



Forecasting of pesticide usage in Pakistan: an application of the Univariate ARIMA Model and Artificial Neural Network

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ABSTRACT: The agriculture sector is one of the important parts of an economy, and the production of crops is beneficial for a country or nation in earning profit. On the other hand, if insects or pests destroy the crops, it will badly influence the country's economy. The most widely exported crops in Pakistan are rice, wheat, and cotton. To save crops, appropriate pesticides should be used. Pesticides are chemical substances meant to kill pests and play a vital role in protecting crop productivity. The purpose of this study is to forecast the usage of pesticides in the agriculture sector for the safety of crops. The time series data from 1961 to 2017 is taken from FORCAST and analyzed using traditional ARIMA and artificial neural network (ANN) methodology. The results revealed that ANN can be suggested as the best among the two methods because it has the least mean square error (MSE). Furthermore, the predicted values through ANN are very close to actual values. It can be concluded that the use of Pesticides in Pakistan will increase in the upcoming years.

Keywords: ARIMA Model; pesticides usage; Artificial Neural Network (ANN); AIC; BIC; MSE.

Previsão do uso de pesticidas no Paquistão: uma aplicação do modelo ARIMA univariado e da rede neural artificial

RESUMO: O setor agrícola é uma das partes importantes de uma economia, e a produção de safras é benéfica para um país ou nação na obtenção de lucro. Por outro lado, se insetos ou pragas destruírem as safras, isso influenciará negativamente a economia do país. As safras mais exportadas no Paquistão são arroz, trigo e algodão. Para salvar as safras, pesticidas apropriados devem ser usados. Pesticidas são substâncias químicas que visam matar pragas e desempenham um papel vital na proteção da produtividade das safras. O objetivo deste estudo é prever o uso de pesticidas no setor agrícola para a segurança das safras. Os dados da série temporal de 1961 a 2017 foram retirados do FORCAST e analisados usando a metodologia tradicional ARIMA e rede neural artificial (ANN). Os resultados revelaram que a ANN pode ser sugerida como a melhor entre os dois métodos porque tem o menor erro quadrático médio (MSE). Além disso, os valores previstos por meio da ANN são muito próximos dos valores reais. Pode-se concluir que o uso de pesticidas no Paquistão aumentará nos próximos anos.

Palavras-chave: modelo ARIMA; uso de pesticidas; Rede Neural Artificial (RNA); AIC; BIC; MSE.

1. INTRODUCTION

Pesticides safeguard crop productivity (UTAILE; CROSS, 2015). Using pesticides is one of the essential measures of modern agricultural practices in protecting crops from different pests (KHAN et al., 2010). Pesticides can also improve the nutritional value of food and sometimes its safety (DAMALAS; ELEFTHEROHORINOS, 2011). In the process of development of agriculture, pesticides have become an important tool as a plant protection agent to boost food security, as these chemicals play a significant role in preventing many dreadful diseases (KUMAR et al., 2013). Although the largest volume of pesticide use is in developed countries, pesticide usage is growing rapidly in developing countries (WILSON; TISDELL, 2000).

Pesticides have numerous beneficial effects. These include crop protection and preservation of food and materials, designed to kill, reduce, or repel insects, weeds, rodents, fungi, or other organisms that can threaten public

health and the economy (WHO, 2008). It has been estimated that 22482 tons of pesticides are being applied in Pakistan, and 59.6 million pesticides are imported from other countries, which keeps increasing over time (MAZARI, 2002). Pesticide utilization increased by 1169% in the last 20 years, which has become an alarming situation for Pakistan, which is already facing environmental hazards. During application, it has been observed that 2% of the sprayed pesticide is vaporized into the atmosphere and causes acid rain (Socorro et al., 2016).

It is estimated that 88.3pc of pesticides are being applied in Punjab, contributing 79pc to the total produce (MAHMOOD, 2019). In addition, natural honey production in Swat Valley decreased by about 75% and is no longer available in the market. Apicultural activities exist, and people keep honeybees, but pesticides are the main hurdle in this business. As estimated, 90% of daily honeybee deaths are due

to pesticides (NAFEES et al., 2008). Pesticide utilization in Pakistan started in 1954 and is currently on the rise. 88.3% of pesticides are applied in Punjab, 8.2% in Sindh, and 2.8% in KPK and Baluchistan. Pesticide use in Pakistan is focused on cash crop cotton (61.92%), followed by fruits and vegetables (11.9%), rice (11.86%), sugarcane (6.14%), maize (4.83%), and oilseeds (2.21%) (RASHID et al., 2022).

2. LITERATURE REVIEW

Many researchers highlighted the use of pesticides and how pesticides affect the environment and human health. Higley; Wintersteen (1992) developed a novel approach to assess environmental risks associated with single-use pesticide. The model was tested by estimating environmental costs and Economic Injury Levels (EILs) for field crop pesticides. Results indicated that environmental EILs could dramatically reduce pesticide use and improve pesticide selection. Killeen (1997) described the development and use of Environmental Quality Standards (EQSS) for Priority Pesticides and introduced the methodology to use pesticides in a specific situation together with a suggestion of how they are used by the NRA (National River Authority) and other devices in the detection of effective environmental protection.

Wilson; Tisdell (2001) examined why farmers continue to use pesticides despite environmental, health, and sustainability costs. He also noticed that acute pesticides are the reason behind mortality and morbidity among agricultural workers, especially in developing countries. The costs of these externalities are large and affect farmers' returns. Brown et al. (2002) studied the prediction of pesticide concentrations found in rivers in the UK. Time series analysis for seven of the 29 catchment pesticide combinations indicated that measured and identified series of applications generally followed similar designs.

Bues et al. (2004) reported the environmental impacts of pesticides on tomato crops over 3 years using two different methods (EIQ & IPEST) at 10 experimental sites of five Mediterranean states and the Reunion Island. Tariq et al. (2007) presented Pakistan with an integrated picture of pesticide exposure to humans, animals, plants, waters, soils/sediments, the atmosphere, etc. Evidence has been found that farmers have overused and misused pesticides, especially in cotton-growing areas. Stenrod et al. (2008) reported the testing and comparison of three pesticide risk indicator models in their study considering certain situations in Norway. The study introduced the Norwegian Environmental Risk Indicator (NERI) and compared it with the other two models, i.e., Environmental Impact Quotient (EIQ) and Surface Water Attenuation (SWAT) model. Unlike other models, the NERI model also focused on the effects of pesticide leaching along with the possible risk exposures. Though the other two models reported risk exposures well, farmers should be aware of the possible effects of leaching pesticides and the possible risk exposures.

Khooharo et al. (2008) empirically analyzed pesticide marketing in Pakistan. The estimates of the quadratic regression model discovered a steeper growth trend than the simple linear regression model. Asi et al. (2008) introduced the Solid Phase Extraction (SPE) of pesticide remains and its metabolites in water samples.

SPE, which had an octadecyl C18 chain bounded to silica particles, was used for isolating and tracing the development

of pesticides in water samples collected from cotton, rice, and community areas. Aktar et al. (2009) revealed the impacts of pesticides on the environment and agriculture fields and the benefits and hazards of using pesticides. The study discussed various methods to eradicate the negative impacts of pesticides on animals and aquatic life. They also suggested various methods to minimize the use of pesticides and the positive impacts of eradicating pesticides shortly.

Kumar et al. (2010) assessed the toxicity of six selected pesticides by exposing freshwater shrimp, *Paratya australiensis*, to these pesticides for 96h. The study predicted the toxicity of all the selected pesticides using different models and presented the results of these toxic pesticides on two types of fishes. According to the study, predicting the toxicity of selected pesticides is very important to avoid certain risks. Shokrzadeh; Saravi (2011) analyzed agricultural products and discussed how to prevent agricultural products from such toxic pesticides.

Agricultural production is associated with the continuous growth of several agrochemicals applied to crops for their protection. These agrochemicals are pesticides that eventually infect the environment and introduce many human health problems worldwide. Cross; Jones (2011) extended a time-series analysis of the variation in pesticide hazards in arable crop production in Great Britain from 1992 to 2008. This study is an update on previous work using the Environmental Impact Quotient (EIQ) to calculate changes in pesticide hazard. Ioriatti et al. (2011) explained the evaluation of the environmental impact of apple pest control strategies using pesticide risk indicators. Various pesticide risk indicators have been established to estimate pesticide impact on human health and the environment.

Silva et al. (2012) performed a time series analysis of suicide rates due to the use of pesticides and medicinal drugs. The study investigated the methods of self-harm in Sri Lanka and explored if recent changes in methods of self-harm could lessen the occurrence of suicide in societies. Kumar et al. (2013) studied the use of pesticides in agriculture and livestock animals and their impact on India's environment. A vast population in India is engaged in agriculture and is, therefore, highly exposed to the pesticides used. Cross (2013) explained the time-series analysis of pesticide hazard trends in orchard fruit production in Great Britain from 1992 to 2008. This study used the environmental impact proportion to evaluate changes in orchard fruit pesticide hazard trends.

Utaile; Cross (2016) performed a time-series analysis of variations in pesticide use and hazard from vegetable production in Great Britain. Pesticide use and hazards modelled by pesticides applied to four target crops grown in the UK showed decreasing trends between 1991 and 2011. Borkar and Bodade (2017) implemented applications of the ARIMA model for forecasting pulse productivity in India. Their study discussed various univariate and multivariate time series techniques that can be applied to forecast such variables.

Rijal et al. (2018) performed a semi-structured interview in Nepal with the vegetable growers at their homes to evaluate their knowledge about the pesticides. The study revealed that about 80% of the growers use pesticides as a primary instrument to manage pests, and 90% of them were aware of pesticides' impacts and side effects. This study highlighted a need for the instant employment of strict pesticide use principles and educational programs for pest control professionals, growers, and pesticide retailers.

Forecasting objectives are important conditions to consider apart from the literature. Previous research papers do not focus on forecasting the utilization of Pesticides in the future. Moreover, it will show how to select the best time series approach to forecast the usage of pesticides. The novelty of the current research work lies in its methodology and development in agriculture because the use of pesticides is one of the essential measures of modern agricultural practices in protecting crops from different pests.

3. METHODOLOGY

In this study, the usage of pesticides in Pakistan (Appendix-I) has been forecasted using the Box-Jenkins method, i.e., Autoregressive Integrated Moving Average (ARIMA), and Artificial Neural Network (ANN) methodology. Time series data from 1961 to 2017 is taken from FAOSTAT (Food and Agriculture Organization Cooperate Statistical Database). The sections below describe a brief overview of the Box-Jenkins and ANN methodologies.

3.1. Box-Jenkins methodology:

A mystery to know what will happen in the future, the index rises or falls; a forecasting methodology was introduced by Box and Jenkins (1970) named as Box-Jenkins methodology. This method applies the Autoregressive Moving Average (ARMA) or Autoregressive Integrated Moving Average (ARIMA) models to present the best time series forecast (DEVI et al., 2013; DIN, 2016).

i. Forecasting Procedure

Firstly, the stationarity of the selected data series has been checked, if the data series is stationary i.e., if time series data do not show any trend or seasonal effect then this data can be used for forecasting otherwise if time series is non-stationary, it should be converted to stationary series by applying differencing i.e., by identifying and removing trends and removing seasonal effects, to fulfill the assumption of stationarity.

ii. Model Identification

Forecasting starts with identifying the data model using autoregressive Integrated Moving Average (ARIMA). In developing the ARIMA model, the Auto-Correlation Function (ACF) and Partial Auto-Correlation Function (PACF) need to be analyzed to determine the values of p, d & q and the unit root test.

iii. Estimation

Once the tentative model has been selected, the parameters for this model have been estimated that you think are appropriate.

iv. Model Identification Criteria

The Information Criterion Akaike (AIC) selects the best model from a group of candidate models. AIC is mathematically defined as,

$$AIC = \ln \sigma^2 + \frac{2}{n} r \quad (01)$$

The Bayesian Information Criterion (BIC) developed by Schwarz (1978) selects the model that produces the least Mean Square Prediction Error (MSPE). BIC is mathematically defined as,

$$BIC = \ln \sigma^2 + \frac{\ln n}{n} r \quad (02)$$

The best model is selected based on the minimum value of both criteria, which will be the smallest value of AIC and BIC (HANKE; WICHERN, 2009).

v. Forecasting Accuracy Measures

After model selection, the next important step is to measure the accuracy to verify the reliability of forecasted value based on the selected model. Various tools are available to verify the reliability of models which includes Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Square Error (MSE) and Mean Percentage Error (MPE) (CHAI; DRAXLER, 2014; MAKRIDAKIS et al., 2003).

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n e_i^2} \quad (03)$$

$$MAE = \frac{1}{n} \sum_{t=1}^n e_t \quad (04)$$

$$MAPE = \frac{1}{n} \sum_{t=1}^n |PE_t| \quad (05)$$

$$MSE = \frac{1}{n} \sum_{t=1}^n e_t^2 \quad (06)$$

vi. Diagnostic Checking

The last step is to check the adequacy of the selected model for forecasting. For this, we have to check residuals of estimated the ARIMA model by a chi-square test based on the Ljung-Box Q-statistic (1976). This test looks at the sizes of the residual autocorrelations as a group

3.1.1. Flowchart of Box-Jenkins Methodology

The following flow chart precisely describes the steps involved in the Box-Jenkins (ARIMA) methodology (HANKE; WICHERN, 2009).

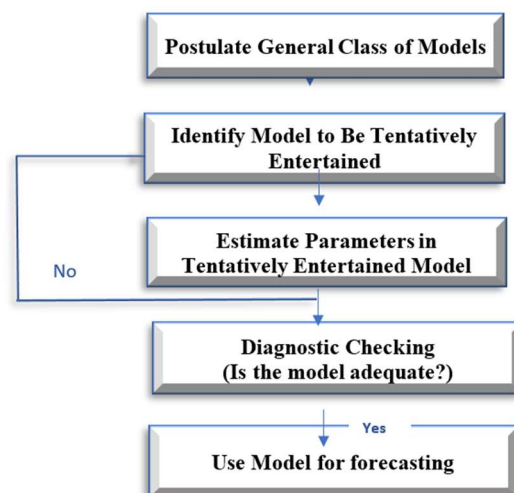


Figure 1. Flow diagram for the Box-Jenkins methodology.

Figura 1. Diagrama de fluxo para a metodologia Box-Jenkins.

3.2. Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs), as a soft computing technique, are the most accurate and widely used forecasting models in many areas, including social, engineering, economic, and business. They are also good predictor with the ability to make generalized observations from the results

learnt from original data, thereby permitting correct inference of the latent part of the population. This contrasts with many traditional techniques for time series predictions, such as ARIMA, which assume that the series is generated from linear processes and, as a result, might be inappropriate for most nonlinear real-world problems. (ADEWUMI; AYO, 2014).

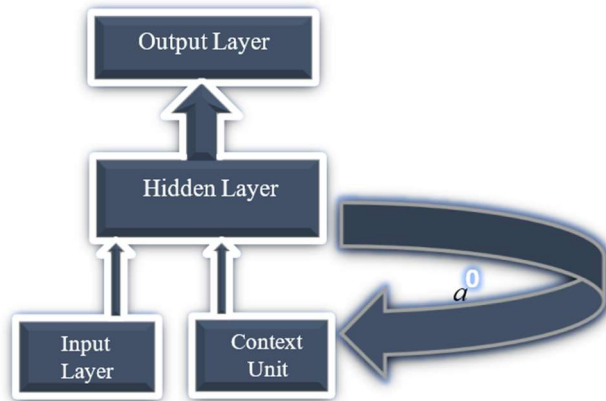


Figure 2. The recurrent neural network. (Source: Ho et al., 2002).
Figura 2. A rede neural recorrente. (Fonte: Ho et al., 2002).

4. DISCUSSION

In Box-Jenkins methodology, the first step is to plot the data to check the stationarity of data. Figure 3 demonstrates the time series plot of modern agricultural practices' pesticides. It indicates an upward trend that depicts that data is not stationary. Therefore, the difference at lag one is taken to eliminate the trend and make the series stationary. Meanwhile, Figure 4 shows the plot after applying the first difference and suggests that data is stationary (MEHMOOD et al., 2019)

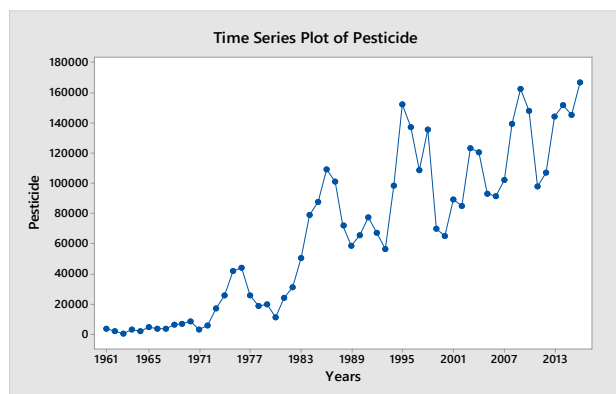


Figure 3. Time series plot at level.
Figura 3. Gráfico de séries temporais no nível.

Unit Root Test:

The augmented Dickey-Fuller t-statistic has been used to check the stationarity of the data (Yusof et al., 2010; Al-Fattah, 2005). The null and alternative hypothesis can be defined as,

H_0 : Series is not stationary.

H_1 : Series is stationary.

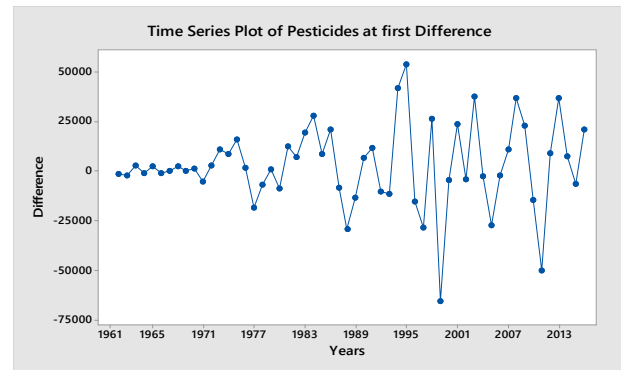


Figure 4. Time series plot at 1st difference.
Figura 4. Séries temporais na 1ª diferença.

Table 1 reveals the unit-root test results at first difference, which turns out to be a stationary process. The p-value for the Augmented Dickey-Fuller (ADF) test is under the rejection region; the p-value is less than the test critical values at $\alpha = 1\%$, 5% , and 10% . It examines that data is stationary, and the alternative hypothesis is accepted at a 1% significance level (DIN, 2016).

Table 1. Unit Root Test to check Stationarity.

Tabela 1. Teste de raiz unitária para verificar estacionariedade.

		t-statistic	P-value
Augmented dickey-fuller test		-6.842124	0.0000
Test critical values:	1% level	-3.557472	
	5% level	-2.916566	
	10% level	-2.596116	

Model Identification

The next step is to identify the model. A correlogram determines the candidates for the ARIMA (p, d, q) model.

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
		1	0.080	0.080	0.3779	0.539
		2	-0.323	-0.332	6.6626	0.036
		3	-0.077	-0.018	7.0287	0.071
		4	-0.232	-0.373	10.401	0.034
		5	-0.030	-0.010	10.460	0.063
		6	0.049	-0.226	10.614	0.101
		7	-0.080	-0.155	11.041	0.137
		8	0.013	-0.184	11.052	0.199
		9	0.045	-0.133	11.191	0.263
		10	-0.003	-0.180	11.191	0.343
		11	0.121	-0.016	12.251	0.345
		12	0.200	0.121	15.194	0.231
		13	-0.038	-0.010	15.301	0.289
		14	-0.012	0.217	15.312	0.357
		15	-0.088	-0.002	15.930	0.387
		16	-0.234	0.019	20.378	0.204
		17	-0.105	-0.150	21.291	0.214
		18	0.108	0.117	22.285	0.220
		19	0.114	-0.043	23.433	0.219
		20	-0.068	-0.179	23.855	0.249
		21	-0.043	-0.158	24.024	0.292
		22	0.170	0.050	26.799	0.219
		23	0.068	-0.130	27.258	0.245
		24	-0.076	-0.186	27.842	0.267

Figure 5. Correlogram at 1st difference.
Figura 5. Correlograma na 1ª diferença.

Figure 5 exhibits the plot of ACF and PACF through a correlogram to decide the ARIMA model's parameters (p, d, q) values. The five ARIMA models that have been proposed are ARIMA (0,1,1), ARIMA (1,1,0), ARIMA (1,1,1), ARIMA (2,1,0), and ARIMA (2,1,1) (BAKER; ROSBI, 2017).

Estimation of Parameters

Subsequently, the autoregressive and Moving Average models need to be estimated to define the model parameters. Table 2 shows the estimation of parameters for different fitted ARIMA models. All the models indicate significant parameter values, as the p-value is less than 0.05 (BADAR et al., 2015).

Table 3 demonstrates different ARIMA models with Akaike Information Criterion (AIC) and Bayesian

Information Criterion (BIC) values. The ARIMA (2,1,0) has the lowest value of both AIC and BIC. Therefore, this model is selected for prediction. Furthermore, to check the accuracy of selected model values of RMSE, MAE, MAPE and MSE are also calculated. The results revealed that ARIMA (2,1,0) has the minimum RMSE, MAE, MAPE, and MSE values. So, this model is recommended as best fitted for forecasting (AMIN et al., 2014).

Table 2. Estimation of parameters.

Tabela 2. Estimativa de parâmetros.

Model	Type	Coefficients	S. E	t-statistic	P-value
ARIMA (0,1,1)	MA (1)	0.251280	0.133102	1.887870	0.006
	Constant	2991.400			
ARIMA (1,1,0)	AR (1)	0.081214	0.137848	0.589155	0.0483
	Constant	3024.252			
ARIMA (1,1,1)	AR (1)	-0.497808	0.232404	-2.141998	0.0369
	MA (1)	0.821735			
	Constant	3107.170			
ARIMA (2,1,0)	AR (2)	-0.328934	0.132122	-2.489620	0.0160
	Constant	2995.468			
ARIMA (2,1,1)	AR (2)	-0.327523	0.135037	-2.425442	0.0189
	MA (1)	0.142894			
	Constant	3033.453			

Table 3. Model identification criteria.

Tabela 3. Critérios de identificação do modelo.

Models	AIC	BIC	RMSE	MAE	MAPE	MSE
(0,1,1)	22.77128	22.84362	29731.41	25350.41	178.3574	436044966
(1,1,0)	22.80306	22.87605	27699.49	23092.55	131.7699	443334262
(1,1,1)	22.71975	22.82924	28517.05	23834.85	120.6796	400692436
(2,1,0)**	22.71560	22.78927	26196.54	21457.24	95.55947	406845450
(2,1,1)	22.73794	22.84844	26772.41	21962.76	97.28266	391155098

Diagnostic Checking:

The last step is to check the adequacy of the selected model. The model is adequate if there is no existence of a correlation between residuals and the residuals are independently identical and normally distributed. One simple method is to plot the ACF and PACF of the chosen model's residuals to check whether they show white noise or not.

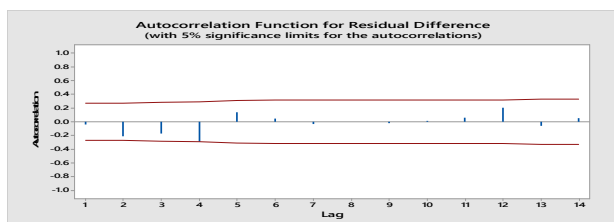


Figure 6. ACF for Residual.

Figura 6. ACF para Residual.

Based on Figure 6, it appears that none of the autocorrelations of the residuals is significant. This means there is no correlation between the residuals and all autocorrelations within the threshold limits, indicating that the residuals are white noise. So, the model meets the assumption that the residuals are independent, random, and white noise. Hence, we can conclude that the model is adequate, and the forecasting can be done (MAHSIN, 2011; FAISAL, 2012; MEHMOOD et al., 2020).

Table 4. Ljung-Box Q Statistic.

Tabela 4. Estatística Ljung-Box Q.

Lag	12	24	36	48
Chi-square	14.5	24.4	27.2	27.7
Df	10	22	34	46
P-value	0.153	0.328	0.789	0.985

A chi-square (χ^2) test based on the Ljung-Box Q-statistic (1976) can also be used to check the overall model adequacy. If the p-value associated with this test is small (say, p-value < 0.05), the model is considered inadequate (HANKE; WICHERN, 2009). Table 4 shows that the p-value for lags 12, 24, 36, and 48 is greater than 0.05, which means that the selected model is adequate (SAEED et al., 2020).

4.2. Artificial Neural Network:

The artificial neural network technique is used to predict the use of pesticides in Pakistan. Figure 8 illustrates the relationship between the actual and predicted values. It shows that the predicted values are quite accurate and stable compared to the actual values, as they are nearly plotted to the actual line (PALOMARES-SALAS et al., 2009).

In Figure 9, the blue line shows the actual values, while the red line shows the forecasted values. The figure shows that the use of pesticides in Pakistan will increase in upcoming years, which means that more pesticides will be introduced in the future than in previous years (AFFAN et al., 2019).

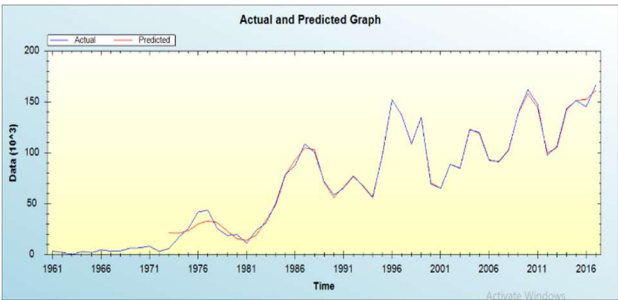


Figure 8. Comparison between actual and predicted values.
Figura 8. Comparação entre valores reais e previstos.

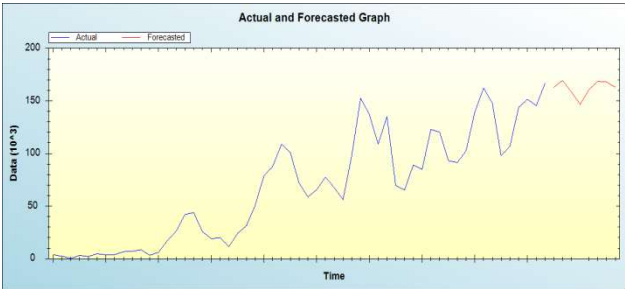


Figure 9. Actual and Forecasted Values.
Figura 9. Valores reais e previstos.

Comparison Between ARIMA and Artificial Neural Network:

In this section, a comparison between ARIMA and Artificial Neural Network (ANN) is examined by comparing the MSE of these methodologies to select the best forecasting technique (MUSA; JOSHUA, 2020; ISMAIL et al., 2018; BURATTO et al., 2019).

The empirical results presented in Table 7 show that the forecasting accuracy level of the ANN model is compared with that of the ARIMA model. It can be argued that both models achieved good forecast performance judging from the mean square of both models, which is quite low, but the mean square error (MSE) for ANN is much lower than the ARIMA. However, the performance of the ANN model is better than that of the ARIMA model in terms of forecasting accuracy from the test data on many occasions. So, we can consider artificial neural networks a promising forecasting technique (MUSA; JOSHUA, 2020).

Table 7. Mean Square values for ARIMA and Neural Network.
Tabela 7. Valores médios quadráticos para ARIMA e rede neural.

Model	MSE
ARIMA	406845450
Neural Network	10500485.01

Table 6 exposes the predicted values examined by the time series methodologies Box-Jenkins and Artificial Neural Network. The results reveal that the forecasted values depict an increasing trend: the use of Pesticides in Pakistan will increase in the upcoming years until 2025 (OKASHA; YASEEN, 2016).

Figure 10 shows the plot of actual observations and predicted values through ARIMA and the Artificial Neural Network (ANN) method. It clearly indicates that forecasted values based on an Artificial Neural Network perform better than ARIMA. The predicted values through ANN are also very close to actual values, which is why this method can be suggested as the best method to forecast the use of pesticides in Pakistan (ADEBIYI et al., 2014).

Table 6. Forecasting.
Tabela 6. Previsão.

Model	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
ARIMA	164645	165594	165190	164835	164918	165232.24	164899.69	164975.91	165089.60	165080.51
ANN	146726.18	160654.42	168692.67	167957.74	162813.80	173212.53	177160.39	181108.24	185056.10	189003.95

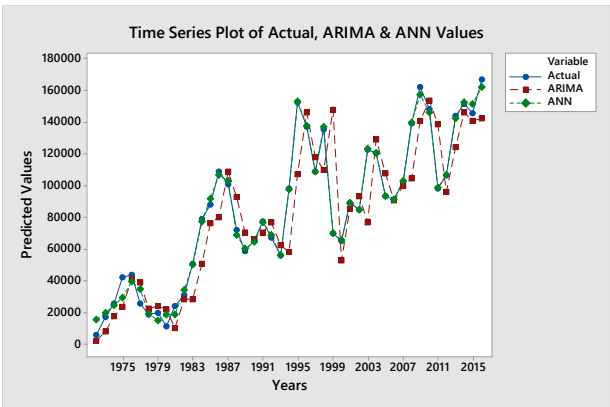


Figure 10. Predicted Values of ARIMA, Actual Values and ANN.
Figura 10. Valores previstos de ARIMA, valores reais e ANN.

4. FINAL CONSIDERATIONS

The world's population is growing daily; therefore, it is necessary to plan to meet the nation's requirements. For this purpose, forecasting is the key tool to alarm about the nation's need in advance. The agriculture sector is the basic need of any country because the production of crops is beneficial for a country or nation to earn a profit. Using

pesticides is one of the essential measures of modern agricultural practices in protecting crops from different pests. If insects or pests destroy crops, it will badly affect the nation's economy. That's why some pesticides are used to save crops from pests.

In this study, two different methodologies, including Box-Jenkins (ARIMA) and Artificial Neural Network (ANN), have been used to forecast the usage of pesticides in Pakistan based on historical data, i.e., 1961-2017. The Box-Jenkins methodology is utilized, and different ARIMA models have been proposed. The best model is selected based on model selection criteria. The ARIMA (2,1,0) has been proposed as the best model because it has a lower value of AIC and BIC than other fitted models. In addition, forecasting accuracy measures were also found to check the precision of the selected model. Secondly, ANN is used for forecasting. Finally, a comparison between ARIMA and ANN is examined. The results revealed that ANN can be suggested as the best of the two methods because it has the least mean square error (MSE). Furthermore, the predicted values through ANN are very close to actual values (Figure 8). It can be concluded that the use of pesticides in Pakistan will increase in the upcoming years.

6. REFERENCES

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Data availability: The dataset used in this study can be downloaded from FORCAST and is also provided in the Appendix.

Conflict of interest: The authors declare no conflict of interest. Supporting entities had no role in the study's design, data collection, analysis, interpretation, manuscript writing, or decision to publish the results.



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Appendix

Years	Value	Years	Value	Years	Value	Years	Value	Years	Value
1961	3814	1973	6185	1985	78977	1997	137075	2009	139279.6
1962	2403	1974	17308	1986	87842	1998	108812	2010	162165.4
1963	359	1975	26029	1987	108926	1999	135292	2011	147917.4
1964	3190	1976	42125	1988	100848	2000	69690	2012	97885.53
1965	2177	1977	43902	1989	71911	2001	65289	2013	106912.7
1966	4750	1978	25654	1990	58716	2002	89052	2014	143865.6
1967	3687	1979	19070	1991	65535	2003	84951	2015	151544.3
1968	3922	1980	20000	1992	77594	2004	122879	2016	145407.3
1969	6707	1981	11496	1993	67494	2005	120339	2017	166727.6
1970	7030	1982	24155	1994	56309	2006	93217		
1971	8558	1983	31340	1995	98279	2007	91354.01		
1972	3308	1984	50752	1996	152421	2008	102377.9		

[http://fenixservices.fao.org/faostat/static/bulkdownloads/Environment_Pesticides_E_All_Data_\(Normalized\).zip](http://fenixservices.fao.org/faostat/static/bulkdownloads/Environment_Pesticides_E_All_Data_(Normalized).zip)