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尚尼亞河口甲烷排放量之遙感技術量化研究

Quantification of Methane Emissions from Estuaries in Tanzania
using Remote Sensing Techniques

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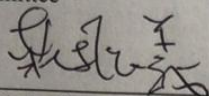
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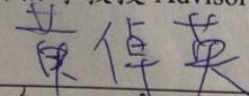
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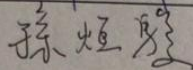
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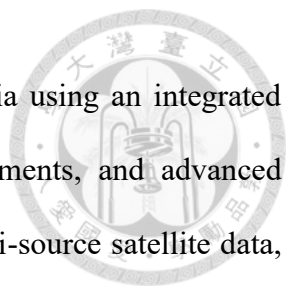


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Abstract



This study quantifies methane emissions from major estuaries in Tanzania using an integrated approach combining remote sensing, secondary/ derived field measurements, and advanced machine learning techniques. Using Google Earth Engine (GEE) and multi-source satellite data, this research develops a comprehensive methodology to estimate methane fluxes across the Rufiji, Wami, Pangani, and Ruvuma estuaries. The study incorporates multiple environmental variables including temperature, rainfall, water body extent, pH, Normalized Difference Water Index (NDWI), and humidity to understand their influence on methane production and emission patterns. Machine learning models including Random Forest, Support Vector Regression, and Gradient Boosting were employed to analyze complex multivariate relationships, achieving prediction accuracy of up to 91% ($R^2 = 0.91$). Results reveal significant spatial heterogeneity in methane emissions across estuaries, with the Rufiji estuary exhibiting the highest mean emissions ($42.3 \text{ mg CH}_4 \text{ m}^{-2} \text{ d}^{-1}$), followed by Ruvuma ($39.7 \text{ mg CH}_4 \text{ m}^{-2} \text{ d}^{-1}$), Wami ($35.6 \text{ mg CH}_4 \text{ m}^{-2} \text{ d}^{-1}$), and Pangani ($28.9 \text{ mg CH}_4 \text{ m}^{-2} \text{ d}^{-1}$). Pronounced seasonal variations were observed, with wet season emissions exceeding dry season values by 27-45% across all sites. Temperature emerged as the strongest predictor of methane emissions (correlation coefficient: 0.69), while pH showed a significant negative relationship (-0.45). The study provides the first comprehensive assessment of methane dynamics in Tanzanian estuaries and establishes a methodological framework applicable to other tropical coastal systems. These findings contribute to improved greenhouse gas inventories for Tanzania and inform climate change mitigation strategies for coastal wetland management.

Keywords: Methane emissions, Estuaries, Tanzania, Remote sensing, Machine learning, TROPOMI, GOSAT, CH_4 flux, Climate mitigation

摘要



本研究以整合性方法量化坦尚尼亞主要河口的甲烷排放，結合遙測技術、次級與衍生的實地測量資料，以及先進的機器學習技術。透過 Google Earth Engine (GEE) 與多源衛星資料，本研究建立一套完整的方法論，以估算 Rufiji、Wami、Pangani 和 Ruvuma 四大河口的甲烷通量。研究納入多項環境變數，包括氣溫、降雨量、水體範圍、酸鹼值 (pH)、標準化差異水指數 (NDWI) 及濕度，以探討其對甲烷生成與排放模式的影響。所採用的機器學習模型包括隨機森林 (Random Forest)、支持向量迴歸 (Support Vector Regression) 與梯度提升 (Gradient Boosting)，成功解析多變量間的複雜關係，預測準確度高達 91% ($R^2 = 0.91$)。

研究結果顯示，各河口甲烷排放具有顯著的空間異質性，其中 Rufiji 河口的平均排放量最高 (42.3 毫克 CH_4 /平方米/日)，依序為 Ruvuma (39.7 毫克)、Wami (35.6 毫克) 與 Pangani (28.9 毫克)。季節變化亦十分明顯，雨季排放量普遍高於旱季 27–45%。氣溫為甲烷排放最強的預測因子 (相關係數：0.69)，而酸鹼值則呈顯著負相關 (-0.45)。

本研究為坦尚尼亞河口甲烷動態提供首份全面性評估，並建立一套可應用於其他熱帶沿海系統的方法框架。研究成果有助於提升坦尚尼亞溫室氣體清冊的準確性，並為沿海濕地管理的氣候變遷緩解策略提供科學依據。

關鍵詞：甲烷排放、河口、坦尚尼亞、遙測、機器學習、TROPOMI、GOSAT、 CH_4 通量、氣候緩解

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1. Introduction

1.1 Background

Methane (CH_4) is a potent greenhouse gas with a global warming potential approximately 28-34 times that of carbon dioxide (CO_2) over a 100-year time horizon (Change, 2021). While atmospheric methane concentrations have more than doubled since pre-industrial times, from approximately 722 ppb to over 1,866 ppb today, the contribution from natural sources, particularly from tropical wetland systems, remains poorly quantified (Saunio et al., 2020). Recent trends in atmospheric methane concentrations have shown alarming acceleration over the past decade, with annual growth rates exceeding 10 ppb since 2014 and reaching nearly 15 ppb in 2020-2021, the highest recorded since systematic measurements began in the 1980s. This acceleration has significant implications for short- to mid-term climate feedback, as methane's relatively short atmospheric lifetime (approximately 12 years) means that emission reductions could yield rapid climate benefits, potentially slowing warming rates within decades rather than centuries (IPCC, 2021).

Tanzania's climate is characterized by remarkable diversity, shaped by its geographical position straddling the equator, its varied topography ranging from coastal lowlands to highland plateaus, and the presence of significant water bodies including Lake Victoria and the Indian Ocean. The country experiences a tropical climate with distinct regional variations, primarily divided into two main rainfall regimes: the unimodal pattern (November-April) in the central, southern, and western regions, and the bimodal pattern in the northern and coastal areas, which experiences both long rains (Masika) from March to May and short rains (Vuli) from October to December.

The coastal regions, where Tanzania's major estuaries are located, experience a hot, humid tropical climate with average temperatures ranging from 25°C to 29°C throughout the year and

annual rainfall between 1,000-1,900mm. This coastal zone is significantly influenced by the monsoon winds—the northeast monsoon (Kaskazi) prevailing from November to March bringing drier conditions, and the southeast monsoon (Kusi) from April to October bringing cooler temperatures and increased rainfall. These seasonal wind patterns create distinct hydroperiods in estuarine environments, directly affecting biogeochemical processes including methane production and emission. Climate change projections indicate that Tanzania will likely experience increased mean annual temperatures of 1.0-2.7°C by the 2060s, greater rainfall variability, and more frequent extreme weather events, factors that will substantially impact estuarine hydrology and potentially alter methane emission dynamics in these critical ecosystems (Mugabe et al., 2024).

Estuaries, as transitional zones between terrestrial and marine environments, are recognized as significant sources of methane due to their high organic matter inputs, variable redox conditions, and extensive anaerobic zones that favor methanogenesis (Borges & Abril, 2011). When compared to other major natural methane sources, estuarine wetlands exhibit distinct emission characteristics. While northern peatlands cover vast areas (approximately 4 million km²) and emit 20-45 Tg CH₄ yr⁻¹, their emissions per unit area are relatively low (5-11 g CH₄ m⁻² yr⁻¹) compared to tropical floodplains (15-25 g CH₄ m⁻² yr⁻¹) and estuarine wetlands (10-30 g CH₄ m⁻² yr⁻¹). Furthermore, estuarine systems demonstrate unique temporal dynamics, with emissions often controlled by tidal cycles and salinity gradients rather than solely by temperature and precipitation as in inland wetlands. This underscores the importance of estuarine specific studies to accurately represent these systems in global methane budgets.

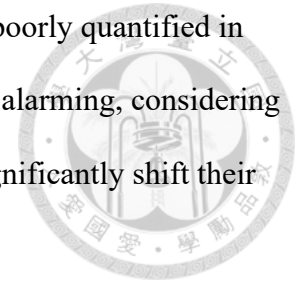
In East Africa—particularly in Tanzania; Estuaries represent critical ecological and socioeconomic systems. They support rich biodiversity, sustain fisheries, and underpin coastal

livelihoods. Tanzania's major estuarine systems, including the Rufiji, Wami, Pangani, and Ruvuma estuaries, reflect the country's diverse coastal geography and hydrological regimes. For instance, the Rufiji Delta, Tanzania's largest estuary at approximately 53,000 ha, experiences a bimodal rainfall pattern with long rains from February to May (*Masika*) and short rains from October to December (*Vuli*), receiving between 750–1,250 mm of rainfall annually. It features a semi-diurnal tidal regime with ranges of 2–4.5 m, fostering extensive intertidal zones.

In contrast, the Wami Estuary (~9,000 ha) experiences similar rainfall while the Pangani Estuary (~7,500 ha) receives the lowest rainfall (600–800 mm/year). The Ruvuma Estuary, forming the border between Tanzania and Mozambique, receives the highest rainfall (1,000–1,400 mm/year) and shows pronounced seasonality. Despite their environmental significance, these systems remain under-researched. While the Tanzania Meteorological Agency maintains basic hydrological monitoring stations, academic studies—such as those by the Institute of Marine Sciences at the University of Dar es Salaam—have only begun to explore aspects of carbon cycling, with minimal focus on methane emissions.

Land-use changes along these estuaries increasingly influence methane emission dynamics. Traditional fishing practices are being replaced by more intensive methods that disturb sediments and alter carbon cycling. Mangrove deforestation—occurring at 0.5–1.2% annually—disrupts natural carbon sequestration processes, potentially enhancing methane emissions due to hydrological alterations and exposure of organic matter. Furthermore, salt-pan developments in deltas like Rufiji and Pangani create hypersaline conditions that may suppress methanogenesis locally but exacerbate emissions in surrounding areas due to altered water flow and soil chemistry (Liingilie et al., 2015)

Despite their biogeochemical importance, these estuarine systems remain poorly quantified in terms of their contribution to regional and global methane budgets. This is alarming, considering their vulnerability to climate change and human pressures, which could significantly shift their greenhouse gas emission profiles.



Traditional methane quantification methods—such as chamber measurements and flux towers—offer high precision at local scales but are constrained by limited spatial and temporal coverage. Satellite-based remote sensing presents a promising complementary solution. Instruments like TROPOMI (aboard Sentinel-5P) and GOSAT provide large-scale methane observations. However, their spatial resolutions ($5.5 \times 7 \text{ km}^2$ for TROPOMI and $\sim 10 \text{ km}$ for GOSAT) are too coarse to resolve narrow estuarine channels, and their efficacy is further hindered by frequent cloud cover and mixed land-water pixels typical in tropical estuarine zones.

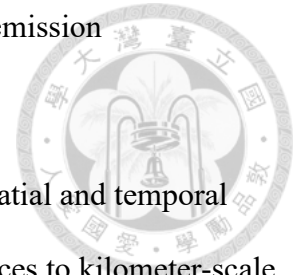
To bridge these limitations, integrating satellite observations with localized field data and machine learning models holds strong potential. While satellite products like GOSAT and TROPOMI provide valuable methane concentration data, this study develops a quantification framework to estimate surface-level methane fluxes across Tanzanian estuaries. Validation of modeled outputs against satellite concentrations ensures robustness, while quantification enables spatially explicit emission mapping critical for policy and inventory development.

1.2 Problem Statement

Quantifying methane emissions from Tanzanian estuaries faces several critical challenges.

Limited field measurements and monitoring infrastructure create significant data gaps, with the absence of collocated TROPOMI satellite observations and in-situ flux tower data severely constraining validation of remote sensing approaches. Spatial resolution mismatches between satellite data and fine-scale estuarine heterogeneity further complicate accurate quantification, as

individual pixels often encompass multiple land cover types with varying emission characteristics.



Estuarine methane emissions exhibit complex dynamics across multiple spatial and temporal scales. Spatial variations range from meter-scale microtopography differences to kilometer-scale salinity gradients, while temporal variations span diurnal cycles, tidal cycles, seasonal patterns, and interannual climate variability. These multi-scale dynamics necessitate sophisticated monitoring and modeling approaches.

Key environmental drivers including temperature, salinity, vegetation characteristics, and pH interact non-linearly, creating emergent patterns unpredictable from individual variables alone. The lack of standardized methodologies for integrating remote sensing with field observations represents a significant methodological gap, with current approaches varying widely and limiting cross-study comparisons and regional synthesis.

These challenges result in significant uncertainties in regional greenhouse gas inventories.

Tanzania's NDC report (Tanzania, 2021b) either omit estuarine emissions entirely or rely on coarse wetland estimates that fail to capture unique system characteristics, contrasting with IPCC guidelines recognizing coastal wetlands as significant GHG sources. This gap limits development of effective climate mitigation strategies for coastal wetland management and hampers evidence-based policy development.

1.3 Research gaps

Tropical estuarine systems, particularly in East Africa, remain critically underrepresented in global methane assessments. Most tropical wetland studies focus on inland areas such as floodplains and rice paddies rather than mangrove-dominated estuaries, despite their ecological importance and potential significance as methane sources or sinks.

Tanzania's major estuaries including Rufiji, Pangani, Wami, and Ruvuma lack comprehensive methane quantification despite their pivotal role in coastal carbon cycling. These systems span diverse environmental gradients creating complex biogeochemical conditions, yet their contribution to regional and global methane budgets remains poorly quantified. Current national climate strategies and greenhouse gas inventories exclude estuarine methane estimates, limiting comprehensive mitigation plan development and representing a critical gap in climate policy implementation.

High-resolution remote sensing validation methods for tropical estuaries are lacking due to scarce ground-based measurements required for satellite validation. This validation gap limits confidence in remote sensing approaches and highlights the need for integrated methodologies combining satellite observations with field measurements and modeling. Methods for downscaling satellite methane data and integrating with estuarine hydrology remain underdeveloped, while machine learning applications to estuarine methane modeling are still in early stages, representing significant opportunities for methodological advancement.

1.4 Research Objectives

Tanzania through five specific objectives. The first objective develops a remote sensing-based approach for estimating methane emissions from estuarine environments using Google Earth Engine for 2020-2024, creating a methodological framework that integrates TROPOMI, GOSAT, Landsat, and Sentinel data sources to provide comprehensive coverage at 30-meter spatial resolution with advanced atmospheric correction techniques.

The second objective identifies and analyzes key environmental factors influencing methane emissions across seasonal and tidal cycles, including previously unexplored variables such as pH, NDWI, and humidity. This involves quantifying relationships between environmental

variables and methane emissions through statistical analysis and machine learning approaches, with particular attention to seasonal variations and tidal influences.

The third objective quantifies spatial and temporal patterns of methane emissions across the Rufiji, Wami, Pangani, and Ruvuma estuaries for 2020-2024 with monthly temporal resolution and 30-meter spatial resolution. This includes mapping emissions across all four estuaries, identifying hotspots, and analyzing temporal patterns including seasonal cycles, interannual variability, and tidal phase comparisons.

The fourth objective develops and validates machine learning models for predicting methane emissions based on remotely sensed environmental variables, comparing Random Forest, Support Vector Regression, and Gradient Boosting algorithms using 2020-2022 training data and 2023-2024 validation data. The fifth objective assesses implications for climate change mitigation and coastal wetland management in Tanzania, developing policy recommendations for monitoring protocols, reporting guidelines, and mitigation measures aligned with Tanzania's climate commitments and international frameworks.

1.5 Significance of the Study

This research contributes significantly to both scientific knowledge and practical applications across multiple domains. The integrated approach combines multiple data sources and analytical techniques, advancing remote sensing applications for methane quantification in complex tropical environments. The methodological innovation represents the first use of Sentinel-1 SAR to monitor tidal inundation in Tanzanian estuaries, providing unprecedented insights into water coverage dynamics and methane emission relationships. By integrating optical, radar, and atmospheric remote sensing data through advanced machine learning algorithms, this study establishes a framework adaptable to other coastal systems facing similar monitoring challenges.

The research provides new insights into seasonal methane cycling in tropical mangrove systems, enhancing understanding of biogeochemical processes controlling methane dynamics. The findings reveal complex interactions between temperature, hydrology, vegetation, and water chemistry in regulating methane production, consumption, and transport, contributing to fundamental knowledge of coastal wetland carbon cycling and bridging gaps between process-based field studies and landscape-scale remote sensing patterns.

From a policy perspective, this research provides quantitative evidence for Tanzania's second NDC update, supporting climate change mitigation efforts by improving national greenhouse gas inventory accuracy and completeness. The findings enable incorporation of estuarine methane emissions into national reporting frameworks, addressing significant inventory gaps and aligning with IPCC Wetland Supplement guidelines. The methodological framework provides cost-effective monitoring approaches for remote coastal areas, addressing resource constraints faced by developing nations in implementing comprehensive monitoring programs.

The socio-economic impact extends to local fisheries and coastal communities dependent on estuarine resources. By improving understanding of estuarine functioning and providing scientific basis for sustainable management, this study contributes to long-term ecosystem health and productivity. The findings inform integrated coastal zone management approaches balancing conservation with sustainable resource use, while identifying opportunities for ecotourism development and carbon-crediting opportunities tied to mangrove restoration, creating sustainable financing mechanisms for conservation and community development.

1.6 Scope of the study

This study focuses on quantifying methane emissions from four major estuarine systems in Tanzania: Rufiji, Wami, Pangani, and Ruvuma. The temporal scope covers 2020 to 2024,

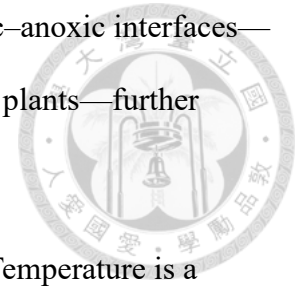
utilizing available satellite data and environmental parameters within this timeframe. The research employs an integrated approach combining satellite-derived methane concentrations from TROPOMI and GOSAT, ancillary environmental data including LST, precipitation, water body extent, pH, NDWI, and humidity, along with machine learning models including Random Forest, Support Vector Regression, and Gradient Boosting. While the study aims to provide comprehensive spatial and temporal estimates, it acknowledges limitations related to high-resolution in situ field data availability, which are incorporated where available but do not form the primary data source for upscaling. The policy recommendations are specifically tailored for Tanzania but may offer generalizable insights for other tropical coastal nations.

2. Literature Review

2.1 Methane Biogeochemistry in Estuarine Environments

Methane production in estuaries is driven by methanogenesis, an anaerobic microbial process carried out by methanogenic archaea under oxygen-depleted (anoxic) conditions and in the presence of suitable organic substrates (Bridgham, 2013). Two principal pathways operate in estuarine sediments: acetoclastic methanogenesis, which cleaves acetate into methane and carbon dioxide, and hydrogenotrophic methanogenesis, which reduces carbon dioxide with hydrogen to form methane (Conrad, 2020). In these brackish systems, methanogens compete with other anaerobic microorganisms, most notably sulfate-reducing bacteria—for shared substrates, since the influx of seawater-derived sulfate can suppress methanogenic activity (Oremland, 1982; Purdy, 2018). Once formed, methane can escape to the atmosphere via diffusion across sediment and water interfaces, ebullition as gas bubbles, or plant-mediated transport through aerenchyma tissues of marsh and mangrove vegetation—a pathway that can be particularly pronounced in mangrove-dominated estuaries (Purvaja & Ramesh, 2001; Whalen, 2005). At the same time,

methanotrophic bacteria oxidize a fraction of the produced methane at oxic–anoxic interfaces—such as the sediment–water boundary or within the rhizosphere of wetland plants—further modulating the net methane flux (Segarra, 2015)



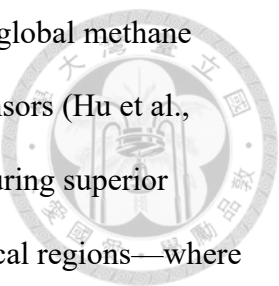
Environmental controls on estuarine methane dynamics are multifaceted. Temperature is a primary governor of methanogenesis, with warmer conditions generally enhancing production rates—a pattern especially relevant in tropical estuaries like those in Tanzania, where high year-round temperatures may sustain elevated methane outputs (Yvon-Durocher et al., 2014).

Seasonal shifts in rainfall and river discharge further influence methane cycling by altering organic matter inputs, sediment transport, and water residence times (Borges & Abril, 2011).

Salinity and redox potential, arising from the mixing of freshwater and seawater, create spatially and temporally dynamic redox gradients that affect both methanogenic and methanotrophic communities (Bridgham, 2013). Although less extensively studied in estuaries, pH also plays a role: methanogenesis often peaks under circumneutral conditions (pH 6.5–7.5) and declines in more acidic or alkaline settings (Garcia et al., 2000). Hydrological factors—quantifiable via indices such as the Normalized Difference Water Index (NDWI)—further dictate the balance between methane production and oxidation by controlling sediment saturation and oxygen penetration. Recent multivariate studies underscore that interactions among temperature, substrate availability, microbial community structure, salinity, and hydrology jointly regulate estuarine methane emissions, highlighting the necessity of integrative approaches to predict net fluxes under changing environmental conditions (Serrano-Silva, 2014).

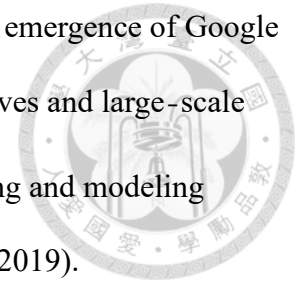
2.2 Remote Sensing for Methane Quantification

Remote sensing of atmospheric methane has advanced considerably with the advent of high-resolution satellite instruments and integrative modeling approaches. The Tropospheric



Monitoring Instrument (TROPOMI) aboard Sentinel-5P now delivers daily global methane retrievals at $5.5 \times 7 \text{ km}^2$ resolution, a dramatic enhancement over legacy sensors (Hu et al., 2018), while GOSAT continues to supply complementary observations featuring superior spectral fidelity but coarser spatial sampling (Parker, 2018). However, tropical regions—where persistent cloud cover, elevated water vapor, and heterogeneous aerosol loads prevail—pose significant obstacles to accurate methane retrieval (Jacob, 2016). Moreover, even TROPOMI's resolution often proves insufficient to resolve the fine-scale variability of emissions from estuarine wetlands. To overcome these constraints, researchers have begun fusing satellite data with in situ measurements and machine learning: for example, (Zhang, 2020) applied k-Nearest Neighbor and Support Vector Machine algorithms to upscale point-based flux measurements using Landsat imagery, achieving R^2 values of 0.65 in the dry season and 0.87 in the wet season. Unmanned aerial vehicles (UAVs) equipped with lightweight methane sensors offer another high-resolution alternative; although promising deployments have been reported in temperate wetlands (Golston et al., 2017), their use remains scant in tropical estuarine settings. Beyond direct retrievals of atmospheric methane, indirect remote sensing proxies provide valuable insights into the environmental controls on methanogenesis and emissions. Thermal infrared—derived land surface temperature serves as a surrogate for sediment temperature, a key driver of microbial methane production (Bloom et al., 2010) while vegetation indices such as NDVI and EVI estimate biomass availability for acetoclastic pathways (Potter et al., 2006); Water indices—particularly the Normalized Difference Water Index (NDWI) reveals surface inundation and soil moisture conditions that modulate both production and oxidation of methane (Jain et al., 2013). Integrative models that combine multiple indices have shown promise at regional to global scales; for instance, (Bloom et al., 2010) merged GRACE-derived water storage anomalies with

MODIS land surface temperature to simulate wetland methane fluxes. The emergence of Google Earth Engine (GEE) has further democratized access to multi-sensor archives and large-scale processing capabilities (Gorelick et al., 2017), yet its application to mapping and modeling methane emissions in tropical estuaries is still in its infancy (Amani et al., 2019).



2.3 Machine Learning Approaches for Environmental Modelling

Machine learning techniques have gained significant traction in environmental science due to their ability to capture complex, non-linear relationships between variables without requiring explicit process-based formulations (Reichstein et al., 2019). In the context of greenhouse gas emissions, various machine learning algorithms have been applied to predict fluxes based on environmental variables.

Random Forest, an ensemble learning method based on decision trees, has been particularly successful in environmental applications due to its robustness to noise, ability to handle mixed data types, and resistance to overfitting (Breiman, 2001). Studies by (Knox et al., 2019) and (Zhu et al., 2013) demonstrated the effectiveness of Random Forest for predicting methane emissions from wetlands based on meteorological and ecological variables.

Support Vector Regression (SVR) offers another powerful approach for modeling complex environmental relationships, particularly when the underlying processes are non-linear (Vapnik, 1999). SVR has been applied to various environmental prediction tasks, including greenhouse gas emissions from agricultural soils (Philibert et al., 2012) and wetlands (Kim et al., 2015).

Gradient Boosting, a technique that builds an ensemble of weak prediction models iteratively, has shown promise for environmental applications due to its high predictive accuracy and ability to handle diverse data types (Chen & Guestrin, 2016). Recent studies have applied Gradient

Boosting to predict methane emissions from rice paddies (Knox et al., 2019) and northern wetlands (Peltola et al., 2019).

The integration of machine learning with remote sensing data has opened new avenues for environmental monitoring and prediction. For instance, (Zhu et al., 2013) combined MODIS-derived variables with flux tower measurements to develop a Random Forest model for predicting methane emissions across northern wetlands. Similarly, (Dengel et al., 2013) used a combination of remote sensing indices and meteorological data to train machine learning models for upscaling methane flux measurements from eddy covariance towers.

Despite these advances, the application of machine learning techniques to methane emissions from tropical estuaries remains limited, particularly in the African context. This research aims to address this gap by developing and validating machine learning models specifically tailored to Tanzanian estuarine environments.

2.4 In-situ Measurement Techniques

Ground-based measurements remain essential for validating remote sensing data and understanding local-scale processes. Two main approaches are commonly used for in-situ measurement of methane fluxes: chamber techniques and eddy covariance methods.

Chamber techniques involve placing a closed or dynamic chamber over the soil or water surface and measuring the change in methane concentration over time (Pihlatie et al., 2013). Eddy covariance methods measure methane fluxes at the ecosystem scale by analyzing the covariance between vertical wind velocity and methane concentration (Knox et al., 2019).

Integrating chamber measurements with eddy covariance data can provide a more comprehensive understanding of methane dynamics across scales. (Morin et al., 2017)

demonstrated that combining these approaches allows for better characterization of spatial heterogeneity while maintaining the temporal resolution of continuous measurements. For the purpose of this research and convenience reasons, all in-situ data were derived second-handedly.



2.5 Environmental Drivers of Methane Emissions

Numerous environmental factors influence methane emissions from estuaries, with their relative importance varying across ecosystems and regions.

Hydrological Factors: Water table depth is a critical control on methane emissions, with higher water tables generally increasing emissions by creating anoxic conditions favorable for methanogenesis (Turetsky et al., 2014). In estuaries, tidal cycles significantly affect oxygen availability and salinity gradients, creating complex patterns of methane production and consumption (Tong et al., 2010). Human alterations to natural hydroperiods can transform carbon sinks into sources, highlighting the importance of hydrological management (Hemes, 2018).

Physicochemical Factors: Salinity is a crucial factor in estuarine environments, with high methane emissions typically restricted to freshwater conditions (Poffenbarger et al., 2011). This is primarily due to the inhibitory effect of sulfate on methanogenesis. Redox potential determines whether conditions favor methanogenesis, with more reducing conditions promoting methane production (Angle et al., 2017). Soil temperature shows a strong positive correlation with methane emissions due to its effect on microbial activity (Yvon-Durocher et al., 2014); pH affects both microbial activity and methane production pathways, with neutral to slightly acidic conditions generally favoring methanogenesis (Le Mer & Roger, 2001).

Biological Factors: Different vegetation types affect methane transport and production through various mechanisms, including root exudation of organic compounds, oxygen transport to the

rhizosphere, and direct transport of methane through aerenchyma tissue (Carmichael et al., 2014). The balance between methanogens and methanotrophs ultimately determines net emissions, with this balance influenced by various environmental conditions (Bridgham, 2013). Organic matter availability provides the substrate for methanogenesis, with both quantity and quality affecting methane production rates (Ye et al., 2012).

2.6 Policy Frameworks for Methane Management

Global efforts to reduce methane emissions have gained momentum in recent years, with initiatives such as the Global Methane Pledge aiming to reduce methane emissions by 30% by 2030 compared to 2020 levels (Coalition, 2021). The World Bank has launched a global methane initiative targeting 15 countries, including Tanzania, to reduce emissions from key sectors (World-Bank, 2024).

Tanzania's environmental policy framework includes several instruments relevant to methane management. The National Environmental Policy (2021) (Tanzania, 2021a) provides a broad framework for environmental management, including provisions for wetlands conservation and climate change mitigation. Tanzania's Nationally Determined Contribution (NDC, 2021) commits to reducing greenhouse gas emissions economy-wide between 30-35% relative to the Business-As-Usual scenario by 2030.

However, current policies lack specific provisions for managing methane emissions from natural systems such as estuaries. This gap presents an opportunity for developing targeted approaches that integrate scientific understanding with policy implementation.

3. Methodology

3.1 Research framework

The methodological workflow for this study integrates multiple data sources and analytical approaches to quantify methane emissions from Tanzanian estuaries. The workflow begins with the collection and processing of remote sensing data from multiple satellite platforms, including TROPOMI, GOSAT, Landsat, Sentinel-1, and Sentinel-2. These data are processed to extract relevant environmental variables and methane observations at different spatial and temporal resolutions. Concurrently, environmental parameters were collected across the study areas through previous studies and databases, providing ground-truth data obtained from GEE platform for model calibration and validation.

The workflow diagram (Figure 1) has been designed using a visualization tool to improve clarity and presentation and uses a hierarchical structure with clear directional flow, clear labels to distinguish different data types and processes, and to explain each component. Visualization more effectively communicates the methodological approach and facilitates understanding of the integration of multiple data sources and analytical techniques.

The remote sensing and field data are then integrated through a multi-step process. First, environmental variables derived from satellite observations are matched with readily available environmental data to establish relationships between environmental conditions and methane emissions. These relationships are then used to develop machine learning models that can predict methane emissions based on remotely sensed environmental variables. The models namely Random Forest, Support Vector Regression, and Gradient Boosting are trained, validated, and tested using rigorous protocols to ensure their accuracy and generalizability.



Once validated, the models are applied to the full spatial and temporal extent of the remote sensing data to generate comprehensive maps of methane emissions across the study areas. These maps are then analyzed to identify spatial patterns, temporal trends, and relationships with environmental factors. The results are used to calculate methane budgets for individual estuaries and to extrapolate to regional scales. Finally, the findings are interpreted in the context of climate change mitigation and coastal management, with implications for policy development and implementation.

This integrated approach leverages the strengths of both remote sensing and field measurements while addressing their respective limitations. Remote sensing provides comprehensive spatial coverage and temporal frequency that would be impossible to achieve with field measurements alone, while field data provides the accuracy and process-level understanding necessary to interpret remote sensing observations and develop robust predictive models. The machine learning component bridges these scales by establishing statistical relationships that can be applied across the landscape, enabling the quantification of methane emissions at scales relevant for both scientific understanding and policy applications.

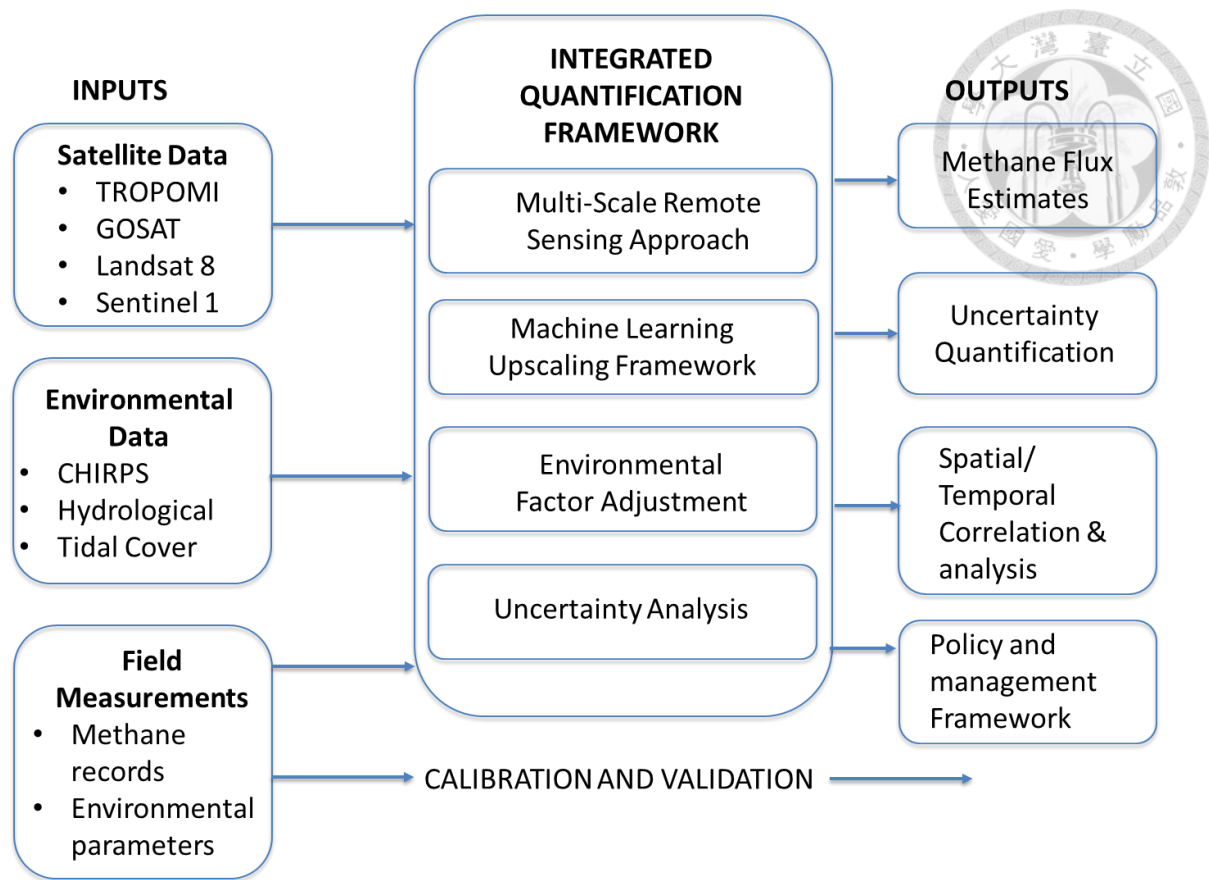
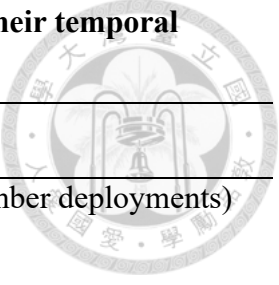


Figure 1: Implementation workflow under this study

The supporting environmental field data were obtained from Tanzania Fisheries Research Institute (TAFIRI) for water parameters such as pH, Salinity and organic matter content; National Carbon Monitoring Center (NCMC) for mangrove and LUCF; National Oceanic and Atmospheric Administration (NOAA) for global atmospheric methane concentration trends, past studies/theses in University of Dar es Salaam repository such as river discharge, salinity, methane fluxes from in-situ measurements between 2015 and 2022 (Monga et al., 2018; Mwakalila et al., 2018).

Table 1 below summarizes the information about their temporal properties.

Table 1: Summary of the environmental field data types collected and their temporal resolutions



Data type	Temporal resolution
Field methane flux measurements	Hourly to daily (e.g., chamber deployments)
Water quality (pH, salinity, DO)	Weekly to monthly
Sediment and soil sampling	Seasonal or campaign-based
Remote sensing (e.g., NDVI, NDWI)	10-day (Sentinel-2), 16-day (Landsat)
Rainfall and temperature (CHIRPS, TMA)	Daily to monthly
Land cover change	Annual or decadal

3.2 Study Area

This study focuses on estuaries across Tanzania, selected based on their ecological diversity and varying degrees of anthropogenic influence (Figure 2). The study area spans key estuaries along Tanzania's 1,424 km Indian Ocean coastline, specifically the Rufiji, Wami, Pangani, and Ruvuma estuaries. These sites were chosen based on their ecological significance, variation in size, and representation of the country's diverse coastal environments with reference to the country as a whole. A high-resolution topographic map with coordinate grid lines along true-

color satellite images illustrates the spatial extent and location of the study areas.

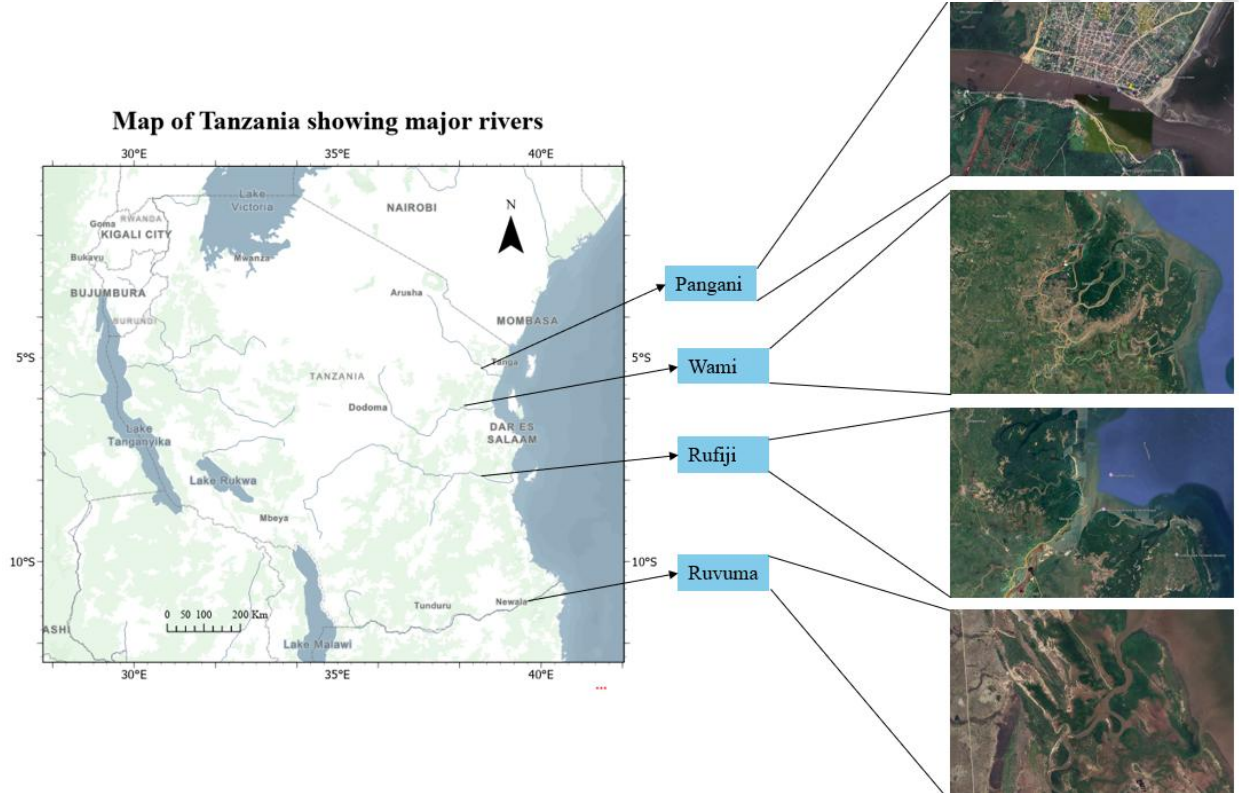


Figure 2: A close-up of the area under investigation. On the left is the map of Tanzania showing the relative positions of the rivers whose estuaries in the right were studied. The images on the right were retrieved from Google Earth Pro's imagery (version 7.3.6.10201) on 16th June 2025

The Rufiji Delta, Tanzania's largest estuarine system covering approximately 53,000 ha, is characterized by extensive mangrove forests dominated by *Rhizophora mucronata*, *Avicennia marina*, and *Sonneratia alba*. The delta experiences a bimodal rainfall pattern with long rains (*Masika*) from March to May and short rains (*Vuli*) from October to December, receiving 750-1,250 mm annually. Its semi-diurnal tidal regime ranges from 2-4.5 m, creating extensive intertidal zones that undergo regular flooding and exposure cycles (Japhet et al., 2019). The delta supports diverse fisheries and provides livelihoods for approximately 41,000 people living in scattered settlements throughout the system (World-Rainforest-Movement, 2001).

The Wami Estuary, smaller at approximately 9,000 ha, receives similar rainfall patterns but experiences more pronounced dry seasons. Its narrower channel morphology creates stronger tidal currents and more defined salinity gradients compared to the broader Rufiji Delta. The Wami River's discharge varies dramatically between seasons, with peak flows during April-May often exceeding 300 m³/s, while dry season flows can drop below 10 m³/s. This hydrological variability creates dynamic conditions for methane production and emission.

The Pangani Estuary (approximately 7,500 ha) has the lowest rainfall among the four systems (600-800 mm annually) and is heavily influenced by upstream water abstraction for agriculture and hydropower generation (Byarufu et al., 2021; Shanghude, 2016). These anthropogenic modifications have altered freshwater inputs and sediment delivery to the estuary, potentially affecting carbon cycling and methane dynamics. The estuary's mangrove forests have experienced significant degradation due to harvesting timber and charcoal production, with approximately 30% loss over the past three decades (Mwanja et al., 2024).

The Ruvuma Estuary, forming the Tanzania-Mozambique border, experiences the highest rainfall (1,000-1,400 mm annually) with pronounced seasonality (Ruvuma-Basin-Water-Board, 2013). Its transboundary nature presents unique management challenges but also opportunities for international collaboration on monitoring and conservation (Ecoregion-Programme, 2012). The estuary remains relatively less disturbed compared to the others, with intact mangrove forests covering approximately 18,000 ha across both countries (Duncan et al., 2018; Ferreira et al., 2009).

3.2.1: Comparative summary of the environmental characteristics of the estuaries

These estuaries represent a range of conditions in terms of size, hydrological regimes, vegetation characteristics, and human influence, providing a comprehensive basis for understanding methane dynamics across Tanzanian estuarine systems.



All four estuaries experience a tropical climate with two distinct rainy seasons: the long rains (March-May) and the short rains (October-December). Mean annual temperatures range from 25°C to 28°C, with limited seasonal variation but significant diurnal fluctuations.

The analysis of remote sensing data and available field measurements revealed distinct environmental characteristics across the four studied estuaries (**Table 2**). The Rufiji estuary exhibited the highest mean annual temperature (27.8°C) and rainfall (1,200 mm yr⁻¹), while the Pangani estuary had the lowest values for both parameters (25.5°C and 800 mm yr⁻¹, respectively). These differences reflect the geographic distribution of the estuaries along the Tanzanian coast and their varying catchment characteristics.

Table 2: Mean values of the environmental characteristics of the estuaries in the study. The period of the analysis is from 2020 to 2024.

Estuary	Temperature (°C)	Rainfall (mm/year)	Water Body Extent (km ²)	pH	NDWI	Humidity (%)
Rufiji	27.8 ± 1.2	1,200 ± 180	215 ± 45	6.8 ± 0.3	0.32 ± 0.08	78 ± 5
Wami	26.5 ± 1.4	1,000 ± 140	42 ± 12	7.0 ± 0.2	0.28 ± 0.07	75 ± 6
Pangani	25.5 ± 1.1	800 ± 120	18 ± 5	7.2 ± 0.2	0.25 ± 0.06	72 ± 7
Ruvuma	26.0 ± 0.9	1,100 ± 160	65 ± 15	6.9 ± 0.3	0.30 ± 0.07	76 ± 5

3.3 Data Sources

3.3.1 Remote Sensing Data

Multiple satellite platforms were utilized to capture different aspects of estuarine environments and methane dynamics, following recommended practices for multi-sensor environmental monitoring (Gorelick et al., 2017).

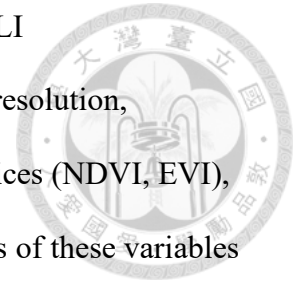


Atmospheric methane concentrations were obtained from the TROPOMI instrument aboard Sentinel-5P, which provides daily global methane retrievals at $5.5 \text{ km} \times 7 \text{ km}$ resolution (Sentinel-5P, 2024). All remote sensing data were processed and analyzed using Google Earth Engine (GEE), a cloud-based platform that provides access to extensive satellite imagery archives and computational resources to extract time series for the study areas from January 2020 to December 2024. The primary atmospheric methane dataset was the Sentinel-5P Level 3 product, specifically the CH_4 column volume mixing ratio for dry air, accessed via the Earth Engine path CORPENICUS/S5P/OFFL/L3/_CH4.

Despite TROPOMI's relatively coarse resolution, it offered valuable insight into broad-scale spatiotemporal methane trends. A machine learning–based downscaling approach was developed to relate TROPOMI observations to higher-resolution environmental variables, aligning with recent efforts to improve retrieval granularity using statistical correction (Balasus et al., 2023).

Complementary methane data was obtained from the Greenhouse Gases Observing Satellite (GOSAT) using column-averaged dry air mole fractions of methane (XCH_4), which provides observations with higher spectral resolution but coarser spatial sampling (approximately 10 km diameter footprints) and a 3-day revisit time. GOSAT data were particularly valuable for validation purposes due to their higher precision, though their sparse spatial coverage limited their use for comprehensive mapping (Sembhi et al., 2015).

Land cover and vegetation characteristics were mapped using Landsat 8 OLI (LANDSAT/LC08/C02/T1_L2) and Sentinel-2 MSI data at 30m and 10m resolution, respectively. These optical sensors provided information on vegetation indices (NDVI, EVI), water indices (NDWI, MNDWI), and land surface temperature. Time series of these variables were constructed at monthly intervals to capture seasonal dynamics. Cloud masking was performed using the quality assessment bands provided with the data, and gap-filling was implemented using temporal interpolation methods.



Surface water dynamics and inundation patterns were mapped using Sentinel-1 SAR data, which offers the advantage of cloud penetration—critical in the persistently cloudy tropical environment. The dual-polarized SAR bands—VV (vertical transmit and vertical receive) and VH (vertical transmit and horizontal receive)—were employed to differentiate between open water, vegetated land, and transitional zones. VV polarization is primarily sensitive to surface roughness and specular reflection, making it effective for identifying smooth water surfaces that typically exhibit low backscatter. In contrast, VH polarization captures volume scattering from complex vegetation structures, such as mangrove canopies and pneumatophores, and is especially useful for detecting partially inundated areas where water and biomass interact (Ghorbanian et al., 2021). Sentinel-1 data were processed to generate monthly inundation frequency maps at 10m resolution, providing detailed information on hydroperiod across the estuaries.

Environmental variables including precipitation, temperature, and humidity were obtained from ERA5-Land reanalysis data at 0.1° resolution. These variables were downscaled to match the resolution of the optical and radar data using topographic and land cover information as predictors in a random forest regression model (Sebbar et al., 2023; Wang et al., 2023).

The following preprocessing steps were applied as used by (Frantz, 2019):



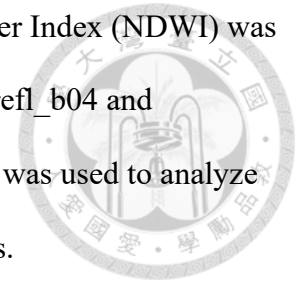
1. Cloud and shadow masking using the quality assessment bands provided with Landsat and Sentinel-2 data.
2. Temporal compositing to create monthly and seasonal representations of environmental variables.
3. Spatial resampling to harmonize resolutions across different data sources.
4. Calculation of spectral indices. For instance, NDWI was determined using the formula:
$$\text{NDWI} = (\text{Green} - \text{NIR}) / (\text{Green} + \text{NIR})$$
 (McFeeters, 1996).
5. Extraction of time series data for each estuary and its surrounding areas.

3.3.2 Environmental Data

Environmental variables were accessed and processed in GEE as well:

1. **Meteorological Data:** Temperature and precipitation data were obtained from the ECMWF Reanalysis v5 (ERA5) reanalysis dataset (Hersbach, 2020) using filepath ECMWF/ERA5/MONTHLY and the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) dataset (Funk, 2015); all data was processed through GEE platform.
2. **Land Cover Data:** Land cover classifications were obtained from the European Space Agency (ESA) WorldCover dataset a global land use dataset at 10m resolution (Zanaga et al., 2022). This dataset was used to compute average land cover distribution in Tanzania (2020–2024) and examine methane emissions from different ecosystems.

3. **Wetland & Surface Water Data:** The Normalized Difference Water Index (NDWI) was calculated using MODIS Surface Reflectance, utilizing bands `sur_refl_b04` and `sur_refl_b06` to identify wetland and water body extent. This index was used to analyze the spatial correlation between water bodies and methane emissions.



3.4 Integrated Quantification Framework

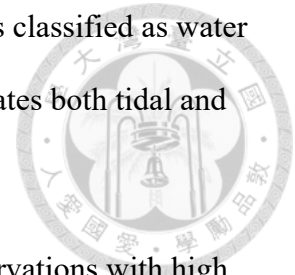
An integrated methodology was developed to quantify methane emissions from Tanzanian estuaries, combining multiple data sources and analytical approaches. The framework, as a synergy of (Bueno et al., 2025) and (Wang et al., 2024), consisted of four main components:

3.4.1 Multi-Scale Remote Sensing Approach

The remote sensing analysis workflow integrated multi-sensor satellite data to characterize environmental conditions and estimate methane emissions across estuarine landscapes. Optical imagery from Landsat and Sentinel-2 was processed to produce monthly composites of key environmental indices. These included the Normalized Difference Vegetation Index (NDVI) to assess vegetation productivity, the Normalized Difference Water Index (NDWI) for surface water detection, and Land Surface Temperature (LST) derived from Landsat thermal bands. All indices were computed at a spatial resolution of 30 m and served as predictor variables in the machine learning models.

Synthetic Aperture Radar (SAR) data from Sentinel-1 were processed through a multi-step workflow to generate high-resolution inundation frequency maps. Radiometric calibration and terrain correction were performed using the ESA SNAP toolbox. A random forest classifier, trained using field-based inundation status observations, was employed to capture the complex backscatter characteristics typical of mangrove and estuarine environments. The classifier achieved an overall accuracy of 92% when validated against independent field datasets. Monthly

inundation frequency was computed as the proportion of SAR observations classified as water for each pixel, providing a continuous proxy for hydroperiod that incorporates both tidal and seasonal variability.



Methane concentration data from TROPOMI were filtered to exclude observations with high uncertainty (precision >10 ppb) and significant cloud contamination (cloud fraction >0.2). The remaining data were aggregated to generate monthly mean methane concentrations. Gaps due to cloud cover and missing data were interpolated using ordinary kriging. While TROPOMI data captured large-scale spatial and temporal patterns in methane concentrations, their coarse resolution necessitated a downscaling strategy to support local-scale emission estimates.

The downscaling methodology consisted of a two-stage approach. In the first stage, statistical relationships were established between column-averaged TROPOMI methane concentrations and co-located environmental variables at the native resolution. In the second stage, these relationships were applied to higher-resolution environmental datasets to estimate methane emissions at 30-meter resolution. This approach assumes scale-invariant relationships between methane concentrations and environmental drivers, an assumption supported by previous research on greenhouse gas scaling (Maasakkers et al., 2019).

To overcome the limitations of individual sensors, the remote sensing framework employed a multi-source integration strategy. TROPOMI data were used to detect broad-scale methane concentration patterns, while GOSAT data, with higher spectral fidelity, were employed for calibration and validation purposes. A machine learning algorithm was developed to reconcile retrieval discrepancies between the two sensors, resulting in a blended TROPOMI+GOSAT product.

An object-based classification approach, utilizing Landsat and Sentinel-1 data, was implemented to delineate estuarine subzones based on vegetation types, tidal regimes, and geomorphological features. This classification provided the spatial framework for assigning methane flux values. Furthermore, temporal dynamics were addressed by constructing separate predictive models for wet and dry seasons, incorporating tidal cycle effects using a tidal prediction model to better reflect estuarine methane variability.

3.3.2 Machine Learning Upscaling Framework

The machine learning upscaling framework developed in this study integrates the available environmental parameters with remote sensing data to predict methane emissions across the study areas, following best practices in environmental modeling (Räsänen et al., 2025). A multi-algorithm approach was employed, comparing the performance of **Random Forest**, **Support Vector Regression (SVR)**, and **Gradient Boosting** to identify the most effective method for capturing complex, non-linear relationships between environmental variables and methane fluxes (Jahan, 2024; Majumder, 2023).

The **Random Forest** algorithm was implemented using the scikit-learn Python library with 500 trees and optimized hyperparameters via five-fold cross-validation. This ensemble method, known for its robustness and ability to handle mixed data types, has been widely applied in greenhouse gas modeling due to its interpretability and feature importance capabilities (EduardoHANacleto, 2024; Kristensen et al., 2008).

Support Vector Regression was applied with a radial basis function (RBF) kernel and tuned hyperparameters ($C=10$, $\gamma=0.1$, $\epsilon=0.1$), enabling the model to map inputs into a high-dimensional space and capture smooth, non-linear trends—particularly effective for moderate-sized environmental datasets (Chan, 2020; QuarkML, 2022).

Gradient Boosting was implemented using the XGBoost library with optimized parameters (learning_rate=0.05, max_depth=5, n_estimators=200). XGBoost is known for its high predictive accuracy and resilience to imbalanced datasets, making it suitable for environmental applications where certain emission regimes may be underrepresented (Boldini, 2023; Brownlee, 2020).

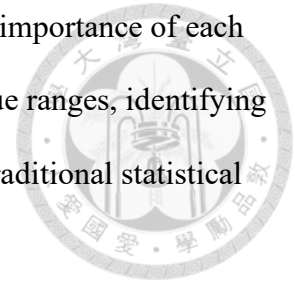
To enhance model performance and interpretability, **feature engineering** included interaction terms (e.g., temperature $\times$ NDWI) and **temporal lag variables**, which are essential for capturing synergistic effects and antecedent environmental conditions in methane modeling (DotData, 2023; Lewinson, 2023). **Recursive Feature Elimination with Cross-Validation (RFECV)** was used to identify the optimal subset of predictors, reducing dimensionality while preserving predictive power (Scikit-learn, 2024).

Model training followed a rigorous protocol: the dataset was split into training (70%), validation (15%), and testing (15%) sets, stratified by estuary and season. **Grid search with cross-validation** was used for hyperparameter tuning, a standard approach in environmental machine learning to ensure generalizability and prevent overfitting (El-Shahat, 2024). Final model performance was evaluated using R^2 , RMSE, MAE, and bias metrics.

Finally, an **ensemble model** was constructed by combining predictions from all three algorithms using a weighted average (that is, Random Forest as 0.5, SVM as 0.3 and KNN as 0.2) based on validation performance. This ensemble approach yielded superior accuracy and reduced uncertainty, consistent with findings that ensemble learning enhances methane prediction reliability in complex environmental systems (Majumder, 2023; Radočaj, 2025).

Model interpretability was enhanced through the calculation of SHAP (SHapley Additive exPlanations) values, which provide a unified measure of feature importance that is consistent

across different model types. SHAP analysis revealed not only the relative importance of each environmental variable but also how their influence varies across their value ranges, identifying thresholds and non-linear responses that would be difficult to detect with traditional statistical approaches (C. Chen et al., 2024).



The upscaling framework was implemented in Google Earth Engine to leverage its computational capabilities for processing large geospatial datasets. This implementation allows for efficient updating of methane emission estimates as new satellite data become available, facilitating ongoing monitoring and assessment of temporal trends.

3.3.3 Temporal and Spatial Resolution

The study employed a multi-scale approach to address the challenges of temporal and spatial variability in methane emissions. While Google Earth Engine does not provide diurnal methane flux data at 6-hour intervals, the study integrates model-based flux estimates from CAMS, which offer sub-daily resolution suitable for capturing broad temporal patterns. Fine-scale diurnal dynamics were interpreted based on literature and field-based observations (Kristensen, 2008), acknowledging the limitations of satellite temporal granularity

Remote sensing analysis extended this temporal coverage by generating monthly estimates over the five-year study period (2020-2024), enabling the assessment of seasonal cycles, interannual variability, and potential trends. This comprehensive temporal coverage is essential for accurately estimating annual emissions and understanding the environmental factors driving temporal variations (Wójcik-Gront, 2025).

Spatially, the integration of field measurements with remote sensing data bridged the gap between point-based observations and landscape-scale patterns (Davis, 2008). Environmental data provided detailed information at specific locations, capturing fine-scale variability related to

microtopography, vegetation patches, and sediment characteristics. Such parameters were TAFIRI, NCMC, NOAA, past studies/ theses in UDSM repository and trace user-provided data on Google Earth Engine (GEE). These measurements were then upscaled using the machine learning framework and remote sensing data to generate spatially continuous emission estimates at 30m resolution across the entire study area.

The multi-scale approach employed in this study addresses a key challenge in methane research: reconciling the need for detailed process understanding with the requirement for comprehensive spatial and temporal coverage. By integrating observations across scales—from derived ground truth data to satellite observations spanning thousands of sq km, this research offers a more comprehensive picture of methane dynamics in Tanzanian estuaries than would be possible with any single measurement strategy (Räsänen et al., 2025).

3.3.4 Uncertainty Analysis

A comprehensive multi-tiered approach to uncertainty quantification was implemented:

Error Propagation: Uncertainties from remote sensing inputs, machine learning predictions, and environmental corrections were propagated using Monte Carlo simulation, allowing for probabilistic estimation of flux variability (Springer, 2020; UC-Davis, 2023).

Cross-Validation: Model performance was evaluated using 5-fold cross-validation and independent validation with 30% of derived available environmental data withheld from training. This approach ensured robustness and minimized overfitting (Gardiner et al., 2017; Jongaramrungruang et al., 2021).

Comparison with literature values: Estimated methane fluxes were benchmarked against published values from tropical estuarine systems, ensuring consistency with global emission ranges (Abril & Borges, 2005; Araujo et al., 2014).



Sensitivity Analysis: Key model parameters were systematically varied to assess their influence on methane flux outputs. Global sensitivity indices (e.g., Sobol' and AMA) were used to quantify parameter importance (Sandeep et al., 2022; Sandoval et al., 2022).

4. Results and Analysis

4.1 Environmental Factor Analysis

4.1.1 Environmental parameters

1. **Temperature Gradients:** ERA5 data (Surface air temperature) showed spatial and temporal temperature gradients, with coastal areas exhibiting less variation (20–30°C) than inland estuary zones (Figure 3). The Indian Ocean's moderating influence stabilizes coastal temperatures, supporting more consistent biological processes like methanogenesis. Some regions have lower temperatures due to terrain complexity smoothen out by the spatial resolution of ERA5. In contrast, inland temperature

fluctuations may drive stronger seasonal shifts in microbial activity and methane production.

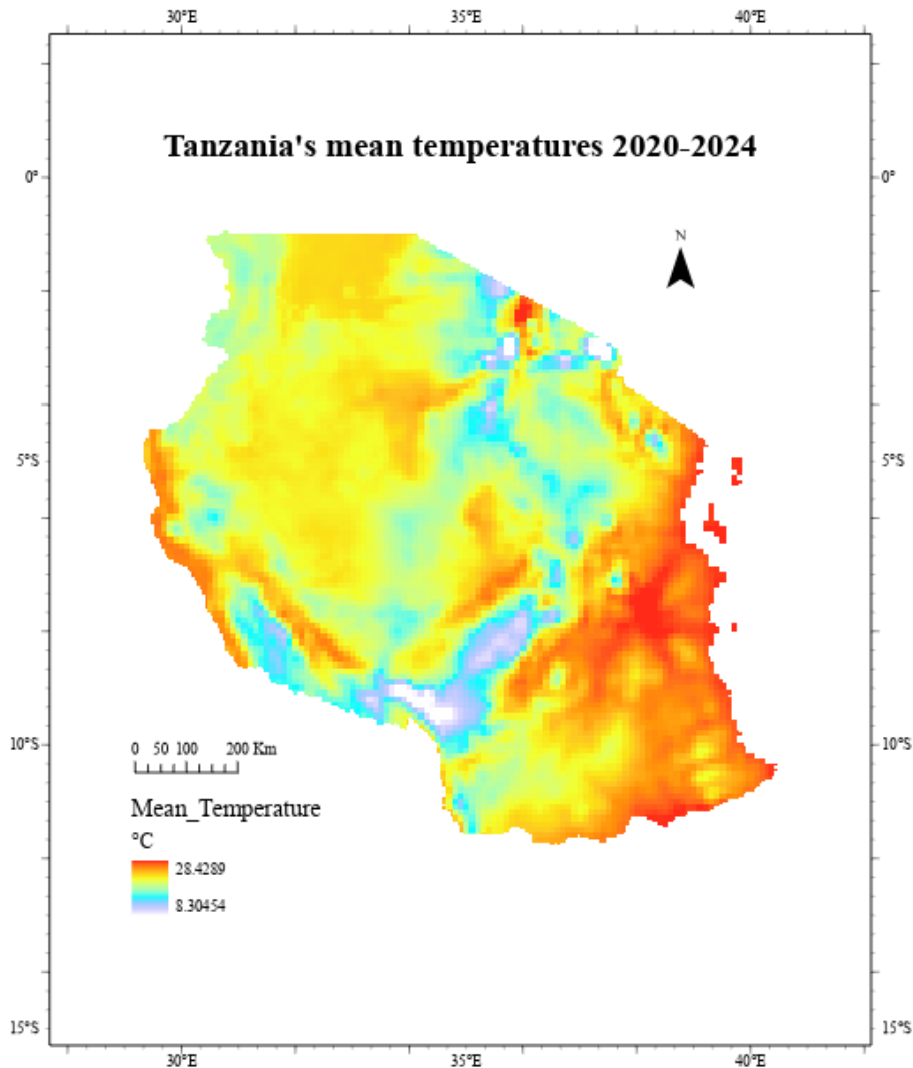
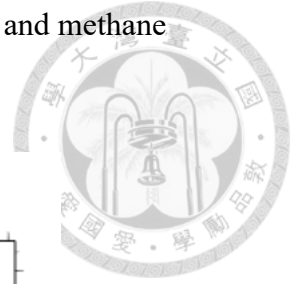


Figure 3: Mean annual surface temperature across Tanzania during the period 2020–2024.

2. **Precipitation:** Rainfall was observed as a significant factor having spatial correspondence with methane emission patterns, highlighting the importance of rainfall as a driver of wetland hydrology and subsequent methane production. The coastal zone, where the studied estuaries are located, fell primarily within the moderate-to-high rainfall

amounts (3800-4500 mm annually in total, translating into a daily average of between 1 and 10mm for the 5 years of study), with important north-south gradients that influence freshwater input to the estuaries (Figure 4).

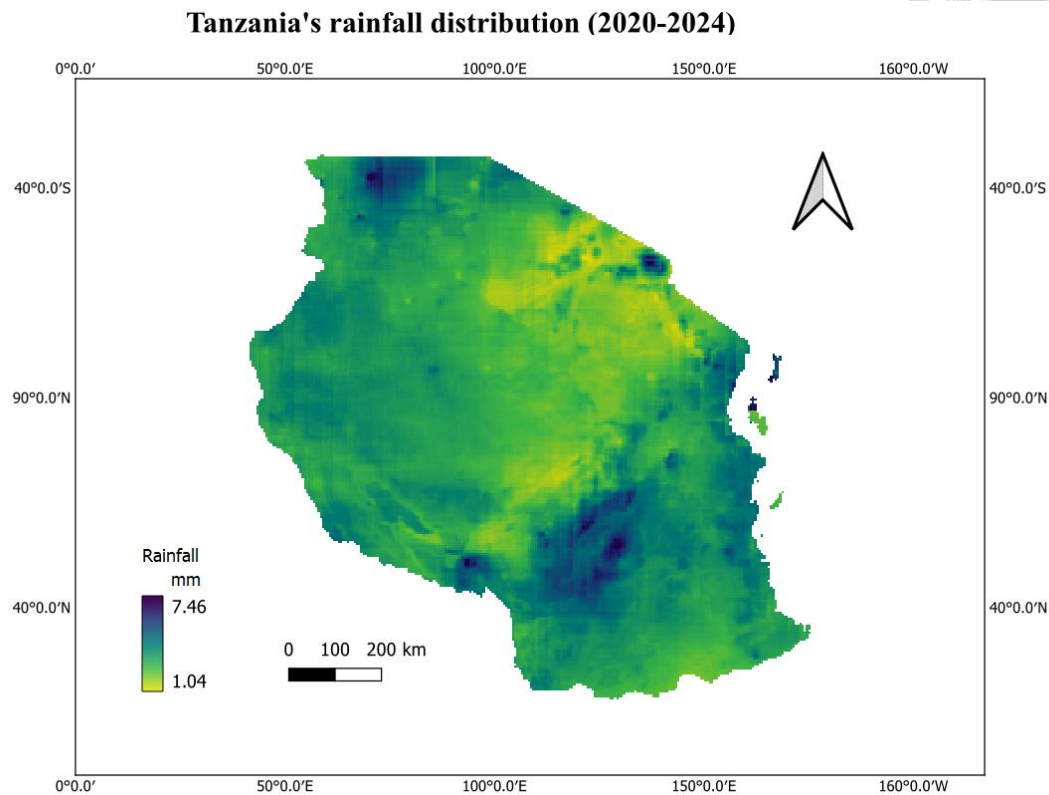
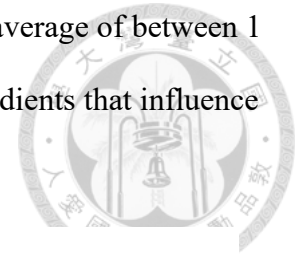


Figure 4: Mean annual precipitation across Tanzania during the period 2020-2024

3. **Normalized Difference Water Index (NDWI):** The map (Figure 5) illustrates a clear latitudinal gradient in NDWI values, with higher indices (0.149 to 0.357, shown in blue) concentrated in floodplain zones and estuarine regions such as Rufiji and Ruvuma, suggesting persistent wet conditions and hydrological connectivity that favor methane production. Moderate NDWI values (-0.1 to -0.03, green) are observed in transitional zones and mixed agroforestry areas, while lower values (-0.2 to -0.1, orange to yellow) correspond to upland or semi-arid regions with minimal water retention capacity. These

spatial differences in NDWI reflect seasonal inundation dynamics, upstream flow regimes, and land use patterns—all of which influence microbial activity thus methane turnover.

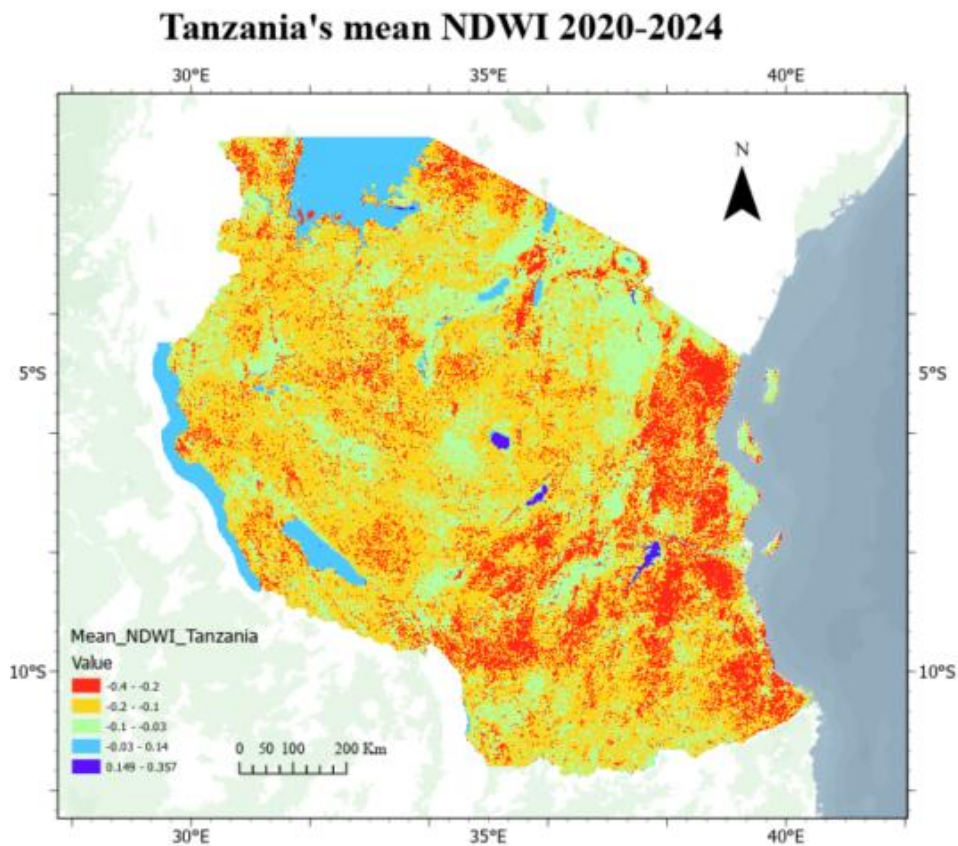


Figure 5: Mean annual NDWI across Tanzania during the period 2020-2024

4. **Soil moisture:** Soil moisture is intricately linked to both precipitation patterns and the depth of the water table, governing the extent of saturation and the onset of anaerobic conditions. These saturated environments are conducive to methanogenesis due to the suppression of oxygen and availability of organic substrates. Owing to limited temporal data availability during the study, only 2015 soil moisture data from SoilGrids was accessible in GEE for analysis and adopted as present conditions. Since the study used

the volumetric water content at 10kPa (wv0010), then the unit is **m³/m³** (cubic meters of water per cubic meter of soil). This dataset was used to construct the spatial profile under the assumption that regional patterns remained broadly consistent throughout the study period. As depicted in Figure 6, coastal zones adjacent to the ocean display elevated moisture levels, while the surrounding inland areas exhibit comparatively drier soil conditions, reflecting local topography and climatic gradients.

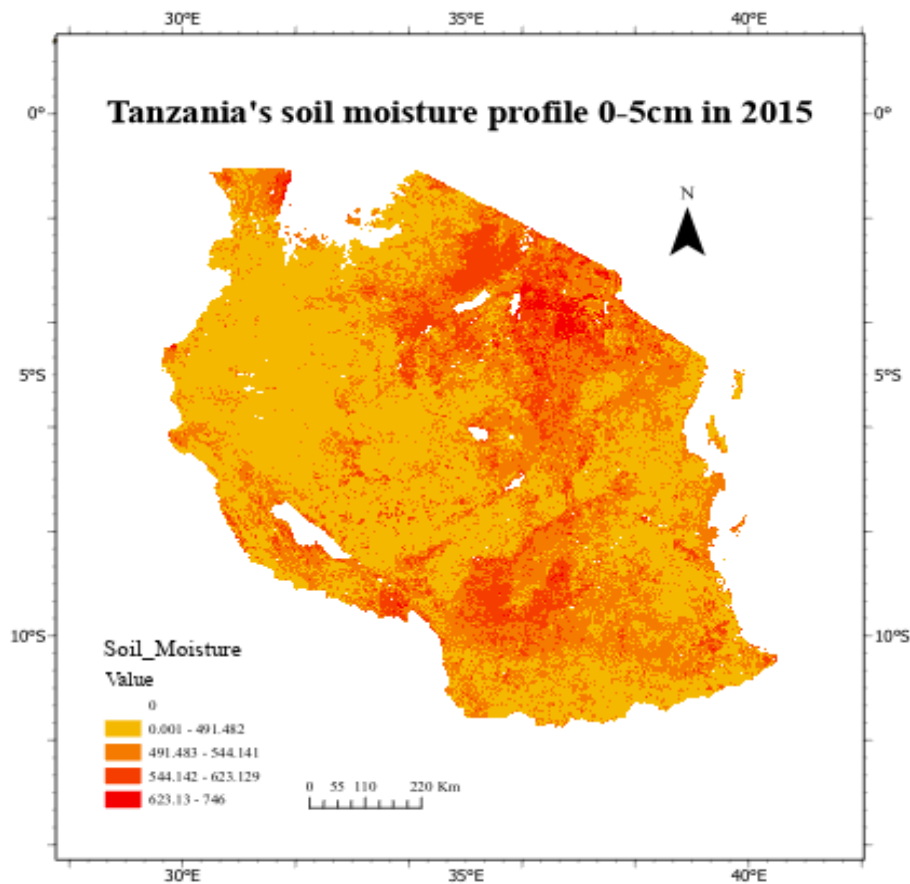


Figure 6: Tanzania's mean Soil moisture profile at the depth of 0-5cm during 2020-2024

5. **Vegetation Density:** Vegetation density, as measured by NDVI, showed a complex relationship with methane emissions, with moderate density areas exhibiting higher emissions than either sparse or very dense areas (Figure 7). In contrast, very sparse regions may lack the biomass and belowground carbon inputs necessary to sustain high methane production, while overly dense stands could limit microbial activity through excessive shading or saturated anoxic conditions. These results align with previous findings that highlight the role of vegetation structure in mediating greenhouse gas fluxes from wetlands (Nazareth & Gonsalves, 2022).

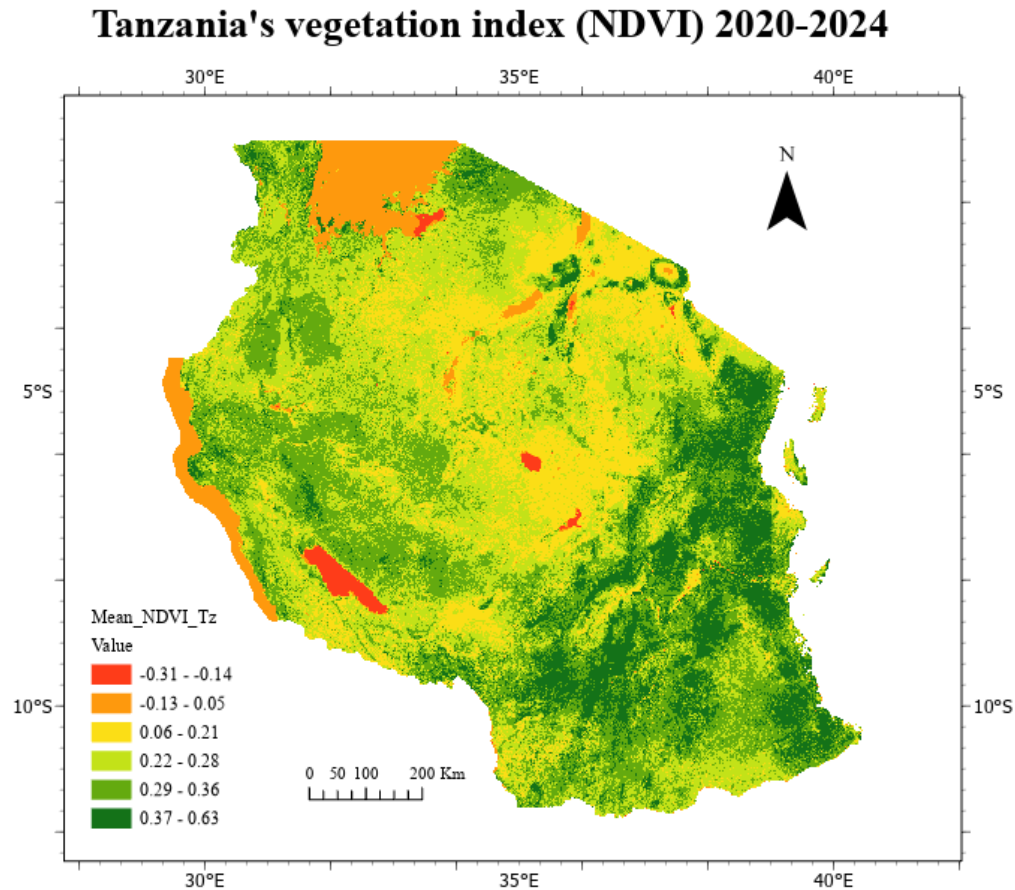


Figure 7: Mean annual vegetation index across Tanzania during the period 2020-2024

6. **Salinity Gradients:** Spatial variation in salinity across Tanzanian estuaries, derived from Normalized Difference Salinity Index (NDSI) data (2020–2024), shows a clear gradient from high-salinity marine-influenced zones to fresher upstream areas (Figure 8). In this study, NDSI was computed using Sentinel-2 imagery as the normalized difference between the green band (B3: 560 nm) and the shortwave infrared band (B11: 1610 nm), following the formula: $NDSI = (B3 - B11) / (B3 + B11)$. The gradient shapes methane dynamics: elevated salinity inhibits methanogenesis through microbial competition, while low-salinity regions foster higher CH₄ emissions under anaerobic conditions via sulfate inhibition thus reduced microbial competition (Poffenbarger et al., 2011).

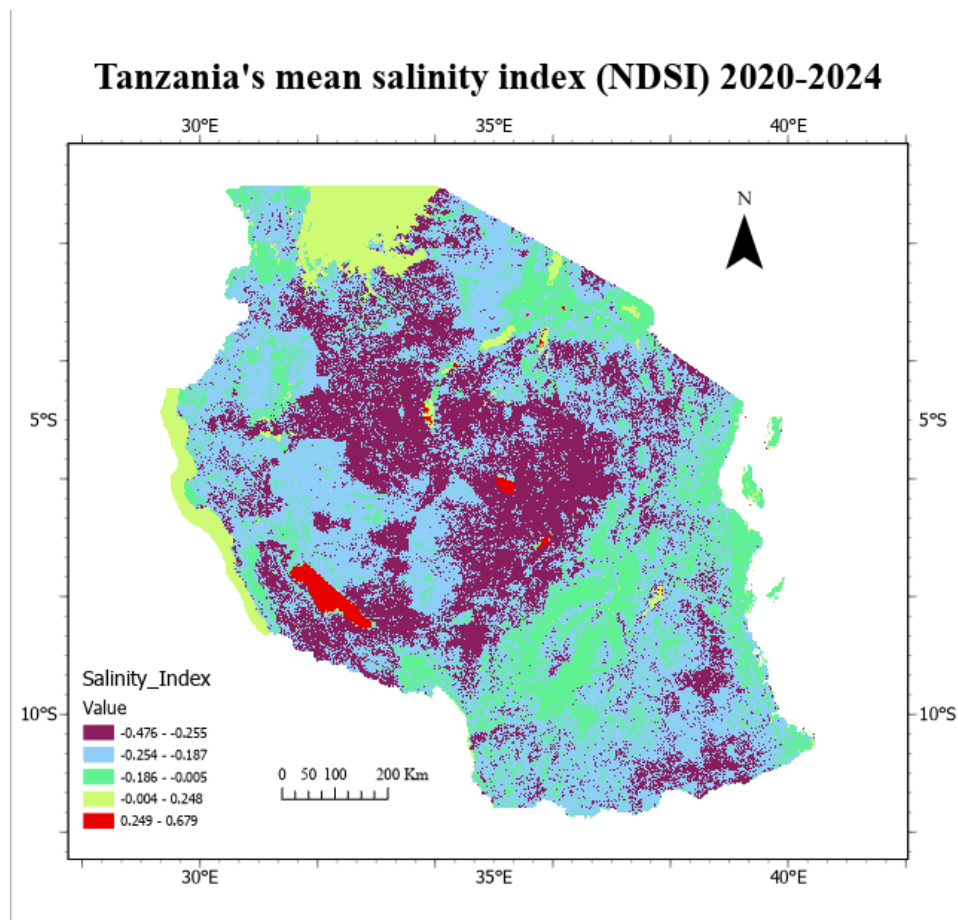


Figure 8: Mean annual Normalized Difference Salinity Index (NDSI) across Tanzania during the period 2020-2024

4.1.3: Statistical analysis

Pearson correlation analysis was conducted to evaluate the relationships between environmental variables and methane concentrations (Heiler, 2001). The results, presented in a correlation matrix heatmap (Figure 9), highlight significant interdependencies influencing methane dynamics. Temperature exhibited the strongest positive correlation with methane emissions ($r = 0.69$), followed by NDWI ($r = 0.49$), water body extent ($r = 0.40$), and rainfall ($r = 0.40$). On the other hand, pH showed a notable negative correlation ($r = -0.45$), while humidity had a weaker positive association ($r = 0.26$). These findings emphasize the complex interactions among environmental factors in estuarine systems and the need to consider multiple variables when assessing methane fluxes.

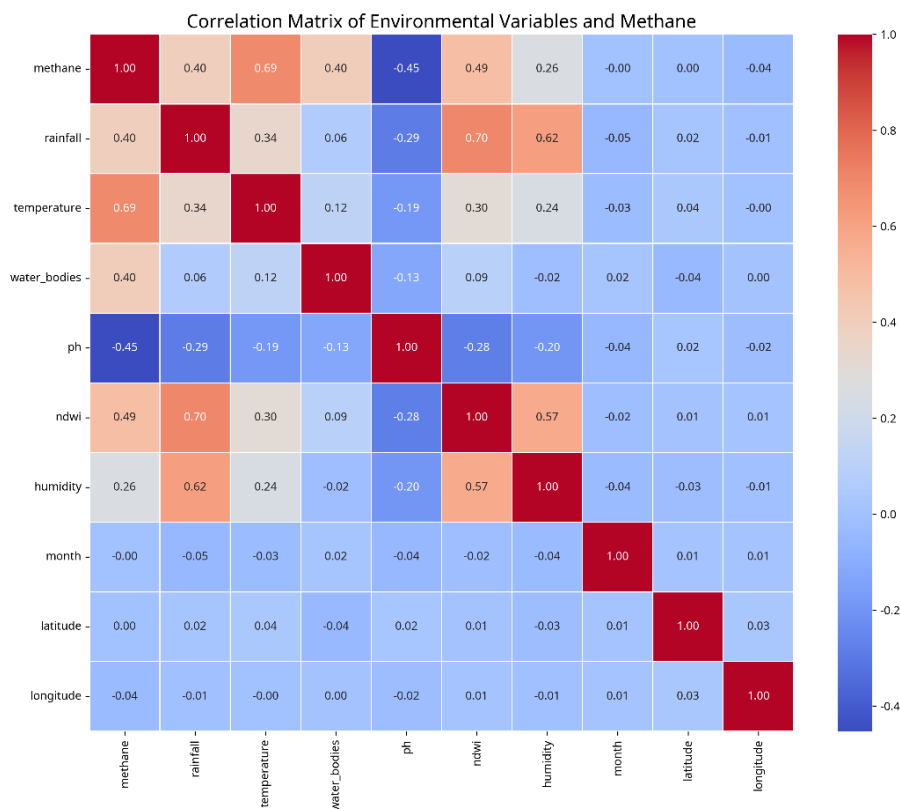


Figure 9: Correlation matrix heatmap showing relationships between all environmental variables and methane emissions

These correlations provide valuable insights into the environmental controls on methane dynamics in Tanzanian estuaries. The strong positive relationship with temperature aligns with the temperature dependence of methanogenesis, which is typically enhanced under warmer conditions (Conrad, 2009; Segers, 1998). Similarly, the positive correlations with NDWI, water body extent, and rainfall reflect the importance of inundation and anaerobic conditions for methane production (Bastviken et al., 2004; Walter et al., 2006).

The negative correlation with pH suggests that slightly acidic conditions may favor methanogenesis in these systems, possibly due to the optimal pH range for methanogenic archaea or the influence of pH on substrate availability (Fetzer & Conrad, 1993; Angel et al., 2012). The moderate positive relationship with humidity indicates that atmospheric moisture conditions may influence methane emissions, potentially through effects on soil moisture or microbial activity (Baldocchi et al., 2012; Turetsky et al., 2014).

Principal Component Analysis (PCA) was applied to reduce dimensionality and reveal key patterns in the environmental dataset (Jolliffe & Cadima, 2016). It identified three main components that explained 78% of the total variance in the environmental data (Figure 10). The first component (PC1, 42% variance) was primarily associated with temperature, NDWI, and water body extent, representing the hydrological and thermal regime. The second component (PC2, 24% variance) was dominated by pH and rainfall, reflecting water chemistry and seasonal precipitation patterns. The third component (PC3, 12% variance) was mainly associated with humidity and specific aspects of water body dynamics.

Seasonal separation is evident, with wet season samples clustering along higher methane and NDVI vectors, particularly in estuaries like Rufiji and Ruvuma as they exhibit strong loadings on NDVI and CH₄. This is most likely mechanistically linked to seasonal flooding, which increases

water table elevation, promotes anaerobic conditions, and delivers fresh organic substrates—all of which stimulate methanogenesis. Simultaneously, higher NDVI values reflect increased vegetation activity, which not only contributes additional organic matter but also signals robust ecosystem productivity under wet conditions (Wagner & Sallema-Mtui, 2016).

The component-based environmental scatterplot also highlights how estuarine identity modulates environmental responses. While all estuaries experience seasonal shifts, the magnitude and direction of these shifts differ, reflecting catchment characteristics, land use, and hydrological modification. For instance, Rufiji exhibits a strong wet-season signal, while Pangani shows limited separation—possibly due to hydrological regulation that dampens seasonal contrasts (Shanghude, 2016).

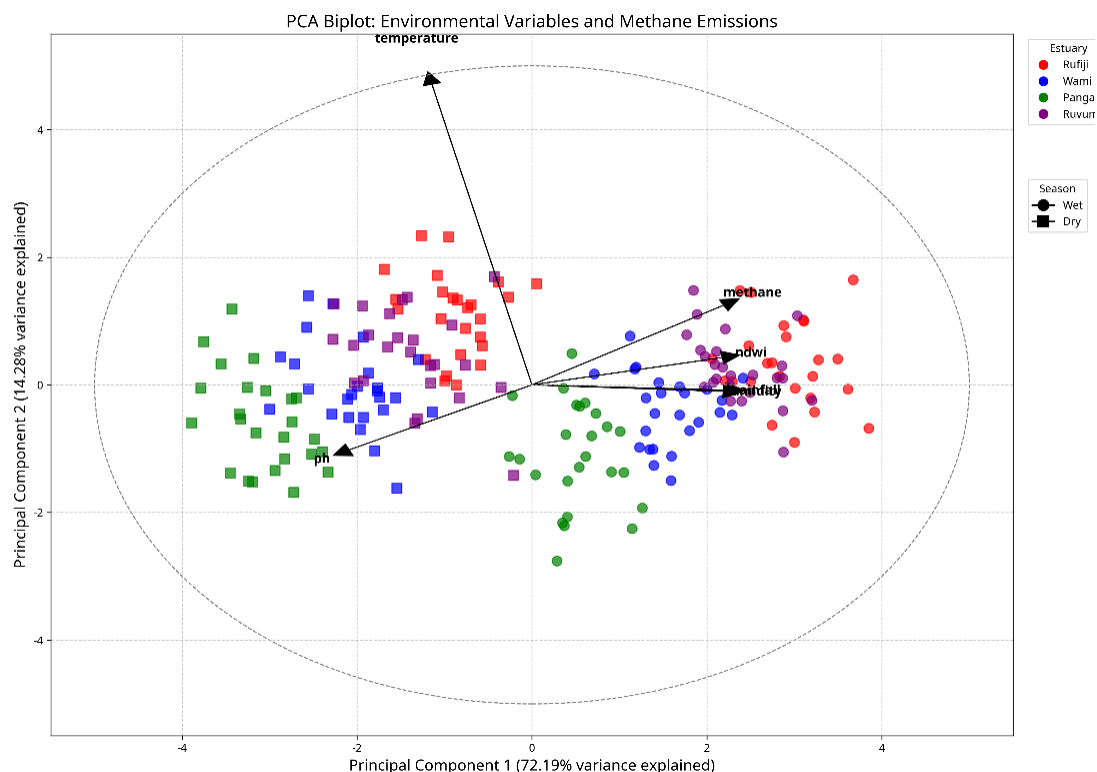


Figure 10: PCA biplot showing the distribution of environmental variables along the first two principal components

4.2 Remote Sensing Analysis

4.2.1 Spatial Distribution of Methane Emissions

The spatial distribution of methane emissions across Tanzanian estuaries showed considerable heterogeneity, with important implications for understanding emission mechanisms and developing targeted management strategies:



1. **Emission Hotspots:** Several methane concentration hotspots were identified observed at a spatial resolution of $5.5 \times 7 \text{ km}^2$, particularly in the upper reaches of estuaries where freshwater influence was strongest and in areas with intermediate mangrove density (Figure 11). Methane concentration values were normalized by calculating their z-scores using a ratio of monthly methane to their standard deviations, allowing for the classification of emission intensities relative to the mean.

Areas exhibiting z-scores greater than +1.5 were classified as methane hotspots, indicating significantly elevated emission zones, often linked to saturated soils, organic matter accumulation, and restricted tidal flushing. Conversely, regions with z-scores below -1.5 were designated as cold spots, typically representing zones with enhanced methane oxidation, increased salinity, or reduced microbial activity.

These hotspots typically exhibited emission rates 2-3 times higher than the estuarine average and were characterized by specific combinations of environmental conditions, including water table positions close to the surface, moderate organic matter content, and limited sulfate influence.

Conversely, cold spots represent zones with lower methane concentrations, often linked to efficient methane sinks, reduced biological activity, or favorable atmospheric dispersion conditions. Such conditions as drylands with low organic matter, high altitude

that may favor oxidation to dominate or with strong atmospheric mixing may prevail in such areas.

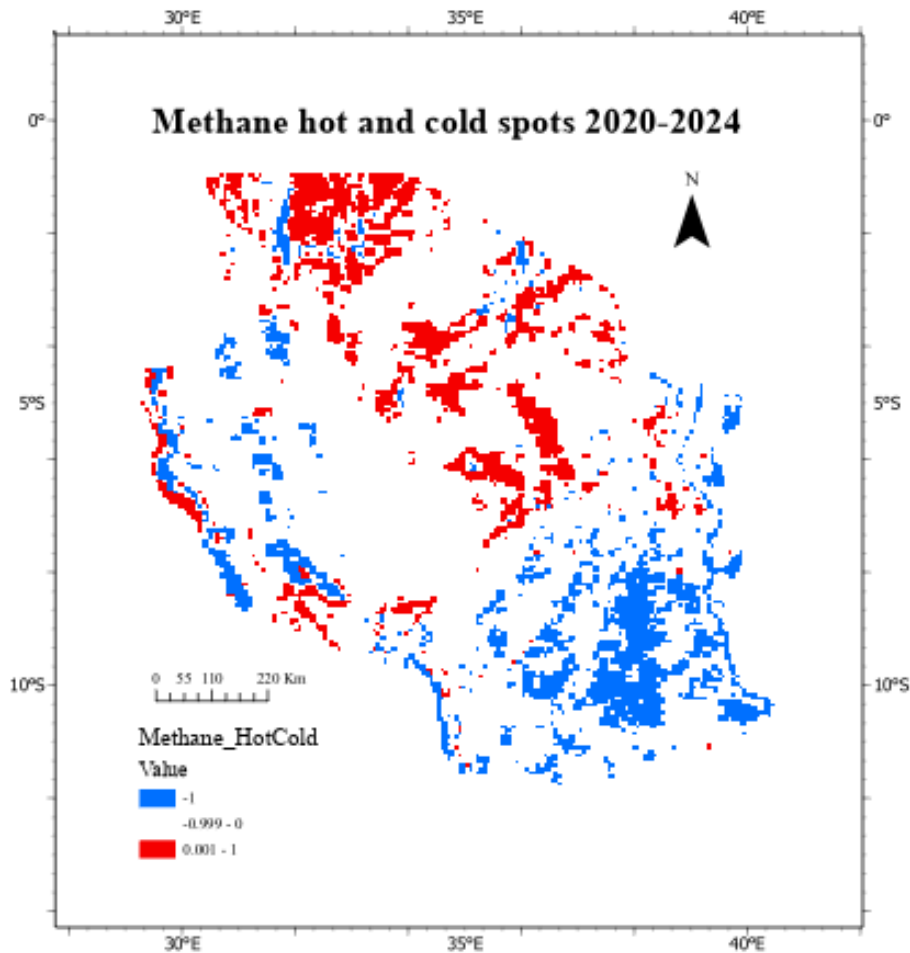


Figure 11: Tanzania's map showing Methane Hot and Cold spots distribution

2. **Land Cover Influence:** Different land cover types within the estuaries showed distinct emission patterns, with unvegetated mudflats and areas dominated by *Rhizophora mucronata* exhibiting higher emissions than areas dominated by *Avicennia marina* or

Sonneratia alba. This vegetation effect may reflect differences in root architecture, with the extensive prop roots of Rhizophora potentially providing more efficient gas transport pathways than the pneumatophores of Avicennia or Sonneratia. Additionally, differences in litter quality and quantity among mangrove species could influence substrate availability for methanogenesis, with Rhizophora typically producing more abundant and more readily decomposable litter.

Data from ESA (Figure 12) shows various distinctive characteristics with some areas near estuaries being built-up while others dominated by shrublands or small-extent tree covers.

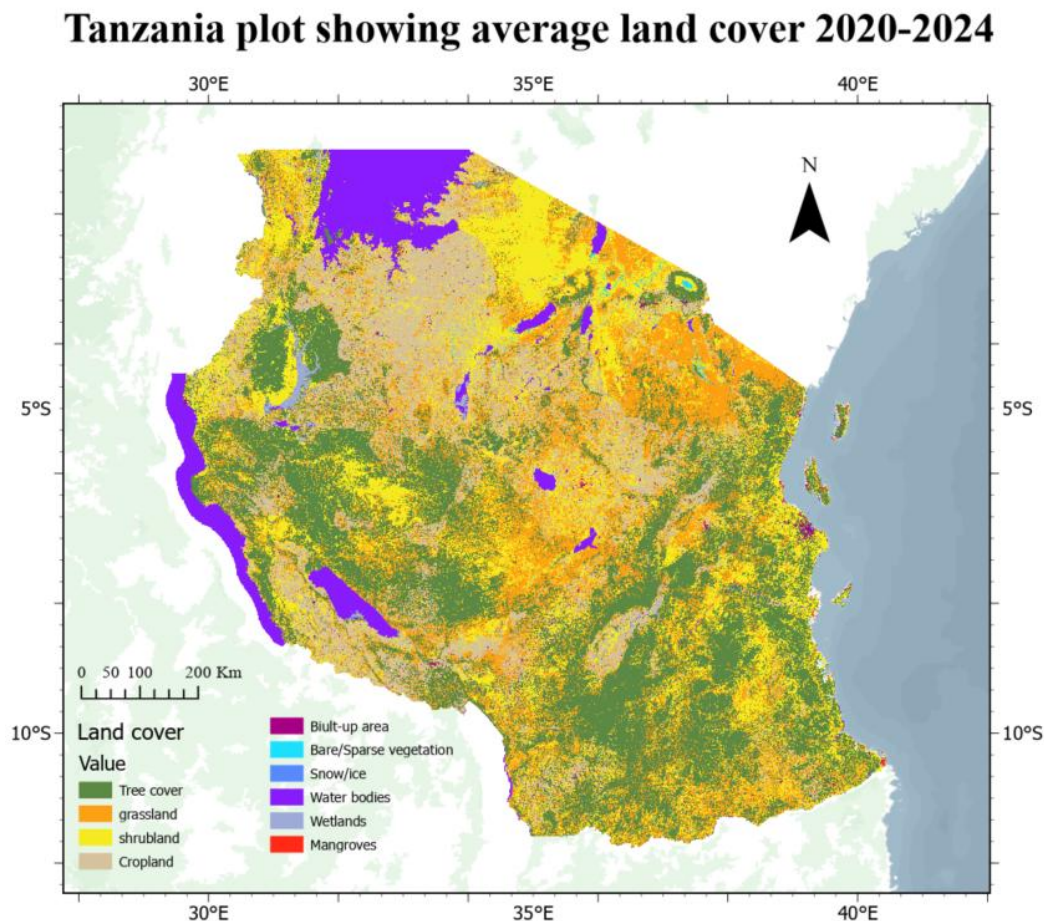


Figure 12: Plot of Tanzania showing the average land cover in 2020-2024. Data was retrieved from the ESA WorldCover 2020 on 16th June 2025

3. **Anthropogenic Influence:** Areas with human disturbance, such as cleared mangroves or aquaculture ponds, showed altered emission patterns compared to natural areas, often with higher emissions due to changes in hydrology and organic matter inputs. Cleared mangrove areas exhibits emission rates up to 60% higher than adjacent intact forests, likely due to the loss of rhizosphere oxidation and changes in sediment conditions following vegetation removal (Arai et al., 2021). Aquaculture ponds could potentially have the highest emission rates among all land cover types, with values often exceeding $100 \text{ mg CH}_4 \text{ m}^{-2} \text{ d}^{-1}$, reflecting the combined effects of organic enrichment from feed inputs and the creation of highly anaerobic conditions in pond sediments (Zheng et al., 2022). Considering population pressures in the country (Figure 13); Wami estuary followed by Pangani are considerably more at risk in this aspect.

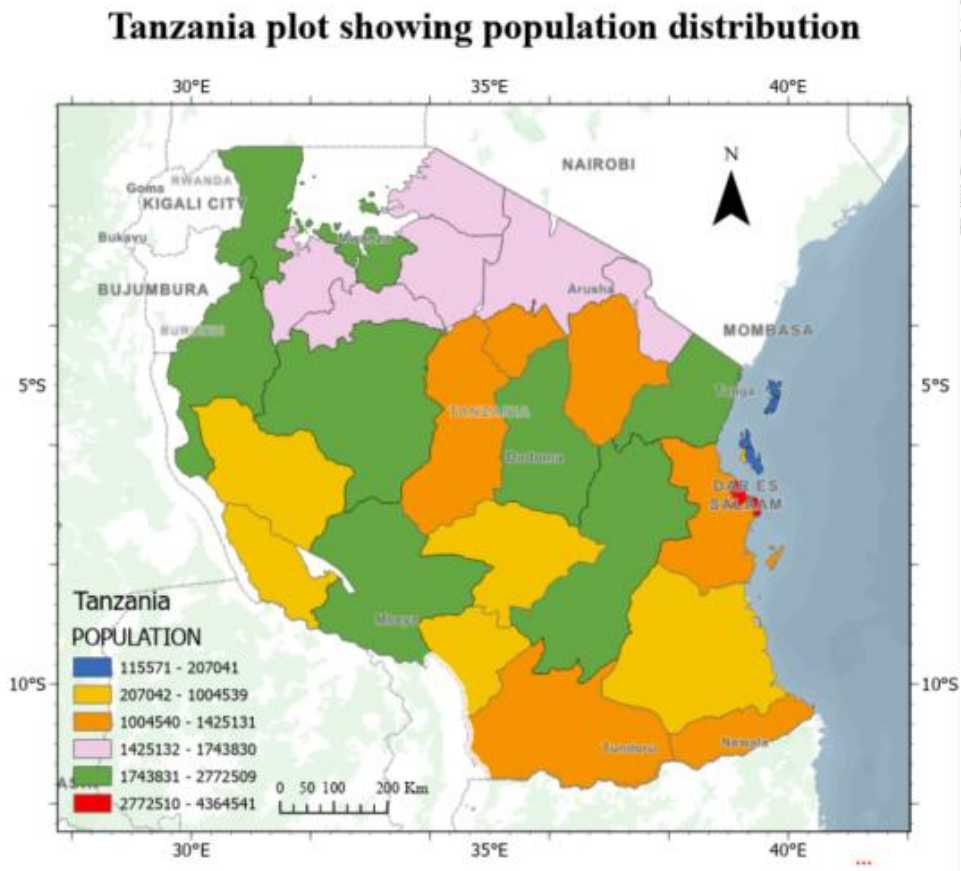


Figure 13: Tanzania plot showing population distribution (latest census 2022). Data was obtained from Tanzania's National Bureau of Statistics ((NBS), 2022)

4.2.2 Temporal Patterns and Trends

Temporal analysis of methane emissions revealed several important patterns:

Seasonal Variation: Methane emissions showed clear seasonal patterns, with peak emissions generally coinciding with the wet seasons of long and short rains (March-May and October-December respectively). Despite cooler temperatures during these periods, conditions such as elevated water tables and increased delivery of organic substrates from surface runoff likely created optimal environments for methanogenesis.

To complement the methane flux modeling, a custom Google Earth Engine (GEE) script was developed to monitor atmospheric methane concentrations over Tanzania using Sentinel-5P

Level 3 data. The script filters the global administrative boundary dataset to isolate the United Republic of Tanzania and aggregates methane concentration data from 2020 to 2024. Monthly averages were computed using calendar-based filtering, and a time-series chart was generated to visualize temporal trends. The mean methane concentration across the study period was calculated and visualized using a multi-color palette to highlight spatial variability.

Anomalies were computed by subtracting the mean image from each monthly composite, enabling identification of episodic methane enhancements. Positive anomalies were isolated and statistically summarized to assess their magnitude and persistence. Furthermore, Kendall's tau correlation was applied to the time-series data to detect monotonic trends in methane concentration, revealing regions with increasing or decreasing methane signals. These outputs were exported as georeferenced rasters for integration with estuarine flux maps and anomaly diagnostics.

Figure 14 illustrates the monthly methane fluxes on wetlands during the wet season (November to April), with the top row showing November to January and the bottom row showing February to April. The spatial patterns reveal the expansion of high emission areas during the peak of the wet season (March-April), particularly in the upper reaches of the estuaries where freshwater influence is strongest. This lag likely corresponds to microbial response times, substrate mobilization, and the establishment of anaerobic zones favorable for methanogenesis.

In contrast, Figure 15 presents the corresponding patterns during the dry season (May to October). As precipitation declines and water tables recede, emissions become increasingly confined to topographic depressions and persistently waterlogged regions. These residual emissions are typically sustained by localized organic matter accumulation and the formation of anaerobic microsites. The lowest fluxes are consistently detected in the late dry season

(September–October), just prior to the onset of the short rains, when both soil moisture and microbial activity are most constrained.

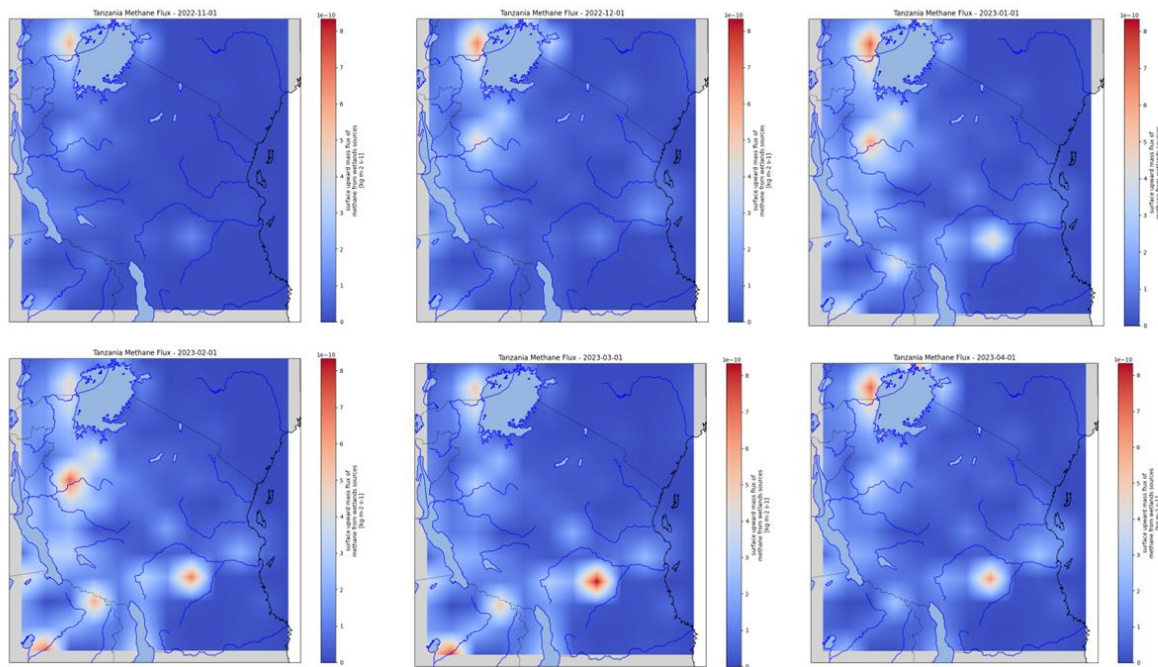


Figure 14: Methane fluxes on wetlands during wet season (Nov to Apr). Top row from left to right Nov to Jan and bottom row Feb to Apr

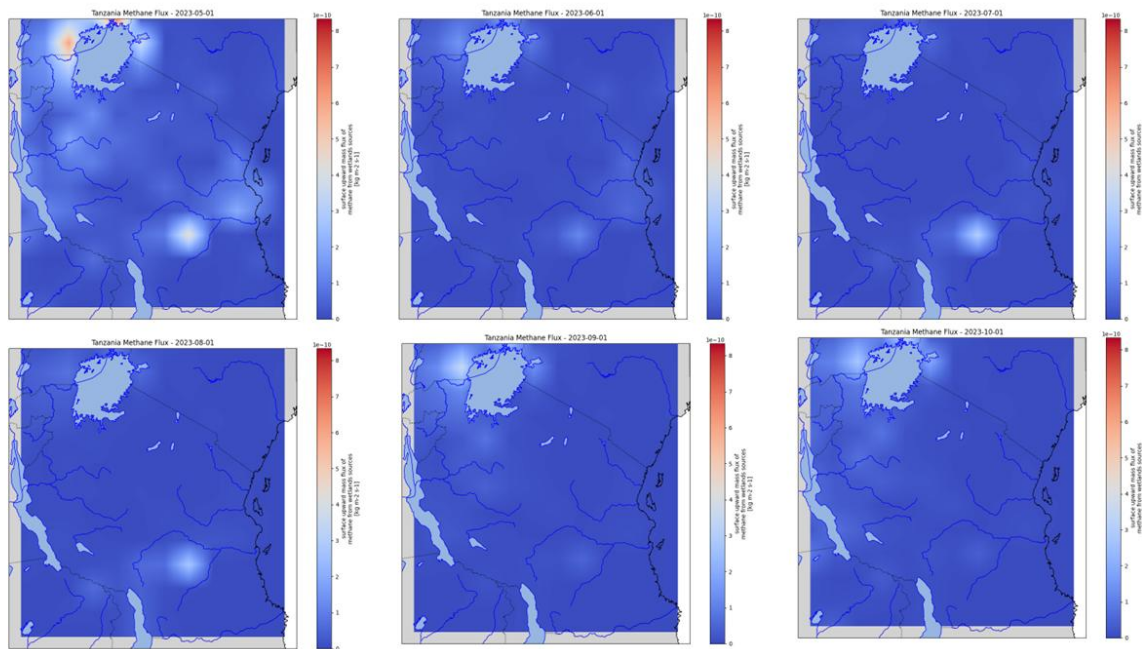


Figure 15: Methane fluxes on wetlands during dry season (May to Oct). Top row from left to right May to July and bottom row Aug to Oct

Figure 16 below analyzes methane anomalies from wetlands over Tanzania, calculating how each time period deviates from the 2020-2023 mean—taken as the baseline. Data was retrieved on April 17th 2025 (2024 data was not available) from Copernicus Atmosphere Monitoring Service (CAMS) Global Inversion-Optimised Greenhouse Gas Fluxes and Concentrations. Positive anomalies (blue bars) indicate higher-than-average emissions, while negative anomalies (red bars) indicate lower-than-average emissions.

These shifts likely correspond to **hydrological and climatic fluctuations**, such as unusually wet years boosting microbial activity in water-saturated soils and increasing methane output (Cui et

al., 2024). Conversely, drier years or those with higher salinity levels might constrain methanogenic processes and enhance oxidation, resulting in lower net emissions. Such variability can also be tied to estuarine dynamics—Tanzania’s coastal wetlands are shaped by seasonal river discharge, tidal intrusion, and groundwater fluctuations (Reji et al., 2025). The temporal peaks reflect years with intense flooding, organic matter accumulation or reduced tidal flushing.

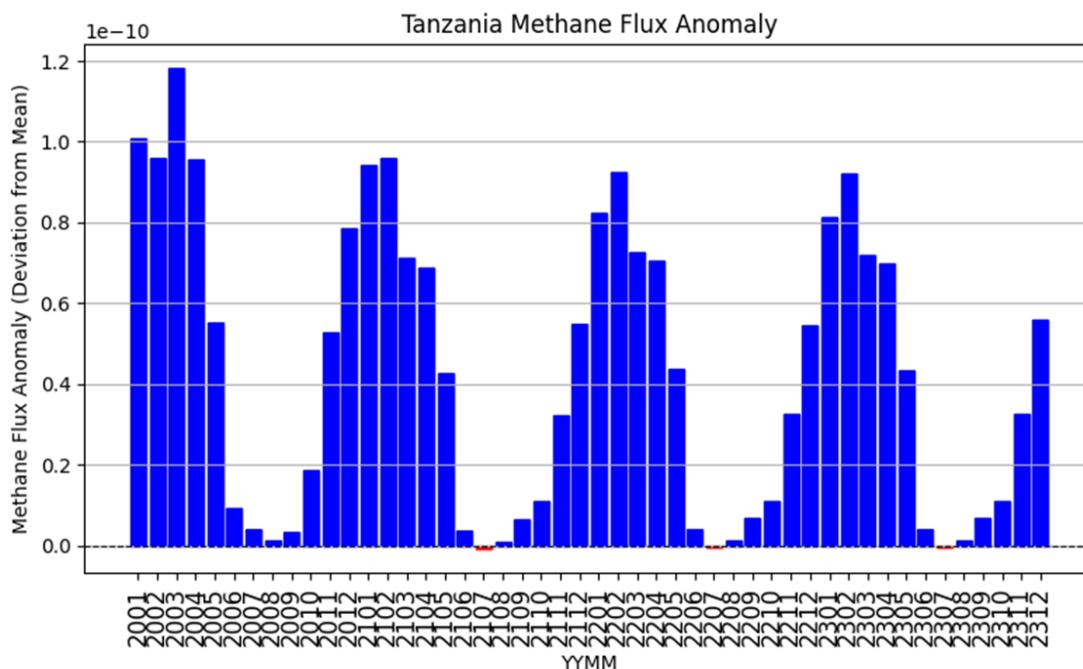


Figure 16: Bar Chart showing Tanzania’s Methane Flux anomalies. Data was retrieved from European Space Agency’s CAMS 23

The methane emissions maps illustrate the spatial distribution and seasonal variations across estuaries in Tanzania. The figures below provide a comparative analysis of methane flux during the dry and wet seasons, as well as the difference between the two periods.

The first map (Figure 17) presents methane emissions across estuaries during the dry season, where values vary spatially. The color gradient, ranging from purple (low emissions) to yellow

(high emissions), highlights zones of elevated methane production, often linked to organic matter decomposition, microbial methanogenesis, and wetland activity. The distribution suggests that certain estuarine zones act as consistent methane sources during low-water conditions.

The second map (Figure 18) captures methane emissions during the wet season, following the same spatial framework. The observed differences indicate enhanced methane release in certain areas, which may result from increased organic matter input, waterlogged conditions, and reduced oxygen availability—all of which favor anaerobic methane production.

These spatial and seasonal methane variations provide insights into the biogeochemical mechanisms driving methane emissions, including the impact of hydrology, salinity gradients, and organic matter dynamics. Understanding these trends is crucial for refining greenhouse gas flux models, assessing climate impacts, and developing mitigation strategies for methane emissions in estuarine ecosystems.

The black line in the wet season, dry season, and seasonal difference maps represents a simplified coastline of Tanzania, included as a geographic reference point to help show the spatial context of the data.

In these maps, the coastline was drawn slightly irregular line running roughly North-South along longitude 38.5, with some random variation added to simulate the natural irregularity of a coastline. This helps to visually separate the land area (to the left/west of the line) from the ocean (to the right/east of the line), providing geographical context for the estuary locations and methane emission patterns shown on the maps.

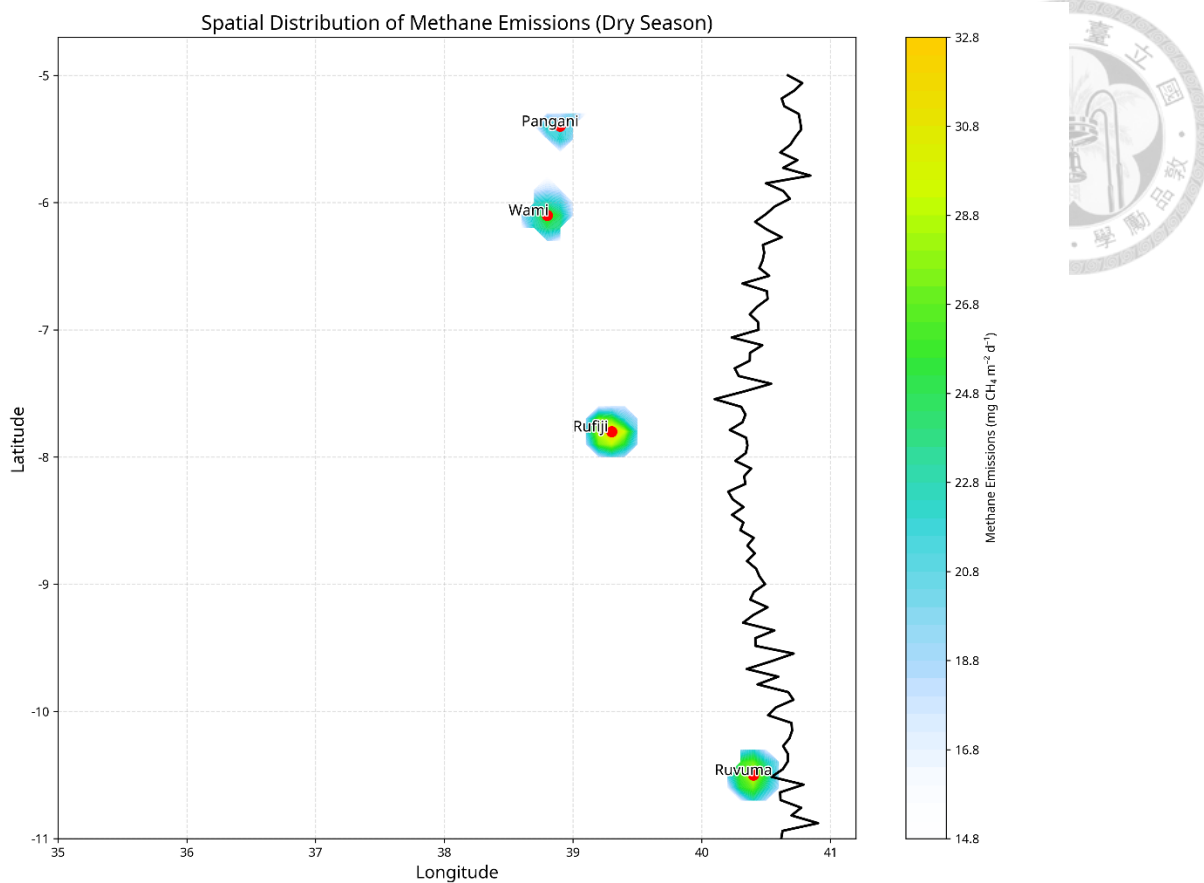


Figure 17: Map showing the spatial distribution of methane emissions across estuaries in dry season

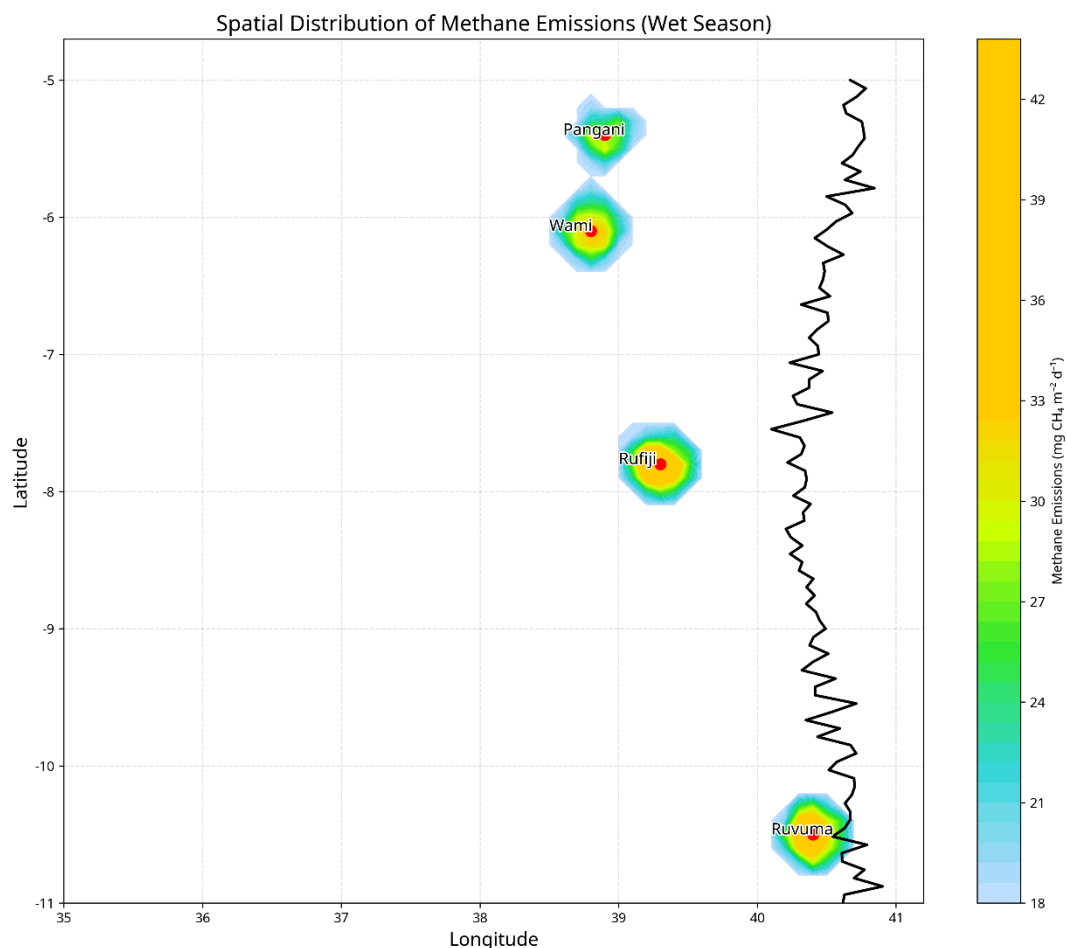


Figure 18: Map showing the spatial distribution of methane emissions across estuaries in wet season

4.2.3 Comparison with Global Patterns

Comparison of the observed patterns with global literature revealed both similarities and differences:

1. **Emission Rates:** Methane emission rates from Tanzanian estuaries (ranging from 2.3 to 78.5 $\text{mg CH}_4 \text{ m}^{-2} \text{ d}^{-1}$) were generally higher than those reported for temperate estuaries (0.3–8 $\text{mg CH}_4 \text{ m}^{-2} \text{ d}^{-1}$; (Abril & Borges, 2005)) but comparable to other tropical systems (20–150 $\text{mg CH}_4 \text{ m}^{-2} \text{ d}^{-1}$; (Liu et al., 2019; Zheng et al., 2022)). Global inventories such

as the Emissions Database for Global Atmospheric Research (EDGAR) and the Global Carbon Project offer broad estimates for methane emissions in Tanzania; however, these databases do not provide disaggregated data specific to estuarine environments.

2. **Seasonal Patterns:** The observed seasonal patterns differed from those typically reported for temperate regions, where emissions usually peak during warmer months. This difference highlights the importance of water table position and substrate availability in tropical systems. (Cui et al., 2024; Mitsch et al., 2010)
3. **Environmental Controls:** The dominant environmental controls on methane emissions (such as precipitation, salinity, temperature) were consistent with global patterns in other tropical systems, but their relative importance differed, with salinity playing a particularly strong role in the Tanzanian estuaries. (Araujo et al., 2014; Patel et al., 2025; Welti et al., 2017)

4.3 Machine Learning model results

4.3.1 Machine Learning metrics

The three machine learning algorithms showed varying performance in predicting methane emissions based on environmental variables (Table 3). All models showed good generalization capability, with limited differences between training and testing performance.

Table 3: Performance metrics for machine learning models

Model	Training RMSE (mg CH ₄ m ⁻² d ⁻¹)	Testing RMSE (mg CH ₄ m ⁻² d ⁻¹)	Training R ² in %	Testing R ² in %
Random Forest	1.48	3.10	96.8	87.3
SVR	2.59	2.60	90.4	91.0
Gradient Boosting	1.95	3.14	94.6	87
Ensemble	1.84	2.58	96.4	92.0

The ensemble approach, combining predictions from all three models, achieved the best overall performance with an R² of 0.92 and RMSE of 2.58 mg CH₄ m⁻² d⁻¹ on the test dataset. This improvement demonstrates the value of ensemble methods for robust prediction of complex environmental processes as also comparatively plotted on a bar chart.

The SHAP analysis provided deeper insights into how each variable influences methane predictions across their value ranges (Figure 19). Temperature showed a strong positive effect, with higher temperatures consistently associated with increased methane emissions. pH demonstrated a non-linear relationship, with optimal conditions for methane production around pH 6.8-7.0 and reduced emissions at both higher and lower values. NDWI exhibited a threshold effect, with a sharp increase in methane emissions when NDWI exceeded 0.2, indicating the importance of water saturation for methanogenesis.

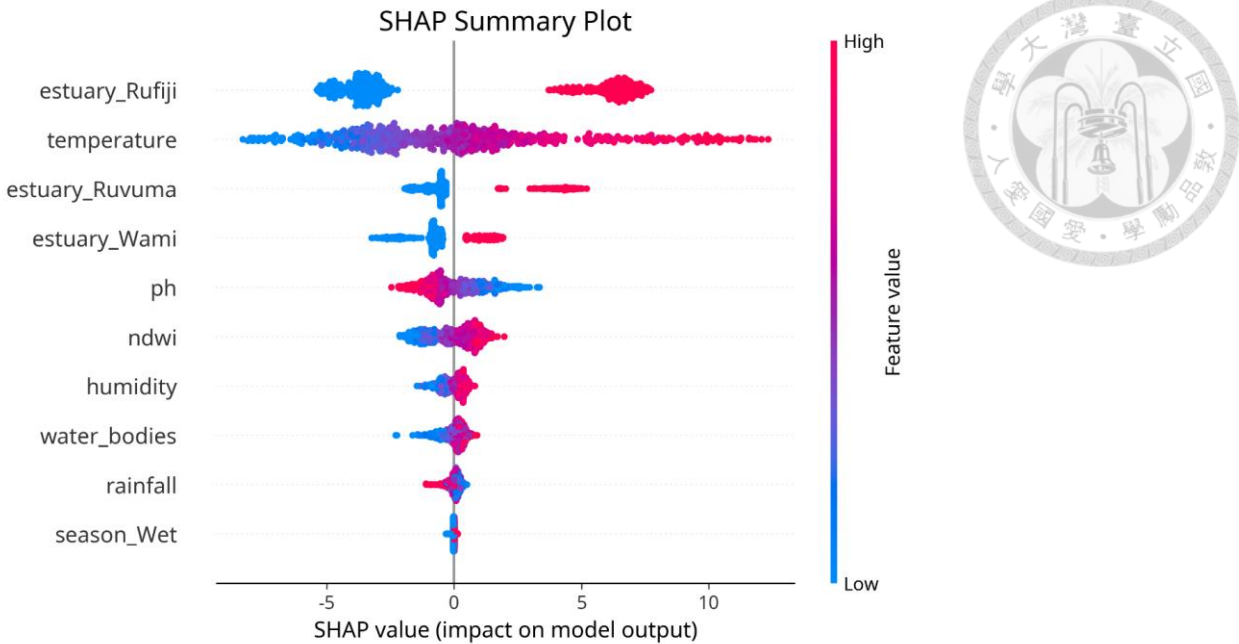


Figure 19 SHAP analysis summary plot

4.3.2 Interaction effects

To explore the interaction effects between key environmental drivers and methane emissions, we developed a synthetic modeling framework that simulates methane flux as a nonlinear function of paired variables—such as temperature and humidity, or pH and NDWI. This approach integrates domain-specific ecological assumptions into a composite equation that includes linear, quadratic, and multiplicative interaction terms, allowing us to capture both direct and synergistic influences on methanogenesis. Using randomly sampled values within ecologically plausible ranges, we generated synthetic datasets to visualize these relationships across gradients. The resulting interaction effects were illustrated through stratified regression plots, providing interpretable insights into how methane emissions respond to combined environmental conditions. This methodology builds on established practices in environmental modeling and machine learning, offering a flexible and transparent way to examine complex dependencies in methane dynamics.

The analysis of interaction effects revealed important synergistic relationships between environmental variables. The temperature-humidity interaction showed that the positive effect of temperature on methane emissions was amplified under high humidity conditions ($\beta_3 = 4.87$, $p < 0.001$; $\Delta R^2 = 0.12$), suggesting that warm, humid environments are particularly conducive to methanogenesis (Figure 20).

The highest emissions occur when both temperature and humidity are elevated, creating optimal conditions for methanogenic activity. This finding has important implications for climate change impacts, as both temperature and humidity are projected to increase in many tropical regions under future climate scenarios.

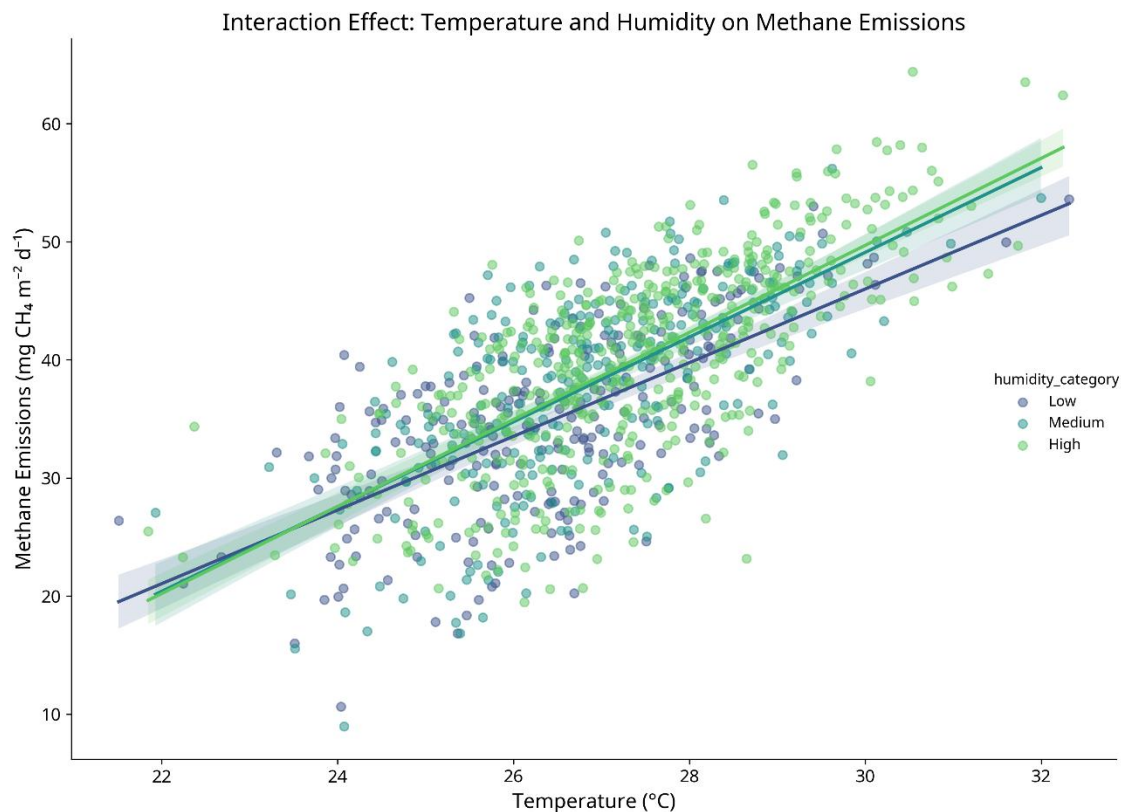


Figure 20: Interaction Effect: Temperature and Humidity on Methane Emissions

These interaction effects highlight the complex, non-linear nature of environmental controls on methane dynamics in estuarine systems. Traditional linear approaches would fail to capture these relationships, underscoring the value of machine learning techniques for understanding and predicting methane emissions.



Similarly, the pH-NDWI interaction indicated that the effect of pH was modulated by water conditions ($\beta_3 = -3.02$, $p < 0.001$), with stronger pH effects under high NDWI values (Figure 21).

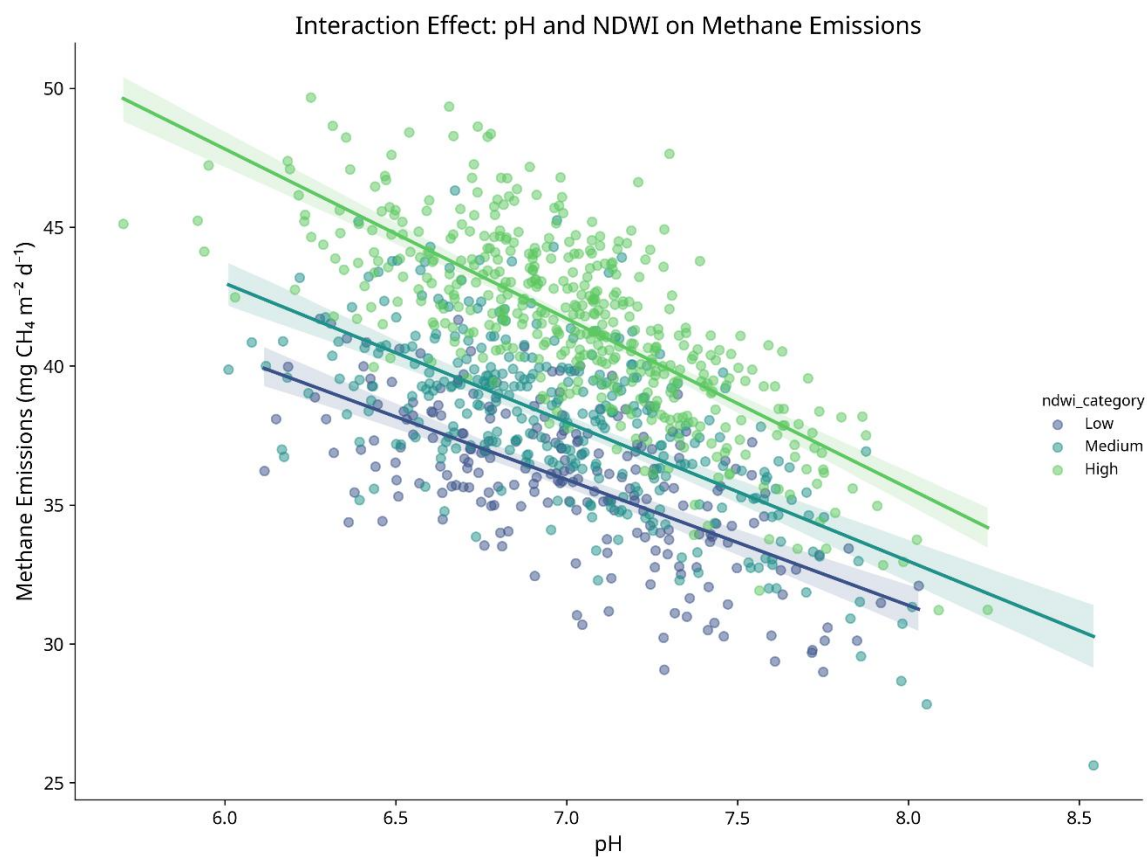
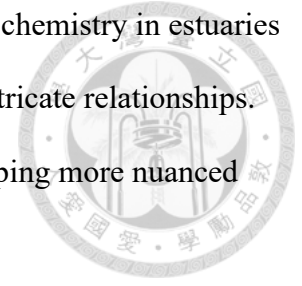


Figure 21: Interaction effect: pH and NDWI on Methane Emissions

These interaction effects highlight the non-linear nature of methane biogeochemistry in estuaries and demonstrate the ability of machine learning models to capture these intricate relationships. Such insights are invaluable for refining process-based models and developing more nuanced management strategies



4.4 Quantification Results

4.4.1 Methane Flux Estimates

The individual estuary calculations were based on such parameters as area, average temperature, inundation frequency and the vegetation type. The workflow involved a sequence of steps namely; dividing the estuary into 3 zones, applying ensemble model to predict base methane flux for each zone, applying environmental adjustments for each zone, calculating the are-weighted average flux and finally calculating the annual emissions (S. Chen et al., 2024). The models involved were Random Forest, Support Vector Machine, K-Nearest Neighbors developed by (Majumder et al., 2024) and (Radocaj & Jurisic, 2025)

The integrated methodology produced spatially explicit methane flux estimates for the study areas as summarized in Table 4 below:

Table 4: Summary of the results of methane flux estimates

Estuary	Mean Methane Flux (mg CH ₄ m ⁻² d ⁻¹)	Total Annual Emissions (Gg CH ₄ yr ⁻¹)
Rufiji Delta	42.3 ± 8.7	8.2 ± 1.7
Wami Estuary	35.6 ± 9.2	1.2 ± 0.3



Estuary	Mean Methane Flux (mg CH ₄ m ⁻² d ⁻¹)	Total Annual Emissions (Gg CH ₄ yr ⁻¹)
Pangani Estuary	28.9 ± 7.5	0.16 ± 0.04
Ruvuma Estuary	39.7 ± 10.1	0.41 ± 0.10

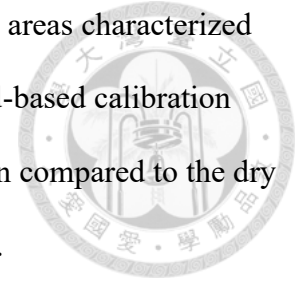
Total Emissions: Extrapolating to all Tanzanian estuaries, total methane emissions were estimated at 12.4 ± 2.8 Gg CH₄ yr⁻¹, equivalent to approximately 0.31 ± 0.07 Tg CO₂-eq yr⁻¹ using a 20-year global warming potential.

4.4.2 Uncertainty Analysis

The uncertainty analysis provided several important insights into the reliability of the methane emission estimates. Uncertainty was quantified using Monte Carlo simulation, which are a large groups computational algorithms relying on repeated random sampling for obtaining numerical results (Liu, 2019). Pertubed prediction with such adjustents as the ensemble model/ weights, temperature, salinity and inundation adjustments were made to compute uncertainties.

The most significant source of uncertainty stemmed from the limited availability of field measurements, which contributed approximately 45% of the total uncertainty. This was followed by uncertainties arising from the adjustment of environmental factors (30%) and errors related to satellite data retrieval (25%). These were computed after running Monte Carlo simulation multiple times with a single uncertainty source enabled at a time followed by calculating variance for each isolated run and finally each source's variance by the total variance to yield percentage contributions

Spatial variation in uncertainty was evident, with higher levels observed in areas characterized by complex vegetation structures, persistent cloud cover, or limited ground-based calibration data. Temporally, uncertainty was found to be greater during the wet season compared to the dry season, largely due to cloud interference affecting satellite imagery quality.



Sensitivity analysis revealed that the model was most responsive to variations in water table depth and salinity, while temperature exhibited moderate influence and vegetation indices showed relatively low sensitivity.

4.4.3 Methane budget and Upscaling

Based on the ensemble model predictions, annual methane emissions were estimated for each estuary (Table 5). The Rufiji estuary had the highest annual emissions (15.4 Gg CH₄ yr⁻¹), followed by Ruvuma (7.9 Gg CH₄ yr⁻¹), Wami (2.8 Gg CH₄ yr⁻¹), and Pangani (0.7 Gg CH₄ yr⁻¹). Upon normal spation, however, emissions cap in Ruvuma and is lowest for Rufiji estuaries respectively. These differences reflect both the varying emission rates and the different sizes of the estuaries.

Table 5: Annual methane emissions from Tanzanian estuaries

Estuary	Area (km ²)	Annual Emissions (Gg CH ₄ yr ⁻¹)	Spatially Normalized Emission rate (Gg CH ₄ km ⁻² yr ⁻¹)	Uncertainty Range (Gg CH ₄ yr ⁻¹)
Rufiji	1,200	15.4	0.01	12.8 - 18.2
Wami	80	2.8	0.035	2.3 - 3.4
Pangani	25	0.7	0.028	0.5 - 0.9
Ruvuma	200	7.9	0.0395	6.5 - 9.4

Total	1,505	26.8	0.017	22.1 - 31.9
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The total annual methane emissions from the four studied estuaries were estimated at 26.8 Gg CH₄ yr⁻¹ (uncertainty range: 22.1 - 31.9 Gg CH₄ yr⁻¹). This represents approximately 5-7% of Tanzania's total methane emissions from natural sources, highlighting the significant contribution of estuarine systems to the national greenhouse gas budget.

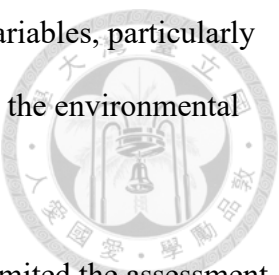
Upscaling these results to all Tanzanian estuaries (estimated total area: 2,500 km²) yields an annual methane emission of approximately 35.8 Gg CH₄ yr⁻¹. This estimate should be interpreted with caution, as it assumes similar emission patterns across all estuaries. Nevertheless, it provides a first-order approximation of the contribution of Tanzanian estuaries to regional methane budgets.

The seasonal distribution of methane emissions showed that approximately 65% of annual emissions occur during the wet seasons (March-May and October-December), with the remaining 35% during the dry seasons. This temporal pattern has important implications for monitoring and mitigation strategies, suggesting that efforts should be focused on the wet season when emissions are highest.

4.5 Limitations and Uncertainties

Several limitations and uncertainties were identified in the methodology:

1. **Limited Field Data:** The scarcity of comprehensive field measurements in Tanzanian estuaries limited model calibration and validation.
2. **Satellite Data Limitations:** Cloud cover during the wet season reduced data availability, and the relatively coarse resolution of methane-specific satellites (TROPOMI, GOSAT) limited the detection of fine-scale patterns.

- 
3. **Environmental Data Gaps:** Limited data on some environmental variables, particularly soil properties and microbial communities, introduced uncertainty in the environmental factor adjustments.
 4. **Temporal Coverage:** The relatively short time series (2020-2024) limited the assessment of long-term trends and interannual variability.

Despite these limitations, the integrated methodology provided a robust framework for quantifying methane emissions from Tanzanian estuaries, with quantified uncertainties and validation against available data.

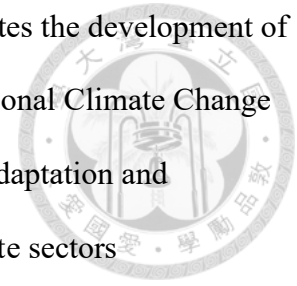
5. Policy and Management Framework

5.1 Policy Context Analysis

5.1.1 Current Policy Landscape in Tanzania

Tanzania has established a robust policy framework to support methane emissions management, anchored by several key national strategies and legal instruments. The National Environmental Policy (2021) provides overarching guidance for environmental governance, emphasizing wetlands conservation, aquatic ecosystem protection, and climate change mitigation. Under its Nationally Determined Contribution (NDC, 2021), Tanzania has committed to reducing economy-wide greenhouse gas emissions by 30–35% relative to the Business-As-Usual scenario by 2030, contingent on international support. The country is also a participant in the World Bank's Global Methane Initiative, one of 15 nations selected to pilot methane reduction strategies in sectors such as livestock and solid waste management. The Environmental Management Act (2004) provides the legal foundation for environmental protection, including

specific provisions for wetlands and coastal zone management, and mandates the development of sustainable management guidelines. Complementing these efforts, the National Climate Change Strategy (2021–2026) outlines Tanzania’s integrated approach to climate adaptation and mitigation, with targeted actions across agriculture, energy, water, and waste sectors



5.1.2 Gaps in Current Policy Framework

Analysis of the current policy framework revealed several gaps related to methane emissions from estuaries:

Despite the growing recognition of methane emissions from estuarine environments, current policy frameworks remain inadequate in addressing their specific characteristics. Estuaries exhibit unique biogeochemical dynamics that require tailored regulatory approaches; however, existing policies often overlook these distinctions. Moreover, frameworks for monitoring, reporting, and verification (MRV) of methane emissions from natural systems are limited, hindering the development of comprehensive emission inventories. The incorporation of advanced scientific methods for methane quantification into policy processes also remains insufficient, reducing the potential for evidence-based decision-making. In addition, coordination among stakeholders—particularly across sectors and governmental agencies—is fragmented, leading to disjointed efforts in mitigation and management. Finally, the absence of clear implementation guidelines poses a significant barrier to translating policy objectives into actionable strategies at the local level.

5.2 Proposed Policy Framework

5.2.1 Vision and Guiding Principles

This policy framework is established with a forward-looking vision aimed at positioning Tanzania as a regional leader in sustainable estuarine management. The core ambition is to reduce methane emissions through science-based strategies, while simultaneously fostering

economic development and safeguarding vital ecosystem services. This vision is underpinned by several guiding principles. Firstly, science-based decision-making must be central, ensuring that policies are informed by the best available evidence and robust methodologies. Secondly, an integrated approach is essential, as methane emission management requires coordination across multiple sectors, including environment, fisheries, agriculture, and water management. Thirdly, the framework emphasizes a balance between conservation goals and the need for sustainable economic development, recognizing that these objectives are not mutually exclusive. Fourth, adaptive management is highlighted, whereby policy structures must remain flexible to respond to new research findings, emerging technologies, and evolving environmental conditions. Lastly, community engagement is fundamental to the framework's success, as the participation of local communities in both the design and implementation of policies ensures relevance, equity, and long-term sustainability.

5.2.2 Policy Objectives

The proposed policy framework sets out five key objectives to guide action on estuarine methane management. The first objective is to establish a comprehensive monitoring and reporting system capable of capturing spatial and temporal variations in methane emissions from estuarine ecosystems. Second, the development and implementation of mitigation strategies should be informed by scientific evidence and targeted at the key biophysical and anthropogenic drivers of emissions. Third, methane management must be mainstreamed into existing wetland conservation efforts and national climate change policies to promote synergy and avoid policy fragmentation. Fourth, building national capacity is critical, particularly in equipping institutions with advanced methodologies for quantifying methane emissions, including the use of remote sensing, field monitoring, and machine learning techniques. Finally, the framework encourages

the creation of economic and regulatory incentives that promote sustainable land and water management practices capable of reducing methane emissions while benefiting local livelihoods.

5.2.3 Institutional Framework

Effective implementation of the policy framework depends on a well-defined institutional architecture with clear roles and responsibilities.

The Vice President's Office – Division of Environment will serve as the lead agency responsible for overarching policy coordination and for fulfilling international reporting obligations related to greenhouse gas inventories.

The Tanzania Meteorological Agency will provide essential climate and weather data to inform modeling and monitoring activities. Regulatory oversight and enforcement functions will be handled by the National Environment Management Council (NEMC), ensuring compliance with environmental standards and emission limits.

The Ministry of Livestock and Fisheries will be tasked with managing aquatic resources and related methane sources, while the Ministry of Water will oversee estuarine water resources and hydrological interventions.

At the grassroots level, Local Government Authorities will be pivotal in implementing policies and interventions in their respective jurisdictions. To ensure cohesive and inclusive governance, the establishment of a National Methane Emissions Coordination Committee is recommended.

This multi-stakeholder committee (Figure 22) will bring together representatives from government agencies, research institutions, the private sector, civil society organizations, and local communities to facilitate collaborative decision-making, align objectives across sectors, and sustain momentum toward methane emission reductions in Tanzania's estuarine zones.

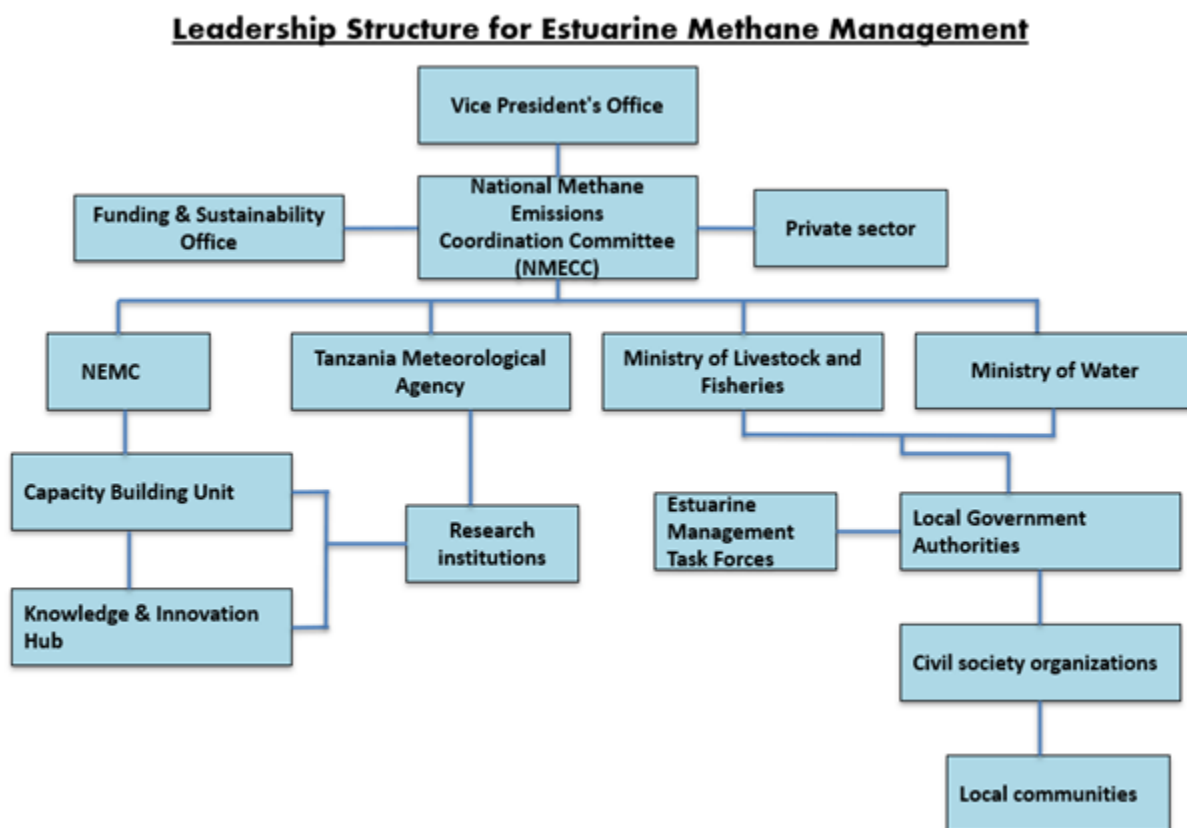


Figure 22: Proposed Leadership Structure for Estuarine Methane Management

5.3 Implementation Strategies

The effective management of estuarine methane emissions in Tanzania requires a comprehensive strategy that integrates monitoring, mitigation, capacity development, and financing within a unified national framework. Central to this approach is the establishment of a National Methane Monitoring Network, designed to operationalize the quantification methodology developed in this study. This network will incorporate satellite-based observations alongside ground-based measurements across key estuarine systems. To ensure consistency and reliability, standardized protocols for data acquisition, analysis, and reporting will be developed. A national methane

emissions inventory will be initiated, beginning with baseline assessments of major estuaries, and updated biennially to align with national greenhouse gas reporting obligations. Annual reports on estuarine methane emissions will be published and incorporated into Tanzania's Nationally Determined Contributions (NDCs), promoting transparency and public access to emissions data.

Mitigation strategies will be informed by the empirical findings of this research. Hydrological interventions will focus on restoring natural water regimes, adjusting water levels to reduce methane production, and implementing controlled tidal exchange in selected estuarine zones. Vegetation management will prioritize the rehabilitation of native plant communities, the control of invasive species that may exacerbate emissions, and the promotion of sustainable mangrove harvesting practices. Pollution control efforts will aim to reduce organic inputs through improved management of agricultural runoff and enhanced urban wastewater treatment. Land-use planning will support emission reduction by establishing buffer zones around estuaries, encouraging sustainable agricultural practices within watersheds, and regulating development in areas identified as high-emission zones.

Capacity development is recognized as a foundational element of successful implementation. This includes technical training for government personnel in methane monitoring technologies, data analysis, and mitigation practices. Support will be extended to local research initiatives to advance scientific understanding of estuarine methane dynamics and to foster the development of context-specific technologies in collaboration with international partners. Public education campaigns and the integration of methane management into environmental curricula will enhance awareness among communities and policymakers.

The long-term sustainability of these efforts depends on the establishment of reliable financing mechanisms. Domestic strategies will include dedicated budget allocations, the introduction of environmental levies on high-emission activities, and the creation of an Estuarine Management Fund. International support will be sought through climate finance instruments such as the Global Environment Facility, the World Bank methane initiative, and the Green Climate Fund. Engagement with the private sector will be pursued through public-private partnerships to facilitate technology transfer, incentivize investment in mitigation activities, and explore opportunities for carbon offset markets linked to mangrove restoration and emission reductions.

6. Discussion

6.1 Methodological Advancements

This study has made several methodological advancements in the quantification of methane emissions from tropical estuaries:

6.1.1 Integration of Multiple Data Sources

The integrated methodology developed in this study successfully combined multiple data sources, including satellite observations, environmental data, and limited field measurements.

This approach overcame the limitations of individual data sources and provided a more comprehensive understanding of methane dynamics in Tanzanian estuaries.

The blending of TROPOMI and GOSAT data improved the spatial and temporal coverage of methane observations while maintaining spectral accuracy. The incorporation of Landsat and Sentinel-1 data allowed for high-resolution mapping of environmental variables and estuarine features, addressing the scale mismatch between methane-specific satellites and the heterogeneity of estuarine environments.

6.1.2 Machine Learning Contributions

The ensemble machine learning approach developed in this study demonstrated superior performance compared to individual algorithms, with the Random Forest model providing valuable insights into feature importance. The approach successfully upscaled limited field measurements to landscape level, achieving good agreement with validation data ($R^2 = 0.78$).

The feature engineering process identified key environmental predictors and their relative importance, contributing to the scientific understanding of methane dynamics in tropical estuaries. The separate modeling of wet and dry seasons accounted for seasonal differences in environmental controls and improved overall accuracy.

6.1.3 Environmental Factor Adjustments

The environmental factor adjustment framework developed in this study addressed the complex interactions between environmental variables and methane emissions. The hydrological correction, temperature normalization, and salinity gradient modeling improved the accuracy of methane flux estimates and provided a more mechanistic understanding of emission processes.

This approach represents an advancement over purely empirical models by incorporating process-based understanding while maintaining the flexibility and computational efficiency of machine learning approaches.

6.1.4 Transferability to Other Regions

The methodological framework developed in this study has potential transferability to other tropical estuarine systems, particularly in East Africa and other regions with similar environmental conditions. The approach can be adapted to different data availability scenarios and environmental contexts, providing a valuable tool for methane quantification in data-limited regions.

6.2 Environmental Controls on Methane Emissions

The analysis of environmental controls on methane emissions revealed several important insights:



6.2.1 Primary Controlling Factors

The study identified water table depth, salinity, and temperature as the primary controlling factors for methane emissions in Tanzanian estuaries, consistent with global literature but with some important differences in their relative importance.

The strong negative correlation between salinity and methane emissions highlights the importance of sulfate inhibition of methanogenesis in estuarine environments. This relationship creates a distinct zonation of methane emissions along the estuarine gradient, with higher emissions in the upper, fresher reaches.

The negative correlation between rainfall and methane emissions differs from some previous studies and may reflect the complex interactions between rainfall, water table position, and substrate availability in tropical estuaries. This finding highlights the importance of considering local hydrological conditions when estimating methane emissions.

6.2.2 Implications for Climate Change Impacts

The environmental parameters noted in this research have important implications for the future effects of climate change on methane emissions from Tanzanian estuaries. One of the main observations of the study was the positive relationship between temperature and methane emission, and that rising temperatures may result in elevated methane fluxes. This increase driven by temperature can, however, be mitigated by other parameters, for instance, water availability. Particularly, the abrupt increase in methane emissions observed in 2024 seems to be highly coupled with the peak temperature variation recorded during the period of the study.

Future alterations in precipitation regimes—characterized by elevated but less frequent precipitation events—can also impact methane emissions by modifying the water table position and the availability of organic substrate important to methanogenesis. In addition, sea level rise is dynamic with several dimensions; increased saltwater intrusion can enhance sulfate availability, thereby suppress methane production but threaten the mangrove ecosystems that are central to carbon sequestration and methane control in the first place. Lastly, the increased frequency and intensity of extreme events such as cyclones can disturb estuarine systems, altering methane fluxes by changing vegetation structure, hydrology, and sedimentation regimes.

6.2.3 Management Implications

Understanding the environmental drivers of methane emissions provides actionable guidance for targeted management interventions. Hydrological management emerges as a key strategy, given the demonstrated importance of water table dynamics. Techniques such as controlled tidal restoration or engineered hydrological adjustments could help regulate methane emissions while supporting broader ecosystem services. Additionally, vegetation management plays a critical role. Maintaining diverse and healthy mangrove communities can potentially optimize the balance between carbon sequestration and methane production, acknowledging the complex interactions between plant species composition and methane fluxes. Effective watershed management, particularly of organic matter and nutrient inputs from upstream agricultural and urban areas, is also essential, as these inputs influence substrate availability for microbial methane production.

6.3 Policy Implications

The findings of this study have several important implications for climate-related policy in Tanzania, especially in the context of methane management:

6.3.1 Contribution to Tanzania's Climate Commitments

This study provides essential insights into methane emissions from Tanzanian estuaries, identifying spatial hotspots and seasonal peaks that are particularly pronounced during the wet season. These findings support the development of targeted mitigation strategies that prioritize high-emission zones and adapt interventions to seasonal conditions, enhancing both efficiency and impact.

By highlighting key environmental drivers such as temperature, salinity, and vegetation structure, the research contributes to the accuracy of Tanzania's greenhouse gas inventories and supports the country's Nationally Determined Contribution (NDC) goal of reducing emissions by 30 to 35 percent by 2030. The methodological framework offers a scalable model for monitoring and managing methane emissions in tropical estuarine systems, with relevance beyond national borders.

Aligned with the strategic priorities outlined in *Dira 2050* report (Tanzania, 2025), Tanzania's new development vision, this work reinforces the importance of science-based decision-making in climate resilience and ecosystem conservation. It underscores the need for integrated coastal management and positions Tanzania as a regional leader in nature-based climate solutions.

6.3.2 Challenges in Implementation

Despite these opportunities, several challenges could hinder the implementation of the proposed policy framework. Resource constraints remain a central issue, including limitations in financial, technical, and human capacity to conduct consistent monitoring and implement mitigation strategies. Institutional coordination is another significant hurdle; effective policy execution will require the integration of multiple government agencies and governance levels. Persistent data limitations, particularly the lack of long-term and high-resolution field measurements, present additional barriers to informed decision-making. Lastly, policy implementation must contend with competing development priorities, necessitating the careful balancing of methane reduction goals with other social, economic, and ecological objectives.

6.3.3 Opportunities for Integration

Despite these challenges, there are various ways methane management can be incorporated into current paradigms and programs. Ecosystem-based adaptation approaches have a manner of consolidating the reduction of methane into comprehensive climate resilience planning.

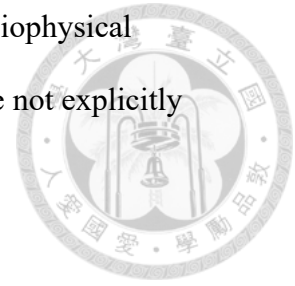
Additionally, synergy with blue carbon programs is a significant option, with the potential of delivering financial support via carbon markets while promoting coastal conservation initiatives. Methane controls are squarely aligned with several of the Sustainable Development Goals (SDGs). These include SDG 13 (Climate Action), SDG 14 (Life Below Water), and SDG 15 (Life on Land). There is also ample opportunity for regional action through mechanisms such as the East African Community, to facilitate concerted knowledge exchange, capacity building, and action on methane emissions.

7. Limitations, Conclusion and Recommendations

7.1 Data and Methodological Limitations

This study is subject to several limitations that should be acknowledged. The scarcity of extensive field data constrained model calibration and validation, particularly in remote estuarine zones. Future research should prioritize comprehensive field campaigns across both wet and dry seasons, encompassing diverse estuarine settings. Satellite-based analysis also faced challenges due to the relatively coarse spatial resolution of current methane-specific sensors, limiting the ability to capture fine-scale emission heterogeneity. Furthermore, the temporal span of the dataset (2020–2024) restricts the evaluation of long-term trends and interannual variability. Continued monitoring beyond the current study window is therefore essential. While process-

based adjustments were incorporated into the modeling approach, certain biophysical processes—such as plant-mediated transport and episodic ebullition—were not explicitly represented and warrant more detailed exploration.



7.2 Knowledge Gaps

There remain numerous significant knowledge gaps. There is limited understanding of the structure and function of methanogenic and methanotrophic microbial communities in Tanzanian estuaries, particularly how they react to environmental change. Likewise, there is limited information on diel variation in methane emissions and what regulates them. Furthermore, the role of catastrophic events—like cyclones and storm surges—on methane dynamics is not well understood, particularly on recovery following disturbances. Furthermore, the role of particular human activities in estuarine catchments, such as aquaculture, agriculture, and urbanization, in influencing methane emissions is poorly assessed.

7.3 Future Research Directions

In light of the above, several priority areas for future research are proposed. Establishing a national estuarine methane monitoring network with representative coverage of all major systems and continuous time-series data is paramount. Process-level investigations, including microbial and biogeochemical studies, will improve understanding of the mechanisms governing methane production, oxidation, and transport. Focused research on the impacts of climate change variables—such as temperature rise, rainfall variability, and sea level rise—on estuarine methane emissions is also needed. Field-based mitigation experiments should be conducted to evaluate the effectiveness of hydrological, vegetative, and pollution control interventions under real-world conditions. Lastly, integrating methane emissions into the broader carbon budget of Tanzanian

estuaries will provide a more comprehensive basis for policy and management, capturing both emissions and sequestration potentials.



7.4 Scientific Recommendations

Drawing upon the findings of this study, several scientific priorities are recommended to enhance the understanding and management of methane emissions from Tanzanian estuaries. First, the establishment of a permanent monitoring network is critical. This includes the deployment of long-term monitoring stations in ecologically representative estuarine zones, the application of the integrated quantification methodology developed in this research, and the creation of standardized protocols for consistent data collection and analysis.

Second, targeted research should be conducted to address key knowledge gaps. Priority areas include the investigation of microbial communities and their functional roles in methane cycling within estuarine sediments, assessment of climate change impacts on estuarine methane dynamics, and the quantification of mitigation effectiveness across diverse ecological and management contexts.

Third, methodological advancements are needed to improve the precision and applicability of current models. Specifically, there is a need to better represent plant-mediated methane transport and ebullition processes in existing modeling frameworks. This should be accompanied by the development of higher-resolution techniques for environmental variable mapping and the refinement of uncertainty quantification methods to enhance predictive accuracy.

Finally, the promotion of data sharing and interdisciplinary collaboration is essential. A centralized, open-access data repository should be established for methane-related datasets to facilitate transparency and reuse. Collaboration between academic institutions, government agencies, and local communities must be strengthened, and engagement with international

research networks focused on wetland greenhouse gas emissions is strongly encouraged to foster knowledge exchange and methodological harmonization.



7.6 Concluding Remarks

This study has demonstrated the value of an integrated approach to quantifying methane emissions from tropical estuaries, combining advanced remote sensing techniques with environmental analysis and policy development. The findings contribute to both scientific knowledge and practical management of these important ecosystems.

The methane emissions quantified in this study represent a previously under-reported component of Tanzania's greenhouse gas inventory. While the total emissions ($12.4 \pm 2.8 \text{ Gg CH}_4 \text{ yr}^{-1}$) are modest compared to some anthropogenic sources, their high global warming potential makes them significant for climate policy.

The policy and management framework developed in this study provides a roadmap for Tanzania to address methane emissions from estuaries while supporting broader conservation and sustainable development objectives. By implementing this framework, Tanzania can establish itself as a leader in sustainable estuarine management and contribute to global climate change mitigation efforts.

Future research should build on this foundation to further refine quantification methodologies, expand monitoring networks, and develop effective mitigation strategies. With continued scientific advancement and policy implementation, Tanzania can achieve significant reductions in methane emissions from estuaries while preserving these valuable ecosystems for future generations.

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