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Predicting Cotton Production in Syria Using the MLP Model

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Abstract

The research aimed to estimate cotton production in Syria (2024-2030) based on time series data on cultivated area and productivity from 1993 to 2023. The descriptive approach summarized time series data for the research variables using statistical methods like tables and charts and descriptive measures of central tendency and dispersion. A standard analytical approach was employed using a neural network model, specifically multi-layer perceptron, to fit the data. The results indicated significant instability in cotton cultivation areas in Syria, with a coefficient of variation of 59.37%. Cotton production exhibited notable fluctuations, reflected in a coefficient of variation of 68.23% while cotton crop productivity showed reasonable stability at a CV of 22.61%. The neural network model 3, 2, 1 was used in the prediction by the feed-forward method, and the backpropagation method updated the weights after calculating the difference between the expected and actual values to improve the model predictive accuracy. The neural network model proved highly efficient in predicting cotton production, recording significant decreases in the squared error 0.009 and the relative error rate 0.001, indicating its ability to analyze the data effectively. The production forecasts for the period 2024-2030 showed a positive trend with an annual growth rate ranging between 0.19% and 0.58%, indicating the possibility of achieving sustainable gains in production.

Keywords: Cotton, Network, Neural, Deep learning, Production.

التنبؤ بإنتاج القطن في سورية باستخدام نموذج (MLP)

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الخلاصة

هدف البحث إلى تقدير إنتاج محصول القطن في سورية خلال الفترة 2024–2030 بالاعتماد على بيانات السلاسل الزمنية الخاصة بالمساحة المزروعة والإنتاجية خلال الفترة 1993–2023. تم استخدام المنهج الوصفي لوصف بيانات السلاسل الزمنية لمتغيرات البحث من خلال عرضها وتلخيصها بطرق إحصائية كالجداول والأشكال البيانية وبعض المقاييس الوصفية كمقاييس النزعة المركزية ومقاييس التشتت كما تم استخدام المنهج التحليلي القياسي باستخدام نموذج الشبكة العصبونية حيث تم العمل على الشبكة (perceptron network) متعددة الطبقات لملائمتها لطبيعة البيانات. أظهرت النتائج أن المساحات المزروعة بالقطن في سورية تعاني من عدم استقرار كبير، حيث بلغ معامل التباين 59.37%، كذلك، بلغ معامل التباين في إنتاج القطن 68.23%، مما يشير إلى تقلبات ملحوظة في الإنتاج، أما إنتاجية محصول القطن، فقد أظهرت مستوى معقول من الاستقرار بمعامل تباين قدره 22.61%. تم استخدام نموذج الشبكة العصبية (1، 2، 3) في التنبؤ بأسلوب التغذية الأمامية، وطريقة التعليم على الخطأ العكسي (Backpropagation) لتحديث الأوزان بعد حساب الفرق بين القيم المتوقعة والفعلية لتحسين دقة النموذج في التنبؤ. أثبت نموذج الشبكة العصبية المستخدم كفاءة عالية في توقع إنتاج القطن، حيث سجل انخفاضاً كبيراً في خطأ المربعات 0.009 ومعدل الخطأ النسبي 0.001، مما يدل على نجاح النموذج في تحليل البيانات بشكل فعال. كما أظهرت نتائج توقع الإنتاج خلال الفترة 2024–2030 أن هناك اتجاهًا إيجابيًا بمعدل نمو سنوي يتراوح بين 0.19% و0.58% مما يشير إلى إمكانية تحقيق مكاسب مستدامة في الإنتاج.

كلمات مفتاحية: القطن، الشبكة، العصبية، التعلم العميق، إنتاج.

Introduction

Global production of ginned cotton, which constitutes 34% of raw cotton, reached 23.08 million tons in the 2004/2005 season, according to estimates by the US Department of Agriculture. This increase was driven by rising purchasing power resulting from a strong global economy, lower cotton prices, and higher prices for hand-spun yarn, leading to increased consumption (4).

A 2025 report by the Food and Agriculture Organization of the United Nations (FAO) addressed the impact of severe drought on Syrian agriculture, including strategic crops such as cotton, within the framework of the 2025–2027 Emergency Action and Recovery Plan adopted by the FAO in collaboration with the Syrian government to boost crop production and improve food security. The report includes a scientific assessment of the agricultural season conditions and their impact on production in Syria in general, and incorporates official data and statistics (5).

Cotton production in Syria during the 2023–2024 season witnessed a significant decline in both cultivated area and actual output compared to the approved agricultural plan. Data from the Syrian Ministry of Agriculture and Agrarian Reform indicated that the production plan for the season targeted the cultivation of approximately 14,419 hectares of cotton in government-controlled areas, with an expected yield of around 43,257 tons. However, actual implementation was limited to the cultivation of only about 7,175 hectares, equivalent to approximately 50% of the planned area, due to limited water resources, high production costs, and irrigation difficulties. This was reflected in the actual production volume, which reached approximately 17,000 tons, while officially marketed quantities did not exceed 15,866 tons by the end of the season. This underscores the continued structural challenges facing cotton cultivation in Syria, negatively impacting its productive efficiency and economic sustainability. (10).

Ginned cotton: a long-established agricultural crop with a rich history, exported in large quantities from the northern and northeastern regions. Neural networks are highly effective in analyzing temporal data, as demonstrated by a comparative study of the Box-Jenkins methodology, and some artificial neural networks have shown superior predictive accuracy. This study used the mean squared error (MSE) criterion, covering 324 observations, to evaluate their performance on maximum temperature data in Mosul from 1983 to 2009. The results showed that neural networks, which differ in their structure from the Box-Jenkins methodology, were more accurate in prediction compared to traditional statistical methods, reflecting their effectiveness in processing temporal data (14).

Artificial neural network models based on a 1-2-2 architecture were used to predict wheat production in Iraq. This architecture consists of an input layer containing two explanatory variables, a hidden layer containing two nodes that function as a logistic function, and an output layer containing a single node representing the dependent variable. The study demonstrated the high efficiency of the models in constructing forecasting models, as the cultivated area had a significant impact on wheat production, highlighting the importance of these models in improving agricultural production (6).

This method proved effective in a study to develop a framework using drone data to determine the accuracy of cotton crop estimates in Texas, USA. Researchers used machine learning techniques to analyze multi-time data extracted from drones, enabling them to assess the impact of various factors, such as weather and soil, on cotton yield. The study also focused on applying advanced machine learning models, such as neural networks, random forests, and XGboost, which demonstrated their ability to handle farmer data and achieve accurate crop predictions, thereby enhancing the effectiveness of agricultural management strategies (1).

In another study in West Tennessee, six machine learning algorithms, including linear regression, random forests, and XGboost, were used to assess the predictive power of cotton yield. The results showed that tree-based models, such as the random forest model and the XGboost model, were the most accurate. The study also revealed the cotton yield's response to management variables, such as nitrogen fertilization rates, and confirmed that optimum nitrogen application at 60 kg/ha improves yield. The study also emphasized the need for data from multiple locations to develop a more robust and generalizable model (3).

In another study on cotton yield prediction using drones and Bayesian neural networks in Texas, the use of attributes such as canopy cover (CC), canopy height (CH), canopy volume (CV), and excess greenness index (ExG) was shown to contribute to the development of an effective cotton yield prediction model. The results showed that this model achieved a radical mean squared error (RMSE) of 365.22 kg/ha, a mean absolute error (MAE) of 294.5 kg/ha, and a coefficient of determination (R^2) of 0.67, demonstrating the accuracy and effectiveness of the prediction (16).

Statistical parameters, such as mean squared errors and differences between actual and estimated values, were used in another comparative study between a regression model and a multilayer neural network model to estimate wheat yield in Syria. This study was based on data from the Food and Agriculture Organization (FAO) for the period 1990–2020. The results showed that the neural network model outperformed the regression model, with a mean squared error of 0.32 compared to 3.49 for the regression model, reflecting its efficiency in handling agricultural data (11)

. Four machine learning models—multi-layered neural networks (MLPs), nearest neighbor (KNN) algorithms, artificial neural networks (ANNs), and Gaussian regression (GPR)—were used to analyze the production efficiency of fatty acid methyl esters (FAMEs) in a study aimed at improving bioenergy production using artificial intelligence (AI) techniques. All models achieved R^2 values exceeding 0.99, demonstrating high prediction accuracy, with root mean square error (RMSE) values of 3.95, 1.09, 0.13, and 3.60, respectively. Optimal FAME productivity was observed to reach 97.8% under optimal parameter conditions, highlighting the importance of using AI techniques to improve bioenergy production (7).

In another study on cotton yield prediction using machine learning algorithms in central Greece, a multi-input neural network model analyzed cotton production based on three data types: soil data, agricultural management data, and crop management data. The results showed the superiority of the proposed model over traditional and modern models, demonstrating its high effectiveness in utilizing mixed data and reducing over-allocation. This enhances the model's flexibility and efficiency in predicting cotton production (9).

A study on the use of artificial neural networks for short-term cotton crop prediction in data-scarce regions analyzed a baseline dataset available for a case study in the Menemen Plain of Turkey. The cotton crop data included thirteen years of records, along with information on cumulative rainfall, cumulative heat units, drought, and vegetation cover indices. The results showed that combining the Enhanced Vegetation Cover Index (EVI) with the Standard Drought Index (SPEI) over a twelve-month period resulted in improved sensitivity for the cotton crop. The model was able to predict the cotton crop four months before harvest, with a coefficient of determination (R^2) exceeding 0.80, highlighting the potential of artificial neural networks as an effective tool in this field (15).

Machine learning techniques were used to predict wheat production based on historical patterns in a study analyzing wheat production data from five major countries (Australia, India, the United States, Canada, and Russia) from 1992 to 2022. Three neural network models were developed: a multilayer model (MLP) with two hidden layers, a recurrent neural network (RNN) with a SimpleRNN layer, and a long-term memory model (LSTM). The RNN model achieved the lowest values for mean absolute error and root mean square error, demonstrating its high predictive power and highlighting the importance of using these techniques to improve the accuracy of strategic crop production forecasts (2).

Machine learning techniques were used to predict wheat production based on historical patterns in a study analyzing wheat production data from five major countries (Australia, India, the United States, Canada, and Russia) from 1992 to 2022. Exponential smoothing was used to predict the expected values of the most important variables determining the food security index for wheat crops in Iraq during the period 2021–2030. The wheat index reached approximately 97.0, indicating that the food security index value is less than one but greater than 50.0, which is sufficient for more than six months. Based on this prediction, the cultivated area is expected to decrease in the coming years due to soil degradation caused by salinization and erosion, while other variables are expected to increase (16).

Predicting cotton production is a crucial issue in agricultural planning and resource management, especially in light of climate change and the instability of environmental factors. Advances in machine learning techniques have contributed to improving the accuracy of crop forecasting models compared to traditional statistical methods. Among these techniques, multilayer perceptron neural networks (MLPs) have emerged as one of the most widely used models due to their high capacity to represent nonlinear relationships between climatic and agricultural variables such as temperature, rainfall, humidity, and cotton production. A recent study demonstrated that the MLP model exhibited superior performance in predicting cotton production when combined with historical and future climate data, making it an effective tool for supporting smart agriculture and sustainable planning (13).

In comparing different machine learning models, recent studies have analyzed the efficiency of artificial neural networks, including the MLP model, against traditional statistical models in predicting cotton production. The results showed that MLP models achieved higher accuracy and lower error values, such as RMSE and nRMSE, especially when dealing with long time series and multiple climate variables. These studies also confirmed that the flexibility of the MLP model in learning from nonlinear data makes it more suitable for predicting cotton yield in complex and changing agricultural environments compared to traditional linear models (8).

A recent study published in 2025 addressed the topic of predicting cotton production using machine learning techniques. The researchers proposed a predictive framework based on the integration of climate data (such as temperature and rainfall), field data, and plant genetic information. The study employed several machine learning algorithms, including Supporting Vector Machines (SVMs) and deep learning models. The results showed that these models are capable of achieving high accuracy in estimating pre-harvest cotton yield, thus contributing to improved agricultural decision-making and production planning. The study confirmed that early prediction of cotton yield can help reduce agricultural risks associated with climate change and pests, and promote precision farming practices (12).

Based on the above, multi-layer artificial neural networks have shown much success in time series predictions particularly in terms of their flexibility and reliability. Time series models help predict the values of a variable, especially if it has unknown determinants or the factors affecting it. This is particularly useful in agricultural production which is subject to numerous factors whose influence is uncertain, such as natural conditions, and others.

The agricultural sector is also witnessing major and rapid economic developments, requiring agricultural economic policy makers to formulate plans that are consistent with these developments, especially since traditional prediction methods have been fairly unreliable. As such, applying artificial neural networks in this field affords high accuracy in predicting complex variables such as agricultural production compared to traditional methods such as regression and others.

In addition, building a model to predict agricultural production for cotton crops creates various economic benefits for the state. It helps in making plans for production such as cultivated areas and the strategies to be applied, production requirements, equipment needed, and others. Statistical analysis based on modern frameworks for predicting time series such as artificial neural network models allows for greater accuracy compared to traditional methods. Accordingly this research aimed to estimate cotton crop production for 2024-30 based on time series data for cultivated area and productivity from 1993 to 2023.

Materials and Methods

Temporal and spatial boundaries and data sources: Data on Syria's cotton production for 1993-2023 were from the annual agricultural statistics issued by the Ministry of Agriculture, in addition to data collected on cotton acreage and productivity per hectare.

Research variables:

(a) Independent variables: Area planted with cotton (hectares) and productivity (kg/hectare)

(b) Dependent variable: Quantity of production from the crop (tons).

Research methodology: The descriptive statistical method and the standard analytical method were used in this research using the neural network model.

(a) Descriptive statistical approach: Describes the time series data by displaying and summarizing them using statistical methods such as tables, charts, and some descriptive measures such as central tendency measures and dispersion measures. This provides details related to data such as trends of increase, decrease, or stability the nature of the changes affecting the series.

(b) Standard analytical approach using the neural network model.

As for building the model using neural networks, work was done on the multi-layer perceptron (MLP) network to suit the nature of the data. The MLP consists of an input layer and one or two processing layers so that they do not exceed two layers. In addition, the weights are adjusted for only one layer of the interconnecting layers linking the previous layers, so that the other layer (if any) remains fixed in weights. The idea how this network works or how to teach these neural networks is summarized in the following 2 stages:

Education stage: Here the weights of the interconnections are adjusted until they reach amounts capable of giving correct answers. This is done by the processing units performing three main operations (13):

(a) Weighted sum**:** Each processing unit performs the summation process for each weight entered into it (the data to be entered) and attached to the interconnection that connects it to the unit in the previous layer, multiplied by the value of that unit, as in the formula: w=ij where, w is the weight attached to the interconnection that connects the processing unit j to the unit i in the previous layer; i is the value from the unit i, and Sj is the result of the summation process for each processing unit j.

(b) Transformation process: This process is done in the last layer of the processing layers, where the result of the summation process mentioned in the previous process is converted to one of the values that are supposed to be among the desired network outputs. For example, if the network is going to learn how to classify numbers into odd and even, giving each odd number the value 0 and each even number the value 1, then the value of Sj, which is the result of the addition operation, will not give the value 0 or 1 most likely. So this result must be converted to one of these two values, using the conversion rule that the programmer determines. For example, the rule is as follows:

If $S_j>0$ then $x_j=1$ Then If $S_j\leq 0$ $x_j=0$

where, X_j is the value output from the jth processing unit.

(c) Network weights adjustment process: After completing the transformation process, the output given by the network is compared with the correct output that the network is supposed to give, by subtracting the target (correct) output from the network output. If the subtraction result is equal to zero, this means that the network has produced a correct output. If not, the network needs to adjust its weights, through the following learning rule:

$$w_{ji}\ new=w_{ji}\ old+c\ (t_j-x_j)a_i$$

where, wjinew is the value of the new weight attached to the interface between unit j and unit i; wjiold is the value of the old weight attached to the interface between unit j and unit i; C is the learning rate, a fixed value usually less than 1; tj is the target value of the network; Xj is the value produced by the network; and ai is the output from unit i.

Testing stage: Testing the network is completely similar to the learning process, except that the network at this stage does not adjust its weights, but only performs the operations of addition and transformation and compares the output produced by the network with the target output. A test class is displayed on the network and this class contains a set of inputs and outputs associated with each input, and it is preferable that the test class be different from the training class (13).

The steps in predicting using neural networks can be summarized as follows:

Step 1: Initialize the initial weights $w=(w_1, w_2,\dots.w_n)$.

Step 2: Select the training pair.

Step 3: Find the actual output value (Actual Output).

Step 4**:** Compare the actual output (Actual Output) with the desired output (Target Output), i.e. if Err = Target-Actual = 0, we return to the second step, otherwise apply the fifth step.

Step 5: Update the weights.

Step 6: Repeat the steps from the second step to the fifth step until the required convergence is obtained (the minimum mean absolute error MAE).

Research hypothesis: Multilayer neural modeling (MLP) contributes to improving the accuracy of cotton production forecasts in Syria through data analysis, which leads to providing more effective models to support decision-making in the agricultural sector.

Results and Discussion

Cotton cultivated areas in Syria (1993-2023): Table 1 shows the areas cultivated with cotton in Syria from 1993 to 2023 and their annual values which allows an understanding of the changes in agricultural production in a volatile agricultural context. The annual growth rates shown for each year helps clarify the changing trends in cotton cultivation. In analyzing this data, the impact of economic factors, such as price changes, and environmental challenges, such as drought, on cotton production in Syria can be inferred. The table also reflects the challenges faced by the agricultural sector in recent years, especially those that witnessed a significant decrease in cultivated areas.

Table 1: Fluctuations in cotton cultivated areas in Syria, 1993 – 2023.

Year	Area (hectares)	Annual growth rate %
1993	196475	-
1994	189412	**-3.59**
1995	204338	**7.88**
1996	219500	**7.42**
1997	250600	**14.17**
1998	274585	**9.57**
1999	243835	**-11.20**
2000	270290	**10.85**
2001	257063	**-4.89**
2002	199773	**-22.29**
2003	205360	**2.80**
2004	234181	**14.03**
2005	237768	**1.53**
2006	215640	**-9.31**
2007	192790	**-10.60**
2008	176449	**-8.48**
2009	163712	**-7.22**
2010	172414	**5.32**
2011	175147	**1.59**
2012	168145	**-4.00**
2013	62339	**-62.93**
2014	72704	**16.63**
2015	45052	**-38.03**
2016	17231	**-61.75**
2017	16957	**-1.59**
2018	49656	**192.83**
2019	34309	**-30.91**
2020	32504	**-5.26**
2021	29303	**-9.85**
2022	28870	**-1.48**
2023	35896	**24.34**
Arithmetic mean	**150719.3**	**-**
Coefficient of variation (%)	**59.37**	**-**

Source: Annual agricultural statistical compilations.

Table 1 reflects the evolution of cotton-cultivated areas in Syria from 1993 to 2023 and the complex set of trends and changes that reflect the challenges and opportunities faced by the agricultural sector in the country.

In 1993, the area cultivated with cotton stood at 196,475 hectares indicating its importance as a major crop in Syrian agriculture. However, the following years witnessed some fluctuations, decreasing by 3.59% in 1994 and increasing in the subsequent years, primarily until 2000 when it reached 270,290 hectares, reflecting the positive dynamics of the sector. However, this trend did not continue as cotton cultivation entered a sharp decline in the following years, especially between 2011 and 2016, deteriorating to their lowest levels and a sharp decrease in 2013 to 62,339 hectares.

This sharp decline is indicative of the impact of the economic and political crises the country experienced, in addition to the deleterious effects of climate change which harmed overall agricultural production. For example, drought and harsh environmental conditions greatly affected the ability of farmers to maintain sustainable productivity levels. However, recent years have witnessed some signs of recovery, with the high growth rate of 192.83% in 2018, indicating the possibility of recovery. This increase may be attributed to improvements in agricultural techniques and increased awareness of the importance of sustainable agriculture.

By the end of the study period in 2023, cultivated acreage stood at 35,896 hectares, with a positive growth rate, indicating that efforts were made to rehabilitate the sector. The arithmetic mean for the entire study period at 150,719.3 hectares and a coefficient of variation (CV) of 59.37% in growth rates, makes it clear that cotton cultivation in Syria has fluctuated between opportunities and challenges. These figures reflect the instability in agricultural production, which calls for effective agricultural policies to support farmers and enhance sustainability and productivity.

In-depth analysis of the data also indicates the importance of developing comprehensive strategies to address current challenges and ensure that cotton farming remains a major source of income for many Syrian families.

Cotton production in Syria (1993-2020): Table 2 shows the cotton production volumes in Syria from 1993 to 2023 and is an important reference for understanding the development of cotton agricultural production in the country. It includes annual data related to cotton production in tons, in addition to annual growth rates for each year, which facilitates the analysis of trends and changes in production.

The high production volume in 1993 is a good indicator of the robustness of the sector. However, it fluctuated noticeably during the study period, with major declines and noticeable increases, reflecting the complex dynamics of the agricultural sector. The data shows multiple impacts, such as economic and environmental crises that led to a decline in production in certain years, especially between 2011 and 2016, when agriculture was severely affected. However, signs of recovery have begun to appear in recent years, indicating efforts to improve productivity and strengthen the sector.

The arithmetic mean of production and the coefficient of variation (CV) are important tools for understanding the stability of production and the volatility faced by farmers. As such, the table is a valuable source to guide future agricultural policies and enhance understanding of how to develop the cotton sector in Syria.

Table 2: Cotton production in Syria, 1993 – 2023.

Year	Area (hectares)	Annual growth rate %
1993	638992	**-**
1994	535404	**-16.21**
1995	600100	**12.08**
1996	760000	**26.65**
1997	1047355	**37.81**
1998	1017800	**-2.82**
1999	926096	**-9.01**
2000	1081888	**16.82**
2001	1009826	**-6.66**
2002	802178	**-20.56**
2003	811026	**1.10**
2004	1029232	**26.90**
2005	1021996	**-0.70**
2006	685705	**-32.91**
2007	711497	**3.76**
2008	697841	**-1.92**
2009	652058	**-6.56**
2010	472485	**-27.54**
2011	671668	**42.16**
2012	592653	**-11.76**
2013	169094	**-71.47**
2014	162439	**-3.94**
2015	130497	**-19.66**
2016	40696	**-68.81**
2017	34042	**-16.35**
2018	79737	**134.23**
2019	114665	**43.80**
2020	97522	**-14.95**
2021	66480	**-31.83**
2022	76259	**14.71**
2023	93846	**23.06**
Arithmetic mean	**542937.96**	**-**
Coefficient of variation %	**68.23**	**-**

Source: Annual agricultural statistical compilations.

The table also shows the significant changes in production over the years and the related influencing factors. In the first year of the study, production amounted to 638,992 tons, reflecting the importance of cotton as a strategic crop in the Syrian economy. Over the years, production underwent significant fluctuations with declines in some years, such as 1994 where it decreased by 16.21%, indicating the challenges faced by farmers. This was followed by varying increases in subsequent years, including a significant increase in 1997 to 1,047,355 tons and a high growth rate of 37.81%.

However, the period between 2011 and 2016 was the most challenging, as the numbers declined sharply, with production falling to 40,696 tons in 2016, reflecting the devastating impact of economic, political, and environmental crises on agriculture, such as drought and resource shortages. However, signs of recovery have begun to appear in recent years, with 2018 seeing a 134.23% increase, reflecting significant efforts to improve agricultural conditions and boost productivity, especially by adopting new agricultural technologies. Despite these increases, average production remains at 542,937.96 tons, with a CV of 68.23%, indicating instability in production and ongoing challenges in the sector.

Cotton crop productivity in Syria (1993-2023): The data in Table 3 showing the development of cotton crop productivity in Syria provides an in-depth view of the dynamic changes in annual productivity. This data is essential for understanding the efficiency of agricultural performance in the country, as cotton, as one of the strategic crops, reflects the challenges and opportunities available to the agricultural sector. By analyzing this information, the main trends affecting crop productivity can be inferred, including economic crises and climate changes that may lead to fluctuations in production.

These figures also provide a knowledge base for studying the impact of agricultural policies and technologies used in cotton cultivation, enabling stakeholders to make informed decisions to improve efficiency and sustainability. They also highlight the importance of investing in agricultural infrastructure and modern technologies to enhance productivity, which helps achieve food security and strengthen the local economy.

Table 3: Fluctuations in cotton crop productivity in Syria, 1993 to 2023.

Year	Area (hectares)	Annual growth rate %
1993	3252	**-**
1994	2827	**-13.07**
1995	2937	**3.89**
1996	3462	**17.88**
1997	4179	**20.71**
1998	3707	**-11.29**
1999	3798	**2.45**
2000	4003	**5.40**
2001	3928	**-1.87**
2002	4015	**2.21**
2003	3949	**-1.64**
2004	4395	**11.29**
2005	4298	**-2.21**
2006	3180	**-26.01**
2007	3691	**16.07**
2008	3955	**7.15**
2009	3983	**0.71**
2010	2740	**-31.21**
2011	3835	**39.96**
2012	3525	**-8.08**
2013	2713	**-23.04**
2014	2234	**-17.66**
2015	2897	**29.68**
2016	2362	**-18.47**
2017	2008	**-14.99**
2018	1606	**-20.02**
2019	3342	**108.09**
2020	3000	**-10.23**
2021	2269	**-24.37**
2022	2641	**16.39**
2023	2614	**-1.02**
Arithmetic mean	**3269.19**	**-**
Coefficient of variation %	**22.61**	**-**

Source: Prepared based on the annual agricultural statistical compilations.

Table 3 indicates that productivity started at 3252 kg/ha, reflecting a good level of agricultural efficiency during that period. However, the following years witnessed significant fluctuations, such as the 13.07% decline in 1994%, reflecting the challenges faced by farmers, such as climate change or economic crises. In contrast, the following years witnessed periods of recovery, with productivity achieving a significant increase in 1997, reaching 4179 kg/ha, indicating an improvement in agricultural conditions or the adoption of better technologies and advanced agricultural methods. Over time, productivity was significantly affected by the political and economic crises after 2011, as it decreased to 2362 kg/ha in 2016, reflecting the debilitating effects of protests and conflicts on the agricultural sector.

Despite these challenges, periods of recovery emerged, such as in 2019, which witnessed a significant increase of 108.09%, indicating practical efforts to improve agricultural practices and adapt to changing conditions. The arithmetic mean of productivity at 3269.19 kg/ha reflects the general trend of the sector, though the CV of 22.61% indicates instability in productivity, calling for special attention from agricultural policymakers to improve agricultural conditions and enhance sustainability.

This data is a vital analytical tool for understanding the dynamics of agriculture in Syria, helping to guide policies towards improving productivity and enhancing food security, in addition to strengthening cooperation between farmers and government agencies.

Estimating cotton production using the multi-layer perceptron neural network model: The multi-layer perceptron (MLP) module was used together with the statistical software (IBM SPSS 25) to estimate cotton production in Syria for 2024-2030. Table 4 summarizes the processing involved in the neural network, and shows the distribution of data between the training and test groups. It also includes the number of samples used, percentages for each group, and number of valid samples. This summary contributes to understanding how to use data in building the neural network model.

Table 4: Summary of the processing methods in the neural network.

Case Processing Summary			
		N	Percent
Sample	Training	23	74.2
	Testing	8	25.8
Valid		31	100.0
Excluded		0	
Total		31	

Source: Neural network outputs using SPSS.

The total data consists of 31 samples of which 23 or 74.2% were allocated for training and 8 or 25.8% for testing. This distribution represents a practical methodology for dealing with data, as it allows the network to be trained on a large data set, enhancing its ability to learn and generalize well. The training set is essential for teaching the model important patterns and characteristics of the data, while the test set evaluates its performance and its ability to generalize to new data that it has not seen before.

It is worth noting that all the samples used were valid, meaning there was no missing or invalid data in the analysis. This enhances the credibility of the results extracted from the model, as the accuracy of predictions depends on the quality of the input data. Furthermore, the table shows the importance of good planning for the data partitioning process, as it contributes to improving the model’s performance and accurately evaluating it. Distributing data evenly between the training and test sets helps reduce the risk of bias and ensures that the model learns from data and can make accurate predictions when faced with new situations. This integrated process enhances the neural network's effectiveness in various applications, making it a powerful tool in machine learning and artificial intelligence.

Table 5 presents information on the multi-layer neural network showing the network structure and the basic components making up the machine learning model. It details the input layer containing the independent variables, the number of units used in it, and the rescaling method used for the independent variables. As for the hidden layers, the table shows only one layer with two units, and an activation function is used to enhance the learning ability. In the output layer, the dependent variable is specified, at one unit, and a similar rescaling method. The table concludes with information about the error function used, which contributes to measuring the accuracy of the model. In general, the table reflects the design of the neural network and its technical details, making it easier to understand how it works in processing data and achieving predictions.

Table 5: The multi-layer neural network.

Network Information			
Input Layer	Covariates	1	Area
		2	Productivity
	Number of Units		2
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1a		2
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	Production
	Number of Units		1
	Rescaling Method for Scale Dependents		Standardized
	Activation Function		Identity
	Error Function		Sum of Squares
a. Excluding the bias unit			

Source: Neural network outputs using SPSS.

The table offers detailed insights into the multilayer neural network's structure and key components used during the learning process. The network begins with an input layer consisting of two independent variables, area, and throughput, totaling two input units. To enhance the learning process, standardized rescaling is applied, ensuring that the range of these variables is uniform. This uniformity is crucial for accelerating convergence and mitigating gradients-related issues, allowing the model to learn more effectively. The network features a single hidden layer with two units, representing a straightforward yet effective design choice. The hyperbolic tangent activation function is employed in this layer, which is favored in neural networks for its capability to capture complex patterns and nonlinear interactions among variables.

This capacity to manage nonlinear relationships significantly enhances the model’s performance, particularly in contexts requiring a nuanced understanding of variable interdependencies. The dependent variable is the output in the output layer, with a single unit designated for prediction. The same rescaling method applied in the input layer is also used here, ensuring consistency between input and output data. The model's performance is evaluated using the sum of squares as the error function, which aids in measuring the accuracy of its predictions.

Figure 1 shows a model of the neural network used, including details of its structure and the activation functions. The model consists of an input layer with two main variables which are linked to two units in the hidden layer. The arrows represent the directions in which data is passed between the layers, with the synaptic weights that affect the strength of the relationship between the units being distinguished. The different colors indicate positive and negative weights, highlighting how each variable affects the final output comprehensively. The figure reflects the design of the neural network and its mechanism of operation, making it easier to understand how data is processed and predictions are made in different contexts.

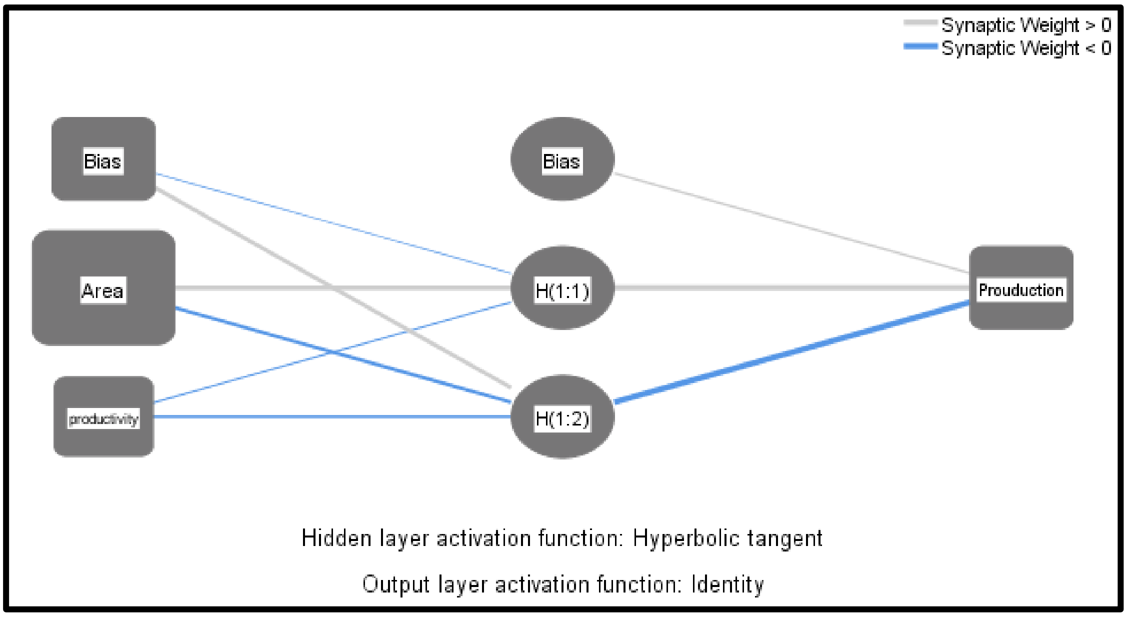

Figure 1: Multi-Layer Perceptron Neural Network Architecture.

The figure comprehensively illustrates the structure of the multi-layer neural network, as it consists of several main elements that contribute to the prediction process. The network starts with the input layer containing two independent variables, "Area" and "Productivity." These variables represent the essential factors that affect the results to be predicted. The "Bias" unit supports these variables, adding a fixed amount that can enhance or mitigate the effect of the input signals. Then, the signals are transferred to the hidden layer that consists of two units, "H(1:1)" and "H(1:2)", where the "Hyperbolic tangent" activation function is applied. This function contributes to processing the data effectively by dealing with negative and positive values, which helps the network learn from complex patterns. Finally, the signals reach the output layer that contains one unit representing the dependent variable "Production." Here, the "Identity" activation function ensures the output is passed directly without modification.

The figure also shows the weights associated between the units, with the grey arrows showing positive weights that enhance the signals and the blue ones showing negative weights that reduce the effect of the signals. This comprehensive design shows how data is processed across the network to arrive at accurate predictions about production based on the independent variables.

Table 6 provides a comprehensive summary of the neural network model used, including performance metrics for both the training and testing phases. It covers several important aspects, starting with the sum of squared errors, which reflects the accuracy of the model during training, as well as the relative error, which shows the percentage of error compared to the actual values.

The stopping rule used indicates the effectiveness of the learning process, and the training duration shows the time-efficiency of the model. Regarding the testing phase, the table also shows the performance of the model by measuring the sum of squared errors and the relative error, which indicates the reliability of the model in predicting the actual values, providing a clear overview of the effectiveness of the model in processing the data and achieving the desired predictions.

Table 6: Summary of the neural network model used.

Model Summary		
Training	The Sum of Squares Error	.009
	Relative Error	.001
	Stopping Rule Used	1 consecutive step(s) with no decrease in error
	Training Time	0:00:00.00
Testing	The Sum of Squares Error	.001
	Relative Error	.000
Dependent Variable: Production		
a. Error computations are based on the testing sample.		

Source: Neural network outputs using SPSS.

The table provides a comprehensive summary of the performance of the neural network model across the training and testing phases, with the values provided as vital indicators of the model's effectiveness. In the training phase, the sum of squares error (0.009) shows the model's ability to minimize the gap between predicted and actual values, reflecting good prediction accuracy. The relative error (0.001) reinforces this assessment, indicating that the error ratio compared to actual values is very small, reflecting the model's reliability. The stopping rule used, which is based on the error not decreasing after a certain number of steps, indicates the model's stability, while the short training duration (0:00:00.00) indicates the model's efficiency in processing data quickly.

In the testing phase, the sum of squares error (0.001) shows significant improvement, meaning that the model can predict more accurately with new data that was not used in training, while the relative error (0.000) reflects almost no error, indicating the model's ability to generalize effectively. The dependent variable, "production," shows the ultimate goal of the model, highlighting its practical use in predicting production levels. In general, these values reflect the high performance and reliability of the model, making it an effective tool in practical applications related to forecasting.

Figure 2 is a visual representation of the importance of variables in the analysis model, showing the relative impact of each of the independent variables on the dependent variable. The relative values displayed express the importance of each variable in the context of the model, providing valuable insights into understanding the main factors that affect the results obtained. This figure is considered an effective tool for analyzing data and supporting strategic decision-making based on the extracted results.

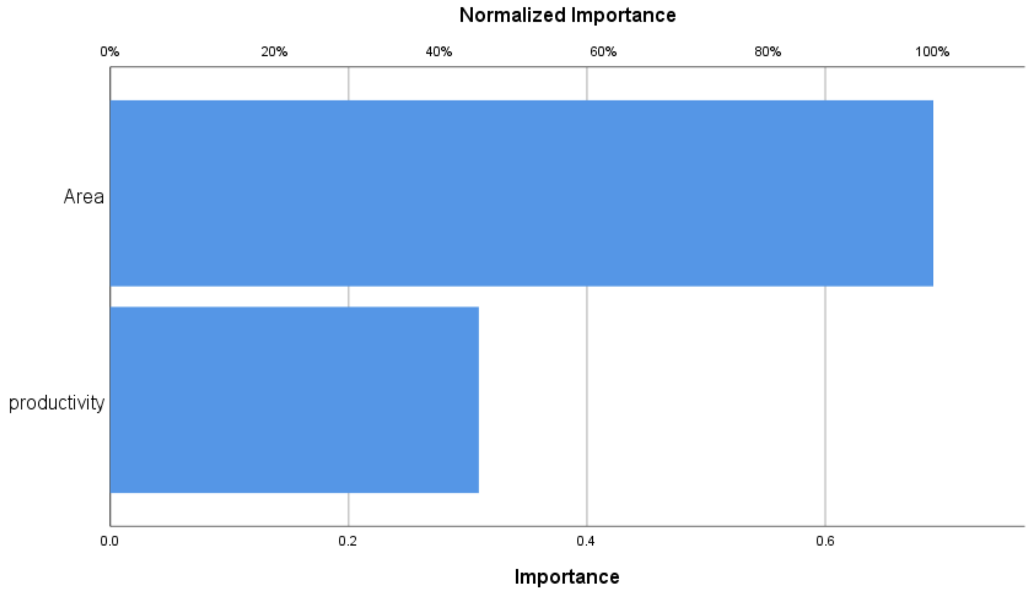

Figure 2: Relative importance of independent variables according to the neural network model.

The figure also provides a graphical analysis highlighting the importance of variables in the analysis model, focusing on two main variables: "area" and "productivity." The area bar extends to about 70% of the value axis, indicating that this variable significantly influences the results. This means that changes in area, whether an increase or decrease, can significantly affect the model's overall performance, making it necessary to consider this factor in decision making.

In contrast, the productivity bar extends to about 30%, indicating that the impact of this variable is much less than the area. Although productivity remains an important factor, the low relative impact suggests that other factors may have a more significant impact or were not included in the current model. This may include crop type, farming techniques, or climatic conditions, which can effectively determine productivity. These values provide a clear contrast in the importance of variables, reflecting the need to focus on area as a key factor to achieve tangible improvements in results.

Therefore, decision-makers and practitioners can use this information to direct their investments and efforts towards improved space management, leading to better outcomes in areas such as agriculture and production. By understanding these dynamics, production strategies can be improved and efficiency increased, contributing to achieving sustainable development goals.

Estimating cotton production in Syria for 2024-2030 using the neural network model: Table 7 provides estimates of the expected production of cotton crop in Syria during the 2024-30 period based on the outputs of the neural network model. It reflects the expected values of annual production in tons, in addition to the annual percentage growth rate, which provides valuable insights into future trends in cotton production. It also shows annual growth rates ranging between negative and positive, indicating a gradual improvement in production. This analysis is an important tool for policy- and decision-makers in the agricultural sector, as they can benefit from these expectations to develop effective strategies that enhance cotton productivity and contribute to the sustainability of this vital sector in Syria.

Table 7: Expected values of cotton production in Syria from 2024 to 2030 using the neural network model.

Annual growth rate%	Expected production (tons)	Year
-	67088.89	**2024**
-0.10	67020.62	**2025**
0.19	67147.35	**2026**
0.37	67399.08	**2027**
0.49	67728.14	**2028**
0.55	68102.87	**2029**
0.58	68498.83	**2030**

Source: Prepared by the researcher based on the outputs of the neural network.

The table provides projected production estimates for cotton crops in Syria from 2024-2030 based on the outputs of the neural network model. The data includes detailed production forecasts, with production expected to reach 67,088.89 tons in 2024, representing a starting point for this time series. However, the table indicates a slight annual decrease in production of 0.10% in 2025 to 67,020.62 tons. This decrease may be attributed to climate change, market challenges, or agricultural techniques. Despite this decrease, subsequent years show continuous improvements in production. In 2026, production is expected to increase by 0.19% to 67,147.35 tons, possibly attributed to improved agricultural practices or new technologies that enhance production efficiency.

This positive trend continues in the following years, with production forecast to reach 67,399.08 tons in 2027 and 67,728.14 tons in 2028, showing higher growth rates of 0.37% and 0.49%, respectively in 2029, production reaches 68,102.87 tons, a growth rate of 0.55%, indicating the success of agricultural policies and technological innovations in enhancing productivity. These positive trends continue in 2030 when production is expected to grow by 0.58% over the previous year to reach 68,498.83 tons. Such data reflects production trends and are important tools for decision-makers and farmers. Understanding them can help identify appropriate strategies to improve agricultural resource management, estimate agricultural input requirements, and develop effective marketing plans.

Therefore, these estimates can contribute to improving the efficiency of agricultural production and enhancing the sustainability of this vital sector, which helps achieve the sustainable development goals in Syria**.**

Conclusions

Cotton cultivation in Syria witnessed significant transformations from 2010 to 2023, with productivity experiencing significant fluctuations between 2010 and 2018 and major declines especially between 2012 and 2016. Production reached its lowest level in 2016 as a result of the agricultural sector being affected by crises and conflicts. Despite some notable increases in production in subsequent years, sustainable stability was not achieved. However, the slight increase in cultivated area in 2023 indicates attempts at recovery, reflecting some positive signs of improvement in the agricultural sector.

The neural network model used in this study proved highly efficient in predicting cotton production, registering a significant decrease in square error and relative error rates, indicating the model's success in analyzing data effectively. It was found that "area" was the most influential variable in determining the level of production, which calls for focusing on improving the management of cultivated areas. Future expectations indicate a gradual improvement in production until 2030, with positive growth rates, reflecting the possibility of enhancing productivity in the future.

Based on these results, it is recommended to focus on improving agricultural strategies and resource management, in addition to providing training programs for farmers to enhance their knowledge of modern technologies. It shows the importance of focusing on the influencing factors and adopting modern technological methods to achieve the goals of food security and sustainable development in Syria.

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