Long-Term Wheat Price Prediction Using Time Series and Deep Learning Models

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DATA300: Machine Learning & DATA201: Time Series Final Project

ABSTRACT

This study aims to evaluate the long-term predictive potential of wheat price using time series, machine learning, and deep learning models. Exogenous features were chosen to capture changes in general commodity pricing as well as macroeconomic and climate factors. Models were trained on data from 1990 to 2018 and tested on its ability to forecast over a six-year period, from 2018 to 2024. Our LSTM model drastically outperformed all other models tested. Despite LSTM's ability to factor non-linear relationships; the errors show significant struggle to capture long-term shocks and movements in the price of wheat.

INTRODUCTION

Forecasting wheat prices is imperative given wheat's role as a global staple crop, influencing food security, agricultural economics, and commodity markets. The motivation for this project stems from the need to support farmers, policymakers, and traders in making informed decisions amidst volatile market conditions. Wheat price volatility, driven by environmental factors like temperature and drought poses significant challenges to agricultural planning. Accurate forecasts can mitigate risks, optimize resource allocation, and enhance market stability. By comparing model performance, the study seeks to provide insights into the suitability of deep learning versus traditional time-series methods for agricultural price prediction.

METHODOLOGY

Data Collection:

Economic indicators were downloaded directly from FRED (commodity export/import indices, corn/oil/flour prices, CPI, wheat prices), climate data came from Our World in Data (global temperatures), and drought indexes from drought.gov.

Data Preprocessing:

Datasets were cleaned and consolidated. Raw price data for both features and the target were transformed to log return values. Log returns were also calculated for all price indexes. For machine and deep learning models, lagged features were introduced, and MinMax scaler was used for the LSTM model.

Models Tested:

We began by testing a basic Autoregressive models, adding important exogenous variables. ARIMA was tested next to test the model with an added moving average term. SARIMAX was tested next, adding a new seasonal aspect to ARIMA. VAR modeling was also tested. For the time series models, we selected the best parameters by maximizing AIC. We then expanded our model to machine learning with a basic Decision Tree model. Next, we tuned an XGBoost model and tested it. Finally, we tested Recurrent Neural Network, using LSTM for the time series data. We tuned this by minimizing MSE.

RESULTS

The models were evaluated on MSE, RMSE, and MAE. Figure 1 shows the comparisons of the model performances based on RMSE and MAE. All series models tested show nearly identical RMSE and MAE values, suggesting that linear autoregressive models can capture a limited amount of variation in wheat pricing.

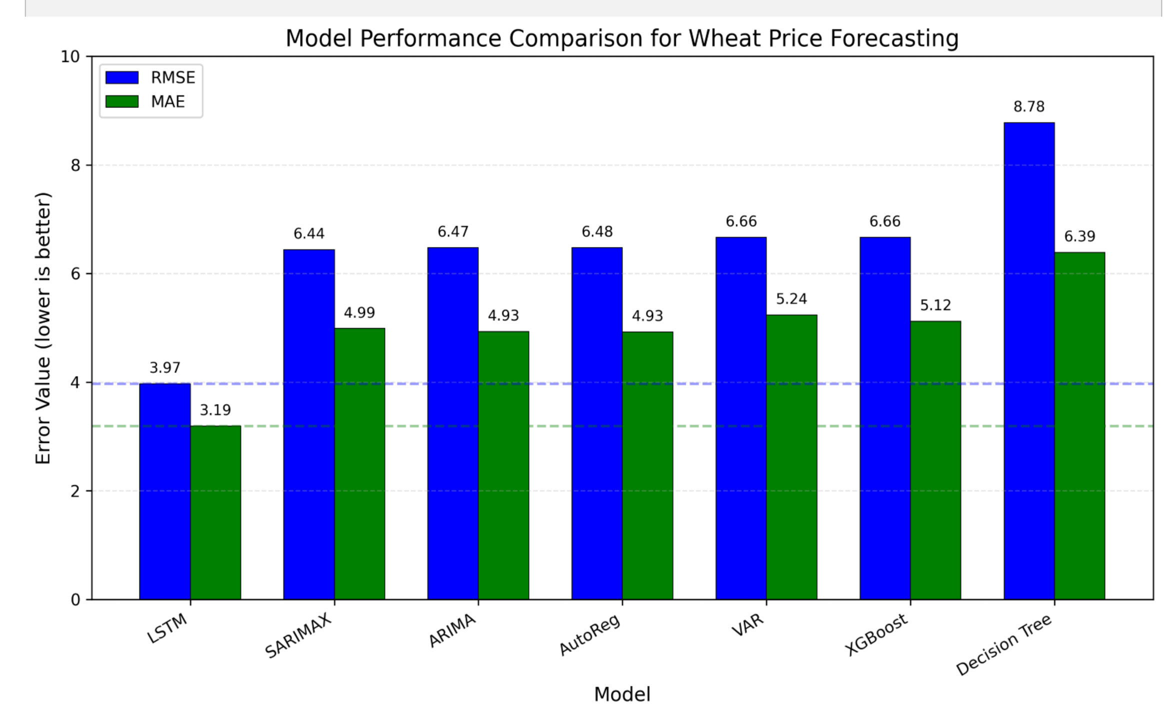

Figure 1: Model Comparison Chart

The LSTM model significantly outperformed other models tested, with an RMSE of 3.97 and a MAE of 3.19.

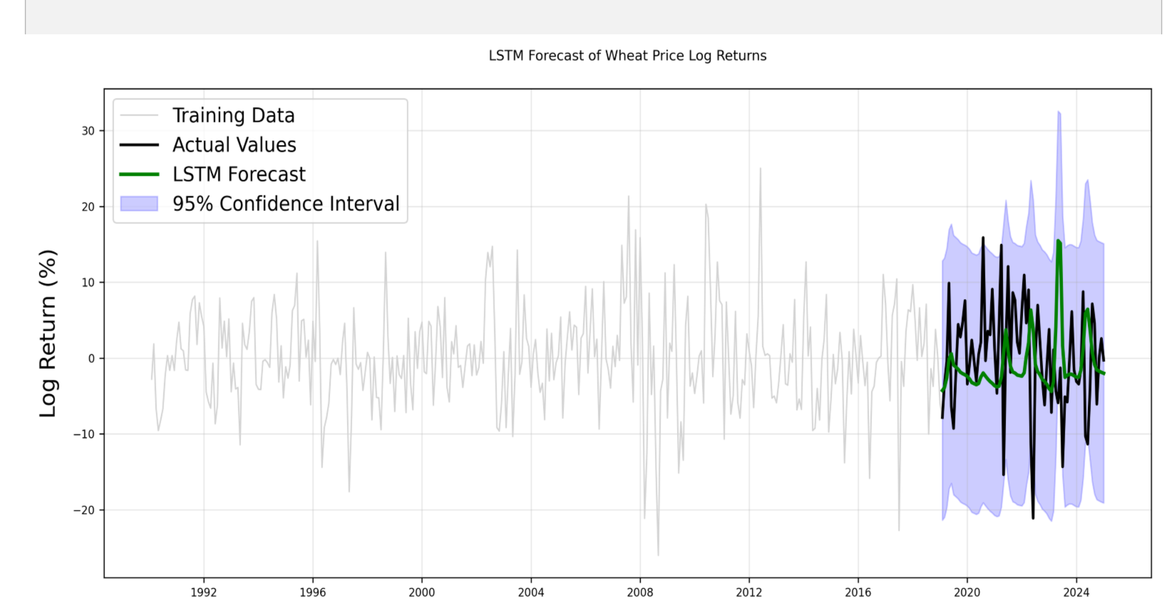

Figure 2: LSTM Model Forecast

CONCLUSION

Our research demonstrates the improvements that deep learning models, particularly LSTM networks, offer substantial improvements over tradition time series forecasting for long-term wheat price modeling. Figure 2 shows the substantial size of the 95% confidence interval, suggesting there is limited predictability, even when using deep learning models. The wide confidence intervals highlight the volatility in the market, making predictive capabilities over a multi-year range very difficult.

Future Work Suggestions:

Future work should focus on developing ensemble models for long-term forecasting. Additional exogenous features should be incorporated, such as geopolitical factors, exchange rates, and climate-related futures.

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