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Forecasting of Cultivated Area in Egyptian Lands Using a Time Series Model for Sustainable Development

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Abstract

The cultivated area is an important component of land resources that has a direct impact on food security. Egyptian cultivated area was estimated to be 3.86 million hectares in 2020. Recently, there has been a decline in cultivated areas, which could be attributed to a number of factors, including climatic changes and urban sprawl, endangering Egyptian sustainable development. So, the aim of the current study was to forecast the values of cultivated areas in Egypt for the next five years using the ARIMA model based on data from 1990 to 2020. The model predicted a decrease in cultivated area in coming years of about 3.06, 3.19, 3.084, 3.082 and 3.21 million hectares, respectively, according to the results. This forecasting will aid the country's policy development for future land using planning and agricultural production.

Keywords

Cultivated Area, Forecasting, ARIMA Model, Egyptian Lands, Sustainable Development

1. Introduction

Future population growth is expected to put additional strain on agriculture sector due to increased food demand, resulting in greater use of natural resources, particularly water and land. This represents a barrier to achieving sustainable development. Furthermore, the world is facing climate change challenges such as rising temperatures, erratic rainfall and an increase in the frequency of extreme events such as droughts and floods [1] [2].

Land is one of the major elements in agricultural production. As a result, effective land use planning is critical to the agricultural sector's long-term production capacity. If land is not properly planned and managed, it will degrade over time. The ongoing degradation of lands results in low productivity [3]. Unparalleled land degradation and arable land loss are currently witnessed by rates of 30 to 35 times higher than in the past. Furthermore, approximately 80% of the Arab region is made up of dryland, which is vulnerable to climate change risks [4]. Thus, land degradation occurs as a result of a variety of natural and human factors, including wind and water erosion, salinity, deforestation, drought, desertification and pollution, as well as environmental degradation, which will result in the depletion of natural resources and a decrease in agricultural production [3] [5] [6].

Therefore, in 2015, the United Nations (UN) established the 17 Sustainable Development Goals (SDGs), where Goal 15 mentions that combat desertification, retrieve degraded land and soil, such as land impacted by desertification, drought and flooding and strive for a world free of land degradation by 2030, as well as management of natural resources that is both sustainable and efficient [7]. Furthermore, conserving agricultural land and other productive resources and inputs leads to increased agricultural productivity when resilient agricultural practices are implemented. As a result, in order to meet Goal 2 (zero hungry), ensure sustainable food production systems and strengthen capacity for climate change adaptation by 2030 [8].

Agriculture plays an essential part in Egyptian economy. In 2020, agriculture was about 81.8% (real value) of total Gross Domestic Product (GDP) [9]. As a result, it is regarded as one of the most important sectors contributing to Egypt's economic development. Furthermore, agriculture plays a significant role in achieving food security. Thus, agriculture is regarded as an important economic resource and one of the most important means of achieving sustainable development [10]. Also, cultivated area is a critical part of land resources that has a direct impact on achieving food security [11]. Egypt pursued two major strategies as a result: the reclamation of vast desert areas into productive land and the intensive cultivation of productive land using high-tech management [5].

Cultivated area is the area of cultivated lands with temporary and permanent crops but without repeating types of crops which are cultivated more than once a year [12]. In 2020, cultivated area represented for about 3.86 million hectares. It was divided into old and reclaimed lands. The old lands are located in the Nile Valley and Delta, which cover approximately 2.47 million hectares and the Nile's water is primarily used for irrigation. While reclaimed lands cover approximately 1.39 million hectares [13]. Furthermore, the amount of cultivated area depends mainly on population and crop yield, as well as the fact that the cultivated area does not grow at the same rate as the population; that the annual population grows by 2% [14].

In recent years, there has been a deterioration in cultivated areas, which could be attributed to a variety of factors, including climatic changes and urban sprawl, which threatens Egypt's sustainable development. In addition, Egypt is situated in an arid to semi-arid zone. So, climate variability has a greater impact on the arid and semi-arid Lands [15] [16]. Also, traditional agriculture in arid and semi-arid regions caused salinization or desertification as a result of excessive evapotranspiration, poor irrigation practices and intensive land use [17]. It could lead to more droughts and food insecurity.

Furthermore, according to Intergovernmental Panel on Climate Change [18] Egypt's Nile Delta was ranked third in the world for being the most vulnerable to climate change. This is due to its low elevation, which is often below sea level in many places, causing the low-lying lands to be gradually submerged. Also, coastal erosion and groundwater contamination caused by seawater intrusion in coastal zones [19]. In Egypt, one of the potential threats to sustainable development is urban sprawl, especially in the Nile Valley and Nile Delta regions due to the increase in population, this has resulted in a decrease in agricultural land area. Thus, agricultural productive lands that have been converted into urban land, roads and transportation infrastructure… etc. [20] [21].

In this context, in Egypt, the management of diverse natural resources (land and water) is required to keep food deliveries and achieve agricultural development sustainability; however, natural resources face severe pressures from a growing population and ongoing land degradation [22].

As a result, this study aims to forecast the values of cultivated areas in Egypt for the next five years using time series analysis based on data from 1990 to 2020. The study hypothesis assumes that cultivated areas will decrease in the future, resulting in a decrease in per capita cultivated area, which will have a negative impact on food security and sustainable development.

Furthermore, this study adds to the limited literature on cultivated area forecasting in Egypt, where it could be a critical tool for mitigating the effects of climate change and achieving sustainable development.

2. Data and Methodology

2.1. Data

This study is based on published data regarding Egypt's cultivated land and population from 1990 to 2020. The data were obtained from the Egyptian Ministry of Agriculture and Lands Reclamation (MALR), Food and Agriculture Organization of the United Nations (FAO), Ministry of Planning and Economic Development (MPED), the Central Agency for Public Mobilization and Statistics of Egypt (CAPMAS) and previous studies for this subject.

2.2. Methodology

According to the study's objective, the Box-Jenkins approach [23] was employed to develop a model forecast of Egyptian cultivated area, with the EViews 12 program [24] used for the entire analysis. Forecasting is important because it is the primary tool used by decision-makers to manage all processes efficiently and effectively, resulting in more accurate information for optimal natural resource management [25] [26].

The Auto Regressive Integrated Moving Average (ARIMA) model class, also known as the Box-Jenkins approach, is only used for univariate time series modelling. The ARIMA model forecast is based on the past of the process and is best suited for short-term forecasting [27]. The ARMA model is a technique for analyzing and forecasting future values in time series. The model is divided into two parts: an autoregressive (AR) and a moving average (MA). Autoregressive (AR) modelling is a technique for forecasting values within a time series based on lagged values from the same time series. A moving average (MA) model predicts values within a time series by utilizing the residual error from a moving average model applied to lagged observations within the same time series [23] [28].

The model is often referred to as ARIMA (p, d, q) model, where p is AR rank, d is difference and q is MA rank, that follows [23] Equation (1):

$$\phi(B)(1-B)^d z_t = \theta_0 + \theta(B) a_t \tag{1}$$

where: $\phi(B)$ and $\theta(B)$ are operators in B of degree p and q, respectively, d is a non-negative integer difference.

If the original time series is stationary $d = 0$, then ARIMA (p, d, q) = ARMA (p, q).

Box-Jenkins approach consists of four stages identification, estimation, diagnostic checking and forecasting.

1) Identification stage: The stationarity of time series must be checked before developing the Box-Jenkins model. The Augmented Dicky-Fuller (ADF) [29] and the Phillips-Perron (PP) [30] are applied for stationarity check of time series variables. The null hypothesis assumes H_0 that a unit root is exist (the variables are non-stationary) and the alternate hypothesis H_1 does not have unit root (the variables are stationary). Also, to check for stationarity, the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) are used. Furthermore, the ACF and PACF functions are applied to estimate the order of the models.

2) Estimation stage: Maximum likelihood methods are used to estimate the parameters. The best model is chosen employing model selection criteria including Akaike information criteria (AIC) [31], Bayesian information criteria (BIC) [32], Root mean square error (RMSE) and mean absolute error (MAE). In addition, the high value of adjusted R^2.

3) Diagnostic checking stage: is obtained by plots of the residual and Ljung-Box [33] statistical test of residual for white noise inspecting.

4) Forecasting stage: The in-sample and out-of-sample forecasts are employed to validate and predict the selected model [27]. Out-of-sample forecast is a better test of how well the model works in general because they use data that were not included in the model's estimation [34].

3. Results

3.1. Descriptive Statistics of Cultivated Area in Egypt

Table 1 shows cultivated area in Egypt during the study period (1990-2020). It represents about 3.44 million hectares, which increases from 2.64 in 1991 to 3.86 in 2020 million hectares during this period with significant annual growth rate of about 1%. It implies that the amount of cultivated land has increased insignificantly. Furthermore, that may have a negative impact on crop production. Egypt's population, on the other hand, increased by approximately 76.9 million people during the same period, from 56.1 million in 1990 to 102.7 million in 2020, with a significant annual growth rate of about 2%. That is, the increase in population is approximately twice as large as the increase in cultivated area.

As a result, per capita cultivated area decreased during the study period. Per capita represents approximately 0.045 hectares, which decreases from 0.053 hectares in 1995 to 0.038 hectares in 2020 at a significant annual decrease rate of about 1%.

3.2. Time Series Analysis

3.2.1. Stationarity Tests

This study applied ADF and PP tests to ensure the stationarity of cultivated area time series. Table 2 shows that values of unit root tests were about 3.044 and 3.689, respectively and the ρ value is less than the significance level of 5%. It means that the cultivated area series is a stationary at level of the significance at 0.01. Thus, the ARMA (p, q) model is fit for this series.

Furthermore, the ACF and PACF for the stationary series are examined to determine the values of AR and MA in order to find an appropriate ARIMA model. Figure 1 shows that the autocorrelation coefficient is a lag in the series and AR model should be tested here. Also, there are points outside the bound, which is AR (1 or 2 or 3). Similarly, one lagged number could be obtained from partial

Table 1. Descriptive statistics of cultivated area (1000 h) during 1990-2020.

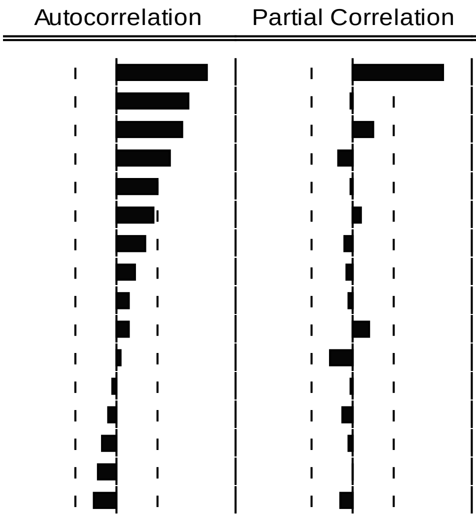
Variable	Mean	Std. Deviation	Maximum	Minimum	Growth rate%
Cultivated area	3442	326	3863	2643	1***
Per capita	0.0455	0.0043	0.0527	0.0376	−1***
Population (1000 people)	76,902	13,808	102,662	56,134	2***

(***) Statistically significant difference at 0.001. Source: https://www.fao.org/.

Table 2. Unit root tests.

Tests	value	ρ value	I(d)
ADF	−3.044276	0.004	I(0)
PP	−3.689328	0.009	I(0)

Notes: ADF refers to Augmented Dickey-Fuller & PP refers to Phillips-Perron are unit root tests. Source: The authors' calculations using EViews 12 program.



	AC	PAC	Q-Stat	Prob
1	0.801	0.801	21.860	0.000
2	0.637	-0.013	36.153	0.000
3	0.573	0.186	48.134	0.000
4	0.467	-0.125	56.406	0.000
5	0.361	-0.021	61.544	0.000
6	0.323	0.082	65.823	0.000
7	0.259	-0.080	68.688	0.000
8	0.172	-0.056	70.003	0.000
9	0.110	-0.046	70.566	0.000
10	0.115	0.139	71.207	0.000
11	0.039	-0.202	71.285	0.000
12	-0.033	-0.011	71.345	0.000
13	-0.072	-0.083	71.641	0.000
14	-0.120	-0.027	72.514	0.000
15	-0.165	-0.004	74.249	0.000
16	-0.198	-0.104	76.919	0.000

Figure 1. Autocorrelation and partial autocorrelation functions of the cultivated area series.

autocorrelation. So, MA model should be tested and there is a point outside of the bounds that is MA (1).

As a result, to find the best-fitting model for cultivated area, the ARMA (*p*, *q*) results should be applied for various parameters. Therefore, Table 3 shows ARIMA model (3, 0, 1) was chosen as the best-fitting model on the basis of the lowest AIC, BIC, RMSE and MAE.

Table 3 shows that the model coefficients are significant at 0.001 and 0.05. Also, the model is used to fit the LCA data, where the actual data correspond to the fitted values, that is shown in Figure 2.

The estimated model will be written as:

$$\begin{aligned} \mathrm{LCA}_t &= 15.1 + \underset{(9.198)^{***}}{0.901265}\mathrm{LCA}p_{t-1} + \underset{(2.420)^{**}}{0.431621}\mathrm{LCA}q_{t-1} + e_t \end{aligned} \tag{A}$$

3.2.2. Diagnostic Checking

Following the selection of the model, it is necessary to determine whether the model adequately represents the data. Some diagnostic tests are carried out for this purpose, such as plots of the residual and Ljung-Box test (Figure 3). Ljung-Box test shows that the p value > 0.05, so the null hypothesis (H_0) accepted. It means that there is no autocorrelation and the residual is a white noise. As a result, the ARIMA (3, 0, 1) model is appropriate for representing this time series data.

3.2.3. Forecasting

Following the development of the best-fitting time series model, the model is utilized to analyze the fitting impact with the cultivated area value in 2020 as an in-sample forecast. The forecast value in 2020 is 3,832,469 hectares. The actual value is 3863486 hectares as well as the relative error is 0.88%. It was noticed that the forecast value is near to the actual result, which means that the model is

Table 3. Results of selected model ARIMA (3, 0, 1).

Variables	Coefficients	Std.Error	t-Statistic	Ŕ²
AR (3)	0.901265	0.097982	(9.198257)***	0.78
MA (1)	0.431621	0.178355	(2.420006)**	

Notes: *** and ** significant levels at 0.001 and 0.05. Source: The authors' calculations using EViews 12 program.

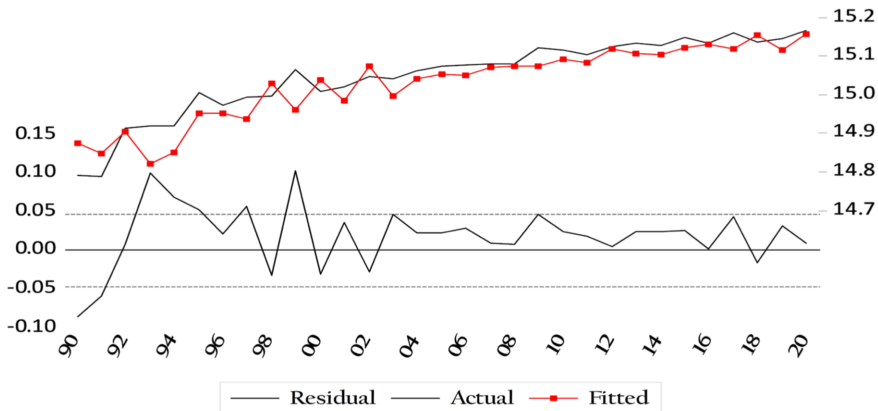
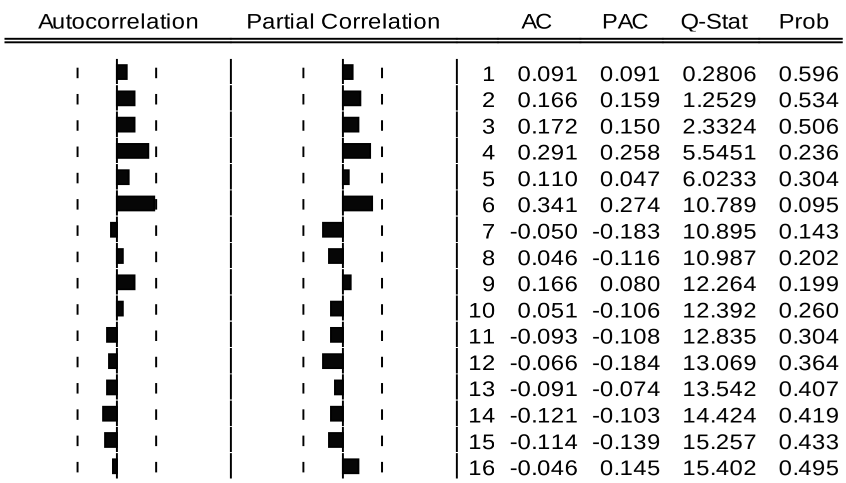


Figure 2. Actual, fitted and residual of the LCA.



	AC	PAC	Q-Stat	Prob
1	0.091	0.091	0.2806	0.596
2	0.166	0.159	1.2529	0.534
3	0.172	0.150	2.3324	0.506
4	0.291	0.258	5.5451	0.236
5	0.110	0.047	6.0233	0.304
6	0.341	0.274	10.789	0.095
7	-0.050	-0.183	10.895	0.143
8	0.046	-0.116	10.987	0.202
9	0.166	0.080	12.264	0.199
10	0.051	-0.106	12.392	0.260
11	-0.093	-0.108	12.835	0.304
12	-0.066	-0.184	13.069	0.364
13	-0.091	-0.074	13.542	0.407
14	-0.121	-0.103	14.424	0.419
15	-0.114	-0.139	15.257	0.433
16	-0.046	0.145	15.402	0.495

Figure 3. Autocorrelation and partial autocorrelation functions of the ARIMA (3, 0, 1).

well-fitting. Furthermore, all predicted numbers are very close to the observed values using 95% confidence, confirming the selected model's good prediction, which is shown in **Figure 2**.

Also, because the Egyptian Ministry of Agriculture and Land Reclamation has not yet officially released cultivated area data for 2021, the study will forecast cultivated area from 2021 to 2025 with 95% confidence. **Table 4** shows that the ARIMA model gives the forecasted values for the next five years are 3.06, 3.19, 3.084, 3.082 and 3.21 million hectares, respectively. It denotes that a decrease in cultivated area is expected. These projections will help the country to develop policies for future land use planning and agricultural production.

Table 4. Cultivated area forecasting from 2021 to 2025.

Years	2021	2022	2023	2024	2025
Forecast (1000 hectares)	3058	3196	3084	3082	3207

Source: The authors' calculations using EViews 12 program.

4. Discussion & Conclusion

This study aims to forecast the values of cultivated areas in Egypt using ARIMA model. According to the findings, there was an increase in cultivated area during the period (1990-2020) as a result of horizontal expansion in reclaimed lands. Recently, the Egyptian government began implementing a comprehensive plan for horizontal expansion in green spaces in order to increase agricultural area, crop productivity and food security in order to meet population growth as a factor influencing crop productivity [12]. This is consistent with Abd-Elmotaal *et al.* [11], which confirmed that the total cultivated area increased in 2020 as a result of horizontal expansion in reclaimed lands. Also, El-Khalifa *et al.* [2] confirmed that horizontal expansion contributed to an increase in agricultural production from 2009 to 2019. Whereas, Abd-Elmotaal *et al.* [11] expected that the old and new lands would still be able to meet future needs and be self-sufficient from cereal crops, oil crops and legume crops in 2030, thus the ability of cultivated land to meet future needs and be self-sufficient.

Furthermore, the results showed that the ARIMA (3, 0, 1) model is appropriate for forecasting cultivated area in Egypt from 2021 to 2025. This model predicted a decrease in cultivated area in the coming years of about 3.06, 3.19, 3.084, 3.082 and 3.21 million hectares, respectively. This could occur as a result of the negative impacts of climate change or urban sprawl in old lands. According to CAPMAS, old lands tend to diminish as a result of encroachments on agricultural lands, with the area infringed reaching 1213 hectares in 2020, up from 1001 hectares in 2019, a 21.2% rise [13]. This is consistent with Omoyo *et al.* [15] who confirmed that climate change is expected to lead to the loss of agricultural land due to reduced soil moisture, rising aridity, high salinity and groundwater drain. Furthermore, Hendawy *et al.* [21] reported that during the period from 1984 to 2016, soil sealing reduced agricultural areas in Kafr El-Sheikh Governorate, Egypt, mainly on productive soil that had been converted to urban land. Also, soil sealing and urban sprawl were predicted to rise in the study area in the future. Additionally, this result is consistent with Abdullah *et al.* [35] who predicted that as temperatures rise due to climate change, Bangladesh would lose more agricultural land in upcoming years. Furthermore, rising temperatures reduce agricultural yield over time, particularly in winter crops. Also, Baroudy *et al.* [22] emphasized that farming practices including ground preparation for cultivation, tillage, fertilization, irrigation management and planting methods have the potential to change soil characteristics in the short and long run, influencing both the sustainability and crop performance systems.

In addition, by using ARIMA model, Ahmad *et al.* [3] expected that the increase in cultivated land will be very slow in Pakistan. Also, Negm [26] predicted that Egypt will continue to rely on wheat imports in upcoming years if current policies remain unchanged. Devi *et al.* [36] used ARIMA model to forecast the production behavior of wheat in Haryana, India. In addition, Gautam and Sinha [25] reported that forecasting *via* using ARIMA model could be useful in developing appropriate strategies for managing and sustaining water resources in India. Furthermore, Abdel-Fattah *et al.* [37] stated that ARIMA model's results will assist water resource managers and decision-makers in managing irrigation water resources that may be implemented in Egypt in the future.

In this context, because of rapid population growth and the need for food supply, especially in arid and semi-arid areas such as Egypt. Forecasting would assist decision makers in anticipating the future situation of cultivated areas and selecting appropriate policies to achieve agricultural development. As a result, the government should take proactive measures to provide its citizens with an agricultural and high-productivity environment in order to improve the agricultural sector, such as increasing funding for fertilizers and pesticides, providing high-quality seeds, and developing new farming methods. This is consistent with Ayyad and Khalifa [1] who predicted that significant amounts of water and land could be secured by 2050 if vertical development paths are followed. By employing a scenario-based approach to evaluate four development paths toward adequate crop production by 2050 in order to achieve sustainable natural resource development, as well as water and food security. In contrast, Egypt is predicted to face massive challenges in meeting its future needs for major crops by 2050.

Protecting cultivated areas entails preventing encroachment and conducting periodic improvement operations to prevent deterioration and increase productivity, as well as horizontal expansion to increase the cultivated area of strategic crops in reclaimed lands. On the other hand, adapting to climate change through scientific understanding of the effects and consequences of climate variability and change, the agricultural sector then will be improved, as farmers apply this information and put decision into action, this will enhance farmers' adaptive capacity. Furthermore, cultivable areas are the most important input in the agricultural production process, making them a primary strategic goal of development plans. As a result, future studies will employ time-series data to analyze the influence of climate change on agricultural production, specifically the effects of CO_2 emissions.

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Conflicts of Interest

The authors declare no conflict of interest.

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