PLANT SCIENCE TODAY
Vol 12(4): 1-12
https://doi.org/10.14719/pst.9291

eISSN 2348-1900

RESEARCH ARTICLE

Ginger price dynamics in the Eastern Himalayan Region: A case study of Meghalaya

N Uttam Singh[1], Abhishek Thakur[1*], Anjoo Yumnam[1], A Roy[1], N Laitonjam[1], Pampi Paul[1], Kamni P Biam[1], C Gowda HR[1], AK Jha[2], Wanbiang Dkhar[1], BP Singh[1] & SB Singh[1]

[1]Division of Technology Assessment and Capacity Building, ICAR Research Complex for Northeastern Hill Region, Umiam 793 103, Meghalaya, India
[2]Division of Natural Science Management, Directorate of Knowledge Management in Agriculture, ICAR, Pusa, New Delhi 110 012, India

*Correspondence email - thakurabhishek7188@gmail.com

Received: 04 May 2025; Accepted: 12 July 2025; Available online: Version 1.0: 07 September 2025; Version 2.0: 01 October 2025

Cite this article: Uttam NS, Abhishek T, Anjoo Y, Roy A, Laitonjam N, Pampi P, Kamni PB, Gowda CHR, Jha AK, Wanbiang D, Singh BP, Singh SB. Ginger price dynamics in the Eastern Himalayan region: A case study of Meghalaya. Plant Science Today. 2025; 12(4): 1-12. https://doi.org/10.14719/pst.9291

Abstract

Ginger contributes substantially to the agricultural sector in Meghalaya, yet comprehensive forecasting analyses that integrate both traditional and volatility-sensitive time series approaches to study its price movements are still scarce. In this study, we explore common time series yet very powerful forecast models, namely the autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA) and ARIMA with exogenous inputs (ARIMAX), along with autoregressive conditional heteroscedasticity (ARCH) and generalized autoregressive conditional heteroscedasticity (GARCH) models, to forecast the monthly price of ginger in Meghalaya. During the estimation process, attention was given to the intrinsic forecasting strengths and limitations of these models, as well as to essential time series diagnostics, including stationarity, parsimony and overfitting. The discussion in this study is based on the forecast results obtained from a real-time monthly price dataset spanning 10 years. While fitting the models to the dataset, special care was taken to select the most parsimonious model. To evaluate forecast accuracy and compare the performance of the different models applied to the time series of monthly ginger prices, we used seven forecast performance measures: ME (mean error), RMSE (root mean square error), MAE (mean absolute error), MAPE (mean absolute percentage error), MASE (mean absolute scaled error), AIC (Akaike information criterion) and BIC (Bayesian information criterion). The GARCH (1,1) model outperformed the others, yielding the lowest MAE (1,212.28), MASE (0.2817) and a high persistence in volatility (β_1 = 0.99772). The average price during the study period was ₹4400.47. The forecasts indicated a decline in prices from ₹11910 in March 2024 to ₹10938 in July 2024.

Keywords: ARIMA; ginger; time series; trend

Introduction

Ginger (*Zingiber offficinale* Rosc.) is a perennial spice and medicinal crop renowned for its rhizomes, cultivated primarily for its underground branched stem, known as a rhizome (1). Belonging to the family Zingiberaceae, ginger is a subtropical perennial herbaceous plant with widespread cultivation worldwide. India, a dominant producer, contributes approximately 35 % to the global production capacity of ginger (2). With a cultivation area of 0.17 million hectares and a production output of 1.84 million tons, India maintains a productivity rate of 10.72 tons per hectare (3). The versatility of ginger is reflected in its use across various products, both as a fresh vegetable and a dried spice, in India (4).

Ginger rhizome holds significant importance as a spice, flavoring agent and traditional herbal remedy, exhibiting anti-emetic, antioxidant and anti-inflammatory properties against respiratory tract infections (5). Owing to its remarkable health benefits, ginger cultivation has proliferated globally, with extensive growth observed in tropical and sub-tropical regions. The dynamics of ginger pricing present significant challenges due to the inherent characteristics of agricultural commodities, including high volatility, non-stationarity, non-linearity, seasonality and calendar effects (6). Despite efforts to predict ginger prices using various methodologies, such as the popular univariate method auto regressive integrated moving average (ARIMA) employed in previous studies, pricing remains influenced by numerous unquantifiable factors (7). Overall, the historical significance and therapeutic properties of ginger underscore its widespread cultivation and usage, while the intricacies of price forecasting highlight the complexity of agricultural commodity markets.

Worldwide scenario of ginger production and price movement

Ginger production is significant in several countries, including India, China, Nepal, Nigeria, Thailand, Indonesia, Bangladesh, Japan and Cameroon, collectively contributing to almost 50 % of global production. India, the second-largest producer after China, dominates ginger cultivation, covering 40.1 % of the global cultivation area (8, 9). Ginger is cultivated for both fresh vegetables and dried spices (10). A trend analysis of ginger prices (in naira) and output in metric tonnes (MT) from 1990 to 2020 reveals fluctuating trends. Various factors such as forces of demand and supply, random variation and government policies and programs have triggered structural changes in both prices and output of ginger (11). India, being the second-largest exporter of ginger after China, underscores its importance in the global market. However, ginger production in Bangladesh is relatively low and identifying the shortcomings is crucial for enhancing production (12). Efforts to increase ginger production could result in significant improvement. Establishing an efficient marketing organization is essential for sustainable ginger farming in Bangladesh. Ginger cultivation involves several varieties and farmers use them to produce ginger. However, the volatile nature of the ginger market may discourage farmers from cultivation (13). Despite this, ginger possesses high export potential, contributing to foreign currency earnings and uplifting the living standards of farmers, thereby benefiting the national economy (NTIS, 2016).

Ginger production and price movement in India

Madhya Pradesh stands as the largest producer of ginger in India, contributing 22.29 % to 31.18 % of the country's total output. Major ginger-growing regions in Madhya Pradesh include Chhindwara and Balaghat. In 2022, Madhya Pradesh alone produced nearly 692 million metric tons of ginger, surpassing Karnataka with 306.34 metric tons and Assam with 170.73 metric tons. Price fluctuations in garlic and ginger over recent years have subjected growers to significant risks. These fluctuations, exacerbated by climate risks, impact both production and market arrivals (14).

Increasing awareness of various market channels, crop weather advisories and market intelligence services can aid farmers in mitigating these risks. Accurate and timely price information provided by market intelligence services also facilitates policymakers in formulating policies regarding price stabilization. The agriculture development strategy (2015-2035), guiding Nepal's agricultural sector, prioritizes the ginger sub-sector for value chain development (ADS, 2014). Several challenges hinder the efficient marketing of ginger in India. These challenges include the diversity of ginger varieties cultivated, the absence of organized primary and terminal markets, unavailability of quality inputs (such as hybrid seeds), inadequate technology in cultivation and post-harvest management, lack of credit facilities and asymmetric price information among growers (15).

Spices produced in the Darjeeling sub-division of West Bengal, including ginger, cardamom and turmeric, face constraints such as poor crop management and post-harvest management practices, resulting in low production per unit area and low value of produce due to poor marketing strategies (16). Similarly, an examination of the efficiency of various ginger marketing channels in Himachal Pradesh revealed issues such as non-payment of sale proceeds at the time of sale, non-availability of scientific storage facilities and inadequate information relating to market prices and arrivals, all of which hinder marketing efficiency (17). In Kerala, an institution was found to be in place for marketing ginger, consisting of growers, merchants and other intermediaries' institutions, while the cooperative sector was observed to play a minimal role (18). A study on the management of marketing and export of ginger in the eastern Himalayan region identified three major marketing channels (19). Lack of price information among growers in subsequent market chains and terminal markets, absence of coordination among growers, accessibility problems and transportation costs and absence of storage facilities remain major challenges in the study areas.

Ginger production and price movement in Northeastern India

Ginger cultivation is widespread in almost all the states of the Northeastern region, with the leading states being Meghalaya, Mizoram, Arunachal Pradesh and Sikkim (20). According to the Government of India (2015), the leading producers of ginger in the Northeastern region are Assam (33.03 %), Meghalaya (17.01 %) and Sikkim (14.07 %), with Manipur being the least producer (1.03 %). The significance of ginger cultivation in the northeast was emphasized, highlighting it as a major cash crop (21). A notable feature of agriculture in the northeast region is the prevalence of jhum cultivation in large parts.

In the hilly regions, ginger is generally cultivated on raised beds called "buns" in the jhum fields (22). Four stakeholders for ginger marketing in Mizoram were identified, namely local agents (brokers), local traders, floating traders and itinerant dealers from outside the state (23). There was no organized system in place and outside traders were identified as the main actors in procurement and price determination in the state. It was reported that especially in Sikkim, the extraction of mother was done by female members and in Meghalaya, Mizoram and Nagaland, females played a dominant role in the retail selling of ginger (24). Adopting recommended practices in Sikkim led to higher average returns (Rs. 255 lakh) compared to traditional farming practices (Rs. 1.31 lakhs) (25). The region boasts several cultivated types of ginger, generally named after the localities they are grown in. Certain indigenous types, namely Maran, Bhola and Jorhat local of Assam, have been reported to be equally good in rhizome yield as well as in size. In Mizoram, local types such as Thingpui, Thingaria and Thinglaidum are grown on a large scale. Black ginger, with rhizomes having a bluish-black tinge inside, is reported to have medicinal properties and is grown by the inhabitants of Mizoram for commercial as well as personal use. In Sikkim, local types such as Bhainse and Gorubathan are grown commercially due to their high yield potential and large size rhizomes (26).

Ginger production and price movement in Meghalaya

Ginger cultivation is a traditional practice in Meghalaya's Umroi region (27). Due to the labor-intensive nature of ginger cultivation, it may not be ideal to grow it on the same piece of land year after year in the west Garo hills of Meghalaya (28). Price volatility stands out as one of the main issues affecting ginger marketing and production in the west Garo Hills of Meghalaya (29). The constraints faced by ginger growers in the region include a lack of skilled and unskilled labor availability, followed by high prices (30). Ginger not only generates income for farmers but also contributes significantly to the health sector with its medicinal value.

The pungency in ginger is attributed to gingerol, which is found to have the highest concentration in the Meghalaya local genotype, known for its medium size and suitability for export purposes. In addition to local varieties such as Meghalaya local and Tura local, considerable acreage in Meghalaya is dedicated to selected types like Nadia (26).

In Meghalaya, compared to earlier studies, this research presents a novel approach to analyzing and forecasting the monthly market price of ginger using advanced time series forecasting techniques. It involves a comprehensive analysis of price trends from 2014 to February 2024, including white noise testing, visual inspection and unit root tests to assess stationarity (31, 32). Advanced models such as ARIMA, ARIMAX and ARCH/GARCH are identified to select the best model for precise prediction of future price movements of ginger (33). The models have been chosen based on Parsimony that adequately fit the data selecting the simplest model for ARIMA and GARCH models. This involved selecting the lowest-order parameters (p, d, q) that balance fitness and forecast accuracy without overfitting. Evaluation criteria such as AIC, BIC, log-likelihood and accuracy metrics (ME, MAE, MAPE, RMSE, MASE) supported this process by penalizing overly complex models and ensuring optimal model simplicity and performance.

These models are selected based on their ability to minimize forecast errors and provide reliable predictions (34). The models have been compared based on the lowest values of various accuracy measures such as ME, MAE, MAPE, RMSE, MASE, log-likelihood and the AIC. Model comparison using BIC, AIC, RMSE and MAPE identifies the most effective models, which are then used to predict prices for the next five months (35). The accuracy of these forecasts is evaluated through statistical measures to ensure reliability (36). The findings offer critical insights for policymakers, traders and ginger growers, enabling informed decision-making and effective market planning (37). This study, therefore, contributes significantly to the literature on ginger price dynamics by delivering both analytical depth and practical forecasting tools tailored to the context of Meghalaya.

Materials and Methods

Autoregressive moving average (ARMA) models

An ARMA (p, q) model is a combination of autoregressive (AR) (p) and moving average (MA) (q) models and is suitable for univariate time series modelling. In an AR (p) model, the future value of a variable is assumed to be a linear combination of p past observations and a random error together with a constant term. Mathematically the AR (p) model can be expressed as:

$$y_t = c + \sum_{i=1}^{p} \varphi_i y_{it} + \varepsilon_t = c + \varphi_1 y_1 + \varphi_2 y_2 + \cdots + \varphi_p y_{t-p} + \varepsilon_t \qquad \text{(Eqn.1)}$$

Here, y_t and ε_t are respectively the actual value and random error (or random shock) at time period t, ϕ_i(i= 1, 2..., p) are model parameters and c is a constant. The integer constant p is known as the order of the model (38).

Stationarity analysis (unit root test)

To test for a unit root using the Augmented Dickey Fuller (ADF) test, one estimates the following model:

This is a regression of first-differenced series ($\triangle y_t$) on a constant term (α_0), a linear trend (α_2t), lagged levels (YY_{t-1})and augmented with lagged differences to ($\sum_{s=1}^{m} \beta_i \Delta y_{t-1}$) capture the whole dynamic nature of the process and fix autocorrelation of the residuals (39).

$$\Delta y_t = \alpha_0 + \alpha_2 t + \gamma y_{t-1} + \sum\nolimits_{s-1}^{m} \beta_i \Delta y_{t-1} + \varepsilon_t \qquad \text{(Eqn. 2)}$$

Autocorrelation and partial autocorrelation functions (ACF and PACF)

ACF and PACF analysis reflect how the observations in a time series are related to each other. For modelling and forecasting purposes it is often useful to plot the ACF and PACF against consecutive time lags to determine the order of AR and MA terms. The autocorrelation at lag k is defined as:

$$\rho_k = \frac{\gamma_k}{\gamma_0} \qquad \text{(Eqn. 3)}$$

Autoregressive integrated moving average (ARIMA) models

ARIMA model is a generalization of an ARMA model to include the case of non-stationarity in the model (37, 38, 40). In ARIMA models, a non-stationary time series is made stationary by applying finite differencing of the data points. The mathematical formulation of the ARIMA (p, d, q) model using lag polynomials is given below (38, 40):

$$\varphi(L)(1-L)^d y_t = \theta(L)\varepsilon_t \;\; i.e., (1 - \sum_{i=1}^{p} \varphi_i L^i)(1-L)^d y_t = (1 + \sum_{j=1}^{q} \theta_j L^j)\varepsilon_t \qquad \text{(Eqn. 4)}$$

Here, p, d and q are integers greater than or equal to zero and refer to the order of the autoregressive, integrated and MA parts of the model respectively. The integer d controls the level of difference.

Autoregressive conditional heteroscedastic (ARCH) model

One of the earliest time series models allowing for heteroscedasticity is the ARCH model. The ARCH (q) model for series {ε_t} is defined by specifying the conditional distribution of ε_t given information available up to time t-1.

Generalized autoregressive conditional heteroscedastic (GARCH) model

The GARCH model is an econometric term, in which conditional variance is also linear function of its own lags. A GARCH model has the following functional form:

$$\varepsilon_t = \xi_t \, h_t^{\frac{1}{2}} h_t = a_0 + \sum_{i=1}^{q} a_i \, \varepsilon_{t-1}^2 + \sum_{j=1}^{p} b_j \, h_{t-j} \qquad \text{(Eqn. 5)}$$

Where, εt ~ IID (0, 1) A sufficient condition for the conditional variance to be positive is ao > 0, ai ≥ 0, i = 1, 2,. . .., q. bj ≥ 0, j = 1, 2, . . ., p.

ARIMAX models

The ARIMAX model extends the ARIMA model to include exogenous input series. It expresses the response series as a combination of past values of random shocks and past values of other input series. The general ARIMA model with input series, also called the ARIMAX model, is written as:

$$W_t = \mu + \sum_i \frac{\omega_i(B)}{\delta_i(B)} B^{k_i} X_{i,t} + \frac{\theta(B)}{\emptyset(B)} a_t \qquad \text{(Eqn. 6)}$$

Ollech-Webel test (WO test)

The WO test aggregates the findings from the QS-test and the kw-test, which are both based on the residuals of a seasonal ARIMA model. The given time series will be classified as seasonal by the WO test, if the *p*-value of the QS-test is less than 0.01 and the *p*-value of the kw-test is less than 0.002 (41).

Forecast accuracy measures

To evaluate the amount of forecast error, the following measures are used (42-45). Let at is the actual data and Ft represents the forecast and n denotes the number of forecasts made. Then the mean error (ME) is merely the average error.

$$ME = \frac{1}{n} \sum_{t=1}^{n} (A_t - F_t) \qquad \text{(Eqn. 7)}$$

The mean absolute error (MAE) or mean absolute deviation (MAD)

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|A_t - F_t| \quad \text{(Eqn. 8)}$$

The mean squared error (MSE)

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2 \quad \text{(Eqn. 9)}$$

The root mean square error (RMSE)

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2} \quad \text{(Eqn. 10)}$$

The mean percentage error (MPE)

$$MPE = \left[\frac{1}{n}\sum_{t=1}^{n}\left(\frac{A_t - F_t}{A_t}\right)\right]100 \quad \text{(Eqn. 11)}$$

Mean absolute percentage error (MAPE).

$$MAPE = \left[\frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|\right]100\% \quad \text{(Eqn. 12)}$$

Kruskal Wallis test

Kruskal Wallis test is a nonparametric method for testing whether samples originated from the same distribution. It extends the Mann-Whitney U test to more than two groups. The null hypothesis of the Kruskal Wallis test is that the mean ranks of the groups are the same. Unlike the analogous one-way analysis of variance (ANOVA), the nonparametric Kruskal Wallis test does not assume a normal distribution of the underlying data. This test is useful as a general nonparametric test for comparing more than two independent samples.

Results and Discussion

The series chosen for forecasting is the monthly market price of ginger in Meghalaya for a period of 10 years, from January 2014 to February 2024. Over the 10-year period, events such as the COVID-19 pandemic and major agricultural policy reforms may have introduced regime shifts in ginger price dynamics. These disruptions-impacting supply chains, labor availability and market access-can alter the statistical properties of agricultural price series, potentially influencing forecast reliability. The pandemic-induced lockdowns resulted in price spikes of up to 60 % in horticultural commodities such as tomatoes and onions, highlighting the vulnerability of agricultural markets to external shocks (46). Although structural break tests were not applied in this study, their relevance is acknowledged for future research to more accurately capture such shifts in ginger price behavior.

In the identification stage, the response series and price were specified to identify candidate ARIMA models. The mean of the series was found to be 4400.47, with a standard deviation of 2882.03.

Trend in ginger price

The time series analysis of ginger prices in the Mawiong regulated market of Meghalaya from January 2014 to February 2024 was conducted to evaluate the trend and determine the presence of any significant changes over the period. The results are presented in Fig. 1 and Table 1. Fig. 1 illustrates the fluctuations in ginger prices over the specified period. The trend line equation, y = 0.2432x-6175.9, suggests a positive slope. However, a more robust analysis was needed to confirm the statistical significance of this trend.

To assess the significance of the observed trend, the Mann-Kendall trend test was employed. This non-parametric test is widely used to detect monotonic trends in time series data. Additionally, Sen's slope estimate was calculated to quantify the magnitude of the trend. The *z* value obtained from the Mann-Kendall test is -0.53552, with a corresponding *p* value of 0.5923. Since the *p* value is significantly higher than the 0.05 threshold, we do not reject the null hypothesis. This indicates that there is no statistically significant trend in ginger prices over the period analyzed. The slope estimate calculated by Sen's method is -2.97775. This negative value suggests a slight decrease in ginger prices. However, the wide confidence interval,

Table 1. Mann-Kendall trend test and Sen's slope estimate for price of ginger

Period	*z* value	*p* value	Sense slope estimate	Lower 95 % confidence level	Upper 95 % confidence level
2014 -2024	-0.5355	0.5923	-2.97775	-14.464375	9.016292

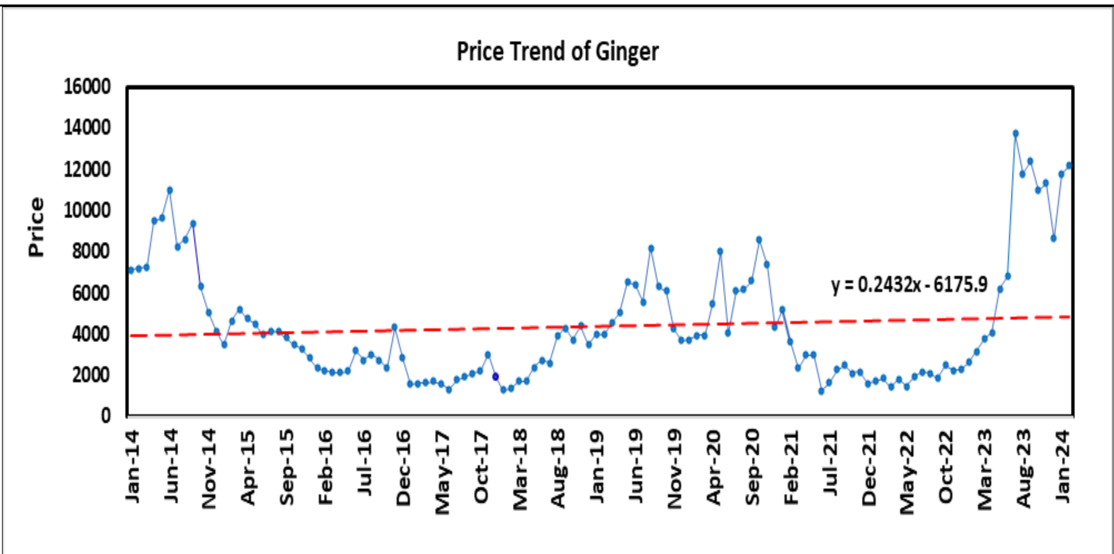

Fig. 1. Time series plot for market price of ginger.

ranging from -14.464375 to 9.016292, indicates considerable uncertainty around this estimate. The overlap of zero within this confidence interval further confirms the lack of a significant trend. This finding is essential for stakeholders in the ginger market, including farmers and policymakers, as it suggests that price fluctuations during this period are likely due to random variations rather than any underlying trend. Consequently, future strategies for market intervention should consider this lack of a significant trend in price behavior.

White noise (no autocorrelation) test

The test for white noise in the ginger price series was performed by examining autocorrelations up to lags 6 and 12. The results reveal significant autocorrelation across the specified lags, as indicated by the high Chi-square values and very low *p*-values ($p < 2.2e\text{-}16$) (Table 2). For lag 6, the Chi-square statistic was 325.11 (df = 6), while for lag 12, it was 340.39 (df = 12), both highly significant, thus rejecting the null hypothesis of no autocorrelation. At lag 6, autocorrelation coefficients ranged from 0.869 at lag 1 to 0.381 at lag 6, indicating a strong positive autocorrelation. Similarly, for lag 12, the coefficients gradually decreased from 0.268 at lag 7 to 0.021 at lag 12. These findings strongly suggest that the ginger price series exhibits significant autocorrelation, implying that an autoregressive (AR) process may be appropriate for modeling the underlying time series behavior.

Seasonality analysis

This is a test on autocorrelations at seasonal lags for time series data, which helps in detecting seasonality. The autocorrelation value at lag 12 indicates a strong seasonal pattern every 12 time periods. A value close to 1 means that the data at lag 12 is highly correlated with the current data point, suggesting strong seasonality on a yearly basis if the data is monthly as in the case of the current study. The autocorrelation value at lag 24 also indicates moderate seasonality every 24 time periods. A value of 0.7006 shows some seasonal effects at this lag, but not as strong as at lag 12. Chi-square (X^2) with 2 degrees of freedom shows its value 258.5028 (Table 3). This is a large test statistic, indicating a significant deviation from the null hypothesis of no autocorrelation. The very small *p*-value (< 0.01) indicates strong evidence against the null hypothesis of no seasonality. In other words, the test suggests that seasonality is present in the data at the seasonal lags tested. Based on the high autocorrelation values and the significant Chi-square test, there is strong evidence of seasonality in the time series data. The data shows a strong pattern of seasonality every 12 time periods, with some weaker seasonality at 24 periods. This result would typically lead to this seasonality explicitly prompting seasonal models.

Autocorrelation function (ACF) plot

The ACF plot of the ginger price series illustrates the correlation between the observations and their lagged values over time (Fig. 2). The ACF values demonstrate a rapid decay after lag 1, confirming that the time series is stationary. The significant spike at lag 1, with an autocorrelation coefficient of approximately 0.869, suggests a strong relationship between the current and the previous period's observations, supporting the presence of a non-seasonal first order MA (1) process. Subsequent lags show diminishing correlations, as all values lie within the confidence bounds (represented by the dotted blue lines), further reinforcing the notion of a stationary process supporting the conclus1ions drawn from Augmented Dickey-Fuller test.

Building on this, a detailed examination of the autocorrelation patterns at lags corresponding to multiples of the seasonal period (S = 12) was conducted, considering the monthly nature of the data. The analysis extended to lags 12, 24, 36 and up to 72. Significant spikes were identified at lags 7, 19 and 31 in the ACF, signaling potential seasonal components. Furthermore, the tapering pattern observed in the PACF is indicative of a seasonal MA process. These findings suggest the inclusion of one to three seasonal MA terms in the SARIMA model to accurately capture the

Table 2. Autocorrelation check for white noise of price of ginger

To lag	Chi square	df	*p* > Chi square	Autocorrelations					
6	325.11	6	2.2e-16	0.869	0.782	0.698	0.583	0.476	0.381
12	340.39	12	2.2e-16	0.268	0.160	0.114	0.054	0.042	0.021

Table 3. QS test for seasonality

Lags	Autocorrelations	Df	Chi-square	*p*-value
12	0.8238	2	258.5028	0.000
24	0.7006			

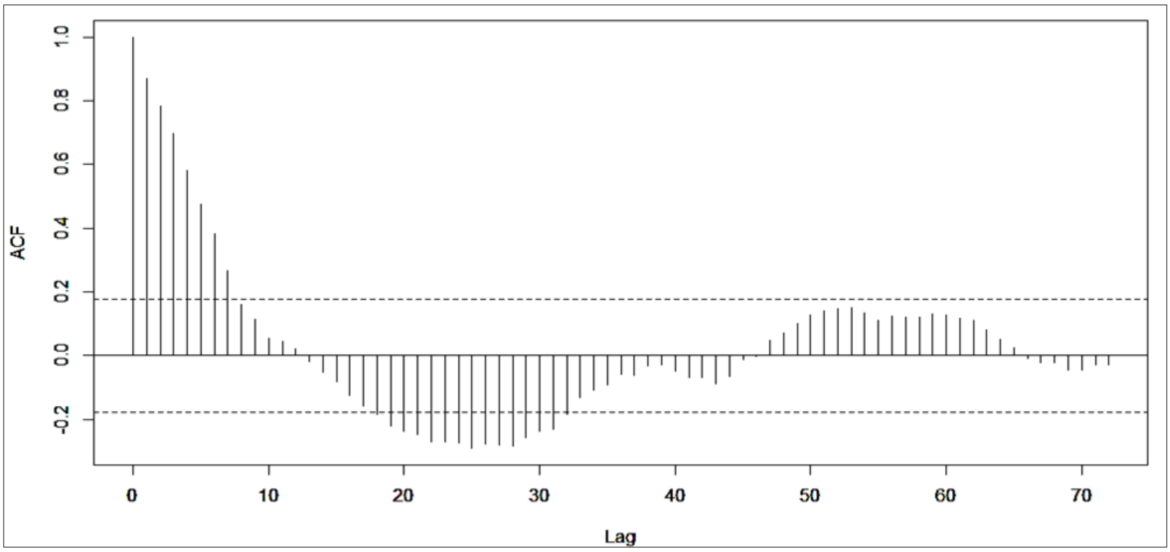

Fig. 2. ACF plot of market price of ginger.

underlying seasonal dynamics in the data.

Partial autocorrelation function (PACF) plot

The PACF plot provides additional insights into the direct relationships between observations at different lags after accounting for correlations at shorter lags (Fig. 3). A significant spike at lag 1, with a partial autocorrelation coefficient close to 0.869, highlights a strong first-order non-seasonal autoregressive (AR (1)) process. The rapid decline in partial autocorrelations at subsequent lags indicates minimal additional direct autocorrelations. All other lag values remain within the confidence bounds (indicated by the dashed blue lines), confirming the lack of significant autoregressive behavior beyond lag 1. This finding suggests that an AR (1) model would likely be suitable for modelling the ginger price series, aligning with the results of the white noise and stationarity tests. Subsequently, we analyzed the patterns across lags that are multiples of the seasonal period (S = 12). Seasonality was assessed at lags 12, 24, 36 and up to 72 lags. The investigation of seasonal autoregressive components in the ginger price series shows no significant autocorrelation spikes beyond the 5^{th} lag in the PACF plot. The gradual tapering of the ACF and the diminishing PACF values indicate the absence of a seasonal AR process. This behavior suggests that autoregressive terms do not significantly contribute to the seasonal dynamics of the time series.

ADF test for non-stationarity (unit root test)

The augmented Dickey-Fuller (ADF) test was conducted to assess the presence of a unit root and determine whether the time series data for ginger market prices is stationary. The test was performed with a lag length of 6 and the results are summarized in Table 4. The ADF test results indicate statistical significance at all lag lengths tested, with *p*-values less than the conventional significance threshold of 0.05. This suggests that the null hypothesis of a unit root is rejected at each lag length, confirming that the series is stationary. Therefore, no difference was necessary to achieve stationarity. The consistently significant *p*-values across lags suggest that the series does not exhibit non-stationarity and thus, the data can be used for further analysis without requiring differencing.

Table 4. Augmented Dickey-Fuller or unit root tests for market price of ginger

Type	Lags	*F* value	*p* > *F*
Single mean	1	-1.293	0.0403
	2	-1.4813	0.03
	3	-1.9164	0.02
	4	-1.9718	0.011
	5	-1.5761	0.034
	6	-1.6611	0.047

Table 5 presents the identified models with their corresponding accuracy measures for forecasting the price of ginger, based on various statistical metrics including ME, RMSE, MAE, MAPE, MASE and information criteria such as AIC and BIC. The table includes a mix of ARIMA and GARCH models to assess both the level and volatility of ginger prices in Meghalaya. Among the nine models, several variations of ARIMA and seasonal ARIMA (SARIMA) were tested, each capturing different autocorrelation structures. Three ARIMA models and three seasonal ARIMA models were evaluated to capture both non-seasonal and seasonal components of the time series.

The ARIMA models tested include ARIMA (1, 0, 2), ARIMA (2, 0, 1) and ARIMA (1, 0, 1). Among these, the ARIMA (2,0,1) model was selected as the best fit for the data, based on its relatively lower RMSE (1226.42), MAE (794.011) and AIC (2091.97),

Table 5. Identified models with different accuracy measures for price of ginger

Model	ME¹	RMSE²	MAE³	MAPE⁴	MASE⁵	AIC⁶	BIC⁷
ARIMA (1,0,2)	-20.999	1218.23	800.439	20.342	0.995	2093.58	2107.6
ARIMA (2,0,1)	-22.323	1226.42	794.011	20.074	0.987	2091.97	2105.99
ARIMA (1,0,1)	-22.602	1233.77	802.002	20.064	0.997	2092.99	2104.21
ARIMA (1,0,1) (0,0,1)	-22.602	1233.77	802.002	20.064	0.997	2092.99	2104.21
ARIMA (1,0,2) (0,0,1)	-20.999	1218.23	800.439	20.342	0.995	2091.97	2105.99
ARIMA (1,0,3) (0,0,1)	-21.056	1216.63	801.742	20.308	0.997	2093.63	2110.45
sGARCH (0,1)	17.671	1263.98	823.603	20.038	0.958	17.173	17.264
sGARCH (1,0)	-339.968	2991.93	2429.974	78.585	2.827	19.189	19.281
sGARCH (1,1)	-72.453	1252.66	811.162	20.229	0.943	16.965	17.103

ME[1]: mean error; RMSE[2]: root mean square error; MAE[3]: mean absolute error; MAPE[4]: mean absolute percentage error; MASE[5]: mean absolute scaled error; AIC[6]: Akaike information criterion; BIC[7]: Bayesian information criterion.

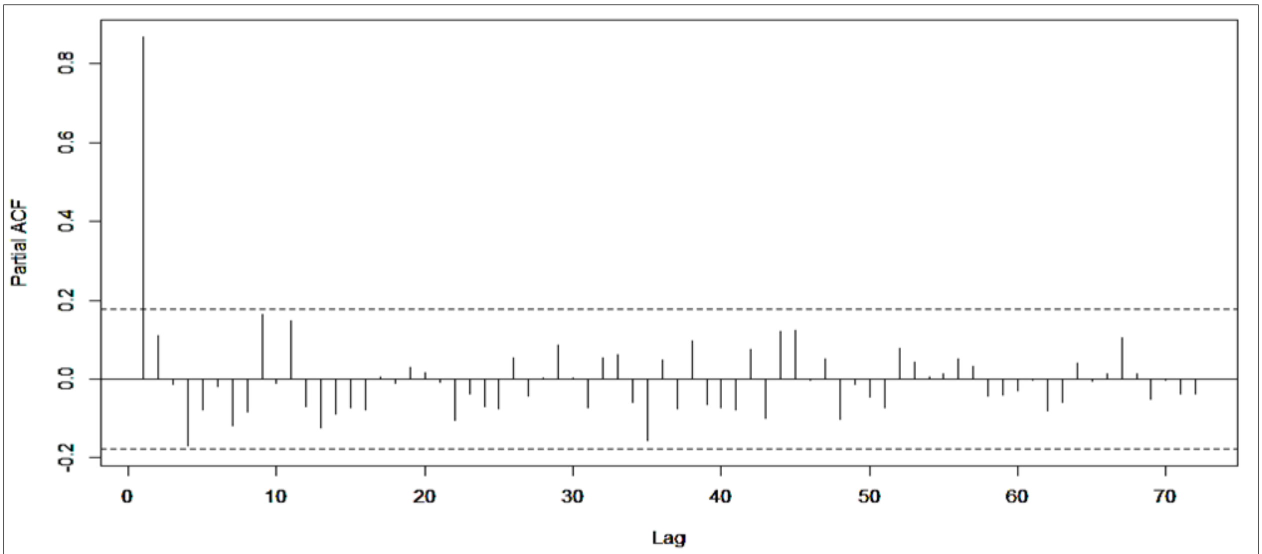

Fig. 3. PACF plot of market price of ginger.

indicating superior performance in modelling the non-seasonal behaviour of ginger prices. For the SARIMA models, ARIMA (1, 0, 1) (0, 0, 1), ARIMA (1, 0, 2) (0, 0, 1) and ARIMA (1, 0, 3) (0, 0, 1) were assessed. Among these, the ARIMA (1, 0, 2) (0, 0, 1) model was chosen due to its comparatively better fit, as reflected by its RMSE (1218.23), MAE (800.439) and AIC (2091.97). This model effectively captures the seasonality present in the data while maintaining accuracy across multiple metrics.

In summary, the ARIMA (2, 0, 1) model was identified as the best choice for non-seasonal dynamics, while the ARIMA (1, 0, 2) (0, 0, 1) model was selected for its superior performance in accounting for seasonal effects (Table 6). However, the ARIMA models alone may not fully capture the volatility inherent in ginger prices, as evidenced by the consistently high MAPE values across these models. These models, in conjunction with the GARCH (1, 1) model for volatility, provide a comprehensive approach to modelling ginger prices in Meghalaya.

To address volatility, three specifications of the GARCH model were also evaluated which are sGARCH (0, 1), sGARCH (1, 0) and sGARCH (1,1). Among these, the sGARCH (1, 1) model emerged as the most appropriate based on its low RMSE (1252.66), AIC (16.965) and BIC (17.103) values. Although the sGARCH (1, 0) model showed larger errors, suggesting poor fit, sGARCH (1, 1) effectively captures both the mean and volatility components of the series, making it the preferred model for assessing the price volatility of ginger in Meghalaya. The GARCH (1, 1) model's ability to account for time-varying volatility aligns with the observed fluctuations in ginger prices, which are influenced by various market and environmental factors. Hence, the GARCH (1, 1) model was selected as the best representation of the data due to its robust performance across multiple accuracy measures. While these models effectively represent the mean dynamics, they do not adequately capture the volatility observed in the ginger price series. Thus, to address this, the sGARCH (1, 1) model was ultimately selected as the best model for handling price volatility, as detailed earlier.

Comparison of forecast models

The selection of four models for forecasting ginger prices was supported by model evaluation metrics such as AIC, BIC, ME, RMSE, MAE, MAPE and MASE. Comparable outcomes were observed in previous studies conducted in Brazil and in the Indian cities of Delhi, Kanpur and Rajkot (47-49). The first two are ARIMA models: ARIMA (2, 0, 1) and ARIMA (1, 0, 2) with seasonal parameters (0, 0, 1). An ARIMAX model incorporating rainfall as a predictor was also evaluated; however, the rainfall was found to be statistically insignificant in this context (Table 7). Although rainfall was found insignificant in the ARIMAX model used for forecasting ginger prices in Meghalaya, its inclusion was based on sound agronomic and climatic reasoning. Ginger cultivation in the region is highly dependent on seasonal rainfall, which influences both sowing and harvesting outcomes. Meghalaya, particularly areas like Mawsynram and Cherrapunji, is known to receive among the highest annual rainfall levels in the world, often exceeding 10,000 mm per year (50). Despite this, year-to-year fluctuations in rainfall patterns—such as early monsoon onset or prolonged dry spells—can severely impact crop health, potentially influencing price volatility due to reduced supply. According to Indian meteorological department data, in 2022 and 2023, these areas experienced irregular distribution of rainfall despite maintaining high cumulative values. Therefore, rainfall was selected as the most logical and readily available exogenous variable for inclusion in the forecasting model.

However, in this study, the ARIMAX model results revealed that rainfall had no statistically significant effect on ginger price dynamics, with a p-value of 0.9132. This underscores the complexity of modeling agricultural price dynamics in regions where non-climatic variables may exert stronger or more localized effects. This suggests that while rainfall remains crucial agronomically, its quantitative influence on monthly price variation during the studied period may have been overshadowed by other unmeasured variables, such as market demand shifts, transportation disruptions or export fluctuations. Additionally, the spatial variability of rainfall even within high-rain zones like Mawsynram and Cherrapunji may not uniformly reflect growing conditions across all ginger-producing areas in Meghalaya.

Due to the lack of consistent time-series data for alternative exogenous variables such as transport costs, labor shortages, or policy changes, rainfall remained the most viable option for inclusion. In the present investigation, price volatility was modelled using the sGARCH (1,1) specification from the ARCH/GARCH family, while the AR (1) model emerged as a viable alternative for forecasting ginger prices. The predictive performance of these models was assessed using standard forecast evaluation metrics, including RMSE, MAPE, ME, MAE, MASE and log-likelihood (Table 8). The modelling approach and outcomes are consistent with those reported in a previous study conducted in Brazil, thereby reinforcing the validity of the selected models under different agro-economic contexts (47). Similarly, a study compared classical time-series models (ARIMA, SARIMA, ARCH/GARCH) with machine-learning approaches (ANN, RNN) for banana price forecasting, using MAPE, RMSE, SMAPE and MASE to evaluate performance. The results showed that the RNN (LSTM) model consistently achieved the lowest errors across all metrics, clearly outperforming ARIMA/GARCH and ANN models, highlighting the ability of advanced sequence models to capture complex price dynamics in horticultural

Table 6. Identified forecast models for monthly price based on AIC, BIC and other accuracy measures

Technique	Price of ginger
ARIMA	ARIMA (2,0,1) ARIMA (1,0,2) (0,0,1)
ARIMAX	
ARCH/GARCH	sGARCH (1,1)
AR	AR (1)

Table 7. Regression of price of ginger with rainfall in Meghalaya

Parameters	Estimate	Standard error	*z* value	*p* value
ar1	0.387689	0.444407	0.8724	0.3830
ar2	0.493489	0.395948	1.2463	0.2126
ma1	0.388201	0.479379	0.8098	0.4181
Intercept	4913.075	1205.968	4.0740	4.622e-05*
Rainfall	-0.04067	0.373028	-0.109	0.9132

* Significant at 5 percent level of significance.

Table 8. Accuracy measures of the forecast models for monthly price of ginger

Models	ME[1]	MAE[2]	MAPE[3]	RMSE[4]	MASE[5]	Log likelihood
ARIMA (2,0,1)	-101.03	1225.54	0.1192	1467.46	0.2848	-996.23
ARIMA (1,0,2) (0,0,1)	-101.03	1225.54	0.1192	1467.46	0.2848	-995.03
sGARCH (1, 1)	-678.45	1212.28	0.123 (marginally)	1540.98	0.2817	-996.102

ME[1]: mean error; MAE[2]: mean absolute error; MAPE[3]: mean absolute percentage error; RMSE[4]: root mean square error; MASE[5]: mean absolute scaled error.

commodities (51). Similarly, a study applied ARIMA models to Indian turmeric prices and found that the seasonal ARIMA (1, 1, 0) (0, 0, 0) provided the best fit, selected based on the lowest MAPE of about 7.07 %. The fitted model forecasted a declining price trend over the following five months (e.g., ~Rs.7170/quintal by September), reflecting increased supply and demonstrating the usefulness of standard ARIMA approaches for commodity price projection (52). To do this, we started forecasting by holding (omitting) the recent five months data points of the response variable (ginger price). Forecasting was made using only the remaining 117 months data points. sGARCH (1, 1) model had smallest values in all the accuracy measures ME, MAE, MASE, RMSE, MAPE and log likelihood compared to other models.

In selecting the optimal model for forecasting ginger prices with consideration of both forecast accuracy and parsimony, several key factors were evaluated. First, based on model accuracy measures, GARCH (1, 1) exhibits a higher ME (-678.45), indicating a greater bias in predictions compared to the ARIMA models, which have a consistent ME (-101.03). However, when assessing MAE, GARCH (1, 1) performs slightly better, with a lower MAE (1212.28) compared to the ARIMA models (1225.54), suggesting that GARCH provides more accurate predictions on average. In terms of MAPE, GARCH (1, 1) shows a marginally higher percentage error (12.30 %) relative to ARIMA (11.92 %).

While ARIMA outperforms GARCH in RMSE (1467.46 vs. 1540.98), indicating fewer extreme forecast errors, GARCH (1, 1) performs marginally better in MASE, with values of 0.2817 and 0.2848, respectively. In addition to accuracy, the log-likelihood values for the models were considered, with ARIMA (1, 0, 2) (0, 0, 1) achieving a slightly better log likelihood (-995.03) compared to ARIMA (2, 0, 1) (-996.23) and GARCH (1, 1) (-996.10). A higher log likelihood reflects a better fit to the data, suggesting ARIMA (1, 0, 2) (0, 0, 1) may offer a stronger fit under certain conditions. However, an important consideration in forecasting ginger prices is the volatility present in the data. The GARCH (1, 1) model is specifically designed to handle time-varying volatility, making it well-suited for data with heteroscedasticity, a common feature in financial and commodity price series. Similarly, a study modelled monthly onion prices (2003-2020) using an AR (1)-GARCH (1,1) framework and demonstrated that this specification effectively captures the observed volatility. The forecasts indicated that conditional volatility would remain relatively stable through mid-2024, while onion prices were expected to decline steadily over 2023-24. These findings suggest that producers may face reduced price risk but could benefit from timely marketing strategies before anticipated price declines (53). In addition, another study analyzed volatility in Indian onion markets using ARIMA, ARMA-GARCH and ensemble EEMD-ARIMA/ANN models. The results showed that volatility was moderate to high and that hybrid EEMD-based approaches produced the most accurate forecasts. In particular, the EEMD-ARIMA/ANN models achieved very low MAPE values (e.g., ~6.8-17.7 % for arrivals and ~9.8-10.2 % for prices), clearly outperforming conventional models. This highlights the importance of incorporating nonlinearity and structural breaks when modeling agricultural price volatility (54). Given that ginger prices in Meghalaya exhibit significant fluctuations and volatility clustering, GARCH (1, 1) is more effective at capturing the dynamic nature of price volatility, which ARIMA models cannot adequately model. Furthermore, parsimony was considered in model selection. ARIMA (1, 0, 2) (0, 0, 1) stands out as a more parsimonious model, utilizing fewer parameters while maintaining reasonable accuracy. Despite this, the trade-off lies in its limited capacity to address volatility compared to GARCH.

In conclusion, while ARIMA models, particularly ARIMA (1, 0, 2) (0, 0, 1) may be preferable for short-term forecasts due to their lower RMSE and better log likelihood, GARCH (1,1) is scientifically more appropriate for capturing the volatility inherent in ginger price data. GARCH (1, 1)'s ability to model fluctuating price patterns makes it the recommended model for forecasting under volatile conditions, especially in scenarios requiring longer-term predictions. Thus, despite slightly worse performance in some accuracy metrics, GARCH (1, 1) is better suited to account for the varying volatility in ginger prices, providing a more comprehensive understanding of price dynamics over time. Parameter estimates of the sGARCH (1, 1) model for the price of ginger are presented in Table 9. In this model, the first autoregressive term and the Garch term were found to be significant. The forecasted prices from March 2024 to July 2024 are provided in Table 10. Additionally, a plot comparing the actual price and predicted price of the sGARCH (1, 1) model is presented in Fig. 4.

The findings of the present study reveal that the autoregressive component AR (1) exerts a significant influence on ginger price dynamics, indicating that historical price movements are strong determinants of current prices. The estimated coefficient, being close to one, reflects a high level of persistence in the price series, suggesting that deviations from the mean following external shocks tend to persist over time rather than dissipate rapidly. These results are consistent with earlier empirical evidence, which reported comparable patterns

Table 9. Parameter estimates given by the model GARCH (1, 1) for price of ginger

Parameter	Estimate	Standard Error	t value	*p*-value
Mu (mean)	6694.33	1205.70	5.55235	0.00000*
ar1	0.94978	0.03636	26.11831	0.00000*
Omega (constant)	8273.29	13606.00	0.60805	0.54315
alpha1 (Arch)	0.00000	0.01507	0.00000	1.00000
beta1 (Garch)	0.99772	0.01045	95.49468	0.00000*

* Significant at 5 percent level of significance

Table 10. GARCH (1, 1) forecasted values

Period	Point forecast	Low 95 %	High 95 %	Low 99 %	High 99 %
March 2024	11910.09	9090.348	14729.84	8204.142	15616.05
April 2024	11648.14	8825.974	14470.31	7939.007	15357.27
May 2024	11399.34	8574.764	14223.92	7687.039	15111.65
June 2024	11163.04	8336.057	13990.02	7447.576	14878.50
July 2024	10938.61	8109.225	13767.99	7219.991	14657.22

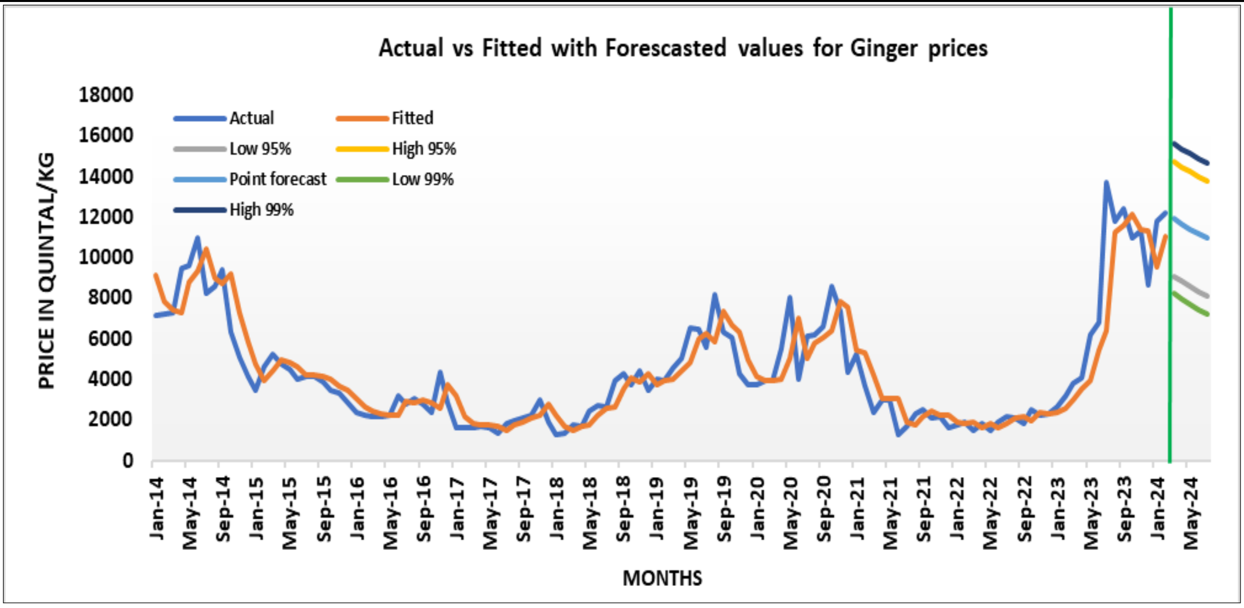

Fig. 4. Actual price versus predicted market price of ginger given by the model GARCH (1, 1).

of prolonged mean reversion in agricultural commodity prices (55). In the variance equation of the GARCH model, the constant term (ω), with a value of 8273.29, indicates a high baseline level of volatility in the ginger market. This high value suggests that even in the absence of significant shocks or external disturbances, the ginger market in Meghalaya inherently experiences volatility. This aligns with the nature of agricultural markets, which are affected by factors such as weather conditions, transportation logistics and seasonal supply variations.

The ARCH term ($\alpha1$) has a value of 0, meaning that the immediate impact of price shocks on volatility is negligible. Essentially, this indicates that short-term shocks do not significantly contribute to an increase in volatility. Therefore, sudden changes in ginger prices, such as those due to market news or disturbances, do not lead to heightened price fluctuations. This is further supported by the GARCH term ($\beta1$), which has a value of 0.99772. The high $\beta1$ value suggests long-lasting volatility, indicating that once volatility increases, it remains elevated for an extended period before gradually dissipating. This characteristic of persistent volatility aligns with the behavior of agricultural markets, where periods of price fluctuations tend to be prolonged due to unpredictable external factors.

In summary, the AR (1) term demonstrates that ginger prices are strongly influenced by their own past values, indicating persistent price trends. The high $\beta1$ value suggests that once volatility is triggered by market conditions or external factors, it will remain elevated for a considerable duration. The low $\alpha1$ value indicates that short-term shocks do not significantly affect volatility, reinforcing the notion that volatility is driven by more persistent factors. Given the strong persistence in both price trends and volatility, the GARCH (1, 1) model is well-suited to capturing the fluctuating nature of ginger prices in Meghalaya. This model allows for more accurate forecasting by accounting for extended periods of price instability, making it an effective tool for understanding and predicting ginger market dynamics. The forecasted values for the price of ginger indicate a decreasing trend for the next five months, from March 2024 to July 2024, following the GARCH forecast.

Furthermore, the study observed negative price trends for dried ginger in the months of January, February, June, July, November and December, indicating reduced market feasibility during these periods due to potential gluts in rural markets (56). This finding aligns closely with the results of the present study, which also identified negative trends in ginger prices in Meghalaya. The observed declining trends can be attributed to limited market incentives and the lack of effective market support for rural farmers and marketers, leading to reduced prices during these months. Both studies emphasize the need for targeted interventions to address the volatility of ginger prices. Enhancing the dissemination of information on prices, supply and demand at the local level is particularly crucial.

Providing farmers and traders with timely and accurate market data can help them better anticipate market conditions, optimize their marketing strategies and mitigate the risks associated with seasonal gluts and price declines. Additionally, a study in Nigeria revealed the existence of seasonality in the price series of both tomatoes and dried ginger in the market (56). This finding is consistent with the present study, which also identified significant seasonal patterns in the pricing of ginger. The seasonal fluctuations in prices suggest that certain periods within the year experience higher or lower prices due to factors such as supply variations, market demand and potential gluts or shortages.

The findings from the present study on ginger prices in Meghalaya align with broader patterns observed in related agricultural commodities, underscoring the interplay of market dynamics, seasonality and regional factors. In the recent past, the ginger market has exhibited pronounced price volatility, which has escalated the financial risk borne by producers. This increased uncertainty has likely influenced farmers' production decisions, resulting in a downward trend in cultivated area and output. Such dynamics have also been empirically observed in the context of Meghalaya (57). Moreover, anticipatory price forecasting of ginger has proven instrumental in supporting policy interventions aimed at market stabilization and has become an essential component of effective agricultural market intelligence systems. Comparable implementations have been documented in China as well as in Delhi, Patna and Rajkot (48, 49). Following proper identification and diagnostic procedure, models were identified based on stability with maximum iterations as the first phase of finding candidate models.

Conclusion

This study applied advanced time series model-ARIMA, ARIMAX and GARCH-to forecast monthly ginger prices in Meghalaya using a ten-year dataset (2014-2024). Diagnostic assessments for stationarity, autocorrelation and seasonality guided model selection. Among the models tested, the GARCH (1,1) model outperformed others, capturing both price dynamics and volatility with significant autoregressive (AR1 = 0.94978) and volatility persistence (β_1 = 0.99772) coefficients. Forecasts for March to July 2024 showed a declining price trend from ₹11910 to ₹10938, underscoring market instability and the need for policy intervention. While ARIMA models were adequate for level forecasting, they failed to capture volatility, a key factor affecting farmer's income and decision-making. To strengthen policy relevance, the study proposes actionable interventions. To strengthen policy relevance, the study proposes actionable interventions.

The Ministry of Agriculture and Farmers' Welfare, Government of India (2025) reports that the agriculture infrastructure fund provides financial assistance for developing storage, cold-chain and post-harvest facilities aimed at reducing losses and stabilizing prices. Additionally, the digital agriculture mission, launched by the same ministry in 2024, promotes platforms such as Agri Stack and e-NAM to enhance market intelligence, digital access and real-time price forecasting for farmers. In line with collective marketing objectives, the ministry also highlights the establishment of 8875 farmer producer organizations (FPOs) across the country under a dedicated scheme to improve aggregation, market access and bargaining power of smallholder farmers. Furthermore, revised guidelines on minimum support prices (MSP), as published in June 2024, reaffirm the government's commitment to safeguarding farmer incomes by aligning price floors with production costs. Together, these measures create a resilient and responsive agricultural marketing ecosystem. Integrating these national schemes with region-specific planning in Meghalaya can mitigate price volatility, enhance market access and support sustainable income security for ginger farmers.

Acknowledgements

The authors are highly grateful to ICAR Research Complex for Northeastern Hill Region, Umiam, Meghalaya for their financial support.

Authors' contributions

NUS participated in the concept and design of the study. NUS and AT carried out the experiment, data collection and wrote the article. NUS and AT participated in the analysis and interpretation of the results. AY, AR, NL, PP, KPB, CGHR, AKJ, WD, BPS and SBS involved in the critical revision of the article. All authors read and approved the final manuscript.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interest to declare.

Ethical issues: None

Declaration on the Use of AI-Assisted Technologies: The authors acknowledge the use of generative AI tools (such as ChatGPT by OpenAI) to assist in language refinement, grammar correction and paraphrasing during the preparation of this manuscript. No generative AI tools were used for content generation, data analysis, or intellectual contribution to the core ideas or findings. All content has been critically reviewed and approved by the authors to ensure accuracy, originality and integrity.

References

1. Das A, Layek J, Babu S, Kumar M, Yadav G, Patel D, et al. Influence of land configuration and organic sources of nutrient supply on productivity and quality of ginger (*Zingiber officinale* Rosc.) grown in Eastern Himalayas, India. Environ Sustain. 2020;3:59–67. https://doi.org/10.1007/s42398-020-00098-x
2. Giri NC, Mohanty RC. Traditional versus underneath farming of turmeric and ginger in Odisha, India. Int J Agric Stat Sci. 2022;18 (1):189–95.
3. Food and Agricultural Organization. FAOSTAT [Internet]. Rome: FAO; 2020. Available from: https://www.fao.org/faostat/
4. Kumar S, Singh SP, Sharma RR. Constraints perceived by the farmers in adoption of improved ginger production technology: A study of low hills of Himachal Pradesh. Int J Bioresour Stress Manag. 2018;9(6):740–44. https://doi.org/10.23910/IJBSM/2018.9.6.1911
5. Shahrajabian MH, Sun W, Cheng Q. Clinical aspects and health benefits of ginger (*Zingiber officinale*) in both traditional Chinese medicine and modern industry. Acta Agric Scand B Soil Plant Sci. 2019;69(6):546–56. https://doi.org/10.1080/09064710.2019.1606930
6. Wang Y, Liu P, Zhu K, Liu L, Zhang Y, Xu G. A garlic-price-prediction approach based on combined LSTM and GARCH-family model. Appl Sci. 2022;12(22):11366. https://doi.org/10.3390/app122211366
7. Wang B, Liu P, Zhang C, Wang J, Peng L. Prediction of garlic price based on ARIMA model. In: Liu J, Yang Y, Ma J, Chen J, editors. Cloud computing and security: Proceedings of the 4th International Conference, ICCCS 2018; 2018 Jun 8-10; Haikou, China. Part I. Cham: Springer; 2018. p. 731–39.
8. Gogoi M. Production performance of ginger: A study among Indian states. Int J Manag. 2021;11(12):845–50. https://doi.org/10.34218/IJM.11.12.2020.078
9. District Crop Forecast Committee. District crop forecast report for the month of January 2021. Tura: The Committee; 2021.
10. Mathew M, Vani N, Aparna B. Economics of production of ginger in Wayanad district of Kerala, India. Econ Aff. 2018;63(3):627–32. https://doi.org/10.30954/0424-2513.3.2018.6
11. Zhang XX, Liu L, Su CW, Tao R, Lobonţ OR, Moldovan NC. Bubbles in agricultural commodity markets of China. Complexity. 2019;2019

(1):2896479. https://doi.org/10.1155/2019/2896479

12. Hasan MK, Haque MM, Rabbani MG. Production and price relationship of ginger (*Zingiber officinale*) in Bangladesh: A distributed lag model. Agriculturists. 2017;15(1):1–9. https://doi.org/10.3329/agric.v15i1.33423
13. Geta E, Kifle A. Production, processing and marketing of ginger in Southern Ethiopia. J Hortic For. 2011;3(7):207–13.
14. Jhade S, Singh A. Integration and causality of major garlic markets in Uttar Pradesh state. J Res ANGRAU. 2021;49(2):100–106.
15. Kithu CJ. Marketing and export prospects of ginger. In: Singh HP, Tamil Selvan M, editors. Indian ginger - Production and utilization. Kerala: Directorate of Arecanut and Spice Development; 2003.
16. Moktan MW, Dhiman Mukherjee DM. Trade and marketing strategy for spice crops in Darjeeling district. Environ Ecol. 2008;26(3A):1302–305.
17. Saini AS, Sood AK, Thakur DR. Evaluation of ginger marketing system in Himachal Pradesh. In: Singh LP, Garg S, editors. Agricultural marketing. Jaipur: Arihant; 1992. p. 260–82.
18. George L. The ginger economy of Kerala [PhD dissertation]. Kerala: Cochin University of Science and Technology; 1996.
19. Datta SK, Gurdev S, Millindo C. Management of marketing and export of ginger with special reference to Eastern Himalayan region. In: Singh HP, Tamil Selvan M, editors. Indian ginger - Production and utilization. Kerala: Directorate of Arecanut and Spice Development; 2003.
20. Aleem M, Khan MI, Shakshaz FA, Akbari N, Anwar D. Botany, phytochemistry and antimicrobial activity of ginger (*Zingiber officinale*): A review. Int J Herb Med. 2020;8(6):36–49. https://doi.org/10.22271/flora.2020.v8.i6a.705
21. Rymbai H, Jha AK, Talang HD, Deshmukh NA, Verma VK, Baiswar P, et al. Organic ginger cultivation in North Eastern region. Umiam (Meghalaya): ICAR Research Complex for NEH Region; 2018. https://doi.org/10.13140/RG.2.2.11901.64482
22. Gosh D. Shifting cultivation in northeast India: A historical perspective. In: Bhattacharyya RHHW, Das RT, editors. Agriculture in northeast India. New Delhi: B.R. Publishing Corporation; 1984. p. 45–59.
23. Zonuntluanga R. Problems and prospects of agricultural marketing in Mizoram [PhD dissertation]. Aizawl: Mizoram University; 2002.
24. Rahman H, Ramaiyan K, Kishore K, Denzongpa R. Traditional practices of ginger cultivation in Northeast India. Indian J Tradit Knowl. 2009;8(1):23–28.
25. Kumar A, Avasthe RK, Lepcha B, Mohanty AK, Shukla G. Impact of frontline demonstrations on yield enhancement of ginger (var. Majauley) in tribal reserve biosphere of Sikkim Himalaya. J Agric Sci. 2012;3(2):121–23. https://doi.org/10.1080/09766898.2012.11884693
26. Jha AK, Deka BC. Present status and prospects of ginger and turmeric in NE States. Meghalaya: Kiran Publications, ICAR Research Complex for NEH Region; 2012. p. 1–5.
27. Mawlong M. Ginger cultivation in Umroi, Ri Bhoi District, Meghalaya. IOSR J Humanit Soc Sci. 2017;22(7):36–45. https://doi.org/10.9790/0837-2207033645
28. Sharath AM, Dhanajaya KB. Organic farming in India – A study of ginger cultivation. Excellence Int J Edu Res. 2015;2(6):50–61.
29. Panme PH, Thangjom LS. Prospects and challenges in ginger cultivation: Livelihood of the rural farmers in Dima Hasao district, Assam. Int J Agric Sci. 2021;17(2):724–28. https://doi.org/10.15740/HAS/IJAS/17.2/724-728
30. Sharma V, Longkumer J, Mary NO, Das S. Constraints in ginger cultivation by farmers of West Garo Hills district of Meghalaya. Int J Econ Plants. 2023;10(3):252–55. https://doi.org/10.23910/2/2023.526d
31. Enders W. *Applied econometric time series.* 4th ed. New York: University of Alabama; 2015.
32. Hyndman RJ, Talagala TS, Athanasopoulos G. Meta-learning how to forecast time series. Monash Econom Bus Stat Work Pap. 2018;6(18):16–44. https://business.monash.edu/econometrics-and-business-statistics/research/publications
33. Taylor JW. Exponentially weighted methods for forecasting intraday time series with multiple seasonal cycles. Int J Forecast. 2010;26(4):627–46. https://doi.org/10.1016/j.ijforecast.2010.02.009
34. Wei H, Lai KK, Yu L, Wang S. A novel nonlinear neural network ensemble model for financial time series forecasting. In: Proceedings of the 6th International Conference in Computational Science; 2006 May 28; UK. Berlin: Springer; 2006. p. 790–93. https://doi.org/10.1007/11758501_106
35. Claeskens G, Hjort NL. Model selection and model averaging. Cambridge (England): Cambridge University Press; 2008. https://doi.org/10.1007/S11336-011-9219-3
36. Chatfield C, Xing H. The analysis of time series: An introduction with R. New York: Chapman and Hall; 2019. https://doi.org/10.1201/9781351259446
37. Box GEP, Jenkins GM. Time series analysis: Forecasting and control. San Francisco: Holden Day; 1976.
38. Hipel KW, McLeod AI. Time series modelling of water resources and environmental systems. Amsterdam: Elsevier; 1994. https://doi.org/10.1002/iroh.19950800107
39. Dickey DA, Fuller WA. Distribution of the estimators for autoregressive time series with a unit root. J Am Stat Assoc. 1979;74(366a):427–31. https://doi.org/10.2307/2286348
40. Lombardo R, Flaherty J. Modelling private new housing starts in Australia. Paper presented at: Pacific-Rim Real Estate Society Conference. Sydney, Australia; 2002.
41. Webel K, Ollech D. An overall seasonality test based on recursive feature elimination in conditional random forests. In: Proceedings of the 5th International Conference on Time Series and Forecasting. Granda; 2018. p. 20–31.
42. Armstrong JS, Collopy F. Error measures for generalizing about forecasting methods: Empirical comparisons. Int J Forecast. 1992;8(1):69–80. https://doi.org/10.1016/0169-2070(92)90008-W
43. Armstrong JS. Evaluating forecasting methods. In: Armstrong JS, editor. Principles of forecasting: A handbook for researchers and practitioners. Boston: Kluwer Academic Publishers; 2001. p. 443–72. https://doi.org/10.1007/978-0-306-47630-3_20
44. Gooijer JGD, Hyndman RJ. 25 years of time series forecasting. Int J Forecast. 2006;22(3):443–73. https://doi.org/10.1016/j.ijforecast.2006.01.001
45. Hyndman RJ, Koehler AB. Another look at measures of forecast accuracy. Int J Forecast. 2006;22(4):679–88. https://doi.org/10.1016/j.ijforecast.2006.03.001
46. Yeasin M, Sharma P, Paul RK, Meena DC, Anwer ME. Understanding price volatility and seasonality in agricultural commodities in India. Agric Econ Res Rev. 2023;36(2):177–88. https://doi.org/10.5958/0974-0279.2023.00031.9
47. Ospina R, Gondim JA, Leiva V, Castro C. An overview of forecast analysis with ARIMA models during the COVID-19 pandemic: Methodology and case study in Brazil. Math. 2023;11(14):3069. https://doi.org/10.3390/math11143069
48. Pandit P, Sagar A, Ghose B, Paul M, Kisi O, Vishwakarma DK, et al. Hybrid modelling approaches for agricultural commodity prices using CEEMDAN and time delay neural networks. Sci Rep. 2024;14(1):26639. https://doi.org/10.1038/s41598-024-74503-4
49. Li F, Meng X, Zhu K, Yan J, Liu L, Liu P. Research on ginger price prediction model based on deep learning. Agriculture. 2025;15(6):596. https://doi.org/10.3390/agriculture15060596
50. Ministry of Earth Sciences. India Meteorological Department.

Rainfall statistics of India - 2023 [Internet]. Available from: https://mausam.imd.gov.in

51. Kumari P, Goswami VNH, Pundir RS. Recurrent neural network architecture for forecasting banana prices in Gujarat, India. PLoS One. 2023;18(6):e0275702. https://doi.org/10.1371/journal.pone.0275702
52. Uma M, Rajarathinam P, Venkatachalam S, Baskaran T. Growth and forecast performance of turmeric in India: An empirical analysis. Madras Agric J. 2022;109(1–3):1–6. https://doi.org/10.29321/MAJ.10.000658
53. Nath B, Bhattacharya D. Modeling onion price volatility with AR–GARCH framework. Environ Ecol. 2025;43(1):79–88. https://doi.org/10.60151/envec/twwk2894
54. Shankar SV, Chandel A, Gupta RK, Sharma S, Chand H, Kumar R, Gowsar SN. Exploring the dynamics of arrivals and prices volatility in onion (*Allium cepa*) using advanced time series techniques. Front Sustain Food Syst. 2023;7:1208898. https://doi.org/10.3389/fsufs.2023.1208898
55. Setiawan B, Ben Abdallah M, Fekete-Farkas M, Nathan RJ, Zeman Z. GARCH (1, 1) models and analysis of stock market turmoil during COVID-19 outbreak in an emerging and developed economy. J Risk Financ Manag. 2021;14(12):576. https://doi.org/10.3390/jrfm14120576
56. Mani JR, Hudu MI, Ali A. Price variation of tomatoes and ginger in Giwa Market, Kaduna State, Nigeria. J Agric Ext. 2018;22(1):91–4. https://doi.org/10.4314/jae.v22i1.9
57. Das TK, Singh M, Borah S. Value chain and constraints analysis of ginger in West Garo Hills district of Meghalaya. J Krishi Vigyan. 2024;12(2):435–40. https://doi.org/10.5958/2349-4433.2024.00076.4

Additional information

Peer review: Publisher thanks Sectional Editor and the other anonymous reviewers for their contribution to the peer review of this work.

Reprints & permissions information is available at https://horizonepublishing.com/journals/index.php/PST/open_access_policy

Publisher's Note: Horizon e-Publishing Group remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Indexing: Plant Science Today, published by Horizon e-Publishing Group, is covered by Scopus, Web of Science, BIOSIS Previews, Clarivate Analytics, NAAS, UGC Care, etc
See https://horizonepublishing.com/journals/index.php/PST/indexing_abstracting

Publisher information: Plant Science Today is published by HORIZON e-Publishing Group with support from Empirion Publishers Private Limited, Thiruvananthapuram, India.