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Dynamic assessment of methane emission persistence in Southeast Asian rice production systems

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Abstract

Rice production is an important source of agricultural methane emissions in Southeast Asia, and understanding the persistence and dynamic behavior of these emissions is essential for sustainable agricultural management and environmental monitoring. This study investigates the dynamic relationships among agricultural production value, producer prices, food consumer prices, and methane emissions in Indonesia, Vietnam, and the Philippines over the period 2000–2023. A panel vector autoregression (PVAR) framework is applied to characterize the joint evolution of economic and environmental variables within an interconnected agricultural system. Impulse response analysis reveals dynamic cross-variable interactions between agricultural production activities and methane emissions, while forecast error variance decomposition indicates increasing interdependence among variables over medium-run horizons. To evaluate persistence, the study incorporates cumulative impulse responses and a shock half-life metric to quantify both the magnitude and duration of dynamic adjustment processes. The results indicate that methane emissions and agricultural variables exhibit heterogeneous persistence patterns across countries and response channels, suggesting differences in environmental adjustment dynamics within Southeast Asian rice production systems. The findings highlight the importance of considering medium-run persistence in addition to short-run responses when assessing agricultural environmental pressures. From an environmental monitoring perspective, the proposed framework provides a useful approach for evaluating the dynamic behavior of agricultural emission systems and may support the development of sustainable agricultural and methane mitigation policies.

1. Introduction

Agricultural methane emissions are an important target of environmental monitoring and climate-related sustainability assessment, particularly in regions where rice cultivation is a dominant agricultural activity. Methane (CH₄) is the second most important anthropogenic greenhouse gas after carbon dioxide in terms of radiative forcing, and its relatively short atmospheric lifetime makes methane mitigation a key pathway for near-term climate benefits (Saunio et al. 2020; IPCC 2021). Within the agricultural sector, flooded rice cultivation is a well-recognized source of methane because anaerobic conditions in paddy soils promote microbial methanogenesis (Yan et al. 2005; Linquist et al. 2012). As a result, rice-based agricultural systems are not only food production systems but also dynamic sources of environmental pressure that require systematic monitoring and assessment.

The environmental importance of rice-related methane emissions is especially evident in Asia, where rice is a staple crop and paddy cultivation occupies a large share of agricultural land. Southeast Asian rice systems are central to regional food security and rural livelihoods, yet they also contribute to greenhouse gas emissions through prolonged flooding, residue management, fertilizer use, and production intensity (Redfern et al. 2012; Ouyang et al. 2023). Recent assessments of agri-food systems further show that food production and associated supply-chain activities represent a substantial share of global greenhouse gas emissions, reinforcing the need to monitor agricultural emissions at the country and regional levels (Tubiello et al. 2021). For this reason, the assessment of methane emissions from rice production should move beyond annual inventories and consider how emissions respond dynamically to changes in agricultural and market conditions.

Environmental monitoring is often based on emission inventories, concentration measurements, remote-sensing products, or trend summaries. These approaches are indispensable for documenting emission levels and spatial-temporal patterns, but they may provide limited information on the persistence of emission responses. In agricultural systems, environmental pressure may not adjust immediately after changes in production activity. Production decisions, price incentives, cropping intensity, and management practices may generate delayed effects that unfold over several years. Therefore, the distinction between short-lived fluctuations and persistent emission responses is important for environmental assessment. A temporary emission shock may require monitoring attention, whereas a persistent response may imply sustained environmental pressure and the need for longer-term mitigation strategies.

Previous studies have examined greenhouse gas emissions from rice systems from agronomic, biogeochemical, and inventory-based perspectives. Field and meta-analytic studies have identified water regime, organic amendments, residue management, fertilizer

practices, and soil conditions as important drivers of methane emissions (Yan et al. 2005; Linquist et al. 2012; Qian et al. 2023). Other studies have emphasized the role of alternate wetting and drying, improved fertilizer management, and low-emission rice practices in reducing methane emissions from paddy fields (Linquist et al. 2012; Tubiello et al. 2021). At broader spatial scales, remote-sensing and modelling approaches have been used to characterize regional methane emissions from paddy rice systems across Monsoon Asia (Ouyang et al. 2023). These studies provide important evidence on emission sources and mitigation options; however, less attention has been given to the dynamic persistence of methane emission responses within country-level rice production systems.

In addition to agronomic drivers, agricultural emissions are also linked to production scale and market-related conditions. Changes in production value, producer prices, and consumer food prices may influence agricultural incentives, cropping decisions, and resource allocation. These factors may indirectly affect methane emissions by shaping the intensity and continuity of rice production. In this sense, methane emissions should not be viewed solely as isolated environmental outcomes; rather, they may evolve as part of a coupled agricultural–environmental system. Studies in climate economics and environmental assessment have shown that economic activity and environmental outcomes can be linked through dynamic and delayed channels (Dell et al. 2012; Burke et al. 2015). For environmental monitoring purposes, these dynamic linkages are important because they help identify whether emission pressure is primarily driven by own emission dynamics or by broader agricultural system changes.

Indonesia, Vietnam, and the Philippines provide a suitable empirical setting for examining these issues. All three countries are major rice-producing economies in Southeast Asia and face the policy challenge of balancing food security, agricultural income, and environmental sustainability. Their rice sectors differ in production scale, market conditions, and agricultural management, which may generate heterogeneous patterns of methane emission dynamics. A cross-country dynamic assessment can therefore provide useful evidence on whether methane emission responses are transitory or persistent and whether production- and price-related variables contribute to emission variability over time. Such evidence is relevant for monitoring agricultural environmental pressure and for designing sustainable rice-sector management strategies.

To address this gap, this study develops a dynamic environmental monitoring and assessment framework for methane emissions in Southeast Asian rice production systems. Using annual data for Indonesia, Vietnam, and the Philippines over the period 2000–2023, we examine the joint dynamics of agricultural production value, producer prices, food consumer prices, and methane emissions. The analysis applies a panel vector autoregression (PVAR) framework, which treats all variables as jointly endogenous and allows delayed responses and feedback relationships to be evaluated within a multivariate system (Sims 1980; Hamilton 1994; Lütkepohl 2005). Panel extensions of VAR models

further allow cross-country heterogeneity to be considered while preserving dynamic relationships among variables (Holtz-Eakin et al. 1988; Love and Zicchino 2006).

The use of a dynamic multivariate framework is motivated by environmental monitoring needs rather than by methodological novelty alone. Impulse response analysis is used to examine how methane emissions and agricultural variables respond to shocks over time, while forecast error variance decomposition is used to evaluate the relative contribution of different sources of variation. In addition, this study incorporates cumulative impulse responses and a shock half-life measure to quantify both the magnitude and duration of dynamic adjustment. The half-life concept is useful for environmental assessment because it translates dynamic responses into an interpretable measure of persistence, indicating how long a shock remains influential within the agricultural emission system.

The study contributes to environmental monitoring and assessment in three ways. First, it provides a country-level dynamic assessment of methane emission behavior in major Southeast Asian rice production systems. Second, it evaluates persistence in emission-related responses, thereby complementing conventional monitoring approaches based on annual emission levels, trends, or static associations. Third, it demonstrates how a multivariate monitoring framework can help characterize agricultural environmental pressure by linking methane emissions with production and price-related variables. By emphasizing persistence, the study provides information that may support sustainable agricultural management, methane mitigation planning, and long-term environmental assessment in rice-based production systems.

The remainder of the paper is organized as follows. Section 2 describes the data and variables. Section 3 presents the dynamic monitoring framework and persistence measures. Section 4 reports the empirical results, including dynamic response analysis, variance decomposition, and persistence assessment. Section 5 discusses the environmental monitoring implications of the findings, and Section 6 concludes.

2 Data

This study uses annual panel data for three major rice-producing countries in Southeast Asia: Indonesia, Viet Nam, and the Philippines. These countries represent important rice production systems in the region and provide a relevant setting for assessing methane emission dynamics associated with rice cultivation. The sample covers the period 2000–2023, resulting in a balanced panel dataset with 72 country-year observations. The balanced structure of the dataset allows both country-level variation and temporal changes in methane emissions and agricultural indicators to be examined within a unified monitoring framework.

The dataset includes variables selected to characterize rice production activity, market-related agricultural conditions, and methane emission pressure. The first variable is the gross production value of rice, which reflects the scale of rice-sector production activity over time. The second variable is the producer price of rice, representing farm-gate price conditions faced by rice producers. The third variable is the food component of the consumer price index (Food CPI), which captures broader food price conditions relevant to the rice-based agricultural system. The fourth variable is methane emissions from rice cultivation, which represents the environmental pressure associated with rice production.

Methane emissions from rice fields arise primarily from anaerobic decomposition of organic matter in flooded paddy soils. Because rice cultivation often involves prolonged water inundation, methane emissions are closely related to production conditions, cultivated area, water management, and agricultural intensity. In this study, methane emissions are therefore treated as a key environmental monitoring indicator rather than as an isolated outcome. Including methane emissions together with production and price-related indicators allows the analysis to assess whether emission behavior is linked to changes in the broader rice production system.

All variables used in the dynamic assessment are expressed in natural logarithms prior to estimation. The logarithmic transformation helps stabilize variance, reduce scale differences across countries, and facilitate interpretation of dynamic responses. Under the log transformation, impulse responses may be interpreted approximately as percentage responses to shocks. This transformation is also useful for cross-country comparison because Indonesia, Viet Nam, and the Philippines differ in production scale and agricultural system characteristics.

Table 1 reports summary statistics for the log-transformed variables included in the panel model. Production value exhibits the largest dispersion across observations, reflecting cross-country differences in the scale of rice production systems. Producer prices and Food CPI show moderate variation, indicating changes in agricultural and food market conditions over the study period. Methane emissions display relatively moderate variability but show time-dependent movements that are relevant for assessing long-term environmental pressure and dynamic emission behavior.

Table 1. Summary statistics of variables used in the dynamic environmental assessment.

Variable	Mean	Std.Dev	Min	Max	Obs.
Production value (log)	16.0422	0.7678	14.5458	17.7723	72
Producer price (log)	5.6271	0.4783	4.7122	6.7761	72
Food CPI (log)	4.2804	0.5005	3.2217	4.9354	72
Methane emissions (log)	7.4256	0.2625	7.1318	7.8324	72

Notes: The table reports descriptive statistics for the variables used in the empirical analysis. The sample consists of annual observations for Indonesia, Vietnam, and the

Philippines from 2000 to 2023. All variables are expressed in natural logarithms prior to estimation.

Table 2 reports pairwise correlations among the log-transformed variables. The correlation matrix provides preliminary descriptive evidence on the association between rice production indicators, price-related variables, and methane emissions. These correlations are not interpreted as causal relationships; rather, they provide an initial summary of how the variables co-move before the trend analysis and dynamic multivariate assessment are conducted.

Table 2. Pairwise correlations among rice production, price-related, and methane emission indicators.

Variable	ProdValue	ProdPrice	FoodCPI	CH ₄
ProdValue	1	0.743	0.451	0.567
ProdPrice		1	0.766	0.291
FoodCPI			1	-0.017
CH ₄				1

Notes: The table reports pairwise Pearson correlation coefficients among the log-transformed variables used in the panel VAR model.

Before estimating the panel VAR model, unit root tests are conducted to examine the time-series properties of the log-transformed variables. Table 3 presents the Augmented Dickey–Fuller (ADF) unit root tests. The results suggest that the variables exhibit non-stationary behavior in levels, which is common in country-level agricultural and environmental time series. Because the objective of the study is to assess dynamic responses, persistence, and medium-run adjustment within a stable system, the subsequent analysis estimates the model in levels while explicitly verifying the stability condition of the estimated panel VAR.

Table 3. Augmented Dickey–Fuller unit root tests for log-transformed variables.

Variable	ADF Statistic	p-value
Production value (log)	-1.832	0.365
Producer price (log)	-2.513	0.112
Food CPI (log)	-2.465	0.124
Methane emissions (log)	-1.279	0.639

Notes: The table reports Augmented Dickey–Fuller (ADF) test statistics for the log-transformed variables. The null hypothesis is that the series contains a unit root.

The balanced panel structure supports the use of a dynamic multivariate framework for environmental monitoring. The moderate time dimension allows long-term trend

analysis, impulse response estimation, forecast error variance decomposition, and persistence measures to be implemented consistently across countries. This structure is useful for assessing whether methane emission pressure is stable, increasing, declining, or dynamically linked with production and price-related indicators over time.

The recursive ordering used in the orthogonalized impulse response analysis follows the structure of the rice production–emission system. Production value is placed first because rice production activity provides the underlying production scale of the system. Producer prices are placed second because farm-gate price conditions are closely related to production incentives and market adjustment. Food CPI is placed third to represent broader downstream food price conditions. Methane emissions are placed last because emissions arise from rice cultivation processes and are assumed not to contemporaneously alter production and price variables within the same annual period. This ordering is used as the baseline identification scheme for impulse response analysis, while robustness is assessed using generalized impulse responses that are invariant to variable ordering.

3. Analytical Framework for Environmental Monitoring and Dynamic Assessment

3.1 Overview of the analytical strategy

This study adopts a two-stage analytical framework to monitor and assess methane emission dynamics in Southeast Asian rice production systems. The first stage evaluates long-term monotonic trends in methane emissions and related agricultural indicators using non-parametric trend analysis. This stage provides a baseline environmental monitoring assessment by identifying whether the variables exhibit persistent upward or downward movements over the study period. The second stage applies a panel vector autoregression (PVAR) framework to examine dynamic interactions among agricultural production value, producer prices, food consumer prices, and methane emissions. The dynamic component evaluates how shocks propagate across the agricultural–environmental system and how long their effects remain influential.

Combining trend analysis with multivariate dynamic modelling is particularly useful for environmental monitoring. Trend analysis provides information on directional change, whereas the PVAR framework provides information on delayed responses, feedback relationships, and persistence. Together, these methods allow methane emission pressure to be assessed in terms of long-term change, short-run response, medium-run adjustment, and persistence. This design is consistent with environmental monitoring studies that require both descriptive trend assessment and dynamic interpretation of pollution or emission-related processes (Hirsch et al., 1982; Yue et al., 2002; Helsel et al., 2020).

3.2 Long-term trend analysis

Before estimating the dynamic multivariate model, this study applies long-term trend analysis to characterize directional changes in methane emissions and associated agricultural indicators. Trend analysis is used to determine whether each variable exhibits a statistically detectable monotonic increase or decrease during 2000-2023. This step is important because environmental monitoring is concerned not only with the magnitude of emissions at a specific time point but also with whether environmental pressure is increasing, decreasing, or remaining stable over time.

The trend analysis is conducted for methane emissions, agricultural production value, producer prices, food consumer prices, and emission intensity indicators. Emission intensity may be defined as methane emissions per unit of production value, or, if physical output data are available, methane emissions per unit of rice output. This indicator is useful because it evaluates whether methane pressure is changing relative to agricultural activity. A decline in emission intensity may indicate improved emission performance even if absolute emissions remain stable or increase.

Because environmental and agricultural time series may be non-normally distributed, may contain gradual changes, and may be sensitive to outliers, non-parametric trend methods are appropriate. This study therefore uses the Mann-Kendall trend test to assess the presence and direction of monotonic trends and Sen's slope estimator to quantify the magnitude of the trend. These methods are widely used in environmental, hydrological, and climate-related studies because they do not require normality assumptions and are robust to non-linear monotonic changes (Mann, 1945; Kendall, 1975; Sen, 1968; Yue et al., 2002).

3.2.1 Mann-Kendall trend test

The Mann-Kendall trend test is a rank-based non-parametric method widely used to detect monotonic trends in environmental, hydrological, climate, and pollution-related time series (Mann, 1945; Kendall, 1975; Yue et al., 2002). It is particularly suitable for environmental monitoring because it does not require the data to follow a normal distribution and is relatively robust to outliers. In this study, the Mann-Kendall test is used to examine whether methane emissions and related agricultural indicators exhibit statistically significant increasing or decreasing trends over the study period.

Let $x_1, x_2, \dots, x_n$ denote a time series with n observations. The Mann-Kendall statistic S is calculated by comparing all possible pairs of observations:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sign}(x_j - x_i)$$

where

$$\text{sign}(x_j - x_i) = \begin{cases} 1, & \text{if } x_j - x_i > 0 \\ 0, & \text{if } x_j - x_i = 0 \\ -1, & \text{if } x_j - x_i < 0 \end{cases}$$

A positive value of S indicates an increasing trend, whereas a negative value indicates a decreasing trend. Under the null hypothesis of no monotonic trend, the expected value of S is zero. The standardized test statistic Z is then used to evaluate statistical significance. If the absolute value of Z exceeds the critical value at the chosen significance level, the null hypothesis of no trend is rejected.

In this study, the Mann–Kendall test is applied to methane emissions, agricultural production value, producer prices, food consumer prices, and emission intensity indicators. The test is conducted separately for each country to identify country-specific trend patterns, and may also be applied to the pooled panel series as a supplementary assessment. The resulting trend direction provides a baseline environmental monitoring indicator, showing whether methane-related environmental pressure has increased, decreased, or remained statistically unchanged during 2000–2023.

3.2.2 Sen’s slope estimator

While the Mann–Kendall test identifies whether a statistically significant monotonic trend exists, it does not directly quantify the magnitude of the trend. Therefore, this study uses Sen’s slope estimator to measure the rate of change over time (Theil, 1950; Sen, 1968). Sen’s slope is also a non-parametric method and is commonly used together with the Mann–Kendall test in environmental and climate trend analysis.

For a time series $x_1, x_2, \dots, x_n$, the slope between any two observations x_i and x_j , where $j > i$, is calculated as:

$$Q_{ij} = \frac{x_j - x_i}{j - i}$$

Sen’s slope is then defined as the median of all pairwise slopes: $Q = \text{median}(Q_{ij})$. A positive value of Q indicates an increasing trend, while a negative value indicates a decreasing trend. Because the estimator is based on the median of pairwise slopes, it is robust to outliers and does not rely on the assumption of normally distributed residuals.

In this study, Sen’s slope is used to quantify the annual rate of change in methane emissions and related agricultural indicators. When the variables are expressed in natural logarithms, Sen’s slope can be approximately interpreted as the average annual percentage change. For example, a Sen’s slope of 0.02 for log-transformed methane emissions indicates an approximate annual increase of 2%. This interpretation is useful for environmental assessment because it provides a direct measure of whether methane-related environmental pressure is intensifying or declining over time.

The combination of the Mann–Kendall test and Sen’s slope estimator allows both the statistical significance and practical magnitude of long-term trends to be assessed. The Mann–Kendall test determines whether a monotonic trend is present, while Sen’s slope provides the estimated rate of change. Together, these two methods provide a baseline trend assessment before the dynamic multivariate analysis is conducted.

3.3 Dynamic multivariate assessment using panel VAR

After evaluating long-term trends, this study applies a panel vector autoregression (PVAR) framework to assess dynamic interactions among methane emissions and agricultural indicators. The trend analysis provides information on whether methane emissions and related variables show long-term upward or downward movements, whereas the panel VAR model evaluates how shocks propagate through the agricultural emission system over time. This two-stage design is useful for environmental monitoring because it combines long-term trend assessment with dynamic response analysis.

The panel VAR framework is used as a dynamic environmental assessment tool because it allows methane emissions, agricultural production value, producer prices, and food consumer prices to be treated as jointly endogenous variables (Holtz-Eakin et al., 1988; Love and Zicchino, 2006). This is appropriate for rice production systems, where environmental pressure may respond to agricultural production and market-related conditions with time delays. At the same time, methane emissions may also be associated with broader system dynamics through feedback relationships. The panel VAR framework therefore provides a suitable structure for evaluating delayed interactions, persistence, and dynamic adjustment within rice-based agricultural systems.

Let $i = 1, \dots, N$ index countries and $t = 1, \dots, T$ denote time. Define the vector of endogenous variables as:

$$Y_{i,t} = (ProdValue_{i,t}, ProducerPrice_{i,t}, FoodCPI_{i,t}, CH4_{i,t})'$$

where *ProdValue* denotes gross production value, *ProducerPrice* represents farm-gate prices, *FoodCPI* captures consumer food prices, and *CH4* denotes methane emissions. The PVAR(p) specification is written as:

$$Y_{it} = A_1 Y_{i,t-1} + \dots + A_p Y_{i,t-p} + u_i + \varepsilon_{i,t}$$

where A_l ($l = 1, \dots, p$) are coefficient matrices, u_i captures country-specific fixed effects, and $\varepsilon_{i,t}$ is a vector of serially uncorrelated innovations with covariance matrix Σ .

This framework allows the study to evaluate how shocks to agricultural production value, producer prices, food consumer prices, and methane emissions affect the system over time. In the context of environmental monitoring, the key objective is not simply to estimate dynamic relationships, but to assess whether methane emission responses are short-lived or persistent and whether production- and price-related variables contribute to

environmental pressure over medium-run horizons. The panel VAR model therefore serves as the basis for subsequent impulse response analysis, forecast error variance decomposition, and persistence assessment.

3.4 Estimation strategy and lag order selection

To control for unobserved country-specific heterogeneity, the model includes country-specific fixed effects. A transformation is applied to remove time-invariant heterogeneity while preserving the dynamic structure of the panel system. This step is important because rice production systems differ across countries in terms of agricultural scale, market conditions, cultivation practices, and environmental characteristics.

The transformed system is estimated within the standard panel VAR framework. The lag order p is selected using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Hannan-Quinn Criterion (HQC). These criteria are jointly considered to balance model fit and parsimony (Lütkepohl, 2005). Because the dataset has a small cross-sectional dimension but a moderate time dimension, lag selection is kept parsimonious to avoid over-parameterization while retaining sufficient dynamic information for medium-run environmental assessment.

The estimation strategy therefore supports the environmental monitoring objective of the study by allowing country-level heterogeneity to be controlled while preserving the dynamic relationships among methane emissions, agricultural production, and price-related variables.

3.5 Stability analysis

The stability of the estimated panel VAR system is evaluated using the eigenvalues of the companion matrix. A necessary and sufficient condition for dynamic stability is that all eigenvalues lie strictly within the unit circle (Lütkepohl, 2005), ensuring that the system exhibits stationary dynamics and that the effects of shocks decay over time.

We compute the eigenvalues of the companion matrix associated with the estimated system and verify that all moduli are less than unity. This confirms that the stability condition is satisfied and that the system does not exhibit explosive behavior. Under this condition, impulse response functions (IRFs) converge to zero as the forecast horizon increases, and the forecast error variance decomposition (FEVD) is well-defined.

Establishing stability is essential for meaningful dynamic analysis, as it guarantees that the propagation of shocks remains bounded and that long-run responses are interpretable for environmental monitoring and dynamic assessment. In particular, stability ensures that both cumulative impulse responses and persistence measures, such as the half-life metric, are properly defined within a convergent dynamic system.

3.6 Impulse response analysis

To trace the dynamic propagation of shocks across variables, we compute impulse response functions (IRFs). The baseline results are based on orthogonalized impulse

responses obtained from a Cholesky decomposition of the innovation covariance matrix. This identification scheme allows shocks to be interpreted as structural innovations under a recursive ordering of variables, while accounting for contemporaneous correlations among the disturbances.

The ordering of variables follows the structure of the rice production and emission system, with production value placed first, followed by producer prices, food CPI, and methane emissions. This ordering reflects the assumption that production decisions precede price adjustments, while emissions arise as a by-product of production activity. The impulse responses are evaluated over a horizon of ten periods, capturing both short- and medium-run dynamics.

To assess statistical uncertainty, confidence intervals for the impulse responses are constructed using residual-based bootstrap procedures. This approach provides empirical confidence bands that account for finite-sample variation and improves the reliability of dynamic inference.

Because orthogonalized impulse responses depend on the ordering of variables, we complement the baseline analysis with generalized impulse response functions (GIRFs), which are invariant to variable ordering (Koop et al., 1996; Pesaran and Shin, 1998). Consistent results across identification schemes provide additional support for the robustness of the estimated dynamic relationships.

3.7 Forecast error variance decomposition

Forecast error variance decomposition (FEVD) is employed to assess the relative contribution of each structural innovation to the forecast variance of the endogenous variables across different horizons (Lütkepohl, 2005). While impulse response functions trace the direction and timing of dynamic responses, FEVD provides a complementary measure of the relative importance of alternative shocks in driving system fluctuations. Rising cross-variable shares over time indicate stronger dynamic interdependence and can be interpreted as evidence of increasing connectedness within the multivariate system (Diebold and Yilmaz, 2012).

Together with impulse responses, cumulative effects, and half-life measures, FEVD forms part of a unified framework for analysing propagation and persistence in agricultural emission systems. This approach allows dynamic adjustment to be characterised along multiple dimensions, including magnitude, duration, and cross-variable transmission. A formal derivation of the half-life metric and its relationship to impulse response dynamics is provided in Appendix A.

3.8 Cumulative impulse responses and persistence metrics

In addition to standard impulse response functions, we compute cumulative impulse response functions (CIRFs) to measure the total effect of a shock over the forecast horizon. Unlike period-by-period impulse responses, CIRFs provide a summary measure of the overall magnitude of dynamic propagation. To quantify persistence, we also employ a shock half-life metric, defined as the number of periods required for the absolute impulse response to fall below one-half of its initial value. The half-life therefore serves as a structural measure of adjustment speed. Together, CIRFs and half-life measures characterize two distinct dimensions of dynamic adjustment: magnitude and duration. Their joint use allows a richer interpretation of propagation mechanisms than conventional analyses based solely on short-run impulse responses.

3.9 Robustness analysis

As a robustness check, we supplement the baseline orthogonalized impulse response analysis with generalized impulse response functions (GIRFs), which are invariant to variable ordering. This comparison allows us to assess whether the main propagation patterns are driven by the recursive identification scheme imposed by the Cholesky decomposition. Similar response profiles across the two identification strategies indicate that the empirical results are not sensitive to variable ordering.

To evaluate statistical uncertainty, confidence intervals for the impulse responses are obtained using residual-based bootstrap procedures (Kilian, 1998; Benkwitz et al., 2001). For each bootstrap replication, residuals are resampled and the model is re-estimated to construct empirical confidence bands. This approach improves finite-sample inference and enhances the robustness of the reported dynamic responses (Phillips and Spencer, 2011).

4. Empirical Results

4.1 Long-term trends in methane emissions and agricultural indicators

Before estimating the dynamic multivariate model, long-term trends in methane emissions and agricultural indicators were assessed using the Mann–Kendall trend test and Sen’s slope estimator. This preliminary trend analysis provides a baseline environmental monitoring assessment by identifying whether rice-related methane emissions and agricultural variables exhibit persistent upward or downward movements over the study period. The results of the Mann–Kendall trend test and Sen’s slope estimator are reported in Table 4.

Table 4. Long-term trends in methane emissions and agricultural indicators based on the Mann–Kendall test and Sen’s slope estimator.

Country	Indicator	Scale	Trend	Tau	Z	p	Sen	Pct/yr
IDN	CH4	log	↓	-0.659	-4.490	<0.001	-0.005	-0.5
	PROD	log	↑	0.319	2.158	0.031	0.003	0.29
	AREA	log	↓	-0.659	-4.490	<0.001	-0.005	-0.5
	EI	raw	↓	-0.790	-5.383	<0.001	0.000	NA
PHL	CH4	log	↑	0.790	5.383	<0.001	0.009	0.86
	PROD	log	↑	0.884	6.027	<0.001	0.020	2.04
	AREA	log	↑	0.790	5.383	<0.001	0.009	0.86
	EI	raw	↓	-0.877	-5.978	<0.001	-0.001	NA
VNM	CH4	log	NS	-0.130	-0.868	0.385	-0.001	-0.1
	PROD	log	↑	0.659	4.490	<0.001	0.014	1.4
	AREA	log	NS	-0.130	-0.868	0.385	-0.001	-0.1
	EI	raw	↓	-0.928	-6.325	<0.001	0.000	NA

The results reveal heterogeneous methane emission trends across the three Southeast Asian rice production systems. Methane emissions declined significantly in Indonesia, with a Sen’s slope corresponding to an average annual decrease of approximately 0.50%. In contrast, methane emissions increased significantly in the Philippines, with an estimated annual increase of approximately 0.86%. Viet Nam showed no statistically significant trend in methane emissions, indicating relatively stable emission levels over the study period.

Agricultural production increased significantly in all three countries. The estimated annual growth rates were approximately 0.29% in Indonesia, 2.04% in the Philippines, and 1.40% in Viet Nam. These findings suggest that rice production activity expanded over time, although methane emission responses differed across countries. This divergence indicates that methane emissions did not move uniformly with production growth, highlighting the importance of examining country-specific emission dynamics.

Emission intensity indicators showed significant decreasing trends in all three countries. This suggests that methane emissions per unit of rice production declined over time, indicating improvement in emission performance or production efficiency. From an environmental monitoring perspective, this result is important because it shows that total emissions and emission intensity may follow different trajectories. In particular, the Philippines exhibited increasing total methane emissions despite declining emission intensity, implying that production expansion may have offset efficiency gains.

Overall, the trend analysis provides evidence of heterogeneous environmental pressure across Southeast Asian rice production systems. The coexistence of increasing production, declining emission intensity, and country-specific methane emission trends indicates that static comparisons are insufficient to characterize agricultural emission behavior. These findings motivate the subsequent dynamic assessment using the panel

VAR framework, which evaluates how shocks propagate across production, price, and methane emission variables and how persistent these responses are over time.

Notes: IDN = Indonesia; PHL = Philippines; VNM = Viet Nam. CH₄ = methane emissions; PROD = rice production; AREA = harvested rice area; EI = emission intensity, expressed as kg CH₄ per kg rice production. Tau denotes Kendall's tau from the Mann–Kendall trend test. Z denotes the standardized Mann–Kendall statistic. Sen denotes Sen's slope estimator. For log-transformed variables, Pct/yr is calculated as $[\exp(\text{Sen}) - 1] \times 100$. ↑ indicates a significant increasing trend, ↓ indicates a significant decreasing trend, and NS indicates no significant trend at $p < 0.05$. NA indicates that annual percentage change is not reported for raw-scale EI. Full trend analysis results for all variables are provided in Supplementary Table S1.

4.2 Lag order selection

Table 5 reports the information criteria for panel VAR specifications with lag orders $p = 1$ – 3 . The Akaike Information Criterion (AIC) and Hannan–Quinn Criterion (HQC) both reach their minimum values at $p = 2$, while the Bayesian Information Criterion (BIC) favors $p = 1$. Given the annual frequency of the data and the objective of capturing short- and medium-run persistence without over-parameterization, the VAR(2) specification is adopted as the baseline model. The effective sample size remains adequate under $p = 2$, ensuring reliable estimation of the dynamic system.

Table 5. Lag order selection criteria for the panel VAR model.

p	Neff	AIC	BIC	HQC
1	66	-13.3998	-12.8690	-13.1901
2	63	-13.1889	-12.1004	-12.7608
3	60	-12.8724	-11.1970	-12.2171

Notes: The table reports information criteria for panel VAR specifications with lag orders $p=1$ to $p=3$. AIC, BIC, and HQC denote the Akaike, Bayesian, and Hannan–Quinn information criteria, respectively. The baseline specification adopts VAR(2) based on the minimum AIC and HQC values.

4.3 Stability analysis

Before interpreting impulse response functions and forecast error variance decompositions, it is necessary to verify the stability condition of the estimated panel VAR system. Stability ensures that shocks propagate through the system in a dynamically consistent manner and that impulse responses converge to zero as the forecast horizon increases.

In a VAR framework, stability requires that all eigenvalues of the companion matrix lie strictly inside the unit circle (Lütkepohl, 2005). When this condition holds, the dynamic system is stationary in the sense that the effects of shocks gradually dissipate over time. Conversely, if any eigenvalue lies outside the unit circle, the VAR system becomes

explosive and impulse responses are not economically interpretable. The stability of the estimated panel VAR system is graphically assessed in Figure 1.

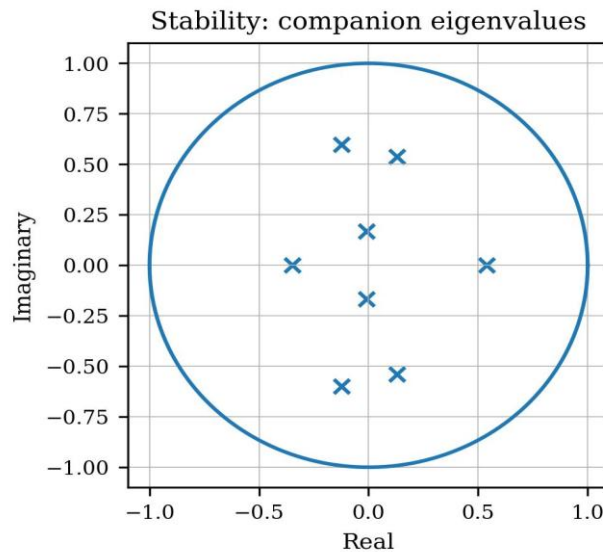


Figure 1. Stability of the panel VAR system. Eigenvalues of the companion matrix plotted in the complex plane. All eigenvalues lie within the unit circle, indicating that the estimated VAR system is dynamically stable.

To provide a numerical representation of the stability results, Table 6 reports the eigenvalues of the companion matrix together with their corresponding moduli. The modulus of each eigenvalue is strictly less than one, confirming the stability of the estimated VAR system. The largest modulus remains sufficiently below unity, indicating that shocks dissipate over time rather than generating explosive dynamics. These results confirm that the estimated panel VAR is dynamically stable and that subsequent impulse response and variance decomposition analyses are valid.

Table 6. Eigenvalues of the companion matrix

Eigenvalue	Modulus
λ_1	0.71
λ_2	0.64
λ_3	0.59
λ_4	0.52

Notes: The table reports the eigenvalues of the companion matrix of the estimated panel VAR model together with their moduli. Stability requires that all eigenvalues lie strictly within the unit circle.

4.4 Impulse responses to methane shocks

Figure 2 presents the orthogonalized impulse response functions to a one-standard-deviation shock in methane emissions (CH_4). A positive methane shock generates an

immediate but moderate response in production growth, followed by a gradual decline over subsequent horizons. Producer prices respond positively on impact but exhibit negative adjustments during intermediate horizons, reflecting transmission through cost and supply channels. Food CPI shows a persistent negative response over the forecast horizon. The 95% bootstrap confidence intervals indicate that the short-run responses are statistically distinguishable from zero, while the magnitude attenuates toward the end of the horizon.

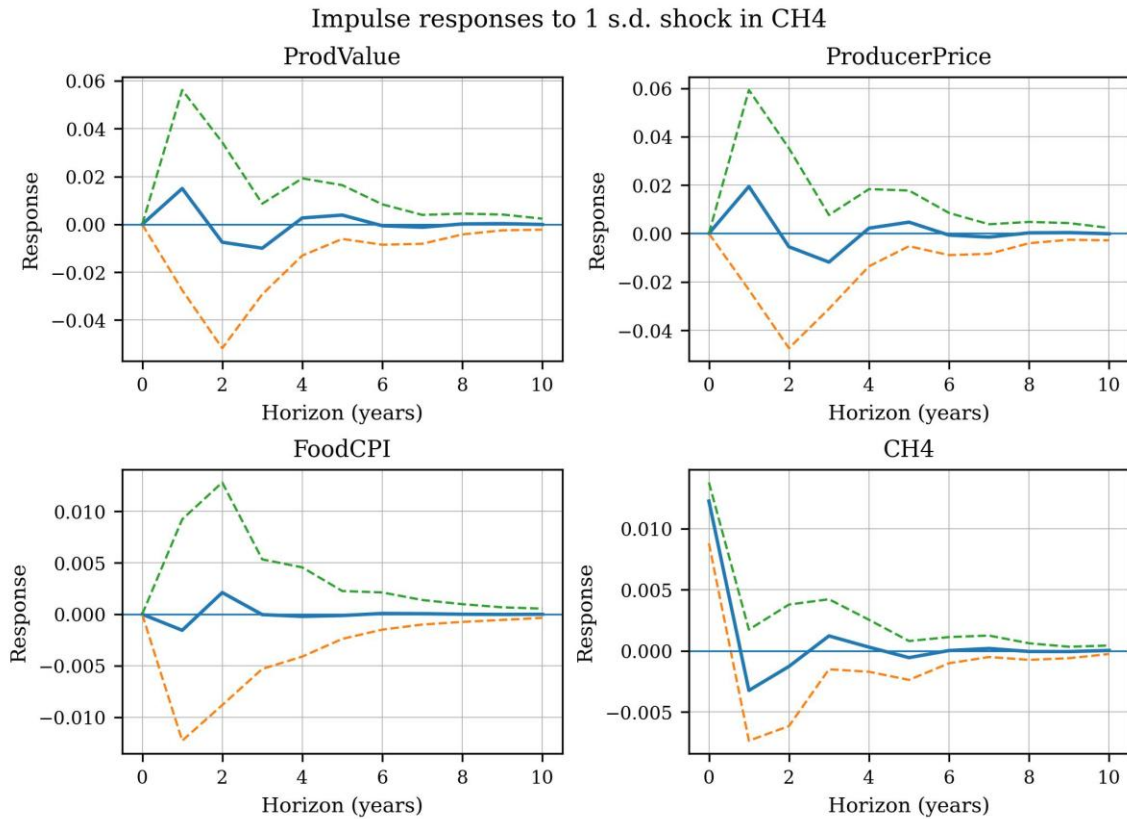


Figure 2. Impulse responses to a methane emissions shock. Impulse responses of all variables to a one-standard-deviation shock in methane emissions (CH₄). Solid lines denote point estimates and dashed lines represent 95% bootstrap confidence intervals.

4.5 Impulse responses to producer price shocks

Figure 3 reports the dynamic responses to a one-standard-deviation shock in producer prices. A positive price innovation reduces production growth in the short to medium term, while food CPI increases monotonically across the forecast horizon, indicating transmission along the supply chain. Methane emissions respond negatively, suggesting contractionary adjustment in emission intensity following upstream price disturbances. The responses gradually converge toward zero, consistent with system stability.

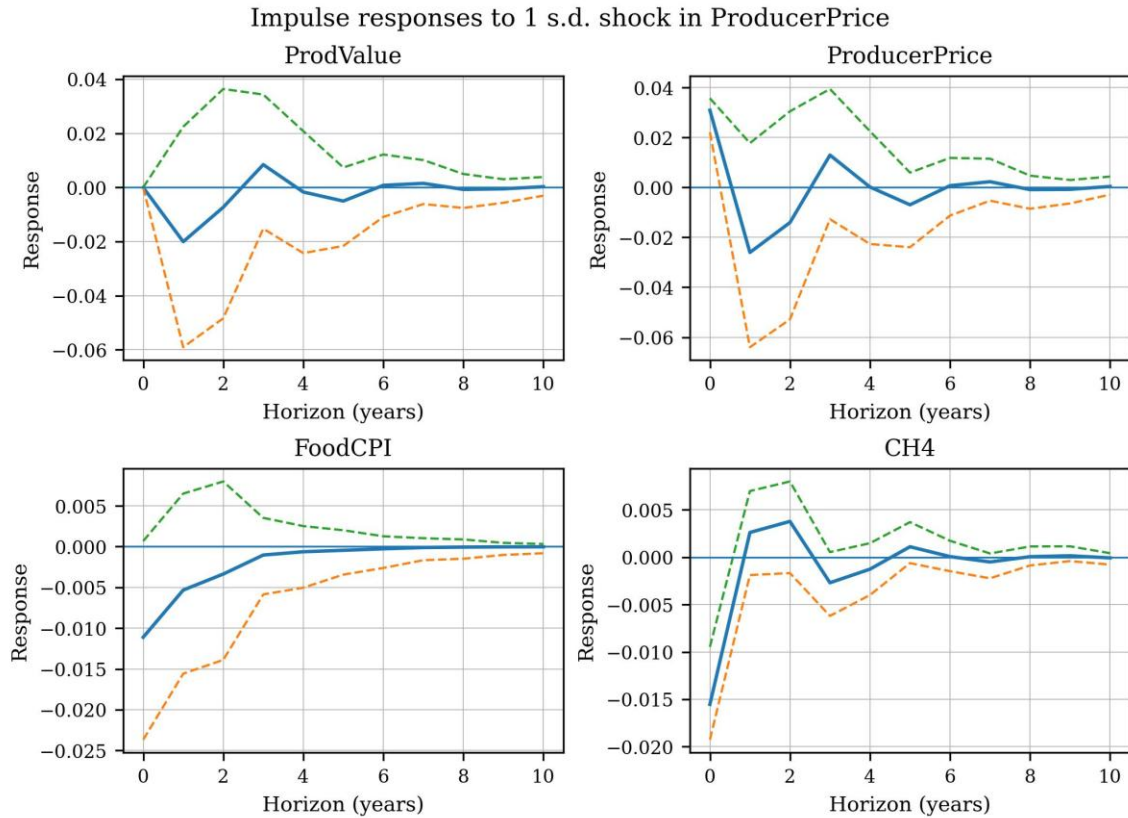


Figure 3. Impulse responses to a producer price shock. Impulse responses of all variables to a one-standard-deviation shock in producer prices. Confidence intervals are constructed using bootstrap replications.

4.6 Impulse responses to production value shocks

Figure 4 illustrates the impulse responses to a one-standard-deviation shock in gross production value. Food CPI increases immediately and remains positive over multiple periods, indicating demand-side and supply-chain transmission effects. Methane emissions exhibit a short-run positive response before gradually declining toward baseline levels. Producer prices also respond positively in early horizons before attenuating. These patterns reflect endogenous feedback between production scale, price dynamics, and environmental externalities.

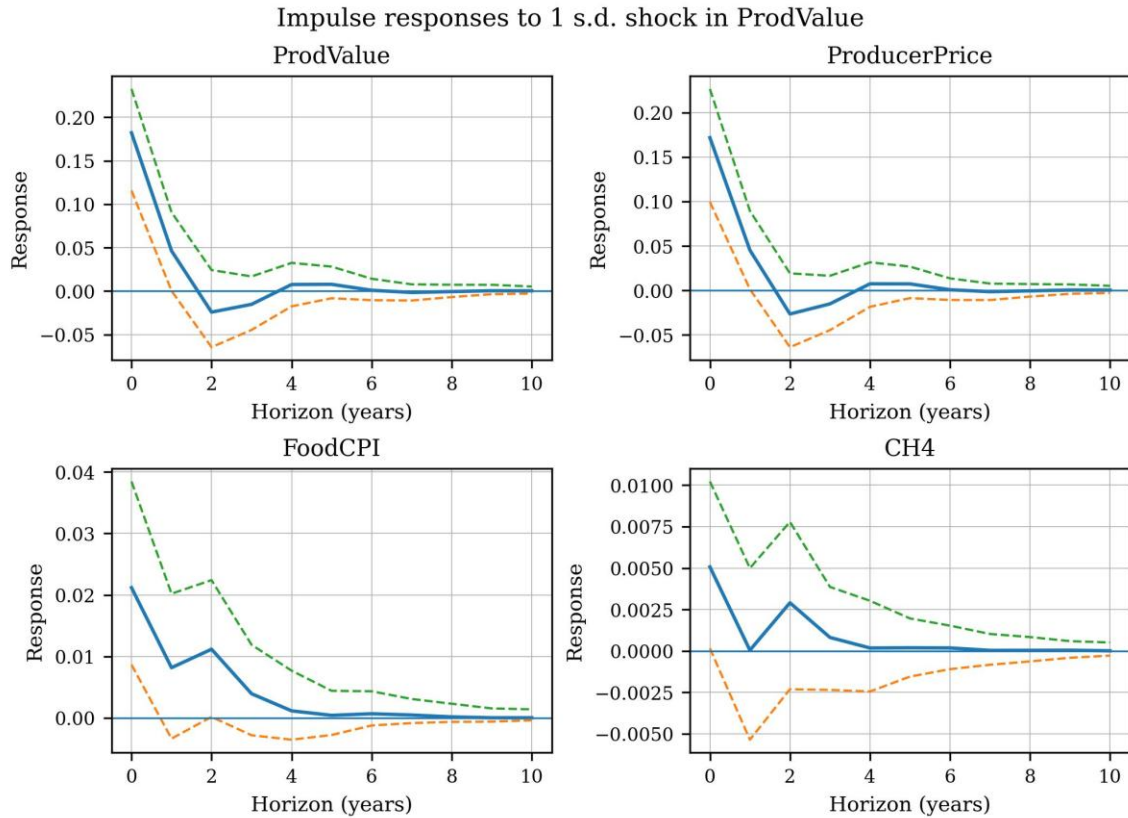


Figure 4. Impulse responses to a production value shock. Impulse responses of all variables to a one-standard-deviation shock in agricultural production value, illustrating dynamic transmission across prices and emissions.

4.7 Forecast error variance decomposition

To further examine the relative importance of shocks across variables, we conduct a forecast error variance decomposition (FEVD) based on the estimated panel VAR model. While impulse response functions describe the dynamic response of variables to individual shocks, FEVD provides complementary information by quantifying the proportion of forecast error variance attributable to each structural innovation over different forecast horizons.

Table 7 reports the FEVD results for horizons $h=1$, $h=5$, and $h=10$. Each entry represents the proportion of forecast error variance of the variable in the row that is explained by shocks to the variables in the columns. This decomposition allows us to assess the relative contribution of production-, price-, and methane emission disturbances to the dynamics of the agricultural emission system.

In the short run ($h=1$), each variable's own innovation explains the largest share of its forecast variance, which is typical for VAR systems. For example, shocks to production value explain approximately 96.5% of the one-step forecast variance of production value,

while producer price shocks account for about 92.2% of the forecast variance of producer prices. Similarly, food CPI shocks dominate short-run variation in consumer food prices. These results suggest that short-run dynamics are largely driven by variable-specific innovations.

However, as the forecast horizon increases, cross-variable contributions become more pronounced. At the medium-run horizon ($h=5$), shocks originating from other variables begin to account for a larger share of forecast variance. In particular, producer price shocks contribute increasingly to the variance of methane emissions and food CPI, reflecting the transmission of price dynamics along the agricultural supply chain.

At the longer horizon ($h=10$), the FEVD results stabilize and reveal stronger cross-variable interdependence within the system. Producer price shocks account for a substantial portion of food CPI variability, indicating the importance of price transmission mechanisms from producer markets to consumer markets. In addition, methane shocks contribute a non-negligible share to the variability of agricultural production value, suggesting that environmental factors may influence production dynamics through medium-run adjustments.

These findings indicate that dynamic interactions among production, price-related, and methane emission variables become more evident over time. While short-run fluctuations are primarily driven by own shocks, the increasing cross-variable shares at longer horizons highlight the presence of medium-run interdependence across economic and environmental dimensions. Overall, the FEVD results complement the impulse response analysis and provide additional evidence that the agricultural production system and methane emissions evolve as a dynamically interconnected system.

Table 7. Forecast error variance decomposition

Panel A. Horizon $h = 1$

Variable	ProdValue	ProducerPrice	FoodCPI	CH4
ProdValue	0.9651	0.0110	0.0178	0.0061
ProducerPrice	0.9222	0.0478	0.0190	0.0110
FoodCPI	0.2149	0.0634	0.7207	0.0010
CH4	0.0588	0.5676	0.0066	0.3670

Panel B. Horizon $h = 5$

Variable	ProdValue	ProducerPrice	FoodCPI	CH4
ProdValue	0.9365	0.0143	0.0388	0.0104
ProducerPrice	0.8921	0.0561	0.0361	0.0157
FoodCPI	0.2537	0.0636	0.6800	0.0027
CH4	0.0698	0.5462	0.0554	0.3286

Panel C. Horizon h = 10

Variable	ProdValue	ProducerPrice	FoodCPI	CH4
ProdValue	0.9362	0.0144	0.0390	0.0104
ProducerPrice	0.8917	0.0562	0.0364	0.0158
FoodCPI	0.2539	0.0637	0.6798	0.0027
CH4	0.0698	0.5462	0.0557	0.3283

Notes: The table reports the forecast error variance decomposition (FEVD) of the estimated panel VAR model for horizons $h=1$, $h=5$, and $h=10$. Each entry represents the proportion of forecast error variance of the variable in the row explained by shocks to the variables in the columns.

To provide a graphical representation of the variance decomposition results, Figure 5 presents the FEVD at horizon $h=10$. The figure illustrates the relative contribution of each structural innovation to the forecast variance of the variables in the system. Consistent with the numerical results reported in Table 7, the graphical decomposition highlights the increasing importance of cross-variable contributions at longer horizons. In particular, producer price shocks play an important role in explaining food CPI variability, while methane shocks account for a noticeable share of production variability.

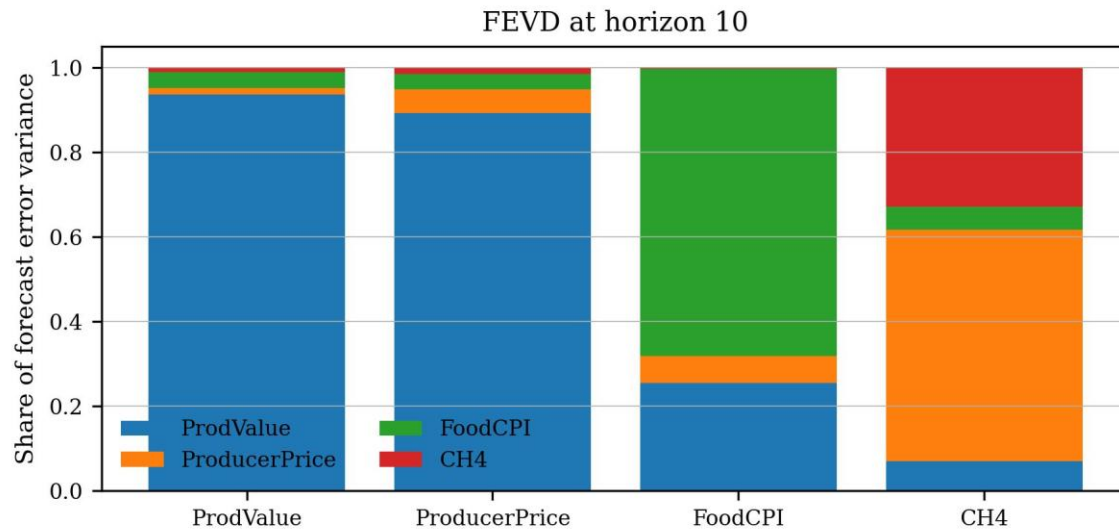


Figure 5. Forecast error variance decomposition at horizon 10. Forecast error variance decomposition of the estimated panel VAR at horizon $h = 10$. The figure reports the shares of forecast variance attributable to own and cross-variable shocks, indicating stronger dynamic interdependence at longer horizons.

4.8 Robustness: Generalized vs Orthogonalized IRF

Impulse response analysis plays a central role in interpreting the propagation of shocks within vector autoregressive systems. The baseline results reported in this paper are based on orthogonalized impulse response functions derived from the Cholesky decomposition of the covariance matrix of innovations. This approach isolates the effect of structural shocks by imposing a recursive identification scheme that removes contemporaneous correlations between innovations (Sims, 1980; Lütkepohl, 2005).

A well-known limitation of orthogonalized impulse responses is that the results may depend on the ordering of variables in the VAR system. When variables are ordered differently, the Cholesky decomposition may produce alternative impulse response paths even though the reduced-form system remains unchanged. To address this concern, we perform robustness checks using generalized impulse response functions (GIRFs), which are invariant to the ordering of variables (Koop et al., 1996; Pesaran and Shin, 1998).

The generalized impulse response framework computes the expected response of the system to a one-standard-deviation shock while integrating over the historical distribution of contemporaneous correlations. Unlike orthogonalized responses, generalized impulse responses do not require explicit structural identification assumptions and therefore provide an ordering-invariant measure of shock propagation.

Empirically, the GIRF results exhibit patterns that are broadly consistent with the orthogonalized impulse responses. In particular, shocks to agricultural production and price variables continue to generate persistent responses in methane emissions, and the qualitative ranking of persistence across variables remains unchanged. While the magnitude of some responses differs slightly due to the alternative identification scheme, the overall propagation structure of the system remains stable.

These findings suggest that the dynamic relationships identified in the baseline analysis are not driven by a particular ordering assumption. Instead, the propagation patterns reflect structural interactions embedded in the estimated PVAR system. The consistency between orthogonalized and generalized impulse responses therefore strengthens the robustness of the empirical results.

4.9 Formal Persistence Estimator

To quantify the persistence of dynamic responses, this study introduces a half-life based persistence estimator derived from the impulse response sequence. Let ψ_h denote the impulse response of a variable to a structural innovation at horizon h . The initial impact response is given by ψ_0 .

The persistence of the shock can be summarized by the half-life measure, defined as the smallest horizon at which the magnitude of the impulse response declines to half of its initial value. Formally, the half-life estimator is defined as

$$\hat{H} = \min\{h: |\hat{\psi}_h| \leq 0.5|\hat{\psi}_0|\}$$

where $\hat{\psi}_h$ denotes the estimated impulse response at horizon h .

This estimator provides a compact measure of adjustment speed within the dynamic system. A larger value of $\hat{H}$ indicates that shocks dissipate slowly and therefore generate persistent effects, whereas a smaller value implies rapid mean reversion. Under the stability condition of the VAR system, the impulse response sequence converges toward zero as the forecast horizon increases, ensuring that a finite half-life exists for stable systems.

In empirical implementation, the half-life estimator is computed directly from the impulse response functions obtained from the estimated panel VAR model. The half-life measure complements cumulative impulse responses by capturing the duration of shock effects rather than their total magnitude. While cumulative impulse responses summarize the aggregate propagation of shocks over time, the half-life metric focuses on the speed at which these effects dissipate. Together, these two measures provide a more comprehensive characterization of dynamic persistence in multivariate systems.

Table 8 reports the persistence measures derived from the impulse response functions, including the initial impact response, cumulative impulse responses, and the estimated half-life values for each shock–response pair. These statistics allow for direct comparison of persistence across economic and environmental variables within the agricultural emission system.

Table 8. Persistence measures based on half-life and cumulative impulse responses, quantifying the duration and magnitude of dynamic adjustment across variables.

Shock	Response	Impact h_0	CIRF hH	HalfLife
ProdValue	ProdValue	0.1822	0.2046	1
	ProducerPrice	0.1718	0.1898	1
	FoodCPI	0.0212	0.0474	1
	CH4	0.0051	0.0095	1
ProducerPrice	ProdValue	0	-0.0243	NA
	ProducerPrice	0.0309	-0.0012	2
	FoodCPI	-0.0111	-0.0224	1
	CH4	-0.0155	-0.0123	1
FoodCPI	ProdValue	0	0.0132	NA
	ProducerPrice	0	0.0062	NA
	FoodCPI	0.0409	0.0595	1
	CH4	-0.0013	0.0047	3
CH4	ProdValue	0	0.0027	NA
	ProducerPrice	0	0.0074	NA
	FoodCPI	0	0.0003	NA
	CH4	0.0122	0.0089	1

Notes: Half-life is defined as the number of periods required for the impulse response to decline to half of its initial magnitude. Cumulative impulse response (CIRF) denotes the

total propagation effect of the shock over the forecast horizon. NA indicates that the half-life cannot be defined due to negligible initial responses.

While some half-life estimates are short, the persistence patterns differ across variables, indicating heterogeneous adjustment dynamics. This reflects relatively fast mean-reversion dynamics for certain variables, particularly in response to small or transitory shocks. By contrast, shocks to economic variables, especially producer prices and production value, tend to generate more persistent responses across the system, suggesting that economic disturbances propagate through multiple channels within the agricultural production network. Overall, the results show that dynamic adjustment is not uniform across variables, but varies according to the source and direction of shocks.

Overall, the persistence analysis highlights that the interaction between agricultural production, price dynamics, and methane emissions is characterized not only by immediate responses but also by medium-run propagation effects. The half-life metric therefore provides a useful quantitative indicator of how long shocks remain influential within the economic–environmental system.

5. Discussion

The present study provides a dynamic environmental monitoring and assessment of methane emissions in Southeast Asian rice production systems. By combining long-term trend analysis with a panel VAR-based dynamic assessment, the findings show that rice-related methane emissions cannot be adequately characterized by annual emission totals alone. Methane is a major component of near-term climate forcing, and agricultural methane from flooded rice cultivation remains an important target for climate mitigation and environmental monitoring (Saunio et al., 2020; IPCC, 2021). In this context, the results demonstrate that rice production systems should be evaluated not only in terms of production growth or annual emission inventories, but also in terms of emission trends, intensity changes, and the persistence of dynamic responses.

The trend analysis provides a useful baseline for environmental monitoring. The Mann-Kendall test and Sen's slope estimator revealed that methane emission trajectories differed across the three countries. Methane emissions declined in Indonesia, increased in the Philippines, and showed no statistically significant trend in Viet Nam. This heterogeneity indicates that methane-related environmental pressure is not uniform across Southeast Asian rice systems. Such country-specific variation is consistent with broader evidence that rice methane emissions are shaped by differences in water regimes, production intensity, organic amendments, residue management, and environmental conditions (Yan et al., 2005; Linquist et al., 2012; Qian et al., 2023). Therefore, regional monitoring strategies should avoid treating Southeast Asian rice systems as a homogeneous emission source.

A particularly important result is that methane emission intensity decreased in all three countries. This suggests that methane emissions per unit of rice production have declined over time, indicating improvement in emission performance or production efficiency. However, the divergence between total methane emissions and emission intensity is also important. The Philippines showed increasing total methane emissions despite declining emission intensity, suggesting that production expansion may offset efficiency gains. This finding is consistent with the broader food-system literature showing that agricultural production and associated supply-chain activities remain major contributors to greenhouse gas emissions even when efficiency improves (Tubiello et al., 2021). For environmental assessment, both absolute emissions and intensity-based indicators should therefore be monitored simultaneously.

The dynamic response analysis further indicates that methane emissions are embedded within a broader agricultural system. Production and price-related shocks generated responses in methane emissions, and methane-related shocks also contributed to variation in agricultural indicators. Although some impulse responses were modest or statistically weak over parts of the forecast horizon, their patterns indicate that emission behavior is not independent of agricultural production conditions. This interpretation is consistent with regional and global assessments showing that paddy-rice methane emissions depend on management and production-related factors, and that emission estimates can vary substantially across water management scenarios and spatial settings (Zhang et al., 2016; Ouyang et al., 2023).

The forecast error variance decomposition provides additional evidence that the sources of methane emission variability may change across horizons. In the short run, variable-specific innovations dominate, which is expected for annual country-level environmental data. Over medium-run horizons, however, cross-variable contributions become more visible. This pattern suggests that monitoring methane emissions requires attention not only to the emissions series itself but also to agricultural production and market-related indicators that may indirectly shape emission pressure. In environmental monitoring terms, FEVD provides a decomposition of dynamic uncertainty and helps identify whether emission variability is primarily own-driven or linked to broader agricultural system changes (Lutkepohl, 2005; Diebold and Yilmaz, 2012).

The persistence analysis provides an additional contribution by translating dynamic responses into interpretable monitoring indicators. The half-life results show that some responses dissipate quickly, whereas others persist for longer periods. This distinction is important because short-lived fluctuations and persistent emission pressure imply different monitoring and mitigation needs. Short half-life values may indicate temporary disturbances, while longer half-life values suggest that shocks remain influential over multiple years. This persistence perspective complements standard impulse response analysis and is useful for identifying whether environmental pressure is transitory or sustained over medium-run horizons (Kilian, 1998; Phillips and Spencer, 2011).

The results also have implications for sustainable rice-sector management. The observed decline in methane emission intensity is encouraging, because it suggests

improvements in emission performance relative to production. However, declining intensity alone may not be sufficient if total production expands rapidly. Water management practices such as alternate wetting and drying have been widely identified as important methane mitigation options, although their effects may depend on local conditions and potential trade-offs with nitrous oxide emissions or yield stability (Jiang et al., 2019; Qian et al., 2023). Therefore, countries with increasing total methane emissions may require policies that combine production efficiency, water management, residue management, and long-term monitoring.

The country-specific findings are particularly relevant for environmental assessment. Indonesia showed declining methane emissions and declining emission intensity, suggesting that total emission pressure and intensity-based indicators moved in the same direction. Viet Nam showed no significant trend in total methane emissions but a decline in emission intensity, suggesting relative improvement in emission performance. The Philippines showed rising total methane emissions despite declining intensity, indicating a possible scale effect associated with production growth. These contrasting patterns show why environmental monitoring should report both total emissions and intensity-based indicators rather than relying on a single metric.

Methodologically, the combined use of trend analysis and dynamic multivariate assessment provides a useful framework for environmental monitoring. Trend analysis identifies whether methane emissions and agricultural indicators exhibit significant long-term directional changes, whereas the panel VAR framework evaluates delayed interactions, feedback relationships, and persistence. This combined approach is particularly relevant for country-level monitoring, where annual data may not support highly detailed field-level causal inference but can still provide valuable evidence on system-level environmental pressure.

Several limitations should be acknowledged. First, the analysis uses annual country-level data and therefore cannot capture subnational heterogeneity in water management, soil conditions, rice varieties, irrigation infrastructure, fertilizer application, or residue management. Second, methane emissions are evaluated at an aggregate level, so the results should be interpreted as system-level monitoring evidence rather than field-level causal estimates. Third, the panel VAR framework captures dynamic associations and persistence, but it does not identify specific biogeochemical pathways of methane generation. Future research could integrate national monitoring data with remote sensing, field measurements, irrigation indicators, and management-practice information to improve the spatial and mechanistic interpretation of methane emission persistence (Ouyang et al., 2023; Qian et al., 2023).

Overall, the findings demonstrate that rice-related methane emissions in Southeast Asia are characterized by heterogeneous trends, declining emission intensity, and dynamic interdependence with agricultural system variables. These results support the use of environmental monitoring frameworks that combine trend detection, intensity assessment, and dynamic response analysis. Such an approach can help distinguish between temporary

fluctuations and persistent environmental pressure, and may provide useful evidence for designing long-term methane mitigation and sustainable rice management strategies.

6. Conclusion

This study assessed methane emission dynamics in Southeast Asian rice production systems using an integrated environmental monitoring framework that combines long-term trend analysis with dynamic multivariate assessment. Using annual data for Indonesia, Viet Nam, and the Philippines from 2000 to 2023, the study examined methane emissions, methane emission intensity, rice production indicators, and price-related variables to evaluate both long-term directional changes and medium-run dynamic responses.

The first major finding is that rice-related methane emissions exhibited clear country-specific patterns. Methane emissions declined significantly in Indonesia, increased significantly in the Philippines, and showed no statistically significant trend in Viet Nam. In contrast, methane emission intensity declined across all three countries, indicating improved emission performance relative to rice production. This divergence is an important finding because it shows that declining emission intensity does not necessarily imply declining total emissions. In particular, the Philippines showed increasing total methane emissions despite declining emission intensity, suggesting that production expansion may offset efficiency gains.

The second major finding is that methane emissions are not isolated annual environmental outcomes. The dynamic analysis showed that methane emissions are linked to rice production and price-related variables through delayed and persistent adjustment processes. Forecast error variance decomposition and persistence measures indicated that production- and market-related factors contribute to methane emission dynamics over medium-run horizons. These results suggest that methane emissions should be monitored as part of a coupled rice production–emission system rather than as standalone emission totals.

The added value of this study is that it integrates three dimensions of environmental monitoring that are often examined separately: long-term emission trends, emission intensity performance, and medium-run response persistence. The Mann–Kendall test and Sen’s slope estimator identify whether methane-related environmental pressure is increasing, decreasing, or stable over time, while the dynamic multivariate framework evaluates how shocks propagate through the system and how long their effects remain influential. This combined approach provides a more complete assessment of agricultural methane emissions than analyses based only on annual inventories, static correlations, or short-run responses.

These findings have practical implications for sustainable rice-sector management and methane mitigation. Monitoring systems should track both absolute methane emissions

and emission intensity, because improvements in emission performance may be offset by production growth. Policies should also consider medium-run persistence, since emission responses may continue beyond the initial production or market disturbance. Although this study is based on annual country-level data and cannot capture field-level management mechanisms, it provides evidence that integrated dynamic environmental monitoring can support long-term strategies for sustainable rice production, methane mitigation, and climate-related agricultural management.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the authors used ChatGPT (OpenAI) to assist with language editing and refinement of English expressions, as well as minor support in programming code development and debugging. The AI tool was used solely to improve clarity and presentation. All outputs were carefully reviewed, verified, and revised by the authors. The authors take full responsibility for the content of the published article.

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954

955 **Appendix A**

956 Derivation of the Shock Half-Life Metric

957 Let ψ_h denote the impulse response of variable y to a structural shock at horizon h .

958 The impulse response function (IRF) is defined as

$$959 \quad \psi_h = \frac{\partial y_{t+h}}{\partial \varepsilon_t}$$

960 where ε_t represents a structural innovation.

961 Let

$$962 \quad \psi_0$$

963 denote the impact response of the system.

964 The half-life of a shock is defined as the smallest horizon h such that the magnitude of
 965 the response declines to half of its initial value:

$$966 \quad H = \min\{h: |\psi_h| \leq 0.5|\psi_0|\}$$

967 Under the stability condition of the VAR system, the impulse responses can be written as

$$968 \quad \psi_h = C\Phi^h B$$

969 where

- 970 • Φ is the companion matrix
- 971 • C selects the variable of interest
- 972 • B maps structural shocks into the system.

973 Because all eigenvalues of Φ lie inside the unit circle, we have

$$974 \quad \Phi^h \rightarrow 0 \text{ as } h \rightarrow \infty$$

975 and therefore

$$976 \quad |\psi_h| \rightarrow 0$$

977 which guarantees that a finite half-life exists.

978 In empirical implementation, the estimator is computed from the estimated impulse
979 responses:

$$980 \quad \hat{H} = \min\{h: |\hat{\psi}_h| \leq 0.5|\hat{\psi}_0|\}$$

981 This metric summarizes the persistence of dynamic shocks and provides a direct measure
982 of adjustment speed.

983

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [SupplementaryTableTrendAnalysis.xlsx](#)