Colegio de Postgraduados

Current challenges and forecasts in maize grain production and consumption in Mexico

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ABSTRACT

Objective: to analyze production and consumption of maize grain in Mexico, with time series and recurrent neural networks, to describe the present and future situation of maize cultivation.

Design/Methodology/Approach: key variables were analyzed in graphs and maps created in Excel® and SCImago Graphica®, respectively. Forecasts for the year 2050 were obtained in Python© with Recurrent Neural Network (RNN) of the Long Short-Term Memory (LSTM) type, and were compared with the years 1980 and 2020.

Results: the largest production of white and yellow maize grain was obtained by the United States and China. Mexico ranks seventh, is not competitive in exports, and relies on imports of yellow maize grain from the United States to supply demand. The Mexican states that implemented technology packages showed higher yields and production. By 2050, maize grain production in Mexico will increase due to the technological advances of Agriculture 5.0 Although it would not be enough to supply the apparent consumption of the growing population, for this reason imports will increase.

Limitations/Implications of the study: analysis of the possible future, created from time series through RNN-LSTM, helps to guide decision-making in the present.

Findings/Conclusions: new agricultural public policies are needed to guide, in the long term, the challenges of maize grain production and consumption in Mexico to guarantee food sovereignty.

Keywords: yields, imports, exports, time series, deep neural networks.

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INTRODUCTION

Maize (*Zea mays* L.) has its center of origin and domestication in Mexico. It is one of the most economically important crops in the world, as it is necessary for human food, animal feed, and to obtain industrial products. Maize grain, and green maize fodder are harvested (López-Torres *et al.*, 2016; Cadet Díaz and Guerrero Escobar, 2018). There are several varieties; their use depends on agricultural goals (Sánchez-Ramírez *et al.*, 2023).

In 2021, maize grain was the second most produced crop in the world, with 1210 million tons [Megagrams] (M Mg), and with the second largest harvested area, about 206 million hectares. For this reason, it ranked only after sugarcane (1859 M Mg) and wheat (221 million ha), respectively (FAO, 2023). However, it is necessary to increase yields with the least use of resources to meet global demand in the future (FAO, 2022).

Maize yields in Mexico increased due to the management of improved varieties, agrochemicals, machinery, credits, and irrigation (Cadet-Díaz and Guerrero-Escobar, 2018). In self-consumption production, farmers conserve native maize varieties (Sánchez-Ramírez *et al.*, 2023) that will be necessary in the genetic improvement of Agriculture 5.0. In addition to biotechnology, in the long term, artificial intelligence, Big Data, blockchain and automation will increase productivity and the supply of maize grain (Ahmad and Nabi, 2021; Martos *et al.*, 2021).

Time series are used to characterize the supply and demand of maize grain in Mexico. In addition, they make it possible to calculate forecasts necessary to guide decision-making in the present (Aladag, 2017; Mills, 2019). One of the most widely used methods is recurrent neural networks – RNNs, especially those of the deep LSTM type, because they give more accurate results to complex linear and nonlinear problems (Abbasimehr *et al.*, 2020).

The objective of this research was to analyze production and consumption of maize grain in Mexico, with time series through recurrent neural networks, to describe the present and future situation of maize cultivation.

MATERIALS AND METHODS

Data set

Data were downloaded from the Mexican Agri-Food and Fisheries Information Service (SIAP, 2023b) and the United Nations Food and Agriculture Organization (FAO, 2023). The key variables analyzed for maize grain in Mexico were production, apparent consumption, exports, imports, yields, and harvested area.

Time series analysis

Discrete time series were implemented with annual data (x_t), from 1961 to 2021, x_{t-1}, x_{t-2},... x_{t-n} (Aladag, 2017; Mills, 2019). A descriptive analysis was performed in the time series with graphs created in Excel®, maps in SCImago Graphica® and forecasts towards 2050 in Python© version 3.12, with the use of recurrent neural networks – RNN, for the variables production, apparent consumption, import and export to compare the present (2020) with the data from 30 years ago (1990) and up to 30 years towards the future (2050).

Recurrent Neural Networks

A Deep Neural Network (DNN) model of the recurrent type, known as recurrent neural networks for short- and long-term memory analysis (RNN-LSTM), was selected to obtain the forecasts to 2050. They were designed under the theory of Greff *et al.* (2017) and Abbasimehr *et al.* (2020), with the following architecture: an input layer, six hidden layers with 32 neurons each, and an output layer (Figure 1). The input layer of the RNN-LSTM received the time series data, and the output layer of the network generated the forecast up to 2050. An RNN-LSTM was trained for each of the key variables to be predicted.

For the RNN-LSTM performance evaluation, the root mean squared error (RMSE) was used $\sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(x_t-\hat{x}_t\right)^2}$, where x_t and $\hat{x}_t$ are the actual and predicted values of the series, respectively; n is the length of the test set (Abbasimehr *et al.*, 2020).

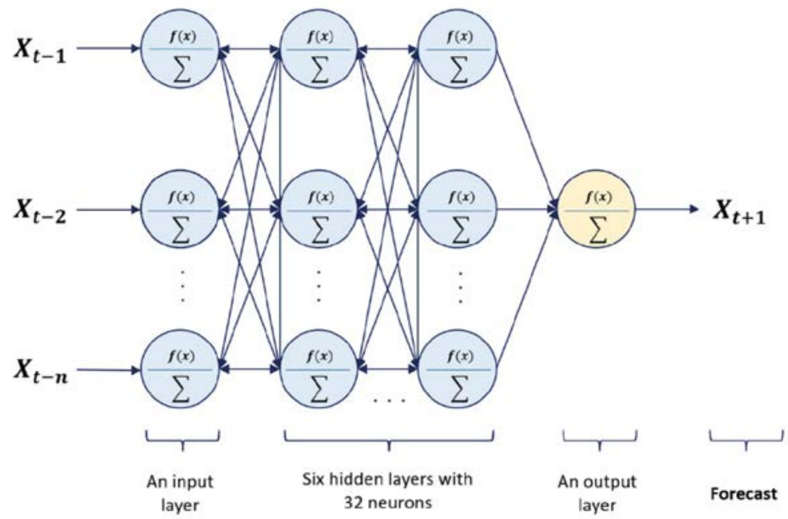

Figure 1. Architecture of a recurrent neural network for short- and long-term memory analysis (RNN-LSTM). Source: elaborated by the authors with information from Greff *et al*. (2017) and Abbasimehr *et al*. (2020).

RESULTS AND DISCUSSION

World scope of maize grain production

In 2021, the countries with the highest corn grain production (M Mg) were the United States, 384; China, 273; Brazil, 89; Argentina, 61; Ukraine, 42; India, 32; and Mexico, 28 (Figure 2). The United States and China contributed 54% (657 M Mg), with respective 320 and 1413% rates of change. This unprecedented increase led to a 490% increase in global maize production (FAO, 2022; 2023).

In order to maintain this pace further, production systems need to be oriented to solve the following challenges: climate change; pandemics; war and conflicts; genetically modified organisms; lack of credit; high prices; scarce and underage skilled labor (Cadet-Díaz and Guerrero-Escobar, 2018; Kato-Maldonado and Huerta-Moreno, 2022; Shahini *et al*., 2022).

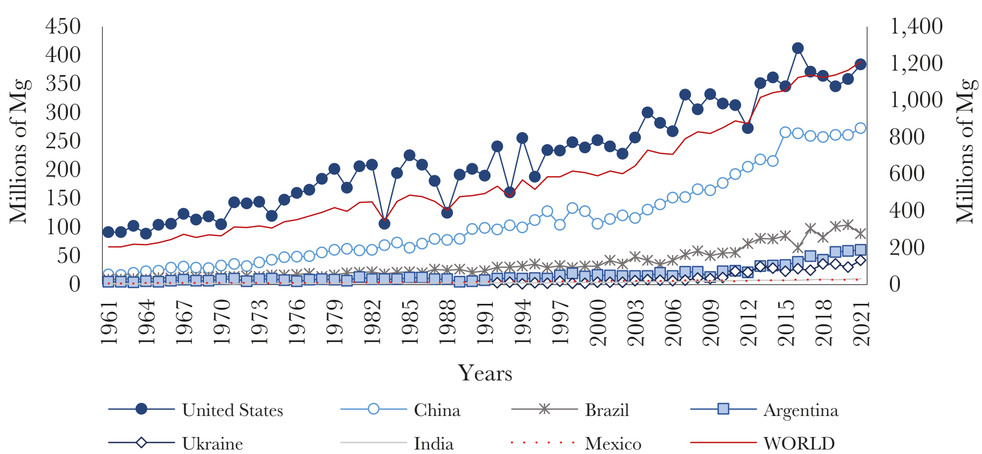

Figure 2. Behavior of maize grain production in the main producing countries and world total, 1961-2021. Source: elaborated by the authors using data from FAO (2023).

Production and consumption perspectives of maize in Mexico

The problems described are aggravated in developing countries, such as Mexico, because it disrupts free trade, raises prices for supplies (Shahini *et al.*, 2022) and poverty levels. In 2022, 46.8 million Mexicans (36.3%) were in poverty and 9.1 million (7.1%) in extreme poverty (CONEVAL, 2023). In addition, these are maize producers for self-consumption who are located in rural and peri-urban areas (López-Torres *et al.*, 2016; FAO, 2022).

Another challenge faced by Mexico is to supply the apparent domestic consumption (44.80 M Mg, Figure 3) (FAO, 2023) for 127 million Mexicans (ONU, 2023), with the domestic production of white (24.29 M Mg) and yellow (2.80 M Mg) maize grain. The latter was not enough and 15.81 M Mg of yellow maize grain was imported from the United States in 2021 (SIAP, 2023a).

Yellow maize was destined for livestock feed (15.50 M Mg) and the starch industry (3.02 M Mg; SIAP, 2023a). This makes Mexico dependent on production from the United States (Espinosa Cortés, 2022) and uncompetitive in exports [0.097 M Mg] (FAO, 2023).

On the other hand, in 2021 the main producer states of this staple in Mexico were Sinaloa, Jalisco, State of Mexico, Guanajuato, and Michoacán, with 5.54, 3.95, 1.94, 1.93, and 1.91 M Mg, respectively (Figure 4). Sinaloa, Guanajuato, Chihuahua, Michoacán, and Sonora produced 5.47, 1.48, 1.43, 0.82 and 0.79 M Mg, under irrigation systems. The states with the highest rainfed production were Jalisco, State of Mexico, Guerrero, Veracruz, Chiapas, and Michoacán, with 3.60, 1.57, 1.29, 1.25, 1.24, and 1.08 M Mg, respectively (SIAP, 2023b).

The production of rainfed maize in these states was significant due to the greater amount of harvested area (Figure 5) not to yields. Jalisco only obtained a yield of 6.66 Mg ha^{-1}; State of Mexico 3.74; Guerrero, 2.80; Veracruz, 2.26; Chiapas, 1.83; and Michoacan, 3.16 Mg ha^{-1} (SIAP, 2023b). The importance of rainfed maize production is based on the diversity and conservation of native maize varieties, grown by small-scale producers in traditional production systems, under extreme climatic and topographic conditions (López-Torres *et al.*, 2016).

In contrast, the highest yields (Mg ha^{-1}) of cultivated maize obtained with irrigation systems were Sinaloa, 11.89; Sonora, 11.56; Baja California, 11.47; Chihuahua, 11.13; and

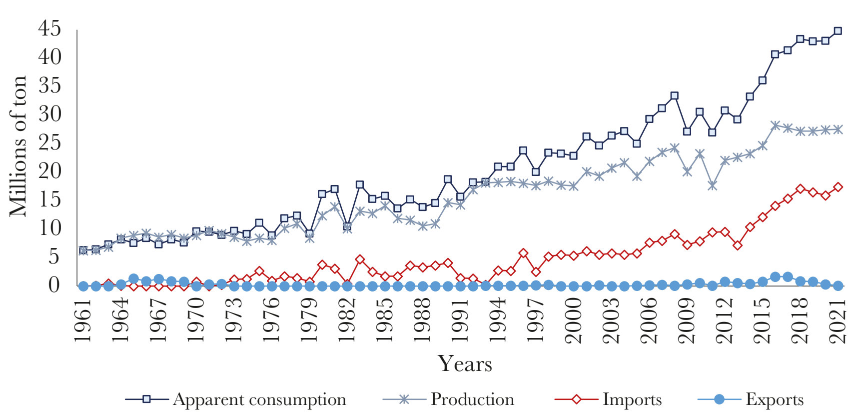

Figure 3. Historical behavior of apparent consumption, production, imports, and exports of maize grain in Mexico, 1961-2021. Source: elaborated by the authors using data from FAO (2023).

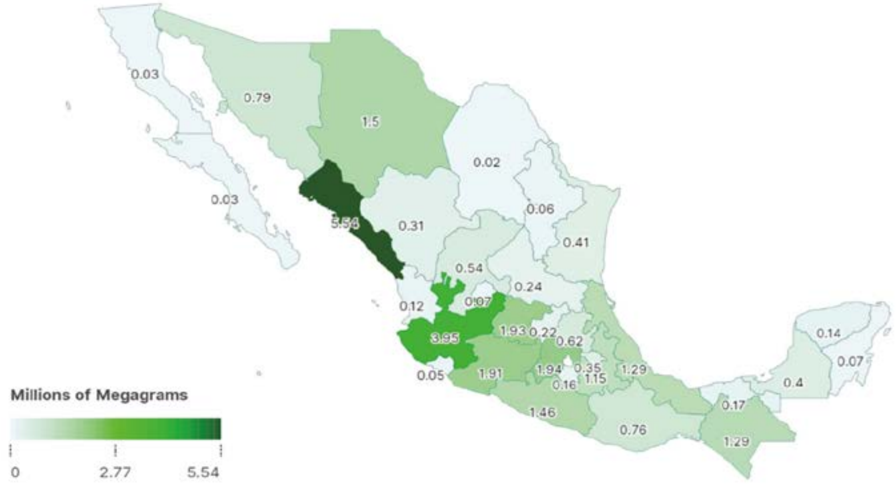

Figure 4. The states in Mexico with the highest production of maize grain in 2021. Source: elaborated by the authors using data from SIAP (2023b).

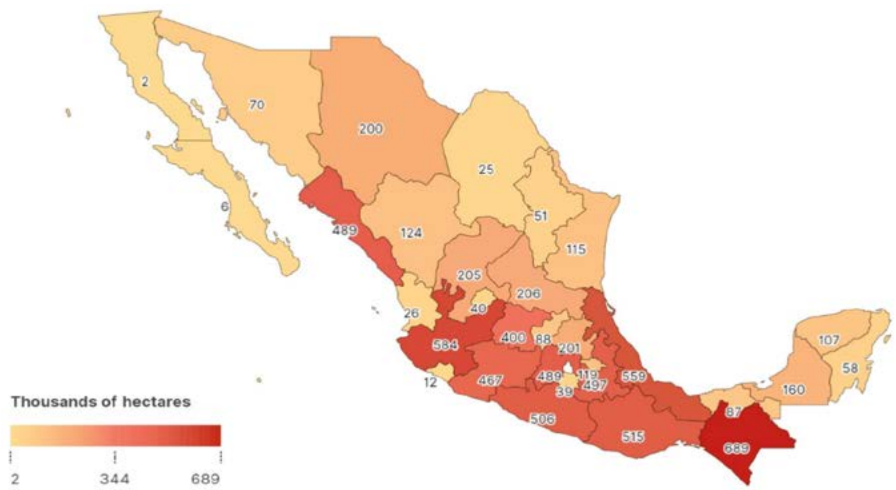

Figure 5. The states in Mexico with the largest harvested area of maize grain in 2021. Source: elaborated by the authors using data from SIAP (2023b).

Guanajuato, 10.20 Mg ha^{-1} (SIAP, 2023b). In order to be more competitive in these states, big-scale producers use, in addition to irrigation, genetically improved maize varieties, machinery, credits, fertilizers, and more efficient controls for pest and diseases (Cadet-Díaz and Guerrero-Escobar, 2018). Therefore, generating a 288% rate of variation in domestic yields (Figure 6; FAO, 2023).

In this scenario, maize grain production is expected to increase 37% by 2050, compared to 27.42 M Mg in 2020, in turn the equivalent of 2.57 times what was produced in 1990 (Figure 7; FAO, 2023). However, it will depend on digital education and the effective technological adoption of Agriculture 5.0 in Mexico, which emphasizes artificial intelligence, Deep Learning models; internet of things; Big Data; cloud computing; Blockchain, wireless sensors; drones, self-operated tractors, and robots; 3D printing; vertical farming, and urban

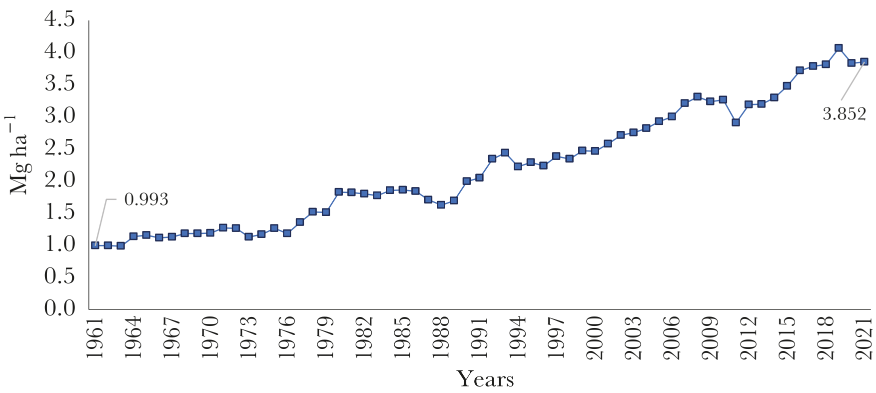

Figure 6. Behavior of the domestic yield of maize grain in Mexico, 1961-2021. Source: elaborated by the authors using data from FAO (2023).

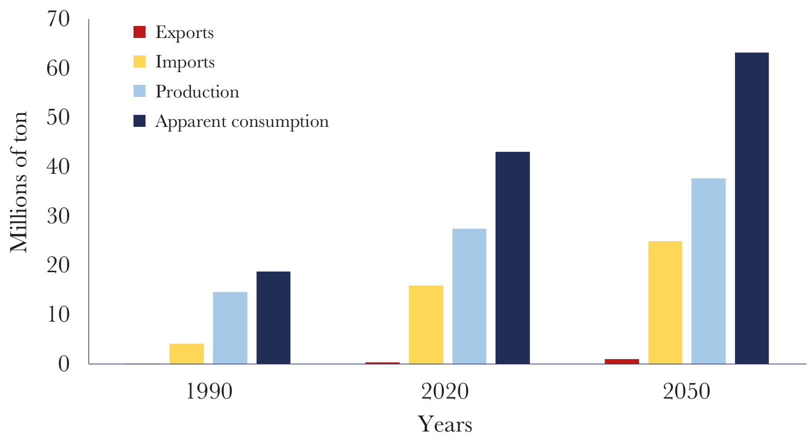

Figure 7. Forecasts for the year 2050 of the export, import, production and apparent consumption of grain corn in Mexico. Source: elaborated by the authors using data [1990 and 2020] from FAO (2023).

production of organic crops (Cadet-Díaz and Guerrero-Escobar, 2018; Ahmad and Nabi, 2021; Martos *et al.*, 2021; Buka *et al.*, 2022).

Agriculture 5.0 will also bring new challenges: reduction of repetitive jobs; skilled labor; modernization of educational programs; unprecedented polarization of producer types; exclusion, complexity, scarcity and the high costs of big Deep Learning models and Artificial intelligence; vulnerability of the privacy and security of data; technological dependence; environmental impact resulting from digitalization and robotics; reduction of traditional agriculture; oligopolistic markets for a global food production order; and loss of sovereignty in food production (Ahmad and Nabi, 2021; Martos *et al.*, 2021; Buka *et al.*, 2022; Espinosa Cortés, 2022; FAO, 2022; Kato-Maldonado and Huerta-Moreno, 2022).

These and other challenges that may arise in the future and have not been identified at present, shall reduce maize supply to satisfy the apparent consumption of this staple in Mexico (63.16 M Mg; FAO, 2023) due to the demand of the estimated 144 million people that would be here in 2050 (ONU, 2023). Consequently, for 2050 an increase of 8.99 M

Mg in imports will be required, compared to 2020; this value will be equivalent to a 6-fold increase on what was demanded in 1990. Further domestic demand will cause exports to a 0.682 M Mg increase in maize grain production, compared to values today (FAO, 2023).

CONCLUSIONS

Maize is one of the most important grains in world agriculture production. The United States, China and Brazil focus their resources on yield and production increases in the future. In Mexico, maize grain production was deficient to meet current demand, so there is dependence on the imports of yellow maize grain from the United States.

According to the 2050 forecasting scenario, maize grain production in Mexico may increase due to education, development, and adoption of advanced Agriculture 5.0 technologies. But it will not be enough to meet domestic demands, for it is predicted that imports of yellow maize grain will still be needed. Agricultural public policies adapted to each region and type of producer are required to go beyond the short term, in order to design sustainable and resilient production systems that guarantee food sovereignty, restoration of natural resources and conservation of native maize varieties.

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