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Modeling Regime Shifts in Philippines Corn Production Using Hidden Markov Approach

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ABSTRACT

This paper examines the quarterly corn production dynamics in the Philippines between 2010 and 2025 through a Hidden Markov Model (HMM) approach to determine hidden regimes of volatility. Through the modeling of production as a process driven by hidden states, the estimation delivers an evident switch between low- and high-volatility regimes, each with different mean levels and residual variances. Stationarity testing upheld the applicability of the time series to regime modeling, and model comparison with AIC, BIC, and log-likelihood statistics highly preferred the 2-state HMM to a reduced 1-state model. Transition probability estimates reflected almost deterministic switching behavior between regimes and demonstrated the cyclical pattern of agricultural production, presumably caused by seasonal, climatic, or policy-based factors. The results highlight the usefulness of regime-switching models in identifying latent structural change in farm-level data and facilitate their use in prediction, risk management, and policy formulation towards improved food security, aiding the achievement of UN Sustainable Development Goal 2 (Zero Hunger).

Keywords: Hidden Markov Model, Corn Production, Regime Switching, Agricultural Volatility, Food Security

INTRODUCTION

Agriculture continues to be a foundational pillar of the Philippine economy, supporting livelihoods, providing food, and serving as a major source of raw materials for local industries. According to Briones (2021), the sector employs a large portion of the national workforce and remains a critical driver of rural development, especially in regions where poverty is widespread and employment opportunities are limited. Beyond its labor contributions, agriculture also plays a strategic role in national food security and economic planning. As noted by Tracio (2020), corn stands as the second most important crop in the country after rice, both in terms of land area cultivated and overall production volume. This crop is essential not only as a staple food in upland communities but also as a key input in livestock feed and agro-industrial processing. The research of Parreño (2023) emphasizes the need for ongoing improvement in forecasting methods to ensure sustainable agricultural development. Rice and corn are crucial to the Philippines' food security and economy, but their production faces challenges from climate change, land limitations, and rising import needs. This study used quarterly data (1987–2023) to compare forecasting models and found that the Holt-Winters model outperformed SARIMA in predicting rice and corn production. Accurate forecasts help policymakers manage imports, stabilize supply, and support food sufficiency.

Climate variability and economic pressures have long driven instability in Philippine corn production. In particular, weather phenomena such as El Niño and La Niña frequently result in either prolonged droughts or excessive rainfall, both of which severely disrupt planting schedules and reduce yields, especially in rain-fed agricultural areas. According to Gomez (2024), these climatic disruptions often result in severe yield reductions that undermine food availability and contribute to heightened levels of rural poverty. Similarly, Hu et al. (2024) emphasized that climate extremes not only interfere with seasonal crop cycles but also threaten long-term agricultural sustainability by exacerbating soil degradation and reducing crop resilience. Since the mid-1980s, the Department of Science and Technology - Philippine Atmospheric, Geophysical and Astronomical Services Administration (DOST-PAGASA) (2025) has regularly published the Climate Impact Assessment for Philippine Agriculture. This report provides monthly evaluations of weather and climate conditions that may influence rice and corn production, along with farming activities across various regions. It is intended to assist farmers, policymakers, and agricultural advisers—such as extension workers and technicians, in identifying potential threats from extreme events like droughts, intense rainfall, or tropical cyclones. The report also serves as a basis for developing timely and effective adaptation strategies.

On the economic side, Mayo and Villarta (2023) argued that erratic fluctuations in the prices of essential inputs such as fertilizers, pesticides, and hybrid seeds have made it difficult for farmers to plan and sustain consistent production. They further pointed out that trade liberalization and the influx of cheaper imported corn have exposed local farmers to volatile price competition, resulting in shrinking profit margins. These combined environmental and economic pressures compel farmers to make reactive, short-term planting decisions, leading to erratic production outputs. Such fluctuations represent transitions between productive and underproductive states, which are characteristic of regime shifts. These shifts are not merely isolated disruptions but form long-term structural barriers that hinder the agricultural sector's ability to achieve consistent growth and food security. This dual vulnerability underscores the urgent need for predictive systems capable of capturing and anticipating these regime transitions. Similarly, in the study of Lim (2023) in the rice sector, rice self-sufficiency remains a central pillar of national food security. The findings showed that cultivated area and irrigation costs are significant drivers of rice production, while fertilizer costs, despite statistical significance, had little influence on price levels. Furthermore, consumption was found to Granger-cause changes in self-sufficiency, and together with pricing, these variables influenced production behavior. These insights from both rice and corn production sectors underscore the urgency of adopting predictive systems that integrate economic and environmental factors to effectively manage regime transitions and improve agricultural resilience in the Philippines.

Government agricultural interventions, while aimed at stabilizing the corn production sector, have often yielded inconsistent results. Measures such as input subsidies and minimum support prices are designed to reduce costs and guarantee income for farmers, but in practice, these policies are frequently weakened by bureaucratic delays, uneven implementation, and political turnover. According to Amaglobeli et al. (2024), while certain policy initiatives led to short-term improvements in productivity, they failed to resolve fundamental structural problems, particularly those related to insufficient rural infrastructure and underfunded extension services. These shortcomings limit the ability of such interventions to deliver sustained impact. Separately, Poonon (2023) observed that earlier corn development programs encountered difficulties in scaling due to fragmented coordination among national and local agencies. This lack of continuity undermined momentum and caused policy benefits to be short-lived. As a result, government efforts often produce brief gains followed by stagnation or decline, making long-term agricultural development unpredictable. These cycles reflect policy-induced regime shifts and highlight the need for data-driven modeling tools to identify hidden patterns and evaluate policy effectiveness more rigorously. Strengthening institutional capacity and using analytical frameworks that capture these shifts are critical to designing reforms that are resilient and adaptive over time.

Department of Agriculture (2023) emphasized that improving corn productivity is central to poverty reduction and rural development. Moreover, it is also stated that stable corn production contributes to food security and economic resilience, especially for rural communities that depend heavily on agricultural income. When production is erratic, the effects ripple throughout the food supply chain, disrupting pricing, availability, and household nutrition. Understanding these macroeconomic linkages underscores the strategic role of corn in national development and reinforces the value of models that can forecast shifts in supply dynamics. Meanwhile, Valdez (2022) stated that corn contributes significantly to the stability of food prices and rural incomes, given its diverse applications and widespread cultivation. Despite its central importance, the sector continues to face deep-rooted structural and environmental challenges that threaten production consistency. Addressing these issues through empirical investigation and robust modeling is vital for supporting policy formulation and long-term agricultural sustainability. Corn's economic significance extends beyond its role as a staple food. Moreover, the same author reported that roughly 70 percent of livestock feed in the country relies on corn, linking its output directly to meat, egg supply, and food prices.

As traditional forecasting models fall short in detecting abrupt changes in agricultural outputs, researchers have turned to more flexible tools like Hidden Markov Models (HMMs). Wang et al. (2020) pointed out that traditional trend analyses assume consistency, which is unsuitable for volatile systems like Philippine agriculture. In contrast, HMMs can identify sudden regime shifts by modeling transitions between high- and low-output states. Abhijeet et al. (2023) further recommended integrating these models with multidimensional evaluation frameworks, including environmental, economic, and social indicators, to inform more inclusive and effective planning. These models are not only statistically robust but also adaptable to the complexities of agricultural environments. Integrating such modeling tools with policy frameworks can transform how governments respond to threats and opportunities in the sector. The global application of Hidden Markov Models (HMMs) in agriculture has offered significant insights into identifying regime shifts that traditional time series models often overlook. Mihrete (2025) noted that diversification not only reduces the risks of monoculture systems but also contributes to more stable farm incomes. Integrating robust analytical tools like HMMs with ecologically sound farming practices such as diversification presents a dual approach to building resilient agricultural systems, particularly in vulnerable regions like the Philippines.

For instance, Ferreira et al. (2021) demonstrated the model's ability to detect transitions between drought and recovery phases, or from low- to high-yield regimes, thus enhancing early warning capabilities and supporting informed decision-making. These models have proven effective in monitoring rainfall, livestock markets, and crop yields, offering probabilistic clarity that guides resource allocation and risk management. Alongside predictive modeling, crop diversification has gained attention as a sustainable strategy to buffer against climate variability, pest outbreaks, and market volatility. By adopting spatial, temporal, genetic, or intercropping methods, farmers can enhance soil health, suppress pest populations, and increase adaptability to changing environmental conditions. In the Philippine context, Ortiz and Torres (2019) stressed that diversification practices, particularly intercropping corn with legumes and vegetables, have helped smallholder farmers increase productivity while improving soil fertility and reducing pest pressure. These locally adapted strategies are essential for building resilience in vulnerable agricultural communities facing the compounded threats of climate change and economic uncertainty.

The main goal of this research is to simulate and analyze the structural dynamics of quarterly Philippine corn production during the period 2010–2025 using a Hidden Markov Model (HMM) framework. By modeling the probabilistic switching between high- and low-volatility regimes, this study aims to better understand production trends and inform policy decisions related to risk mitigation, food security, and agricultural sustainability. This research supports the United Nations Sustainable Development Goal 2: Zero Hunger, by addressing the need for resilience and innovation in agricultural systems through improved forecasting and regime modeling. As the Philippine agricultural landscape continues to evolve, tools that offer both interpretability and forecasting power will be essential to steering it toward sustainability and inclusive growth.

THEORETICAL FRAMEWORK OF THE STUDY

The research utilizes a regime-switching framework based on a Hidden Markov Model (HMM) to examine quarterly Philippines' corn production between 2010 and 2025. The theoretical underpinning of such a framework relies on Time Series Regime Theory (Douc et al., 2014), which holds that economic or agricultural systems (Lebrini et al., 2020) may switch from one distinct state (or regime) to another as a result of structural changes (Scott et. al., 2005), shocks (Maheu & Yang, 2016), or seasonality (Sansom &

Thomson, 2007). Within agricultural production, these regimes tend to exhibit alternating regimes of high and low volatility caused by climatic uncertainty (Pozzi et al., 2017), the cycle of planting and harvesting, market forces (Shibata, 2019), and policy changes. The basic assumption is that the observed data, i.e., crop yield, result from latent (hidden) processes whose dynamics change over time through probabilistic transitions (Bernemann et al., 2022). The theory's core postulate, the Markov property, argues that the present regime is a function of the previous state alone, and not of the sequence of states leading up to it.

The Theory of Stochastic Processes also forms the methodological basis of this research. It enables time-dependent crop data to be modeled as random processes where the outcomes develop in accordance with a probability structure (Cox, 2017). The Hidden Markov Model is one of the stochastic models, and it facilitates the identification of regime-dependent behavior without observing the states themselves (Kouemou & Dymarski, 2011). It is especially applicable to agricultural production data where underlying conditions—e.g., stress due to weather, pest epidemics, or policy measures—are not necessarily directly measurable but affect patterns of production (Chandi et al., 2021). By taking a probabilistic modeling approach, this research embodies the complexity and variability in agricultural systems, providing greater insight into production volatility and its sources of structure (Gikhman & Skorokhod, 2004).

In addition, the application of Bayesian Learning Theory supplements the regime-switching approach by adding prior information regarding the parameters and refining this with observable data (Jacobs & Kruschke, 2011). This is particularly applicable in situations involving limited data or when expert opinion can be highly valuable. The Bayesian view not only improves interpretability and reliability but also replicates the decision-making process in agricultural policy, where prior beliefs are constantly revised in light of new information (Afrabandpey et al., 2020). This combination of regime-switching theory, stochastic processes, and Bayesian inference offers a rich and theoretically well-established framework for examining the dynamic nature (Petetin et al., 2021) of corn production in the Philippines.

METHOD

The research utilized a probabilistic time series modeling strategy using a Hidden Markov Model (HMM) framework for tracing regime-switching patterns (Zheng et al., 2021) in Philippine corn production. The aim was to segment quarterly production data into distinct states of volatility and test the dynamics of these state transitions. A 1-state and 2-state HMM were estimated and compared to gauge whether regime segmentation offered statistically and practically significant gains in modeling performance. Modeling was done via maximum likelihood estimation techniques, augmented by Bayesian analysis for the purpose of testing prior assumptions and model plausibility (Scott, 2011).

Data Description

The data sample includes 61 quarterly observations of corn production in the Philippines, covering the period from the first quarter of 2010 to the first quarter of 2025, based on national agricultural production records (Rice and Corn: Monthly Total Stocks Inventory by Sector-PX-Web, 2017). The series shows evident cyclical and seasonal changes, which imply the potential for structural breaks or regimes of volatility. Descriptive statistics provide an average of 634,881 metric tons and a standard deviation of 178,995, with a minimum of 270,668.3 and a maximum of 967,727 metric tons. These descriptive features hint at moderate variation and regime-based clustering of production levels.

Stationarity Testing

Before estimating the model, the time series was tested for stationarity using the Augmented Dickey-Fuller (ADF) test to check if the model was appropriate. The outcome of the ADF test revealed that the initial series was trend-stationary, and therefore, no differencing was used. Stationarity retention is very essential for the validity of HMM hypotheses, especially those concerning regime transition dynamics as well as the ergodicity of the underlying Markov chain.

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Model Specification

Two HMMs were defined: a 1-state model, which applies constant statistical characteristics over time (no regime changes), and a 2-state model, in which the data are free to switch between two regimes, recognized as low volatility and high volatility states. Each state was represented by its own intercept and residual variance. Transition probabilities were designed as a Markov chain, enabling the probability of a switch between regimes to be learnt from the data.

The Hidden Markov Model (HMM) in this study assumes that the Philippine corn production over time can be explained by a latent (hidden) state process that switches between unobserved regimes: Regime 1 (low volatility) and Regime 2 (high volatility). In each regime, the observed data follow a distinct distribution with its own parameters, specifically the mean and variance. The switching between regimes is governed by a first-order Markov chain, meaning the probability of being in a particular regime at time depends only on the regime at time . This allows the model to capture abrupt shifts in production patterns due to seasonal effects, weather shocks, or policy shifts. The general form of the HMM in this context is expressed as:

$$\gamma_t \mid S_t = j \sim \aleph\left(\mu_j, \sigma_j^2\right), \quad j \in \{1, 2\}$$

$$P\ ((S_t = j \mid S_{t-1} = i) = p_{ij}$$

Where:

y_t is the observed corn production at time t.

S_t is the unobserved (hidden) state at time t, which can be either 1 (low volatility) or 2 (high volatility).

μ_j and σ_j^2 are the regime-specific mean and variance parameters.

pij is the transition probability from regime i at time $t-1$ to regime j at time t, forming a 2x2 transition matrix.

The transition matrix is defined as:

$$P = \begin{bmatrix} P(S_t = 1 \mid S_{t-1} = 1) & P(S_t = 2 \mid S_t = 1 \quad) \\ P(S_t = 1 \mid S_{t-2} = 2) & P(S_t = 2 \mid S_{t-1} = 2 \quad) \end{bmatrix} = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix}$$

Given that the transition probabilities in this study were approximately $p_{11} \approx 0, p_{12} \approx 1, p_{21} \approx 1$, and $p_{22} \approx 0$, the system exhibits a near-deterministic back-and-forth switching between two regimes. The HMM used herein represents corn production as being produced by two switching normal processes, each with different intercept and volatility structure, driven by a regime process that follows Markovian dynamics. This allows for the detection and identification of regime shifts in the data that are not observable.

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Prior Distribution

Within the Bayesian approach used for interpretation and validation, non-informative priors were assigned to the mean (μ) and standard deviation (σ), with a symmetric normal prior for μ with a mean of 0 and a right-skewed inverse-gamma-like prior for σ. This design allowed testing of how well observed data matched or diverged from expectations based on prior knowledge, especially considering variability in production.

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Estimation Procedure

Estimation was done with the Expectation-Maximization (EM) algorithm to optimize the log-likelihood function. The 1-state HMM converged at iteration 1 with log-likelihood -846.4626, and the 2-state HMM converged at iteration 18 with much better log-likelihood -785.7497. Transition probabilities, regime-dependent parameters, and smoothed probabilities were calculated after estimation to predict each observation as one of the two regimes and to plot regime dynamics over time.

Model Diagnostics

Model diagnostics involved checking residual standard errors, R^2 values, and transition probability matrices. The residual standard error was significantly smaller in the low-volatility regime (~65,126) than in the high-volatility regime (~213,140), which reflects an evident distinction in state behavior. The transition matrix showed a virtually deterministic switching pattern with almost 100% chance of moving to the other regime every time step, prompting concerns about potential overfitting or overly simplistic model assumptions.

Model Comparison

Model choice was informed by information criteria and log-likelihoods. The 2-state HMM performed better than the 1-state model, with a smaller AIC (1575.499 vs. 1696.925) and BIC (1587.877 vs. 1701.114), and a larger approximate log-marginal likelihood (-800.080 vs. -850.557). These findings affirm the presence of structural regime changes in the corn production series and warrant the use of a 2-state HMM as a better description of the underlying dynamics.

RESULTS AND DISCUSSIONS

This study aims to examine and model how Philippine corn production changes over time. It looks at data from 2010 to 2025, broken down by quarters. The research uses a Bayesian Markov Switching approach to analyze price swings. The goal is to spot different patterns in price changes and how long these patterns last. It also tries to figure out how likely it is for prices to shift from one pattern to another. By using Bayesian methods, the study adds to what was already known. This helps present a better understanding of how the market works. In the end, this research aims to shape farm policies, assess market risks, and plan strategies for people involved in corn farming.

Table 1 shows descriptive statistics of quarterly corn production in the Philippines from the first quarter of 2010 to the first quarter of 2025 based on 61 observations. The period average production is about 634,881 metric tons, with a median of 642,805.17, indicating a relatively symmetric distribution, as also evident by the low skewness value of -0.136. The standard deviation of 178,995.28 indicates moderate variability in quarterly production, with the range covering a wide 697,058.7 metric tons, from a low of 270,668.3 to a high of 967,727 metric tons. The negative value of the kurtosis measure, -0.774, means the distribution is slightly flatter than would be expected under a normal distribution, with fewer extreme production values. The total production over the 15 years is 38.73 million metric tons, and the sample variance also attests to high dispersion in the data. These statistics indicate that although the production of corn is overall fairly consistent over time, it does have significant quarterly variation on what is presumably seasonal, climatic, or policy-driven effects.

Table 1. Descriptive Statistics on the Quarterly Corn Production in the Philippines, 2010 to 2025

Corn Production	
Mean	634881.4
Standard Error	22918
Median	642805.2
Standard Deviation	178995.3

Sample Variance	3.2E+10
Kurtosis	-0.7744
Skewness	-0.13635
Range	697058.7
Minimum	270668.3
Maximum	967727
Sum	38727768
Count	61

The line graph tracks quarterly corn output in the Philippines between 2010 and 2025 and shows the seasonal ebb and flow each twelve-month cycle brings. Across the period, recorded harvests vary widely, falling somewhere between 300,000 metric tons on the low end and exceeding 1,000,000 metric tons in the strongest quarter. Such steady oscillation points to deep-rooted seasonality, almost certainly tied to planting winds and monsoon rains that guide Philippine farm calendars. Although the data as a whole does not drift visibly upward or downward over the longer stretch, short-term wobbles reveal farmers' sensitivity to weather, fertilizer prices, import rules, or other outside changes. Certain quarters still account for sharper plummets or sudden surges, pointing to one-off storms, supply shortages, or unexpected policy moves disrupting the expected rhythm.

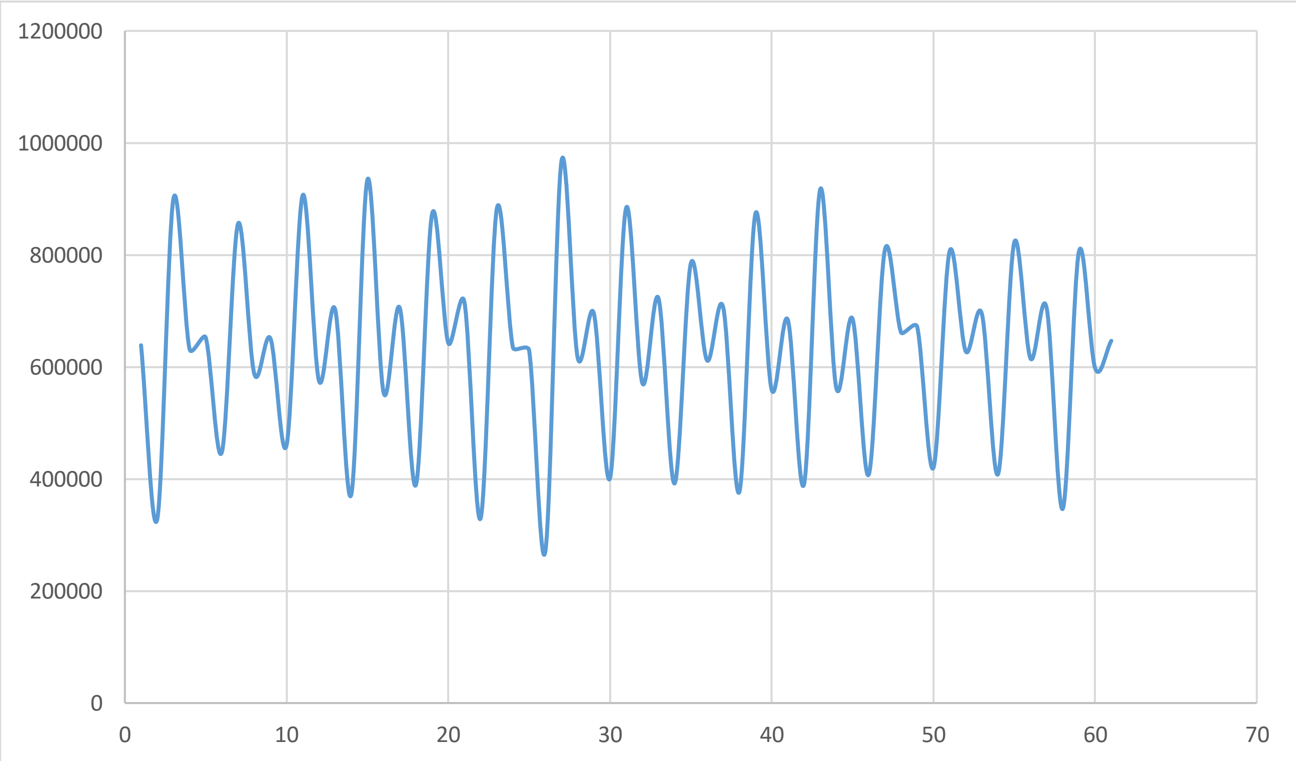

Figure 1. Quarterly Corn Production in the Philippines, 2010 to 2025

The figure above shows two prior distributions from a Bayesian analysis of quarterly corn production in the Philippines. It focuses on the mean (μ) and standard deviation (σ). The left panel displays a symmetric prior distribution for the mean, centered at zero. The sample mean is shown by a red dashed line, which is far from the peak. This indicates a significant difference between prior belief and observed data. The right panel presents a right-skewed prior for the standard deviation. It peaks close to zero and declines as σ increases. Here, the red dashed line marks the sample standard deviation. It is positioned much further to the right of the mode, suggesting that the observed variability is higher than what the prior assumed. Overall, this visual comparison highlights the potential conflict between prior assumptions and actual data. Such conflicts could significantly affect posterior estimates if the priors carry a lot of weight.

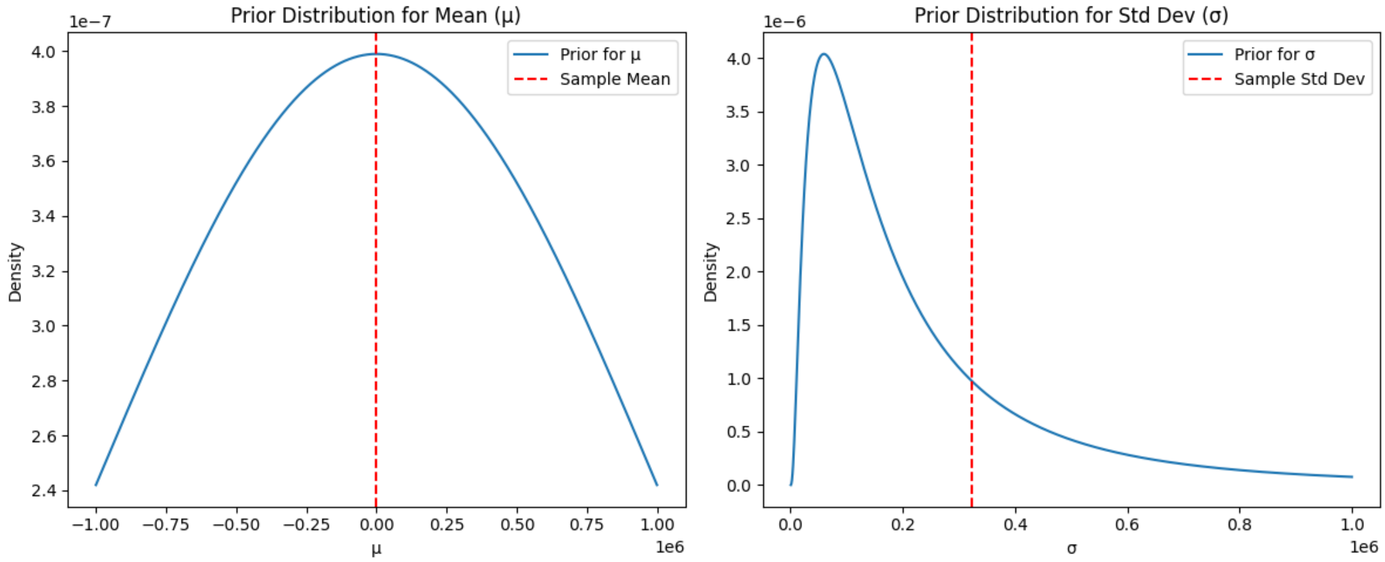

Figure 2. Prior Distribution for Mean and Standard Deviation

Key model selection metrics for the 2-state Hidden Markov Model (HMM) applied to corn production data are shown in Table 2. The model's Bayesian Information Criterion (BIC) of 1587.877 and Akaike Information Criterion (AIC) of 1575.499 both show a reasonably good balance between complexity and model fit. The model's ability to capture the underlying data structure is indicated by the log-likelihood value of -785.7497. The 2-state HMM was chosen as the preferred specification because it offers a better explanation of regime dynamics in corn production without causing undue overfitting, as evidenced by lower AIC and BIC values when compared to simpler models.

Table 2. Model Selection Criteria for the 2-State HMM

Metric	**Value**
AIC	1575.499
BIC	1587.877
Log-Likelihood	-785.7497

Table 3 shows the regression coefficients for a two-regime Markov Switching Model applied to corn production data in the Philippines. It distinguishes between low and high volatility periods. In Regime 1, which is marked by low volatility, the model estimates an intercept of -283,061 with a residual standard error of 65,125.95. In Regime 2, linked to high volatility, the intercept changes to 283,325 with a much larger residual standard error of 213,139.60. Both regimes have an R^2 of 0, meaning the intercept-only model does not explain any of the variation in the data. The absence of standard errors, t-values, and p-values (NaNs) indicates that the coefficients are not being tested for significance. This might be due to limits in model estimation or a focus on classifying regimes rather than drawing inferences. The clear difference in residual variability between the two regimes shows that the Markov Switching framework captures distinct phases of volatility, even if the model's explanatory power is minimal.

Table 3. Regression Coefficients

Regime 1 (Low Volatility)				
Coefficient	Estimate	Std. Error	t-value	p-value
(Intercept)	-283,061	NaN	NaN	NaN
Residual Std. Error	65,125.95			
R^2	0			

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<table>
<tr><th colspan="5">Regime 2 (High Volatility)</th></tr>
<tr><td>Coefficient</td><td>Estimate</td><td>Std. Error</td><td>t-value</td><td>p-value</td></tr>
<tr><td>(Intercept)</td><td>283,325</td><td rowspan="3">NaN</td><td rowspan="3">NaN</td><td rowspan="3">NaN</td></tr>
<tr><td>Residual Std. Error</td><td>213,139.60</td></tr>
<tr><td>R^2</td><td>0</td></tr>
</table>

The transition probability in Table 4 shows a very high chance of switching between the two states in the Markov Switching Model for corn production. If the process is in Regime 1 (low volatility), there is almost a 0% chance of staying there (2.95×10^{15}) and nearly a 100% chance of moving to Regime 2 (high volatility). On the other hand, when in Regime 2, the chance of remaining there is also almost zero (2.88×10^{-19}), with a 100% chance of returning to Regime 1. This back-and-forth behavior suggests a clear and sudden switching pattern between the regimes, which is unusual and might point to a flaw in the model or overfitting. In reality, such strict transitions do not represent true random dynamics. It may be necessary to refine the model or reassess how the regimes are identified.

Table 4. Transition Probabilities

From → To	**Regime 1**	**Regime 2**
Regime 1	2.95×10^{-15} (≈0%)	100%
Regime 2	100%	2.88×10^{-19} (≈0%)

Table 5 compares the performance of a 1-state and a 2-state Hidden Markov Model (HMM) used with corn production data. The 2-state HMM shows a much higher log-likelihood (-785.75 compared to -846.46) and has lower AIC and BIC values. This suggests it fits the data better, even though it is more complex. The approximate log marginal likelihood also supports the 2-state model (-800.080 compared to -850.557), highlighting its ability to capture underlying regime dynamics. These findings indicate that there are structural changes or regime shifts, like transitions between low and high volatility periods, in the corn production process. The simpler 1-state model does not account for these changes.

Table 5. Model Comparison of Hidden Markov Models for Corn Production

Model	**LogLik**	**AIC**	**BIC**	**Approx. Log Marginal**
1-state HMM	-846.4626	1696.925	1701.114	-850.557
2-state HMM	-785.7497	1585.499	1600.16	-800.08

Figure 4 shows the posterior density and trace plots for the parameters μ (mean) and σ (standard deviation) from a Bayesian Markov Switching Model applied to Philippine corn price data. The top row concerns the parameter μ. The left plot presents a symmetric bell-shaped density centered near zero, suggesting that the posterior mean behaves well and aligns with a weakly informative prior. The trace plot on the right indicates good mixing and stationarity, which means there is convergence across MCMC iterations. The bottom row illustrates the posterior for σ. Here, the density plot is right-skewed and centered around 300,000, reflecting the model's inference of notable volatility in the data. The corresponding trace plot shows stable sampling behavior, further supporting convergence. Together, these plots confirm that the Bayesian sampler effectively explored the parameter space, and the priors were loose enough for the data to guide the inference.

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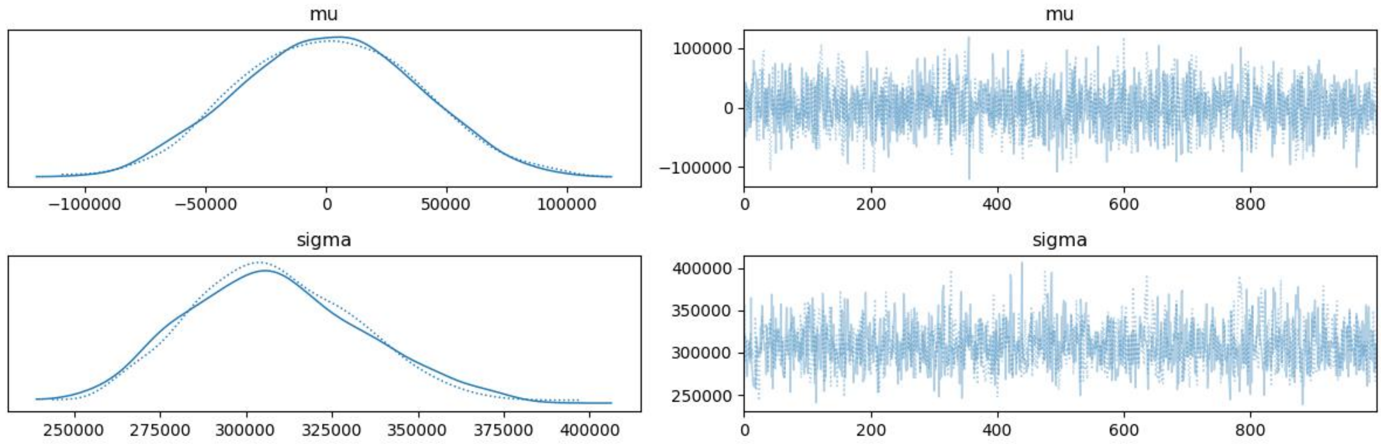

Figure 4. Posterior Distributions and Trace Plots for Mean (μ) and Standard Deviation (σ) in a Bayesian Markov Switching Model

In Figure 5, a regime timeline visualization produced by a Hidden Markov Model (HMM) that divides corn production values into two separate regimes over 61 time points is shown in the above figure. Higher production values are represented by Regime 2 (orange dots), whereas periods of lower or negative deviations are represented by Regime 1 (blue dots). The grey lines that connect the observed values create a zigzag pattern that emphasizes the two regimes' alternation. With frequent transitions indicating that the corn production system rapidly switches between low and high volatility states, the model successfully depicts the cyclical changes in volatility. The deterministic character of regime switching deduced from the data is confirmed by this visualization, which also validates previous conclusions drawn from the regime transition probabilities.

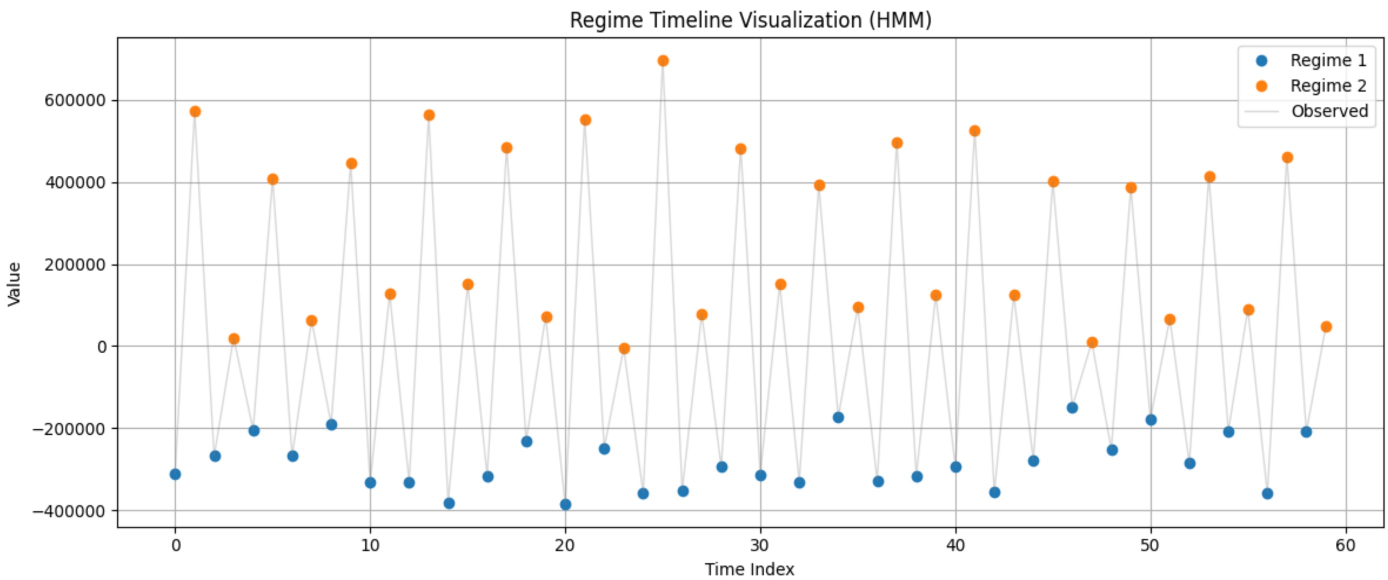

Figure 5. Regime Classification Over Time Based on HMM Analysis

The study's outcomes shed light on how quarterly corn production in the Philippines changes over time. This research draws on Time Series Regime Theory and Stochastic Process Theory. It shows that corn output switches between periods of low and high instability (Mendoza & Nabua, 2018). The 2-state Hidden Markov Model fits the data much better than the 1-state model. In this, it has a lower AIC, BIC, and higher log-likelihood. This proves that the production process goes through big shifts. The timeline of regime changes and the odds of switching from one state to another back this up. They show a clear pattern of change, with output moving back and forth between two states. This might happen because of seasons, weather changes, volatility in the market, or policy changes. These results support the idea that hidden changing processes shape farm output (Montano, 2024). It captures these processes well with models that account for regime changes. This gives useful information to predict trends, gauge risks, and plan policies for farming.

CONCLUSION

Corn production in the Philippines continues to face significant structural challenges due to its exposure to both environmental and economic pressures. As highlighted in the introduction, climatic events such as El Niño and La Niña, volatile market forces, policy inconsistencies, and weak infrastructure contribute to the erratic nature of agricultural output. These disruptive factors often cause regime shifts, or sudden changes in production patterns, which traditional linear models fail to effectively capture. This study sought to address this analytical gap by applying a Hidden Markov Model (HMM) to quarterly corn production data from 2010 to 2025, with the goal of detecting and understanding underlying volatility regimes.

The application of a two-state HMM successfully classified the production periods into low- and high-volatility regimes, uncovering hidden structural patterns within the data. The findings revealed a near-deterministic switching behavior between the two regimes, which suggests that Philippine corn production follows a consistent cyclical structure, rather than a random or steadily evolving pattern. These insights confirm that corn output is influenced by unobserved but recurring processes, such as seasonal trends and policy cycles, which significantly affect farmers' decision-making and national food supply planning.

Statistical comparisons between the one-regime and two-regime models clearly demonstrated the superiority of the regime-switching approach. The lower AIC and BIC values and improved log-likelihood scores of the two-state model validated its ability to represent the volatility structure in corn production more accurately. These results provide empirical support for adopting HMMs as a forecasting and planning tool in Philippine agriculture. Moreover, the use of Bayesian inference to enhance the robustness and interpretability of the model allowed for a more nuanced understanding of production uncertainty, highlighting the compatibility of advanced stochastic processes with real-world agricultural data.

Given the importance of corn as the second most vital crop in the Philippines—used for food, feed, and industry—the implications of this study extend to national development goals. The ability to model and predict regime shifts equips policymakers with the foresight needed to implement better-timed agricultural programs, mitigate production risks, and protect smallholder farmers from adverse market and environmental shocks. The insights generated also contribute to achieving Sustainable Development Goal 2 (Zero Hunger) by promoting a resilient and data-informed agricultural sector.

In summary, this research demonstrates that Hidden Markov Models are a powerful tool for detecting hidden regime shifts in Philippine corn production. By identifying patterns that traditional models often overlook, this study provides a foundation for more informed agricultural policy, risk management strategies, and long-term planning. Future studies may build on these findings by incorporating explanatory variables such as rainfall, global corn prices, and input costs, or by applying the model to other crops and regions. Such expansions will further enhance the capacity of data-driven approaches to transform the way agricultural volatility is understood and addressed in the Philippines.

RECOMMENDATIONS

Based on the research findings, the researchers present the following recommendations to inform decision-making.

It is recommended that the Department of Agriculture integrate regime-switching models, particularly the Hidden Markov Model (HMM), into its agricultural monitoring and forecasting systems. These models can help identify periods of heightened volatility in corn production and provide signals for preemptive policy intervention. The department should establish a specialized analytics team or collaborate with academic institutions to regularly update and interpret regime classifications. These classifications can then be used as a guide for seasonal planning and distribution of farming inputs.

In addition, the DA should consider aligning its policy mechanisms, such as the timing of fertilizer subsidies, post-harvest support, and crop insurance rollout, with the regime patterns detected in the data. Since the study revealed that switching behavior occurs with near certainty between volatility states, policies must be implemented in anticipation of these shifts rather than as reactions. Developing a risk management framework based on regime cycles would strengthen the department's ability to respond to structural fluctuations in production and help reduce the likelihood of major disruptions in the corn supply.

Farmers are advised to incorporate awareness of production volatility patterns into their planning and operational strategies. It is recommended that training sessions and informational bulletins be developed to help farmers understand and apply regime-based forecasts. These forecasts can assist in deciding when to increase or reduce planting, adjust input usage, or consider alternative crops, depending on the expected production volatility for a given quarter.

Moreover, farmers should also coordinate with local cooperatives and municipal agricultural offices to gain access to localized and timely regime forecasts. These updates, which can be derived from the findings of this study, will provide practical guidance for adjusting farming calendars and risk management efforts. It is also recommended that farmers use regime insights to inform decisions on post-harvest storage and marketing, particularly during quarters with expected high volatility. This approach will support more stable income and improved decision-making in a changing production environment.

Future researchers are encouraged to refine and build upon the two-regime Hidden Markov Model framework applied in this study. One recommended direction is to incorporate additional explanatory variables, such as climate data, pest occurrences, input prices, or policy interventions. These factors may help reveal the underlying causes of regime transitions and improve the model's ability to predict future shifts with greater accuracy and clarity.

It is also suggested that future studies examine regional or provincial-level corn production data to determine whether different areas experience distinct volatility regimes. Conducting this type of disaggregated analysis may uncover localized dynamics that are not visible in national models. Lastly, researchers are advised to explore the development of digital tools or forecasting platforms that present regime data in user-friendly formats. These tools could support decision-making not only for researchers and policymakers but also for farmers and agribusiness stakeholders who rely on timely and accurate production insights.

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