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Chaotic Dynamics and Analysis with Artificial Neural Networks of Aftershocks of 2019 Silivri Earthquake

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Abstract

Earthquakes, whose physical, economic, psychological, and social damages can last for many years, are of vital importance for Türkiye, which is located in the most active earthquake zone that causes many earthquakes in the world. The North Anatolian Fault (NAF) is one of Türkiye's most important tectonic elements as it is the world's fastest-moving right-lateral and strike-slip active fault zone consisting of many segments. The recent 5.8 magnitude 2019 Silivri earthquake, which occurred in the part of the NAF zone crossing the Marmara Sea, is an indicator that earthquake activity continues in the region. Aftershocks play a crucial role in seismicity research and seismic hazard assessments in terms of providing data and usable information in the examination of seismic dynamics with the changes observed in their time-dependent behavior and regional distribution. In this study, the aftershocks of the Silivri earthquake were examined as a natural laboratory using nonlinear analysis methods. Within the scope of the study, aftershocks of the Silivri earthquake were analyzed with a hybrid artificial neural network as well as different neural network structures, and for this purpose, data from 361 aftershocks with a magnitude greater than 1.5 in the year following the earthquake were used.

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1. INTRODUCTION

Earthquakes, the effects of which can last for many years due to the physical, economic, psychological, and social damages they cause, are of vital importance for Türkiye, which is located on the most active earthquake zone called Mediterranean-Alpine-Himalayan and where many earthquakes occur at frequent intervals resulting in serious loss of life and economic loss (Chang et al., 2024). The North Anatolian Fault (NAF) is one of the most important tectonic elements of Türkiye and is the fastest-moving right-lateral and strike-slip active fault zone consisting of many segments (Bolt, 1993). The NAF, which is known in the world earthquake literature for its westward migration and earthquakes of very high magnitudes, is divided into two main branches: the southern branch, which passes south of Lake Iznik and connects to the Gemlik Bay, and the

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northern branch, which extends to the Gulf of Izmit and passes through the Marmara Sea and connects to the Ganos Fault (Türker, 2021).

Linearity refers to the direct proportionality of the output of a system to its input. In linear systems, small changes lead to small changes and the behavior of the systems can be predicted. Nonlinearity is when the output of a system is not directly proportional to the input. In nonlinear systems, small changes can lead to large changes and the behavior of the systems can be unpredictable (Hilborn, 2003). Earthquakes are nonlinear systems caused by the movements of the earth's crust. For example, small-scale fault movements can lead to earthquakes and small changes can lead to large earthquakes. In other words, the dynamics of seismicity involve nonlinear elements and processes (Takanashi et al., 1975).

Earthquake predictions are of great importance in minimizing the possible risks of earthquakes. These prediction studies are very important in terms of being able to predict seismic hazards and manage the emergency system. As mentioned above, earthquakes have dynamics that contain nonlinear elements (Kamgar et al., 2022). Therefore, in the analysis of such dynamic systems, it is possible to refer to the analysis methods carried out within the framework of chaos theory (Çalım et al., 2023). Chaos theory focuses on examining nonlinear irregular systems (Davies, 1999). These systems can produce large results even with small changes and exhibit unpredictable behaviors. This theory is widely studied in mathematics, physics, biology, economics, social sciences, and other branches of science. One of the important characteristics of chaos is that chaotic systems are extremely sensitive to initial conditions (Abarbanel et al., 1993).

All interdisciplinary studies carried out to minimize the possible risks of earthquakes are of great importance. In addition, regarding both preparations and precautions before earthquakes and the accuracy and applicability of decisions taken during and after earthquakes, it is also very important to gain appropriate attitudes and behaviors by using the symbols and icons related to earthquakes effectively. In this phenomenon, which can be referred to as earthquake literacy (Gurel, 2024), studies and research that bring together different disciplines, such as communication, engineering, science, and earth sciences, are of vital importance. In the digital age we live in, it is possible to raise public awareness about natural disasters such as earthquakes through the widespread use of traditional media tools as well as rapidly developing new media (internet, social media, etc.) and to provide society with the ability to be minimally affected by the possible risks of earthquakes through earthquake literacy.

Among machine learning techniques, artificial neural networks (ANNs) are particularly preferred because they do not require any prior assumptions or knowledge about the system and can learn by adapting parameters on their own using the data obtained (Mignan & Broccarda, 2020), unlike model-based techniques where success is directly related to the accuracy and completeness of the model. Alves has undertaken one of the first studies in which ANNs were used in the field of earthquake prediction (Alves, 2006). Based on the fact that both systems have a chaotic structure, the author applied a method similar to financial forecasting applications for earthquake prediction. In Lakshmi and Tiwari (2007), a similar approach was used to predict earthquakes in three regions of the Himalayas (central, western and northeastern). The authors created a time series using the number of earthquakes that occurred in each month in the relevant regions between 1960 and 2003 and tried to predict the number of earthquakes that will occur in the next month using 5-month windows in this time series. The earthquake prediction studies conducted by Moustra et al. (2011) for the Greek region consist of two main parts. In the first part of the study, the focus was on estimating the next day's largest seismic event using only time series and earthquake magnitude data, while in the second part, seismic electrical signals (SES) were used to estimate the magnitude of the next seismic event. ANN was preferred in both studies, and a time series containing the maximum seismic activity magnitudes recorded for each day between 1980 and 2001 was used to determine the input signals of the ANN used in the first part of the study. In the above-mentioned studies, time and/or magnitude information of previous earthquakes was used as the basis for earthquake estimation in a specific region. Although the results obtained are promising, many researchers have argued that these data alone are not sufficient for earthquake modeling and that additional indicators are required. Eight seismic indicators were proposed to estimate the magnitude of the largest seismic event that could occur in a predefined time interval and in a given area (Panakkat & Adeli, 2007). These suggested indicators were widely accepted by researchers in the field of seismology and used in many studies. In the study (Panakkkat et al., 2007), the magnitudes of the earthquakes were divided into various classes according to the Richter scale and these classes were used as the outputs of the ANN, and the inputs of the network were these 8 indicators suggested by the authors. As a result of their studies, the authors determined that probabilistic neural networks provide better predictions for small and medium-sized earthquakes with magnitudes ranging from 4.5 to 6.0, while cyclic neural networks provide better predictions for larger earthquakes.

Aftershocks are very important in seismic hazard studies in terms of providing usable information. The 5.8 magnitude (M=5.8) Silivri earthquake, which occurred in the part of the NAF zone passing through the Marmara Sea and recently occurred on this fault line (Utkucu et al., 2023), is an indicator that earthquake activities continue in the region. In this study, the aftershocks of the 2019 Silivri earthquake are examined as a natural laboratory using nonlinear analysis methods. In addition, hybrid structures using ANNs together with other machine learning techniques and computational intelligence methods have become a widely used method by many researchers recently (Konstantaras et al., 2008; Joelianto et al., 2009; Zamani et al., 2013; Asim et al., 2017). In this study, aftershocks of the 2019 Silivri earthquake were analyzed with a hybrid artificial neural network as well as different neural network structures. For this purpose, data from 361 aftershocks with magnitudes greater than 1.5 in the year following the earthquake were used. The data in the study were obtained from the earthquake catalogs of the Disaster and Emergency Management (AFAD) and the Kandilli Observatory Earthquake Research Institute (KOERI). Since the distribution of earthquake stations of the institutions whose data will be used is not homogeneous, the number of earthquakes in the catalogs of the institutions for different regions or the quality of their solutions vary. In the studies conducted within the scope of the article, data recorded and cataloged by active earthquake stations were included. Thus, the aftershocks of an earthquake occurring in our Türkiye can be analyzed in detail with the methods presented in this study, which have a unique value for modeling seismic time series and making seismic hazard predictions.

2. MATERIAL AND METHOD

Many of the processes in nature are complex and mutually related. In this respect, dynamic systems can describe events that occur in nature, such as earthquakes. Very few dynamic systems are inherently isolated from the environment and form a whole within themselves. Due to a nonlinear variable in a model that defines a dynamic system, unpredictable dynamics may occur in the system. Chaos theory and nonlinear analysis techniques are used to analyze such unpredictable dynamics.

The first step in the nonlinear analysis techniques, which constitute the analysis methods applied in this study, is the collection of data based on experiments and observations and the extraction of reliable data to be used. AFAD and KOERI earthquake catalogs were combined to obtain the final catalog. In the first stage, the AFAD and KOERI catalog data were filtered according to the study area corner coordinates. In the merging of the catalogs of the two institutions, if there was a difference of more than 5 s between earthquakes that were close in time, both events were processed in the catalog as separate earthquakes. A locational query was also performed for two events that were smaller than 5 s in time. At this stage, earthquakes with a difference of more than 0.2 degrees in latitude and longitude were also considered as separate events and both events were processed in the catalog. In the events that did not meet the criteria, AFAD data was processed in the events after 2012 and KOERI data was processed in the events before. Time series, phase space, power spectrum and recurrence graphs were obtained using these seismic data.

2.1. Time Series

Time series is a concept that refers to the frequency of data that can be measured at periodic time intervals. Time series are sequences of data recorded at a given time taken at equidistant time points. Time series analysis is a method for examining how data changes over time. It allows the extraction of meaningful statistics that can be attributed to dependency relationships between observations and is used to model, predict, and understand recurring events over time. This process includes the mathematical construction of the phase space with the obtained time series data using sampling and sorting methods (Cambel, 1993; Scott, 1999; Rızaoğlu & Sünel, 2011; Devaney, 2021; Simuratli, 2023).

2.2. Phase Space Structures

The first step for nonlinear analysis is to reconstruct the signal in the form of data in phase space. Thus, it is possible to obtain information about the entire phase space of the system thanks to the time series recorded from the system while analyzing the system. It is shown as a scalar measurement. The scalar measurement is denoted as $x(t_0 + n\tau_s) = x(n)$, where t_0 is the start time and τ_s is the sampling time used in the experiment. Phase space is a mathematical space consisting of all possible states of the dynamic system and is a concept frequently used in the analysis of dynamic systems. Each state corresponds to a point in the phase space and shows all possible states of this system on a single graph. Time of analysis describes the motion or evolution of the system as the movement of a point in phase space, and this movement can be expressed by a mathematical model of the system. Phase space analysis can be used to understand various properties of a dynamic system (Cambel, 1993; Scott, 1999; Rızaoğlu & Sünel, 2011; Devaney, 2021; Simuratli, 2023).

2.3. Power Spectrum

It is possible to distinguish a chaotic signal from a non-chaotic signal by looking at its power spectra. Periodic signals give spikes (peaks) at certain frequencies, while if the signal is chaotic, it gives broadband components in the power spectrum. The power spectrum is also known as the energy spectral density. The power spectrum of the phase space of a system is a powerful tool for understanding the fundamental physical processes that drive the behavior of the system. It can be used to study a wide range of phenomena in many scientific fields, from the behavior of simple oscillators to the dynamics of complex systems such as the earth's climate (Cambel, 1993; Scott, 1999; Rızaoğlu & Sünel, 2011; Devaney, 2021; Simuratli, 2023).

2.4. Recurrence Plots

One way to visualize the recurring nature of states by their trajectory through a phase space is the recurrence plot proposed by Eckmann et al. In chaos theory, a recurrence plot is a plot that shows, for each moment i in time, the times at which the state of a dynamical system returns to the previous state in i, i.e., when the phase space trajectory rotates. In an iteration, the trajectory returns to a previously visited position (state) in phase space, up to a small error of ε (Cambel, 1993; Scott, 1999; Rızaoğlu & Sünel, 2011; Devaney, 2021; Simuratli, 2023).

2.5. Forecasting Studies with Artificial Neural Networks

A total of 361 aftershocks with magnitudes greater than Mw=1.5 were recorded in the year following the earthquake that occurred off the coast of Silivri on September 26, 2019. Nonlinear time series generated using the data from these earthquakes have been used to create predictive models in the field of earthquake seismology. In this study, artificial neural networks (ANN), long short-term memory (LSTM) networks, convolutional neural networks (CNN), echo state networks (ESN) and adaptive network-based fuzzy inference system (ANFIS) were used for prediction studies on aftershocks of the earthquake. 361 aftershock data for the aftershocks after the Silivri earthquake were obtained from catalogs. 300 of the obtained data were used to create the training time series of the networks, and the remaining 61 were used to create the test time series. In the studies, the magnitude of the aftershocks, the distance between two consecutive shocks, and the duration of raw seismic data were used as input signals for networks with different architectures.

The most typical form of feed-forward artificial neural network structures can be established by sequentially combining layers formed from neurons. The layer to which the inputs are applied is called the input layer, and the layer from which the outputs are received is called the output layer. In this structure, there may be one or more hidden layers between the input layer and the output layers.

In this study, various earthquake characteristics, such as magnitude, duration, and distance between consecutive aftershocks, were employed to estimate the characteristics of the next aftershock. For this purpose, (n, n-1, n-2, 0)-step delayed time series of consecutive aftershocks are applied to the input connections of artificial neural networks to predict the characteristics of the next aftershock. The error value calculated by comparing the obtained output value with the relevant characteristics of the next aftershock was used in the training of the network with gradient descent-based learning algorithms. After the error value was calculated for the first input data, the time window was shifted one step, and the same processes were repeated until the entire data set was covered.

For the ANNs, the number of layers and number of neurons in each layer can be called among the parameters that have the most effect on the performance of the ANNs. Although increasing the number of layers might enable the network to capture more complex data, it can also lead to the overfitting problem. Similarly, increasing the number of neurons in a layer can help the network capture more features and thus increase the accuracy; it can also lead to the overfitting problem. In the current study, as the number of available data points is limited, the number of hidden layers has been restricted to one, and the best performance has been attained for 50 neurons. The time window size is the same as the number of neurons in the input layer. After normalization, the time series data were applied to the network as the input signal. In training the network, the learning coefficient was selected as 0.25 and the momentum coefficient as 0.1. In another study, the long short-term memory (LSTM) neural network architecture, which has the ability to learn long-term connections with its memory transition mechanism, was used. The most important feature that distinguishes the LSTM network, which is frequently preferred in time series prediction, from the traditional ANN structure is the presence of forget gates and memory cells that provide “remembering” for the neurons in the hidden layer. To better understand the effects of the forget gates and memory units on the performance, the same number of LSTM cells, 50, as the number of hidden neurons in ANN has been utilized. The output cell consists of a single neuron. The learning coefficient was determined as 0.1 using empirical methods.

In addition to these two methods, which are frequently used in time series forecasting, the echo state network (ESN) architecture was also applied to the nonlinear time series of aftershocks since aftershocks are found to exhibit chaotic characteristics. The most important features that distinguish this network from other architectures, which have a recurrent neural network structure, are that the weights between the input-hidden layer ('reservoir') are randomly assigned and not trained, the hidden layer is very sparsely connected, and learning is provided only by adapting the weights between the output layer and the reservoir. In addition to these structural features, since learning in echo state networks is performed at once for the entire data set with the linear regression method, it is possible to solve the prediction problem very quickly compared to networks with the traditional backpropagation networks. In the literature, it was observed that the applications where ESNs were previously used in the field of earthquake prediction were very limited. In general, increasing the reservoir size helps to capture more intrinsic patterns; however, if the training data is limited, this might increase the risk of overfitting. In the present study, the best performance has been attained for a reservoir size of 750 neurons while keeping only five percent of the connections active (non-zero).

Due to the limited size of the available data, two convolutional layers, each followed by a max pooling layer, have been employed for the CNN architecture. To avoid overfitting, the maximum kernel size and the number of filters have been set to 10 and 3, respectively, as larger values of these parameters result in better performance for training but lower accuracy in the testing part.

The prediction performance of ANFIS highly depends on the number of membership functions. More membership functions enable a finer input space division but also make the training process more difficult and time-consuming as the number of adaptable parameters increases with the number of membership functions. In the present study, three membership functions were used to “fuzzify” each input signal (Simuratli, 2023) as the simulations for higher values of membership functions take considerably longer time while better performance couldn’t be attained.

3. RESULTS AND DISCUSSION

Aftershocks play a crucial role in seismicity research and seismic hazard assessments in terms of providing data and usable information in the examination of seismic dynamics with the changes observed in their time-dependent behavior and their regional distribution. The 5.8 magnitude Silivri earthquake, which occurred on September 26, 2019 at 13:59 off the coast of Silivri and in the part of the NAF zone passing through the Sea of Marmara, is a medium-high magnitude earthquake that occurred on this fault line recently and has been observed that earthquake activities continue in the same region. Considering the earthquakes that may occur in the future in this region, the examination of the aftershocks of the Silivri earthquake by means of the techniques proposed within the scope of this study and the nonlinear time series modeling will be the first time in the literature that the aftershocks of an earthquake have been examined with methodologically original techniques. The time series, phase space structure, power spectrum, and recurrence graphs obtained for the Silivri earthquake aftershocks are given in Figure 1, 2, 3 and 4:

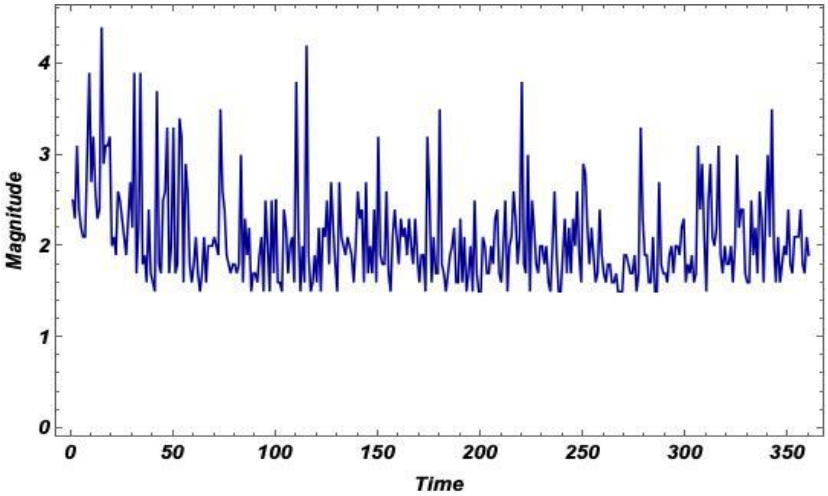

Figure 1. *Time Series Graph for Silivri Earthquake Aftershocks*

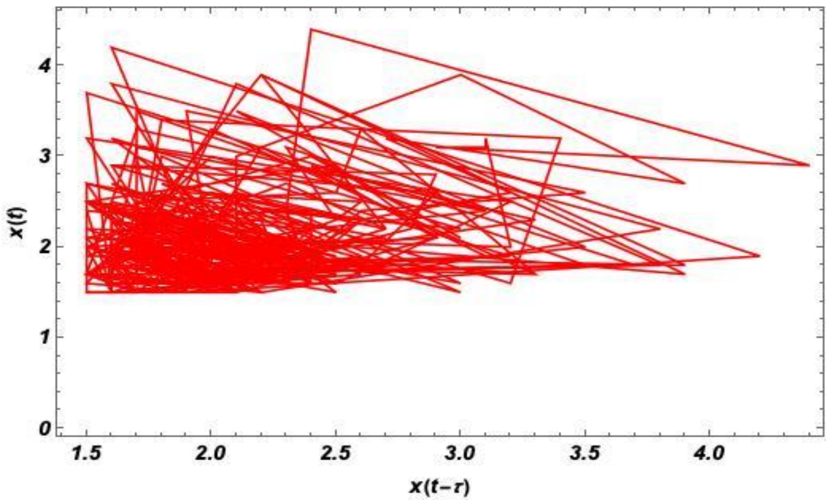

Figure 2. *Phase Space for Silivri Earthquake Aftershocks*

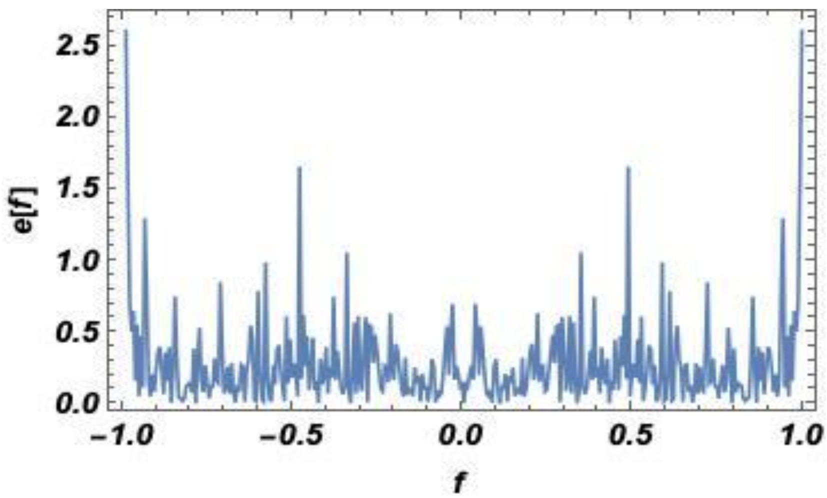

Figure 3. *Power Spectrum Graph for Silivri Earthquake Aftershocks*

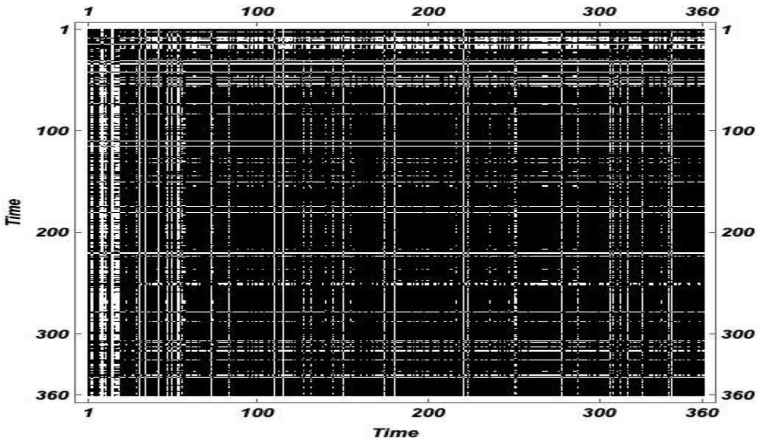

Figure 4. *Recurrence Graph for Silivri Earthquake Aftershocks*

The time series graph for the Silivri earthquake data is given in Figure 1. The data obtained by experiment, measurement or observation and characterizing the behavior of any dynamic system constitute the time series of the system. These are the values that the variables describing the system can take. We can see the change of the time series by drawing the graph of this data according to time or iteration step. If the change in question does not occur according to any order, but is completely random and irregular, the behavior of the system determined by these numbers may indicate chaos. Since there can be a very large number of numerical values in the time series, it is not easy to understand whether the time series contains any order by just looking at the graph we mentioned above. In order to understand the existence of order in the time series, it is necessary to perform other analyses such as phase space structure, power spectrum, and recurrence graphs. The phase space, where each state of the dynamic system is represented by a point in the phase space of the system, is presented in Figure 2, the power spectrum in Figure 3 and the recurrence graph in Figure 4. The results given in Figures 1, 2, 3 and 4 show that the dynamics of the aftershocks of the 2019 Silivri earthquake contain chaotic elements. In addition, the maximum Lyapunov exponent was determined as 0.00872464 using the code written in Python programming language. In addition to the results given above, the fact that the maximum Lyapunov exponent calculated for the data set was positive is another important indicator that the seismic process is chaotic.

In the prediction studies carried out with different neural network architectures, 300 of the 361 aftershocks recorded were used for training, and the remaining 61 were used to test the performance of the network used. In the studies carried out using different time window sizes for five different network architectures, raw seismic data of the magnitude of the earthquakes, the distance between two consecutive shocks and the duration were used. Root mean squared error (RMSE) values were calculated to evaluate the performance of different models. The simulations have been carried out five times, and average RMSE values have been reported Table 1. When this table is examined, it is seen that increasing the time window size does not always provide better results due to the overfitting problem resulting from the limited number of data.

Table 1. *RMSE values obtained for different architectures*

Magnitude						
	RMSE	**h=1**	**h=3**	**h=5**	**h=8**	**h=10**
ESN	**Training**	0.391	0.303	0.286	0.287	0.264
	Test	0.575	0.592	0.618	0.618	0.624
LSTM	**Training**	0.432	0.412	0.423	0.421	0.418
	Test	0.511	0.492	0.487	0.493	0.490
ANN	**Training**	0.469	0.429	0.427	0.424	0.412
	Test	0.535	0.553	0.556	0.540	0.534
CNN	**Training**	0.384	0.392	0.420	0.431	0.455
	Test	0.594	0.528	0.545	0.530	0.486
ANFIS	**Training**	0.462	0.424	0.444	0.436	0.432
	Test	0.514	0.523	0.506	0.512	0.498

Table 1. *continued*

Distance between two consecutive aftershocks						
	RMSE	**h=1**	**h=3**	**h=5**	**h=8**	**h=10**
ESN	**Training**	3.416	3.379	3.364	3.389	3.393
	Test	3.706	3.769	3.548	3.999	3.816
LSTM	**Training**	3.523	3.137	3.266	3.357	3.416
	Test	4.081	4.318	4.264	4.258	4.175
ANN	**Training**	3.755	3.742	2.738	3.742	3.732
	Test	3.571	3.697	3.862	4.014	4.088
CNN	**Training**	3.726	3.628	3.625	3.612	3.611
	Test	4.732	4.541	4.651	4.696	4.783
ANFIS	**Training**	3.487	3.224	3.554	3.678	3.592
	Test	4.143	4.458	4.511	4.486	4.481
Time between two consecutive aftershocks						
	RMSE	**h=1**	**h=3**	**h=5**	**h=8**	**h=10**
ESN	**Training**	0.123	0.113	0.101	0.092	0.091
	Test	0.938	0.991	1.132	1.095	1.030
LSTM	**Training**	0.115	0.089	0.078	0.065	0.082
	Test	0.921	0.835	0.844	0.868	1.027
ANN	**Training**	0.233	0.234	0.235	0.236	0.237
	Test	1.276	1.303	1.320	1.366	1.400
CNN	**Training**	0.131	0.132	0.182	0.119	0.117
	Test	1.073	1.340	1.156	1.231	1.257
ANFIS	**Training Training m**	0.164	0.298	0.265	0.242	0.241
	Test	0.942	0.975	0.969	0.961	0.956

4. CONCLUSION

Within the scope of this study, our main objective in time series analysis is to identify the dynamics underlying the seismicity and to make prediction studies in accordance with the dynamics. Before nonlinear time series modeling is performed, the identification and analysis of the nonlinear system is performed, which constitutes the most important part of the work. In this study, the aftershocks of the 2019 Silivri earthquake (Mw = 5.8) that occurred in the Marmara Region of the NAF zone and recently off the coast of Silivri were examined and dynamic analysis of tectonic movements in the epicenter region after an earthquake was performed. The magnitudes of these aftershocks within certain periods were reconstructed in the signal phase space in the form of scalar data, and it was determined whether the data was random, periodic, or chaotic. Phase space structures were constructed by obtaining the time series of the data. In addition, the aftershocks of the 2019 Silivri earthquake were analyzed using a hybrid artificial neural network. Other analyses and numerical results obtained are given in detail under the subheadings above, and as a result of the analyses, the time delay from the time-dependent data of the Silivri earthquake's aftershocks was found to be 1 month and the embedding size for this delay time was calculated as 4. In addition, the maximum Lyapunov exponent for this time series was found to be 0.00872464. These results show us that there is a chaotic structure in the dynamics of the 2019 Silivri earthquake's aftershocks. These results provide us with the opportunity to use the techniques, algorithms, and models we use in many nonlinear dynamic systems in earthquake analysis, modeling, and prediction studies.

The results we obtained for the 2019 Silivri earthquake, which is the subject of this article, show the suitability of using these techniques in earthquake prediction studies. By looking at the Lyapunov exponents obtained with fault-based data, comparative evaluations can be made for each earthquake magnitude data. For example, by using the data produced by only one fault, the change in the Lyapunov exponents in the system in the temporal evolution can be examined. The earthquake generating activity of the fault over time and its positivenegative effects on triggering a new earthquake can be discussed. A new perspective can be gained for earthquake predictions by extracting the long-term temporal evolution of a fault that has produced a large earthquake and by nonlinear analysis of the time series to be created. More reliable prediction studies can be carried out by observing the dynamics of the time series created with data taken at certain time intervals and the changes in the Lyapunov exponents in dynamic systems such as earthquakes.

AUTHOR CONTRIBUTIONS

Conceptualization, F.A. and Y.Ö.; methodology, F.A., Y.Ö and E.T.; software, F.A., Y.Ö, E.S. and E.T; title, F.A.; validation, F.A., Y.Ö., A.K.M. and İ.K.; formal analysis, F.A., Y.Ö., E.S. and İ.K.; research, F.A. Y.Ö., E.S., E.T., A.K.M., D.Ç., İ.K., H.T. and Z.Ç.; sources, E.S., E.T., A.K.M. and Z.Ç.; data curation, F.A., Y.Ö., E.S.; manuscript-original draft, F.A.; manuscript-review and editing, Y.Ö., İ.K., A.K.M. and H.T.; visualization, F.A., E.T., Y.Ö., D.Ç. and E.S.; supervision, F.A.; project management, F.A. All authors have read and legally accepted the final version of the article published in the journal.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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