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ORIGINAL ARTICLE

Masked Self-Supervised Temporal Modeling of Agricultural Prices: A Case Study of Wheat MSP in Rajasthan Region

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Abstract

Objectives: To develop a data-efficient Masked Self-Supervised Temporal framework for wheat Minimum Support Price (MSP) forecasting under sparse and irregular agricultural time-series conditions. **Method**: District-level wheat production and price data from all districts of Rajasthan Region, for 2016–2025 were pre-processed and segmented into temporal windows. In this work, we propose a Masked Self-Supervised Temporal learning framework for MSP forecasting that emphasizes representation learning rather than direct label dependence using masked reconstructive temporal learning. Performance was compared with ARIMA and supervised LSTM using mean squared error (MSE) on log-transformed prices. **Findings**: ARIMA produced the MAE (164.97), while supervised long short-term memory (LSTM) achieved 60.58. The proposed Masked Self-Supervised Temporal Learning (MSSTL) framework achieved a MAE of 32.67 and showed stable convergence and improved data efficiency. MSSTL learned temporal representations capturing seasonal patterns, production–irrigation interactions, and longer-term market memory without relying exclusively on labeled price observations. The results indicate that Masked Self-Supervised Temporal learning can provide a useful balance between forecasting performance and robustness when agricultural datasets are limited. The future-trend analysis emphasizes directional stability rather than exact long-horizon price values. **Novelty**: The study applies two-stage Masked Self-Supervised Temporal representation learning to wheat MSP forecasting in a data-scarce district-level agricultural setting, reducing dependence on labeled price data.

Keywords: Crop Price; Minimum Support Price; Deep Learning; Masked Self-Supervised Learning; Temporal Learning

1 Introduction

The agricultural industry is a crucial sector that contributes significantly to the global economy. With the increase in demand for food products, crop production and procurement have become vital areas of focus for agricultural stakeholders. However, crop price volatility and unpredictability pose significant risks to the industry, affecting both producers and buyers. Farmers continue to struggle with price volatility, distrust in digital projections, and comprehension of complicated data, issues that current methods are unable to resolve because of gaps in literacy and accessibility.

To address this challenge, researchers have explored various machine learning (ML) and deep learning(DL) algorithms to predict crop prices accurately. For instance, Poudel, Bibas(2024) [1] proposed an ARIMA model for maize price prediction in Nepal, while Wang C. (2025) [2]. used a long short-term memory(LSTM) neural network for predicting cotton prices in China. Jaiswal Ronit et al. (2023) [3] developed a LSTM based model for accurately predicting a nonlinear agricultural price series. Zhang et al., (2025) [4] proposed a novel hybrid model based on dual decomposition and enhanced BiLSTM for price prediction. It was for improving agricultural commodity allocation and market regulation.

But conventional statistical and supervised learning models offer limited understanding of the temporal patterns underlying their predictions [5], which reduces stakeholder confidence in their practical use. Also time series data (like crop price) is hard to label.

In order to overcome this challenge contrastive learning (CL) based self-supervised learning can be used for better understanding [6]. CL is a powerful method within self-supervised learning for extracting useful features from unlabeled time series data, which can then be applied to complex tasks like price prediction [7]. Self-supervised pre-training with contrastive and masked methods can better deal with small datasets [8]. This approach is particularly valuable for time series analysis because it can capture temporal dynamics and representations without requiring manual labeling, thus saving significant expert time and effort [9], [10].

Now, we want to add that there is a difference between crop price and Minimum Support Price (MSP). Crop price is basically market price for a crop whereas MSP is announced by the Government of India based on recommendations of the Commission for Agricultural Costs and Prices (CACP), along with various economic and agricultural factors which is influenced by several other factors, including production, cultivated area, irrigation, and historical data for MSP and government policies. As existing research explored the crop price [11], [12], [13], there are some review papers available only one experimental research found on MSP data. [14], [15], [16]. Table 1 summarized the Reviewed Literature based on Crop Price Prediction and MSP.

The MSP plays a vital role in stabilizing agricultural prices and protecting farmers from market fluctuations therefore the upgraded model using advanced AI is needed to be designed for more accuracy in MSP prediction. As researchers have experimented with various ML and DL algorithms to predict crop prices therefore taking into consideration of those research of price prediction this framework designed with advanced AI approaches to improve the accuracy and reliability of MSP prediction.

In this work, we propose a masked self-supervised temporal learning framework for MSP Prediction that emphasizes representation learning rather than regional label dependence. From regional-level historical production data of Rajasthan Region, the framework first learns intrinsic temporal representations through masked self-supervised pretext tasks, which including sequences are masked, reconstructed and temporal consistency learning, without relying on price labels. These learned embeddings capture latent intra-year seasonal trends from the annual observations, production–irrigation interactions and relationships among historical MSP and auxiliary variables, which are subsequently utilized for downstream MSP prediction.

Comparative analysis against classical ARIMA and supervised LSTM baselines determine the higher predictive performance of the proposed MSSTL framework, particularly under limited-data conditions. The study presents a simple framework for using masked self-supervised temporal learning in agricultural markets and shows it's potential for reliable price forecasting and better policy decisions when data are limited.

The objectives of the study are: (i) to learn meaningful temporal patterns from district-level agricultural time series without direct dependence on price labels and limited-data conditions; (ii) to evaluate the downstream wheat MSP forecasting capability of the learned representations; and (iii) to compare the proposed framework with ARIMA and supervised LSTM baselines under data-scarce conditions.

2 Methodology

The author is working in the Food Corporation of India, Rajasthan Region and collected the dataset from the procurement division of her department. The dataset received from primary source. Dataset (msp_dataset_clean.csv) captures Rajasthan district-level MSP procurement records for wheat, gram and barley across eight marketing seasons (2016-17 to 2025-26) for

Table 1. Summary of Reviewed Literature based on Crop Price Prediction and MSP.

Reviewed Literature based on Crop Price Prediction

Reference	Dataset	Size of Data	Type of Data	Features in Data	Metrics	models	Result
(11)	FAMA official government website (https://sdvi.fama.gov.my/analisahargaming-guan/DownloadPassword.asp).	11 years Data (no. Of records not mentioned)	Time Series and multi variate	Features in Time series Data not given (Temperature, Humidity, Precipitation and Crude Oil Price) are features of multivariate dataset	MSE	ARIMA, LSTM, SVR, Prophet and XGBoost	LSTM used for final prediction
(12)	Indian Agriculture Crop Price Dataset, which was retrieved on the Kaggle platform and actual market price data released via Agmarknet (Agricultural Marketing Information Network), Government of India	2 years data	multivariate time-series dataset	date, state, city, type of crop, season, temperature, rainfall, volume of supply and volume of demand	R^2, RMSE and MAE	Linear Regression, SVR, Random Forest, AdaBoost and XGBoost	XGBoost
(13)	3 crop dataset for Delhi UP and Maharashtra, from India, is sourced from the government's official agricultural marketing portal, 'AgMarknet' (https://agmarknet. gov. in/) weekly weather-related data such as precipitation and temperature, respective crops, is obtained from NASA POWER (https:// power.larc.nasa.gov/).	20 years data	Time Series and multi variate	Not clearly mentioned	RMSE, MAE, MAPE, MASE and QL	ARIMAX, MLR, ANN, SVR, RFR, XGBoost,NBEATSX, and TransformerX	NBEATSX

Reviewed Literature based on MSP

Reference	Type of Paper	Size of Data	Type of Data	Features in Data	Metrics	models	Result
(14)	Literature review Paper	-	-	-	-	-	-
(15)	The procurement data published by the Food Corporation of India (FCI) and the Ministry of Agriculture and Farmers welfare.	20 years data	time series data	-	-	-	-
(16)	Statistical Paper	25 years data	time series data	MSP	RMSE, MAE, MAPE, MSE, AIC, BIC, R2	LR, ES model, FB-Prophet model, ARIMA	ARIMA was a suitable choice for forecasting MSP

33 revenue districts totaling 1718 records, including procurement area, irrigation status, production and the announced MSP (₹/quintal).

All three models are evaluated using the same strict chronological test observations 70-15-15 train–validation–test. The observations are divided into 70% training, 15% validation and 15% testing with the test period occurs strictly after the training and validation periods.

The study was conducted in four stages: data collection, data preprocessing, model framework development, and results analysis with discussion. It focuses on district-level wheat production and price data from districts of Rajasthan for the period 2016–2025. The dataset contains annual production values and aggregated totals and exhibits common agricultural time-series challenges, including missing observations, zero-valued entries, and abrupt fluctuations associated with climatic variability and policy interventions.

2.1 Data Collection and Preprocessing

During preprocessing, zero values were treated as missing observations to maintain temporal continuity. Missing observations were handled using forward and backward filling. A logarithmic transformation was then applied to stabilize variance and reduce scale effects. The processed multivariate time series was segmented into fixed-length temporal windows to preserve temporal ordering and support sequential learning.

2.2 Proposed Masked Self-Supervised Temporal Learning Framework

The proposed Masked Self-Supervised Temporal Learning (MSSTL) framework uses a two-stage design. In the first stage, masked temporal reconstruction pre-training is achieved to learn meaningful temporal representations from multivariate, district-level time-series data without using price labels. During this, selected observations within temporal windows are masked, and the model is trained to reconstruct the masked information. This process enables the model to learn underlying temporal dependencies, trends, and contextual patterns present in the historical data. A temporal window size of 3 is used, meaning that the model utilizes three consecutive annual observations as historical input to predict the MSP of the subsequent year (Figure 1).

The sequential temporal windows were constructed as X_train.shape = (number_of_windows, 3, 4) where 3 is temporal dimension and 4 is feature dimension.

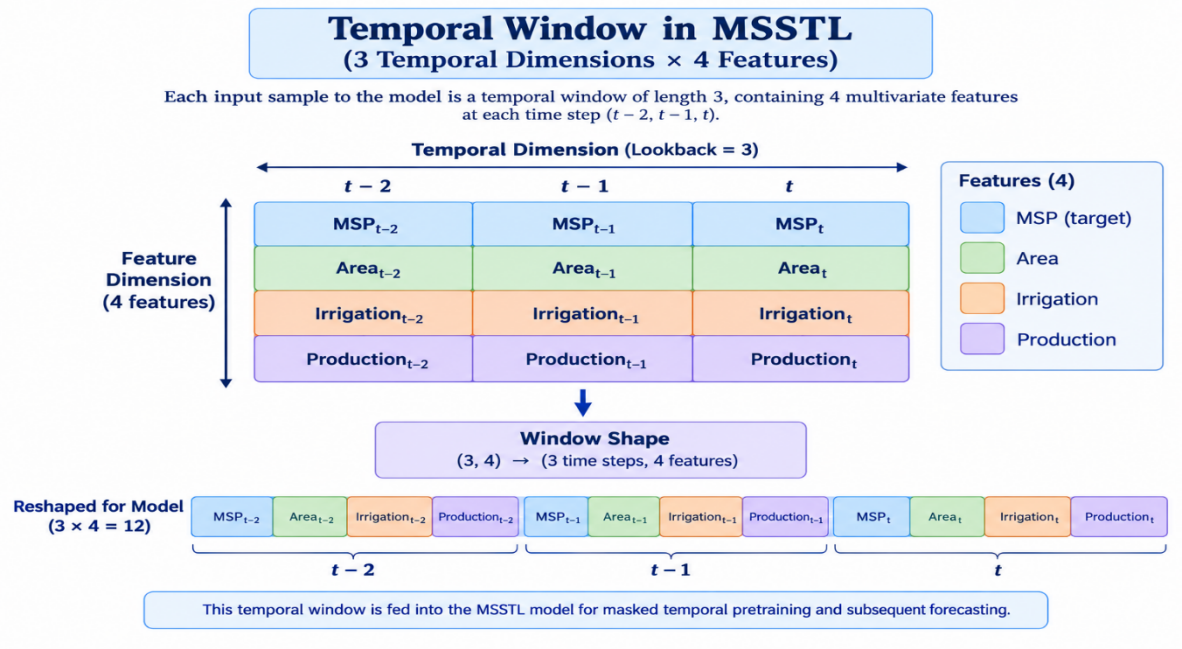


Fig 1. Presenting how sequential temporal windows were constructed.

2.2.1. Self-Supervised Pretext Tasks

The proposed framework employs self-supervised masked reconstruction as the pretext task which learns temporal representations without requiring explicit price labels. The dataset is divided chronologically into 70% training, 15% validation and 15% test periods with temporal windows constructed independently within each partition. Pre-training is performed exclusively on training windows, where selected observations are masked and reconstructed using the remaining historical context. For a window length of three, observations at (t-2), (t-1), and (t) are used to predict the subsequent MSP at (t+1), which is excluded from the input. This preserves temporal ordering while learning inter-year dependencies and multivariate relationships. The learned temporal representations capture the key patterns and temporal relationships in the historical agricultural data, which are then used to forecast MSP.

2.2.2. Downstream Price Prediction

In the second stage, the pre-trained temporal encoder is frozen and connected to a lightweight regression module, such as a linear regressor or multilayer perceptron, to predict future MSP at the regional or aggregated level. The forecasting model is trained using training-period representations, while validation data are used only for model and hyperparameter selection. The test period remains completely isolated from both pre-training and model selection and is used only for final evaluation. This two-stage design separates representation learning from supervised forecasting, preserves chronological data separation and helps reduce overfitting and temporal information leakage under limited labeled observations.

2.3 Baseline Models

The proposed MSSTL framework was compared with a classical ARIMA model and a supervised LSTM model (Figure 2). ARIMA represents a conventional statistical time-series baseline, whereas LSTM represents a nonlinear supervised deep-learning baseline. The comparison was conducted using mean squared error (MSE) on log-transformed price data.

2.4 Evaluation Metric

Model performance was evaluated using mean absolute error (MAE), Mean Squared Error (MSE) root mean squared error (RMSE), mean absolute percentage error (MAPE), and the coefficient of determination (R^2). These metrics were calculated using the predicted and actual MSP values on the original MSP scale. The reported results provide descriptive comparisons of the forecasting performance of MSSTL and the benchmark models under the same chronological evaluation setting. No statistical significance test is reported in the source study; therefore, the numerical comparisons should be interpreted as descriptive model comparisons.

2.5 Statistical Analysis

No formal sample-level statistical significance tests were performed in this study. Similarly, standard deviations, confidence intervals, and repeated-run variability were not estimated. Therefore, differences in the reported performance metrics among the models are interpreted descriptively rather than as evidence of statistically significant differences.

3 Results and Discussion

As no recent work specifically on MSP forecasting is found, therefore; a direct comparison with recent models is not feasible. The present study uses the MSP procurement data obtained from the FCI for MSST framework for MSP prediction. Since existing studies worked with different datasets, crops, forecasting models, their reported results cannot be directly compared with the results of the proposed framework. Therefore, to provide a meaningful and consistent evaluation, two established forecasting methods, ARIMA and supervised LSTM were used and the experiment done using the same dataset, data split, and forecasting setting as the proposed MSSTL framework. This enables a fair comparison of forecasting performance under identical experimental conditions.

3.1 Comparison with Baseline Models

The performance of the proposed MSSTL framework was evaluated against classical ARIMA and supervised LSTM models using MSE on price data. As shown in Table 2, the ARIMA model exhibits the prediction error (MAE = 164.970), indicating instability when applied to agricultural price series characterized by missing observations and abrupt fluctuations. This outcome highlights the limitations of traditional statistical methods under non-stationary and data-sparse conditions.

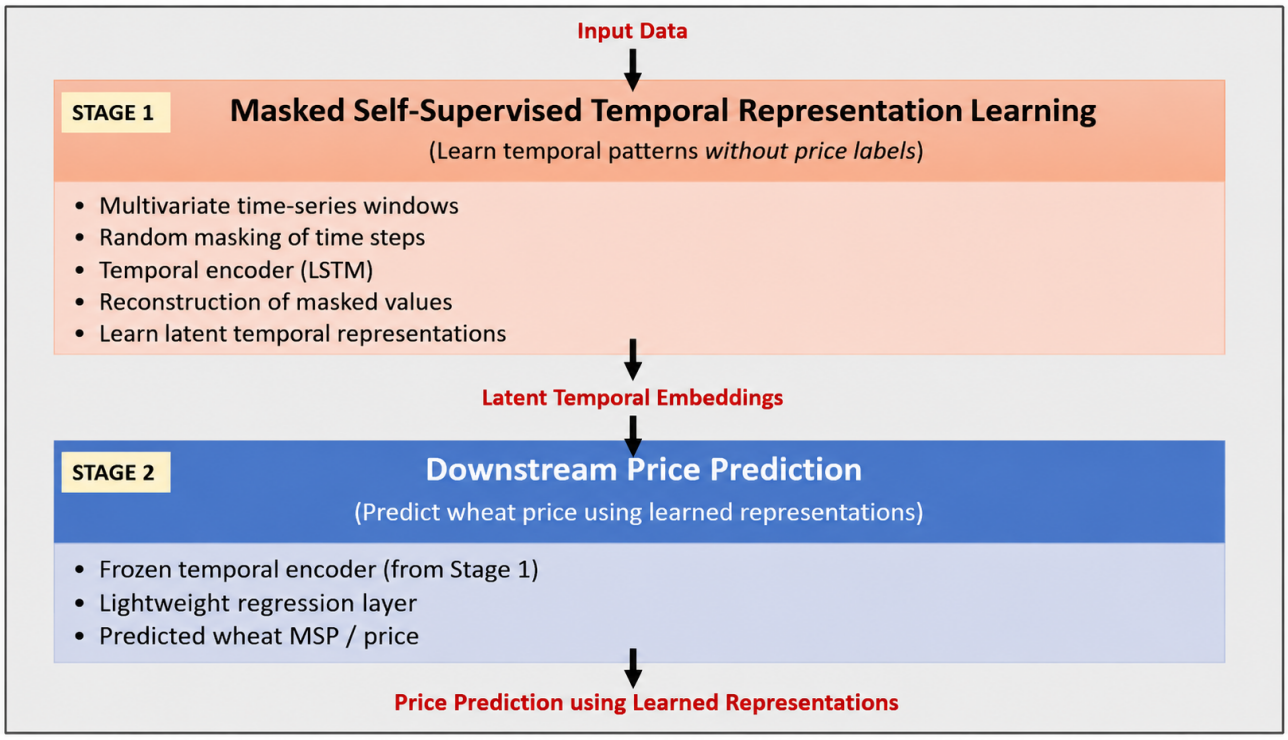


Fig 2. Proposed Masked Self-Supervised Temporal Learning (MSSTL) framework for agricultural price forecasting.

The supervised LSTM model achieves substantially lower error (MAE = 60.579), demonstrating its ability to capture nonlinear temporal dependencies. However, due to the limited number of training samples, the LSTM shows relying heavily on labeled data and exhibiting reduced robustness to unseen temporal patterns.

In comparison, the MSSTL framework attains competitive prediction performance (MAE = 32.670) while maintaining stable convergence and improved data efficiency. Although its numerical error is higher than that of the supervised LSTM, MSSTL benefits from learning robust temporal representations during self-supervised pre-training, reducing reliance on labeled data and improving generalization. These results indicate that Masked Self-Supervised Temporal learning offers a balanced trade-off between accuracy and robustness, making it well suited for agricultural price forecasting in data-scarce environments (Figure 3).

OVERALL TEST METRICS

	Model	MAE	MSE	RMSE	MAPE (%)	sMAPE (%)	R2
0	MSSTL	32.670264	2164.283346	46.521859	1.339783	1.348777	0.998638
1	LSTM	60.579441	5309.421904	72.865780	2.235202	2.238719	0.996658
2	ARIMA	164.970553	36610.642382	191.339077	6.655739	6.986279	0.976954

Fig 3. Overall Test results of all three models.

From the Table 2 it is clear that proposed model MSSTL is found better in all five matrices i.e. Lesser MAE value 32.670 shows smaller prediction error. RSME value is 46.52 which is remarkably lower than other two models LSTM and ARIMA having value 72.87 & 191.34 respectively. Model's R^2 value indicates that MSSTL predictions are much closer to the actual prices, and captures the underlying temporal patterns in an effective manner.

Table 2. Comparison of the proposed MSSTL framework with baseline models.

Model	Learning Type	MAE	MSE	RMSE	MAPE (%)	R^2
ARIMA	Statistical	164.970	36610.64	191.34	6.65	0.9769
LSTM	Supervised deep learning	60.579	5309.42	72.87	2.23	0.9966
MSSTL (Proposed)	Masked Self-Supervised Temporal	32.670	2164.28	46.52	1.34	0.9986

3.2 Actual and Predicted Wheat Price Trend

The study presents an actual-versus-predicted wheat-price trend for Rajasthan using the MSSTL framework. Figure 4(a) shows the trend study Actual vs MSSTL Predicted Wheat Price in Rajasthan. Similarly Figure 4(b) shows future trends of MSP. Future price trends were estimated by extrapolating MSSTL-learned temporal representations using a lightweight linear-regressor. The forecast emphasizes trend direction and stability rather than exact price values. The plot shows actual and MSSTL-based wheat price trends, where MSSTL captures stable temporal patterns and provides a smooth future trend forecast beyond 2025, emphasizing directional recovery rather than exact price values.

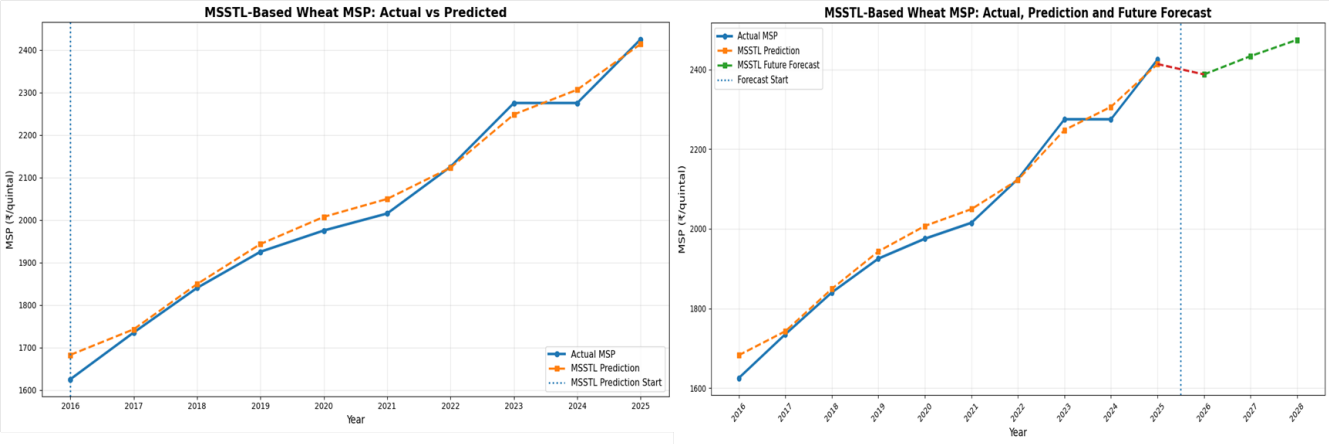


Fig 4. (a). Actual versus MSSTL-predicted wheat price trend for Rajasthan Region. (b). MSSTL-based future wheat price trend for Rajasthan Region.

3.3 Discussion

Based on existing studies on crop price prediction and MSP, it is found that existing research is using ML and DL models for crop price prediction. DL models can predict crop prices well, but they generally perform better with larger datasets. In this study, MSP prediction is considered for the Rajasthan region, where data availability is limited. Hence, a data-specific approach is required. To address this issue, we developed a self-supervised model using contrastive learning (CL), which can learn useful patterns from limited data. Furthermore, the proposed Model MSSTL achieved an R^2 value of 0.9986, which identifies strong predictive capability and captures the underlying temporal patterns in an effective manner. That means the model is working efficiently with limited data conditions.

The results indicate that the self-supervised representation-learning strategy can be useful when agricultural datasets contain limited labeled price observations. The MSSTL MAE of 32.670 is substantially lower than the supervised LSTM MAE of 60.579 and ARIMA MAE of 164.970. The principal methodological distinction is that the MSSTL encoder learns temporal representations before the downstream prediction task, thereby reducing direct dependence on labeled price observations. Nevertheless, the present evidence is limited to the reported dataset, evaluation metric, and experimental comparison. Additional higher-frequency data and repeated evaluation would be required to establish generalizability and statistical significance.

4 Conclusion

This study shows that Masked Self-Supervised Temporal learning effectively captures stable price trends in data-scarce agricultural settings. As conventional forecasting approaches that directly learn the relationship between historical observations and target prices, this framework first learns temporal representations from the available historical data through a masked self-supervised learning strategy. The study examines the effectiveness of the learned temporal representations by comparing MSSTL with established statistical and deep-learning approaches, i.e. ARIMA and LSTM. The experimental results prove that the proposed approach achieves substantially lower forecasting errors and better performance. In view of above, this work is not only the improved predictive performance but also the use of masked self-supervised temporal representation learning to agricultural price forecasting under limited-data conditions.

This study demonstrates that Masked Self-Supervised Temporal learning effectively captures stable price trends in data-scarce agricultural settings. The proposed MSSTL framework outperforms traditional models by providing robust, trend-oriented forecasts that support informed policy and procurement decisions.

The proposed MSSTL framework has many limitations. First, the study is based on a relatively small annual dataset spanning a limited time period, which restricts the model's ability to capture finer-grained temporal dynamics. Second, the analysis relies primarily on production-based indicators and aggregated price values, without incorporating external factors such as weather conditions, market demand, transportation costs, or policy announcements, which may further influence agricultural price behavior. Additionally, while the framework learns latent temporal representations, explicit interpretability of these embedding remains limited, potentially constraining their direct use in policy explanation.

Future work will focus on extending the framework to larger and higher-frequency datasets, including monthly or weekly price series across multiple crops and regions. Incorporating exogenous variables such as climatic data, irrigation intensity, and policy signals is expected to improve predictive performance. Further research may also explore explainable AI techniques to interpret learned temporal representations and enhance stakeholder trust. Finally, the transferability of the self-supervised representations across different agricultural commodities and geographical regions will be investigated to improve the generalizability of the proposed approach.

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Author details: Uma Joshi is a Ph.D. Scholar; Dr. Amita Sharma is an Asst. Professor (Selection Grade).

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