Yayın Geliş Tarihi (Submitted): **10/10/2023**

Yayın Kabul Tarihi (Accepted): **18/01/2024**

Makele Türü (Paper Type): **Araştırma Makalesi – Research Paper**

Please Cite As/Atıf için:
Demirbay, S. G. and Karakaş, E. (2024), Exploing the ecological footprint in Turkey: Analysing the interplay of economic and environmental factors, *Nicel Bilimler Dergisi*, 6(2), 128-157. *doi: 10.51541/nicel.1373907*

EXPLORING THE ECOLOGICAL FOOTPRINT IN TURKEY: ANALYZING THE INTERPLAY OF ECONOMIC AND ENVIRONMENTAL FACTORS

Sevim Gülin DEMİRBAY[1] and Esra KARAKAŞ[2]

ABSTRACT

Nowadays, the world is facing increasing ecological issues due to the rapid growth of the population, the expansion of industrial activity, the fast urbanization process, and the higher levels of consumption. As a result of the current ecological problems, there has been an unchecked increase in the demand for natural resources. This study identified the independent variables that influence the ecological footprint as the Gross Domestic Product (GDP), KOF Globalization Index (KOFGI), and Natural Resource Rent (NRR). The Markov chains approach was used to anticipate the movements of the dependent and independent variables in the future period. Frequency and transition probability matrices were then generated. The dependent and independent variables for the next period were compared to the actual values, and the accuracy of the predictions made using Markov chains was demonstrated. A model of an Artificial Neural Network (ANN) was created to accurately predict the value of the dependent variable. The ANN modeling was used to estimate the ecological footprint, taking into account the values of Turkey's GDP growth rate (% per year), NRR (as a percentage of GDP), and KOF Globalization Index data from 1970 to 2016. The Feed-Forward Backpropagation Method, which is a type of multi-layer network model, was utilized for the

[1] Corresponding Author, Res. Asst., Department of Business Administration, Faculty of Economics, Administrative and Social Sciences, Adana Alparslan Türkeş Science and Technology University, Adana, Türkiye. ORCID ID: https://orcid.org/0000-0003-3878-0332
[2] Assoc. Prof. Dr., Department of Business Administration, Faculty of Economics, Administrative and Social Sciences, Adana Alparslan Türkeş Science and Technology University, Adana, Türkiye. ORCID ID: https://orcid.org/0000-0002-8333-3091

modeling process. The Levenberg-Marquardt optimization algorithm was employed as the network training function to update the weight and deviation values of the network. The study's findings indicate that the dataset as a whole has a significant level of agreement with the model's correctness, with a close proximity of 99.316%. Based on the collected results, it can be inferred that the developed artificial neural network (ANN) model has a notable level of precision in calculating the Ecological Footprint.

Keywords: Artificial Neural Networks, Ecological Footprint, Sustainable Development, Environmental Factors, Economic Factors, Markov Chain

TÜRKİYE'DEKİ EKOLOJİK AYAK İZİNİ ARAŞTIRMAK: EKONOMİK VE ÇEVRESEL FAKTÖRLERİN ETKİLEŞİMİNİ ANALİZ ETMEK

ÖZ

Günümüzde dünya, nüfusun hızla artması, endüstriyel faaliyetlerin yaygınlaşması, hızlı kentleşme süreci ve artan tüketim düzeyleri nedeniyle giderek artan ekolojik sorunlarla karşı karşıyadır. Mevcut ekolojik sorunların bir sonucu olarak doğal kaynaklara olan talepte kontrolsüz bir artış yaşanmaktadır. Bu çalışmada, ekolojik ayak izini etkileyen bağımsız değişkenler Gayri Safi Yurtiçi Hasıla (GSYİH), KOF Küreselleşme Endeksi (KOFGI) ve Doğal Kaynak Kirası (NRR) olarak tanımlamıştır. Bağımlı ve bağımsız değişkenlerin gelecek dönemdeki hareketlerini tahmin etmek için Markov zincirleri yaklaşımı kullanıldı. Daha sonra frekans ve geçiş olasılığı matrisleri oluşturuldu. Bir sonraki döneme ait bağımlı ve bağımsız değişkenler gerçek değerlerle karşılaştırılarak Markov zincirleri kullanılarak yapılan tahminlerin doğruluğu ortaya konuldu. Bağımlı değişkenin değerini doğru bir şekilde tahmin etmek için bir Yapay Sinir Ağı (YSA) modeli oluşturuldu. YSA modellemesi, 1970'den 2016'ya kadar Türkiye'nin GSYİH büyüme oranı (yıllık yüzde), NRR (GSYİH yüzdesi olarak) ve KOF Küreselleşme Endeksi verileri dikkate alınarak ekolojik ayak izini tahmin etmek için kullanıldı. Modelleme işleminde çok katmanlı ağ modelinin bir türü olan İleri Beslemeli Geri Yayılım Yöntemi kullanılmıştır. Ağın ağırlık ve sapma değerlerini güncellemek için ağ eğitim fonksiyonu olarak Levenberg-Marquardt optimizasyon algoritması kullanıldı. Çalışmanın bulguları, bir bütün olarak veri kümesinin modelin doğruluğu ile %99,316'ya yakın bir düzeyde anlamlı düzeyde uyum içinde olduğunu göstermektedir. Toplanan sonuçlara dayanarak geliştirilen yapay sinir ağı (YSA) modelinin Ekolojik Ayak İzi hesaplamasında dikkate değer düzeyde bir hassasiyete sahip olduğu sonucuna varılabilir.

Anahtar Kelimeler: Yapay Sinir Ağları, Ekolojik Ayak İzi, Sürdürülebilir Kalkınma, Çevresel Faktörler, Ekonomik Faktörler, Markov Zincirleri

1. INTRODUCTION

The consumption patterns of individuals have started to undergo transformation due to factors such as fast population expansion, industrialisation, technological advancements, and urbanization. The alteration in consumption patterns has given rise to environmental challenges that pose a significant threat to the survival of organisms on a worldwide level (Özsoy and Dinç, 2016; Demirbay and Gündüz, 2023). With the increase in environmental problems, environmental awareness has begun to increase (Tunç et al., 2012). The notion of ecological footprint has emerged as a result of increased environmental consciousness, hence providing a quantifiable means of assessing sustainability. In recent years, the ecological footprint has gained popularity as a metric for assessing environmental damage (Tosunoğlu, 2014; Solarin and Bello, 2018). The ecological footprint is a quantification of the quantity of natural resources, specifically waterways, that are biologically necessary to sustain the production of all resources consumed by an individual, a community, or a collection of activities (Rudolph and Figge, 2017). It is measured in the global hectare area (kha). In short, it is defined as renewable natural resources used for the production of consumed products by a community or individual (WWF,2012). The discrepancy between resource consumption and production in Turkey suggests the presence of an ecological deficit inside the country (Global Footprint Network, 2021).

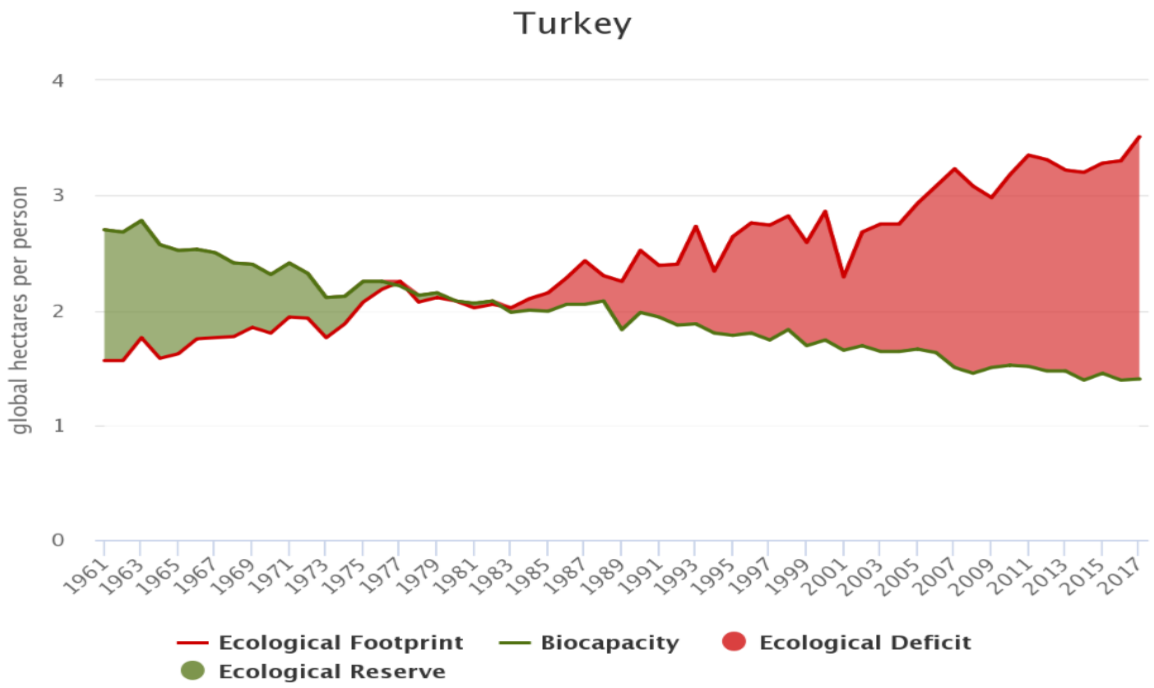

Figure 1. Change of ecological footprint and biocapacity over the years (Global Footprint Network, 2021)

Based on the 2021 data given by the Global Footprint Network, Figure 1 shows that Turkey reached a notable milestone in 1977 when its ecological footprint exceeded its biological capacity. This marked the beginning of a trend characterized by subsequent annual growth in the ecological footprint. As a result, this occurrence has caused a noticeable increase in ecological transparency. According to data from the Global Footprint Network (2021), the ecological footprint had a notable growth in 2007, reaching a value of 3.51 gha, which was about 2.5 times higher than the corresponding biocapacity of 1.4 gha. After 1989, Turkey's import of natural resources surpassed its export of natural resources. Subsequently, there has been a notable escalation in the ecological trade imbalance.

A notable association has been observed between heightened dependence on environmental resources and an elevated Ecological Footprint Index (ECF) inside developing countries, thereby resulting in a deterioration of environmental conditions (Pata et al., 2021).

The decisions made by decision-making units are subject to alter based on anticipated future circumstances. The efficacy of foresight performance holds significant significance for decision-making entities in order to effectively implement appropriate policies (Altan, 2008). According to Ataseven (2013), the notion of foresight refers to the estimation of potential values that a specific variable may assume in subsequent time periods, based on specific assumptions. Artificial Neural Networks (ANN) have gained significant popularity in recent years as a predictive tool. The present study employed the Artificial Neural Network (ANN) methodology to provide predictions pertaining to the ecological footprint. Artificial Neural Networks (ANNs) possess several key characteristics, including computational capabilities, information processing abilities, learning mechanisms, and the capacity for generalization. The subject of study in question is experiencing a steady growth in research because to its ability to effectively address intricate nonlinear challenges (Ergezer et al.,2003).

Initially, an investigation was conducted utilizing Artificial Neural Networks to analyze the correlation between the independent factors, namely economic and environmental variables, and the Ecological Footprint. Artificial neural networks (ANNs) are computational models designed to enhance the impact on the dependent variable by quantifying the influence of each parameter and amplifying the coefficient of the parameter with the greatest influence. The study used the KOF globalization index, GDP, and natural resource rent (per GDP) as the independent variables influencing the ecological footprint.

Several research have been conducted in the existing body of literature to ascertain the factors that influence the ecological footprint. In their comprehensive study encompassing 146 nations, Rudolph and Figge (2017) conducted an analysis to investigate the influence of globalization on the ecological footprint. The study employed the Extreme Bound Analysis (EBA) technique to examine the relationship between the general globalization index and ecological footprints. The findings of the study revealed a statistically significant and positive association between these two variables. Social globalization has a good impact on imports and exports, but it has a negative effect on the ecological footprint through production and consumption. Furthermore, the study conducted by Kirikkaleli et al. (2021) examined the influence of globalization on the ecological footprint of Turkey. The researchers employed a binary fit methodology to regulate energy usage, foster economic development, and promote trade openness in their study. Based on the findings of the research, it is evident that globalization exhibits a favorable association with the ecological footprint over an extended period. Additionally, trade openness demonstrates a reduction in the ecological footprint in the immediate term, albeit temporarily. Furthermore, the rise of GDP exerts a detrimental influence on the ecological footprint, both in the short and long run.

Additionally, the study also investigated the impacts of several additional variables. In a recent study conducted by Altay Topçu (2021), an examination was undertaken to assess the impact of import, export, and renewable energy consumption on Turkey's ecological footprint.

The investigation encompassed the period spanning from 1990 to 2015. The study employed the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. Based on the conducted assessments, it has been discovered that the rate of natural resource use exceeds the rate of production, indicating a progressive expansion of the ecological deficit. The author stated that prioritizing the utilization of renewable energy over fossil fuel-based energy is imperative in order to circumvent this particular dilemma. Demirbay and Gündüz (2023) employed the Neural Network Adaptation Model in MATLAB to construct Artificial Neural Networks (ANN) utilizing data from 1996-2018, with the aim of approximating Turkey's ecological footprint. The independent variables chosen were Urban Population, Renewable Energy Consumption, RandD Expenditures, and Human Development Index. The Levenberg-Marquardt approach was employed to ascertain the optimal number of hidden layers and the number of hidden neurons in each layer for the artificial neural network (ANN). The artificial neural network was trained using feedforward and backpropagation algorithms. The training, testing, and validation groups were assigned R values of 0.999, 0.948, and 1, respectively.

Based on the acquired results, it has been concluded that the independent variable with the most significant influence on the ecological footprint is Urban Population. Pata et al. (2021) accomplished a comprehensive investigation to examine the relationship between economic growth and environmental degradation. The ECF index is utilized as a quantitative and qualitative measure for assessing and describing environmental deterioration. The significance of ECF lies in its capacity to effectively represent the extent of human dependence on natural resources. This study deviates from prior studies by examining the impact of globalization control, renewable energy consumption (REN), human development index (HDI), and natural resource rents (NR rents) on environmental quality, rather than exclusively focusing on GDP as a metric. During the data collection portion of the study, the primary focus was on analyzing the ten countries with the largest ecological impact on a global scale. The research results suggest that there is a positive correlation between a larger richness of natural resources and an increasing ecological footprint. Conversely, a higher dependence on renewable energy sources is linked to a decrease in environmental damage. This study employed Artificial Neural Networks (ANN) to construct a predictive model for the Ecological Footprint. The model incorporated key economic and environmental factors, including Gross Domestic Product (GDP), Natural Resource Rent (NRR), and the Keep Our Forests Green Index (KOFGI). The independent factors in this study were GDP (% annual rise), NRR (% of GDP), and KOFGI, while the dependent variable was the ecological footprint. The definition of these independent variables can be elucidated as follows.

- The term GDP (Costanza et al., 2014) is used to describe the monetary value of products and services that are generated inside a country's borders over a specific period of time.
- The user's text does not contain any information to rewrite. The aggregate of oil, natural gas, coal (both hard and soft varieties), mineral rents, and forest rents constitutes the entirety of natural resource rents. Natural resource rent estimates are derived from the disparity between the price of a commodity and its average production cost (World Bank Group, 2021).
- According to Gygli et al. (2019), the KOFGI framework distinguishes between the economic, social, and political aspects of globalization. The KOFGI is a comprehensive composite index that quantifies the degree of globalization for nearly all countries worldwide, on a scale ranging from 1 (indicating little globalization) to 100 (representing maximal globalization). Annually, the data undergoes updates, accompanied by the inclusion of a new year (Haelg, 2020).

2. METHODOLOGY

2.1. Markov Chain

Markov chain analysis is a highly extensive area of study within the field of stochastic process theory. It was named after the Russian scientist Andrei Markov and emerged in the early 20th century (Şafak vd.,2023). The Markov chains technique is employed to forecast the forthcoming states of variables by constructing a model based on the historical data of their previous states (Kıral and Kaplan, 2023). The Markov chains method is a stochastic methodology employed to examine stochastic systems. If the probabilities of future steps in a process can be calculated only based on the current condition and are independent of previous situations, the process is said to possess Markov qualities (Ross, 2007).

Markov modeling was developed to forecast the future changes and percentage shifts of both dependent and independent variables in the subsequent time period. When modeling the dependent variable, the ecological footprint, the percentage decreases between the ecological footprint and the next year's value are categorized as N1 if they are less than the median value of 0.02, and as N2 if they are more. If the percentage increase of the ecological footprint between the next year's value is less than 0.07, which represents the median value, it is classified as P1. Conversely, if the increase is greater than 0.07, it is classified as P2.

For any non-negative integer n ($n \geq 0$), and any elements i and j in the countable set S ($i, j \in S$),

$$P\{X_{n+1} = j | X_0, \ldots, X_n\} = P\{X_{n+1} = j | X_n\}$$

$$P\{X_{n+1} = j | X_n = i\} = p_{ij}$$

Markov chain is a stochastic process that meets the requirements $X = \{X_n : n \geq 0\}$ (Kıral et al., 2018). p_{ij} represents the probability of transitioning from state i to state j in a Markov chain. It is determined using conditional probabilities derived from the preceding circumstances. The probabilities must adhere to the constraint that the sum of pij equals 1, with each p_{ij} value being between 0 and 1 for every i and j in S. The matrix P, which consists of the probabilities p_{ij}, is referred to as the transition probability matrix of the chain (Serfozo, 2009).

Data on the ecological footprint, which serves as the dependent variable, was collected from 1970 to 2015. Transition probability matrices were constructed based on the annual percentage increments and decrements in the ecological footprint.

Ecological Footprint, transition probability matrix:

	P1	**P2**	**N1**	**N2**
P1	0,47	0,06	0,24	0,24
P2	0,55	0,09	0,09	0,27
N1	0,38	0,25	0,25	0,13
N2	0,11	0,67	0,11	0,11

The ecological footprint, which serves as the dependent variable, exhibited an upward trend from 2015 to 2016. The likelihood of a growth beyond 7%, which represents an increase compared to the previous year, stands at 47%. The possibility of a growth below 7% is 6%, while the probability of a decline is 24%. Given the rise in the ecological footprint from 2015 to 2016 (P1), it may be inferred that there is a 47% likelihood of the ecological footprint increasing in 2016. The ecological footprint value experienced a 0.07 increase from 2016 to 2017. This outcome demonstrates the precision of the forecasts made using Markov analysis.

The transition probability matrix of the KOF Globalization Index, which serves as one of the independent variables:

	A1	A2
A1	0,56	0,44
A2	0,55	0,45

The KOF Globalization Index, an independent variable, experienced a marginal growth of less than 1%, which is the average value, between 2015 and 2016. Although it had growth in 2015, there is a 56% likelihood that it will expand by more than 1% in the following year. Upon examining the KOF globalization index value in 2016, the precision of the Markov analysis was noted.

The transition probability matrix for the independent variable Natural Resources Rent:

	A1	A2
A1	0,84	0,16
A2	0,24	0,76

It was noted that, from 2015 to 2016, the growth in Natural Resources Rent, our other independent variable, was less than the average value of 0.58. In 2017, there is an 84% likelihood that the value will increase below the average, and a 16% likelihood that it will increase beyond the average. Given the likelihood of passage as a percentage, there was a rise below the mean value. The research concluded that each analysis conducted using Markov chains yielded precise predictions on the future increase or drop in the next period.

2.2. Artificial Neural Network

Artificial Neural Networks (ANN) are algorithms that can be modeled and taught, and are based on the human brain's nerve cell (neuron) structure (Atik et al., 2007). ANNs are processors made up of neurons that work in a parallel and distributed manner, storing learnt data and training them to use it, all while performing heavy tasks (Ataseven, 2013). When the overall signal accumulation exceeds a specific threshold, an artificial neuron is described as a network that collects the signals it receives from previous neurons and transfers its own signal to another neuron (Abraham, 2005). Because the structure of the model can be trained to develop learning behavior and can be simply and quickly applied to different challenges in many fields, artificial neural networks are a popular application in solving many difficulties (Kuvvetli et al., 2015). Warren McCulloch and Walter Pitts (1943) pioneered artificial neural networks (ANN) by developing a computational model for neural networks based on threshold logic techniques (McCulloch and Pitts 1943). ANNs are forecasting techniques based on simple brain mathematical models. Models are made up of several layers of basic processing units known as neurons. The neuron has two functions: gathering inputs and producing an output (Dongare et al.,2012). The mathematical model of network consist of inputs, weights, summing function, activation function, outputs (Dongare et al.,2012). ANNs have been widely utilized in a variety of applications, including complicated non linear function mapping, image processing, pattern identification and classification, and etc (Dongare et al.,2012).

2.3. Concept of Artificial Neural Networks

The fundamental constituents of an artificial neural network typically consist of an input layer, one or more hidden layers, and an output layer. Figure 2 illustrates the basic structure of an artificial neural network. In its fundamental configuration, the interconnection between neurons in a neural network occurs through adaptive synaptic weights, as described by Kalogirou (2004).

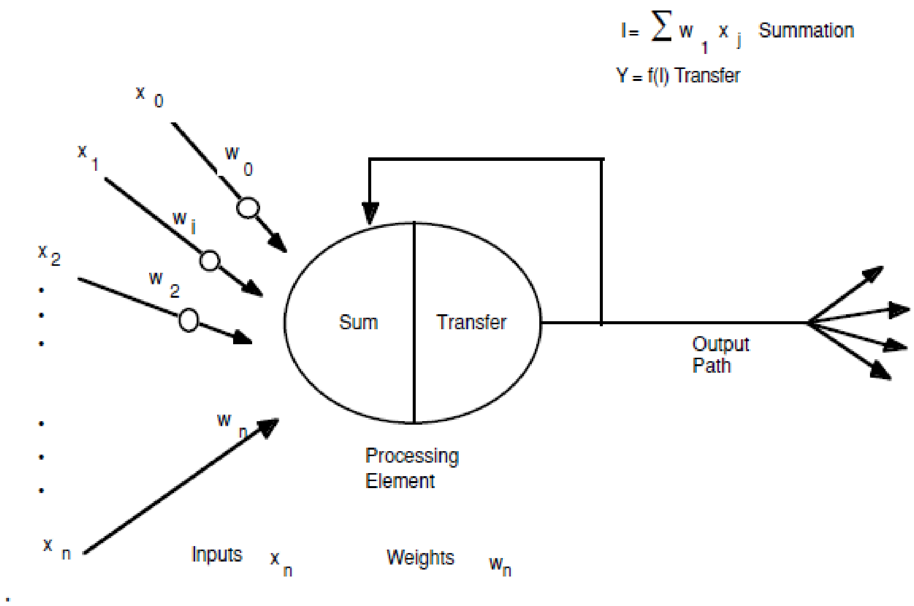

Figure 2. A Basic Artificial Neuron (Anderson and McNeil, 1992)

The diagram illustrates that the different inputs to the network are denoted by the mathematical variable, x(n). Each of these inputs is multiplied by a connection weight. The weights are denoted as w(n). In the most elementary scenario, these products are combined through summation, processed by a transfer function to produce an outcome, and subsequently delivered as output.

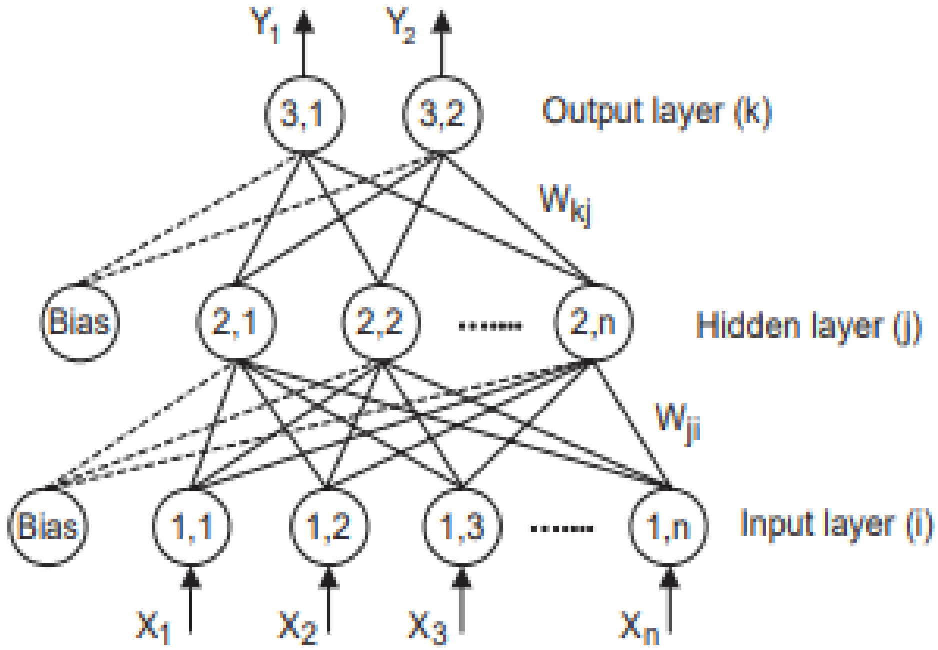

Figure 3. Multilayer Feedforward Neural Network (Kalogirou, 2004)

Figure 3 illustrates a schematic representation of a conventional multilayer feedforward neural network structure.

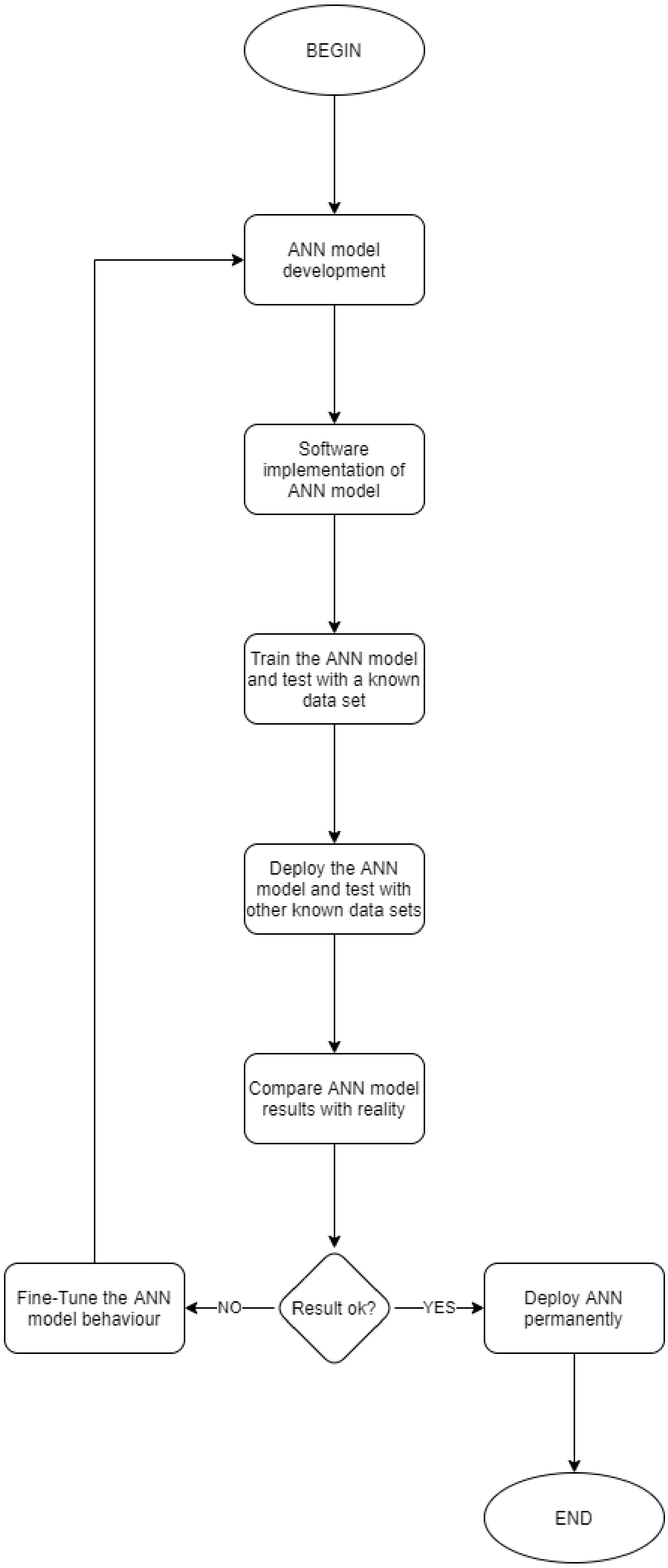

Figure 4. Steps in ANN model design (Ogwueleka et al., 2015)

Artificial neural network models follow a six-step process through their construction. The processes are illustrated sequentially in Figure 4. The network is given with target data and input data in the form of a model. Once the data in the model has been classified into either the training set or the validation set, the determination of the number of neurons in the hidden layer and the topology of the network to be generated takes place. Once the necessary modifications have been implemented, the subsequent step involves the computation of the output based on the provided data and corresponding weights. This phase is commonly referred to as the training of the data. Following the completion of the training, an evaluation process is conducted to ascertain the extent to which the network has acquired knowledge or skills. The evaluation method entails intermittently halting the training process and assessing its performance until a satisfactory outcome is achieved. Upon achieving a satisfactory outcome, the artificial neural network (ANN) model was deemed to have completed its training phase and was deemed suitable for practical application (Ogwueleka et al., 2015).

2.4. Learning Algorithms

Learning in artificial neural networks; is the process of comparing the result obtained as a result of transferring the data to the input layer and producing one or more output values by passing through the activation function and the expected result. This process is continued until the determined error rate is reached by modifying the algorithms if the discrepancy between the obtained and expected results is proportionately significant. Changes are primarily made to the network's weights. The network completes its training when the error rate reaches the desired threshold. The majority of ANN's learning rules are utilized to create process models. Supervised, Unsupervised, and Reinforced Learning are the three types of learning procedures (Ahamed and Akthar, 2016).

2.5. Supervised Learning

The artificial neural network's predicted output value is compared to the network's actual output value. An error is defined as the difference between the two outputs. When building the network, the weights are modified in cycles until the error is reduced by the network, which is generally done randomly at first (Anderson and McNeill, 2006). In supervised learning, the network must be trained before using the neural network. After presenting the input and output information to the neural network, supervised learning is applied. The adviser has complete control over the learning process. By choosing the training set and the mistaken value, the consultant determines how long the training will last. The utilization of real input and output data during training is the most essential characteristic of this approach (Ataseven, 2013). Consider an archaeologist's discovery of a human skeleton. Past examples of male and female skeletons help determine if this skeletal form is male or female. It is possible to establish whether the skeletal structure is male or female based on historical data (Dongare et.al., 2012).

The following are the rules for supervised learning (Şen, 2004):

1. Perceptron Learning Rule
2. Delta Learning Rule
3. Extended Delta Learning Rule
4. Backpropagation Learning Rule

2.6. Unsupervised Learning

Unsupervised learning lacks predefined categories for the purpose of pattern classification. This study employs machine learning techniques to assess and group datasets that lack labels. Even in cases where data cannot be readily categorized, they are nevertheless organized based on their shared characteristics and distinctions. The algorithm in question is capable of autonomously identifying concealed patterns or clusters of data, without any requirement for human involvement. The capacity to identify and analyze similarities and contrasts within information renders this approach the optimal answer. Unsupervised learning algorithms have the capability to execute more intricate processing tasks in comparison to supervised learning systems. Unsupervised learning algorithms have the capability to tackle more intricate processing tasks in comparison to supervised learning systems (Dike et al., 2018; Sun et al., 2018).

2.7. Reinforced Learning

Reinforced Learning is a type of learning that can be considered as an intermediate form of supervised and unsupervised learning. The teacher's role in this learning technique is limited to determining whether the computed result is true or false. Based on the environmental reaction, the learning system evaluates its activity as good (rewarding) or poor (punishable) and modifies its settings appropriately. In general, parameter adjustments are made until a state of equilibrium is reached (Dongare et al., 2012; Jha, 2007).

2.8. Feed-Forward Neural Networks

Feed-forward neural networks are categorized into two types, namely "single layer" or "multi-layer", depending on the number of layers they possess. The transmission of input signals to the output layer occurs via the utilization of weights, while the computation of output signals is carried out by the neurons present in the output layer. In this network, the transmission of signals is unidirectional, occurring solely from the input to the output. The absence of feedback implies that the output of a given layer does not exert any influence on the output of another layer. A multi-layer neural network often consists of an intermediate layer of hidden neurons positioned between the input and output layers (Sazlı, 2006; Senthilkumar, 2010; Öztürk and Şahin, 2018; Kuvvetli et al., 2015).

2.9. Back-Propagation Algorithm

Feedforward neural networks are trained using the backpropagation algorithm. The algorithm's goal is to back-propagate the vector to update the weights of the networks. The discrepancy between the actual network output and the desired output is defined as the error. The supervised learning rule is employed in the backpropagation technique because the processing is done by examining the outputs (Sazlı, 2006). The backpropagation method has the advantage of being simple to use and well-suited to solving all complex patterns (Kishore and Kaur, 2012).

3. MATERIAL AND METHOD

3.1. Collecting Information

As previously stated, the dependent variable in this study was the ecological footprint data, whereas the independent factors included GDP, NRR (% of GDP), and the KOFGI. The study utilized data taken from the publication titled "Are Natural Resources Abundance And Human Development A Solution For Environmental Pressure?" The study conducted by Pata et al. titled "Evidence From Top Ten Countries With The Largest Ecological Footprint" provides empirical data on the ecological footprints of the top ten countries. Table 1 presents an overview of the parameters employed in the investigation. The data shown illustrates the temporal variation in the values of both dependent and independent variables from 1970 to 2016.

Table 1. Variables in the study and parameter change intervals

Parameter Name	Unit	Data Frequency	Range of Change
Year	-	Annual	1970-2016
Ecological Footprint	GHA Per Person	Annual	1.837 - 3.358
Gross Domestic Product	GDP growth (%)	Annual	17.087 - 957.799
Natural Resources Rent	% of GDP	Annual	0,12% - 1.43%
KOF Globalization Index	-	Annual	39.82 - 72.14

Table 2. Descriptive statistics

	N	Mean	Std. Deviation	Variance
Ecological_Footprint	47	2.4733	.66421	.441
Gross_National_Product	47	4.676E11	2.69516E11	7.264E22
Natural_Resources_Rent	47	.5825	.31274	.098
Globalization_Index	47	55.6894	11.06407	122.414
Valid N (listwise)	47			

The Table 2 displays the descriptive statistical values of Turkey's ecological footprint, gross domestic product, natural resource rent, and KOF globalization index data collected from 1970 to 2016. The identification of a disparity between the pace of use of a nation's natural resources and the rate at which these resources are renewed suggests the existence of an ecological deficit. As the population number increases, there is a steady drop in the individual biological capability. The act of allocating resources towards the development of biological capability functions as a preventive measure against the growing reliance on external resources. Ideally, the attainment of an ideal equilibrium is characterized by the simultaneous promotion of GDP growth, mitigation of Ecological Footprint, and restoration of biocapacity. The narrowing disparity between biocapacity and ecological footprint suggests that Turkey is making progress in addressing its ecological debt (Galli et al.,2012).

3.2. Establishment of ANN Model

The construction of the artificial neural network involved the utilization of a feed-forward neural network. In this neural network, the input of a cell in one layer is transmitted to another layer as input through the utilization of weights. The information originating from the input layer is transmitted to the cells within the hidden layer without undergoing any form of processing. According to Sönmez (2018), the processing of data occurs exclusively in the hidden layer and the output layer. After completing an estimation of the ecological footprint, it was concluded that the most suitable artificial neural network model for explaining our data was a 2-layer structure consisting of 5 neurons. The artificial neural network model obtained is depicted in Figure 5. The artificial neural network underwent training utilizing the Levenberg-Marquardt optimization technique, known for its efficient backpropagation methodology.

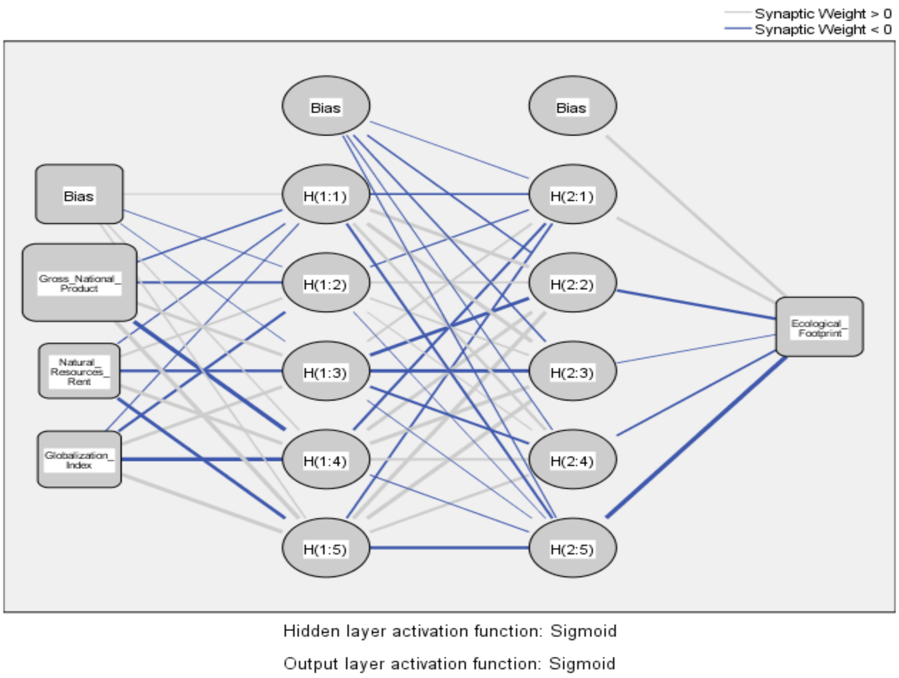

Figure 5. Artificial Neural Network model

Table 3. Parameter weight (W) estimates

Parameter Estimates

Predictor		Predicted										
		Hidden Layer 1					Hidden Layer 2					Output Layer
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	H(2:1)	H(2:2)	H(2:3)	H(2:4)	H(2:5)	Ecological_Footprint
Input Layer	(Bias)	1.064	-.134	-.057	1.325	1.409						
	Gross Domestic Product	-1.917	-4.910	10.256	-20.976	18.912						
	Natural_Resources_Rent	-1.154	3.598	-6.394	13.639	-11.741						
	Globalization_Index	-.592	-5.041	10.919	-21.648	19.276						
Hidden Layer 1	(Bias)						-.231	-1.799	-1.373	-.396	-1.087	
	H(1:1)						-2.241	12.854	13.862	5.142	-3.863	
	H(1:2)						-1.222	3.365	3.095	1.087	-.019	
	H(1:3)						3.694	-12.496	-13.195	-4.647	-.130	
	H(1:4)						-4.412	12.664	14.265	4.928	-.517	
	H(1:5)						-3.098	15.973	18.646	5.552	-9.519	
Hidden Layer 2	(Bias)											8.188
	H(2:1)											6.648
	H(2:2)											-5.578
	H(2:3)											-.388
	H(2:4)											-3.270
	H(2:5)											-22.852

The components of a neural network cell include inputs, weights, a summation function, an activation function, and outputs. The variables utilized in this study encompass Gross Domestic Product (GDP), Natural Resources Rent (NRR), and the KOF Globalization Index. The model is equipped with a concealed layer consisting of two layers and a total of five nodes. The model evaluates the ecological footprint as the output layer. In order to mitigate errors, weight values are generated. The objective is to utilize the activation function to perform computations depending on the relative significance of the input values. Table 3 presents the weight estimations according to the parameters of the model.

The Gross Domestic Product (GDP) exerts the most significant influence on the first and third neurons of the initial hidden layer, whereas the KOF globalization index has the largest impact on the second, fourth, and fifth neurons. Upon examining the interaction between the second hidden layer and the first hidden layer, it is observed that the fourth neuron has the most significant influence on the first neuron. Additionally, the fifth neuron demonstrates the largest impact on the second, third, fourth, and fifth neurons, as depicted in Table 3.

3.3. Determination of ANN Parameters

The selection of proper parameters is crucial for ensuring the accuracy of predictions made by artificial neural networks. The emergence of system complexity can be attributed to the occurrence of erroneous decisions. According to the study conducted by Kuvvetli et al. in 2015, Figures 6, 7, and 8 depict graphical representations of the indices employed as inputs in the model during a span of time. This study investigates the potential relationship between the abundance of natural resources and human development as a potential solution to environmental pressure. The study conducted by Pata et al. (2021) titled "Evidence From Top Ten Countries With The Largest Ecological Footprint" was utilized to analyze the factors influencing the ecological footprint.

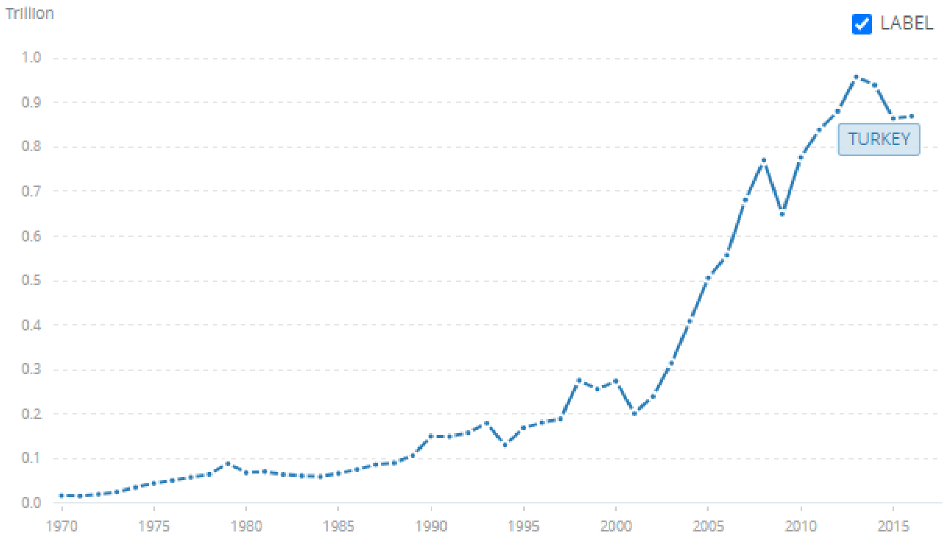

Figure 6. Turkey's gross domestic product (World Bank Group,2021)

GDP refers to the aggregate monetary worth of all goods, products, and services produced within a nation's geographical boundaries over a specific period. The concept of gross domestic product (GDP) is utilized to assess the progression of a nation's economy. The computation takes into account the areas of service and production. Positive GDP growth

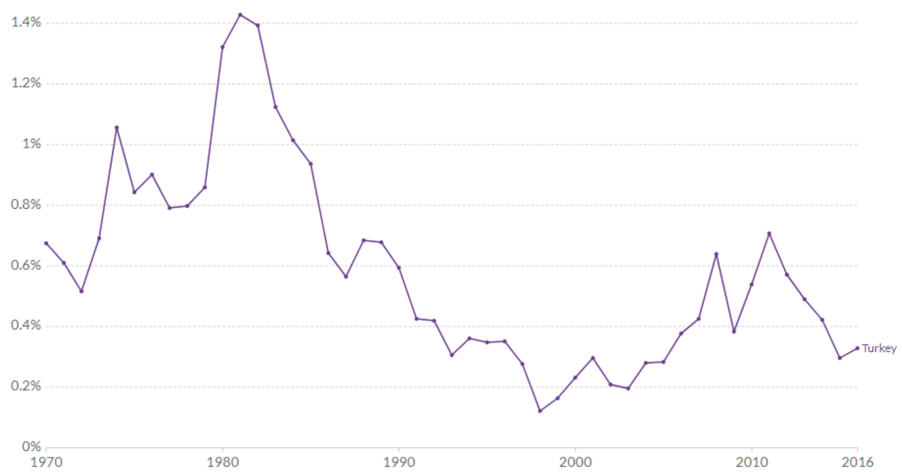

Figure 7. Natural resources rents (% GDP) (World Bank Group,2021)

indicates an upward trajectory in the economy, signifying an improvement, while negative GDP growth implies the occurrence of a recession or economic downturn (Osho et al.,2018).
indicates an upward trajectory in the economy, signifying an improvement, while negative GDP growth implies the occurrence of a recession or economic downturn (Osho et al.,2018).

Natural resources are valuable assets for a nation, as they contribute to the progress of its economy. The total sum of oil, natural gas, coal (including both hard and soft types), mineral rents, and forest rents encompasses the entirety of natural resource rents (Canh et al., 2020; Guan et.al.,2020). However, Emir and Karlilar (2023) report that the exploitation of natural resources in Turkey puts strain on the environmental conditions.

Figure 8. Turkey's KOF globalization index (KOF Swiss Economic Institute,2024)

Table 4. Determining the Number of Layers in the Model

Number of Layers	Number of Neurons	Training Set	Validation Set	Test Set	All Data Set
2	**10N**	**0,99684**	**0,98117**	**0,85034**	**0,9165**
3	10N	0,90533	0,99202	0,89651	0,90563
4	10N	0,96741	0,90378	0,18887	0,58087
5	10N	0,87645	0,94785	0,1061	0,83614

The KOF Globalization Index differentiates among the economic, social, and political facets of globalization. Over the course of time, there has been a general upward trend observed in the KOF globalization index. Upon comparing the globalisation index of Turkey with that of the world, it becomes evident that Turkey exhibits a higher level of globalisation.

Tables 4 and 5 provide a graphical depiction of the hierarchical arrangement and associated amounts of neurons inside artificial neural networks. The process of determining the number of neurons in the hidden layer was accomplished by a trial-and-error approach.

Table 5. Determining the number of Neurons in the model

Number of Layers	Number of Neurons	Training Set	Validation Set	Test Set	All Data Set
2	2N	0,9391	0,48675	0,71298	0,65931
2	3N	0,96668	0,94496	0,99835	0,97608
2	4N	0,79251	0,94918	-0,23644	0,6488
2	**5N**	**0,99298**	**0,99468**	**0,97558**	**0,99316**
2	6N	0,41325	0,93512	0,95482	0,5382
2	7N	0,99659	0,98714	0,77286	0,97636
2	8N	0,99773	0,99502	0,35836	0,93282
2	9N	0,9931	0,92724	0,97939	0,98483
2	10N	0,99684	0,98117	0,85034	0,9165
2	11N	0,99805	0,95488	0,01092	0,85072
2	12N	0,81497	0,92609	0,87106	0,82302
2	13N	0,99911	0,96102	-0,039598	0,75516
2	14N	0,6508	0,90285	0,21718	0,55385
2	15N	0,89134	0,92869	0,47707	0,852
2	16N	0,82706	0,48961	0,29359	0,75494
2	17N	0,99785	0,46706	0,96252	0,85891
2	18N	0,98058	0,99826	0,085285	0,84015
2	19N	0,9938	0,89795	0,96016	0,98274
2	20N	0,90533	0,99202	0,89651	0,90563

The network that had the lowest sum of squares error was chosen for each dataset. The neural network model, consisting of two layers and five neurons, exhibited the most superior level of performance.

4. RESULTS

The analytical methodology considered a dataset spanning 47 years from Turkey. The study utilized the independent variables of Gross Domestic Product (GDP), natural resources rent, and globalization index, which were identified through a review of existing literature as factors that influence the ecological footprint. The ecological footprint value is estimated by modeling these independent variables to provide the most accurate approximation to the actual number. The objective is to identify patterns in the data received from the input layer in order to determine the output that is most similar to the actual output. The construction and refinement of the artificial neural network model were carried out using the MATLAB R2020b and PASW Statistics 18 software tools. During the training phase, 70% of the data set was utilized, while the remaining 30% was allotted for testing reasons. The predetermined number of iterations in the proposed network model is set at 1000. Figure 9 depicts the MATLAB training algorithm.

The utilization of algorithms that need quadratic derivatives, such as the Levenberg-Marquardt algorithm (Çavuşlu et al., 2012), has been found to substantially improve the pace of training. The Levenberg-Marquardt algorithm was utilized by the researchers in this study to train the artificial neural network.

According to the graph in Figure 10, it was noted that epoch 4 had the lowest Mean Squared Error (MSE), during the process of validation, suggesting superior performance in terms of validation, as evidenced by a value of 0.0017205. Based on the evaluation of the model's performance, particularly during epoch 4, the analysis terminates at iteration 160, where a total of 156 mistakes were observed.

For the training, validation, and test datasets in MATLAB, Figure 11 shows the correlation between the goal and output values. The diagram illustrates that the correlation coefficients for both the training and validation datasets demonstrate favorable values, as evidenced by the R values. The correlation coefficient serves as a measure to quantify the extent of the relationship between two variables.

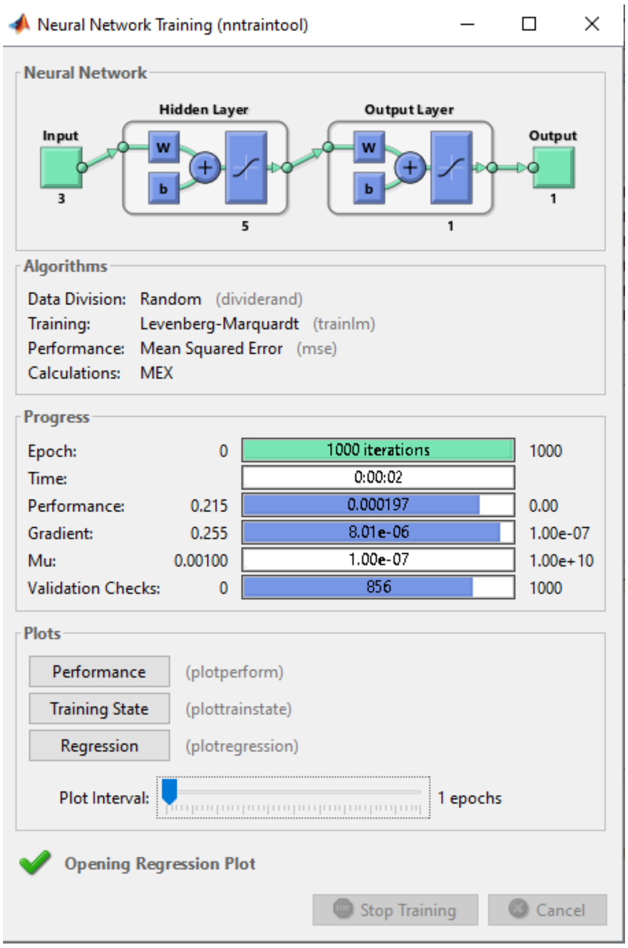

Figure 9. Neural Network training

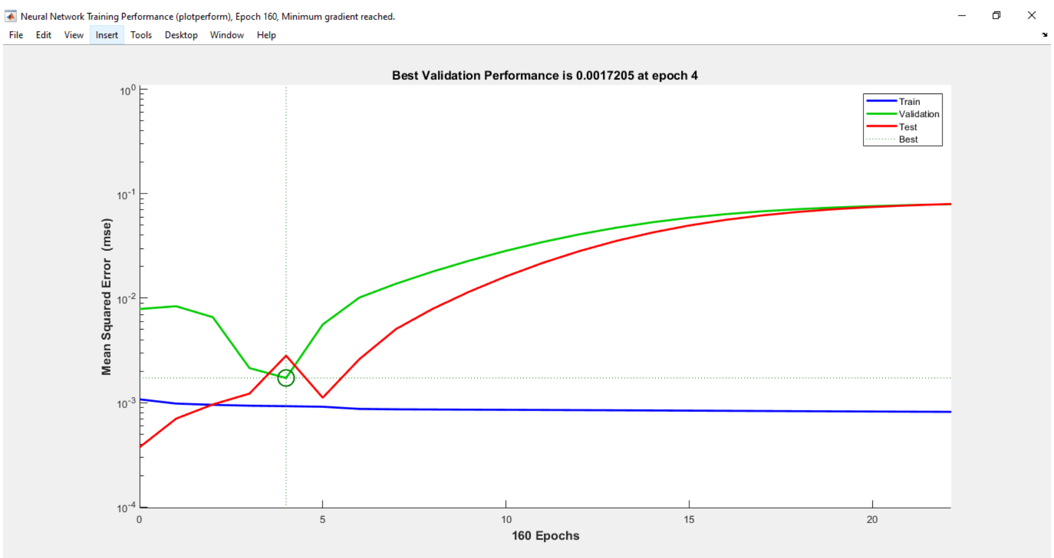

Figure 10. Neural Network training performance

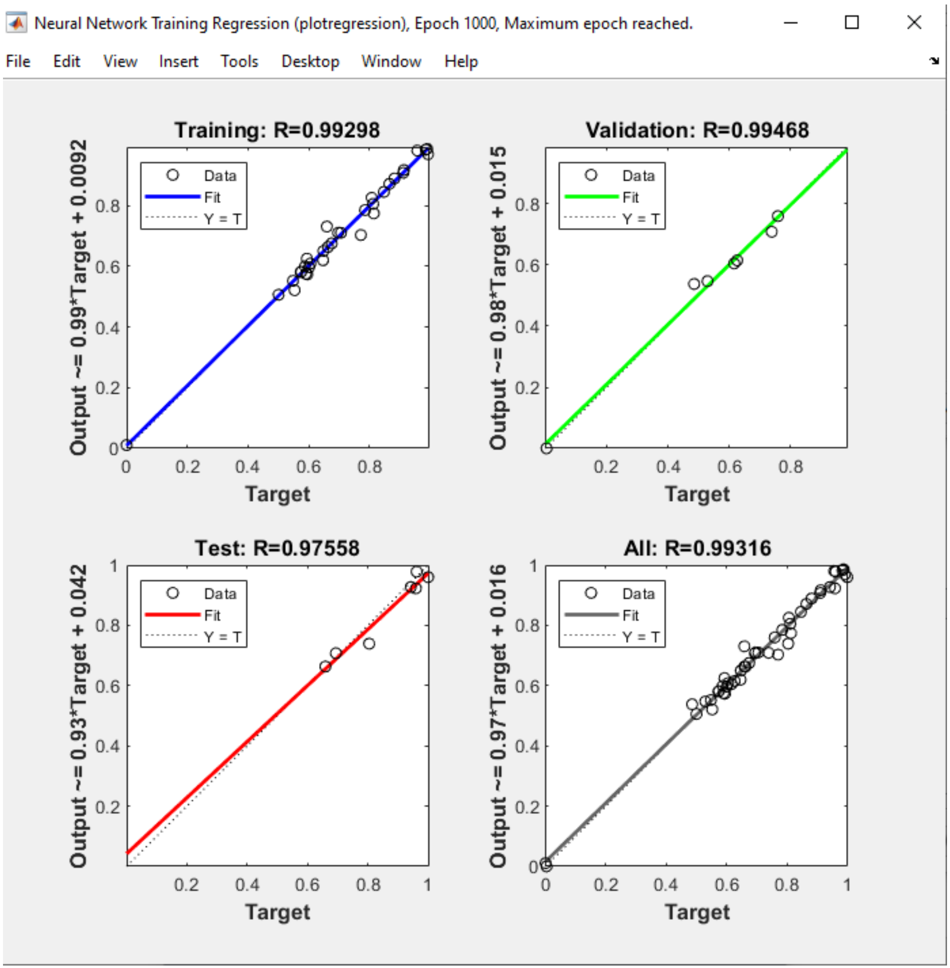

Figure 11. Neural Networks plot regression outputs (5 Neurons with 2 Hidden Layers)

The study's results suggest that the data used for instructional purposes demonstrated a strong alignment with the correctness of the model, exhibiting a close proximity of 99.298%. In a similar vein, the data utilized for the purpose of validation exhibited a high level of concordance with the model's correctness, with a proximity of 99.468%. Moreover, the data employed for testing exhibited a significant level of consistency with the model's correctness, demonstrating a proximity of 97.558%. Finally, the comprehensive dataset demonstrated a significant level of consistency with the model's correctness, exhibiting a degree of proximity of 99.316%. Based on the findings, it can be deduced that the developed artificial neural network (ANN) model has a significant level of precision in forecasting the Ecological Footprint.

ETHICAL DECLARATION

In the writing process of the study titled "Exploring the Ecological Footprint in Turkey: Analyzing the Interplay of Economic and Environmental Factors", there were followed the scientific, ethical and the citation rules; was not made any falsification on the collected data and this study was not sent to any other academic media for evaluation.

REFERENCES

Abraham, A. (2005), *Artificial neural networks*, Handbook of measuring system design.

Ahamed, K. I. and Akthar, S. (2016), A study on neural network architectures. Comp. Eng. Intell. Syst, 7, 1-7.

Altay Topcu, B. (2021), The impact of export, import, and renewable energy consumption on Turkey's ecological footprint, *Journal of Economics, Finance, and Accounting*, 8(1), 31-38.

Anderson, D. and McNeill, G. (2006), Artificial Neural Networks technology. Online: 11.12.2006. *https://www.thedacs.com/techs/neural/neural.title.php*.

Anderson, D. and McNeill, G. (1992), Artificial Neural Networks technology. *Kaman Sciences Corporation*, 258(6), 1-83.

Ataseven, B. (2013), Yapay sinir ağlari ile öngörü Modellemesi, *Öneri Dergisi*, 10(39), 101-115.

Atik, K., Deniz, E. ve Yıldız, E. 2007. Meteorolojik verilerin Yapay Sinir Ağları ile modellenmesi, *KSÜ Fen ve Mühendislik Dergisi*, 10 (1), 148-152.

Bello Mo, Solarin Sa and Yen Yy (2018), The impact of electricity consumption on CO2 emission, carbon footprint, water footprint, and ecological footprint: The role of hydropower. An Emerging Economy. J Environ. Manag. 219, 218–230.

Canh, N. P., Schinckus, C. and Thanh, S. D. (2020), The natural resources rents: Is economic complexity a solution for resource curse?, *Resources Policy*, 69, 101800.

Costanza, R., Kubiszewski, I., Giovannini, E., Lovins, H., McGlade, J., Pickett, K.E. and Wilkinson, R. (2014), Development: Time to leave GDP behind, *Nature News*, 505 (7483), 283.

Çavuşlu, M. A., Becerikli, Y. and Karakuzu, C. (2012), Levenberg-Marquardt algoritması ile YSA eğitiminin donanımsal gerçeklenmesi, *Türkiye Bilişim Vakfı Bilgisayar Bilimleri ve Mühendisliği Dergisi*, 5(1).

Demirbay, S. G. and Gündüz, S. (2023), Determining the factors that most affect the ecological footprint using the artificial neural network classification feature: The case of Turkey, *Ömer Halisdemir Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, 16(4), 904-917.

Dongare, A. D., Kharde, R. R. and Kachare, A. D. (2012), Introduction to the artificial neural network, *International Journal of Engineering and Innovative Technology (IJEIT)*, 2(1), 189-194.

Dreher, A. (2006), Does Globalization affect growth? Evidence from a new index of Globalization, *Applied Economic*, 38(10), 1091-1110.

Emir, F. and Karlilar, S. (2023), Application of RALS cointegration test assessing the role of natural resources and hydropower energy on ecological footprint in Emerging economy, *Energy & Environment*, 34(4), 764-779.

Ergezer, H., Dikmen, M. and Özdemir, E. (2003), Yapay Sinir Ağları ve tanıma sistemleri, *Pivolka*, 2(6), 14-17.

Galli, A., Moore, D., Cranston, G., Wackernagel, M., Kalem, S., Devranoğlu, S. and Ayas, C. (2012) *Türkiye'nin Ekolojik Ayak İzi Raporu*. *https://wwftr.awsassets.panda.org/downloads/turkiyenin_ekolojik_ayak_izi_raporu.pdf?1412/turkiyeninekolojikayakizibilancosu.*

Global Footprint Network (2021), *https://data.footprintnetwork.org/,* Erişim Tarihi: 14/05/2021.

Guan, J., Kirikkaleli, D., Bibi, A. and Zhang, W. (2020), Natural resources rents Nexus with financial development in the presence of globalization: Is the "Resource Curse" exist or myth?, *Resources Policy*, 66, 101641.

Gygli, S., Haelg, F., Potrafke, N. and Sturm, J. E. (2019), The KOF globalisation index–revisited, *The Review of International Organizations*, 14(3), 543-574.

Gygli, Savina, Florian Haelg, Niklas Potrafke And Jan-Egbert Sturm (2019), The KOF Globalisation index – Revisited, *Review Of International Organizations*, 14(3), 543-574.

H. U. Dike, Y. Zhou, K. K. Deveerasetty and Q. Wu, (2018), Unsupervised Learning Based On Artificial Neural Network: A Review, 2018 IEEE International Conference on Cyborg and Bionic Systems (CBS), 322-327.

Haelg, F. (2020), The KOF Globalisation index–A multidimensional approach to globalisation. *Jahrbücher für Nationalökonomie und Statistik*, 240(5), 691-696.

Jha, G. K. (2007), *Artificial neural networks and its applications*. IARI, New Delhi.

Kalogirou, S. A. (2004), Neural Network Modeling of Energy Systems, *Encyclopedia of Energy*, 291–299.

Keçe, A. (2006), *Yapay sinir ağları ile plastik enjeksiyon süreci başlangıç parametrelerinin belirlenmesi.* Yayınlanmamış Yüksek Lisans Tezi. Uludağ Üniversitesi Fen Bilimleri Enstitüsü.

Kıral, E. and Kaplan, K. (2021), COVID-19 vaka artışlarının Türk finansal piyasasına etkisi, *Ömer Halisdemir Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, 16(3), 693-707.

Kıral, E., Mavruk, C. and Kıral, G. (2018), Ekonometri öğrencilerinin sayısal derslerdeki akademik performansı: Markov modeli ile bir hesaplama, *Uluslararası İktisadi Ve İdari İncelemeler Dergisi*, 617-632.

Kirikkaleli, D., Adebayo, T. S., Khan, Z. and Ali, S. (2021). Does globalization matter for ecological footprint ın turkey? Evidence from dual adjustment approach. *Environmental Science And Pollution Research*, 28(11), 14009-14017.

Kishore, R. and Kaur, T. (2012), Backpropagation algorithm: an artificial neural network approach for pattern recognition, *International Journal of Scientific and Engineering Research*, 3(6), 6-9.

KOF Swiss Economic Institute (2024), *https://kof.ethz.ch/en/forecasts-and-indicators/indicators/kof-globalisation-index.html*, Erişim Tarihi: 24.05.2024.

Kongbuamai, N., Bui, Q., Yousaf, H. M. A. U. and Liu, Y. (2020), The ımpact of tourism and natural resources on the ecological footprint: A case study Of Asean countries, *Environmental Science And Pollution Research*, 27(16), 19251-19264.

Kuvvetli, Y., Dağsuyu, C. and Oturakci, M. (2015), Türkiye'deki araç satışları için ekonomik ve çevresel faktörleri göz önüne alan yapay sinir ağı tabanlı bir tahmin yaklaşımı, *Endüstri Mühendisliği*, 26(3), 23-31.

McCulloch, W. S. and Pitts, W. (1943), A logical calculus of the ideas immanent in nervous activity, *The bulletin of Mathematical Biophysics*, 5(4), 115-133.

Ogwueleka, F. N., Misra, S., Colomo-Palacios, R. and Fernandez, L. (2015), Neural Network and classification approach in identifying customer behavior in the banking sector: A case study of an international bank. *Human factors and ergonomics in manufacturing and service industries*, 25(1), 28-42.

Osho, A. E., Omotayo, A. D. and Ayorinde, F. M. (2018), Impact of Company Income Tax on Gross Domestic Products in Nigeria. *Research Journal of Finance and Accounting. United Kingdom*, 2222-1697.

Özsoy, C. E. and Dinç A. (2016), Sürdürülebilir Kalkınma ve Ekolojik Ayak İzi, *Finans Politik ve Ekonomik Yorumlar*, 619, 35-55.

Öztemel, E. (2003), *Yapay Sinir Ağlari*, Papatyayayincilik, Istanbul.

Öztürk, K. and Şahin, M. E. (2018), Yapay sinir ağları ve yapay zekâ'ya genel bir bakış, *Takvim-i Vekayi*, 6(2), 25-36.

Pata, U. K., Aydin, M. and Haouas, I. (2021), Are natural resources abundance and human development a solution for environmental pressure? Evidence from top ten countries with the largest ecological footprint, *Resources Policy*, 70, 101923.

Ross, S. M. (2007), *Introduction to Probability Models*, Sheldon M.

Rudolph, A. and Figge, L. (2017), Determinants of ecological footprints: What is the role of Globalization? *Ecological Indicators*, 81, 348-361.

Sabancı, K., Aydın, C. and Ünlerşen, M. F. (2012), Görüntü işleme ve yapay sinir ağları yardımıyla patates sınıflandırma parametrelerinin belirlenmesi, *Iğdır Üniversitesi Fen Bilimleri Enstitüsü Dergisi*, 2(2), 59-62.

Sazli, M. H. (2006), A brief review of feed-forward neural networks, *Communications Faculty of Sciences University of Ankara Series A2-A3 Physical Sciences and Engineering*, 50(01).

Semtrio. (N.D.), *Ekolojik Ayak İzi Nedir? Semtrio.* https://www.semtrio.com/ekolojik-ayak-izi.

Senthilkumar, M. (2010), Use of artificial neural networks (ANNs) in colour measurement, *Colour Measurement*, 125-146.

Serfozo, R. (2009), *Basics of applied stochastic processes*, Springer Science and Business Media.

Sönmez Çakır, F. (2018), *Yapay Sinir Ağları Matlab kodları ve Matlab toolbox çözümleri*, 1. Baskı, Nobel Kitabevi, Ankara.

Söylemez, Y. (2020), Çok katmanlı Yapay Sinir Ağları yöntemi ile altın fiyatlarının Tahmini, *Sosyoekonomi*, 28(46), 271-291.

Sun, Y., Yen, G. G. and Yi, Z. (2018), Evolving unsupervised Deep Neural Networks for learning meaningful representations. *IEEE Transactions on Evolutionary Computation*, 23(1), 89-103.

Şafak, Y., Sağlam, V. and Sağır, M. (2023), Hazır Giyim Sektöründe Marka Tercihlerinin Markov Zincirleriyle Öngörülmesi, *The Journal of International Scientific Researches*, 8(3), 283-304.

Şen, Z. (2004), *Yapay Sinir Ağları ilkeleri*, Su Vakfı Yayınları,İstanbul

The World Bank, (2023), *https://data.worldbank.org/country/turkey?view=chart.*

Tosunoğlu, B. (2014), Sürdürülebilir küresel refah göstergesi olarak ekolojik ayak izi, *Hak İş Uluslararası Emek Ve Toplum Dergisi*, 3(5), 132-149.

Total Natural Resources Rents (% of GDP) (2021), 1970 to 2016, *https://ourworldindata.org/grapher/natural-resource-rents?tab=chartandcountry=~tur,* Erişim Tarihi: 14.05.2021.

Tunç A. Ö, Ömür G. A. and Düren A. Z (2012), Çevresel farkındalık, *İstanbul Üniversitesi Siyasal Bilgiler Fakültesi Dergisi,* 0(47), 227-246.

World Bank. (N.D.). Databank. *https://databank.worldbank.org/metadataglossary/adjusted-net-savings/series/ny.gdp.totl.rt.zs.*