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Corn Production Forecast in Mexico: Implications for Food Self-Sufficiency

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Abstract. Objective: To analyze corn production data in Mexico from 1980 to 2022, using time series forecasting models to project future production trends and assess their implications for food self-sufficiency. Design/methodology/approach: The ARIMA (1,1,0) model was selected as the primary forecasting method, while SARIMAX (1,1,0) with an intercept was also considered. Production forecasts were generated up to the year 2070, with a specific focus on the year 2030. The projected production for 2030 is 27.91 million tons, with a 95% confidence interval ranging from 15.42 to 50.49 million tons. Results: The forecast suggests that per capita production will generally remain close to the average per capita consumption, with fluctuations above and below this threshold over time. Limitations on study/implications: The study does not account for additional uses of corn beyond direct consumption, which could influence self-sufficiency assessments. Future research should integrate broader economic, environmental, and policy-related factors to refine production estimates. Findings/conclusions: Corn production is expected to remain near historical consumption levels. However, a significant increase in production, approximately 13.5 million tons, is required to meet future demand and ensure food security.

Keywords. ARIMA, time series, forecast, corn production, consumption, food self-sufficiency

1. Introduction

Corn production is an economic activity within the agricultural sector, which in 2023 accounted for 3.9% of the Gross Domestic Product (INEGI, 2024). The World Bank (2022) notes that the agricultural sector's share of the national GDP declined from 13.14% in 1965 to 4.03% in 2022. Furthermore, according to data from the Agri-Food and Fisheries Information Service (SIAP, 2023), in 2022 the production of annual crops in Mexico amounted to 504 million tons, with a value of 475 billion pesos. Corn accounted for 5.26% of the total production with 26.5 million tons and 36.19% of the agricultural value with 172 billion pesos.

According to the National Survey of Occupation and Employment (ENOE) by INEGI (2023), as of the fourth quarter of 2023, the primary sector employed 6.4 million individuals (10.8% of total employment), in contrast to 25.1% in the secondary sector and 63.4% in the tertiary sector. In parallel, the Department of Labor and Social Welfare (STPS, 2023) reports that agriculture generated 5.9 million jobs. Regarding the workforce demographics, 51.3% of agricultural workers are aged 45 or older, 56.1% completed only primary education, and 88.7% are male. Furthermore, the average monthly income in the sector is the lowest recorded, at 3,551 pesos.

The Food and Agriculture Organization of the United Nations (FAO, 2023) reports that Mexico is the world's sixth largest producer of corn, with 26.6 million tons, equivalent to 2.29% of global production; meanwhile, the United States and China together produce 53.81% of the world total. The per capita consumption of corn in Mexico is 196 kilograms (Portillo Vázquez, Sangermán-Jarquín, & Pérez Robles, 2023; SAGARPA, 2017).

Food security encompasses several dimensions, including availability and stability, which are related to food self-sufficiency and the capacity to ensure access to food both now and in the future (Ibarrola-Rivas & Galicia, 2017). Availability refers to the existence of food, considering factors such as production and reserves, whereas stability implies maintaining this availability over time.

The FAO defines food self-sufficiency as being achieved when national food production is equal to or exceeds demand (Clapp, 2017). In Mexico, however, domestic production is limited, and consequently, corn must be imported from the neighboring country. Thus, the corn trade balance has been in deficit. For example, during the 2013–2022 period, the deficit increased to an average of 13.5 million tons (FAO, 2023).

1.1 Conceptual framework

The availability of food is crucial for a country's stability, as self-sufficiency can save foreign currency for other strategic purposes. In Indonesia, food imports are increasing because demand exceeds supply (Hasan, Suryani, & Hendrawan, 2015). Clapp notes that food self-sufficiency alone does not guarantee food security, highlighting the importance of availability without differentiating between local or foreign supplies (Clapp, 2017).

This lack of differentiation in food security regarding the origin of food is crucial for understanding the importance of food self-sufficiency. While food security requires sufficient availability, whether local or imported, food self-sufficiency implies that these foods must be produced locally. During food crises, droughts, and fires, countries dependent on imports face a disadvantage in food security compared to those that rely on self-sufficiency and local food production (Davis, Gephart, & Gunda, 2016).

Recent studies highlight that food self-sufficiency becomes crucial in the face of impacts from international conflicts, such as the war between Russia and Ukraine, which can affect trade and make countries more vulnerable in terms of food security (Abay et al., 2023; Rabbi et al., 2023; Valiyaveettil et al., 2023; Wassénius et al., 2023).

Other studies emphasize the importance of arable land and the improvement of production systems to achieve food self-sufficiency (Kaufmann, Reilly, & Thomas, 2022; Zhang, Fang, Zheng, Fan, & Du, 2023). In this work, the focus is on food production, which is considered the key variable for self-sufficiency, exploring production forecasts generated with the Box & Jenkins methodology (Box, Jenkins, Reinsel, & Ljung, 2015) through ARIMA models, a common approach in the literature.

The use of ARIMA for forecasting crop production has been widely studied and applied in various contexts. For example, it has been used for forecasts of the cultivated area and production of corn in Nigeria (Badmus & Ariyo, 2011), fruit production forecasts in Bangladesh (Hamjah, 2014), wheat production forecasts in Pakistan (M. Amin, 2014), sugarcane and sugar production forecasts in India (K P, Sahu, Dhekale, & Mishra, 2016), cereal production forecasts in Nigeria (Akanni & Adeniyi, 2020), wheat production forecasts in Haryana, India (Devi, Kumar, Malik, & Mishra, 2021), cereal production forecasts in Ethiopia (Bezabih, Wale, Satheesh, Workneh Fanta, & Atlabachew, 2023), and as part of joint models to forecast banana production in Tanzania (Patrick, Mirau, Mbalawata, & Leo, 2023).

2. Materials and methods

Corn production data for the 1980–2022 period were obtained from SIAP (2023), while population data (1980–2023) and their projections up to 2070 were sourced from CONAPO (2023). The average per capita corn consumption was consulted in the National Agricultural Plan (2017) and referenced by Portillo et al. (2023).

Python 3.11.3 and Jupyter Notebook 5.3.0 were used for data modeling, visualization, and analysis. Descriptive statistics such as minimum, maximum, mean, skewness, kurtosis, and simple growth rate were calculated, following Devi (2021). This methodological approach is based on Akanni & Adeniyi (2020) and the guidelines of Huang & Petukhina (2022) for assessing growth and patterns in the time series.

The dataset was divided into 90% for training and 10% for model validation. The training phase covers the period from 1980 to 2017, and the validation phase from 2018 to 2022, following the methodology used in previous studies such as Patrick et al. (2023), Devi et al. (2021), and K P et al. (2016).

A line graph was used to visualize the characteristics of the time series, identify trends, stationarity, and cyclical patterns, which facilitated data analysis and forecasting. According to Badmus & Ariyo (2011), Box et al. (2015), Hamjah (2014), K P et al. (2016), and M. Amin (2014), this visual tool is essential for understanding the temporal dynamics of the data.

The Autocorrelation Function (ACF) plot was used to assess stationarity in the time series by identifying the correlation between successive observations at different lags, as highlighted by (Huang & Petukhina, 2022). Trend analysis was conducted using the Mann-Kendall test to identify patterns of change in Mexico's corn production data, as indicated by Bezabih et al. (2023).

The Augmented Dickey-Fuller (ADF) test was also used to assess the stationarity of the corn production time series, following the recommendations of Devi et al. (2021) and Akanni & Adeniyi (2020). Both logarithmic transformation and the differencing method were applied to Mexico's corn production data, following the approaches proposed by Bezabih et al. (2023) and Akanni & Adeniyi (2020).

Logarithmic transformation was used to stabilize the variance and facilitate the identification of trends, stationarity, and cyclical patterns in the time series, while differencing was applied to achieve stationarity and improve the understanding of temporal dynamics. Subsequently, the previous analyses were repeated using the transformed and differenced data, which provided a deeper insight into the evolution of corn production.

The ARIMA model identification process was performed using ACF and PACF, which are fundamental tools for selecting the appropriate forecasting model, following the recommendations of Bezabih et al. (2023), Patrick et al. (2023), Akanni & Adeniyi (2020), K P et al. (2016), and M. Amin (2014). The adequacy of the ARIMA model was evaluated using

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the AIC, BIC, and Hannan-Quinn criteria, in accordance with the studies by Bezabih et al. (2023), Devi et al. (2021), Akanni & Adeniyi (2020), and M. Amin (2014). [TN 4] Ninety percent of the data was used to train the ARIMA model, ensuring a 95% confidence level in the projections, following the guidelines of Akanni & Adeniyi (2020) and Box et al. (2015).

3. Results and discussion

The analysis shows an average production of 19.2 million tons over 43 observations, with a standard deviation of 5.3 million tons, indicating fluctuations but no major deviations from the mean. The minimum value was observed in 1982 (10.1 million tons), with a general upward trend, highlighting increases from 2005 to 2008 and a decline between 2010 and 2011. Production reached its peak in 2016 at 28.2 million tons and concluded in 2022 at 26.5 million.

The behavior of the time series can be observed in Figure 1.

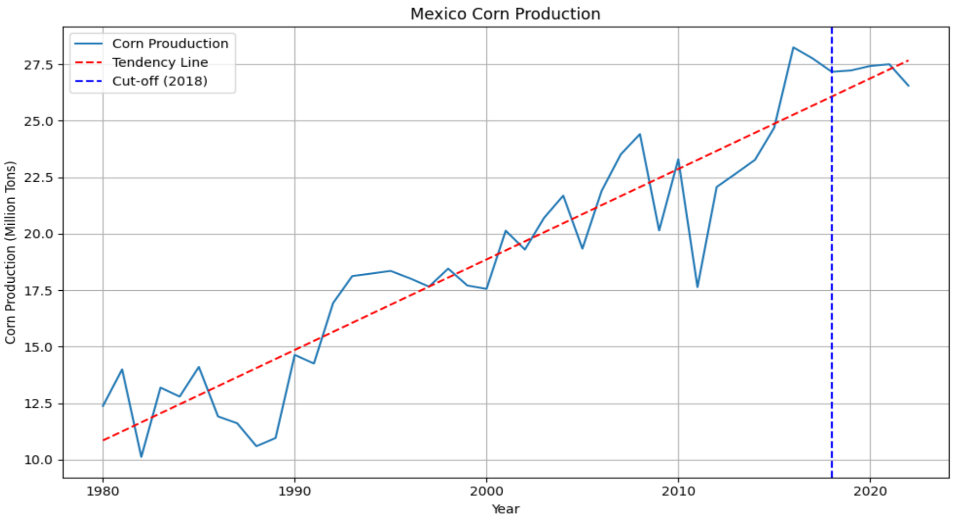

Figure 1. Line graph of corn production in Mexico for the 1980–2022 period with a trend line.

The descriptive statistics reveal a kurtosis of -0.997, suggesting a distribution less peaked than a normal distribution, and a skewness of 0.039, indicating a slight rightward skew. The trend value of 337,601 reflects an average annual increase in production, with a growth rate of 114%, which indicates a significant increase over the analyzed period.

Model selection

For ARIMA modeling, stationarity is a key feature of the time series. The line graph in Figure 1 shows a clear upward trend over time, with no regular cycles, which indicates that the series is not stationary. The ACF plot, presented in Figure 2, shows lags that gradually decrease, maintaining positive values up to lag 15, which reinforces the notion that the time series is not stationary and lacks cyclical patterns.

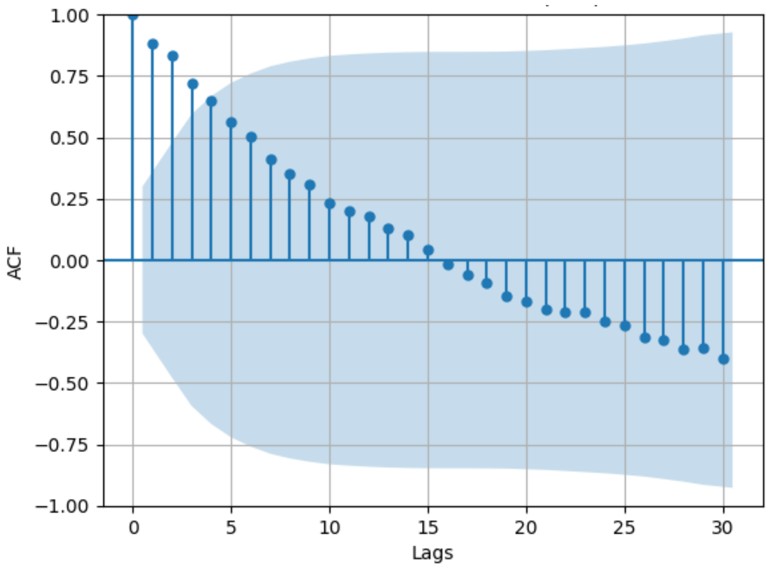

Figure 2. ACF plot of corn production in Mexico for the 1980–2022 period

The Mann-Kendall test was performed to analyze the trend, yielding an S statistic of 356.4, which indicates an upward trend. The Z-value of 3.7, being greater than the critical value of 1.9, and the p-value of 0.00019 confirm that the trend is statistically significant. To verify the non-stationarity of the time series, the Augmented Dickey-Fuller (ADF) test was applied to the training data (1980–2017). The p-value of 0.9081 and the S statistic of -0.411, being greater than the critical value of -2.96, indicate that the null hypothesis of a unit root is not rejected, thus confirming that the series is not stationary

Due to this result, a logarithmic transformation was performed, followed by the ADF test to assess stationarity. The results show an S statistic of -1.523 and a p-value of -2.967. These values are greater than the critical value of -2.967 at the 5% significance level. This indicates that the null hypothesis of a unit root is not rejected, suggesting that the time series remains non-stationary.

Subsequently, first-order differencing was applied, resulting in Figure 3, where a clear trend was no longer observed. This alteration in the trend line suggests that the mean and variance are closer to 0, indicating possible stationarity. To confirm this hypothesis, the ADF test was performed again, yielding an ADF statistic of -9.96, which is much lower than the critical value of -2.945 at the 5% level, allowing for the rejection of the null hypothesis of a unit root and concluding that the time series is stationary.

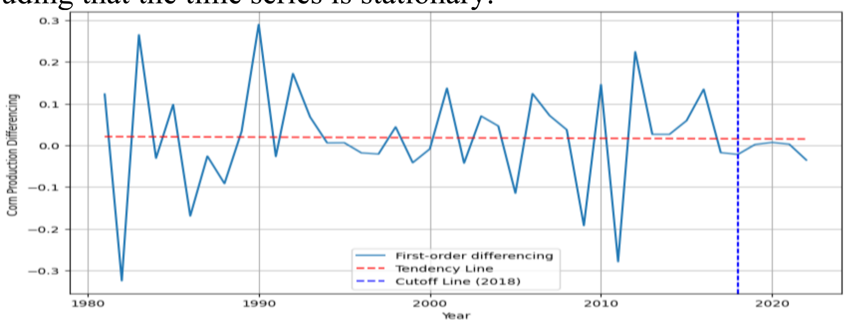

Figure 3. Line graph of the first difference of the logarithm of corn production in Mexico with a trend line for 1980–2022

Technium Social Sciences Journal
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For the identification of the ARIMA model, ACF and PACF plots are created. The order is (p,d,q), where p refers to autocorrelation, d to the level of differencing, and q to the moving average. Up to this point, the time series has been differenced once, therefore d=1. The ACF and PACF plots shown in Figure 4 display a significant value at lag 1 but decrease rapidly within the confidence interval, which indicates that p=1. The ACF values do not show a significant peak at subsequent lags; thus, a moving average component is not considered for the model, making the model an ARIMA(1,1,0).

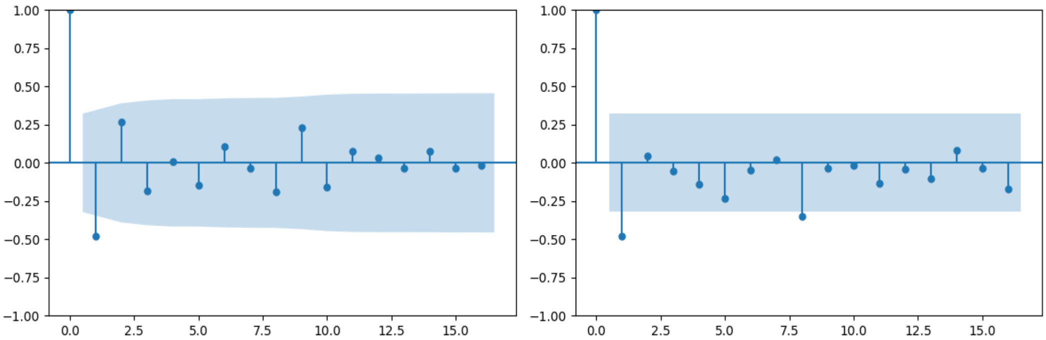

Figure 4. ACF and PACF plots of the first difference of the logarithm of corn production in Mexico with a trend line for the 1980–2022 period

Once the ARIMA(1,1,0) model was selected, it was fitted using the logarithmically transformed training data from 1980 to 2017, reserving the last 5 years to evaluate the model's quality. [TN 2] Using the ARIMA function from *statsmodels.tsa.arima.model*, the following results were obtained: 38 observations and a Log-Likelihood of 26.7272. The AIC, BIC, and HQIC values were -49.455, -46.233, and -48.319, respectively. The first-order AR coefficient (ar.L1) was -0.4419 with a p-value of 0.004, and the variance (sigma2) was 0.0137 with a p-value of 0. The Ljung-Box (L1) test had a p-value of 0.97, the Jarque-Bera test p=0.25, the heteroskedasticity test p=0.38, skewness was -0.58, and kurtosis was 3.66.

The model was subjected to diagnostic tests, which included analysis of the autocorrelation function (ACF), QQ plots of the residuals, the ACF of the squared residuals, and the Ljung-Box test for white noise detection. The ACF plot of the residuals, shown in Figure 5, was carefully examined. A white noise ACF indicates that the model is well-fitted, as it suggests that the residuals do not exhibit autocorrelation. The analysis showed that the ACF of the residuals presented white noise characteristics, indicating that the model adequately captures the data's structure.

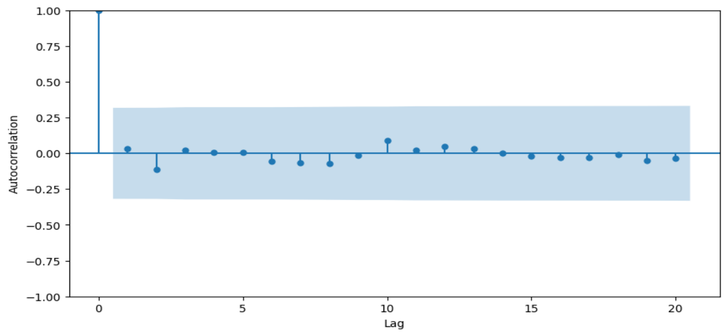

Figure 5. ACF of the residuals from the ARIMA(1,1,0) model..

Technium Social Sciences Journal
Vol. 82, 298-311, April, 2026
ISSN: 2668-7798
www.techniumscience.com

The results of the Ljung-Box white noise test at lags 5, 10, 15, and 20 show an increase in the p-value, from 0.9878 at lag 5 to 0.9999 at lag 20, which suggests less evidence to reject the null hypothesis of white noise as the number of lags increases. The Ljung-Box statistic also increases from 0.6047 to 2.3661, which indicates that the dependency among the residuals grows over time.

The QQ plot of the squared residuals for the ARIMA(1,1,0) model, shown in Figure 6, shows that the residuals resemble a normal distribution, albeit with an outlier in the upper right corner, which suggests a somewhat heavier tail than expected in a normal distribution. Despite this outlier, most values follow the diagonal line, indicating that the residuals are reasonably close to a normal distribution. Furthermore, the analysis suggests that no significant problems of heteroskedasticity or autocorrelation are present in the residuals. Taken together, these results indicate that the model is adequate for forecasting and correctly captures the underlying patterns in the data.

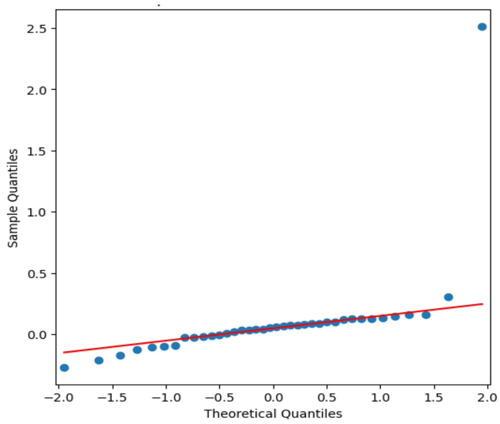

Figure 6. QQ plot of the residuals from the ARIMA(1,1,0) model..

The ACF plot of the squared residuals, shown in Figure 7, suggests that there is no significant autocorrelation, indicating the absence of heteroskedasticity (ARCH effect) in the ARIMA(1,1,0) model.

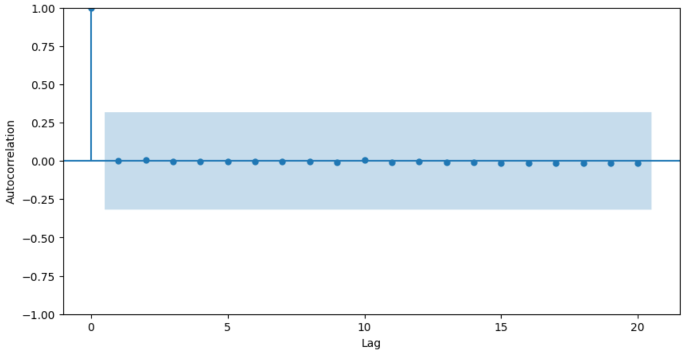

Figure 7. ACF plot of the squared residuals from the ARIMA(1,1,0) model.

The results from the diagnostic tests and plots indicate that the model is suitable for generating forecasts. The AIC, BIC, and HQIC metrics penalize more complex models in favor of simpler ones, and the log-likelihood measures the model's fit to the data, with higher values indicating a better fit. These values are essential for model comparison and selecting the most appropriate one. Functions such as *auto_arima* in Python use these criteria to automatically select the optimal model.

The *auto_arima* function was applied to the logarithmically transformed training dataset to confirm the model selection. Previously, the choice was based on the inspection of line graphs, ACF, and PACF of the first-differenced time series. The selected model was SARIMAX(1,1,0)(0,0,0) [0], with a log-likelihood of 28.056 and AIC, BIC, and HQIC values of -50.112, -45.279, and -48.408, respectively. The inclusion of the intercept, which suggests a trend, was validated by the Mann-Kendall test, which confirmed its statistical significance. The AR(1) coefficient was found to be significant (p = 0.013), but the intercept was not (p = 0.157). Diagnostic tests, such as Ljung-Box and Jarque-Bera, confirmed the model's adequacy by showing no significant autocorrelation or substantial deviations from normality.

Diagnostic tests were performed for the SARIMAX(1,1,0) model with an intercept to compare its adequacy for generating forecasts. The ACF plot of the residuals showed a similar pattern to the previous model, suggesting the model is adequate as it appears to be white noise. Similarly, the QQ plot and the ACF of the squared residuals showed no significant differences compared to the model without an intercept, indicating a similar fit.

The results of the Ljung-Box test for lags 5, 10, 15, and 20 show that the p-value increases over time, from 0.9875 at lag 5 to 0.9999 at lag 20, reducing the evidence to reject the null hypothesis of white noise. Furthermore, the test statistics increase, suggesting an increment in the autocorrelation of the residuals, from 0.6106 to 2.4274, implying greater dependency among the residuals as time progresses.

According to the summary in Table 1, the autoarima function selects the ARIMA(1,1,0) model with an intercept. When compared to the model without an intercept, the Log-Likelihood is higher, indicating a better fit. Furthermore, it has lower AIC and HQIC values but a higher BIC, suggesting lower complexity, though not significantly so. Based on these criteria and diagnostics, both models are similar, with a slight superiority in AIC for the model with an intercept. Forecasts are generated with both models to evaluate if there is a significant difference.

<table>
<tr><td colspan="7">1. Table 1. Model comparison results</td></tr>
<tr><th>2. Model</th><th>3. Order</th><th>4. Log Likelihood</th><th>5. AIC</th><th>6. BIC</th><th>7. HQIC</th><th>8. P>|z</th></tr>
<tr><td>9. ARIMA (1,1,0)</td><td>10. (1,1,0)</td><td>11. 26.727</td><td>12. -49.455</td><td>13. -46.233</td><td>14. -48.319</td><td>15. .004</td></tr>
<tr><td>16. SARIMAX (1,1,0) intercept</td><td>17. (1,1,0)</td><td>18. 28.056</td><td>19. -50.112</td><td>20. -45.279</td><td>21. -48.408</td><td>22. .013</td></tr>
</table>

Source: Author's own elaboration

The forecast for the 2018–2022 period is generated using the same training data for both models, ARIMA(1,1,0) and SARIMAX(1,1,0) with an intercept, reserving 10% of the data for validation. The ARIMA model, when fitted with 90% of the data, predicts values close to the actuals, with acceptable accuracy: 2018 (3.33139), 2019 (3.327986), 2020 (3.32949), 2021 (3.328825), and 2022 (3.329119), compared to the actual values of 2018 (3.302091), 2019

TECHNIUM SOCIAL SCIENCES JOURNAL
Technium Social Sciences Journal
Vol. 82, 298-311, April, 2026
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www.techniumscience.com

(3.304255), 2020 (3.311455), 2021 (3.314312), and 2022 (3.279152). On the other hand, the SARIMAX model overestimates the values, with higher forecasts: 2018 (3.363466), 2019 (3.375919), 2020 (3.401424), 2021 (3.420695), and 2022 (3.442944). Although both models generate acceptable forecasts, ARIMA demonstrates greater precision and fit.

Forecasting quality metrics for both models are compared. The ARIMA(1,1,0) model presents a lower MAPE of 0.82% compared to the 2.99% of the SARIMAX model with an intercept, indicating a smaller discrepancy between predicted and actual values. Additionally, ARIMA has an RMSE of 0.0298, significantly lower than the SARIMAX model's 0.1050, reflecting greater accuracy. The MSE is also lower in ARIMA at 0.0009 versus 0.0110, and the MAE is 0.0271 compared to 0.0986 for the model with an intercept, indicating less dispersion in absolute errors. Collectively, these metrics demonstrate that ARIMA(1,1,0) offers better performance in terms of accuracy and fit between predicted and actual values.

Following this, Figure 8 displays a comparative graph for both models. In the SARIMAX(1,1,0) model with an intercept, it is observed how the forecasts, although maintaining the trend seen in the data, progressively deviate from the actual values. On the other hand, in the ARIMA(1,1,0) model, the forecasts follow a more horizontal trend, as it does not incorporate the original trend of the data into its model structure.

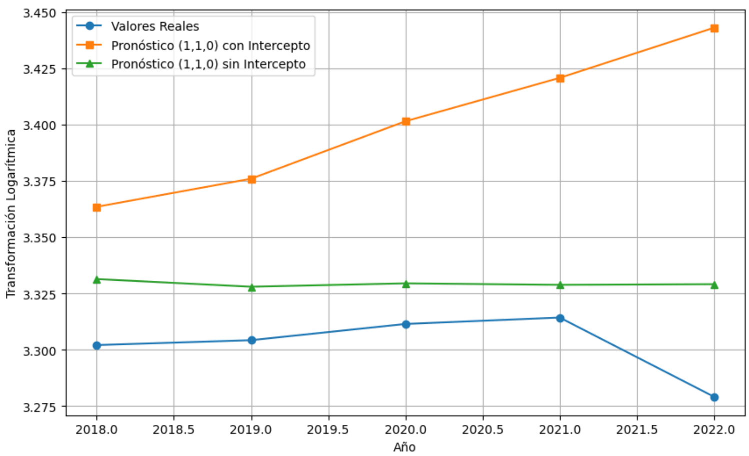

Figure 8. Actual Values vs. Forecast for SARIMAX(1,1,0) with intercept and ARIMA(1,1,0)

Figure 9 displays a comparative graph of corn production forecasts up to 2070 for both models. The ARIMA(1,1,0) model reaches its peak in 2029 and stabilizes, while the SARIMAX(1,1,0) with an intercept reflects continuous growth, suggesting improvements in productive capacity. The model without an intercept, conversely, assumes a limit, presenting more realistic forecasts unless there are constant innovations.

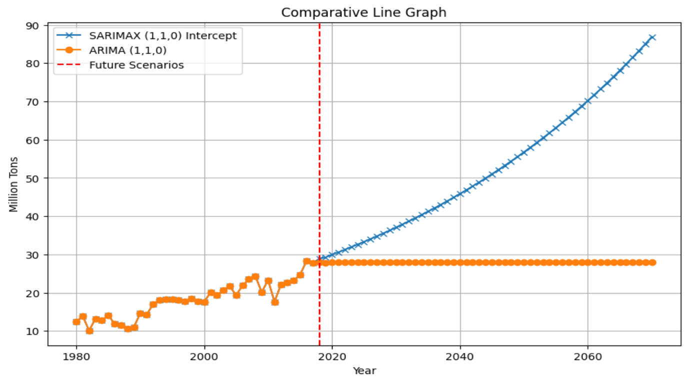

Figure 9. Comparative line graph for forecasts of ARIMA(1,1,0) and SARIMAX(1,1,0) with intercept

3.3.2 Forecast comparison

Figure 10 shows the forecasts for ARIMA(1,1,0) up to 2030, where the confidence interval to some extent encompasses the values generated by SARIMAX(1,1,0) with an intercept. This indicates that the interval captures the trend of the original data, suggesting that corn production could fluctuate between its upper and lower bounds. Thus, two scenarios are presented: one with greater innovation and agricultural mechanization, and another with stagnation or reduction, which could negatively affect production.

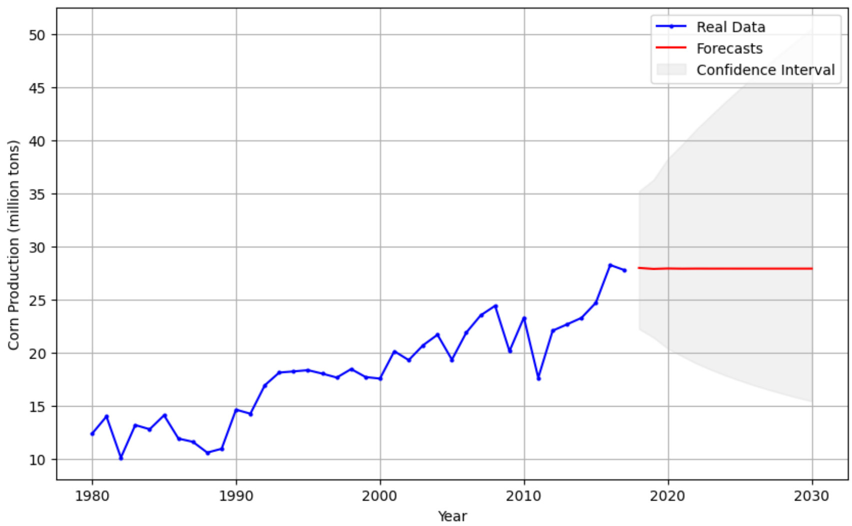

Figure 10. ARIMA (1,1,0) corn production forecast to 2030

Table 2 presents the forecasts from 2018 to 2030 in millions of tons and their confidence intervals for ARIMA(1,1,0) and SARIMAX(1,1,0) with an intercept. While the model with an intercept maintains an increasing trend with wide upper intervals, ARIMA(1,1,0) shows a more linear evolution with more conservative confidence intervals.

TECHNIUM SOCIAL SCIENCES JOURNAL
Technium Social Sciences Journal
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www.techniumscience.com

Table 2. Comparison of forecasted values for ARIMA (1,1,0) and SARIMAX (1,1,0) with intercept

	ARIMA 1,1,0			SARIMAX 1,1,0 with intercept		
Year	**Forecast**	**Lower Bound**	**Upper Bound**	**Forecast**	**Lower Bound**	**Upper Bound**
2018	27.9772	22.2374	35.19852	28.88916	23.15187	36.04822
2019	27.88213	21.43505	36.2683	29.25116	22.78591	37.55086
2020	27.92409	20.38366	38.25393	30.00681	22.22975	40.50467
2021	27.90554	19.66371	39.60184	30.59068	21.95026	42.63229
2022	27.91374	18.98081	41.05075	31.27891	21.69821	45.08992
2023	27.91012	18.39661	42.34337	31.93717	21.52522	47.38548
2024	27.91172	17.86157	43.61676	32.63144	21.3903	49.78008
2025	27.91101	17.37702	44.83072	33.32999	21.29485	52.16699
2026	27.91132	16.92996	46.01559	34.04877	21.2286	54.61117
2027	27.91118	16.51622	47.16782	34.78047	21.18833	57.09186
2028	27.91124	16.13038	48.29629	35.52916	21.16995	59.62796
2029	27.91122	15.76905	49.40286	36.29335	21.17089	62.21784
2030	27.91123	15.42912	50.49133	37.07427	21.18888	64.869

The per capita production forecast by ARIMA(1,1,0) was compared with the average per capita consumption, 95% confidence intervals, and actual production, all in kilograms. Between 2018 and 2022, the model closely follows the actual production, with predicted values of 223.14 kg in 2018 and 215.77 kg in 2022, compared to actuals of 216.70 kg and 205.26 kg, respectively.

The upper bound of the confidence interval projects sustained growth, reaching 405.04 kg in 2037 and 633.68 kg in 2070. Conversely, the lower limit anticipates a severe decline to 94.58 kg in 2037 and 61.20 kg in 2070, which would imply a significant deficit compared to the average consumption of 196.4 kg per capita.

By 2037, average production would fall below consumption (195.73 kg per capita), marking a potential critical point for food insecurity. However, with the population reaching its peak in 2053, production would again surpass consumption in 2070 at 196.94 kg per capita. These results indicate that, without measures to increase production or improve resource use efficiency, corn supply may not meet future demand, raising the risk of food insecurity in the country.

4. Conclusion

The use of ARIMA models for forecasting has been widely accepted due to their accuracy, versatility, and adaptability to time series. The implementation of these models has been facilitated by tools such as Python.

This research applied SARIMAX(1,1,0) with an intercept and ARIMA(1,1,0), showing good accuracy with respect to actual values. The model with an intercept, obtained via autoarima, maintains the observed trend, as confirmed by the Mann-Kendall test. However, assuming constant growth is unrealistic without continuous innovations in agricultural mechanization. Furthermore, long-term factors such as climate change and water availability must be considered to strengthen future studies.

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The selection of ARIMA(1,1,0) was based on time series modeling, where the ADF test confirmed non-stationarity. A logarithmic transformation and first-order differencing were applied to achieve stationarity. The ACF and PACF analysis determined the inclusion of an autoregressive term and the exclusion of a moving average term, ensuring the theoretical soundness of the model.

Both models were evaluated using ACF plots of residuals, QQ plots, the Ljung-Box test, and ACF of squared residuals, confirming their validity for forecasting. However, the final selection was based on accuracy metrics (MAPE, MSE, RMSE, and MAE), for which ARIMA(1,1,0) obtained better results.

When evaluating the upper bound of the confidence interval, ARIMA(1,1,0) showed greater proximity to the actual values, providing more conservative forecasts but within a realistic range of fluctuations. This model better captured the series' variability without imposing a constant growth trend.

The analysis of per capita values forecasted with data from CONAPO (2023) showed that the ARIMA(1,1,0) forecasts remain close to average consumption. Initially, they fall slightly below as the population increases, but then surpass consumption when population growth decelerates.

Although the forecasts do not indicate an immediate shortage, it is essential to maintain and improve agricultural production to achieve the best possible scenario. A comparison with imports and exports, which affect self-sufficiency, was not included.

Based on import and export data from the FAO (FAO, 2023) for Mexico between 1980 and 2022, a conservative approach is considered, which includes an additional increase of 31% over national production (the average trade deficit for the 1980–2022 period relative to total production).

It is concluded that production must increase by an average of approximately 6.5 million tons. However, considering the 51% increase in the average trade deficit relative to production during the 2013–2022 period, this average increase should be approximately 13.5 million.

It is crucial to further investigate climatic factors, water availability, and other elements that impact corn production in Mexico. It is also recommended to generate forecasts on imports and exports to assess self-sufficiency and adjust strategies to reduce dependency on imports. Of course, producers must be supported with sufficient subsidies that allow them to contribute to food self-sufficiency. Furthermore, it is important to guarantee a secure income for corn growers so they can remain rooted in their territory and do not migrate elsewhere due to economic needs.

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