Colegio de Postgraduados

Comparison of models for estimating the planted area of *Agave* spp. for mezcal production in Mexico

Cruz-Ramírez, Angel Saul[1]; **Martínez-Gutiérrez, Gabino Alberto**[2*]; **Morales-García, Isidro**[2]; **López-García, María del Rosario**[3]; **Castillo-Martínez, Carlos Roman**[1]

[1] Instituto Nacional de Investigaciones Forestales, Agrícolas y Pecuarias y Forestales, Centro Nacional de Investigación Disciplinaria en Conservación y Mejoramiento de Ecosistemas

[2] Instituto Politécnico Nacional, Centro Interdisciplinario de Investigación para el Desarrollo Integral Regional, Unidad Oaxaca.

[3] Secretaría del Trabajo y Previsión Social.

* Correspondence: gamartinezg@ipn.mx.

ABSTRACT

Objective: The aim of this study was to compare forecasting models for the planted area of agave mezcalero from 2023 to 2027, using data from the 1982-2022 period through autoregressive integrated moving average (ARIMA) models, in order to promote the efficient management of natural resources.

Design/methodology/approach: To validate the forecasting efficiency, an out-of-sample comparison was conducted between ARIMA models and simple forecasting methods such as the mean and naïve approaches.

Findings: The results identified a growth scenario for the planted area of agave mezcalero during the 2023-2027 period. The most accurate model, the autoregressive (4,0,0), projected that the maximum planted area would be reached in 2024, ranging from 22,723 to 60,280 hectares, followed by a gradual decline starting in 2025.

Research limitations/implications: The predictions are constrained by the availability and quality of the databases. The main limitation faced by the study was the lack of historical data.

Originality/value/conclusions: It is concluded that the ARIMA model can be an efficient tool for estimating the planted area of agave intended for mezcal production. The cultivation of agave mezcalero is currently in a context of overproduction. The information generated may be useful for planning and investment decisions by the industry, agave producers, and government authorities.

Keywords: ARIMA, *Agave angustifolia*, agricultural forecasting models, time series, non-timber forest products.

Citation: Cruz-Ramírez, A. S., Martínez-Gutiérrez, G. A., Morales-García, I., López-García, M. del R., & Castillo-Martínez, C. R. (2025). Comparison of models for estimating the planted area of *Agave* spp. for mezcal production in Mexico. *Agro Productividad*. https://doi.org/10.32854/6q7dtw68

Academic Editor: Jorge Cadena Iñiguez
Associate Editor: Dra. Lucero del Mar Ruiz Posadas
Guest Editor: Daniel Alejandro Cadena Zamudio

Received: February 6, 2025.
Accepted: June 18, 2025.
Published on-line: September XX, 2025.

Agro Productividad, 18(7). July. 2025. pp: 185-196.

INTRODUCTION

In Mexico, the planted area (PA) of espadín agave (*Agave angustifolia* Haw.) for mezcal production is experiencing unprecedented growth (Lira *et al.*, 2022a; Olvera-Vargas *et al.*, 2022). In 2023, the Agrifood and Fisheries Information Service (SIAP, by its acronym in Spanish) reported a PA of 24,506 hectares nationwide (SIACON-SADER, 2024). This represents a 69% increase compared to 2018, when 14,460 hectares were reported.

The Mexican Regulatory Council for Mezcal Quality (COMERCAM, by its acronym in Spanish) publishes a statistical report presenting data from its affiliated members. In 2023, it reported 64.79 million agave plants nationwide, representing a 152% increase compared to 2020 (25.66 million plants) (COMERCAM, 2024). Additionally, it provided data on the "registered area" with agave, which includes various types of forest vegetation and therefore differs from the planted area (PA) reported by SIAP.

Mezcal production represents the main value-added product derived from *Agave angustifolia* Haw. For this reason, it is identified in SIAP's publications as agave mezcalero (AM) or Agave espadín, a name that refers to the elongated and pointed shape of its leaves. AM has a rich cultural history and, over the past fifteen years, has become an economic development opportunity for marginalized communities in Mexico (Fonseca & Chalita, 2021; Martínez *et al.*, 2014). This crop is essential for small-scale artisanal farming systems: according to the report published by COMERCAM (2024), 125,000 families earned income from mezcal production in 2023.

However, studies on the agave mezcalero value chain (VC) highlight issues related to competitiveness (Espejel *et al.*, 2019; Moctezuma-López *et al.*, 2023), organization (Martínez *et al.*, 2014; Sánchez-Gómez *et al.*, 2022), market dynamics (Lira *et al.*, 2022a; García-Vásquez *et al.*, 2018), deforestation, and natural resource pollution (Antonio *et al.*, 2017; Palma *et al.*, 2016). It is worth noting the significant presence of small-scale producers and the predominance of communal land tenure as key characteristics of this value chain (González *et al.*, 2023; Lira *et al.*, 2022b).

The *Agave* genus has generated significant economic benefits in the regions where it is cultivated (Moctezuma-López *et al.*, 2024; Landa-Vidal *et al.*, 2023). However, over the past 40 years, high uncertainty has arisen due to price fluctuations (Antonio & Terán, 2008; Palma *et al.*, 2016). Sharp changes in prices between periods have caused substantial financial losses for producers involved in this crop (Martínez *et al.*, 2014).

The increase in monoculture plantations of *Agave angustifolia* has led to a higher incidence of pests and diseases (Figueroa-Castro *et al.*, 2017). This is mainly caused by the improper use of agrochemicals and the lack of experience among new producers, whose numbers increase every year (Rodríguez *et al.*, 2020; COMERCAM, 2024). Additionally, negative socioeconomic and environmental impacts have been documented in the regions where this crop is developed, such as the decline in the price of agave piña (Palma *et al.*, 2016), soil erosion due to planting in rows along the slope direction (Lira *et al.*, 2022b), and deforestation to establish new cultivation areas (Antonio *et al.*, 2017; Antonio & Smit, 2012), among others. However, statistically based information on future changes in the growth or trend of the PA of *A. angustifolia* remains scarce.

Due to the economic and environmental importance of agave, it is essential to create conditions that ensure it remains profitable for small- and medium-scale agave mezcalero producers and the industrial sector involved in this value chain (Valencia-Sandoval *et al.*, 2020; Camacho-Vera *et al.*, 2021; Cervantes-Luna *et al.*, 2022). One possible solution to the overproduction of raw material could be agroforestry systems for establishing new plantations (Antonio *et al.*, 2017). These agroforestry systems reflect traditional practices inherent to peasant culture.

The establishment of new plantations, whether agroforestry or monoculture systems, must be planned taking into account the trends in demand and availability of AM (Martínez *et al.*, 2014). The planning aims to ensure that agroforestry systems, although a viable option, are implemented sustainably and efficiently (Antonio *et al.*, 2017). The same applies if the choice continues to favor monoculture production systems.

The years required to reach maturity in agave cultivation (6-8 years) and the species cultivated contribute to increased financial risk linked to fluctuations in the price of the "piña" as raw material (Antonio *et al.*, 2017; Valencia-Sandoval *et al.*, 2023). If trends in the expansion of the PA and thus the supply of raw material are unknown, the stakeholders involved may not be prepared to respond to market changes, potentially facing severe economic losses and continuing to impact the vegetation in the territories where agave mezcalero is cultivated. Therefore, the objective of this research was to compare autoregressive integrated moving average (ARIMA) models for estimating the growth of the planted area with agave mezcalero in Mexico, based on statistical data, to promote efficient management of the natural resources involved in this value chain.

MATERIALS AND METHODS

Characteristics of the agave mezcalero planted area database

The PA of AM reported by SIAP includes information on different agave species, both cultivated and wild (*Agave* spp), with Agave espadín (*A. angustifolia* Haw.) being the predominant species in plantations. The SIAP methodology for data collection on agave is based on a monitoring process that involves agricultural authorities, beneficiaries of agricultural programs, and key producers (SIAP, 2019). SIAP publicly provides only the historical annual databases for the PA (SIACON-SADER, 2024). In this study, the annual data for PA were used to perform a time series analysis.

Statistical Analysis

The study was conducted at the national level using a database covering the period from 1982 to 2022. The time series data correspond to the variable PA, measured in hectares (ha), and were obtained from the Agro-Food Information System for Consultation (SIACON-SADER). The dataset was divided into two time series: a training period spanning 1982 to 2014 and a validation period from 2015 to 2022.

Data were analyzed using R software version 4.1.2 (R Core Team, 2023) employing autoregressive integrated moving average (ARIMA) models, following the procedure described by Hyndman & Athanasopoulos (2021). This method was selected because it allows estimation with univariate data. This allows to optimize resources by not requiring the collection of information on other variables that might affect the variable of interest in the study.

Stationarity of the series was verified using the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. The ARIMA methodology is based on autoregressive (AR) models (p), moving average (MA) models (q), and autoregressive moving average (ARMA) models (p, q) (Box *et al.*, 2016). If, in addition to these components, the model includes an integration component (d), it is called an ARIMA (p, d, q) model (Shumway & Stoffer, 2019).

To understand the behavior of the data series, an exploratory analysis was conducted, including the creation of a line plot as well as autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. The series was identified as non-stationery and stationarity was induced through logarithmic transformation (West, 2022) and double differencing (Shumway & Stoffer, 2017). Stationarity tests were performed on the differenced series using the ADF and KPSS tests. Once the series was identified as stationary, the optimal ARIMA model was selected using the Auto ARIMA algorithm in R (Hyndman & Khandakar, 2008).

The transformed model was compared with another model without logarithmic transformation but with the same level of differencing and autoregressive order identified by the Auto ARIMA algorithm procedure in R. Additionally, a manually selected model was included to compare its accuracy with the previous models. Following the manual procedure described by Hyndman & Athanasopoulos (2021), the autoregressive order (p) and moving average order (q) were identified using the ACF and PACF functions and plots. The Akaike Information Criterion (AIC) was used as the selection measure to choose between the manually identified models and those selected by the Auto ARIMA function algorithm, opting for the model with the lowest AIC value.

Additionally, as a reference point, a comparison was made with two simple forecasting methods: the mean and Naïve methods. The performance of the five models was evaluated with out-of-sample data through accuracy tests for an eight-year forecast period. Parameter estimation was carried out using the conditional least squares estimation method. This method is one of the most popular in statistical inference due to its accuracy and reliability in data analysis (Harring & Harring, 2022). To verify the suitability of the estimated model for the analyzed data, residuals were evaluated using a line plot, an ACF plot, a residual histogram, and the Ljung-Box test (Box *et al.*, 2016).

A forecast was made for the years 2023-2027 using the model with logarithmic transformation and two differencing steps, which showed the highest accuracy according to the statistical tests performed. According to Shumway & Stoffer (2017), transforming the data can cause issues when interpreting the results. For this reason, an adjusted ARIMA model was estimated based on the information obtained in the previous steps for the components of the ARIMA model. This last model did not apply transformation to the original data in order to establish a reference point for evaluating the back-transformation process in the transformed time series. Subsequently, upper confidence intervals were estimated for the predictions.

RESULTS AND DISCUSSION

Stationarity analysis

The training data series showed a positive trend during the period 1982-2014 (Figure 1). Stationarity tests were applied to this series. In the Augmented Dickey-Fuller (ADF) test, whose null hypothesis states the presence of a unit root (it is non-stationary), a p-value of

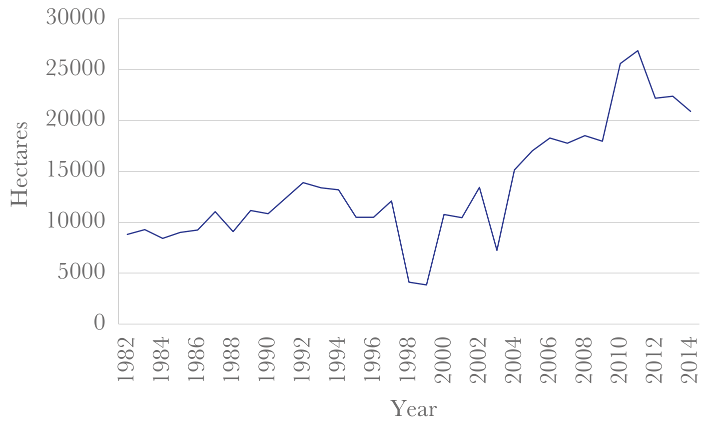

Figure 1. Training data series for the ARIMA model, period 1982-2014, of the planted area of agave mezcalero in Mexico.

0.8259 was obtained, which is greater than 0.05. Therefore, the null hypothesis was not rejected, indicating that the series is non-stationary.

In the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, whose null hypothesis states that the series is stationary, the test statistic was 0.6178. This value is below the critical value at the 1% significance level (0.739), but above the critical values at the 2.5% (0.574), 5% (0.463), and 10% (0.347) levels. Consequently, the null hypothesis was not rejected, suggesting that the series can be considered stationary at the 1% significance level.

Since the results of the ADF test indicated that the series was non-stationary, natural logarithm transformations and differencing were applied to induce stationarity prior to fitting the ARIMA model. After the first differencing of the logarithmic series, the ADF test still indicated non-stationarity, while the KPSS test suggested the opposite.

A second-order differencing was therefore applied to the series. Following this procedure, both tests (ADF and KPSS) confirmed that the series was stationary (Figure 2). Subsequently, the automatic ARIMA model selection process was carried out using the Auto ARIMA function in R with the transformed data.

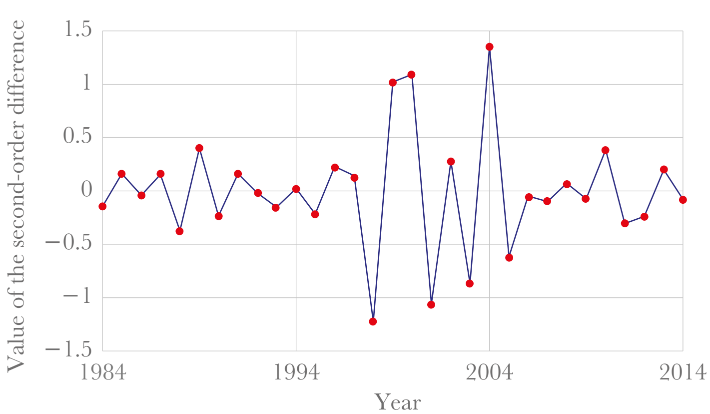

Figure 2. Second-order difference of the natural logarithm of the planted area of agave mezcalero in Mexico, period 1982-2014.

Model Selection

The ARIMA (4,0,0) model with zero mean (*i.e.*, no intercept included) presented the lowest AIC value. This model suggests significant autocorrelations up to four years back in the time series. To validate these results, the model's performance was evaluated using out-of-sample data and forecast accuracy tests.

To obtain forecasts in the original units of the time series, the inverse of the transformation previously applied to the data was performed. In order to assess the benefit of the logarithmic transformation on model accuracy, it was compared to an ARI (4,2,0) model. This model includes four lags and second-order differencing, but without applying a logarithmic transformation to the data.

According to Hyndman & Athanasopoulos (2021), ARIMA model components can be manually selected based on ACF and PACF plots. Following this approach, the models AR (2,0,0) (AIC=44.65), ARMA (2,0,2) (AIC=36.64), and ARMA (2,0,1) (AIC=34.35) were identified. The AIC values of these models were compared with the AR (4,0,0) model selected by the Auto ARIMA function, which had an AIC of 35.29. Although the AR (4,0,0) model showed a lower AIC than the first two models, the ARMA (2,0,1) model had a slightly lower AIC. Therefore, the ARMA (2,0,1) model was also included in the out-of-sample comparison.

Out-of-sample comparison

The out-of-sample evaluation of the ARIMA model's efficiency was conducted for the 2015-2022 period. The performance of the AR (4,0,0) model was compared against an ARI (4,2,0) model and an ARMA (2,0,1) model, as described in the previous section. The comparison with simple forecasting methods (SFMs) was used as a reference framework.

SFMs can outperform more complex models in certain contexts, such as financial indices or stock market data, according to Hyndman and Athanasopoulos (2021). The AR, ARMA, and ARI models were compared to the SFMs: Naïve (the last observed value) and mean (Figure 3). The estimation results indicated that the AR model better captured the behavior of the PA.

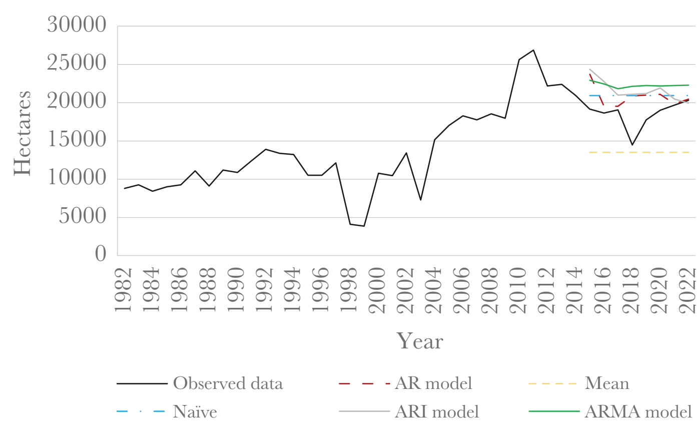

Figure 3. Comparison of forecasting methods for the planted area of agave mezcalero in Mexico, period 2015-2022.

Forecast accuracy was evaluated based on genuine forecasts (Box *et al.*, 2016; López-García *et al.*, 2022) using indicators such as: root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), mean absolute scaled error (MASE), autocorrelation of residuals at lag 1 (ACF1), and Theil's U statistic. For the mean error (ME) and the mean percentage error (MPE), the smallest deviation from zero was considered (R Core Team, 2023). The AR (4,0,0) model deviated the least from the actual observed data, obtaining six of the eight most efficient values in the accuracy tests (Table 1).

Forecast 2023-2027

The AR (4,0,0) model was applied to the transformed data for the period 1982-2022. The ADF test applied to the transformed series yielded a p-value of 0.01, allowing rejection of the null hypothesis and indicating stationarity. The KPSS test returned a statistic of 0.061, which is below the critical values at all significance levels, reinforcing this conclusion.

Using the Auto ARIMA function, the AR (4,0,0) model with zero mean presented the lowest AIC (33.38). Residual analysis revealed oscillations around zero without discernible patterns and constant variance. The residual ACF plot showed autocorrelations within confidence limits. The Ljung-Box test ($p=0.7228$) did not reject the null hypothesis of no autocorrelation. All these findings suggest an adequate model.

An ARI (4,2,0) model without logarithmic transformation was also fitted. It presented an AIC of 753.37. The autoregressive component of order 4 indicates dependence up to four lags, and the two differentiations performed reflect the need to induce stationarity.

Forecasts were made with both models for the period 2023-2027 (Figure 4). The AR (4,0,0) model projected a peak in 2024 of 22,723 ha, followed by a declining trend until 2027, reaching 20,965 ha. In contrast, the ARI (4,2,0) model estimated an increasing trend, with a peak in 2027 of 24,039 ha.

The document analysis highlighted the need to carefully examine the growth projections of AM plantations that the ARIMA model can identify. Upper confidence intervals for the point estimates were constructed using the ARIMA methodology. The results correspond to the two models with the lowest AIC values: the AR model with transformed data and the ARI model with untransformed data (Table 2).

Table 1. Accuracy test of the models.

Model	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1	Theil's U
Mean	5012.24	5285.07	5012.24	26.37	26.37	2.32	0.15	2.19
Naïve	−2408.95	2934.69	2408.95	−14.11	14.11	1.12	0.15	1.31
ARI(4,2,0)	−3075.87	3737.79	3160.51	−17.71	18.13	1.46	0.17	1.48
AR(4,0,0)	−2245.29	3119.58	2245.29	−13.26	13.26	NA	0.01	1.23
ARMA(2,0,1)	−3765.24	4109.93	3765.24	−21.48	21.48	NA	0.06	1.79

ME: MeanError; RMSE: Root Mean Squared Error; MAE: Mean Absolut Error; MPE: Mean Percentage Error; MAPE: Mean Absolute Percentual Error; MASE: Mean Absolute Scaled Error; ACF1: Autocorrelation of Errors at Lag 1; Theil's U statistic.

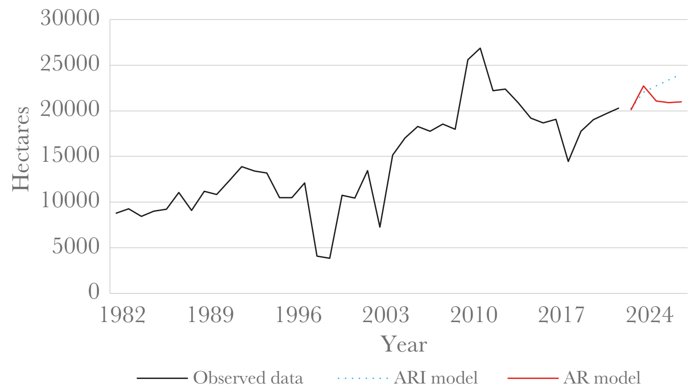

Figure 4. Comparison of forecasting methods for the planted area of agave mezcalero in Mexico, period 2023-2027.

Table 2. 95% Upper Confidence Intervals for the Forecast of agave mezcalero Planted Area (hectares) from 2023 to 2027.

Año	**AR (4,0,0)**	**Upper confidence interval for AR model at 95%**	**ARI (4,2,0)**	**Upper confidence interval for ARI model at 95%**
2023	20,128.27	38,341.02	20,275.81	26,874.14
2024	22,723.36	60,280.33	22,033.64	31,138.74
2025	21,064.68	49,735.97	22,729.64	34,339.05
2026	20,913.96	53,397.18	23,363.45	37,851.83
2027	20,965.33	54,305.34	24,039.87	42,192.84

AR: Autoregressive model forecast; ARI: Integrated autoregressive model forecast.

The projections indicate a significant growth trend in the area allocated for AM plantations, which could have important implications for the use of agricultural land and productive planning in the sector. The difference in projections between the two models may reflect different interpretations of the trends in the AM planted area data. The AR model captures a possible short-term significant increase in supply, while the ARI model indicates a steadily increasing trend.

The results of the ARIMA models for the PA of AM in Mexico were consistent with the observed data in 2023. Although the analysis was conducted with data up to 2022, the estimates aligned with the figures reported by COMERCAM (2024) and SIAP (SIACON-SADER, 2024) for the year 2023. In the case of COMERCAM, the validation was performed using data on "registered plants."

Martínez *et al.* (2014) reported an average density of 1,740 plants per hectare in the master plan for the maguey-mezcal production system. Meanwhile, OEIDRUS (2011) recorded different densities in the most recent agave plantation census, considering 2,000 plants per hectare for semi-intensive planting systems. According to COMERCAM (2024), in 2023, 64,792,341 agave plants were registered by its associates for the PA of AM in Mexico.

By dividing the number of plants registered by COMERCAM in 2023 by the average planting density reported by Martínez *et al.* (2014), a national planted area of 37,237 hectares is estimated for 2023. Using the planting density reported by OEIDRUS (2011), the estimated area would be 32,396 hectares. In contrast, SIAP (SIACON-SADER, 2024) reported a national PA of 24,506 hectares for the same year. These values fall within the confidence intervals projected by the AR model presented in Table 2 for 2023.

In this ARIMA model estimation, the diversity of agave species included in the AM cultivation must be taken into account. According to the OEIDRUS (2011) census conducted in 2008, 97.4% of the registered plantations corresponded to Agave espadín. Similarly, in 2023, COMERCAM (2024) reported that 86.23% of the mezcal produced came from this same species. Therefore, the increase in AM PA could mainly refer to Agave espadín and not necessarily reflect the situation of other wild species used in mezcal production. One factor that could be contributing to the expansion of the planted area with AM is the inclusion of this species in governmental programs for establishing new plantations. Escobar-Flores and Sandoval (2022) document that the "Sembrando Vida" program promoted the repopulation of agaves in the state of Durango. In this context, proper planning is required to ensure that the new plantations meet the objectives of these programs.

ARIMA models provided estimates consistent with the observed data, presenting confidence intervals that encompass possible future values. This demonstrates that ARIMA models are useful tools for managing uncertainty in forecasting agricultural variables. Castañeda *et al.* (2021) and Elsamie *et al.* (2021) provide additional evidence of their applicability in crops such as passion fruit and cotton, respectively. The PA of AM is part of the agricultural agave market. The effectiveness of ARIMA models in analyzing time series of agricultural products has been demonstrated in studies on cotton (Korivi *et al.*, 2023) and cabbage (Yang & Hu, 2013). The results obtained in this research reinforce the usefulness of these models to analyze time series with complex and non-stationary patterns, as occurs in the AM market.

Previous research highlights multiple applications of ARIMA models, ranging from estimating vanilla production (Luis-Rojas *et al.*, 2020) to estimating the planted area of staple crops such as maize (Tipi & Erdal, 2021) and wheat (Fawzy *et al.*, 2019). Tipi and Erdal (2021) emphasize the relevance of these models for estimating cultivated areas, a key aspect for agave and other crops. More recently, this methodology has been applied to crops such as apple (Ajit *et al.*, 2021) and papaya (Shafiya *et al.*, 2022).

The cited studies confirm the widespread use of ARIMA models in the analysis of agricultural data, where trend identification is fundamental for food security and economic stability, as in the case of the PA of AM. However, it must be considered that predictions are limited by the quality and availability of data. Unexpected events, such as natural disasters, changes in public policies, or economic crises, can significantly alter projections (Box *et al.*, 2016; Shumway & Stoffer, 2019).

CONCLUSIONS

The cultivation of AM is currently experiencing a context of overproduction. Statistical analysis results indicate that in 2024 a production peak could be reached, equivalent to nearly three times the maximum planted area historically recorded by SIAP. From 2025 onward, a decline in the planted area is projected.

Among the compared models, the autoregressive model (4,0,0) showed the best performance in predicting the planted area of AM in Mexico during the 2023-2027 period. This model presented the lowest value in the Akaike Information Criterion and achieved better results in the precision tests conducted, outperforming other evaluated models, including the mean model, the naïve model, the integrated autoregressive model (4,2,0), and the autoregressive moving average model (2,0,1).

The results obtained confirm the feasibility of using integrated autoregressive moving average models to estimate the planted area of AM. The analysis indicates potential growth in this area between 2023 and 2024, with a possible maximum value within the range of 22,273 to 60,280 hectares for the year 2024. Subsequently, a decreasing trend is projected, with an estimated range between 20,965 and 54,305 hectares for 2027.

The estimates generated by the integrated autoregressive models were consistent with the observed data and those reported for 2023 by COMERCAM and SIAP, especially regarding the upper limit of the confidence interval. The agreement between the model's projections and the official data reinforces the validity of the statistical analysis performed. This scenario of growth in the planted area can support decision-making in agricultural public policy, as well as the design of investment strategies by the business sector.

ACKNOWLEDGMENTS

We thank INIFAP for the facilities provided and the National Polytechnic Institute, CIIDIR Oaxaca Unit, for the support given.

REFERENCES

Ajit, S., Shilpa, & Gupta, R. K. (2021). Pragmatic investigation for forecasting apple area and production in himachal pradesh. *International Journal of Agricultural and Statistical Sciences*, 16, 1059-1065. https://connectjournals.com/03899.2020.16.1059

Antonio, B. J., Antonio Jose, A. A., & León Nuñez, M. J. (2017). Efectos socioeconómicos y ambientales de la sobreproducción de maguey mezcalero en la región del mezcal de Oaxaca, México. *Agricultura Sociedad y Desarrollo, 14*(4). https://doi.org/10.22231/asyd.v14i4.700.

Antonio, B. J., & Smit, Mascha. (2012). Sustentabilidad y agricultura en la "región del mezcal" de Oaxaca. *Revista Mexicana de Ciencias Agrícolas, 3*(1), 5-20. https://doi.org/10.29312/remexca.v3i1.1477.

Antonio B., J., & Terán, M. (2008). Estrategias de producción y mercadotecnia del mezcal en Oaxaca. *El Cotidiano, 23*(148), 113-122. https://www.redalyc.org/pdf/325/32514811.pdf

Box, G. E. P., Jenkins, G. M., & Reinsel, G. (2016). Time Series Analysis, Forecasting and Control. (5a ed.). Wiley. New Jersey, United States of America. pp. 720.

Camacho-Vera, J. H., Vargas-Canales, J. M., & Durán-Ferman, P. (2021). Avatares de la producción de Mezcal en la región miahuateca de la Sierra Sur de Oaxaca. *LiminaR Estudios Sociales y Humanísticos, 19*(1). https://doi.org/10.29043/liminar.v19i1.794.

Castañeda, L. N. R., Angarita, G. P. G., & Cleves-Leguizamo, J. A. (2021). Mathematical modeling of climatological data to estimate passion fruit crop yield (*Passiflora edulis* sims l. f. *flavicarpa* y *purpurea*). *Revista Brasileira de Fruticultura, 43*(3). https://doi.org/10.1590/0100-29452021182.

Cervantes-Luna, J. O., Hernández-Ortiz, J., Valdivia-Alcalá, R., Melo-Guerrero, E., Sandoval-Romero, F., & González-Juárez, A. (2022). Análisis de la cadena de valor del mezcal en San Felipe, Guanajuato. *Revista Mexicana de Ciencias Agrícolas, 13*(3). https://doi.org/10.29312/remexca.v13i3.2873.

COMERCAM. (2024). Informe estadístico 2024. Consejo Mexicano Regulador de la Calidad del Mezcal A.C.

Elsamie, M. A., Ali, T., & Zhou, D. (2021). Using a dynamic time series model (ARIMA) for forecasting of Egyptian cotton crop variables. *Journal of Animal and Plant Sciences, 31*(3), 810-823. https://doi.org/10.36899/JAPS.2021.3.0271.

Escobar-Flores, J. G., & Sandoval, Y. S. (2022). Artificial intelligence to model the potential distribution of *Agave durangensis*. International Geoscience and Remote Sensing Symposium (IGARSS), 2022-July. https://doi.org/10.1109/IGARSS46834.2022.9883767.

Espejel García, A., Barrera Rodríguez, A., Ramírez García, A. G., & Cuevas Reyes, V. (2019). Innovación en la cadena agroindustrial de Mezcal en tres municipios en Oaxaca, México. *Revista Venezolana de Gerencia, 24*(2), 188-209. https://doi.org/10.37960/REVISTA.V24I2.31488.

Fawzy, E., Mahmoud, B., & Mongy, A. (2019). Modeling and forecasting of wheat production in Egypt. *Advances and Applications in Statistics, 59*(1). https://doi.org/10.17654/as059010089.

Figueroa-Castro, P., López-Martínez, V., Silva-García, F., & González-Hernández, H. (2017). Food Attractants to Increase Pheromone-Baited Trap Performance for *Scyphophorus acupunctatus* (Coleoptera: Dryophthoridae) in Mezcal Maguey. *Florida Entomologist, 100*(1), 203-205. https://doi.org/10.1653/024.100.0135.

Fonseca, M., & Chalita, L. E. (2021). Evaluación financiera de producción de agave y mezcal: caso de estudio Caltepec, Puebla. *Revista Mexicana de Ciencias Agrícolas, 12*(2). https://doi.org/10.29312/remexca.v12i2.2583.

García-Vásquez, A. J., Jaramillo-Villanueva, J. L., Vargas-López, S., Bustamante-González, A., & Barrera-Rodríguez, A. L. (2018). Tipología de las unidades de producción de mezcal artesanal del Distrito de Tlacolula, Oaxaca, México. *Agro Productividad, 11*(12). https://doi.org/10.32854/agrop.v11i12.1309

González Venegas, S. E., Tapia Guerrero, L. A., Martínez Gutiérrez, G. A., & To-ledo López, A. (2023). Agricultural resilience in small agave producers in Oaxaca. *Revista mexicana de ciencias agrícolas, 14*(2), 197-209. https://doi.org/10.29312/REMEXCA.V14I2.3055.

Harring, J. R., & Harring, E. K. (2022). Estimation approaches: least-squares, maximum likelihood and Bayesian. In International Encyclopedia of Education: Fourth Edition. https://doi.org/10.1016/B978-0-12-818630-5.10089-2.

Hyndman, R.J., & Khandakar, Y. (2008). Automatic time series forecasting: The forecast package for R. *Journal of Statistical Software, 27*(3), 1-22. https://doi.org/10.18637/jss.v027.i03.

Hyndman, R. J, & Athanasopoulos, G. (2021). Forecasting: Principles and Practice. (3a ed.). OTexts. Melbourne, Australia. pp. 442. https://otexts.com/fpp3/

Korivi, N., Sravani, P., Ali, J., & Sobin, C.C. (2023). Analyzing Market Dynamics of Agricultural Commodities: A Case Study Based on Cotton. In: Sarkar, R., Pal, S., Basu, S., Plewczynski, D., Bhattacharjee, D. (eds) Proceedings of International Conference on Frontiers in Computing and Systems. COMSYS 2022. Lecture Notes in Networks and Systems, vol 690. Springer, Singapore. https://doi.org/10.1007/978-981-99-2680-0_2

Landa-Vidal, E. A., Rojas-Rojas, M. M., Valencia-Sandoval, K., & Ybarra-Moncada, Ma. C. (2023). Agroempresa social sostenible: actor estratégico de la cadena de valor del maguey pulquero en el Estado de México. In Empresas sociales y consumo responsable: una oportunidad de reconversión en los modelos de negocio (Vol. 1, pp. 161-183). Plaza y Valdes.

Lira, M.G., Robson, J. P., & Klooster, D. J. (2022a). Commons, global markets and small-scale family enterprises: the case of mezcal production in Oaxaca, Mexico. *Agriculture and Human Values, 39*(3), 937-952. https://doi.org/10.1007/s10460-021-10293-z.

Lira, María G, Davidson-Hunt, I. J., & Robson, J. P. (2022b). Artisanal Products and Land-Use Land-Cover Change in Indigenous Communities: The Case of Mezcal Production in Oaxaca, Mexico. *Land, 11*(3), 387. https://doi.org/10.3390/land11030387.

López-García, M. del R., Martínez-Damián, M. Á., & Arana-Coronado, J. J. (2022). Predictores del precio de maíz blanco en Jalisco y Michoacán. *Revista Mexicana de Ciencias Agrícolas, 13*(2). https://doi.org/10.29312/remexca.v13i2.2740.

Luis-Rojas, Samuel, Ramírez-Valverde, B., Díaz-Bautista, M., Pizano-Calderón, J., & Rodríguez-López, C. (2020). La producción de vainilla (*Vanilla planifolia*) en México: análisis y pronóstico. *Revista Mexicana de Ciencias Agrícolas, 11*(1). https://doi.org/10.29312/remexca.v11i1.2065.

Martínez Tenorio, S., Cisneros Méndez, T., & Linares Martínez, A. (2014). Plan rector sistema producto maguey mezcal. SAGARPA - SEDAPA - FUNDACION PRODUCE.

Moctezuma-López, G., Pérez-Miranda, R., González Hernández, A., Romero Sánchez, M. E., & Velasco Bautista, E. (2024). Rentabilidad de las plantaciones de agave mezcalero (*Agave angustifolia*) en el distrito valles centrales del estado de Oaxaca. *Revista Mexicana de Agronegocios*, 55, 12-23. https://www.redalyc.org/revista.oa?id=141

Moctezuma-López, G., Pérez-Miranda, R., González Hernández, A., Romero Sánchez, M. E., Velasco Bautista, E., & Ramírez Ojeda, G. (2023). Agave Mezcalero: Importancia del contexto económico a nivel estado de Oaxaca y su comparación a escala país México. *Revista Mexicana de Agronegocios*, 53, 535–550. https://www.redalyc.org/journal/141/14178290010/

OEIDRUS. (2011). Maguey Mezcal regiones productoras de Oaxaca 2011. Sistema Nacional de Información para el Desarrollo Rural Sustentable, Gobierno del Estado de Oaxaca.

Olvera-Vargas, L. A., Pardo-Núñez, J., Aguilar-Rivera, N., & Contreras-Medina, D. I. (2022). Detection of *Agave angustifolia* and *Agave cupreata* with geomatic techniques in Guerrero, Mexico. *Ciencia y tecnología Agropecuaria, 23*(2). https://doi.org/10.21930/RCTA.VOL23_NUM2_ART:2241.

Palma, F., Pérez, P., & Meza, V. (2016). Diagnóstico de la Cadena de Valor Mezcal en las Regiones de Oaxaca. https://www.oaxaca.gob.mx/coplade/wp-content/uploads/sites/29/2017/04/Perfiles/AnexosPerfiles/6.%20CV%20MEZCAL.pdf

R Core Team. (2023). R: A language and environment for statistical computing (4.1.2. https://www.R-project.org/). Foundation for Statistical Computing.

Rodríguez, W. D., Navarrete-Heredia, J. L., MacÍas, R. R., Vásquez-Bolaños, M., Briceño-Félix, G. A., & Jones, R. W. (2020). Abundance of *Scyphophorus acupunctatus* Gyllenhal (Coleoptera: Dryophthoridae) in *Agave tequilana* Weber (Asparagaceae) Fields of Different Age and Agronomic Management. *Proceedings of the Entomological Society of Washington, 122*(2), 450-461. https://doi.org/10.4289/0013-8797.122.2.450.

Sánchez-Gómez, J., Pardo-Núñez, J., Cuevas-Reyes, V., & Romero-Romero, Y. (2022). Characteristics and socio-productive problems of women mezcal producers in Oaxaca, México. *Agro Productividad, 15*(3). https://doi.org/10.32854/agrop.v15i3.2134

Shafiya, R., Mohan Naidu, G., Ravindra Reddy, B., Vani, N., & Govinda Rao, S. (2022). Statistical modeling on area, production and productivity of papaya crop in Andhra Pradesh. *International Journal of Agricultural and Statistical Sciences, 18*(2), 611-618.

Shumway, R.H., & Stoffer, D. S. (2019). Time Series: A Data Analysis Approach Using R. (1a ed.) Chapman and Hall/CRC. New York, United States of America. pp. 271.

Shumway, Robert H, & Stoffer, D. S. (2017). Time series analysis and its applications With R Examples. (3a ed.) Switzerland. pp. 562.

SIACON-SADER. (2024). Sistema de Información Agroalimentaria de Consulta. https://www.gob.mx/siap/documentos/siacon-ng-161430.

SIAP. (2019). Normatividad Técnica para la Generación de Estadística Básica Agropecuaria. Servicio de Información Agroalimentaria y Pesquera. https://www.gob.mx/siap/prensa/normatividad-tecnica-para-la-generacion-de-estadistica-basica-agropecuaria?idiom=es.

Tipi, T., & Erdal, B. (2021). The forecast of corn production fields in turkey with ARIMA model. *Romanian Agricultural Research, 2021*(38). https://doi.org/10.59665/rar3850.

Valencia-Sandoval, K., Rojas-Rojas, M. M., Alvarado-Lagunas, E., & Duana-Avila, D. (2020). Innovación agroindustrial del agave (*Agave tequilana* Weber var. azul): valoración financiera para la obtención de inulina. *Agro Productividad, 13*(3). https://doi.org/10.32854/agrop.vi.1632

Valencia-Sandoval, K., Rojas-Rojas, M. M., & Godínez-Montoya, L. (2023). Innovación en Negocios Tradicionales: El Caso del Agave, Más Allá del Tequila. *InnOvaciOnes de NegOciOs, 1*(1). https://doi.org/10.29105/revin1.1-442

West, R. M. (2022). Best practice in statistics: The use of log transformation. *Annals of Clinical Biochemistry, 59*(3), 162-165. https://doi.org/10.1177/00045632211050531.

Yang, H., & Hu, J. (2013). Forecasting of fresh agricultural products demand based on the ARIMA model. *Advance Journal of Food Science and Technology, 5*(7). https://doi.org/10.19026/ajfst.5.3172.