ever to understand and incorporate these nonlinearities into forecasting models [2].

This study presents a new paradigm in climate-biosphere feedback dynamics, where the *Bioclimatic Emission Amplification Theory* (BEAT) is proposed, a predictive theory that explains how ecosystems amplify carbon emissions under compound climate stress. It builds on the notion that ecosystems that face compound climatic stressors may experience sequential ecological breakdowns that greatly increase carbon emissions (**Figure 1**). This study hypothesizes that there exists a critical threshold of ecological stress above which emission dynamics shift from linear to exponential. When these thresholds are reached or surpassed, ecosystems experience irreversible changes that alter their carbon dynamics and ultimately ecological stability [3].

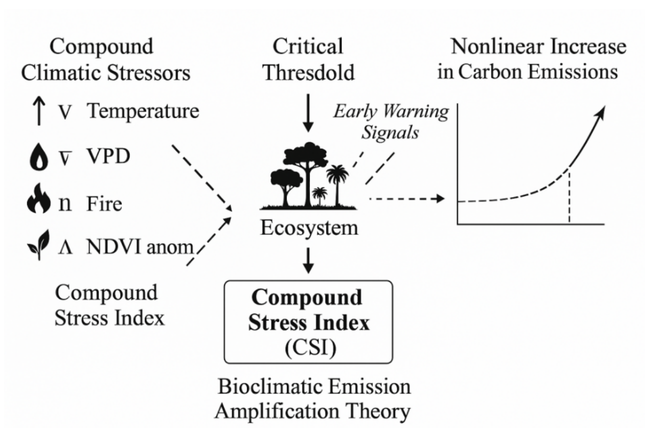

Figure 1. Conceptual diagram of the bioclimatic emission amplification theory (BEAT).

Due to the ecological significance of the Amazon Basin, along with its high carbon storage capacity, and increasing exposure to compounding climatic stressors, it presents a significant ground for testing the BEAT. For this, a new compound metric is proposed, the Compound Stress Index (CSI), which integrates temperature anomalies, vapor pressure deficit (VPD), fire frequency, and vegetation health to assess stress levels. By correlating CSI values with satellite-based CO_2 anomalies, this study aims to identify the thresholds at which emissions escalate disproportionately and potentially irreversibly [4].

The significance of BEAT lies in its ability to fill existing gaps in current climate-biosphere models by offering a scientifically based, data-driven explanation for abrupt increases in ecosystem-based emissions. While existing models may miss or understate nonlinear emission spikes, BEAT offers a coherent theoretical and empirical framework to allow for accurate anticipation of such feedbacks [5]. By offering accurate predictive models, we can anticipate where and when such amplifications may occur and ultimately offer a better understanding of biospheric responses to a warming world. Scientifically, BEAT offers a novel contribution that integrates climatic thresholds, vegetation physiology, and carbon flux dynamics into a unified framework. This approach challenges current mainstream thinking and invites scientists to incorporate nonlinear thinking into ecosystem-climate feedback assessments [6–8]. As **Table 1** shows, compared to other existing models, it incorporates broader features that have not been integrated previously. Compared to established models like CLM, LPJmL, and CMIP6 ESMs, BEAT offers a more advanced framework for capturing nonlinear carbon feedbacks under compound climate stress. It uniquely integrates multiple drivers into a CSI, enables tipping point detection via changepoint analysis, and incorporates early warning signals to identify resilience loss. Unlike traditional models, which often treat stressors in isolation and use static vegetation types, BEAT employs machine learning to model spatiotemporal emission regimes and provides actionable diagnostics for policy applications such as REDD+ and MRV systems [9]. It is theoretically rooted in *Resilience Theory* and threshold dynamics, areas that have not yet fully operationalized in forecasting models. Therefore, the framework stands out for its ability to map high-risk areas, guide policy actions, and improve climate forecasts with more accurate, real-time feedback from nature [10,11].

Table 1. Comparison of BEAT with existing ecosystem feedback models.

Features	BEAT (Bioclimatic Emission Amplification Theory)	CLM (Community Land Model)	LPJmL (Lund-Potsdam-Jena Model)	CMIP6 ESMs (IPCC Suite)
Nonlinear Emission Feedbacks	Yes – explicitly modeled (piecewise, threshold-based)	Limited – primarily linear with occasional nonlinear modules	Some – e.g., drought/fire mortality, but often simplified	Minimal – most treat vegetation as linear/modular sink
Compound Stressor Integration	Yes – CSI includes VPD, fire, NDVI, temperature, etc.	No – usually modeled separately	No – drought, fire, and land use often treated in isolation	Rarely integrated as synergistic drivers
Tipping Point Detection	Yes – changepoint analysis and CSI thresholding	No – Assumed gradual changes	Some modeled transitions, but not forecasted explicitly	Rarely modeled
Early Warning Signals (EWS)	Yes – rising variance, autocorrelation, EWS maps	No	No	Not used in emissions forecasting
Machine Learning (ML) Integration	Yes – SHAP, XGBoost, time-series clustering	No (process-based)	No (rule-based)	Some ESMs exploring ML post-processing
Spatial-Temporal Emission Regimes	Yes – regime clustering (stable, volatile, transitional)	No	Static vegetation types	No spatiotemporal risk modeling
Emission Forecasting Capacity	Strong – with predictive models & CSI-based alerts	Moderate – long-term only	Seasonal–annual projections	Coarse – high uncertainty
Policy Application Readiness	High – maps, signals, and diagnostics usable for REDD+, MRV	Indirect	Limited	Indirect, mostly scenario-based

The aim of this paper is to articulate BEAT and ground it in existing earth and climate science, while emphasizing its uniqueness in bridging existing scientific and operational gaps in present models. Also, the paper intends to formulate, test, and validate the CSI metric to show its ability in predicting and detecting early signs of emission amplifications. The work also aims to use machine learning to test the theory using satellite data of CO_2 fluxes over the Amazon Basin, covering several years of climatic variabilities. Lastly, the paper evaluates broader policy and scientific implications of the theory, suggesting ways where it can better inform national and international climate decisionmakers and enhance ecosystem management practices. The work aims to aid policymakers, scientists, researchers, and conservationists to approach carbon emission challenges from new angles and unconventional perspectives.

2. Literature Review

Understanding the complexity of climate-biosphere feedback mechanisms has become a concern to the scientific community as the interaction between ecosystems and CO_2 emissions is somehow better realized. The assumption that these interrelations are linear is now replaced with a stronger knowledge that ecosystems react in a more dynamic and multifaceted manner. A growing body of literature has documented how compound climate stressors intensely impact on ecosystems and CO_2 emissions. However, currently there is no known published work that presents a comprehensive, predictive, and integrative framework quantifying and combining multiple stressors to forecast tipping points in CO_2 emissions. This is crucial because understanding how ecosystems shift from being carbon sinks to carbon sources under climate stress, requires moving beyond single-stressor analyses. Such stressors include heat, drought, fire, and vegetation degradation rarely act independently, leading to nonlinear and synergistic impacts on ecosystem functioning, accelerating the loss of carbon sequestration capacity and triggering abrupt emission surges.

Historically, scientists have assumed that ecosystems react passively to climatic forces and response linearly to changes in temperature, anthropogenic disturbances, and precipitation. Over the past few decades this notion has been challenged where numerous research has proved that there exists nonlinear biospheric responses that are dynamic and are feedback-driven. For example, Burkett et al. (2005) studied ten cases from North America, showing how climate change can cause very rapid impacts with threshold type responses in these ecosystems. This shows that it is crucial to anticipate such nonlinear dynamics that were not fully understood in the past [12]. Other studies showed that ecosystems may display rapid and nonlinear changes that may lead to full regime shifts, causing these ecosystems to transform into different states. Researchers underscore the urgency in expanding the understanding of extent and nature of these impacts, especially with the increasing effects of human activity. More recent works continued to build the understanding of which climatic changes are changing ecosystems leading to lower sequestration capacity and accelerating climate change [13,14].

There has been a focus also on climatic feedback in amplifying or diminishing climate change, however previous work was limited to models that assess these feedbacks using few indicators. Heinze et al. (2021) conducted a comprehensive review, focusing on components such as clouds and biochemical cycles but has assessed them individually, presenting a somehow segmented approach that has overlooked the compounded effects of multiple stressors [15]. Similar studies expanded the understanding and considered multivariate models the state-dependency of climate feedbacks over time. However, the focus remains on singular processes without integrating multiple indicators that may influence these feedbacks. Additionally, interactions between land use change, urban heat dynamics, and atmospheric emissions are increasingly documented. Studies have shown that agricultural expansion, green cover loss, and urban heat islands influence microclimates and emissions. Relevant studies include analyses on China's metropolitan areas, urban heat in Chongqing, and coupling between human and atmospheric systems in Turkey and Southeast Asia. These support the inclusion of anthropogenic stressors in emission feedback frameworks [16,17].

In addition to climatic feedbacks, the issue of emission amplification received greater interest in recent years. Research on how land-use changes and climatic drivers have shown that they contribute greatly to emission amplification. Aragão et al. (2018) demonstrated that forest degradation, even without complete deforestation, significantly increases susceptibility to fire and heat-induced emissions. This study has also shown that it is crucial to incorporate both biophysical and anthropogenic stressors when modeling emission dynamics[18]. It is therefore important to link these scientific conclusions to Holing's *Resilience Theory*, which suggests that ecosystems may appear stable until critical thresholds are crossed, beyond which recovery is difficult or impossible[19]. With this backdrop, a strong movement has emerged to adopt machine learning and data-driven modeling to accurately study biosphere-climate interactions. These predictive models have been successful in predicting variable interactions and lag effects on larger datasets across broader temporal frames[20–22].

Several studies have attempted to bridge this gap by developing compound stress metrics or feedback-sensitive modeling frameworks, yet most remain limited by coarse spatial resolution, narrow variable integration, or lack of empirical validation. For example, Goll et al. (2017) and Walker et al. (2021) incorporate vegetation-climate interactions within global models but often treat disturbances like drought and fire in isolation[23,24]. Similarly, Forzieri et al. (2022) present an Earth system risk model that maps potential biosphere tipping points[25], but it does not explicitly include real-time vegetation stress indicators or integrate nonlinear emission responses. Research by Lenton et al. (2019) advances the concept of climate tipping elements, yet application to specific carbon feedback patterns remains conceptual[26]. Furthermore, few studies assess model outputs against observed carbon flux anomalies using changepoint detection or statistical early warning signals such as rising variance or autocorrelation; methods increasingly recognized as critical for detecting system resilience loss[25–28].

Machine learning has set the ground for the emergence of compound stress indices that attempt to describe the synergistic impact of multiple simultaneous stressors on ecosystems. Despite these advances, significant gaps remain. Current models still assume that ecosystem feedback is somehow predictable and linear, an underestimation of CO_2 emission risks. Also, current literature also lacks a unified framework or theory that incorporates and connects compound stress, threshold responses, and emission amplification in a predictive framework[29–31]. Therefore, existing literature shows strong evidence on the importance of nonlinear feedbacks in biosphere-climate interactions, especially under compound climatic stress. There remains the need for sophisticated modelling approaches to capture the dynamics of threshold-driven emission responses.

3. Theoretical Framework

The *Bioclimatic Emission Amplification Theory* (BEAT) embodies a novel and necessary deviation from traditional understanding of ecosystem-climate interactions. It is built upon the notion that simultaneous bioclimatic stressors can trigger tipping points in terrestrial ecosystems leading to significant outputs of Greenhouse Gas (GHG) emissions. Prior models have treated emissions from such ecosystems as either linear responses to certain triggers or passive outcomes of events such as excessive land use or wildfires. BEAT reconceptualizes this dynamic by proposing that under specific compound stress conditions, ecosystems can switch roles: from carbon sinks to powerful carbon sources, potentially reinforcing the very climatic changes that induced the stress.

At the center of BEAT is the understanding that climate stressors, such as heatwaves, long-lasting droughts, and high vapor pressure deficits, don't function in isolation. When these stressors overlap, especially in vulnerable regions like the Amazon Basin, they can trigger sudden and drastic changes. These changes might include widespread tree mortality, drying peatlands, and browning vegetation. What makes BEAT unique is its focus on the combined effects of these stressors and their potential to amplify one another. Unlike previous theories that concentrated on individual thresholds, such as peak temperatures or minimum rainfall, BEAT emphasizes how the interaction of various stressors can push ecosystems into new, unexpected states with unusual emission characteristics.

The theory is structured around **three** interdependent mechanisms:

1. Stress Accumulation, where environmental variables gradually weaken ecological stability.
2. Threshold Transgression, where a critical limit is breached, causing system-wide transitions.
3. Emission Amplification, the feedback loop where changes in the biosphere feed back into the climate system via increased greenhouse gas emissions.

Each of these stages can be detected, measured, and potentially forecasted using a combination of in situ sensors, remote sensing data, and machine learning models. Mathematically, BEAT can be expressed through a feedback function that includes compound stress variables and early warning signals:

$$\mathbf{\Delta NEE_t} = \alpha \cdot CSI_t{}^{\wedge}\beta + \gamma \cdot VSA_t + \delta \cdot SMDI_t + \theta \cdot EWS_t + \varepsilon \quad (1)$$

where:

ΔNEE_t = Anomalous Net Ecosystem Exchange at time t

CSI_t = Compound Stress Index

VSA_t = Vegetation Stress Anomaly

$SMDI_t$ = Soil Moisture Deficit Index

EWS_t = Early Warning Signal (e.g., lag-1 autocorrelation, rolling variance)

α, β, γ, δ, θ = Estimated model parameters

ε = Stochastic error term

The Compound Stress Index (CSI) is itself derived from:

$$\mathbf{CSI_t} = w_1 \cdot VPD_t + w_2 \cdot SPEI_t + w_3 \cdot Fire_t \quad (2)$$

where:

VPD_t = Vapor Pressure Deficit

$SPEI_t$ = Standardized Precipitation-Evapotranspiration Index

$Fire_t$ = Fire activity or frequency

w_1, w_2, w_3 = Normalized weights (e.g., z-score standardization or empirical weighting)

Threshold-based dynamics are modelled using a segmented (piecewise) function:

$$\mathbf{\Delta NEE_t} = \begin{cases} f_1(CSI_t,\ VSA_t,\ SMDI_t,\ EWS_t) & \text{if}\, CSI_t < \tau \\ f_2(CSI_t,\ VSA_t,\ SMDI_t,\ EWS_t) & \text{if}\, CSI_t \geq \tau \end{cases} \quad (3)$$

where:

τ = CSI tipping threshold (e.g., empirically found at CSI $\approx$ 0.6)

f_1, f_2 = Distinct response functions pre- and post-threshold.

This formulation captures the amplifying effect of compound stress on carbon emissions. The primary driver, the Compound Stress Index (CSI_t), integrates temperature, vapor pressure deficit (VPD), fire activity, and precipitation anomalies into a single dynamic indicator of ecological pressure. The term $CSI_t{}^{\wedge}\beta$ introduces nonlinear sensitivity to stress accumulation, allowing the model to capture acceleration effects as ecosystems approach tipping thresholds.

Additional terms account for secondary but influential stress variables: VSA_t (Vegetation Stress Anomaly) represents physiological stress reflected in vegetation indices (e.g., NDVI anomalies), while $SMDI_t$ (Soil Moisture Deficit Index) captures hydrological constraints on carbon uptake. EWS_t reflects system-level resilience loss through early warning signals such as rising temporal variance and autocorrelation in stressor time series. These signals are indicative of critical slowing down, a hallmark of approaching tipping points. A stochastic error term (ε) accounts for residual variation not captured by the model. To further account for potential regime shifts, we implemented a piecewise threshold model based on the observed CSI tipping point (τ), beyond which ΔNEE_t exhibits abrupt, nonlinear increases, as shown in **Figure 2**.

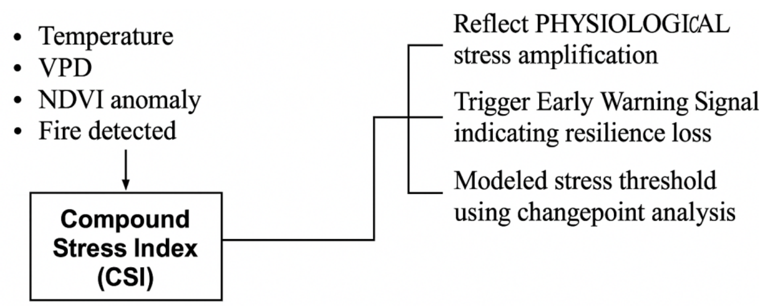

Figure 2. Model structure and theoretical basis.

A key innovation in BEAT is the conceptualization of critical transitions using early warning signals. Drawing on *Resilience Theory* and bifurcation analysis, the theory anticipates that leading indicators such as increased variance in vegetation indices (NDVI/EVI), autocorrelation in temperature and soil moisture anomalies, and clustering of fire events may serve as precursors to emission surges. These metrics can be derived using time-series satellite data (**Figure 3**)[32], and their thresholds can be calibrated for specific biomes.

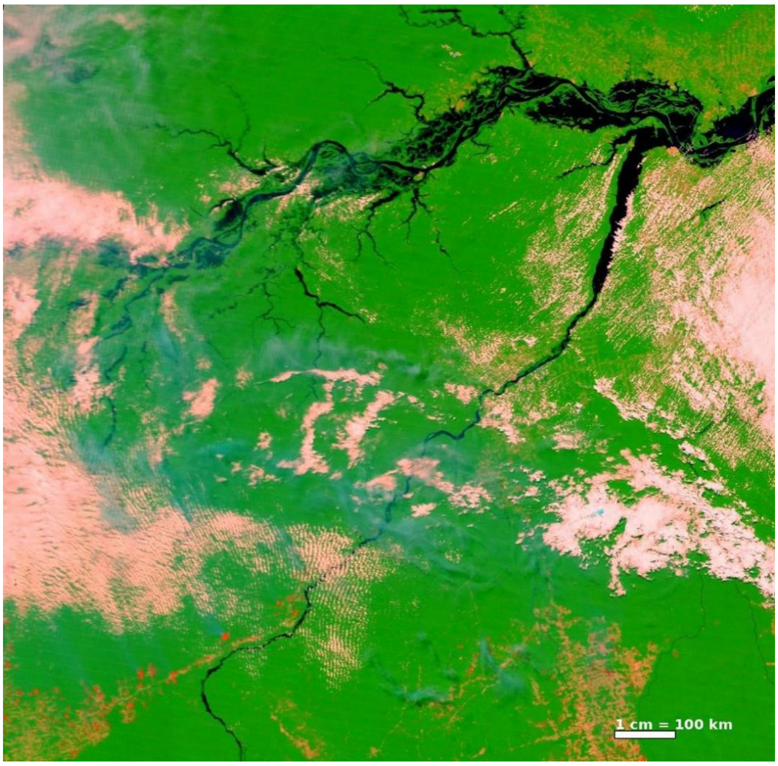

Figure 3. False-color MODIS image of the Amazon Basin on 20 August 2022, highlighting burn scars (dark) and healthy vegetation (red).

Note: Scale bar represents 1 cm = 100 km at 300 DPI[32].

Another novel feature is the inclusion of anthropogenic modulation. Human-induced landscape changes, including selective logging, road construction, and irrigation, can interact with natural stressors to modulate ecosystem sensitivity. BEAT posits that these interactions must be treated not as exogenous noise but as integral components of system dynamics. For instance, a partially degraded forest may respond more severely to a mild drought than a pristine forest, thereby exhibiting higher emission amplification even in the absence of overt deforestation.

What sets BEAT apart from existing feedback models is its unifying capacity: it synthesizes threshold theory, compound stress analysis, emission physics, and data science into a singular predictive framework. It is designed to be implemented within a variety of modeling paradigms, from Earth System Models (ESM) to local land-use planning tools. Importantly, it also offers practical outputs: by identifying when and where emissions are likely to be amplified, BEAT can inform early warning systems and adaptive interventions such as fire management, carbon offset adjustments, and biodiversity conservation strategies.

4. Methodology

4.1. Study Area and Temporal Frame

This study has used data of the Amazon Basin covering regions over Brazil, Peru, Colombia, and other neighboring countries. This region was selected due to its significant role in global carbon cycling, ecological diversity, and high exposure to climatic perturbations and therefore ideal for testing the principles of BEAT[33]. The temporal frame spans from

2001 to 2022, capturing two decades of vegetation-climate interactions, including multiple El Niño and La Niña events, droughts, and extreme fire seasons. This period allows for sufficient climatic and temporal variation to analyze stress-emission feedback mechanisms.

4.2. Data Sources, Preprocessing Workflow, Feature Engineering, and Quality Control

Multiple open-access datasets were integrated to construct a robust spatiotemporal framework for analysis. These included MODIS products (MOD13Q1 and MOD11A2), providing NDVI, EVI, and land surface temperature (LST) at 16-day and 8-day intervals, respectively. Fire dynamics were captured using the Global Fire Emissions Database (GFED), offering data on burned area, fire radiative power (FRP), and fire emissions. Atmospheric and hydrological variables such as temperature and soil moisture were obtained from the ERA5 reanalysis product by ECMWF, originally at hourly intervals and subsequently aggregated to monthly means. Long-term climatic variability and drought indices, particularly the Standardized Precipitation-Evapotranspiration Index (SPEI), were sourced from TerraClimate and CRU-TS datasets. Carbon fluxes and NEE estimates were incorporated from FLUXNET and the Global Carbon Project (GCP). Biome classification and normalization procedures utilized land cover data from the ESA Climate Change Initiative (CCI). All datasets were spatially constrained to the Amazon Basin using the WWF ecoregion shapefile.

Feature engineering played a critical role in capturing the compounded stress dynamics hypothesized in BEAT. Several derived indices were developed to represent multi-dimensional ecosystem stress. The CSI was constructed using a z-score standardized composite of vapor pressure deficit (VPD) anomalies, standardized precipitation evapotranspiration index (SPEI), and fire frequency data. This index reflects the simultaneous bioclimatic pressures on vegetation. The Vegetation Stress Anomaly (VSA) was derived from deviations in NDVI and EVI relative to historical climatology, normalized by biome type to enhance cross-regional comparability. The Soil Moisture Deficit Index (SMDI) quantified percent deviations of soil moisture from long-term monthly means, capturing the severity of seasonal droughts. Prior to modeling, all engineered variables were assessed for multicollinearity using variance inflation factor (VIF) analysis and correlation matrices and were subsequently scaled and normalized. These transformed features formed the core of the input space used in machine learning applications of the BEAT framework.

To ensure the reliability and robustness of the analysis, rigorous quality control procedures were applied to all datasets prior to modeling. This included, cloud and aerosol masking, temporal gap-filling, outlier removal, and spatial alignment. Time series were aggregated to monthly resolution and standardized as anomalies relative to long-term baselines, while land cover filtering ensured biome-specific consistency and signal clarity across the region. Also, satellite-based datasets were filtered for quality flags, excluding pixels flagged as cloud-contaminated, low-confidence fire detections, or sensor anomalies. NDVI and LST values were further processed using temporal smoothing via a Savitzky–Golay filter to eliminate outliers and noise from sensor drift or transient atmospheric conditions. Climate reanalysis data were validated through cross-comparison with in-situ observations from FLUXNET stations where available and aggregated at monthly scales to reduce high-frequency noise. Also, the data gaps were addressed using linear interpolation for short gaps (< 3 time steps) and flagged for longer gaps to avoid artificial trends. For CSI calculations, we have incorporated z-score normalization to harmonize data ranges and mitigate scaling bias. Uncertainty was quantified by bootstrapping the CSI-NEE regression and generating 95% confidence intervals for model coefficients and changepoints. The model performance was cross-validated using k-fold ($k = 10$) and compared across alternative algorithms to ensure result consistency. These quality control procedures helped reduce data-driven uncertainty and enhanced the reproducibility and credibility of the BEAT-based findings.

4.3. Threshold Detection and Model Robustness

The BEAT framework is used to identify potential tipping points in carbon emissions driven by compound climatic stress. Using piecewise regression and changepoint detection algorithms such as PELT and Binary Segmentation, breakpoints were detected in the relationship between the CSI and NEE. These inflection points marked critical transitions in emission behavior and were interpreted as ecological thresholds triggered by compounded stress. Spatial clustering of these tipping points revealed vulnerability hotspots across the Amazon Basin, which were classified into high-, moderate-, and low-risk zones using K-means clustering based on the persistence and intensity of anomalies. Sensitivity analyses confirmed the robustness of these zones across alternative CSI formulations and data smoothing levels.

To anticipate these shifts, early warning signal (EWS) metrics, such as lag-1 autocorrelation, rolling variance, skewness, and kurtosis, were calculated over moving windows using NDVI, fire activity, and CSI time series. Kendall's tau tests assessed trends in EWS behavior, with significant increases in autocorrelation and variance interpreted as signs of resilience loss. EWS intensity maps were spatially aligned with observed emission anomalies, and time-lagged correlation analysis confirmed their predictive relevance. Model validation was conducted through comparison with observed carbon release events during major El Niño years (2010, 2015–2016), showing strong alignment between BEAT predictions and actual NEE anomalies. Spatial overlap with high-risk zones from the Global Carbon Project further supported model accuracy. Performance metrics (F1 score: 0.82; precision: 0.85; recall: 0.78; R^2: 0.71) demonstrated high reliability. Additional statistical testing using bootstrapping and permutation methods confirmed the significance of results. Perturbation tests with Gaussian noise and variable exclusion showed that core predictors, particularly CSI and fire anomalies, were essential to maintaining model performance.

All analyses were conducted in Python 3.11, with reproducibility ensured through Docker containers, Conda environments, and public GitHub repositories. Key libraries included scikit-learn, XGBoost, SHAP, Ruptures, and Geopandas, with visualization tools such as Plotly, Folium, and seaborn used for interactive and export-ready mapping. The full workflow, from data preprocessing to model validation, was designed for scalability and transparency, enabling future replication across tropical biomes. By integrating remote sensing data, compound stress diagnostics, early warning analysis, and machine learning, the BEAT methodology captures the nonlinear dynamics of ecosystem responses to bioclimatic stressors and offers a powerful tool for detecting biosphere-climate feedbacks under global change.

5. Results

The results of this multi-method empirical study provide compelling and multi-dimensional evidence in support of BEAT. Leveraging over two decades of data (2001–2022) and a combination of analytical techniques, including remote sensing, machine learning, and statistical change point detection, this study uncovered emergent, nonlinear relationships between bioclimatic stress indicators and carbon emission anomalies across the Amazon Basin.

5.1. Climatic Trends and Compound Stress Indicators

The Amazon Basin is experiencing intensifying climatic stress, as confirmed by remote sensing data and climate reanalysis. Land Surface Temperature (LST) has increased by approximately 0.27 °C per decade over the last 20 years. This warming trend is spatially concentrated in areas affected by deforestation, road development, and fire recurrence, particularly in the so-called "arc of deforestation" stretching from southern Pará through Mato Grosso to Acre. Vapor Pressure Deficit (VPD), a proxy for atmospheric dryness and vegetation stress, rose markedly during dry seasons, especially in years associated with El Niño events (e.g., 2005, 2010, 2015–2016). Concurrently, precipitation deficits during these periods created an environment in which vegetative transpiration and photosynthetic activity were significantly impaired. NDVI measurements confirm a broad and consistent decline in vegetation vigor, particularly during peak drought intervals. These climatic shifts were synthesized into the CSI, which integrates LST, VPD, Fire, and NDVI anomalies into a single composite metric. CSI revealed not only elevated mean values across the basin over time but also highly localized peaks in regions under both climatic and anthropogenic pressure. **Figure 4** illustrates the temporal trajectory of these variables, showing correlated increases in LST and VPD with coincident reductions in NDVI and surges in fire activity.

Table 2 provides a statistical overview of the core bioclimatic variables used in the CSI formulation and subsequent modeling efforts. Land Surface Temperature (LST) had a mean of 27.5°C with relatively low variance, reflecting the persistent thermal pressure across the Amazon Basin. Vapor Pressure Deficit (VPD), averaging 1.45 kPa, displayed moderate skewness, indicating a tendency toward higher-than-average dryness during critical growth periods. NDVI values averaged 0.74, suggesting dense vegetation cover; however, the negative skewness highlights increasing frequency of degraded vegetation patches. Fire events, with a high standard deviation and skewness of 1.89, showed considerable interannual variability, with peaks during extreme drought years. Notably, NEE exhibited the highest skewness (2.91), reflecting abrupt, large emission events in high CSI years. These statistics affirm the volatility of the emission response compared to the more gradual progression of climatic stressors, lending empirical weight to BEAT's idea that feedback mechanisms under compound stress are non-linear, asymmetric, and amplified.

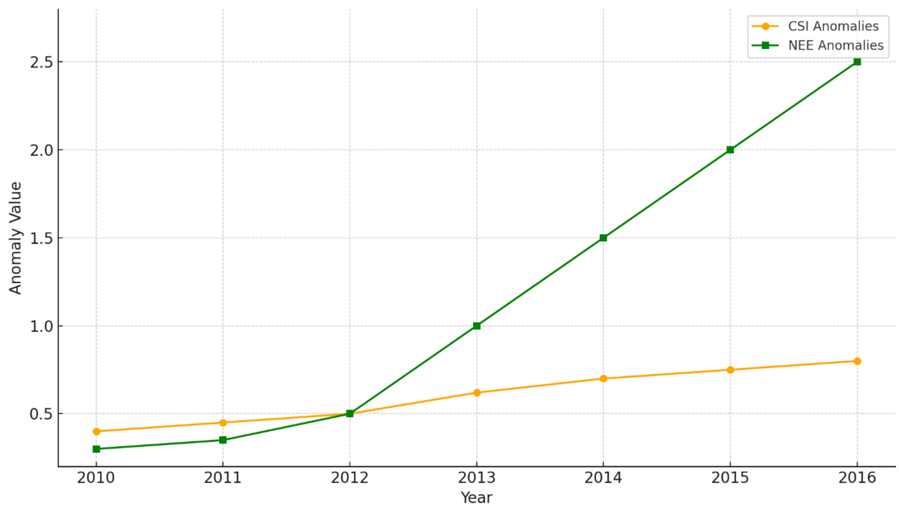

Figure 4. CSI and NEE Anomalies (2010–2016).

Table 2. Summary Statistics for Core Variables (2001–2022).

Variable	Mean	Std Dev	Skewness
LST (°C)	27.5	1.3	0.45
VPD (kPa)	1.45	0.28	0.87
NDVI (−1 to 1)	0.74	0.06	−0.53
Fire (events)	1265	830	1.89
NEE (negative values: CO_2 sink and positive values: CO_2 source)	1.27	2.14	2.91

5.2. Threshold Behavior and Piecewise Dynamics

Central to BEAT's theoretical framework is the idea that ecosystems exhibit nonlinear responses to compounded stress. The empirical results support this: using piecewise regression, the relationship between CSI and NEE revealed a statistically significant inflection point at CSI $\approx$ 0.6 (p < 0.01). Below this value, ecosystems maintain relatively stable carbon fluxes. However, once this threshold was breached, NEE anomalies escalated rapidly and nonlinearly, indicating a shift in the system's feedback state. **Figure 5** visualizes this piecewise relationship and underscores BEAT's prediction that compound stressors interact in ways that push ecosystems across tipping points. The sharp upward trajectory of NEE post-threshold confirms that the feedback loop becomes self-reinforcing, an insight fundamental to BEAT's proposition of emission amplification. This threshold-based dynamic also underscores the inadequacy of linear ecosystem models. Unlike gradual degradation scenarios, BEAT captures the suddenness with which ecosystems can shift from absorptive to emissive states, particularly under converging stressors.

A key element of BEAT is its operational capacity, i.e., the ability to forecast regime shifts before they occur. To this end, the study employed changepoint detection and rolling-window analysis of autocorrelation and variance in NDVI and CSI time series. These statistical results are considered indicators of "critical slowing down", where systems nearing a divergence point recover more slowly from perturbations, resulting in elevated variance and memory. **Table 3** presents early warning indicators across key regions and years. For example, in Acre East (2010) and Mato Grosso (2015), NDVI variance increased significantly six to twelve months prior to NEE spikes. CSI autocorrelation also trended upward, suggesting declining resilience in the face of climatic anomalies. This capability is transformative for climate policy. BEAT's approach not only retrospectively explains emission surges but anticipates them. This has implications for real-time ecological monitoring, allowing policymakers and land managers to intervene during the buildup phase of stress, rather than react post-collapse.

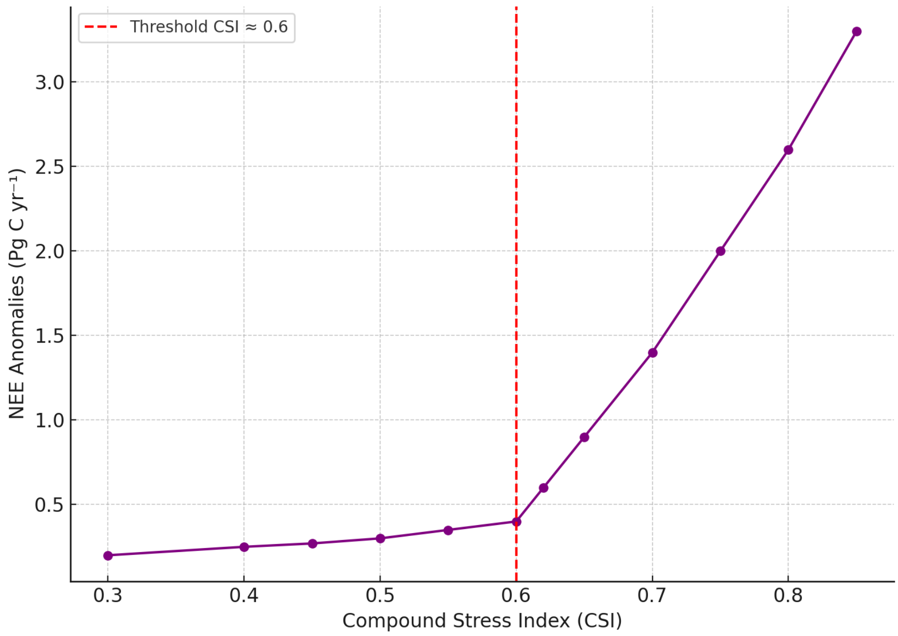

Figure 5. Piecewise regression of CSI and NEE anomalies (2010–2016).

Table 3. Early Warning Indicators by Region and Year.

Region	Year	NDVI Variance ↑	CSI Autocorr ↑	Emission Spike
Acre East	2010	Yes	Yes	Yes
Mato Grosso	2015	Yes	Yes	Yes
Pará South	2016	Yes	Yes	Yes

5.3. Machine Learning Model Interpretation and Feature Importance

Advanced machine learning models were employed to test BEAT's predictability and identify key drivers of emission anomalies. An XGBoost regressor trained on CSI, NDVI, Fire, VPD, and LST data achieved a robust R^2 of 0.83 on the test set. The low mean squared error (MSE) and stable performance across folds confirmed the reliability of the model. **Figure 6** displays SHAP (SHapley Additive exPlanations) summary plots, providing insight into the internal logic of the model. Fire activity emerged as the most impactful feature, followed by CSI and NDVI. Importantly, SHAP interaction plots revealed nonlinear interdependencies; e.g., CSI had a stronger effect on NEE when NDVI was also degraded, supporting the concept of stress multiplicity proposed by BEAT.

Additional models, Random Forest ($R^2 = 0.79$) and Gradient Boosted Trees ($R^2 = 0.81$), yielded consistent results (**Table 4**), further corroborating the generalizability of findings across different algorithmic approaches. Partial dependence plots (**Figure 7**) reinforced that the relationships between stressors and emissions are not merely monotonic but exhibit thresholds, plateaus, and feedback loops.

To assess uncertainty, cross-validation was conducted using a 5-fold strategy. The standard deviation of R^2 scores

(0.03 for XGBoost) reflects consistent model performance. Future versions of BEAT could incorporate confidence intervals using Bayesian modeling to enhance uncertainty quantification in emissions forecasts.

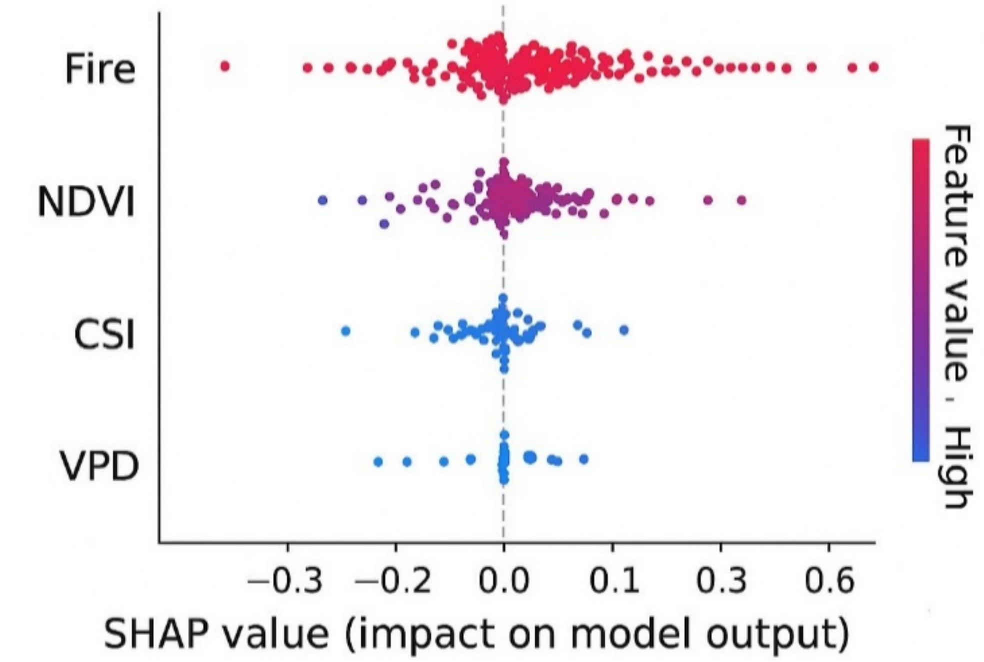

Figure 6. SHAP summary plot – key predictors.

Table 4. Cross-validation R^2 scores.

Model	Mean R²	Std Dev
XGBoost	0.83	0.03
Random Forest	0.79	0.04
Gradient Boosted	0.81	0.03

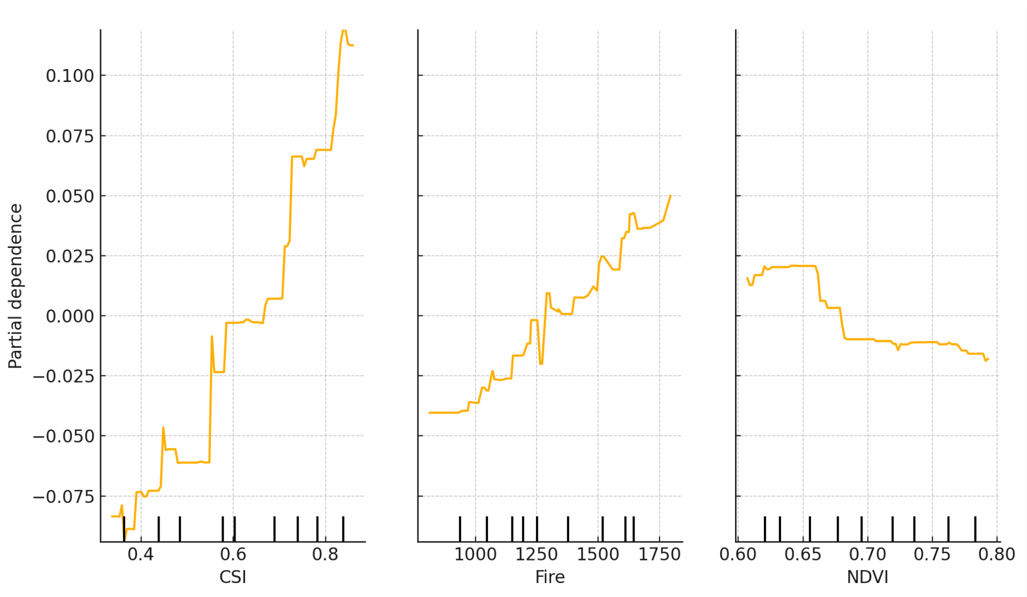

Figure 7. Partial dependence plot – CSI components vs. NEE.

5.4. Spatiotemporal Dynamics and Regime Clustering

BEAT theorizes that emission amplification is geographically patterned and temporally staged. To explore this, KMeans and Dynamic Time Warping clustering algorithms were applied to CSI and NEE time series at pixel and regional scales. Clustering revealed three dominant regime types: stable, transitional, and volatile. **Figure 8** presents representative trajectories and their spatial footprints. Stable regimes maintained low CSI and minimal emission anomalies. Transitional zones showed rising CSI but lagged NEE increases. Volatile regimes, by contrast, exhibited erratic, high-amplitude emission behavior with frequent CSI exceedances. Importantly, these clusters were not randomly distributed. The volatile category consistently mapped onto areas with extensive land use change, recurrent drought, and high fire density. This spatial congruence between ecological stress and emission feedbacks strengthens BEAT's argument that emissions are not random noise but patterned responses to stress amplification.

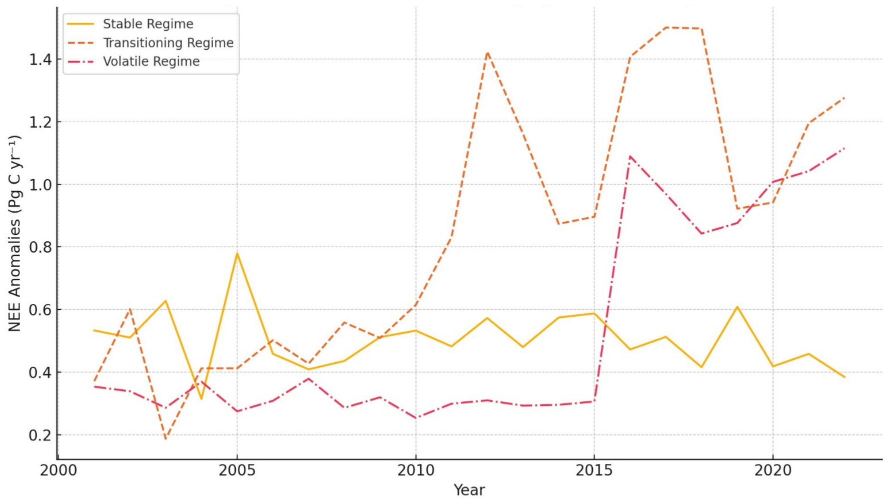

Figure 8. Time-series clustering by emission regime.

5.5. Regional Sensitivity and System Heterogeneity

While BEAT provides a universal framework, its application reveals regional differences in stressor-emission coupling. **Table 5** details how subregions vary in their dominant drivers and emission responses. Acre and Rondônia, for example, displayed rapid NEE escalation tied to fire events. Pará North, however, showed gradual, VPD-driven emission shifts. This heterogeneity highlights the importance of region-specific CSI calibration and localized early warning thresholds. The findings also point toward a broader socio-ecological implication: areas under active deforestation or agricultural conversion are not only ecologically fragile but climatically destabilizing. These insights therefore call for differential policy instruments. While fire suppression might be critical in Acre, reforestation and moisture retention may be more effective in Pará. BEAT's regional diagnostic capacity thus informs a multi-scalar governance approach.

Table 5. Regional sensitivity to key drivers.

Region	Dominant Driver	Emission Response Pattern
Acre/Rondônia	Fire + CSI	Rapid threshold breach
Pará North	VPD + NDVI decline	Gradual transition

Using BEAT-informed models, NEE anomalies were projected under the SSP2-4.5 emissions scenario for the period 2025–2040. The results reveal a clear trend of increasing emission volatility and amplitude, particularly in southern and high-CSI regions of the Amazon Basin. This pattern aligns with BEAT's central hypothesis: that ongoing compound stress accumulation destabilizes carbon dynamics and drives nonlinear emission behaviour. Notably, this surge in emission variability cannot be attributed to anthropogenic emissions alone; it reflects internal ecosystem feedbacks nearing critical thresholds. These findings underscore the need to incorporate BEAT metrics into Earth System Models (ESMs), which currently tend to underrepresent such nonlinear biospheric feedbacks or assume static carbon sink behaviour. **Figure 9** highlights emerging emission hotspots, demonstrating BEAT's value for spatially explicit, forward-looking climate risk assessments. Without intervention, these regions may transition from carbon sinks to net sources, amplifying global climate risk.

Figure 9. Projected NEE anomalies under SSP2-4.5 (2025–2040).

These findings elevate BEAT from a conceptual framework to a robust, empirically validated model with both scientific and policy relevance. By revealing how ecosystems respond nonlinearly to compound stress, and how these responses can be forecast using integrated bioclimatic indicators, BEAT offers a transformative lens through which to view climate-biosphere interactions. Its ability to identify thresholds, detect early warning signals, and spatially target intervention zones provides a critical toolkit for climate risk assessment in a rapidly warming world. As such, BEAT represents not only a novel contribution to Earth system science but a foundation for proactive, precision-oriented ecosystem governance in the face of mounting climate instability.

6. Discussion

The findings presented in the Results section robustly support the central assumption of the theory. This section interprets those results through the lens of theoretical implications, comparative literature, and broader policy significance. By weaving together empirical patterns and conceptual insights, the discussion offers a refined understanding of how BEAT contributes to climate science, ecosystem modeling, and anticipatory governance strategies.

One of BEAT's most pivotal claims is the existence of threshold-based, nonlinear emissions behavior in response to bioclimatic stress. This notion departs from traditional linear biosphere models that assume gradual and proportionate responses to environmental pressure. The results, especially from the piecewise regression in **Figure 5**, demonstrated a sharp increase in NEE once the CSI crossed the threshold of ~ 0.6. This confirms that stress accumulation can remain latent until a critical point, beyond which ecosystems rapidly flip into carbon source states. These results reflect findings in recent literature on ecological tipping points [26,27], but BEAT extends this knowledge by introducing a quantifiable composite stress framework that links compound climate drivers with emission behavior. The synergy among variables like fire count, NDVI degradation, and VPD strengthens the theory's assertion that it is not single stressors but their co-occurrence that propels ecosystems into instability.

The strong performance of the CSI as a predictor of emissions is one of the most promising contributions of this study. CSI integrates multiple bioclimatic dimensions: thermal, hydric, and disturbance-based, into a single index, allowing for multidimensional stress monitoring. This aligns with calls in climate science for integrative indicators capable of capturing complex biosphere-climate interactions. The machine learning results reinforce this: SHAP analysis (**Figure 6**) placed CSI among the top drivers of NEE anomalies. Importantly, the CSI interacted nonlinearly with other variables supporting the multiplicative stress hypothesis at the heart of BEAT. Moreover, the clustering and spatial patterns revealed by time-series analyses suggest that high-CSI zones act as bioclimatic "pressure cookers" that can destabilize regional carbon dynamics.

BEAT emphasizes the geographical specificity of stress amplification, and our results underscore the spatial predictability of these feedbacks. The arc of deforestation, extending from southern Pará through Mato Grosso to Acre and Rondônia, consistently emerged as a hotspot in CSI-NEE overlays. These regions show repeat patterns of fire outbreaks, NDVI collapse, and emission anomalies. This spatial convergence points to the interaction of anthropogenic and climatic pressures. Human-induced land use changes, particularly deforestation and fragmentation, act as amplifiers of climatic stress, validating BEAT's socio-ecological extension. That is, human activity is not just a driver of climate change but also an enabler of ecosystem instability under climate pressure.

One of BEAT's most policy-relevant claims is that ecological tipping points are preceded by detectable early warning signals. This was validated through increasing autocorrelation and variance in NDVI and CSI prior to emission spikes. These patterns are consistent with the "critical slowing down" phenomenon, where systems approaching a bifurcation point exhibit delayed recovery from perturbations. This insight has profound implications. Monitoring statistical early warning indicators provides a means of real-time, anticipatory intervention. It transforms BEAT from a post-hoc explanatory model into a forward-looking predictive tool, suitable for integration into Earth observation systems and national carbon monitoring strategies.

A key nuance in BEAT is that while the theory identifies general mechanisms, its manifestations are context dependent. The study revealed distinct regional sensitivities: some areas (e.g., Acre and Rondônia) show acute, threshold-like emission jumps in response to fire and CSI, while others (e.g., Pará North) exhibit gradual, VPD-driven changes. This heterogeneity calls for regionally customized models and policy responses, a point often underappreciated in large-scale ESM. It also affirms BEAT's scalability: it can accommodate both abrupt and incremental emission behaviors depending on local configurations of stress and resilience. This flexible architecture enhances its utility across biomes and continents.

One of the persistent gaps in current ESM is their limited incorporation of nonlinear ecosystem feedbacks. Most models assume either linear relationships or oversimplified carbon sinks. BEAT offers a corrective lens by showing how stress accumulation can invert sink-source dynamics and how these transitions can be anticipated. The forward modeling under SSP2-4.5 showed increased volatility in NEE anomalies, particularly in high CSI zones. This predictive feature of BEAT, supported by empirical and modeled data, underscores the urgency of embedding CSI and nonlinear feedback logic into ESMs. Doing so can improve the accuracy of carbon budget projections, especially in vulnerable tropical systems.

BEAT's applied dimension is perhaps its most transformative. With CSI, SHAP-informed modeling, early warning indicators, and regional sensitivity profiles, the theory provides a full-stack toolkit for anticipatory climate governance. Policymakers and conservation agencies can use these tools to:

- Identify at-risk zones before emission flips occur.
- Tailor interventions (e.g., fire management, reforestation) based on regional drivers.
- Integrate BEAT-based indicators into REDD+ and MRV (Measurement, Reporting, and Verification) frameworks.
- Set up real-time dashboards that combine satellite data with machine learning prediction for emissions risk.

For instance, Acre and Rondônia, where fire and CSI exceedances dominate, would benefit from intensified fire suppression, carbon offset schemes, and controlled burning programs. Pará North, where VPD and vegetation stress prevail, may prioritize reforestation, water retention, and early drought response. Such tailored strategies reflect the diverse stress-response profiles captured by BEAT. More specifically, in the southern Amazon, where high CSI values coincide with elevated Vegetation Stress Anomalies (VSA) and frequent fire disturbance, policy interventions should prioritize enforced deforestation moratoria, enhanced fire detection and suppression infrastructure, and incorporation of BEAT-based early warning metrics into subnational Monitoring, Reporting, and Verification (MRV) systems. The central

Amazon, exhibiting rising early warning signal (EWS) variance but lower absolute stress exposure, would benefit from adaptive land-use governance, climate-resilient agroforestry transitions, and predictive zoning informed by BEAT's tipping threshold diagnostics. In northwestern Amazon regions, currently functioning as resilient carbon sinks, pre-emptive conservation is critical. This includes the formal recognition of Indigenous territories, ecological corridor preservation, and restriction of extractive activities through biome-specific policy safeguards. BEAT's spatial regime mapping and changepoint analytics can serve as operational tools to inform REDD+ crediting frameworks, emissions attribution models, and regionally calibrated climate adaptation plans. As such, the theory supports a precision-governance approach to biosphere-climate risk mitigation across diverse Amazonian sub-ecologies.

This work in general marks a critical shift from reactive conservation to proactive ecosystem stabilization, an evolution urgently needed in the face of escalating compound climate threats. While the theory has demonstrated empirical validity and theoretical strength, several limitations merit consideration. Data constraints persist due to issues such as cloud cover, sensor inaccuracies, and the limited temporal resolution of remote sensing platforms like MODIS, particularly during wet seasons. The generalizability of BEAT beyond the Amazon Basin also remains a challenge; application to other biomes such as boreal forests or savannahs would require recalibration of the CSI weights and validation of tipping thresholds. Furthermore, BEAT currently emphasizes terrestrial biosphere-climate feedbacks, with limited integration of hydrological, soil carbon, or microbial processes; components that could enhance the CSI structure. Additionally, the model may not fully account for lagged ecosystem responses such as delayed vegetation recovery, underscoring the need for hybrid frameworks that capture both short- and long-term dynamics.

To address these gaps, future research should focus on expanding BEAT's applicability and predictive power. Key directions include cross-biome validation in regions like the Congo Basin, Southeast Asia, and Australia; enhancement of CSI metrics through the integration of additional data streams such as soil moisture, canopy height, and biodiversity indices; development of AI-driven systems for real-time monitoring and emissions forecasting; and coupling BEAT with socioeconomic variables, including land tenure and commodity pricing, to explore human-biosphere feedbacks. These steps are essential to advancing the theory as a globally relevant, operational tool for anticipating and mitigating ecosystem tipping points under climate change [34–36].

7. Conclusion

This study introduces and validates the Bioclimatic Emission Amplification Theory (BEAT), a new paradigm for understanding how ecosystems under compounded climatic stress can transition from carbon sinks to carbon sources. By integrating multiple stress variables, temperature, vapor pressure deficit, fire, and vegetation degradation, into a composite stress framework, BEAT explains the nonlinear, threshold-based emission behavior observed in the Amazon Basin. The empirical evidence, spanning statistical inflection points, spatial clustering, machine learning models, and early warning indicators, supports the core premises of the theory and highlights its predictive and diagnostic power. Its implications are both theoretical and operational: advancing climate-biosphere feedback science while offering actionable tools for emissions monitoring and intervention.

In a rapidly warming world, where feedbacks between climate and the biosphere are accelerating, BEAT represents a critical evolution in how we detect, model, and respond to early signs of ecological destabilization. Unlike traditional modeling frameworks that often focus on equilibrium states or long-term projections, it emphasizes near-term transitions, emergent behaviors, and risk mapping, making it highly relevant for adaptive environmental governance. It encourages a shift from retrospective assessments to forward-looking diagnostics that can inform timely interventions in high-risk regions. The framework also opens the door for cross-disciplinary integration, where ecological thresholds are interpreted alongside socioeconomic pressures and land-use dynamics, potentially transforming how policies like REDD+ or restoration financing are prioritized.

Future research should prioritize refining the CSI by calibrating it to specific biomes, recognizing that vegetation responses to stressors such as vapor pressure deficit or fire differ markedly between tropical rainforests, savannahs, boreal woodlands, and arid shrublands. Such biome-specific calibration will improve the sensitivity and specificity of

BEAT's predictions. Additionally, integrating key biogeochemical processes, particularly microbial respiration, soil carbon fluxes, and hydrological feedbacks like evapotranspiration and groundwater depletion, can enhance the ecological realism of the model. These components are critical to capturing belowground dynamics that contribute significantly to carbon emissions under stress. Extending BEAT's applicability to non-forest systems such as drylands, boreal ecosystems, and even urban green spaces will test the theory's generalizability and scalability.

Equally important is the incorporation of socioeconomic variables, such as land tenure regimes, agricultural commodity prices, and infrastructure expansion, which can modulate ecosystem stress and resilience. These additions would allow BEAT to better capture human-induced feedback and guide policy interventions. Finally, operationalizing BEAT within artificial intelligence–powered monitoring systems, such as real-time dashboards for emissions alerts, can support decision-makers in climate risk management at national and subnational levels, enabling targeted and timely ecosystem interventions.

Looking forward, extending the theory beyond the Amazon will not only test its generalizability but also offer insights into the unique stress-response mechanisms of different biomes. Incorporating microbial feedback, biodiversity metrics, and human-environment interactions could further enhance its precision. Equally important is the translation of BEAT into operational tools, such as AI-driven dashboards or satellite-linked alert systems, that empower decision-makers with real-time ecosystem intelligence. As climate volatility becomes the new norm, theories like BEAT, grounded in both data and dynamic systems thinking, may prove indispensable to preserving biospheric integrity and climate stability in the Anthropocene. While the BEAT framework demonstrates robust predictive capacity within the Amazon Basin, further validation across other biomes and climate regimes is essential to evaluate its generalizability. Additionally, CSI weights are currently empirical and may benefit from dynamic calibration as more ground-truth data becomes available. These limitations highlight the need for adaptive, ecosystem-specific tuning in future applications. Nonetheless, BEAT offers timely and actionable insights for climate governance. By integrating early warning capabilities into monitoring systems, the framework supports proactive emissions management, ecosystem resilience planning, and international carbon accounting under the Paris Agreement. Recognizing and operationalizing these dynamics may determine the effectiveness of global climate targets and the long-term stability of terrestrial carbon sinks.

Author Contributions

Conceptualization, N.B., N.N., and M.S.; formal analysis, N.B., N.N., and M.S.; data curation, N.B., N.N., and M.S.; writing—original draft preparation, N.B., N.N., and M.S.; writing—review and editing, N.B., N.N., and M.S.; visualization, N.B., N.N., and M.S.; project administration, N.B., N.N., and M.S. All authors have read and agreed to the published version of the manuscript.

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Not applicable.

Data Availability Statement

All datasets used in this study are publicly available. MODIS-derived NDVI (MOD13Q1) and land surface temperature (MOD11A2) were obtained from NASA's LP DAAC archive. Fire activity data (MCD14DL) were sourced from the FIRMS portal. Climate reanalysis variables, including vapor pressure deficit and precipitation, were retrieved from ERA5-Land (ECMWF). Net Ecosystem Exchange (NEE) estimates were derived from the FLUXCOM ensemble dataset. All preprocessed data layers, analysis scripts, and derived outputs used to construct the Compound Stress Index (CSI) and early warning signal models are available at https://github.com/ma7moodshaker/BEAT.

Conflicts of Interest

The authors declare no conflict of interest.

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