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PREDICTION OF TÜRKİYE'S BURNED FOREST AREAS USING ARIMA MODEL

Türkiye'nin Yanan Orman Alanının ARIMA Modeli ile Tahmini

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ABSTRACT

Abstract: Large-scale forest fires can cause significant ecological losses. Additionally, preserving forest areas may help to slow down climate change. Statistical models are one of the tools used in planning fire management strategies. In this study, the burned forest area of Türkiye is modeled using the Autoregressive Integrated Moving Average (ARIMA) method following the identification, estimation, validation, and forecasting steps. As is known the ARIMA analysis is one of the popular techniques used in time series analysis. Annual total burned forest areas in Türkiye over the period 1940-2021 are considered in the analysis. Three preliminary models are considered for evaluation of their modeling and prediction performances. The models' validities are investigated with Ljung–Box statistics, residual analysis, and cross-validation. According to the results, the ARIMA (3,1,0) model is found to be the most suitable model for predicting the future values of the burned forest area time series in Türkiye. Forecasts for Türkiye’s burned forest areas series are obtained for the next 3 years accordingly.

Anahtar Kelimeler
ARIMA, orman yangını, Türkiye, yanan orman alanı, zaman serisi

ÖZ

Büyük ölçekli orman yangınları önemli ekolojik kayıplara neden olmaktadır. Ayrıca ormanlık alanların korunması iklim değişikliğini yavaşlatmaya yardımcı olabilmektedir. İstatistiksel modeller, yangın yönetimi stratejilerinin planlanmasında kullanılan araçlardan biridir. Bu çalışmada, Türkiye'nin yanan orman alanı, tanımlama, tahmin, doğrulama ve öngörü adımları izlenerek Otoregresif Bütünleşik Hareketli Ortalama (ARIMA) yöntemi kullanılarak analiz edilmiştir. ARIMA yöntemi zaman serileri analizinde kullanılan popüler tekniklerden biridir. Analizde 1940-2021 yılları arasında Türkiye'deki yıllık toplam yanan orman alanı ölçümleri kullanılmıştır. Modelleme ve tahmin performanslarının değerlendirilmesi için üç model ele alınmıştır. Modellerin geçerliliği, Ljung–Box istatistikleri ve çapraz doğrulama ile araştırılmıştır. Sonuçlara göre, ARIMA (3,1,0) modeli Türkiye'nin yanmış orman alanı zaman serilerinin gelecek değerlerinin tahmin edilmesi için en uygun model olarak bulunmuş ve öngörüler önümüzdeki 3 yıl için elde edilmiştir.

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1. Introduction

Forest fires are one of the natural disasters that are experienced more destructively in recent years. According to European Environment Agency (EAA, 2021), climate change has increased forest fire risk across Europe. Forest fires have been challenging in the past few years in Türkiye as well. In addition, forest fires have a significant impact on nature and human life (Oncel Cekim, Güney, Şentürk, Özel, & Özkan, 2021:2189). It is therefore of great interest to analyze and predict future burned forest areas in order to decide on suitable forest fire management strategies and to reduce the negative effects of forest fires (Tedim et al., 2018).

Forestry records and regulations in Türkiye date back to the late 1910s. The first Forest Management Plan is made in 1917. The planned period started with the Five-Year Development Plan and the first forest inventory is published in 1980. The number of fires recorded in Türkiye from 1937 to 2021 is 117,734 hectares. According to 2021 official forest fire statistics in Türkiye, it has been reported that besides the factors such as intent and negligence (nearly %32 and %32 of forest fires in 2021, respectively), the cause of 32% of the forest fires could not be detected. As reported by the Strategic Plan of the General Directorate of Forestry (2019-2023), the amount of area burned per fire is aimed to be reduced to 2.2 hectares by 2023 (OGM, 2018). Consequently, studies in this field are important given the cause of the high percentage of fires is unknown.

The predictability of forest fire or wildfire incidents implies the use of statistical models (Kouassi, Wandan, & Mbow, 2020). Besides the classical statistical methods, machine learning techniques are also widely used in forest fire studies. Although machine learning methods are promising techniques in time series forecasting, it is pointed out in various studies (e.g. Makridakis, Spiliotis, & Assimakopoulos, 2018; Maleki, Nasseri, Aminabad, & Hadi, 2018:3239) that in cases of univariate time series the classical methods are superior to the machine learning methods. In addition, classical models require less computational process than machine learning methods. A detailed discussion on the comparison of machine learning methods with classical statistical methods in time series analysis is provided by Makridakis et al. (2018). Previous studies have utilized a variety of methods from different approaches. For example, Amatulli, Camia, & San-Miguel-Ayanz (2013), used machine learning methods and classical regression analysis in estimating future burned areas in Mediterranean countries considering different climatic scenarios.

Mohammadi, Bavaghar, & Shabanian, (2014) used logistic regression to evaluate the most influential factors affecting forest fires. Probabilistic models are also employed in predicting forest fire occurrence in studies by Boubeta, Lombardía, Marey-Pérez, & Morales, (2015), Papakosta & Straub (2017), and Podur, Martell, & Stanford (2010). Supervised and unsupervised classification methods are also used for mapping burned forest areas in the studies of Chen, Moriya, Sakai, Koyama, & Cao (2016) and Küçük Matcı & Avdan (2020). Another approach is to use non-parametric techniques as in Oncel Cekim et al. (2021). Although time series analysis is commonly used in forecasting future changes in environmental data, there are a limited number of studies evaluating burned forest areas as a time series (Oncel Cekim et al., 2021). Owing to this, the ARIMA method, one of the well-known methods used in time series analysis, is employed in this study. It should be noted that it is especially useful to use the ARIMA method when little knowledge is available about the data generation process or when there is no satisfactory explanatory model linking the predictor variable to others as in this study (Kouassi et al., 2020).

To the best of the author's knowledge, there is only one study that employed the ARIMA method in predicting burned forest areas of Türkiye, but it was carried out a decade ago. Here a more comprehensive study with a different model using the updated data comprising 1940-2021 years is presented. In addition, preliminary models are cross-validated, and forecast length is determined by following a cross-validation step. Besides using a well-known time series analysis method, another contribution of the study is that instead of focusing on only the Mediterranean region, it is considered to forecast burned forest areas using complete data in Türkiye. Although forest fire incidents in Türkiye generally occurred in the south of Türkiye, the severity of forest fires in other areas may be increased with climate change. In this manner, using overall data considering all regions of Türkiye might help plan resources and strategies.

The remainder of the study is given as follows. Section 2 is reserved for literature review. Afterward, in section 3 the data set and the ARIMA method, and the analysis steps are described. In section 4, the results are presented. In section 5, the study is finalized with some concluding remarks.

2. Overview of Previous Studies

Recently, the countries with the highest absolute fire danger in Europe are expressed as Portugal, Spain, and Türkiye (EAA, 2021) also Giannakopoulos et al. (2009) indicated that Türkiye could be one of the most affected Mediterranean countries due to the fire season getting longer by 2–6 additional weeks. Although there are some studies using time series analysis methods conducted in Portugal and Spain (Boubeta, Lombardía, González-Manteiga, & Marey-Pérez, 2016:674; Xie & Peng, 2019:4546), the studies conducted in Türkiye generally focused on forest fire risk zone mapping for certain regions. For example, Satir, Berberoglu, & Donmez (2016) presented a forest fire risk mapping study in the Mediterranean region using an artificial neural network. Sari (2021) conducted a study using multi-criteria decision analysis in Muğla, Küçük Matcı & Avdan (2020) compared unsupervised classification methods for mapping forest fire risk in Antalya and Çolak & Sunar (2020) modeled the fire risk using remote sensing technology in the Menderes region. In addition, a limited number of studies are available concerning predicting indicators such as the number of forest fires and burned forest areas. Özbayoğlu & Bozer (2012) employed outcomes from different estimation methods such as Multilayer Perceptron, fuzzy logic, and Support Vector Machines in predicting burned area. Their work is based on 7,920 forest fire records in Türkiye between 2000-2009 years. They concluded a Multilayer Perceptron model using humidity and wind speed as inputs, provides the best performance. Çekim, Kadilar, & Özel (2013) utilized the ARIMA and compound Poisson models in describing the annual total burned area in Türkiye. Their study is conducted for the burned forest area data between 1937 and 2009 years and suggested using ARIMA(0,1,1) model in forecasting future values of the burned forest area of Türkiye. Recently, Oncel Cekim et al. (2021) proved that non-parametric time series approaches are effective in predicting burned forest areas. Their study is based on vector singular spectrum analysis and vector multivariate singular spectrum analysis. A monthly data set is collected from the Mediterranean region of Türkiye considered in their work.
Some of the other important studies in related literature using the ARIMA model are also given below. Tasker & Arima (2016) compared four different estimators using the burned forest area data in examining the general spatial-temporal trends of fire in Amazonia between 2001 and 2013. They emphasized the importance of preventing further forest degradation. Fernández-Manso, Quintano, & Fernández-Manso (2011) developed a seasonal ARIMA (SARIMA) model and used it in the prediction of drought, fire risk, and forest disease. In addition, Mueller et al. (2020) fitted an ARIMA model to different climate indicators and burn severity data collected from Arizona and New Mexico. They found that the size of the area burned, and fire severity has increased over the past three decades. Kouassi et al. (2020) employed an ARIMA model to forecast wildfire incidents and burnt areas. They stated that the ARIMA model is provided accurate forecasts and can help develop a decision-support tool for the considered ecosystem.

2. Material and Methods

2.1. Data set

The annual total burned forest area of Türkiye from 1940-2021, is employed in the analysis. The data is collected from three different sources. The data for 1940-1960 and 1961-1988 are collected from Küçükosmanoğlu (1987) and Baş (2014), respectively. The 1988-2021 part of the time series is obtained from the General Directorate of Forestry's (OGM) website. The complete data set is given in the Appendix for brevity (Table 1).

2.2. Method

In time series, unlike a static model, it is preferable to allow the dependent variable to be affected by its past values and possibly the past values of the independent variables (Shumway, Stoffer, & Stoffer, 2000). In autoregressive models, the value of Y_t is explained as a function of its past values (Shumway et al., 2000). In general, ARIMA models (p,d,q) is a combination of three types of processes p, d, and q, where parameters p, d, and q are non-negative integers, p is the order of the autoregressive model, d is the order of integration, and q is the order of the moving-average model. A general expression of the ARIMA (p,d,q) model is given as follows,

$$\boldsymbol{\varphi(L)(1-L)^d Y_t = \theta(L)\varepsilon_t} \quad \textbf{(1)}$$

where $\varphi(L)$ and $\theta(L)$ are the autoregressive and moving average polinoms, Y_t is the value of the burned forest area measurement Y at a given time t, ε_t is the uncorrelated random error term with zero mean and unit variance (white noise) and L is the lag operator.

Table 1. Türkiye's annual total burned forest area (BFA) between 1940-2020 years (in hectares)

Date	BFA	Date	BFA	Date	BFA	Date	BFA
1940	18732	1961	8989	1982	4018	2003	6644
1941	33415	1962	16059	1983	3556	2004	4876.2
1942	73210	1963	5178	1984	7358	2005	2821
1943	46723	1964	13348	1985	26007	2006	7761.6
1944	39315	1965	3945	1986	11037	2007	11664.4
1945	165307	1966	6664	1987	10746	2008	29749
1946	125115	1967	8441	1988	18210	2009	4679
1947	59999	1968	7540	1989	13099	2010	3317
1948	32463	1969	16364	1990	13742	2011	3612
1949	36502	1970	15019	1991	8081	2012	10454
1950	69068	1971	7532	1992	12232	2013	11456
1951	18884	1972	6914	1993	15393	2014	3117
1952	62271	1973	17002	1994	30828	2015	3219
1953	17496	1974	14743	1995	7676	2016	9156
1954	35580	1975	17515	1996	14922	2017	11993
1955	27773	1976	6396	1997	6317	2018	5644
1956	38983	1977	43076	1998	6764	2019	11332
1957	28634	1978	13233	1999	5804	2020	20971
1958	26862	1979	34122	2000	26353	2021	139500
1959	8070	1980	10428	2001	7394		
1960	8559	1981	5470	2002	8514		

To choose a suitable model, the data set is analyzed using the Box and Jenkins methodology by following the identification, estimation, validation, and forecasting steps; see more on Box and Jenkins methodology in Pena, Tiao, & Tsay (2011). Additionally, stationarity is an important assumption of the ARIMA model. First, the stationarity of the time series is examined by using the Augmented Dickey-Fuller (ADF), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests. After checking whether the series is stationary, in the identification step, the ARIMA model(s) that could be suitable for the data are evaluated. In the second step, the coefficients of the models are estimated and Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values are given. The AIC and BIC are used in comparing the modeling ability of the models.

In the validation step, the prediction performances of the models are evaluated by residual analysis and cross-validation. In this step, for testing the normality of the residuals Kolmogorov-Smirnov (KS) and Shapiro Wilk's (SW) tests are employed and for testing the randomness of the residuals, the Ljung box test is employed.

For cross-validation, the observations up to 2002 are reserved for training, and the remaining part of the data set is reserved for testing. In addition, a different cross-validation approach called time series cross-validation analysis (Hyndman, 2014) is used for determining the forecast horizon (h). Finally, the most suitable model is used for forecasting burned forest area time series. Forecast errors, root mean square error (RMSE), mean absolute error (MAE), mean absolute scaled error (MASE), and mean absolute percentage error (MAPE) are used in the comparison of the cross-validated model's prediction performances. See the formulas for the RMSE, MAE, MAPE, and MASE from (Hyndman, 2014) since they are not provided here for brevity.

3. Results

In this section, ARIMA models are fitted to the annual burned forest area data. Results are evaluated by using the criteria previously mentioned. In the analysis of the annual burned forest areas data R software is used. The plot for the burned forest area time series is given in Figure 1. According to Figure 1, there are extreme increases in 1945-1946 and 2021. To determine a suitable ARIMA model, the natural logarithm of the burned forest area time series is taken to stabilize the variance.

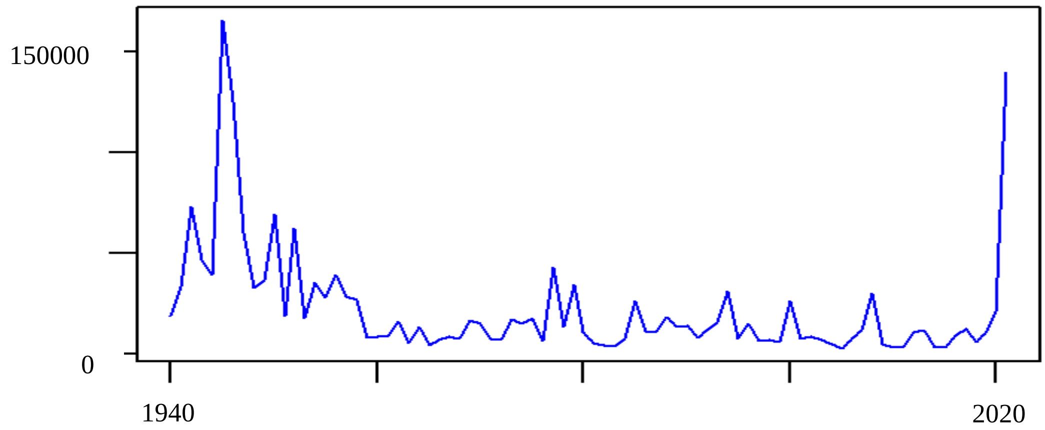

Figure 1. The burned forest area time series.

As mentioned in the previous section, the stationarity of the time series is examined by using ADF and KPSS tests. The null hypothesis for the ADF test is, the series has a unit root, namely non-stationary, and the null hypothesis for the KPSS test is, the series is trend stationary. The p-values and test statistics for the ADF and KPSS tests are given in Table 1. According to Table 1, without differencing (d=0), the null hypothesis can not be rejected for the ADF test at a confidence level of %95 and rejected for the KPSS test (See the critical values from Kwiatkowski, Phillips, Schmidt, & Shin (1992). It should be noted that the trend of the series can not be modeled explicitly according to the KPSS test. For this reason, differencing (d=1) is considered to make the series stationary. After the first difference, the stationarity of the burned forest area series is evaluated with the ADF and KPSS tests again. The p-values and test statistics for the ADF and KPSS tests are provided in Table 1 for the differenced series as well. It can be seen from Table 1, the series is stationary after differencing.

Table 1. The ADF and KPSS tests results

	ADF Test	ADF Test	KPSS Test	KPSS Test
Order	d=0	d=1	d=0	d=1
Test statistics	-1.5721	-5.2393	0.24068	0.081123
P-values	0.7511	0.001	<0.01	>0.1

The plots of ACF and PACF against the lag values are given in Figures 2 (a) and (b) for the logarithm of the burned forest areas series. The plots of ACF and PACF for the series after the first difference are given in Figures 2 (c) and (d) as well. With the help of Figures 2 (c) and (d), orders of the AR and MA components of the preliminary ARIMA(p,d,q) models are determined. The burned forest area data is modeled with the ARIMA(0,1,1), ARIMA(3,1,0), and ARIMA(1,1,1) models. The AIC, BIC values, and coefficients for the ARIMA models are given in Table 2. Significant coefficients in the models are marked in Table 2. The p-values of the coefficients compared to the significance levels 0.05, 0.01, and 0.001 marked with an asterisk accordingly (<0.05:*,<0.01:**,<0.001:***).

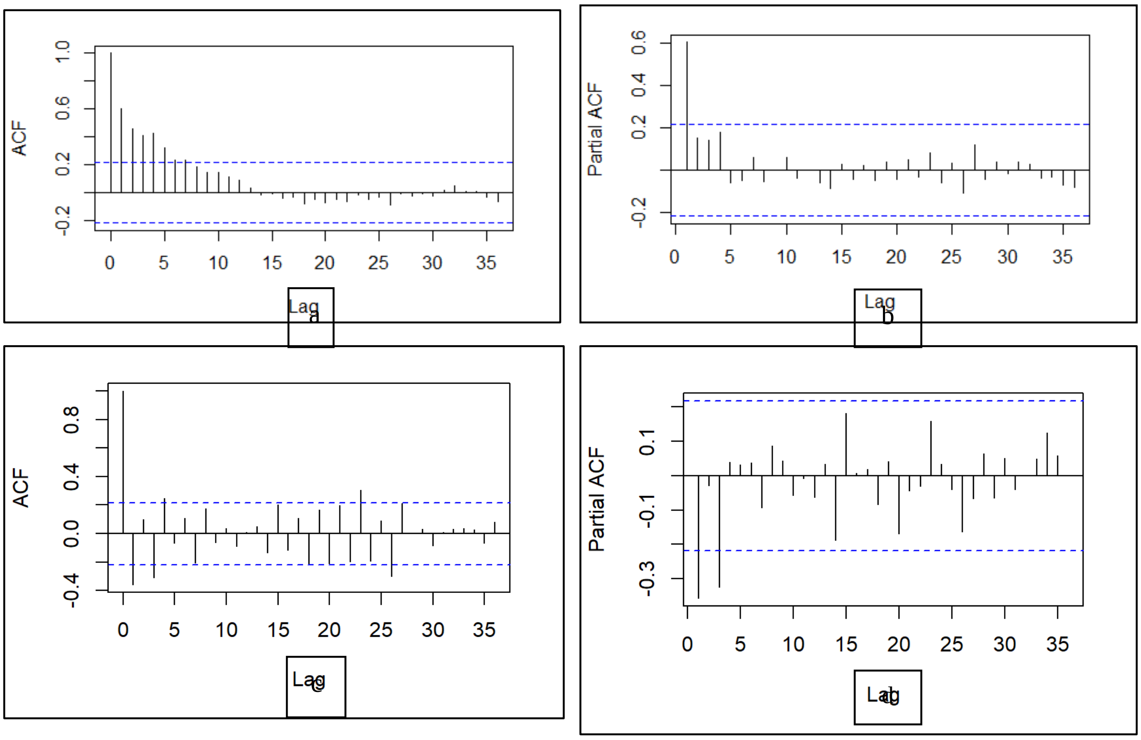

Figure 2. The ACF and PACF for the original and differenced series.

Table 2. The coefficients and AIC values of the ARIMA(p,d,q) models fitted to the burned forest area series

Model	Ar1	Ar2	Ar3	Ma1	AIC	BIC
ARIMA(0,1,1)				-0.59	183.65	188.2937
ARIMA(3,1,0)	-0.45 ***	-0.25*	-0.40***		179.84	188.8963
ARIMA(1,1,1)	0.23			-0.76***	184.24	191.4264

According to Table 2, ARIMA(3,1,0) model has the lowest AIC value and the coefficients in this model are significant. The ARIMA(0,1,1) model has the lowest BIC value but the coefficient in this model is not significant.

In the first stage of the validation step, the Ljung-Box Q-statistics are given for each model in Table 3. The null hypothesis for the Ljung-Box test is, that the residuals of the model are nearly white noise or not distinguishable from white noise. According to Table 3, the null hypothesis can not be rejected and it can be said that the residuals of all models are nearly white noise. Subsequently, the normality of the residuals is examined with the KS and SW tests. For the test of normality, the null hypothesis is, that the residuals of the model follow a normal distribution. The null hypothesis for the SW tests is rejected for the ARIMA(0,1,1) model, namely the residuals of the model does not fit the normal distribution. According to p-values obtained from the KS and SW tests, the null hypothesis can not be rejected (p-values>0.05) for the other two models, thus the residuals of the ARIMA(3,1,0) and ARIMA(1,1,1) models are normally distributed.

Table 3. Residual Analysis

Model	Ljung-Box p-value	SW	KS
ARIMA(0,1,1)	0.3194	0.0486	0.5926
ARIMA(3,1,0)	0.9192	0.4644	0.9593
ARIMA(1,1,1)	0.1339	0.9757	0.5326

In the second stage of the validation step, preliminary models are cross-validated. Table 4 shows the prediction performances of preliminary models. Lower values of forecast errors indicate better prediction performance. It was mentioned that the ARIMA (3,1,0) model performed better in terms of the information criterion (AIC).

According to Table 4, the ARIMA (3,1,0) model provided the lowest values for testing forecast errors as well. Consequently, the ARIMA(3,1,0) model is chosen for forecasting the time series. It should be noted that the testing errors of the models are slightly higher than the training errors indicating that the fitted ARIMA models performed well. The ARIMA(3,1,0) model is also cross-validated for different values of forecast horizon (h). For this purpose, the time series cross-validation analysis is used in evaluating the forecast performance of the ARIMA(3,1,0) model for different values of the forecast horizon (h). See more on (Hyndman, 2014) for the time series cross-validation method. The RMSE and MAE values are given in Table 5 for h values ranging from 1 to 10. It is seen that the lowest values of forecast errors are obtained for a 3-year period. It should be noted that it is possible to use different forecast lengths. Here, RMSE and MAE values for various forecast lengths are given and forecasts for the only lowest h are provided.

Table 4. Forecast errors for the models

Model	Train/Test	RMSE	MAE	MAPE	MASE
ARIMA(0,1,1)	Train	0.653417	0.524354	4.936942	0.830227
	Test	0.650409	0.527225	5.630351	0.834773
ARIMA(3,1,0)	Train	0.640657	0.509393	4.792402	0.806538
	Test	0.622514	0.48258	5.140622	0.764084
ARIMA(1,1,1)	Train	0.653423	0.524408	4.937289	0.830312
	Test	0.650099	0.527006	5.627930	0.834425

Table 5. Forecast errors for different h values using the ARIMA(3,1,0) model

h	1	2	3	4	5	6	7	8	9	10
RMSE	1.377	1.329	1.246	1.333	1.354	1.374	1.359	1.366	1.369	1.379
MAE	1.188	1.144	1.064	1.146	1.169	1.190	1.176	1.183	1.188	1.199

Actual values and predicted values of the burned forest area time series are visualized in Figure 3 (a). According to Figure 3 (a), the model can describe the burned forest area well.

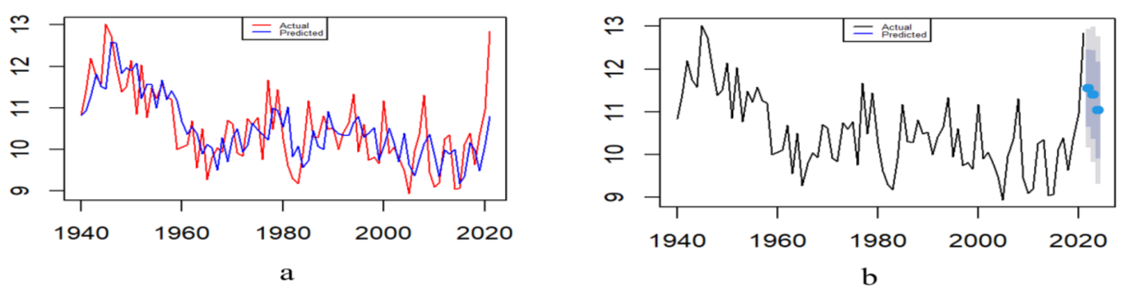

Figure 3. Actual values and predicted values of the burned forest area time series.

Forecasted values for the burned forest area series by using ARIMA(3,1,0) model are obtained as 103928.48 89637.33 62273.53 for the next 3 years. Forecasts of the burned forest area series are visualized in Figure 3 (b). The gray areas in this figure show that the forecasts of the series are within the % 95 confidence interval.

4. Discussion and Conclusion

Forest fires can be experienced more destructively as a result of climate change in the future. The countries with the highest absolute fire danger in Europe are expressed as Portugal, Spain, and Türkiye (EEA, 2021). As mentioned previously, similar studies using the ARIMA model are available for Spain and Portugal. However, the studies conducted in Türkiye generally concentrated on forest fire risk mapping in the Mediterranean region. In this study, the future values of the burned forest areas are predicted using the ARIMA method. Although the ARIMA (0,1,1) model was used in a study by Çekim et al. (2013) a different model is suggested in this study since the residuals of the ARIMA(0,1,1) are not normally distributed for updated data. The ARIMA (3,1,0) model is selected as the most suitable model for the burned forest area time series. Results showed that the suggested model performed well in describing data. Forecasts of burned forest areas series for 3 years are provided. Although this study provides an overview, it would be beneficial to include external climate variables in the analysis in future studies. It is hoped that the study will be useful in planning resources to deal with forest fire incidents that may occur in the future.

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Etik, Beyan ve Açıklamalar

1. Etik Kurul izni ile ilgili;

☑ Bu çalışmanın yazar/yazarları, Etik Kurul İznine gerek olmadığını beyan etmektedir.

2. Bu çalışmanın yazar/yazarları, araştırma ve yayın etiği ilkelerine uyduklarını kabul etmektedir.

3. Bu çalışmanın yazar/yazarları kullanmış oldukları resim, şekil, fotoğraf ve benzeri belgelerin kullanımında tüm sorumlulukları kabul etmektedir.

4. Bu çalışmanın benzerlik raporu bulunmaktadır.