***Original Research Article***

**Application of Grey Model for Forecasting Rice Prices**

**ABSTRACT**

**Aim:** To forecast modal paddy prices in the three zones of Telangana (Northern, Southern, and Central) using the GM (1,1) grey model, addressing the challenge of limited long-term price data and providing a reliable tool for stakeholders to manage price volatility.

**Study Design:** A forecasting study applying the GM (1,1) grey prediction model to annual price data.

**Place and Duration of Study:** The study was conducted across the three zones of Telangana, India, using annual paddy price data from 2014 to 2024.

**Methodology:** Annual modal price data for paddy from Telangana’s Northern, Southern, and Central zones were collected. The GM (1,1) grey model, suitable for small and uncertain datasets, was applied to each zone’s data to estimate model parameters. Forecast accuracy was evaluated using Mean Absolute Percentage Error and Root Mean Squared Error. Price forecasts were generated for the years 2025 to 2027.

**Results:** The GM (1,1) model produced accurate forecasts with MAPE values below 10% for all zones. Forecasts indicate a consistent upward trend in modal paddy prices across Telangana from 2025 to 2027.

**Conclusion:** The GM (1,1) grey model effectively forecasts short-term paddy prices in Telangana despite limited data, serving as a valuable decision-making tool for farmers and policymakers to anticipate price fluctuations and plan interventions accordingly.

**Keywords**

*Grey Model GM (1,1), modal prices, paddy prices forecasting, zonal analysis, forecast accuracy.*

**1. INTRODUCTION**

Paddy, recognized as one of India's most important food crops, especially within Telangana, plays a vital role in sustaining the agricultural economy. India ranks as the second-largest producer of rice on a global scale (Mahajan *et al.,*2017), so it contributes approximately 26.5% of the world's total rice production (indiastat.com). India's prominence within the global agricultural landscape is shown by the fact that India produced around 137.82 million metric tons of paddy in the 2023-2024 agricultural year (indiastat.com). Telangana ranks 4th in India in terms of paddy production. In India, Telangana is the top paddy-producing state (Economic Survey 2023-24).  Paddy productivity of Telangana reached a level of about 3,602 kg per hectare during 2023–2024 (indiastat.com). This productivity growth is explained by advancements in agricultural practices and improved seed varieties. Government initiatives for improving farmers' production capabilities also play a key role. Agricultural product prices are affected by various factors, such as supply and demand, climate change, policy intervention, market competition, international trade, etc. Agricultural price forecasting is not only about the economic stability of individual countries or regions, but also about the global balance of food supply and demand. Frequent and sharp fluctuations in agricultural commodity prices may affect national and global food security. Scholars have also conducted studies on the transmission mechanism of prices and found that agricultural price transmission is asymmetric. The study of agricultural price forecasting methods is of special importance for improving the safety of agricultural products in terms of quantity and promoting economic and social development. For stakeholders, farmers, agricultural policy makers and others, effective decision-making needs accurate paddy price forecasts.

Various methodologies have been employed to predict agricultural prices, including classic and modern approaches in recent years (Sun *et al.,* 2023). The Grey Model (GM) has emerged among these as a particularly relevant and effective tool, distinguished by its ability to manage uncertainties in data and make reliable forecasts even when historical records are limited. The Grey Model draws on grey system theory concepts, and adaptability makes it a good fit for short-term predictions (Julong 1989). Also, Telangana's zones differ in paddy growing, pricing, and market access, it's key to examine these factors zone by zone. The Grey Model for zonal study allows for a deeper insight into local market conditions while creating strategies that take into account each zone's unique features. This study aims to use the Grey Model to predict paddy prices by looking at past price data from each zone. Agricultural price forecasts also help the researchers and policy makers in planning appropriate policies (Sun *et al.,* 2023). The predicted results of this study could help to improve price stability, lower financial risks, and boost economic resilience for those involved in Telangana's paddy market.

The numerous advantages of the Grey model, especially the GM (1,1) version, over traditional approaches like ARIMA, SARIMA, ARIMAX, GARCH, and LSTM make it an appropriate choice for time series data forecasting. It requires only a small amount of historical data, making it a great option when data is scarce, unlike ARIMA or LSTM, which often require enormous datasets. The Grey Model can manage rising and falling trends of the data. It also assumes less about the distribution of data, which lowers the possibility of errors from techniques like GARCH, which frequently assume normality. This model performs exceptionally well in short-term forecasts because it can quickly adjust to new data, which makes it ideal for accurate prediction requirements. In real-world scenarios where data quality may fluctuate, its capacity to withstand noisy or inconsistent data improves reliability. When compared to LSTM, the Grey model requires less computing power.

 The model has higher precision and many wide applications in different areas. Successful engineering, environmental science, and economics applications indicate its efficacy and versatility. The grey prediction model, particularly GM (1,1), has gained significant attention recently due to its high accuracy and minimal data requirements, making it especially valuable in medical research. The versatility of the grey model is demonstrated by its successful application in forecasting and evaluating a wide range of datasets, such as rural logistics demand (Zeng *et al*., 2022), unemployment rates (Nguyen *et al*., 2021 and Pavithra *et al*., 2024), rainfall patterns (Chutiman *et al*., 2022), electricity consumption (Kartikasari and Prayogi, 2018), population dynamics (Gao *et al*., 2017), genetics (Lin *et al*., 2011), and GDP trends (Wang *et al*., 2022). In the health sector, it has been employed for various predictive tasks by Iqelan (2017), Lixia *et al.,* (2019), Ye *et al*., (2019), Nieszporska (2022), and Yang (2024). Additionally, its use in agriculture includes predicting food crop yields (Muqtadir *et al*., 2016) and assessing residue biomass availability (Zhang *et al.*, 2019). It is applied in forecasting of Indonesia’s domestic coffee consumption (Wang and Ghalih, 2017). These studies underscore the grey model’s adaptability and robust performance across various domains.

**2. MATERIAL AND METHODS**

**2.1 Data Collection**

The annual modal price data for paddy over 11 years (spanning January 2014 to December 2024) in Telangana was employed to predict future prices. The time series data for yearly paddy prices was obtained from the AGMARKNET website. With this information, paddy prices were estimated for the upcoming three years.

The Grey model GM (1,1) helps to examine and predict single-variable time series data. This makes it useful in cases with limited and incomplete information. The model works best for data sequences that are monotonically increasing or decreasing in nature. GM (1,1) uses an accumulated generating operation (AGO) to smooth the data. It then builds a first-order differential equation to forecast future values. Many fields, such as economics and agriculture, use this model for short-term predictions. It’s popular because it's effective with small sample sizes and can handle uncertainty in the data.

**2.2 Methodology**

Professor Deng Julong introduced the grey model of M-order partial differential equations with N variables (G (M, N)) in 1982 as part of grey system theory, a framework for analysing systems with incomplete information. GM (1,1) is a single-variable grey prediction model with a first-order difference equation. A grey system is typically defined as one where some information is known while other information remains uncertain. Grey system theory addresses challenges related to data scarcity and uncertainty. The grey theory approach to data processing does not focus on identifying statistical laws or probability distributions. Instead, it transforms the original data into regular time series data, the foundation for developing a mathematical model. The term “grey” represents that the model contains white and black parts. The white part has theoretical support, while the black part depends on empirical data. The Grey model is a powerful tool for time series forecasting when traditional statistical assumptions violate requirements due to limited data availability. Grey prediction is a technique for developing a GM model that extrapolates from past known or uncertain information to forecast future trends. Due to its advantages of requiring less raw data and high accuracy, it has been widely applied across multiple domains, including economics and industry, energy and environmental studies, healthcare, and risk assessment. Grey systems theory has been effectively used across various disciplines, with the grey theory of prediction as a key component of this framework.

This theory encompasses five primary categories of grey prediction (Xie and Liu 2009):

(i) Time series forecasting, which focuses on predicting future values based on past data

(ii) Calamity forecasting, aimed at anticipating disasters or adverse events

(iii) Seasonal calamity forecasting aims to identify patterns and trends associated with seasonal changes

(iv) Topological forecasting, which involves predictions based on spatial or structural relationships and

 (v) Systematic forecasting is concerned with identifying and predicting outcomes based on systematic patterns within the data.

The GM (1,1) model operates as an exponential model by applying an accumulated generating operation to a data series. This transformation results in a non-negative, monotonically increasing sequence. This minimises the randomness present in the original data while highlighting the emerging key trends. This model identifies data series that exhibit internal patterns or regularities. GM (1,1) is the simplest and most widely applied model of the grey forecasting theory. Its most notable characteristic is that GM (1,1) involves only a dependent variable and does not require any independent variables. We must assess the original data series x(0) using the class ratio to develop a grey forecasting model. As defined by Deng (2002), the class ratio is given by the formula, $λ^{(0)}\left(k\right)=x^{(0)}\left(k-1\right)/x^{(0)}\left(k\right)$, where k = 1, 2, 3, ..., n. For the effective construction of a GM (1,1) model, it is crucial to ensure that the class ratio$ λ^{(0)}\left(k\right)$ falls within the range of (0.135, 7.389). (Chen and Chen, 2011; Deng, 2002; Hung *et al*., 2009; Wang *et al*., 2010).

The annual paddy prices for all three zones in Telangana from 2014 to 2024 are utilised to construct a GM (1,1) model. This model will be employed to forecast the annual modal paddy prices for the years 2025,2026, and 2027.

The general steps for constructing a grey forecasting model are outlined as follows:

**Step 1: Prepare the Original Data Series**

The following equation expresses the original series of x(0):

 $x^{\left(0\right)}=\left(x^{\left(0\right)}\left(1\right),x^{\left(0\right)}\left(2\right),x^{\left(0\right)}\left(3\right),x^{\left(0\right)}\left(4\right),. . . . ,x^{\left(0\right)}\left(n\right)\right)=x^{\left(0\right)}\left(k\right)$, (1)

where k = 1,2,3,….,n and n$\geq 2$.

**Step 2: Check the Class Ratio**

The class ratio,$ λ^{(0)}\left(k\right)=\frac{x^{(0)}\left(k-1\right)}{x^{(0)}(k)}$ , k=2,3,4,. . . , n

Ensure that $λ^{(0)}\left(k\right) $of $ x^{(0)}$ is within the interval $\left(e^{-\frac{2}{n+1}},e^{\frac{2}{n+1}}\right)$.

**Step 3: Accumulated Generation Operation (AGO)**

A new sequence, denoted as x(1), is produced using the Accumulated Generation Operation (AGO).

 $x^{(1)}\left(k\right)=\sum\_{i=1}^{k}x^{(0)}(i)$ (2)

We can derive $x^{(1)} ,$Which is referred to as the first-order cumulative sequence or 1-GAO. This transformation helps to mitigate fluctuations in the x(0) data series and minimises systematic errors during the accumulation process, thereby enhancing the accuracy of the prediction model.

 $x^{(1)}=\left(x^{(1)}\left(1\right),x^{(2)}\left(2\right),x^{(3)}\left(3\right),. . . ,x^{(1)}(n)\right)=x^{(1)}\left(k\right)$ , (3)

Where k = 1,2,3, . . . , n .

**Step 4: Calculate the background Value Sequence**

Compute the background value z(1) built by the method of generations based on the average.

 $z^{(1)}= \left(z\_{2}^{(1)},z\_{3}^{(1)},z\_{4}^{(1)}, . . . ,z\_{n}^{(1)}\right)$ (4)

 $z^{(1)}\left(k\right)=0.5\left(x^{(1)}\left(k-1\right)+x^{(1)}(k)\right)$, k = 2,3, . . . . ,n. (5)

**Step 5:** **Formulate and Solve the Grey Differential Equation**

Establish a first-order linear differential equation of the GM (1,1) model, which is denoted as follows:

 $x^{\left(0\right)}\left(k\right)+az^{(1)}\left(k\right)=b$, where k = 2,3, . . . , n, (6)

where$ z^{(1)}\left(k\right)$ is the whitened value, and a & b are developing coefficient and grey input, respectively. Where 0 < a < 1, and $α$=0.5 is typically used. The AGO is used to identify potential regularities hidden in the data sequences even if the original data are finite, insufficient, and chaotic.

From Eq. (6) and by the Least Ordinary Square Method, the coefficient $\hat{θ}$ becomes

 $\hat{θ}=\left(\genfrac{}{}{0pt}{}{a}{b}\right)= \left(B^{T}B\right)^{-1}B^{T}Y\_{N} $, (7)

where $B=\left(\begin{matrix}-z^{(1)}(2)&1\\-z^{(1)}(3)&1\\\vdots &\vdots \\-z^{(1)}(n)&1\end{matrix}\right)$ , and YN = $\left(\begin{matrix}x^{(0)}(2)\\x^{(0)}(3)\\\vdots \\x^{(0)}(N)\end{matrix}\right)$

**Step 6: Construct the Time Response Function**

 By employing the white process, Equation (6) can be reformulated as a grey difference equation, as shown below:

 $\frac{dx^{(1)}(k)}{dk}+ax^{(1)}(k)=b$ (8)

To solve Eq. (8), the discrete sequence x(1) whitening equations are used:

 $\hat{x}^{(1)}\left(k+1\right)=\left[x^{(0)}\left(1\right)-\frac{b}{a}\right]e^{-ak}+\frac{b}{a}$ (10)

**Step 7: Apply Inverse Accumulated Generating Operation (AGO)**

The grey forecasting model relies on data derived from the Accumulated Generating Operation (AGO) instead of the original dataset, allowing the Inverse Accumulated Generation Operation (IAGO) to be employed for reversing the forecasted values.

Then, $\hat{x}^{(0)}\left(k\right)=\hat{x}^{(1)}\left(k\right)-\hat{x}^{(1)}\left(k-1\right)$ , k = 2,3, . . . . , n.

i.e., $\hat{x}^{(0)}\left(k\right)= \left[x^{(0)}\left(1\right)-\frac{b}{a}\right]e^{-a(k-1)}\left(1-e^{a}\right)$ , k = 2,3, . . . . ,n. (11)

Given k = 1,2,3,,,..., n, the series of reduction is obtained as follows:

 $\hat{x}^{(0)}= \left(\hat{x}^{\left(0\right)}\left(1\right),\hat{x}^{\left(0\right)}\left(2\right),\hat{x}^{\left(0\right)}\left(3\right), . . . .,\hat{x}^{\left(0\right)}(n)\right).$

**2.3 Forecasting Performance:**

Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) are used to measure the accuracy of the forecast:

 MAPE = $\frac{1}{n}\sum\_{i=1}^{n}\left|\frac{y\_{t}-\hat{y}\_{t}}{y\_{t}}\right|×100$ ,

 RMSE=$\sqrt{\frac{1}{n}\sum\_{i=1}^{n}\left(y\_{t}-\hat{y\_{t}}\right)^{2}}$ ,

where $y\_{t}$ represents the actual value of the data at time t, $\hat{y}\_{t}$ represents the predicted value of the data at time t, and n represents the total amount of data (Darvishi *et al.*, 2017). According to standard criteria, a MAPE value of less than 10% indicates highly accurate forecasting power. If the MAPE falls between 10% and 20%, the forecast is considered good. A MAPE in the range of 20% to 50% is generally seen as reasonable, while a value greater than 50% suggests the forecast is inaccurate. The criteria for RMSE are the same as MAPE. These thresholds provide a practical framework for interpreting MAPE & RMSE results and assessing the reliability of different forecasting approaches.

The data suggests that the grey GM (1,1) model parameters for a, b, as well as performance indicators, differ across NTZ, STZ, and CTZ zones with respect to paddy price forecasting in Telangana.

**3. RESULTS AND DISCUSSION**

**3.1 Model Parameters**

**Table 1**. Forecasting Performance Metrics and Model Parameters for the three zones

|  |  |  |  |
| --- | --- | --- | --- |
| **Value** | **NTZ** | **STZ** | **CTZ** |
| a | -0.0501 | -0.0498 | -0.042 |
| b | 1294.211 | 1283.137 | 1369.857 |
| MAPE | 1.193 | 1.935 | 3.467 |
| RMSE | 23.809 | 42.188 | 74.614 |

For all three zones, the class ratio test confirms the validity of the GM (1,1) grey model, and the error metrics support the reliability of the forecasts (Table 2).

**3.2 Northern Telangana Zone (NTZ)**

For the NTZ, the grey model GM (1,1) was applied to forecast modal prices, yielding strong statistical performance. The model parameters were estimated as a=−0.0501 and b=1294.211(Table 1). The Mean Absolute Percentage Error (MAPE) was 1.193, and the Root Mean Squared Error (RMSE) was 23.809, indicating high accuracy and a reliable fit to the historical data. The class ratio test was valid for this zone, confirming the appropriateness of the grey model. The forecasted modal prices for the next three years are 2306.050 in 2025, 2424.642 in 2026, and 2549.333 in 2027, suggesting a steady upward price trend. These results provide confidence in the model's ability to predict future price movements in NTZ.

**3.3 Southern Telangana Zone (STZ)**

In the STZ, the GM (1,1) grey model provided effective forecasts for the modal prices. The estimated parameters for this zone are a=−0.0498 and b=1283.137. The model achieved an MAPE of 1.935 and an RMSE of 42.188, reflecting good accuracy and reliability in its predictions(Table 1). The class ratio test was satisfied, indicating that the model suits this data series. The forecasted modal prices for 2025, 2026, and 2027 are 2278.113, 2394.448, and 2516.723, respectively. These forecasts indicate a consistent upward trend in modal prices for the STZ.

**3.4 Central Telangana Zone (CTZ)**

For the CTZ, applying the GM (1,1) grey model resulted in the following parameter estimates: a=−0.042and b=1369.857. The model's MAPE is 3.467, and the RMSE is 74.614, which are within acceptable limits for forecasting in this context(Table 1). The class ratio test was valid, confirming the model's suitability for the CTZ time series. The predicted modal prices for the next three years are 2222.494 for 2025, 2318.066 for 2026, and 2417.748 for 2027. These results indicate a positive trend in modal prices, and the model demonstrates reasonable accuracy for future projections in the CTZ.

A comparative analysis of three zones of Telangana (NTZ, CTZ, STZ) reveals notable differences in forecasting performance and model fit. It can be clearly seen that NTZ has the least MAPE and RMSE values, which validates the hypothesis that the price series in NTZ is more stable and the GM (1,1) model is very efficient here as it prolongs forecast error. STZ also performs well in accuracy, though its relatively high errors indicate that the price data in STZ is significantly more volatile or complex compared to NTZ. Meanwhile, CTZ has the highest MAPE and RMSE out of all the regions, meaning that its price trends are highly volatile. This may come into conflict with the accuracy of the model, but still remains within acceptable limits. Regardless of these distinctive features, all zones are consistent in their expectations of an increase in modal prices for the next three years, although NTZ and STZ are predicted to achieve higher prices than CTZ. The pattern suggests that there are regional differences in market dynamics, which could be driven by differences in supply, demand, or structural elements. Nonetheless, its efficacy may change due to the behaviour and the nature of the time series. All in all, the GM (1,1) model offers good forecasting capability across all three zones.

The results of this study highlight the effectiveness of the GM (1,1) grey model in forecasting modal prices across the NTZ, STZ, and CTZ zones. The low MAPE and RMSE values obtained for each zone indicate a high level of predictive accuracy, while the class ratio test confirms the model’s validity for all datasets. These findings are consistent with previous research in other agricultural and economic forecasting contexts, where the grey model has demonstrated versatility and robustness, especially in data-scarce environments. The consistent upward trend in forecasted prices across all zones suggests that market fundamentals, such as demand growth, production costs, and policy interventions, will likely sustain price increases in the short term. This trend aligns with the broader context of rising agricultural input costs and evolving market dynamics in Telangana. The consistent upward trend in forecasted prices for the next three years underscores the model’s ability to capture underlying market dynamics. These findings suggest that the GM (1,1) model can serve as a reliable decision-support tool for stakeholders in the agricultural sector. Moreover, the approach is particularly valuable in contexts with limited or uncertain data, as is often the case in agricultural markets. This study's high accuracy of the GM (1,1) model highlights its potential as a practical tool for stakeholders. For farmers, accurate price forecasts can inform planting and marketing decisions, helping to mitigate price risk. Policymakers and market regulators can use these forecasts to design interventions that enhance market stability and food security. Additionally, the model’s ability to function effectively with limited data makes it especially valuable in regions without comprehensive datasets. The study thus contributes to the growing body of evidence supporting grey models for practical, data-driven forecasting in agriculture.

**4. CONCLUSION**

The application of the GM (1,1) grey model across the NTZ, STZ, and CTZ has demonstrated strong forecasting performance, as evidenced by low MAPE and RMSE values in each zone and the validation of the class ratio test throughout. The model parameters were robust, and the forecasted modal prices for 2025, 2026, and 2027 consistently indicate an upward trend across all regions. This suggests that the grey model is practically reliable for predicting future price movements in these agricultural zones. The accurate and consistent forecasts provided by the model offer valuable insights for policymakers, traders, and farmers, enabling informed decision-making and strategic planning for the coming years. And also, the results accord with the previous studies that predicted that the GM (1,1) model could be a suitable method for pattern change to price and could result in a high simulation performance, even in the case of limited or uncertain information. Recent works have also demonstrated that the approach can be flexible and more accurate than other methods, especially in cases with limited or missing historical data. Overall, the GM (1,1) grey model is a powerful and effective tool for short-term price forecasting in the agricultural sector.

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**Table 2: Comparison of Class Ratio Values**

|  |  |  |
| --- | --- | --- |
| **NTZ** | **STZ** | **CTZ** |
| 0.9621 | 0.9702 | 0.9715 |
| 0.9385 | 0.9436 | 0.9381 |
| 0.9778 | 0.9465 | 0.9108 |
| 0.9590 | 0.9890 | 1.0248 |
| 0.9095 | 0.9121 | 0.8895 |
| 0.9841 | 0.9575 | 1.0402 |
| 0.9581 | 0.9983 | 0.9946 |
| 0.9439 | 0.9573 | 0.9370 |
| 0.9413 | 0.9045 | 0.9491 |
| 0.9448 | 0.9362 | 0.8832 |



Fig 1: Actual vs Fitted Modal Prices (Rs/Qtl) of (a) NTZ (b) STZ and (c) CTZ from 2014 to 2024