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Research Article

An ARIMA model approach for predicting wheat production in India and China

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ABSTRACT

Wheat production is of paramount importance in both India and China, as it is very essential in food security and the livelihood of millions of people. Accurate forecasting of wheat production is essential for ensuring stable food supplies and effective agricultural policies. The ARIMA technique applied to time series analysis to assess and forecast wheat production in India and China. The process of inquiry begins with collecting historical wheat production data from Kaggle dataset. The ARIMA-based models are used to provide interesting insights within the parameters and dynamics of wheat production in India and China. The models effectively capture the seasonality and trend components of historical data, enabling accurate prediction. This study concludes that ARIMA models offer a valuable tool for forecasting wheat production in India and China, provided that data quality, model specification, and external factors are appropriately considered. Accurate wheat production forecasts are crucial in providing food security and making informed agricultural and economic decisions in both countries. This analysis leads to the specific broader form of agricultural forecasting while emphasizes the potential for time series analysis to address agricultural challenges. For the most part, ARIMA (0,1,0) model appears to fit the data over India efficiently, and ARIMA (1,1,0) structure appears for delivering reasonable forecasts for the China wheat production time series. The forecasted values for the next 10 years are 2020 to 2029, along with 95% prediction intervals (Lo 95 and Hi 95).

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INTRODUCTION

Wheat production holds significant importance within the agricultural sectors of India and China, both of which rank among the best wheat farmers in globally. It is highly critical in both India and China, serving as a fundamental component of food security and their respective economies. It is a primary good supply of nutrients and substances in the diets of their populations. Wheat is commonly cultivated and consumed cereal grains throughout globally, and it serves various purposes for humans like food, Bread, Pasta and Noodles, Cereals, Pastries and Baked Goods, Pizza Snack foods, Animal feed, Flour based desserts, Wheat germ oil and various Wheat-Based Ingredients are

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used in food processing and manufacturing to improve texture and consistency [1]. In India, wheat is cultivated across 29.55 million hectares, contributing to a remarkable output of 101.20 million tonnes with a record-breaking a report by the Ministry of Agriculture and Farmers Welfare›s (2019) third advance estimates, average national productivity is 3424 kg/ha. According to official reports, wheat output in 2023 reached a record high of 112.74 million metric tons, marking an increase from the previous year›s 107.7 million metric tons. The Second Advance Estimates for the agricultural year 2022-23 suggest that wheat production in India has surged to 112.18 million tonnes, surpassing the previous year›s production by 4.44 million tonnes [2,3]. During the marketing year 2022/2023, China emerged as the leading global wheat producer, with a production volume exceeding 137 million metric tons, surpassing the European Union›s production volume of over 134 million metric tons. Although China is the globe›s originating wheat crop manufacturer, contributing 17% of the global total in the early 21st century, it is also the world›s most significant consumer of wheat, driven by its population of 1.4 billion people. Both countries possess expansive agricultural land suitable for wheat cultivation [4,5]. The present challenges in wheat production as factors like climate change, water scarcity, and fluctuations in market demand.

ARIMA models are common application for estimating future values over time [6]. These models take into account past observations and trends to make predictions about future values. This is crucial in various fields such as finance, economics, weather forecasting, and inventory management. Utilizing the ARIMA model and the Box-Jenkins approach to analyze historical wheat production data in India and China provides valuable insights into underlying patterns and dynamics. Additionally, the use of information criteria such as AIC, BIC, and AICc assists in choosing the most appropriate model for forecasting future wheat production trends. This analysis is vital for policymakers, farmers, and stakeholders in both countries to make informed decisions related to crop management, food security, and economic planning. An ARIMA models are important tools in the field of statistics and data analysis, particularly when dealing with data that varies over time. Some key reasons why time series analysis using ARIMA are important. Some of the reasons why ARIMA models are essential for time series data and predictive data analysis, Trend Analysis, Seasonality Detection, Anomaly Detection, Economic and Financial Analysis, Quality Control, Policy and Decision Making, Scientific Research, Resource Allocation, Performance Evaluation and Data Visualization. The analysis aims to uncover seasonality and trend components within the data and provide insights into the effect of these variables on wheat production [7,8].

In the case of India, ARIMA models are applied to predict wheat yield, considering factors such as monsoon patterns, government policies, and technological advancements [9]. For China, a similar approach is undertaken, but with a particular focus on the role of climatic factors and land use changes. Understanding the interplay of these variables with wheat yield is essential for policymakers in the region, as China faces unique challenges related to climate change and urbanization.

The study then compares the performance of ARIMA models between India and China. By assessing the accuracy of predictions and examining forecast errors, the research sheds light on the distinct influences affecting wheat production in these two countries. This comparative analysis offers valuable insights into the agricultural systems of India and China and can guide policymakers in developing strategies for sustainable wheat farming and food safety.

In summary, the utilization of ARIMA models in forecasting wheat yield in India and China provides a robust framework for understanding and predicting the complexities of wheat production in these two nations. The findings of this research will contribute to informed decision-making in the agricultural sector, ensuring the stability of wheat supply and food security in both countries.

Review of Literature

The Box-Jenkins model for forecasting both rice and wheat cultivation throughout India. In addition, production of rice and wheat figures come from India›s Ministry of Agriculture and Farmers Welfare and the range from 1966-1967 to 2019-2020 in the study [10]. The prediction of electricity prices in central Spain and California, encompassing both short term and long-term contracts. Several research studies affirm that the meticulous and accurate choice of an ARIMA can be chosen on time series data with single factor, resulting in highly accurate forecasts of future values within the series [11]. Furthermore, this investigation sought to predict forthcoming Sugarcane cultivation values in India through the application of an ARIMA model for 62 years of time series data on Sugarcane production. Deep learning beats ARIMA in predicting BIST 30, 50, and 100. ARIMA outperforms LSTM and GRU for BIST indices based on root mean square evaluation. ARIMA was proposed as a suitable tool for addressing such complexities. to forecast the next 12 months› values, evaluated against 1981 data, not used for parameter estimation. Mean error was approximately 14%, suggesting ARIMA›s potential in predicting Greek pilchard fishery variations caused by environmental and biological fluctuations [12]. Based on the goodness of fit criteria, the most effectively fitted model was chosen namely RMSE (Root Mean Square Error), BIC (Normalized Bayesian Information Criterion) and AIC (Akaike Information Criterion). The research discovered that the highest performing model for wheat consumption and production is ARIMA (0,1,1) with drift. Based on the ARIMA forecast, both production and consumption will rise over the coming eight years. A machine learning tool using GP to predict the XU100 index, comparing it with SARIMA and ARCH models. SARIMA model was first applied, showing heteroscedasticity in residuals, then ARCH model was used to address it, resulting in a SARIMA-ARCH model. A mixed predicting model for COVID- 19 created by [13]. An Utilization of ARIMA modelling techniques on a 68-year time series dataset identified the ARIMA (1,1,0) model with drift as the primarily fitting. This approach was subsequently employed to estimate wheat production in India over the next ten years. Projections indicated a consistent growth in wheat production at an average annual rate of approximately 4%. The chosen ARIMA (1,1,0) model appeared to yield a satisfactory predictive framework for Indian wheat production spanning the period from 2017-18 to 2026-27[14]. Despite acknowledging limitations in prediction accuracy, the ARIMA model remains widely employed for forecasting future values in time series analyses. An ARIMA models were employed to analyse and predict wheat production and consumption in India spanning the years 1959 to 2019. The selection of the most appropriate model was determined by evaluating various goodness-of-fit criteria, such as RMSE, NBIC and AIC, to ensure optimal performance. Random forest was the most successful, showing high correlations and low errors for ICU patients, intubations, and deaths.

MATERIALS AND METHODS

A time series data points are gathered consistently, like hourly, daily, or monthly, or at irregular intervals. The analysis of time series involves exploring the inherent patterns, trends, and behaviours in the data to make predictions or uncover insights into the underlying processes [15]. Its significance spans across diverse domains, empowering researchers and analysts to make informed decisions and forecasts grounded in historical trends. In more intricate time series forecasting scenarios, advanced methods of machine learning that are applied consist of recurrent neural networks (RNNs) and long short-term memory networks (LSTMs), showcasing the evolving intersection of traditional analysis and cutting-edge technologies [16]. ARIMA models are frequently employed in a wide variety of fields including finance, economics, and environmental science for time series forecasting [17]. It›s important to note that while ARIMA is a powerful and versatile tool, it may not be suitable for all types of time series data, and other models like SARIMA (Seasonal ARIMA) or machine learning approaches may be more appropriate in certain cases. ARIMA is a well-known and extensively utilized statistical method for determining time series data [18]. It involves elements of AR, I and MA models. An ARIMA model is especially good at detecting and predicting sequential patterns in time series data. Auto Regressive (AR) component(p) captures the association among the present observation and its previous values [19,20]. Here, the «p» parameter refers to the number of lag observations included in the model. The model predicts a future value based on the earlier p observations. Integrated (I) component involves differencing the time series data to make it stationary. Stationary data has constant statistical properties that change over time. The «d» parameter belongs to the number of times the series is differencing accomplish stationarity. Moving Average (MA) component accounts for the correlation among the current observation and an error residual from moving average method carried out to lagged observations. The moving average window›s size is represented by the "q" parameter. In time series analysis, several statistical tests are commonly used to assess different aspects of the data. The flow chart of the ARIMA model has been exhibited in figure 1.

ACF is a measurement of correlation regarding a time series and the lagged values. It assists in determining the existence of autocorrelation, i.e., whether there is an association between present value and its prior values. Peaks in ACF plot indicate potential autocorrelation at the corresponding lags. The autocorrelation function (ACF) plots the correlation coefficient towards the lag to give a visual representation of autocorrelation. A model which is an essential part for recognizing is the moving average (MA). This component can be identified primarily through the ACF.

$$X_t = \gamma_1 \varepsilon_{t-1} + \gamma_2 \varepsilon_{t-2} + \cdots + \gamma_q \varepsilon_{t-q} + \varepsilon_t \tag{1}$$

Equation (1) refers, when the ACF is substantially different compared with zero on lags m = 1, 2,..., q and equates to zero subsequent to that, the predictive equation is an MA(q), where γ are the moving average parameters and ε_t are the residuals on time t.

PACF assesses the relationship between variables over time series and its lag data after performing into account the impact of acquiring present lags. It helps identify the direct relationship between an observation and its past observations, excluding the indirect influences through other lags. Significant spikes in the PACF plot at certain lags suggest a direct influence of those lags on the current observation.

$$X_t = \varphi_1 X_{(t-1)} + \varphi_2 X_{(t-2)} + \cdots + \varphi_p X_{(t-p)} + \varepsilon_t \tag{2}$$

Here, equation (2) denotes an Autoregressive aspects are likely identified because the pacf is substantially different

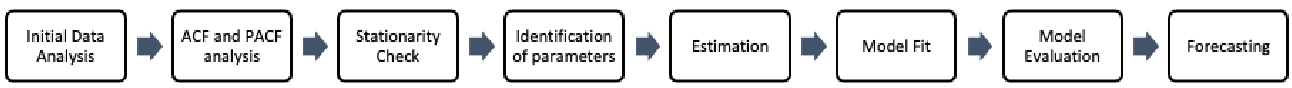

Figure 1. Flow chart of ARIMA model.

from zero at lags m = 1, 2,., p, followed by zero. In this case, an AR(p) is used, where φ are the autoregressive parameters, x_t is the observation at time t, and ε_t is the white noise at time t.

ADF is a statistical technique for testing time series stationarity. It assesses whether a unit root occurs in the autoregressive model of the time series. If the null hypothesis (the failure to have a unit root) fails, the series will be considered to be stationary. The null hypothesis is rejected if the p-value is less than a predetermined level of significance, which suggests that the series is probably stationary.

Error measures in forecasting are metrics used to evaluate the accuracy of a forecasting model by comparing its predictions to actual values. Common error measures include Mean Error (ME), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Percentage Error (MPE), Mean Absolute Percentage Error (MAPE), Mean Absolute Square Error (MASE). The appropriate error measure is chosen by the forecasting problem's specific characteristics as well as the study' goals. A combination of these metrics is frequently utilized to comprehensively evaluate the performance of models.

RESULTS AND DISCUSSION

The analysis involves acquiring data from 1996 to 2019, with a particular focus on wheat production in India and China. We choose to concentrate on forecasting wheat production using ARIMA model in this study. This data is provided by Kaggle dataset. We used the open-source analytical software 'R' in this study, integrating a variety of packages to support our analytical processes.

Figure 2, the ACF plot, which offers insight into the relation involving the time series along with its lag values. The PACF plot, highlighting the direct relationship among time series and its lagged values while eliminating the indirect correlations.

The pattern of ACF and PACF on graph are oscillatory and some of them are positive. In this case applied differences in ARIMA and made the data as stationary.Present paper, the data shows that non-stationary then by using differences it is transformed to the stationary time series data. Then applied ARIMA (p,q,d) models for prediction and forecasting of the series.

The ADF test is frequently utilized for determining whether or not a time series is stationary. The stationarity

Figure 2. Actual wheat production in India and China.

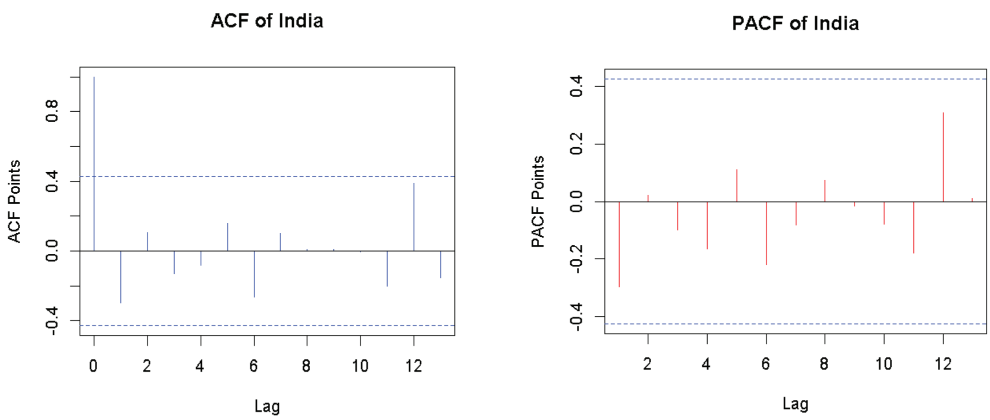

Figure 3. ACF and PACF of wheat production in India and China.

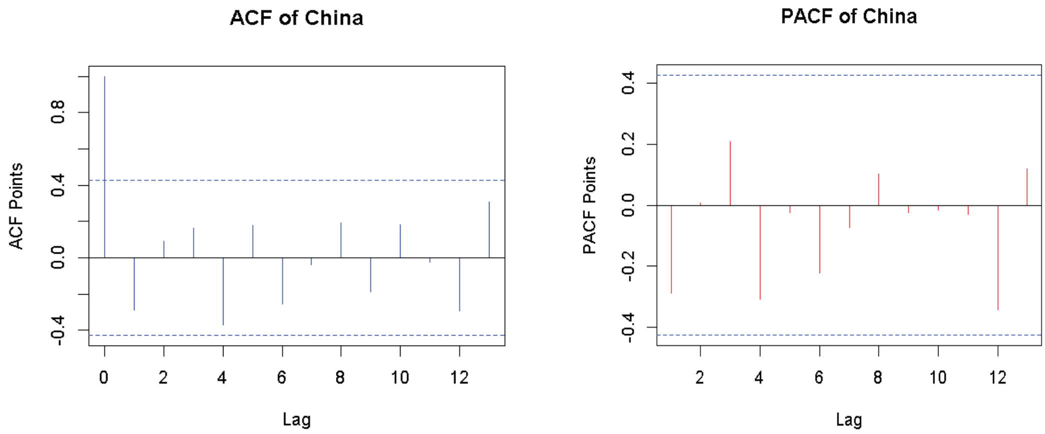

Figure 4. Converting non-stationary data into stationary data.

Table 1. ADF test statistic

India			**China**		
Dickey-Fuller Statistic	**Lag order**	**p**	**Dickey-Fuller Statistic**	**Lag order**	**p**
-2.47	2	0.39	-2.76	2	0.28

is an essential concept in time series analysis, and stationary time period have statistical characteristics such as mean and variance which remain constant over time.

The ADF test statistic defines assuming a time series has a unit root, which suggests non-stationarity. In these cases, table 1 values are -2.47 and -2.76 for India and China respectively. These indicates the number of lagged differences incorporated into the regression. Lag order is a parameter of the test. The p-value is crucial in hypothesis testing. Frequently, the time series is non-stationary, corresponding to the null hypothesis. A p-value closer to one signifies that there is insufficient evidence for rejecting the null hypothesis, indicating that the data may be non-stationary. It indicates that the time series is stationary, which is the alternative hypothesis. However, with a high p-value, do not have enough evidence to reject that the null hypothesis of non-stationarity.

On the basis of these findings, the p-values for both countries are 0.39 and 0.28 respectively. generally, If the p-value is lower than the specified level of significance (typically 0.05), the null hypothesis is rejected and an alternative hypothesis is accepted, and the process is stationary. However, the p-values in both cases are quite high (0.39 and 0.28), it means that there is evidence, but it is not enough to reject the null hypothesis. Therefore, depending on these results, one might infer that the data (Wheat) is non-stationary for both countries.

Fitting different ARIMA models to a time series data with three parameters (p, d, q), which means:

P: The number of lag observations in the predictive model (the order of the Auto Regressive part).

d: The number of times the initial findings have been differed (in what order).

q: The size of the moving average window (the order of the Moving Average part).

The AIC is a measure of the model›s goodness of fit that takes into account the difference over goodness of fit and model complexity. In general, Lower AIC values show better-fitting models.

Depending upon the AIC values in above table, ARIMA (0,1,0) has the smallest AIC (124.68) for India and ARIMA (1,1,0) has the smallest AIC value (123.48) for China. Suggesting that it might be the most appropriate model. Now to perform additional diagnostic checks to ensure that the chosen model adequately captures the patterns in the data.

The ARIMA (0,1,0) model has estimated coefficients for the components of both countries are 1.84 and 0.53 respectively. The precision of the estimation of coefficient can be determined by the standard errors (s.e.). Smaller standard errors represent more accurate estimates. The standard error for India and China, the values are 1.11 and 0.33.

From the table 4, The variance (sigma^2) values that are 25.73 and 23.84 for both the countries, it represents the estimated variance of the residuals within the model. The log likelihood evaluates how well a model describes observed data. In these cases, the log likelihood values are -60.34 and -59.74. For model selection, the information criteria AIC, AICc and BIC are used. Lower values indicate models that fit better. In these cases, the AIC values are 124.68 and 123.48, AICc values are 125.39 and 124.19 and BIC values are 126.67 and 125.47. The AIC suggests that this ARIMA

Table 2. AIC values for different ARIMA models

India		China	
Model	**AIC**	**Model**	**AIC**
ARIMA(2,1,2) with drift	Inf	ARIMA(2,1,2) with drift	Inf
ARIMA(0,1,0) with drift	**124.68**	ARIMA(0,1,0) with drift	127.01
ARIMA(1,1,0) with drift	124.69	ARIMA(1,1,0) with drift	125.45
ARIMA(0,1,1) with drift	124.81	ARIMA(0,1,1) with drift	126.85
ARIMA(0,1,0)	125.28	ARIMA(0,1,0)	125.76
ARIMA(1,1,1) with drift	126.63	ARIMA(2,1,0) with drift	125.97
		ARIMA(1,1,1) with drift	126.61
		ARIMA(2,1,1) with drift	127.97
		ARIMA(1,1,0)	**123.48**
		ARIMA(2,1,0)	124.02
		ARIMA(1,1,1)	124.63
		ARIMA(0,1,1)	125.17
		ARIMA(2,1,1)	126.01

Table 3. Coefficients

Country	Model	Coefficients		Standard error
India	(0,1,0)	ar1 drift	1.84	1.11
China	(1,1,0)	ar1	0.53	0.33

Table 4. Information Criterion values

Information Criterion	Sigma2	Log likelihood	AIC	AICc	BIC
India	25.73	-60.34	124.68	125.39	126.67
China	23.84	-59.74	123.48	124.19	125.47

Table 5. Forecasting values

Year	Forecast (in tonnes)	
	India	**China**
2020	109.44	135.83
2021	111.28	136.63
2022	113.12	137.05
2023	114.96	137.28
2024	116.80	137.39
2025	118.64	137.46
2026	120.48	137.49
2027	122.32	137.51
2028	124.16	137.52
2029	126.00	137.52

(0,1,0) model is preferred among the models based on the information criteria.

From table 5, these are the forecasted values for each year based the model. Each value represents the point estimate for the corresponding year. These forecasts are useful for understanding the expected values of the variable over the forecast period.

The figure 5, shows that the forecasting values of wheat production in India and China

Box-Ljung test

The Box-Ljung test is a statistical test examined to assess a time series model›s goodness of fit. It is commonly used to test for the existence of autocorrelation in time series model residuals. Autocorrelation in residuals implies that

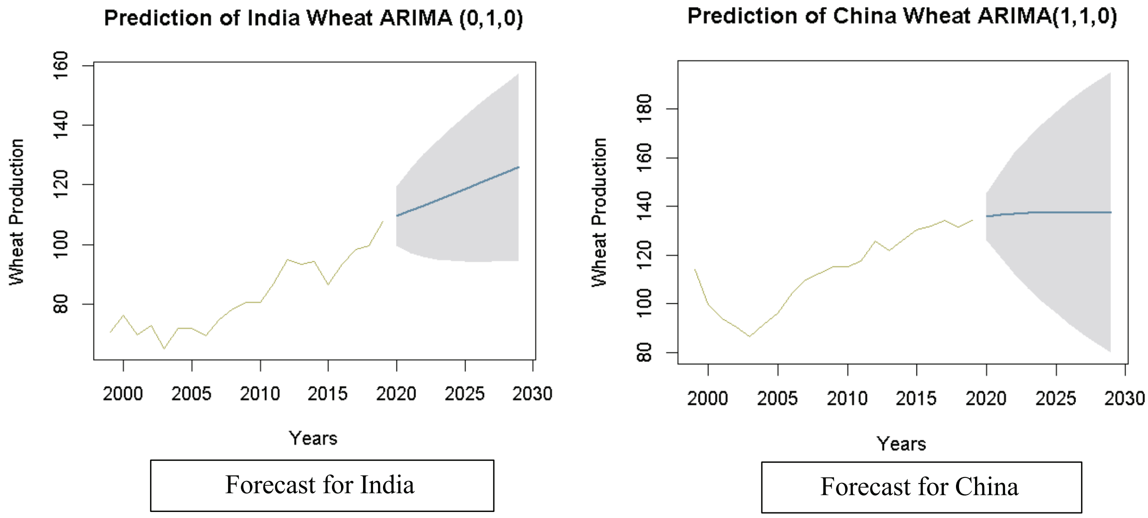

Figure 5. Forecast prediction for India and China**.**

Table 6. Test statistic value

Country	Test statistic	Degrees of freedom	p
India	3.80	5	0.58
China	7.79	5	0.17

Table 7. Error measures

Metrics / Country	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
India	0.01	4.82	3.89	-0.35	4.86	0.87	-0.30
China	0.64	4.65	3.41	0.53	3.07	0.77	-0.29

the model has missed some pattern or information in the residuals.

From table 6, the test statistic (X-squared) is a measure of how much the observed autocorrelations of the residuals deviate from what would be expected under the assumption of no autocorrelation. Degrees of freedom (df) represent the number of lags being tested. The p-value connected with the test for both countries are 0.58 and 0.17 respectively. In hypothesis testing, if p-value is greater than the significance level (commonly 0.05), It indicates do not reject the null hypothesis. In these cases, with high p-values, there is inadequate evidence to reject the null hypothesis, implying that residual autocorrelation is not significant.

From table 7, The measures are provided a comprehensive view of the model›s accuracy and performance on the training set. Lower values for RMSE, MAE, MPE, and MAPE are generally desirable, indicating better model performance. The MASE value close to 1 suggests that the model works reasonably compared favourably to a simple baseline forecast. The ACF1 value being close to zero indicates that the forecast errors do not exhibit significant autocorrelation at lag 1.

CONCLUSION

The analysis of India›s and China's Wheat forecasting time series data underscores the significance of visualizing historical and forecasted values through plotting, despite the absence of the actual plot in the provided information. The emphasized importance of visual inspection for trend identification and model assessment aligns with the subsequent confirmation from the Box-Ljung test, revealing high p-values for both India and China, indicative of no significant autocorrelation in residuals. The detailed specifications of the ARIMA models for India (ARIMA (0,1,0) with drift) and China ARIMA (1,1,0), along with comprehensive evaluation metrics, contribute to a thorough understanding of model performance. Overall, the consistent absence of significant autocorrelation in residuals, as indicated by the Box-Ljung test, affirms the efficacy of both ARIMA models in capturing temporal dependencies and underlying patterns in the wheat forecasting time series data, providing a robust foundation for informed decision-making and reliable future predictions.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

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