

MAPPING GHG EMISSION VULNERABILITY USING CONVOLUTIONAL AUTOENCODER AND MULTI-SENSOR SATELLITE IN BALI, INDONESIA

Moh Saifulloh^{1,2*}, I Gusti Ngurah Santosa³, I Nyoman Sunarta⁴, I Gusti Agung Ayu Ambarawati³, I Made Sudarma⁵, Abd. Rahman As-syakur⁵

¹Faculty of Marine Sciences and Fisheries, Udayana University, Badung, 80361, Indonesia

²Spatial Data Infrastructure Development Center (PPIDS) Denpasar City, 80225, Indonesia

³Faculty of Agriculture, Udayana University, Denpasar, 80225, Indonesia

⁴Doctoral Program of Tourism Sciences, Udayana University, 80225, Denpasar, Indonesia

⁵Research Center for Environmental (PPLH) of Udayana University, Denpasar, 80225, Indonesia

*Corresponding author: m.saifulloh@unud.ac.id

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ABSTRACT. Global warming, driven by the rising concentration of greenhouse gases (GHGs), demands innovative, data-driven approaches to assess emission vulnerability at regional scales. This study developed a novel framework utilizing an unsupervised Convolutional Autoencoder (CAE) deep learning model combined with multi-sensor satellite data to map GHG emission vulnerability. The framework integrated nine environmental indicators, including tropospheric gases, land surface temperature, vegetation cover, anthropogenic proxies, and elevation, all sourced from freely accessible remote sensing platforms. The CAE model effectively captured complex spatial patterns and reduced high-dimensional inputs into 128 latent features, enabling vulnerability assessment without requiring labeled training data. Results indicated that southern coastal regions, particularly Denpasar and Badung, exhibited the highest vulnerability due to dense urbanization and tourism-related activities. Based on zonal statistics, 11.31% of local administrative zones were identified as having high to very high vulnerability, while 18.72% were classified as moderate, and 69.97% as low to very low. The most vulnerable areas were concentrated along the southern coastline, known as a hub for tourism and economic activity, with additional pockets of vulnerability found in several northern coastal zones. These findings demonstrate the capacity of unsupervised deep learning to detect emission hotspots and spatial variability, particularly in data-limited environments. The integration of scalable algorithms with open-access satellite data allows for rapid, cost-efficient assessments to inform evidence-based climate planning and mitigation strategies. This study introduces a practical and transferable approach for spatial quantification of GHG vulnerability, offering actionable insights for advancing global climate policy and supporting the Sustainable Development Goals.

KEYWORDS: greenhouse gas, vulnerability mapping, convolutional autoencoder, remote sensing, deep learning, spatial modeling, climate change

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INTRODUCTION

Global climate change is widely recognized as one of the most urgent environmental challenges of the 21st century, with far-reaching implications for ecological sustainability, human health, and socio-economic development (Scafetta 2024). The primary cause of this phenomenon is the rising concentration of greenhouse gases (GHGs) in the atmosphere, which intensifies the

natural greenhouse effect and contributes significantly to global warming (Yang et al., 2022). GHGs such as carbon dioxide (CO₂), methane (CH₄), nitrogen dioxide (NO₂), and sulfur dioxide (SO₂) trap outgoing longwave radiation (Bhatti et al., 2024), thereby leading to an increase in Earth's surface temperatures (Rahaman et al., 2022). The accumulation of these gases is associated with a wide range of adverse effects, including more frequent extreme weather events, declining air quality, and disrupted

regional climate systems (Edo et al., 2024). These impacts present substantial obstacles to the achievement of the United Nations Sustainable Development Goals (SDGs), particularly Goal 13 on climate action.

Climate change, beyond its atmospheric implications, also affects the structural integrity of ecosystems and the functionality of biomes. The warming of Earth's climate alters species distributions, hydrological cycles, and ecosystem services that support agriculture, forestry, and coastal livelihoods (Dar et al., 2020; Grimm et al., 2013; Pecl et al., 2017). The majority of GHG emissions are anthropogenic, stemming from sectors such as energy, industry, transportation, agriculture, land-use change, and waste management (Priyadarshini et al., 2025). Urbanization exacerbates these emissions, with dense population centers contributing disproportionately through increased infrastructure, vehicular activity, and energy consumption. Over time, these patterns of emission become spatially correlated with zones of intense human activity and temporally aligned with rapid economic expansion (Yu et al., 2024). To address these spatial and systemic complexities, remote sensing and Geographic Information Systems (GIS) have emerged as indispensable tools for environmental analysis. Remote sensing enables continuous monitoring of Earth's surface parameters, while GIS allows for spatially explicit modeling of environmental indicators and anthropogenic pressures. These tools provide a basis for multi-scale climate vulnerability assessments, from local urban settings to regional and global contexts. For example, Valjarević et al. (2022) utilized satellite and GIS-based approaches to update global climate classification, revealing nuanced climate dynamics and spatial vulnerabilities.

Bali Province, Indonesia, a globally recognized tourism hotspot, is experiencing substantial environmental stress due to accelerated land-use transformation (Saifulloh et al., 2025). Recent research indicates that surface temperatures in Bali have been increasing at an average rate of 0.01°C per year (Sunarta et al., 2022). This trend is closely associated with the widespread conversion of natural landscapes into built environments, including hotels, resorts, restaurants, and urban settlements (Andyana et al., 2023; Diara et al., 2024; Sunarta and Saifulloh, 2022a). The loss of vegetative cover resulting from urban expansion significantly reduces the landscape's capacity for carbon sequestration (Sudarma et al., 2024; Susila et al., 2024; Trigunasih and Saifulloh, 2022), while emissions from transportation, hospitality operations, solid waste, and agricultural practices continue to intensify. Despite the significance of these transformations, there remains a lack of spatially explicit data and systematic assessments of GHG emission vulnerability for the region. This data gap highlights the need for robust geospatial methodologies to inform mitigation strategies and policy interventions.

Although various studies have sought to analyze GHG vulnerability, most have been constrained by limited spatial, temporal, or variable coverage. For instance, (Hassaan et al., 2023) assessed CO and PM_{2.5} exposure using discrete point-source data, lacking spatial continuity. Sakti et al. (2023) employed Sentinel-5P to monitor gaseous pollutants such as CO, NO₂, and SO₂, yet failed to incorporate critical environmental metrics such as vegetation and temperature (Pan et al., 2024). While meteorological influences have been examined in studies by (Ayyamperumal et al., 2024; Z. Feng et al., 2023), few efforts have systematically integrated these variables within spatially scalable frameworks. In the region of Bali Province, NO₂ concentrations have been examined

for the year 2020 (Sunarta and Saifulloh, 2022b), though such assessments were not embedded within a broader vulnerability framework. Meanwhile, spatial machine learning models such as fuzzy geographically weighted clustering (Grekousis et al., 2024) have incorporated static demographic indicators but still fall short of accounting for dynamic spatiotemporal GHG variability.

To overcome these limitations, the present study introduces a comprehensive approach for mapping GHG vulnerability through unsupervised deep learning. The framework employs a convolutional autoencoder (CAE), a class of neural networks capable of learning latent feature representations without requiring labeled data (Azarang et al., 2019; Cui et al., 2018). All input variables are derived from freely available multi-sensor satellite datasets, retrieved via the Google Earth Engine (GEE) platform (Gorelick et al., 2017). These include primary GHG indicators (NO₂, CO, SO₂, and Aerosol Optical Depth), environmental variables (temperature and vegetation indices), human activity proxies (population density and nighttime lights), and topographic data.

This method enables detailed spatial and temporal characterization of emission vulnerability, eliminating the need for resource-intensive field data collection. By forgoing reliance on labeled training data, the CAE model supports rapid, cost-effective, and reproducible assessments of environmental vulnerability. The innovation of this research lies in the fusion of multi-source satellite data with unsupervised deep learning to detect spatial patterns of vulnerability, particularly in data-limited regions such as Bali. Ultimately, this research advances both the scientific understanding and practical management of GHG emissions, contributing meaningfully to global climate resilience and sustainability agendas.

MATERIALS AND METHODS

Study area

The study was conducted in Bali Province, Indonesia, an island located in Southeast Asia with significant ecological sensitivity and economic reliance on tourism. Geographically, Bali lies around 8°00'S latitude and 115°40'E longitude, covering a land area of 5,593.60 km² (Fig. 1). Administratively, the province consists of nine regencies and one city: Denpasar, Badung, Gianyar, Buleleng, Tabanan, Jembrana, Klungkung, Bangli, and Karangasem, encompassing 57 subdistricts and 716 villages. According to the 2025 provincial census (BPS Bali, 2025), Bali has a population of approximately 4.46 million, with an average density of 798 people/km². Denpasar City has the highest population density (6,058 people/km²), followed by Gianyar (1,447 people/km²) and Badung (1,426 people/km²), which are the primary centers of tourism and urban development (BPS Provinsi Bali, 2025).

In terms of long-term climatic conditions, Bali experiences a tropical monsoon climate with a distinct wet and dry season. Based on historical records, average temperatures have ranged between 22.5 and 27.5°C, while projections suggest future increases to 25.5–29.5°C. Northern Bali in particular is projected to face temperature anomalies ranging from 1.6 to 2.9°C, coupled with declining humidity levels, especially in the north. In contrast, southern areas may experience slight increases in humidity. Under the representative concentration pathways (RCP) 4.5 climate scenario, Bali is predicted to lose areas with comfortable climate zones (20–26°C), giving way to predominately hot and dry conditions (Toersilowati

et al., 2022). Similarly, long-term projections suggest rainfall will fluctuate annually but remain within a relatively stable range of 2,066–2,170 mm, with both maximum and minimum temperatures continuing to rise by up to 2°C (Puspitasari and Wu, 2025). These climatic shifts pose significant implications for urban planning, agriculture, and environmental resilience in Bali, underscoring the urgent need for spatially explicit assessments of greenhouse gas vulnerability.

Workflow framework and data sources

To assess greenhouse gas (GHG) emission vulnerability spatially, a systematic methodological framework was developed, integrating multi-sensor satellite observations with unsupervised deep learning. The methodological workflow (Fig. 2) comprises three core phases: (1) data acquisition and preprocessing using Google Earth Engine (GEE), (2) deep learning modeling using a convolutional autoencoder (CAE), and (3) postprocessing and interpretation using zonal statistics.

In Phase I, remotely sensed variables were selected to reflect GHG emission sources, environmental sensitivity, and anthropogenic exposure. Table 1 outlines the nine indicators used: NO₂, CO, SO₂ (Sentinel-5P), NDVI, LST, AOD (MODIS), population density (WorldPop), nighttime lights (VIIRS), and elevation (SRTM). All datasets were resampled to 1 km² and reprojected to WGS 1984 UTM Zone 50S.

The open-source remote sensing data utilized in this study originated from multiple sensors with native spatial resolutions ranging from 30 meters to approximately 1,000 meters. Most of the datasets representing sources of greenhouse gas emissions, particularly from atmospheric sensors, are provided at a coarser resolution of around 1 km. Therefore, for consistency and compatibility within the modeling process, all variables were resampled to a

uniform spatial resolution of 1 km². This harmonization of spatial resolution is essential for feeding standardized input into the unsupervised deep learning model, ensuring that data dimensions are consistent (Y. Han et al., 2024; Li et al., 2024). To maintain temporal consistency across datasets, pollutant-related variables and other emission source indicators (such as NO₂, CO, SO₂, AOD, NDVI, and LST) were accessed using mean values coded over the 2022–2024 period via GEE. In contrast, datasets lacking temporal resolution, such as SRTM elevation and WorldPop population data, used the most recent available data. Given that this is a preliminary study conducted at a regional mapping scale, a 1 km² resolution is appropriate and consistent with similar studies implemented in other parts of the world (Garajeh et al., 2023; Maurya et al., 2022; Xiong et al., 2021).

Data preprocessing and tensor construction

Each raster file was imported using the rasterio library and converted to 32-bit floating-point arrays. Missing values were replaced with zero, particularly for elevation data beyond the study boundary. After spatial alignment, each dataset was normalized using min-max scaling to standardize feature ranges to [0, 1], following Eq. 1:

$$x'_{ik} = \frac{x_{ik} - \min(x_k)}{\max(x_k) - \min(x_k)} \quad (1)$$

where x'_{ik} denotes the normalized value of variable k at pixel i , while $\min(x_k)$ and $\max(x_k)$ represent the minimum and maximum values observed across the entire raster for variable k . This ensures comparability among different datasets during model training.

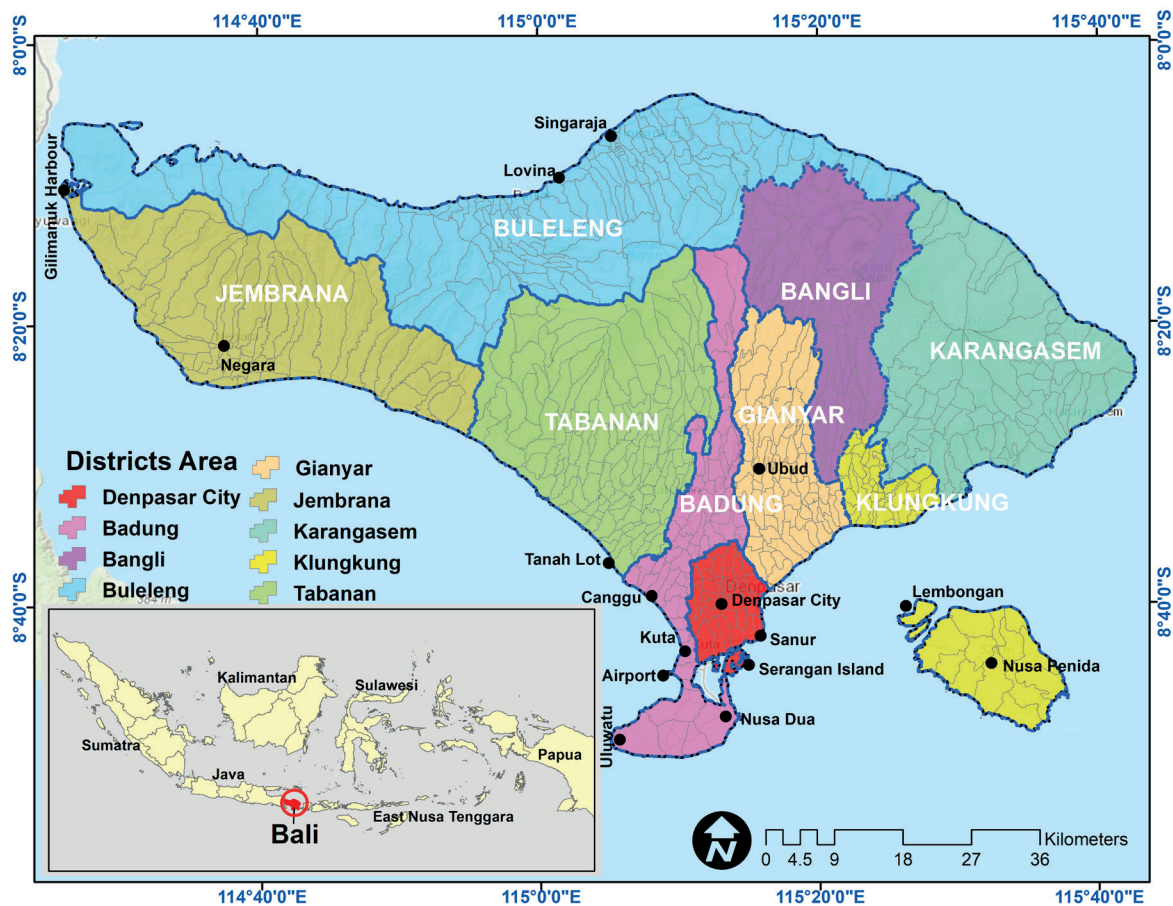


Fig. 1. Research location in Bali Province, Indonesia

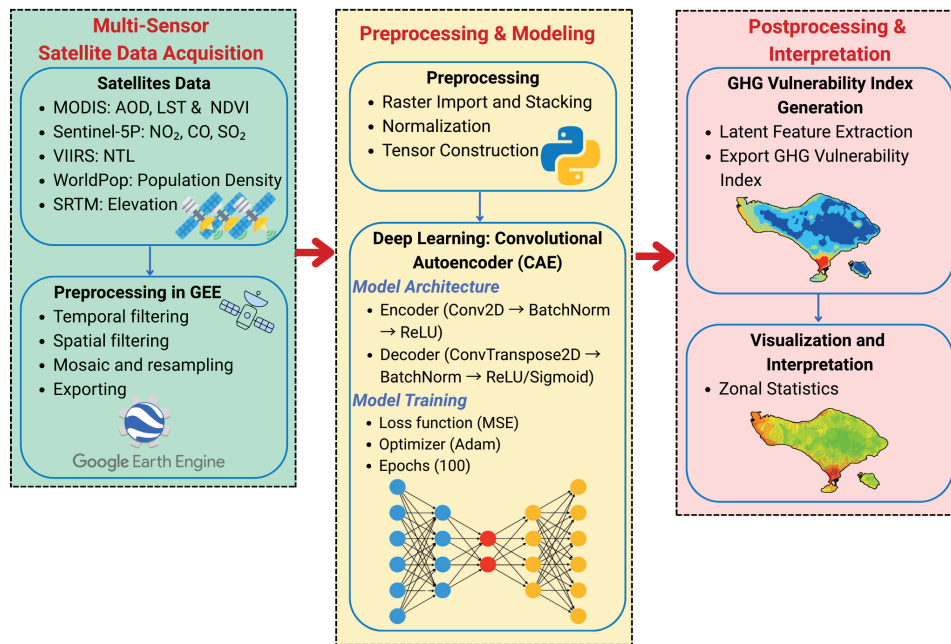


Fig. 2. Workflow Framework of the Research

Table 1. Multi-Sensor Satellite Data and Functional Roles in Regional GHG Vulnerability Modeling

Nº	Data source (GEE)	Extracted variable	Spatial & temporal resolution	Functional role in the model
1	Sentinel-5P TROPOMI (COPERNICUS/S5P/OFFL/L3_NO2)	Tropospheric NO ₂ (mol/m ²)	- Pixel Size: 1113.2 meters - Revisit Interval: 2 Days	Proxy for traffic and industrial emissions; indicates nitrogen-based pollution intensity
2	Sentinel-5P TROPOMI (COPERNICUS/S5P/OFFL/L3_CO)	Tropospheric CO (mol/m ²)	- Pixel Size: 1113.2 meters - Revisit Interval: 2 Days	Represents incomplete combustion from fossil fuel and biomass burning
3	Sentinel-5P TROPOMI (COPERNICUS/S5P/OFFL/L3_SO2)	Tropospheric SO ₂ (mol/m ²)	- Pixel Size: 1113.2 meters - Revisit Interval: 2 Days	Emission from power plants, volcanic activity, and smelting industries
4	MODIS MCD19A2 (MODIS/061/MCD19A2_GRANULES)	Aerosol Optical Depth (unitless)	- Pixel Size: 1000 meters - Revisit Interval: Daily	Indicator of atmospheric particulate concentration; linked to PM2.5 exposure
5	MODIS Terra MOD13Q1 (MODIS/061/MOD13Q1)	NDVI (unitless)	- Pixel Size: 250 meters - Revisit Interval: 16 Days	Vegetative cover and greenness; indicator of carbon sequestration capacity
6	MODIS Terra MOD11A2 (MODIS/061/MOD11A2)	Land Surface Temperature (°C)	- Pixel Size: 1000 meters - Revisit Interval: 8 Days	Surface heat intensity; associated with urbanization and land energy balance
7	WorldPop 100m (WorldPop/GP/100m/pop)	Population Density (people/km ²)	- Pixel Size: 92.77 meters - Revisit Interval: -	Proxy for population exposure to emissions; measures human concentration in space
8	VIIRS Nighttime Lights (NOAA/VIIRS/DNB/MONTHLY_V1/VCMCFG)	Nighttime Light Radiance (nW/cm ² /sr)	- Pixel Size: 463.83 meters - Revisit Interval: Monthly	Indicator of anthropogenic energy use and urban footprint
9	SRTM DEM (USGS/SRTMGL1_003)	Elevation (meters)	- Pixel Size: 30 meters - Revisit Interval: -	Terrain factor affecting air flow and pollutant accumulation in lowland areas

The normalized raster stack was reshaped into a 3D tensor $\mathcal{D} \in \mathbb{R}^{C \times H \times W}$, where C is the number of channels (or features), and H and W are the spatial dimensions of the input. This tensor was further converted into a 4D tensor $X \in \mathbb{R}^{1 \times C \times H \times W}$ to match the input format required by the convolutional autoencoder.

Convolutional autoencoder (CAE) modeling

The CAE model was implemented using the PyTorch library (Costa et al., 2024; Subramanian, 2018). It consisted

of an encoder that extracted feature representations and a decoder that reconstructed the input. The architecture was as follows.

Encoder Layers:

- Conv2D (9 → 32) → BatchNorm → ReLU
- Conv2D (32 → 64) → BatchNorm → ReLU
- Conv2D (64 → 128) → BatchNorm → ReLU

Decoder Layers:

- ConvTranspose2D (128 → 64) → BatchNorm → ReLU
- ConvTranspose2D (64 → 32) → BatchNorm → ReLU
- ConvTranspose2D (32 → 9) → Sigmoid

The model was trained using the Mean Squared Error (MSE) loss function, defined by Eq. 2:

$$\mathcal{L}_{MSE} = \frac{1}{n} \sum_{i=1}^n (x_i - \hat{x}_i)^2 \quad (2)$$

where x_i denotes the original input tensor value at index i , and $\hat{x}_i$ is the corresponding reconstructed output. The loss function penalizes reconstruction errors, thereby guiding the encoder to learn compact yet informative representations. The Adam optimizer was employed with a learning rate of 0.001 over 100 training epochs.

GHG vulnerability index

Upon convergence, the encoder output was extracted as a latent tensor $Z \in R^{128 \times H \times W}$, where 128 is the number of abstract feature channels. To collapse this multidimensional feature space into a single-band vulnerability index, mean pooling was applied across all channels (Eq. 3):

$$GHG_{index} = \frac{1}{128} \sum_{c=1}^{128} Z_c \quad (3)$$

where GHG_{index} is the final greenhouse gas emission vulnerability index, and Z_c is the activation of the c^{th} feature channel. The resulting index was again normalized to the range [0, 1] to facilitate interpretation. Higher index values indicate areas with a greater confluence of emission-related stressors and limited ecological buffering.

For policy-oriented interpretation, the vulnerability index raster was intersected with Bali's district-level administrative boundaries. The average vulnerability score for each administrative unit mm was calculated as Eq. 4:

$$V_m = \frac{1}{|Z_m|} \sum_{i \in Z_m} v_i \quad (4)$$

where V_m represents the mean vulnerability index of zone m , calculated by summing all pixel-level vulnerability values v_i within the set of spatial units Z_m , and dividing the result by the total number of pixels $|Z_m|$ within that zone. This procedure translated fine-resolution pixel values into actionable administrative-level metrics that can guide localized climate mitigation planning, land use policy, and emission reduction initiatives.

RESULTS

Dataset from Multi-Sensor Satellite

This study utilized nine environmental variables derived from freely available multi-sensor satellite products. These included tropospheric gases (NO_2 , CO , SO_2), Aerosol Optical Depth (AOD), Land Surface Temperature (LST), vegetation indices (NDVI), anthropogenic proxies (Nighttime Light Radiance and Population Density), and Elevation (Fig. 3). All raster datasets were resampled to a uniform spatial resolution of 1 km² and aligned to the WGS 1984 UTM Zone 50S coordinate system. Each variable was normalized to a [0,1] scale to ensure consistent input for the convolutional model.

Elevated values of NO_2 , CO , SO_2 , and AOD were predominantly observed in lowland urban regions. These concentrations reflect intense combustion activity and atmospheric pollutant accumulation from transportation and industrial sources. Such hotspots were spatially clustered in urban centers and along coastal corridors characterized by dense infrastructure and minimal vegetative cover. Other variables, such as LST, NDVI, population density, and nighttime lights, mirrored patterns of urban expansion. Built-up zones displayed higher land surface temperatures and lower vegetation greenness. Population and light radiance levels further emphasized anthropogenic pressure, while elevation helped determine pollutant dispersion across terrain gradients.

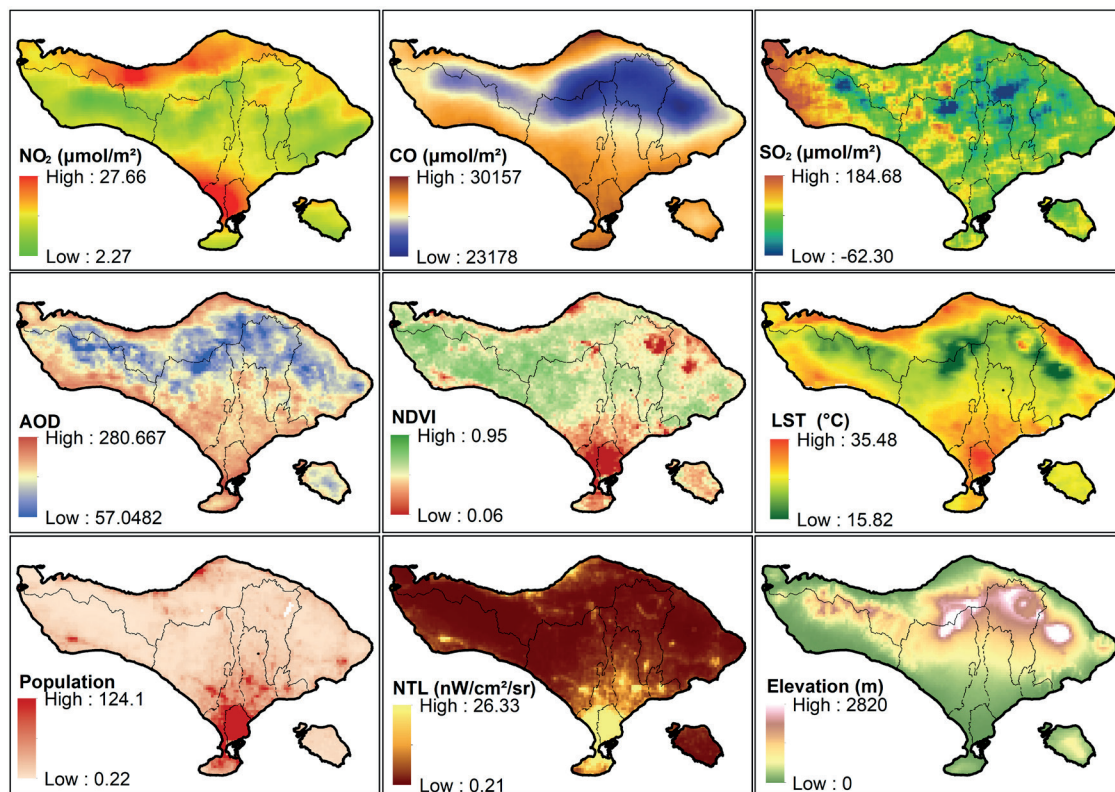


Fig. 3. Environmental variables derived from multi-sensor satellite datasets used in greenhouse gas emission vulnerability modeling

Multivariate Relationships and Feature Space Analysis

The correlation matrix (Fig. 4) identified strong associations among several variables. AOD exhibited high correlation with CO ($r = 0.98$), NDVI ($r = 0.93$), and LST ($r = 0.92$), indicating that areas with higher particulate concentrations often coincide with vegetation decline and thermal stress. NO₂ also showed strong correlations with CO ($r = 0.92$) and LST ($r = 0.88$). Additionally, nighttime light radiance and population density were closely linked ($r = 0.89$), reinforcing their combined role as indicators of urbanization intensity.

Autoencoder Training and Latent Representation

The convolutional autoencoder was trained for 100 epochs using the Adam optimizer with a learning rate of 0.001. Training loss, calculated using mean squared error (MSE), decreased from 0.195 to 0.0021 (Fig. 5), confirming effective convergence. The encoder architecture featured three convolutional layers integrated with batch normalization and ReLU activations, compressing the nine-band input into 128 latent features. The decoder then reconstructed the input using transposed convolutional layers and activation functions.

The latent feature space effectively captured non-linear dependencies among input variables, enabling the model to identify complex spatial patterns of vulnerability. For example, locations with elevated LST, high NO₂, and low NDVI were consistently abstracted into high-risk zones. The low reconstruction error confirmed the model's capability to retain meaningful spatial representations. A single-band vulnerability index was generated via mean pooling across all latent feature channels.

The GHG vulnerability index was classified using the Jenks Natural Breaks method, which separates values into statistically distinct classes by minimizing within-class variance and maximizing variance between classes. This method is widely recognized for its suitability in environmental vulnerability assessments (Hou et al., 2022; Ke et al., 2023; Rzasas and Ciski, 2021). The spatial distribution (Fig. 6) showed that very high vulnerability zones were concentrated in southern Bali, particularly in Denpasar and coastal Badung, where index values exceeded 0.66. These areas exhibited characteristics such as dense urbanization, extensive infrastructure, low vegetation cover, and intensified human activity. High vulnerability also appeared in segments of southern Gianyar and Klungkung. Moderate vulnerability values were observed in transitional inland regions, while low to very low vulnerability was dominant in upland and northern areas with greater ecological stability.

Further analysis of administrative-level units revealed that 11.31% were categorized as high or very high vulnerability, 18.72% as moderate, and 69.97% as low to very low (Fig. 7). These village-level areas represent local jurisdictions responsible for implementing environmental policy. The highest vulnerability scores were recorded in Denpasar, southern Badung, Gilimanuk (Jembrana), and Singaraja (Buleleng), all of which are recognized for concentrated tourism and urban development.

DISCUSSION

This study presents a significant advancement in spatial modeling of greenhouse gas (GHG) emission vulnerability by integrating a convolutional autoencoder (CAE) deep learning approach with multi-sensor satellite

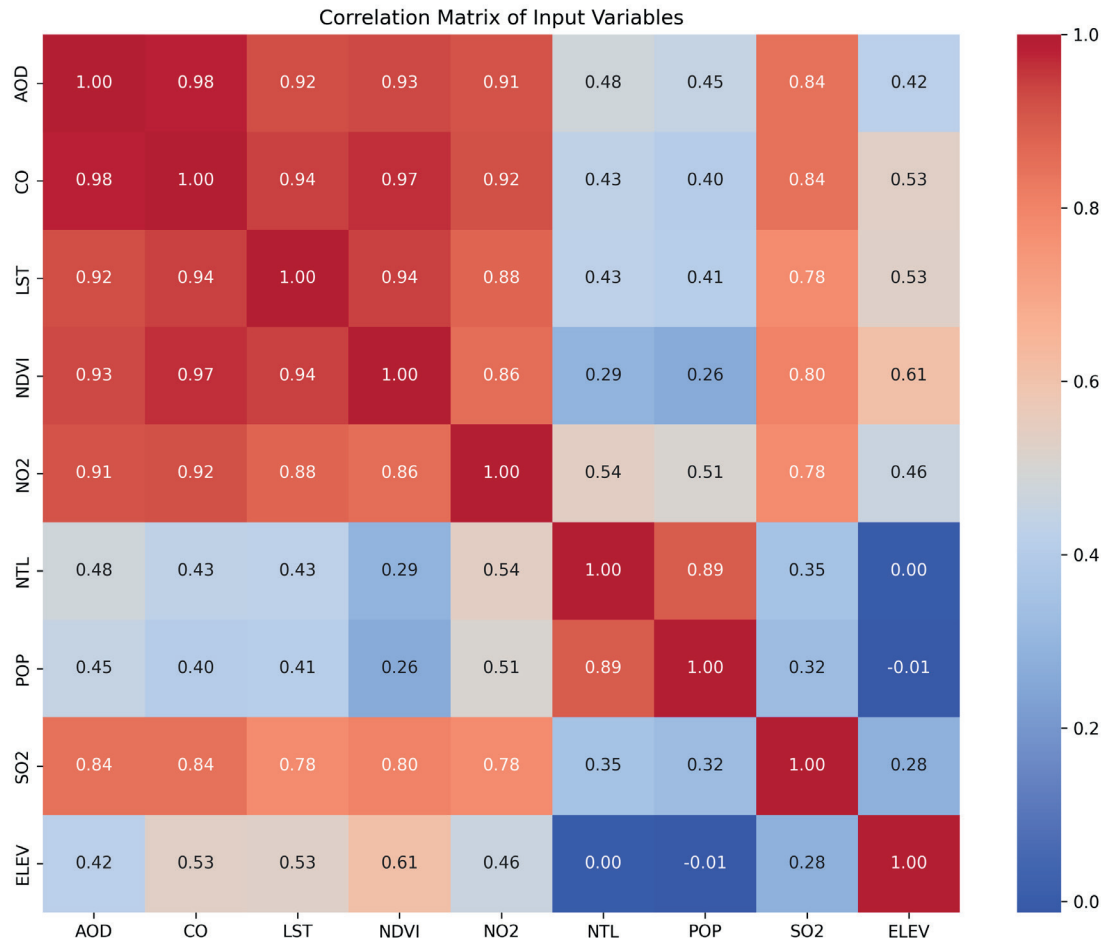


Fig. 4. Correlation matrix of environmental variables used in GHG vulnerability modeling

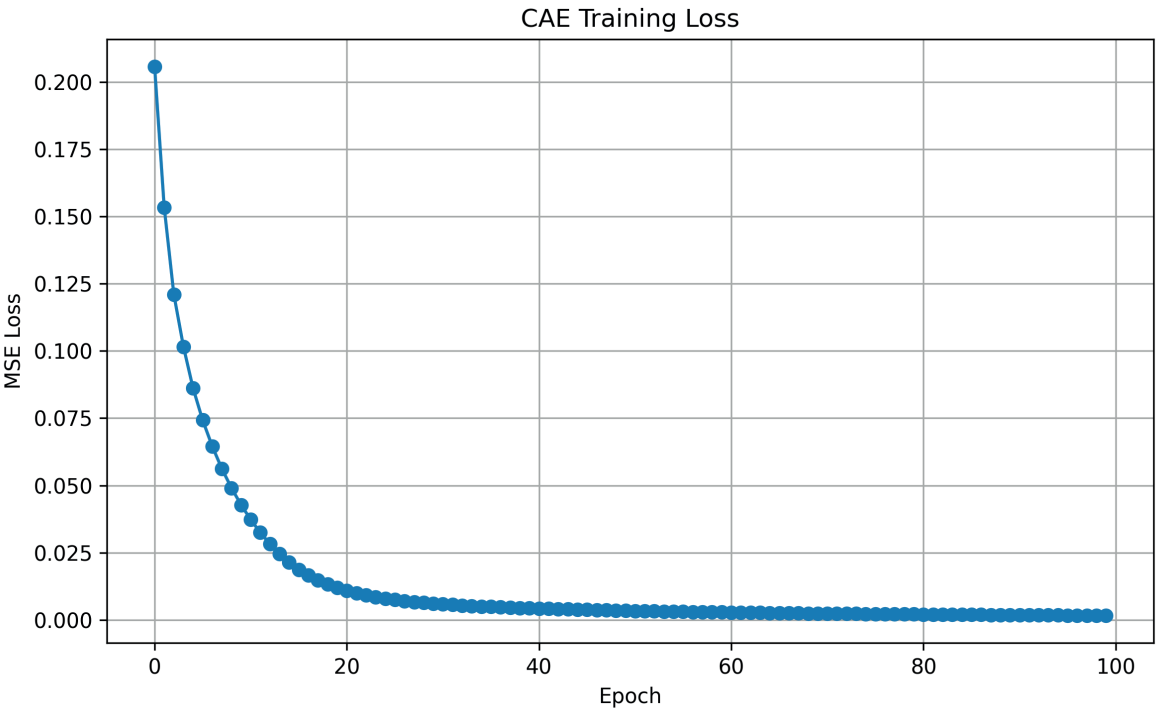


Fig. 5. Convergence of training loss in convolutional autoencoder over 100 epochs

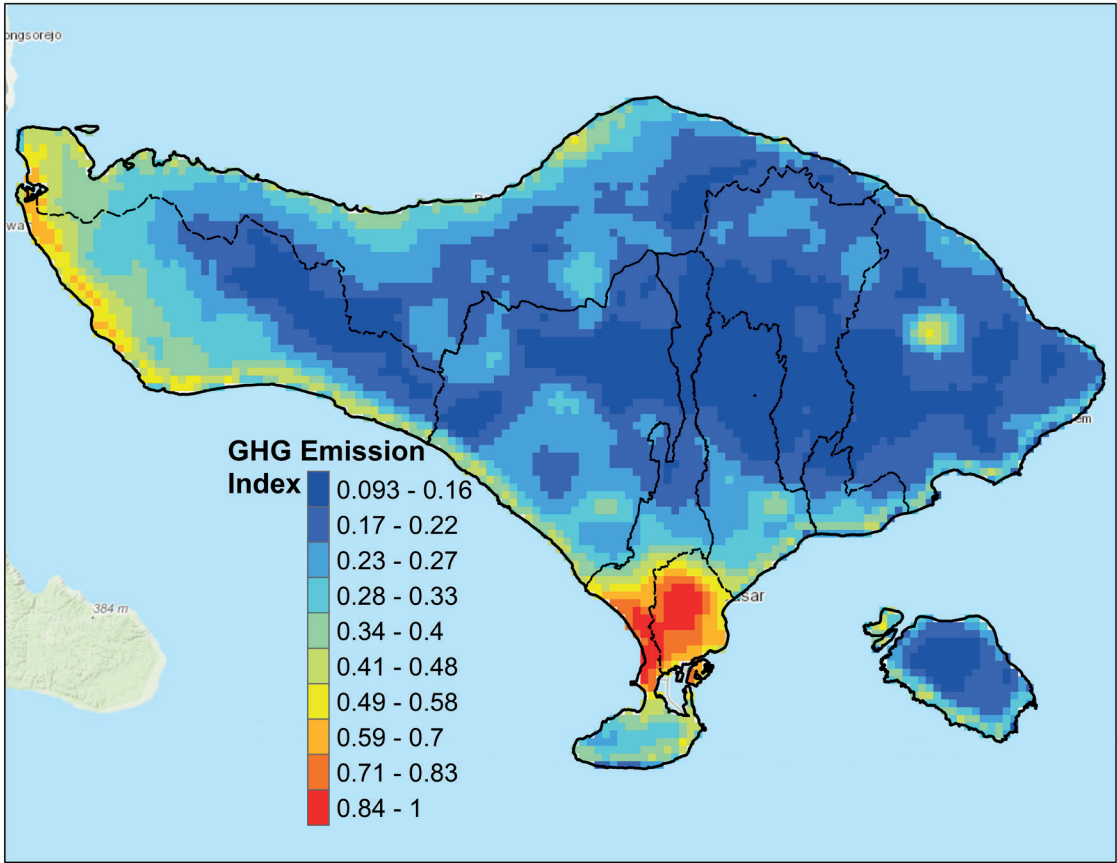


Fig. 6. Spatial distribution and proportional area of GHG emission vulnerability in Bali Province

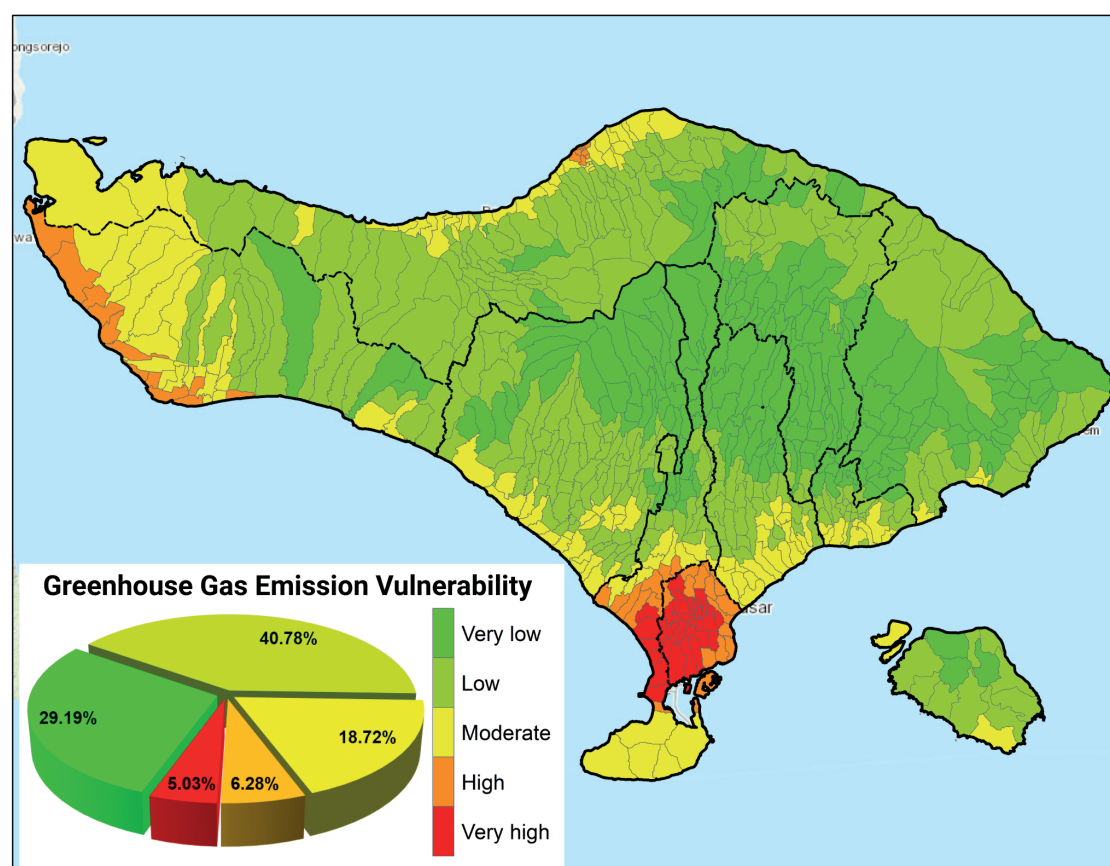


Fig. 7. Spatial alignment of GHG vulnerability with administrative boundaries

data. The unsupervised CAE model eliminated the need for labeled training data, addressing a persistent challenge in regional-scale environmental assessments where ground-based measurements are often unavailable. Previous research has demonstrated that autoencoders are effective for extracting latent features and reconstructing complex geospatial patterns in remote sensing applications (X. Han et al., 2017; Pintelas et al., 2021). In this study, the model achieved rapid convergence and low reconstruction loss, affirming its ability to process and learn from high-dimensional environmental inputs.

The resulting vulnerability index revealed distinct spatial gradients, with high-risk zones concentrated in southern coastal areas, such as Denpasar and southern Badung. These regions are associated with dense urbanization, tourism-related development, and intensive energy use. These findings align with global studies showing that atmospheric pollutants like NO_2 , CO, and AOD are often concentrated in urban-industrial zones (Fioletov et al., 2025; Wang et al., 2025). The integration of land surface temperature, NDVI, nighttime lights, and population density further substantiated the mapping of anthropogenic stressors and ecological degradation (Liu et al., 2015; McRoberts et al., 2020).

A key innovation of this research is its use of openly accessible satellite data and an unsupervised deep learning approach to generate a replicable and cost-effective GHG vulnerability mapping framework. Designed to be compatible with Google Earth Engine and other open-source platforms, this methodology can be scaled to other regions lacking the technical capacity or financial means for traditional emissions monitoring. This approach complements previous efforts in urban classification and land use mapping, where autoencoder-based models have demonstrated effective generalization across geographic contexts (Jiang, 2018). The framework provides critical support for environmental planning and is aligned with the objectives of SDG 13 on climate action.

This study also acknowledges certain methodological constraints. The use of 1 km² spatial resolution, while adequate for regional-scale visualization, may not capture the fine-scale variability needed for local urban or zoning applications. Additionally, while MODIS and Sentinel-5P data offer global consistency, they may lack sensitivity to site-specific emission patterns or infrastructure dynamics. To enhance spatial detail and accuracy, future research should incorporate higher-resolution datasets such as Sentinel-1 and Sentinel-2 imagery. Furthermore, integrating thematic variables like road networks, industrial zones, localized greenhouse gas emissions inventories, and spatially distributed land use categories would provide a more comprehensive picture of emissions at finer scales (Q. Feng et al., 2021). Additional consideration should be given to incorporating landscape circulatory factors and pollutant dispersion mechanisms using digital elevation models and meteorological data that capture prevailing wind directions. The findings validate the effectiveness of combining unsupervised deep learning with multi-sensor remote sensing for emission vulnerability mapping. The proposed framework is transferable, cost-efficient, and capable of identifying high-risk areas, particularly in urbanizing regions. This method serves as a valuable tool for supporting spatially informed climate mitigation strategies and advancing global climate governance.

CONCLUSIONS

This study demonstrated a rapid and cost-effective approach to mapping greenhouse gas (GHG) emission vulnerability by integrating multi-sensor satellite data with an unsupervised convolutional autoencoder (CAE) deep learning model. The framework avoided the need for field-based training data and extracted 128 latent features from a range of environmental indicators, enabling robust spatial characterization of emission risks. The vulnerability

index showed distinct spatial gradients, with the highest values concentrated in southern coastal areas experiencing dense anthropogenic activity, particularly from tourism and urbanization. These results confirm the effectiveness of unsupervised deep learning in identifying emission hotspots and spatial variability in data-limited settings. Utilizing open-access datasets and scalable computational methods, the framework offers a replicable solution for other regions, especially in developing countries where financial and technical constraints hinder regular monitoring. It presents a practical tool to support emission

analysis and planning aligned with climate mitigation strategies. To enhance precision, future improvements should incorporate high-resolution imagery through data fusion techniques, such as integrating Sentinel-2 or commercial satellite data. This advancement would allow for more detailed mapping suitable for urban-scale planning and targeted mitigation. This research contributes a transferable, efficient methodology for spatial quantification of GHG emission vulnerability, offering actionable insights to support climate policy and advance the Sustainable Development Goals (SDGs). ■

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