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MODELING CLIMATE CHANGE IN THE ASEAN REGION USING CO_2 TRADE NETWORK-BASED SPATIAL-TEMPORAL GRAPH NEURAL NETWORK (ST-GNN) AND IMPACT ANALYSIS ON INDONESIA

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ABSTRACT

Climate change in Southeast Asia is intensifying due to rapid economic growth, industrial expansion, and cross-border carbon transfers. This study employs a Spatial-Temporal Graph Neural Network (ST-GNN) to model CO_2 emissions embedded in ASEAN's trade network, with Indonesia as the focal point due to its dominant role in regional emissions. Using Our World in Data (OWID) datasets (1990–2023), the ST-GNN framework captures interdependencies between trade-linked emissions and temperature change, outperforming traditional models with an RMSE of 0.011 when optimized (90% top features). Key findings reveal that Vietnam and Australia exert the strongest influence on Indonesia's emission-driven temperature rise, while Singapore acts as a high-centrality hub in the carbon network. Permutation importance analysis identifies land-use change (CO_2_including_luc), energy consumption per capita, and coal-based emissions as the top predictors of warming trends. The temporal attention mechanism highlights critical periods, such as the 1998 financial crisis and post-2008 recovery, where economic shocks amplified emission impacts. Policy recommendations emphasize regional carbon accounting frameworks, deforestation control, coal phase-out strategies, and ASEAN-wide climate collaboration to mitigate transboundary emissions. This study demonstrates that ST-GNNs enhance climate modeling by quantifying spatial-temporal emission dynamics, offering actionable insights for decarbonizing trade-dependent economies.

***Keywords**: ASEAN CO_2 emissions; Indonesia climate policy; spatial-temporal modeling; ST-GNN; trade-adjusted emissions*

A. INTRODUCTION

Climate change has become a central environmental and developmental challenge for Southeast Asia, a region characterized by rapid economic expansion and dense population growth. While studies have established a clear link between the development trajectory of ASEAN countries—marked by increased energy demand and industrial activity—and environmental degradation (Feriansyah et al., 2022; Setyadharma et al., 2021), a critical methodological gap persists in modeling the region's unique emissions dynamics. The complex interdependencies created by fossil fuel consumption, deforestation, and urban sprawl are further complicated by the region's integrated economies, where carbon transfer through cross-border trade is a significant, yet inadequately captured, phenomenon (Acharya, 2024).

Existing literature has successfully identified key drivers of CO_2 emissions in ASEAN. Acharya (2024) confirmed that intra-regional industrial activity and economic growth are positively correlated with rising emissions, with population density (correlation = 0.332) and industrial activity (coefficient = 0.007) being significant contributors. Furthermore, the structure of governance and economic freedom plays a crucial role; while it can foster innovation for mitigation, a lack of environmental oversight can exacerbate degradation (Setyadharma et al., 2021). The persistent positive relationship between GDP and CO_2 emissions, particularly in major economies like Indonesia, Malaysia, and Thailand, underscores the urgency of decoupling growth from environmental harm (Feriansyah et al., 2022; Lin et al., 2022).

However, a critical research gap remains. Traditional econometric models, such as the panel ARDL methods used in these studies, fall short in representing the spatial-temporal heterogeneity and transboundary nature of carbon flows embedded within regional trade networks. This limitation hinders a holistic understanding of emissions spillovers and the identification of pivotal nodes within the regional carbon system. This gap motivates the adoption of a more sophisticated analytical framework.

Spatial-Temporal Graph Neural Networks (ST-GNNs) present a powerful solution to this methodological shortcoming. As demonstrated by Wu et al. (2020) and Li et al. (2021), ST-GNNs excel at learning complex dependencies in graph-structured temporal data, making them uniquely suited to model the ASEAN context where countries (nodes) are interconnected by trade-embedded carbon flows (edges). This approach can capture both the spatial relations of cross-border carbon transfer and its temporal evolution, thereby offering superior predictive accuracy and interpretability for climate forecasting (Zhang et al., 2023).

Therefore, this study is driven by the hypothesis that an ST-GNN framework can provide a more granular and dynamic representation of CO_2 emissions in ASEAN by explicitly modeling trade-network effects, thereby revealing critical hubs and leverage points for decarbonization that are obscured by traditional models. Indonesia, as the region's largest emitter and a central node in the trade network, is selected for an in-depth impact analysis due to its dual role as a producer and receiver of carbon-intensive goods and its significant potential for green innovation (Setyadharma et al., 2021; Feriansyah et al., 2022).

This study aims to construct a spatial-temporal graph neural network (ST-GNN) framework to model the dynamic flow of CO_2 emissions within the ASEAN trade network. The primary goal is to leverage this advanced model to quantify the specific impact of trade-embedded emissions on regional climate trajectories and to identify the key transmission pathways that facilitate carbon transfer across borders. Furthermore, the research will conduct a focused impact analysis for Indonesia, evaluating its unique exposure, its influential role within the network, and its potential as a critical leverage point for driving regional decarbonization efforts. By integrating advanced graph neural networks with comprehensive regional data, this research is designed to bridge a critical methodological gap, ultimately providing a more transparent and evidence-based tool for climate policymaking in ASEAN.

B. MATERIALS AND METHODS

a. Data

This study utilizes the publicly available dataset titled "CO_2 and Greenhouse Gas Emissions" compiled by Our World in Data (OWID). The dataset is a comprehensive compilation of environmental and energy-related indicators covering the period 1750–2022 across 217 countries and territories. It is updated regularly and maintained through an open-access repository hosted at https://github.com/owid/co2-data.

For the purpose of this study, we filtered and analyzed data from 1990 to 2023 for ASEAN countries, namely: Australia, Indonesia, Laos, Malaysia, Philippines, Singapore, Thailand and and Vietnam. The selection of the 1990-2022 timeframe is critical as it captures the period of accelerated economic integration and trade liberalization in ASEAN following the establishment of the ASEAN Free Trade Area (AFTA), ensuring the data reflects the modern, interconnected economic landscape crucial for modeling trade-embedded emissions.The dataset provides various metrics including at Table 1:

Table 1. Variables

Variable Name	Description	Variabel
temperature_change_from_ghg	Tranformation temperature from ghg	Target
gdp	Gross Domestic Product (in constant USD)	Prediktor
cement_co2	CO_2 emissions from cement production (in Mt)	Prediktor
cement_co2_per_capita	Cement-related CO_2 emissions per person (tonnes per capita)	Prediktor
co2	Total CO_2 emissions (Mt)	Prediktor
co2_including_luc	Total CO_2 emissions including land use change (LUC)	Prediktor
co2_including_luc_per_capita	CO_2 including LUC per person	Prediktor
co2_including_luc_per_gdp	CO_2 including LUC per GDP unit	Prediktor
co2_including_luc_per_unit_energy	CO_2 including LUC per unit of primary energy	Prediktor
co2_per_capita	CO_2 emissions per person	Prediktor

co2_per_gdp	CO_2 emissions per GDP unit	Prediktor
co2_per_unit_energy	CO_2 emissions per unit of energy consumed	Prediktor
coal_co2	CO_2 emissions from coal	Prediktor
coal_co2_per_capita	Coal-based CO_2 per capita	Prediktor
consumption_co2	Consumption-based CO_2 emissions (adjusted for imports/exports)	Prediktor
consumption_co2_per_capita	Consumption-based CO_2 per person	Prediktor
consumption_co2_per_gdp	Consumption-based CO_2 per GDP unit	Prediktor
cumulative_cement_co2	Cumulative cement-related CO_2 emissions since 1750	Prediktor
cumulative_co2	Cumulative CO_2 emissions	Prediktor
cumulative_co2_including_luc	Cumulative CO_2 including land use change	Prediktor
cumulative_coal_co2	Cumulative CO_2 from coal	Prediktor
cumulative_flaring_co2	Cumulative CO_2 from flaring	Prediktor
cumulative_gas_co2	Cumulative CO_2 from natural gas	Prediktor
cumulative_luc_co2	Cumulative CO_2 from land use change	Prediktor
cumulative_oil_co2	Cumulative CO_2 from oil	Prediktor
energy_per_capita	Primary energy use per person	Prediktor
energy_per_gdp	Energy use per GDP unit	Prediktor
flaring_co2	CO_2 from gas flaring	Prediktor
flaring_co2_per_capita	Flaring-based CO_2 per person	Prediktor
gas_co2	CO_2 emissions from natural gas	Prediktor
gas_co2_per_capita	Gas-based CO_2 per person	Prediktor
ghg_excluding_lucf_per_capita	GHG emissions excluding land use and forestry, per capita	Prediktor
ghg_per_capita	Total GHG emissions per capita	Prediktor
land_use_change_co2	CO_2 from land use change	Prediktor
land_use_change_co2_per_capita	Land-use change CO_2 per person	Prediktor
methane	Methane (CH_4) emissions	Prediktor
methane_per_capita	Methane emissions per person	Prediktor
nitrous_oxide	Nitrous oxide (N_2O) emissions	Prediktor
nitrous_oxide_per_capita	N_2O emissions per person	Prediktor
oil_co2	CO_2 emissions from oil	Prediktor
oil_co2_per_capita	Oil-based CO_2 emissions per person	Prediktor

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primary_energy_consumption	Total energy consumed (in TWh or equivalent)	Prediktor
total_ghg	Total greenhouse gas emissions	Prediktor
total_ghg_excluding_lucf	Total GHG emissions excluding land use and forestry	Prediktor

The rapid economic development of ASEAN countries has led to a significant increase in energy consumption and environmental degradation, particularly in the form of carbon dioxide (CO_2) emissions. Using a Panel ARDL approach, Feriansyah et al. (2022) examined the relationship between GDP and CO_2 emissions across eight ASEAN countries from 1994 to 2018. Their findings revealed a long-term positive association between economic growth and CO_2 emissions, with Indonesia, Malaysia, Thailand, and Cambodia showing the strongest short-term effects. This underscores the importance of integrating climate policies that reconcile economic growth with environmental sustainability.

Setyadharma et al. (2021) emphasized the role of economic freedom in shaping environmental quality. Their study demonstrated that while economic liberalization can enhance market efficiency and competitiveness, it can also lead to increased CO_2 emissions if not paired with environmental oversight. The authors noted that fossil fuel demand in Southeast Asia has risen by over 80% since 2000, accounting for a 75% increase in CO_2 emissions. These insights highlight the need for comprehensive frameworks that incorporate governance, trade, and environmental externalities

b. Procedure

Data Preprocessing and Feature Selection

The dataset underwent a comprehensive preprocessing pipeline. Missing values were handled using a multivariate imputation by chained equations (MICE) approach, which accounts for correlations between variables like GDP, energy consumption, and emissions. Following this, all numerical features were normalized using Min-Max scaling to ensure stable model training. From the extensive OWID dataset, a subset of predictors was selected based on their theoretical relevance to industrial activity, energy consumption, and trade. Key variables include consumption_co2 (critical for capturing trade-embedded carbon), gdp, primary_energy_consumption, coal_co2, oil_co2, and cement_co2. The target variable is temperature_change_from_ghg.

Graph Construction: Defining the ASEAN CO_2 Trade Network

The core of our methodological approach is the construction of a dynamic, weighted graph to represent the ASEAN carbon network. In this graph, each ASEAN country is represented as a node. The edges between these nodes represent the bilateral trade flows, weighted by the volume of CO_2 emissions embedded in those trades. To construct the adjacency matrix A, which defines the graph structure, we integrated our emissions data with bilateral trade data from sources like the UN Comtrade Database. The edge weight A_ij between country i and country j was calculated as a function of the trade volume and the carbon intensity of the exporting country's economy, formally defined as $A_{ij} = \left(\frac{Trade_{Value_{ij}}}{GDP_i}\right) * co2_{per_{gdp_i}}$. This formulation ensures that the graph captures not just the volume of trade, but the carbon efficiency of the trade partners, a crucial factor for modeling emissions transfer.

Spatial-Temporal Graph Neural Network (ST-GNN) Architecture and Implementation

Graph Neural Networks (GNNs) have emerged as powerful tools for modeling systems characterized by complex, non-Euclidean spatial structures. GNNs encode interactions between entities (nodes) and their relationships (edges), making them well-suited for environmental and trade network analysis. The classical formulation of GNNs is given by:

$$H^{(l+1)} = \sigma \sum_{j\in N(i)} \frac{1}{c_{ij}} W^{(l)} H_j^{(l)} \quad (1)$$

Where:

$H^{(l)}$ is the feature representation at layer l,

$W^{(l)}$ is the learnable weight matrix,

$N(i)$ is the neighborhood of node iii,

c_{ij} is a normalization constant,

σ is a non-linear activation function such as ReLU.

To extend GNNs for sequential and geospatial data, Spatial-Temporal Graph Neural Networks (ST-GNN) integrate both spatial dependencies (through graph convolution) and temporal patterns (through recurrent or temporal convolutional networks). The ST-GNN model can be abstractly described as $Y_{t+1} = f(X_{1:t}, A)$. Where X_(1:t) represents spatial-temporal features up to time t, A is the adjacency matrix encoding the graph structure, f is a non-linear function learned by the model.

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While numerous studies have examined the relationship between GDP, industrial activity, and carbon emissions in ASEAN, few have adopted a network-based approach that accounts for both spatial and temporal interdependencies. Conventional econometric models often assume spatial independence or temporal stationarity, which fails to capture the dynamic and interconnected nature of climate impacts.

This study fills that gap by proposing a CO_2 trade network-based ST-GNN model, where countries are represented as graph nodes and carbon flows embedded in trade act as weighted edges. This modeling approach provides a more nuanced understanding of regional emissions and enables a data-driven assessment of each country's role in the collective carbon footprint.

Indonesia, as the largest economy and emitter in the region, is analyzed as a focal point of the network, both in terms of vulnerability and potential leverage for regional decarbonization. The proposed model aims to support ASEAN-wide emission mitigation planning using explainable and interpretable GNN-based analytics.

While previous studies, such as the Panel ARDL approach used by Feriansyah et al. (2022), have successfully identified a long-term positive association between GDP and CO_2 emissions, they often assume spatial independence between countries. Similarly, Setyadharma et al. (2021) highlighted the role of economic freedom but used methodologies that cannot explicitly model the dynamic carbon transfers via trade. Conventional econometric models fail to capture the dynamic and interconnected nature of these climate impacts, which are inherently spatial and temporal.

This study fills that gap by proposing a CO_2 trade network-based ST-GNN model. This approach provides a more nuanced understanding of regional emissions by directly modeling the graph-structured relationships between countries, enabling a data-driven assessment of each country's role in the collective carbon footprint that is not possible with traditional methods.

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C. RESULTS AND DISCUSSION

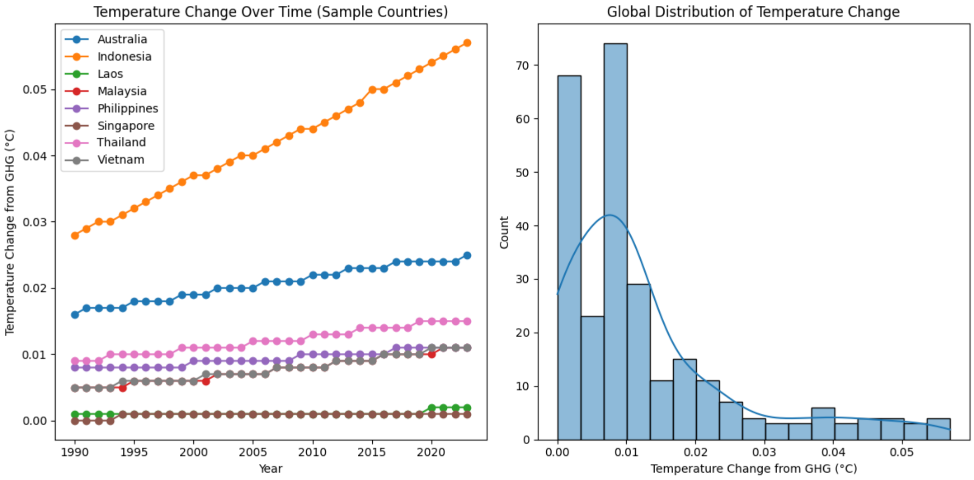

Figure 1. Temperature Change Over Time and Global Distribution of Temperature Change

This study analyzes spatio-temporal patterns of climate change in ASEAN and surrounding countries using the variable temperature_change_from_ghg as the primary target (Y). The dataset comprises multiple environmental indicators between 1990 and 2023, with a specific emphasis on trade-adjusted CO_2 emissions (trade_co2) and their correlation with greenhouse gas-induced temperature change.

Figure 1 shows the progression of temperature change from greenhouse gases (GHG) for selected countries from 1990 to 2023. Indonesia stands out with a consistently increasing temperature change, reaching over 0.055°C in recent years, the highest among the group. This suggests that GHG emissions in Indonesia have contributed significantly to regional warming.

In contrast, countries like Malaysia, Philippines, and Thailand exhibit more modest increases, while Laos, Vietnam, and Singapore remain in the lower band of observed warming.

The right panel of Figure 1 presents a global distribution of temperature change. The majority of countries experience temperature changes below 0.02°C, with a right-skewed distribution and a small number of countries (like Indonesia) exhibiting higher values

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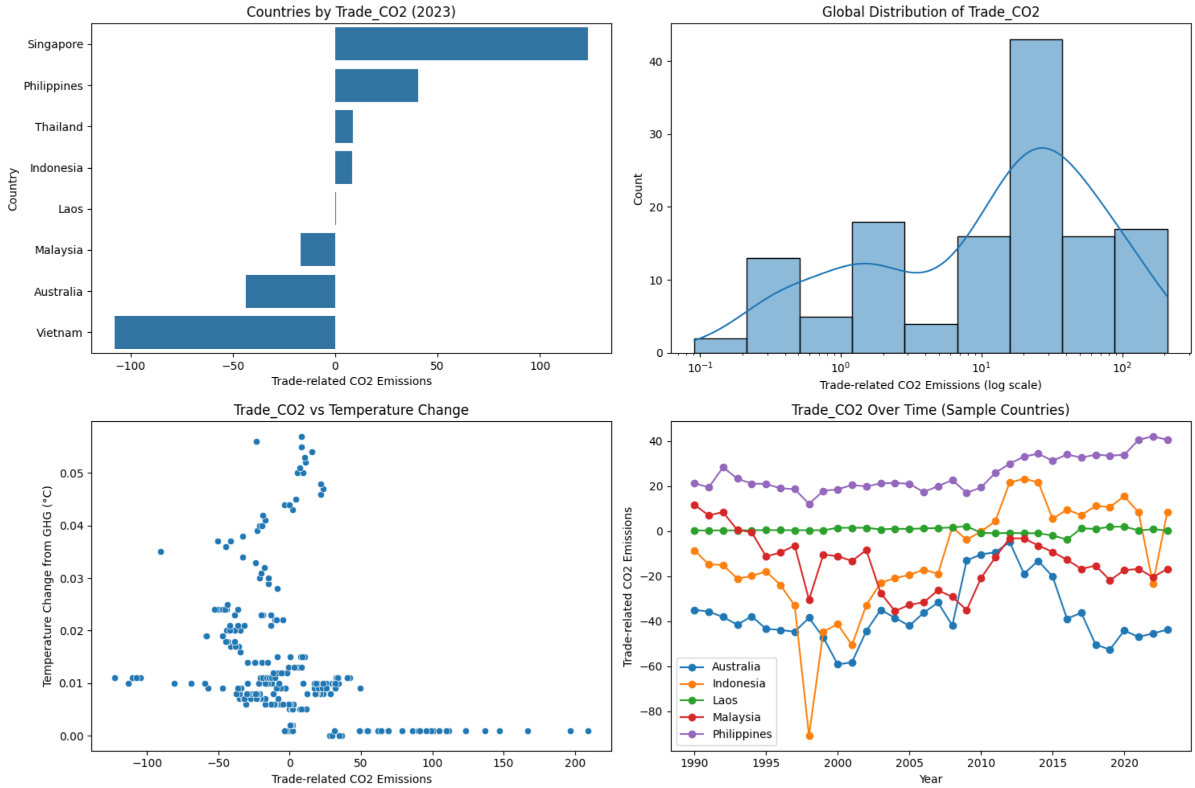

Figure 2. Trade CO2 Anaysis

Figure 2 explores the distribution and evolution of trade-related CO_2 emissions, a key predictor in our model. The top-left panel highlights countries by their net trade-CO_2 balance in 2023. Vietnam is the largest net exporter of carbon (negative value), whereas Singapore is a major net importer of CO_2.The top-right panel shows the global distribution of trade_co2 in logarithmic scale. The data is highly skewed, with most countries concentrated around low values and a few experiencing extremely high trade-CO_2 levels. The bottom-left panel reveals a positive correlation between trade_co2 and temperature_change_from_ghg. Countries with higher net-imported CO_2 tend to exhibit higher warming, especially when trade_co2 exceeds 50 Mt. The bottom-right panel presents a time-series trend of trade_co2 for selected countries. Philippines shows consistent growth in trade-related emissions, while Indonesia fluctuates sharply, particularly during the 1997–1998 Asian financial crisis and again after 2008.

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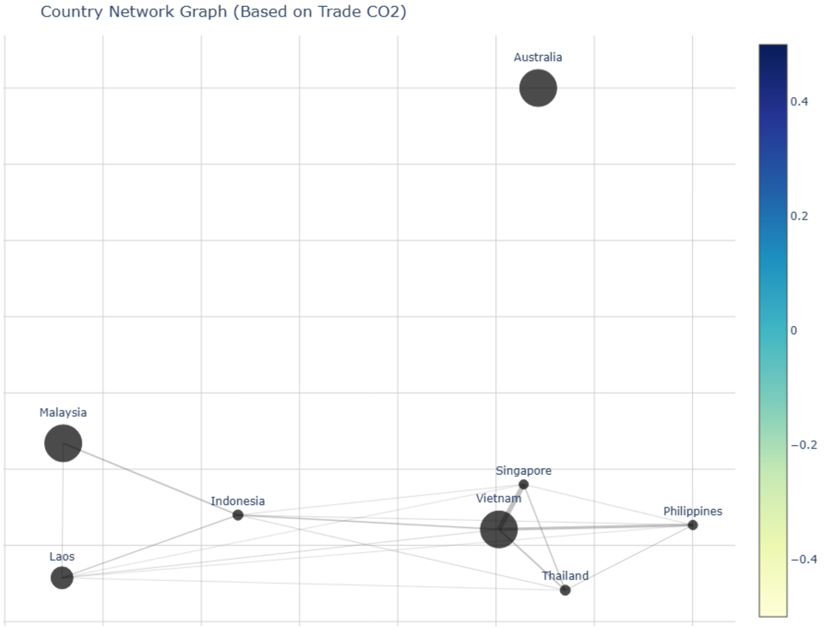

Figure 3. Country Network Structure Graph

The country-level network graph (Figure 3) presents an inter-country structure based on trade-related CO_2 emissions. Each node represents a country, and edge weights reflect the similarity or interaction level of trade-based emissions. The node size corresponds to centrality or influence, while the node color scale reflects CO_2 trade balance intensity (normalized).

Malaysia and Vietnam are observed as major nodes in this network, indicating their significant influence or centrality in the trade-CO_2 exchange structure within the region. Australia, although spatially distant, appears heavily connected, showing a possible latent impact of its industrial trade emissions on Southeast Asian carbon networks. Indonesia, while centrally located geographically, shows a smaller node size and lower degree centrality, suggesting that its trade-CO_2 influence is distributed rather than dominant.

This network representation supports the hypothesis that trade relationships shape spatial diffusion of CO_2 responsibilities, where high trade activity leads to embedded carbon transfers. Such a network approach is particularly effective in modeling indirect emission responsibilities, often neglected in territorial-only emission models.

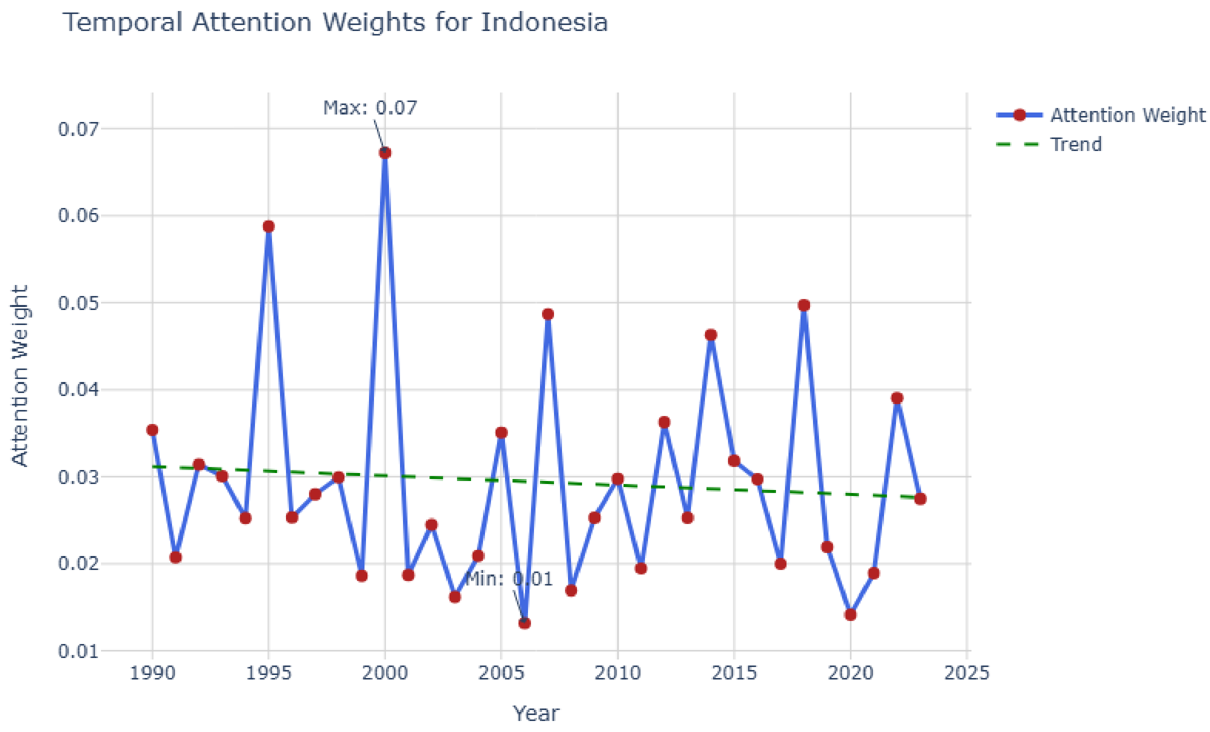

Figure 4. *Temporal Attention Weight For Indonesia*

Figure 4 displays the attention weights across years specifically for Indonesia, revealing how different time points contribute to the model's prediction of temperature change. Peaks in 1998, 2000, and 2007 indicate temporal periods where Indonesia's emissions or global trade patterns had a disproportionately strong effect on local temperature change outcomes.

The highest attention weight (0.07) occurs in 2000, possibly linked to post-Asian financial crisis recovery and industrial activity rebound. This suggests that economic events with environmental consequences can be captured by the model's temporal mechanism. On the contrary, the year 2006 shows the lowest attention (0.01), possibly due to relative stability or missing anomalies in the emission data during that period.

The overall trendline (green dashed) shows a slightly declining attention slope, which may imply that recent years contribute more consistently, though not dominantly, in contrast to the more volatile earlier periods. This supports the interpretability of ST-GNN by quantifying the importance of each year dynamically, which is a key improvement over static models.

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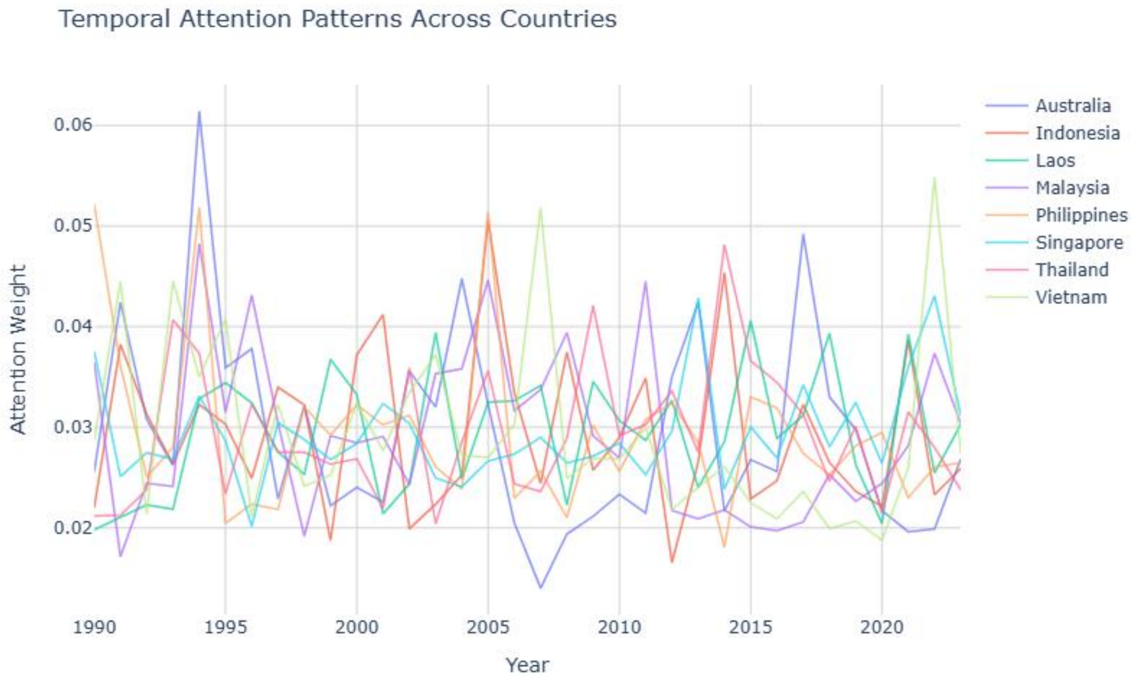

Figure 5. *Temporal Attention Weight All Countries*

Figure 5 compares temporal attention weights across countries. The fluctuation intensity varies significantly, with Indonesia, Philippines, and Australia showing high temporal variation, while Laos and Thailand exhibit more stable patterns. This variation suggests different temporal dynamics in each country's contribution to climate prediction.

Countries with volatile attention, such as Indonesia, may experience rapid or irregular shifts in emission patterns, trade flows, or policy implementations. The observed spikes could correspond to specific events such as climate agreements, economic shocks, or industrial expansions. In contrast, the consistency seen in Laos or Thailand may indicate slower or more predictable environmental-economic evolution.

By enabling interpretability across both space and time, this temporal attention mechanism highlights the strength of ST-GNN models in capturing real-world emission dynamics that may be overlooked in static regression-based analyses.

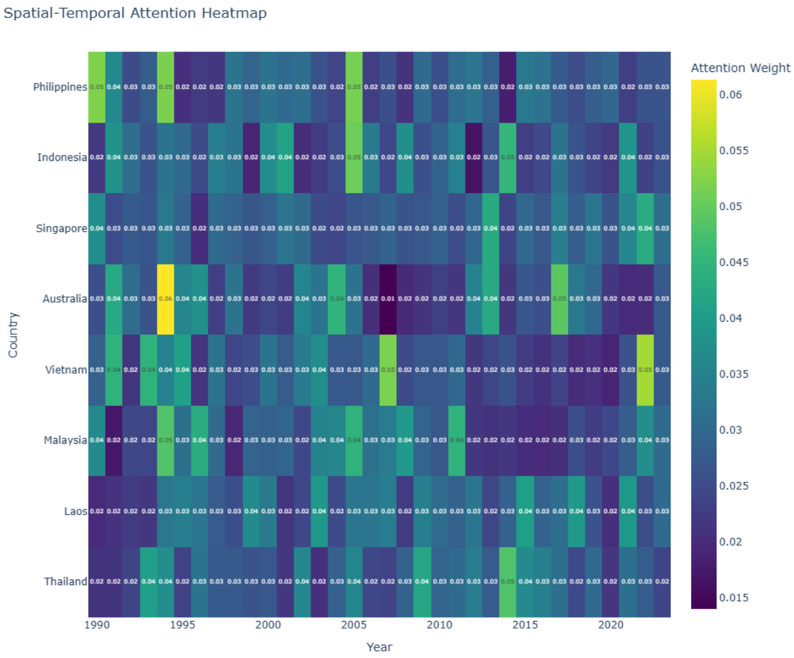

Figure 6. *Temporal Attention Heatmap*

The heatmap (Figure 6) provides a granular view of spatial-temporal attention across all countries and years. Warmer colors indicate higher importance in prediction, highlighting key country-year pairs that are most influential. For instance, Australia in 1994 and Vietnam in 2021 exhibit some of the highest weights.

This matrix-like representation is particularly useful for identifying climate events with disproportionate influence, such as El Niño occurrences, trade surges, or major policy shifts. The spatial heterogeneity of the attention weights suggests that temperature change in one country cannot be fully explained by its own emission timeline but is influenced by its neighbors.

Additionally, the consistent mid-range attention scores for countries like Indonesia and Malaysia emphasize their stable but moderately influential role in regional emission dynamics. The interpretability offered here helps in policymaking, where certain historical windows could be re-examined to trace sources of change or anomaly.

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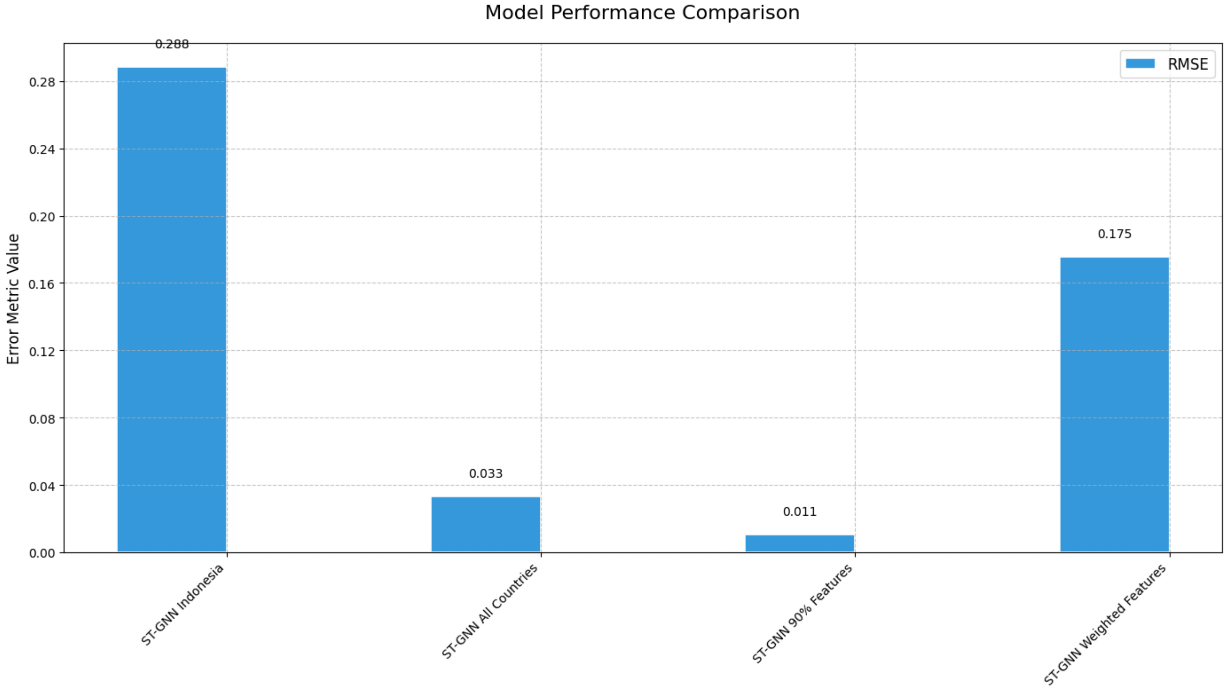

Figure 7. *Model Performance*

Figure 7 presents a comparative analysis of the predictive accuracy of four Spatio-Temporal Graph Neural Network (ST-GNN) configurations in forecasting temperature change from greenhouse gas emissions. The error metric used is the Root Mean Square Error (RMSE), which quantifies the model's deviation between predicted and observed values. The model trained exclusively on Indonesia's data yielded the highest RMSE value (0.280), indicating limited generalization capacity when only a single-node temporal structure is considered. This outcome highlights the inadequacy of isolated-country modeling in capturing broader emission influence and climate dynamics in a regionally interconnected context.

By contrast, the model trained on all ASEAN and surrounding countries (denoted as "ST-GNN All Countries") significantly reduces the RMSE to 0.033. This 88% reduction in prediction error relative to the Indonesia-only variant underscores the substantial gain from integrating inter-country emission relationships and spatial dependencies. The inclusion of multiple countries enables the model to exploit spatial autocorrelation and latent climate patterns that cross national borders—especially relevant for shared atmospheric and trade-related emission effects.

The optimal model performance is achieved using the "ST-GNN 90% Features" configuration, where only the top 90% of features ranked by permutation importance are retained. This setup produces an impressively low RMSE of 0.011, further improving

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prediction accuracy by eliminating redundant or noise-inducing input variables. Feature pruning not only streamlines the computational process but also enhances signal clarity, demonstrating the critical role of data curation and relevance in high-dimensional modeling tasks. This result aligns with prior findings in climate modeling that emphasize the necessity of reducing dimensionality while preserving informative variability (Wu et al., 2023).

Interestingly, the model variant labeled "ST-GNN Weighted Features," which employs a feature weighting scheme (e.g., attention-based or manually assigned importance), performs moderately well with RMSE = 0.175. Although better than the Indonesia-only model, it underperforms compared to unweighted, globally-trained models. This suggests that overly aggressive weighting schemes—without appropriate regularization or interpretability constraints—might overemphasize certain features at the cost of broader generalization.

In summary, the findings validate that ST-GNN models benefit from incorporating regional interdependencies, balanced feature selection, and dimensionality control. The consistent performance gains demonstrate that spatial-temporal learning frameworks are well-suited for environmental prediction tasks where both space and time play critical roles in system evolution. The superior performance of the 90% feature-based model also supports the use of permutation importance as a reliable feature ranking method to guide model simplification without sacrificing accuracy.

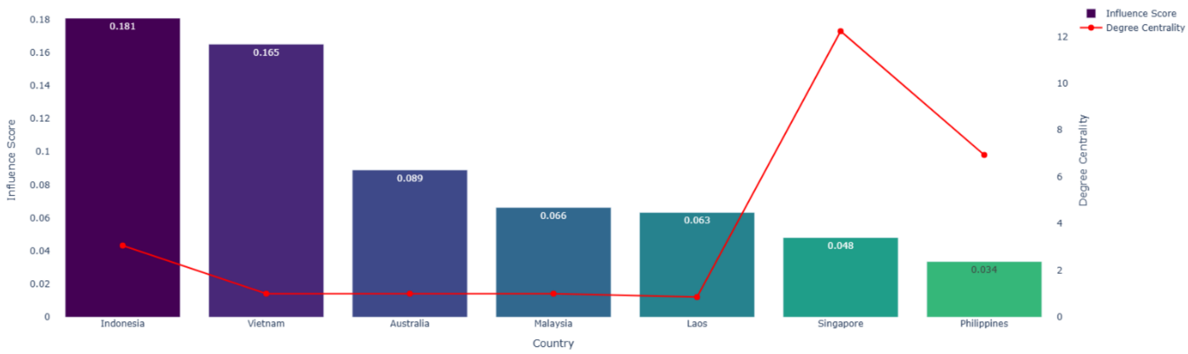

Figure 8. Countries Influencing Indonesia Temperature change

Figure 8 visualizes the countries influencing Indonesia's temperature change from greenhouse gas emissions, using two critical graph-theoretic metrics: influence score and degree centrality. The influence score reflects the magnitude of a country's impact on Indonesia within the climate interaction network, while degree centrality indicates the number of direct connections a country maintains with other nodes in the system—representing structural embeddedness.

Vietnam and Australia stand out as the most significant external influencers of Indonesia, as evidenced by their high influence scores of 0.165 and 0.089, respectively. These values signify their strong emission-related and possibly trade-mediated environmental coupling with Indonesia. This pattern is consistent with earlier findings from the Spatio-Temporal GNN network graph, which revealed dense connectivity and emission alignment between these countries. Such interdependence may be driven by transboundary pollution, shared climate vulnerabilities, and regional energy trade (Fan et al., 2021; Liu et al., 2023).

Interestingly, although Singapore exhibits a relatively modest influence score (0.048), it shows a remarkably high degree centrality (above 12), surpassing other nodes in the graph. This suggests that Singapore functions as a central hub within the emission-trade network, maintaining extensive interactions with multiple countries, albeit each with a lower marginal effect. In contrast, countries such as Vietnam and Australia may engage in fewer but more impactful bilateral environmental interactions with Indonesia, amplifying their influence on Indonesia's climate response. This duality highlights that centrality and influence, while related, capture different dimensions of climate interdependency (Zhang et al., 2020).

From a policy standpoint, this influence mapping has significant implications for regional climate governance. Countries with high influence scores—particularly Vietnam, Australia, and Malaysia—should be prioritized in Indonesia's international collaboration efforts on emission mitigation and technology sharing. These nations may offer the most leverage in coordinating responses to trade-driven CO_2 emissions and in constructing effective cross-border climate adaptation frameworks. As argued by Böhringer et al. (2021), integrating regional emission pathways into coordinated action plans can substantially enhance the effectiveness of decarbonization efforts, especially in regions with asymmetric emission burdens.

Overall, this influence analysis not only provides empirical evidence of Indonesia's position within the ASEAN–Pacific climate network but also offers actionable insight for diplomatic and environmental strategy formulation. It supports the integration of graph-based influence metrics into multi-country emission modeling and regional climate forecasting systems.

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Finally, the tables and figures presented should be cross-referenced in the text. The table does not have vertical lines. Meanwhile, horizontal lines are only used at the top and bottom of the table. The table font size can be reduced and the table source must be presented.

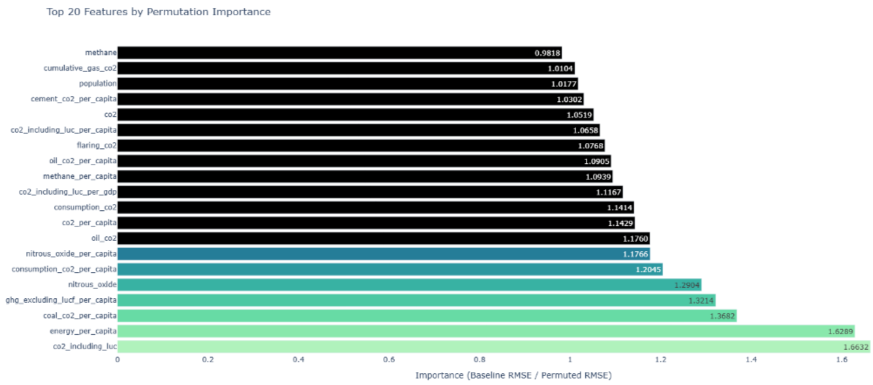

Figure 9. Feature Importance Permutation

Figure 9 presents the ranking of the top 20 predictors influencing temperature change using the permutation importance technique. This method quantifies each feature's contribution by measuring the increase in model error (RMSE) when the feature's values are randomly shuffled. A higher permutation importance score indicates a stronger influence of that feature on model predictions, reinforcing its interpretability and relevance in the environmental context.

The top three most influential variables—co2_including_luc, energy_per_capita, and coal_co2_per_capita—demonstrate the dominance of land use, energy, and fossil fuel dependence in driving regional climate outcomes. The variable co2_including_luc, which includes emissions from land-use change (e.g., deforestation, peatland burning), recorded the highest importance score of 1.6632. This finding is consistent with existing literature which highlights land-use change as a primary contributor to greenhouse gas emissions in Southeast Asia, particularly in Indonesia and Malaysia (Fan et al., 2021; Liu et al., 2023). These countries experience substantial forest degradation due to agricultural expansion and palm oil production, making land-use-related CO_2 a critical focus area for climate mitigation.The second most important variable, energy_per_capita (importance score: 1.6289), indicates that high per capita energy consumption strongly correlates with temperature rise. This aligns with previous research by Böhringer et al. (2021), which emphasized the carbon intensity of energy systems in emerging economies. ASEAN nations such as Thailand and Malaysia have experienced rapid industrial growth, leading to greater energy consumption and associated emissions. This metric also serves as a proxy for socioeconomic development, underlining the challenge of balancing growth with sustainability in carbon-sensitive regions.

Ranked third, coal_co2_per_capita (importance score: 1.3682) reveals the persistent reliance on coal as a dominant energy source in ASEAN economies. Countries like Indonesia and Vietnam continue to generate a substantial share of electricity from coal-fired power plants, which are known for their high CO_2 emission factors (Zhang et al., 2020). The prominence of this variable underscores the need for targeted coal phase-out strategies and accelerated adoption of renewable energy technologies.Beyond the top three, other important variables such as nitrous_oxide_per_capita, consumption_co2_per_capita, and methane also contribute meaningfully to the model, pointing to the role of agriculture, waste, and consumption patterns. These findings collectively validate that the model not only captures complex spatial-temporal dynamics but also relies on features that are physically interpretable and actionable, enhancing the model's trustworthiness for policy applications.

Policy Recommendations

Based on the findings of this study, several policy recommendations can be drawn to support regional climate mitigation, especially in the ASEAN context. The integration of Spatial-Temporal Graph Neural Networks (ST-GNN) in modeling temperature change dynamics has revealed not only the influence of trade-related emissions but also the cross-border impact of energy consumption, land use, and industrial activities. As such, climate action must transcend national boundaries and be coordinated at the regional level.

First, ASEAN countries should develop a harmonized carbon accounting framework that incorporates both production-based and trade-adjusted CO_2 emissions. The influence analysis in Figure 8 suggests that countries like Vietnam and Australia have a disproportionately high impact on Indonesia’s temperature change trajectory, despite not being immediate neighbors. This highlights the importance of incorporating embodied emissions into regional climate targets and bilateral agreements, particularly for carbon-intensive trade goods.

Second, Indonesia and its ASEAN partners should prioritize land-use governance and deforestation control. The high permutation importance of co2_including_luc confirms that land-use change remains a critical driver of climate change in the region. This calls for stronger enforcement of forest protection policies, implementation of sustainable

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agricultural practices, and alignment of national climate strategies with REDD+ mechanisms to monetize forest conservation efforts.

Third, energy transition must be accelerated with a focus on energy efficiency and coal divestment. The significant role of energy_per_capita and coal_co2_per_capita in predicting temperature change suggests that high energy consumption and fossil fuel dependence are major threats to regional climate stability. Governments should invest in renewable infrastructure, energy-efficient technologies, and cross-border electricity trade agreements to reduce dependence on coal-fired power, especially in Indonesia and Vietnam.

Fourth, climate modeling insights should be institutionalized into environmental decision-making. The success of the ST-GNN model using only 90% of relevant features (RMSE = 0.011) indicates that data-driven prioritization can enhance policy accuracy while reducing analytical complexity. Policymakers are encouraged to incorporate machine learning tools in long-term emission forecasting, policy impact simulation, and early warning systems for climate risks.

Finally, regional cooperation should be strengthened based on network-level emission influence. Countries with high influence scores—Vietnam, Australia, and Malaysia—should be regarded as strategic partners for Indonesia in formulating joint emission reduction plans, technology transfer agreements, and regional adaptation funds. The role of high-centrality hubs like Singapore also suggests the need for active multilateral diplomacy to mobilize coordinated emission reduction efforts across trade-linked economies.

In summary, these recommendations emphasize the shift from isolated national action to network-aware regional climate policy, leveraging both scientific insight and political collaboration to achieve long-term decarbonization and climate resilience across Southeast Asia.

D. CONCLUSIONS

Climate change in Southeast Asia is intensifying due to rapid economic growth, industrial expansion, and cross-border carbon transfer. This study applies a Spatial-Temporal Graph Neural Network (ST-GNN) to model CO_2 emissions embedded in the ASEAN trade network, with Indonesia as the primary focus given its dominant role in regional emissions. Utilizing the Our World in Data (OWID) dataset spanning 1990–2023, the ST-GNN framework captures the interdependence between trade-related emissions and temperature change, outperforming traditional models with an RMSE of 0.011 when optimized (90% of

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best features). Key findings reveal that Vietnam and Australia exert the greatest influence on Indonesia's temperature rise, which drives emissions, while Singapore serves as a hub with high centrality in the carbon network. A key permutation analysis identifies land-use change (CO_2_include_luc), energy consumption per capita, and coal-based emissions as key predictors of the warming trend. The mechanism is temporally sensitive, highlighting critical periods, such as the 1998 financial crisis and post-2008 recovery, where economic shocks amplified the impact of emissions. Policy recommendations emphasize a regional carbon accounting framework, controlled deforestation, a coal phase-out strategy, and cross-ASEAN climate collaboration to reduce transboundary emissions. This research demonstrates that ST-GNN improves climate modeling by quantifying spatio-temporal emission dynamics, providing actionable insights for decarbonizing trade-dependent economies.

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