Estimation of Burned Areas In Forest Fires Using Artificial Neural Networks

Estimación de áreas quemadas en incendios forestales utilizando redes neurales artificiales

Estimativa de áreas queimadas em incêndios florestais usando redes neurais artificiais

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Abstract

Introduction: This article is the product of the research "Developing an Artificial Neural Network Based Model for Estimating Burned Areas in Forest Fires", developed at Karadeniz Technical University in the year 2020.

Problem: Forest Fires are an issue that greatly affect human life and the ecological order, leaving long-term issues. It should be estimated because it is not known when, where and how much the fire will be in the area.

Objective: The objective of the research is to use artificial neural networks to estimate the burned areas in forest fires.

Methodology: A feed-forward backpropagation neural network model was used for estimating the burned areas.

Results: We performed a performance evaluation over the proposed model by considering Regression values, Mean Absolute Percentage Error (MAPE) and Mean Square Error (MSE). The results show that the model is efficient in terms of its estimation of burnt areas.

Conclusions: The proposed artificial neural network model has a low error rate and high estimation accuracy. It is more effective than traditional methods for estimating burned areas in forests.

Originality: To the best of our knowledge, this is the first time that this real, unique data has been used for building and testing the model's estimations and the improvements that have been made in producing results faster and more accurately than with traditional methods.

Limitations: Since there are regional differences over different forest areas, effective criteria need to be analysed regarding the target regions.

Keywords: forest fires, burned areas, artificial neural networks, machine learning, estimation.

Resumen

Introducción: Este artículo es el producto de la investigación "Desarrollo de un modelo basado en redes neuronales artificiales para estimar áreas quemadas en incendios forestales", desarrollado en la Universidad Técnica de Karadeniz en el año 2020.

Problema: los incendios forestales son un problema que afecta en gran medida la vida humana y el orden ecológico, dejando problemas a largo plazo. Debe estimarse porque no se sabe cuándo, dónde y cuánto será el incendio en el área.

Objetivo: El objetivo de la investigación es utilizar redes neuronales artificiales para estimar las áreas quemadas en incendios forestales.

Metodología: Se usó un modelo de red neuronal de propagación hacia atrás para estimar las áreas quemadas.

Resultados: Realizamos una evaluación de desempeño sobre el modelo propuesto considerando los valores de regresión, el error de porcentaje absoluto medio (MAPE) y el error de cuadrado medio (MSE). Los resultados muestran que el modelo es eficiente en términos de su estimación de áreas quemadas.

Conclusiones: El modelo de red neuronal artificial propuesto tiene una baja tasa de error y una alta precisión de estimación. Es más efectivo que los métodos tradicionales para estimar áreas quemadas en los bosques.

Originalidad: según nuestro conocimiento, esta es la primera vez que esta información real y única se ha utilizado para construir y probar las estimaciones del modelo y las mejoras que se han realizado para producir resultados más rápido y con mayor precisión que con los métodos tradicionales.

Limitaciones: Dado que existen diferencias regionales sobre las diferentes áreas forestales, es necesario analizar criterios efectivos con respecto a las regiones objetivo.

Palabras clave: incendios forestales, áreas quemadas, redes neuronales artificiales, aprendizaje automático, estimación.

Resumo

Introdução: Este artigo é o produto da pesquisa "Developing an Artificial Neural Network Based for Estimativa de áreas queimadas em incêndios florestais ", desenvolvido na Universidade Técnica de Karadeniz no ano de 2020.

Problema: Os incêndios florestais são uma questão que afeta muito a vida humana e a ordem ecológica, deixando-os de longo prazo problemas. Deve ser estimado porque não se sabe quando, onde e quanto será o incêndio na área.

Objetivo: O objetivo da pesquisa é usar redes neurais artificiais para estimar as áreas queimadas em incêndios florestais.

Metodologia: Um modelo de rede neural de retropropagação de feed-forward foi usado para estimar as áreas queimadas.

Resultados: Realizamos uma avaliação de desempenho sobre o modelo proposto, considerando os valores de regressão, Erro percentual médio absoluto (MAPE) e erro quadrático médio (MSE). Os resultados mostram que o modelo é eficiente em termos de estimativa das áreas queimadas.

Conclusões: O modelo de rede neural artificial proposto tem baixa taxa de erro e alta precisão de estimativa. Isto é mais eficaz do que os métodos tradicionais para estimar áreas queimadas em florestas.

Originalidade: até onde sabemos, esta é a primeira vez que esses dados reais e únicos são usados para construir e testar as estimativas do modelo e as melhorias que foram feitas na produção de resultados mais rápida e com mais precisão do que com os métodos tradicionais.

Limitações: Uma vez que existem diferenças regionais em diferentes áreas florestais, critérios eficazes precisam ser analisados

em relação às regiões-alvo.

Palavras-chave: incêndios florestais, áreas queimadas, redes neurais artificiais, aprendizado de máquina, estimativa.

1. INTRODUCTION

Forests are very important natural resources that provide economic, ecological and sociocultural benefits such as preventing air pollution, adjusting the water order, contributing to the oxygen cycle, preventing erosion and landslides [1-4]. There are 1.31 billion hectares of intact forest land on earth and half of them are located in countries such as Canada, USA, Russia, China and Brazil [5]. These forest areas are threatened by many factors that endanger the continuity and vitality of the forest, such as drought, insect infestations, diseases, anthropogenic occupation and utilization, increased land use change, overgrazing and forest fires. Among these factors, forest fires, seen as an important problem, pose a risk to the continuity of forests in all regions of the world and lead to the complete disappearance of forest ecosystem functions [6, 7].

In this context, forest fire denotes an event where a forest has been destroyed by burning partially or completely. Forest fires are caused by natural events such as lightning strikes, electric lines touching each other, volcanic eruption, excessive

temperature rises, and sometimes cigarette butts or fires that people start unconsciously. Forest fires occur in the forests of various parts of the world every year, causing firefighting costs reaching into the trillions of USD, loss of life, property and recreational spaces. Forest fires create negative effects, especially on the carbon cycle and other biogeochemical cycles, by affecting the growth, structure and location of forest lands and plants [8-10].

Since forest fires affect large areas and cause ecological, social and economic damage, it is of utmost importance to evaluate the burning risk of buildings during forest fires in order to reduce loss of life and property in the fire [11].

The characteristic features of large forest fires are that they spread to very large areas in a very short time due to unstable weather conditions, they cannot be controlled due to heavy winds and, as a result, they end only when they reach natural obstacles such as lakes, seas, large openings in forests and forestless areas [12]. It can occur over very large areas due to reasons such as weather conditions, the presence of flammable materials and the inability to intervene early. Determining the effects of weather conditions, such as hot, dry and windy, will help create systems that can predict the occurrence of small and large forest fires [5].

All these explanations and justifications clearly demonstrate the importance of the study. Nowadays, various methods have been proposed for determining forest fires and possible areas of burning. However, it can be said that the desired point is still not reached. In this context, the artificial neural networks approach, which is one of the artificial intelligence techniques and is also used in the study, was taken into consideration; artificial neural networks are used as an effective method for solving complex problems and especially for estimation.

Therefore, the purpose of this study is to estimate burned areas due to forest fires using artificial neural networks. The article is structured as follows: firstly, a literature review is presented, followed by the materials and methods of the study (artificial neural networks, obtaining and organizing data, creating the model etc.) being detailed in the second part; the findings and discussion can be found in the third part, and finally, the fourth part contains the results and suggestions obtained from the study.

1.1 Literature review

In the literature, many studies have been conducted on subjects such as forest fires, fire prevention, and the determination of burned areas. For example, Maeda et al. proposed a model that uses artificial neural networks and versatile images from MODIS (Moderate Resolution Imaging Spectroradiometer) / Terra-Aqua sensors to detect

areas at high risk of forest fire. They stated that the artificial neural network model is a fast and relatively sensitive method for predicting forest fire events. As a result, they have demonstrated that the model offers a good alternative that reduces uncertainty in the currently used methods to support forest fire prevention policies and assist in the evaluation of burning areas [13].

Bisquert et al. estimated the forest fire hazard from remote sensing and fire history data using artificial neural networks and logistic regression. For this, they used MODIS images to obtain land surface temperature as the main input in forest fire hazard models in the Galicia region. Fire hazard has been classified and fire hazard maps based on this classification have made it easier to prevent and extinguish fires [14].

Elmas and Sönmez developed a forest fire prevention and management system by using artificial neural networks in order to protect existing forests. The system they developed predicts fires and the rate of spread of fires by grading the forest fire hazard. Thus, the system helps to develop correct strategies for fire prevention and combat before the fire, at the start of the fire and during the fire [15].

Cortez and Morais used the data mining technique to estimate the burned area of forest fires and tested their approach on real-world data. They stated that the SVM technique is effective for predicting the burn area of small fires that are more common. They also mentioned the importance of using different technical and predictive approaches, as large fires are rare events [16].

Karouni et al. aimed to predict and help make decisions on forest fires by using backpropagation on decision trees and advanced neural networks. For this, they used four sets of meteorological data: temperature, relative humidity, wind speed and daily precipitation. With the results of the study, they showed that high success was achieved and artificial neural network techniques were effective in such subjects [17].

Safi and Bouroumi proposed a model for the problem of predicting real forest fires using artificial neural networks. The proposed neural networks, the number of hidden layers and the number of neurons per layer is an intuitive multi-layer sensor. In this architecture, a backpropagation learning algorithm and a large real data set, related to the problem investigated, were used. In addition, they demonstrated the success of the study with the results showing the performance and usefulness of the resulting nervous system [18].

Anbaraoğlu proposed a model with support vector machines using data based on forest fires. The model is aimed at estimating the amount of burning area by including the spatial-temporal outsiders in the model with the model created. In order to reduce the dependence of the observed results to the selected data set, the data

was compared to the original and derived data for 10 randomly selected data sets. As a result, the derived data appeared to be both less erroneous and more consistent [19].

Bozer estimated the size of the area lost due to fire by taking into account the burned areas caused by possible forest fires, the geographical conditions of the current environment, the date and time of the fire, meteorological data such as temperature, humidity and wind speed, and the type and number of trees in the unit area. Multilayer Sensors, Radial Basis Function Networks, Support Vector Machines and Fuzzy Logic techniques were used to make estimates. Thus, it provided a method for resource management in firefighting. The results showed that in some models, the performance in the estimation process is high and better than most of the studies available in the literature. The best result was obtained when using MLP [20].

Özkan et al. conducted research on multi-layer sensors, radial basis function and learning vector classification approaches for forest fire detection using SPOT-4. Adaboost and Logitboost algorithms were used for binary and multi-class classifications. It has been demonstrated that Adaboost and Logitboost classifications have great potential as an alternative to traditional techniques [21].

Liu et al. aimed to distinguish vegetation from burned and unburned areas via photon counting LiDAR data, thereby classifying burned areas. First of all, they emphasized the importance of mapping burned areas correctly, analysing carbon emissions and forest fire risk and understanding the effects of climate change on forest structure. As a result, the authors achieved high accuracy in the classification of burned forest areas. They also showed that the use of ICESat–2 data predicts burned biomass and carbon emissions better than the 3D perspective [22].

2. MATERIALS AND METHODS

In this context, the study was given under the following headings, respectively: artificial neural networks, obtaining and preparing of the data used in the study, and finally, creating of the ANN model (normalizing of the data, training and testing process). The general process followed to create the ANN model is given in Figure 1.
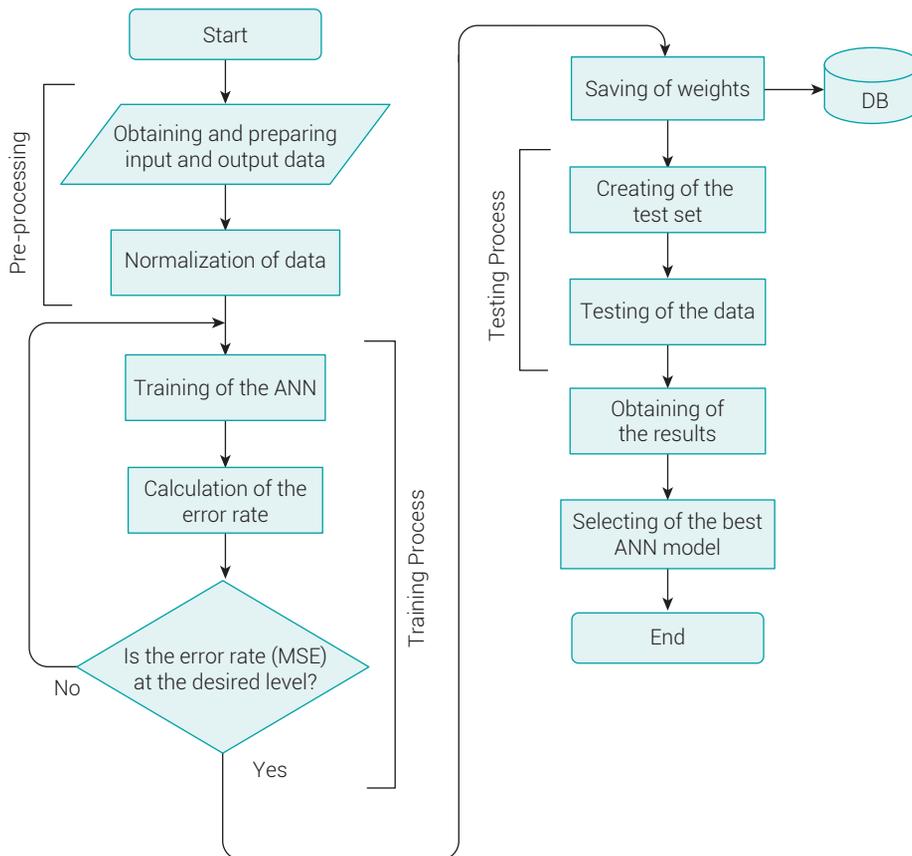
Figure 1. Flowchart used to create the ANN model.
Source: own work

2.1 Artificial Neural Networks

As artificial intelligence has become a critical technology in dealing with real-world problems [23, 24], the use of artificial neural networks is one of the strongest techniques used. Artificial neural networks are information processing systems that are widely used today, capable of performing the learning function by experimentation, which is the most basic feature of the human brain, and is capable of estimation. ANN has a structure that is different from traditional calculation techniques, adapts to the environment in which it is located and can decide in cases of uncertainty. ANN is used effectively in many different fields such as estimation, optical character handling, fingerprint recognition, pattern recognition, robot technology, job scheduling, quality control, power systems, system modelling, finance applications, image processing, industrial applications and defense applications [25-29].

A simple neural network is a structure consisting of a single neuron, very similar to biological neurons with dendrites and axons, with a single output node that connects to the input nodes and each input node. Figure 2 provides an example of how the development of artificial neural networks has been inspired by biological neural networks.
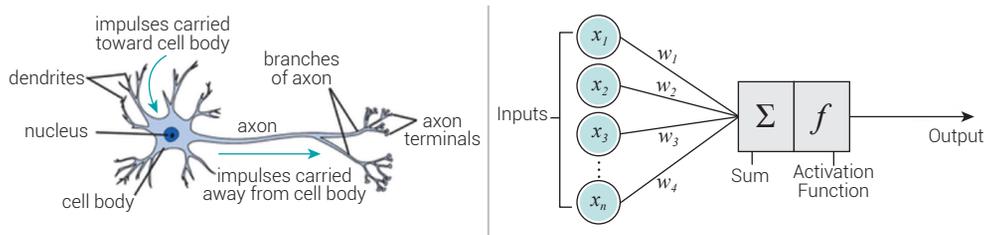
Figure 2. A simple ANN.
Source: [30]

At this point, a typical artificial neural network model can be defined mathematically as in Equation 1.

$$u_k = \sum_{j=1}^{n} w_{kj}\, x_j, \; y_k = \varphi\,(u_k + b_k), \; v_k = u_k + b_k \,, \; y_k = \varphi\,(v_k) \quad (1)$$

ANN is used to solve nonlinear and complex problems. The data that makes up the model is divided into two sets; training and testing. During the training process, the error level is reduced by adjusting weights in the neural network, and this process continues until it reaches the targeted output. The performance of the model is obtained by testing the data that is never used in the training process on the neural network [31-33].

The feed-forward backpropagation neural network architecture is effective in the training of the network. The feed-forward neural network is arranged in cells-layers, and the outputs of cells in one layer are given as the input to the next layer via weights. The output of the network is determined by processing the information in the middle and output layer. With this structure, feed-forward networks perform a nonlinear static function. In the feed-forward neural network, the layer to which inputs are applied is called the input layer, the layer from which the outputs are received is

the output layer, and the layer between the input and output layers is called the hidden layer. The number of neurons in the input and output layers is determined according to the needs of the problem addressed [34-36].

2.2 Obtaining and Preparing the Data

The data were taken from [37] and used in a study by Cortez and Morais [16]. This real data consisted of 517 lines in total. Since there was no data deviating from the normal data, noise removal operation had not been performed. Only, the month and day names were digitized. A sample dataset is given in Table 1.

Table 1. An example for the dataset

Inputs												Output
X	Y	month	day	FFMC	DMC	DC	ISI	temp	RH	wind	rain	area
8	6	8	6	92.2	81.8	480.8	11.9	20.1	34	4.5	0	58.3
4	6	9	7	93.5	149.3	728.6	8.1	28.3	26	3.1	0	64.1
8	6	8	2	96.1	181.1	671.2	14.3	21.6	65	4.9	0.8	0
4	4	9	3	92.9	133.3	699.6	9.2	26.4	21	4.5	0	88.49
1	5	9	7	93.5	149.3	728.6	8.1	27.8	27	3.1	0	95.18
7	5	8	2	96.1	181.1	671.2	14.3	27.3	63	4.9	6.4	10.8
9	4	9	2	84.4	73.4	671.9	3.2	24.3	36	3.1	0	105.66
5	4	8	5	91	166.9	752.6	7.1	21.1	71	7.6	1.4	2.17
6	5	9	6	92.5	121.1	674.4	8.6	25.1	27	4	0	1090.84
4	4	8	2	96.1	181.1	671.2	14.3	20.7	69	4.9	0.4	0

Source: own work

2.3 Creating the ANN Model

Inputs and outputs were determined before creating the model. There are 13 titles in the model (12 inputs and 1 output). Inputs, outputs and attributes used in the model are given in Table 2.

Table 2. Inputs, outputs and their explanations

No	Inputs and Output	Explanation	Range
		Inputs	
1	X	x-axis spatial coordinate within the Montesinho park map	1 to 9
2	Y	y-axis spatial coordinate within the Montesinho park map	2 to 9
3	month	month of the year: "jan" to "dec"	Since there are 12 months in a year, it is numbered from 1 to 12
4	day	day of the week: "mon" to "sun"	Since there are 7 days in a week, it is numbered from 1 to 7
5	FFMC	FFMC index from the FWI† system	18.7 to 96.20
6	DMC	DMC index from the FWI system	1.1 to 291.3
7	DC	DC index from the FWI system	7.9 to 860.6
8	ISI	ISI index from the FWI system	0.0 to 56.10
9	temp	temperature in degrees Celsius	2.2 to 33.30
10	RH	relative humidity in %	15.0 to 100
11	wind	wind speed in km/h	0.40 to 9.40
12	rain	outside rain in mm/m^2	0.0 to 6.4
		Output	
1	area	the burned area of the forest (in ha)	0.00 to 1090.84

† FWI: Fire Weather Index, https://www.nwcg.gov/publications/pms437/cffdrs/fire-weather-index-system

Source: own work

2.3.1 Normalization of the Data

The data was normalized before the ANN model was created to scale the input and output values of the model, limit the data in the range of 0-1, prevent unnecessary data duplication and thus increase the performance of the model to be created (Table 3). The "min-max" normalization method, which is widely used in the literature, was used to normalize the data. Here, v_R represents the actual value of the input, v_{min} represents the minimum input value, and v_{max} represents the maximum input value (Equation 2) [35, 36, 38].

$$V_n = \frac{V_R - V_{min}}{V_{max} - V_{min}} \tag{2}$$

An example of the normalized data before separating the training and test data is given in Table 3.

Table 3. An example for the normalized dataset

Inputs												Output
X	Y	month	day	FFMC	DMC	DC	ISI	temp	RH	wind	rain	area
0.875	1.000	0.000	0.800	0.667	0.078	0.000	0.784	0.000	0.260	0.311	0.000	0.053
0.375	1.000	1.000	1.000	0.778	0.705	0.912	0.441	1.000	0.100	0.000	0.000	0.059
0.875	1.000	0.000	0.000	1.000	1.000	0.701	1.000	0.183	0.880	0.400	0.125	0.000
0.375	0.000	1.000	0.200	0.726	0.556	0.805	0.541	0.768	0.000	0.311	0.000	0.081
0.000	0.500	1.000	1.000	0.778	0.705	0.912	0.441	0.939	0.120	0.000	0.000	0.087
0.750	0.500	0.000	0.000	1.000	1.000	0.701	1.000	0.878	0.840	0.400	1.000	0.010
1.000	0.000	1.000	0.000	0.000	0.000	0.703	0.000	0.512	0.300	0.000	0.000	0.097
0.500	0.000	0.000	0.600	0.564	0.868	1.000	0.351	0.122	1.000	1.000	0.219	0.002
0.625	0.500	1.000	0.800	0.692	0.443	0.712	0.486	0.610	0.120	0.200	0.000	1.000
0.375	0.000	0.000	0.000	1.000	1.000	0.701	1.000	0.073	0.960	0.400	0.063	0.000

Source: own work

2.3.2 Training and Testing Process

The training and testing process were started after the data was normalized. These operations were carried out using the MATLAB package program. 75% (388 data) for training and 25% (129 data) for testing of randomly determined data from a total of 517 real data were allocated. Then, the training and testing processes were implemented to obtain the best ANN model. Many trials were made in different ways to create the model. The model (high R and low error rate) was determined as a result of experiments with different options such as different training functions, activation functions, transfer functions, different number of hidden layers and number of neurons in hidden layers. According to the findings obtained from these experiments, the attributes of the best model are given in Table 4.

Table 4. The attributes of the proposed ANN model.

Dataset	Performance Criteria	Neural Network Model (12-8-8-1)
Training	R	0.99615
Testing	R	0.99017
Validation	R	0.99223
All	R	0.99589
	MSE	0.0021

Source: own work

The best ANN model, as a result of the trials after the data were trained, has the following features: the training R ratio: 0.99615, the test R ratio: 0.99017 and the error rate is 0.0021, and a multi-layered structure (12-8-8-1).

The values obtained were tested with test data to measure the memorization status and performance level of the model. The ANN model with a multi-layered structure is given in Figure 3.
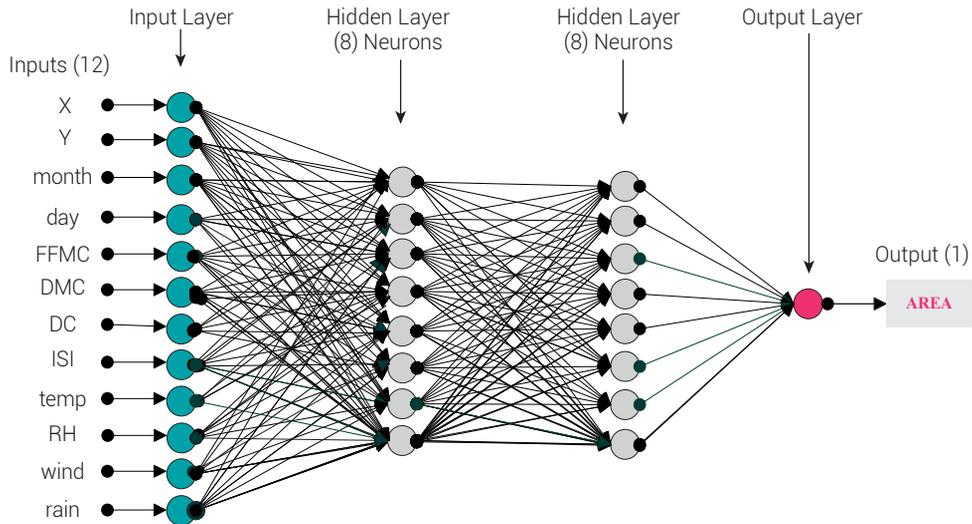
Figure 3. The proposed ANN model
Source: own work

3. FINDINGS AND DISCUSSION

The performance of the model was tested using real data after the model was created, and then the results obtained were analyzed. In the experimental process performed, it was observed that when the created model had a single hidden layer, low performance was achieved, but there was an increase in the performance of the model when it had two or more hidden layers. In addition, it was observed that the performance of the neural network model decreased significantly when the number of neurons in the hidden layer was increased, despite there being two hidden layers. In such a situation, it can be said that the model memorized or learned.

3.1 Experimental Results

10 different burned areas were determined randomly in two different regions in order to measure the performance of the proposed model. The burned areas of each area were formed according to different input values, utilized real data and 20 rows in total. In Figure 4, examples of burned areas, some of which were highlighted with a white line, are given.
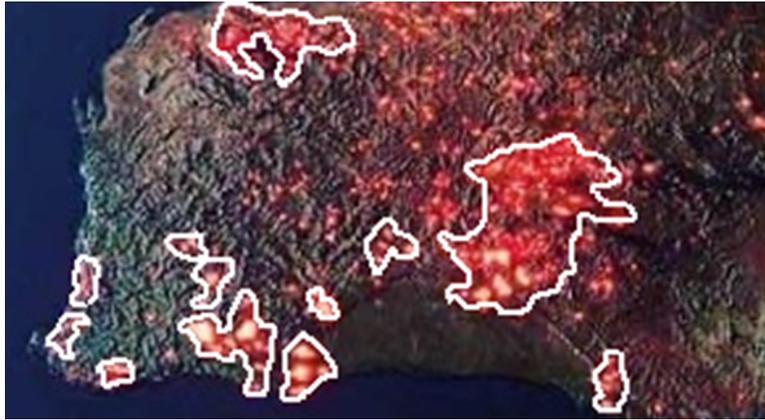
Figure 4. An example for burned areas
Source: own work based on [39].

The Mean Absolute Percentage Error-MAPE (Eq.3), Mean Square Error-MSE (Eq.4) and Absolute Percentage Change-R^2 (Eq.5) formulas are commonly used to measure the estimated performance of network structures [40-43].

$$MAPE = \frac{1}{T}\sum \left| \frac{y_t - \hat{y}_t}{y_t} \right| \times 100 \qquad (3)$$

$$MSE = \frac{1}{T}\sum_{t=1}^{T} \left(y_t - \hat{y}_t \right)^2 \qquad (4)$$

$$R^2 = 1 - \left(\frac{\sum_t (y_t - \hat{y}_t)^2}{\sum_t (\hat{y}_t)^2} \right) \qquad (5)$$

$(y_t = \text{Real Values}, y_t = \text{Estimated Values}, T = \text{Number of Estimates})$

The proposed model was tested by using the values of the burned areas that occurred according to the input values in the sample set. The experimental results were given and analyzed separately because they were taken from two different regions. The estimation results of the first randomly selected region are given in Table 5.

Table 5. The experimental results of the first region

No	Real Values	Estimated Values	MAPE	MSE	R²
1	0.001265	0.001145	0.01198	0.000000014	99.98802
2	0.008113	0.007911	0.01999	0.000000041	99.98001
3	0.016364	0.017250	0.08722	0.000000786	99.91278
4	0.001430	0.001195	0.02346	0.000000055	99.97654
5	0.005995	0.006123	0.01269	0.000000016	99.98731
6	0.019195	0.019871	0.06628	0.000000456	99.93372
7	0.004034	0.003950	0.00830	0.000000007	99.99170
8	0.008498	0.008317	0.01790	0.000000033	99.98210
9	0.002633	0.002210	0.04221	0.000000179	99.95779
10	0.010258	0.011394	0.11243	0.000001290	99.88757
Mean Values			**0.07486**	**0.000001354**	**99.92514**

Source: own work

According to Table 5, it can be seen that high performance success rates were obtained when looking at the mean values: MAPE with a rate 0.07486, MSE with a rate of 0.000001354 and R^2 with a rate of 99.92514. The comparative representation of the real and estimated values obtained from the model is given in Figure 5a and the regression curve is given in Figure 5b. It can be seen that the estimation results obtained with the model, using real project data during the experiment period, were largely overlapping with real results and the error rates were very low (close to zero) (Figure 5). In other words, experimental results revealed that the performance of the model was high and the error rate was quite low.
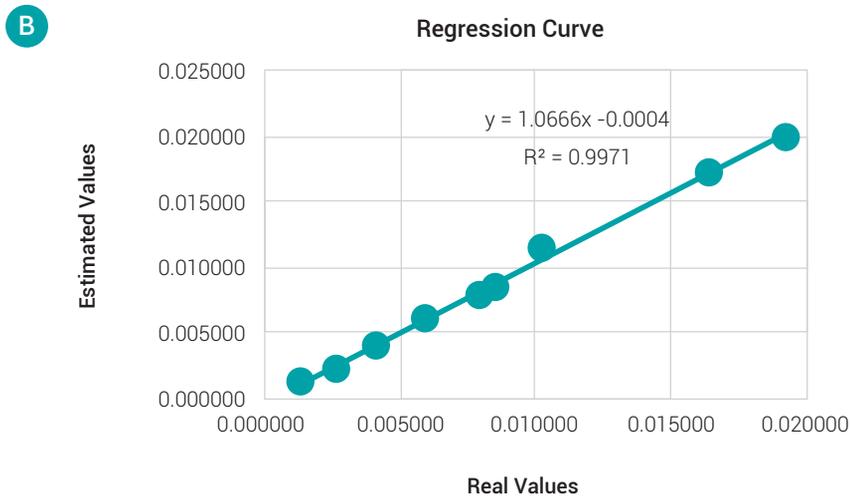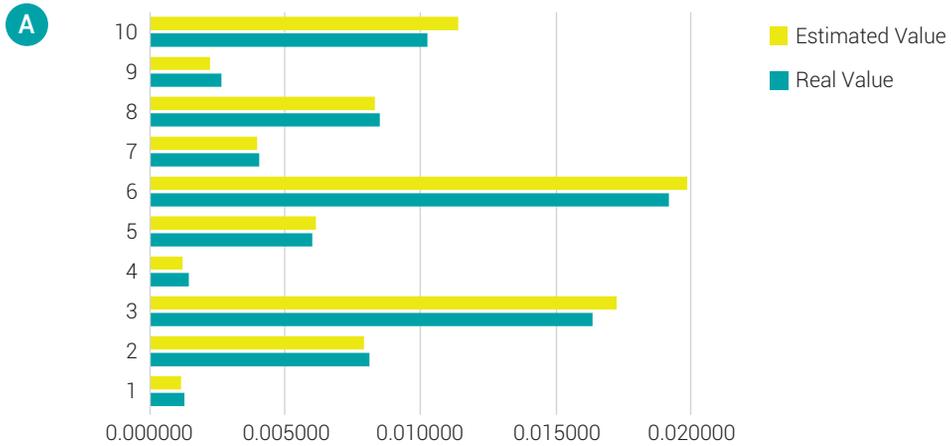
Figure 5. The estimated results and regression curve for the first region
Source: own work

The estimation results of the second randomly selected region are given in Table 6.

Table 6. The experimental results of the second region

No	Real Value	Estimated Value	MAPE	MSE	R²
1	0.054445	0.047562	0.65274	0.000047372	99.34726
2	0.587621	0.540125	2.99162	0.002255827	97.00838
3	0	0.011825	1.18250	0.000139831	98.81750
4	0.381121	0.439852	4.25242	0.003449334	95.74758

(continúa)

(viene)

No	Real Value	Estimated Value	MAPE	MSE	R²
5	0.077254	0.090014	1.18453	0.000162828	98.81547
6	0.049901	0.042872	0.66949	0.000049407	99.33051
7	0.196861	0.210039	1.10101	0.000173649	98.89899
8	0.019893	0.020148	0.02496	0.000000065	99.97504
9	1	0.96204	1.89800	0.001440962	98.10200
10	0.255335	0.229758	2.03746	0.000654183	97.96254
Mean Values			**1.59947**	**0.000837346**	**98.40053**

Source: own work

According to Table 6, high performance rates were also obtained in the second region, as in the first region. That is: MAPE with a rate of 1.59947, MSE with a rate of 0.000837346 and R² with a ratio of 98.40053. The comparative representation of the real and estimated values obtained from the model is given in Figure 6a and the regression curve is given in Figure 6b. In Figure 6, it can be seen that the estimation performance obtained by using the model was high and the error rate was quite low, as in Figure 5.

B

Regression Curve

y = 0.9567x + 0.0085

R² = 0.9922

Estimated Values (y-axis: 0, 0.2, 0.4, 0.6, 0.8, 1, 1.2)

Real Values (x-axis: 0, 0.2, 0.4, 0.6, 0.8, 1)
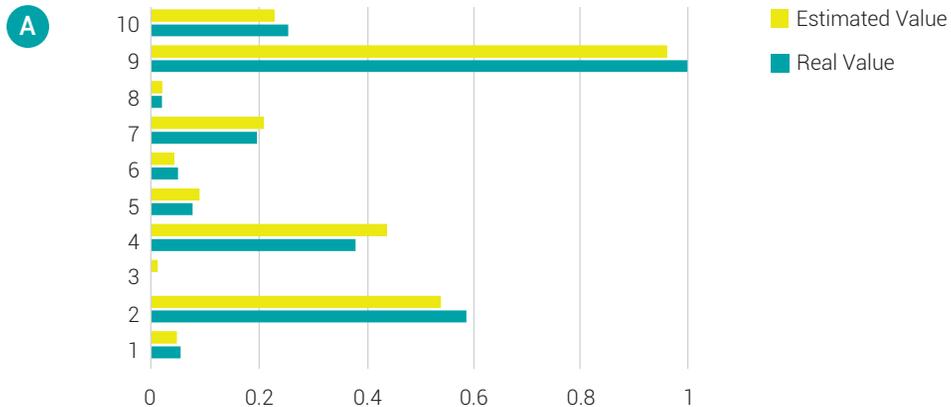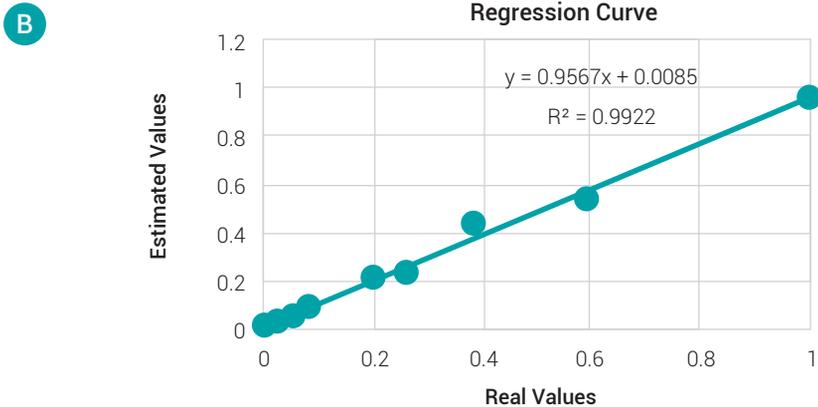
Figure 6. The estimated results and regression curve for the second region
Source: own work

As a result, the estimation results obtained by using burned area values, determined from both regions, clearly revealed the success of the study.

4. CONCLUSION AND RECOMMENDATIONS

In this study, a neural network model was proposed that estimates burned areas in forest fires using artificial neural networks. The model has twelve inputs, two hidden layers (8 neurons) and one output. At this point, one of the most important points to be considered while creating the neural network is to determine the number of hidden layers. The performance of the model was measured using real data for both regions after the model was created. Experimental results showed that the performance of the proposed model was quite good and the error rate was low.

The study clearly demonstrated the importance of using up-to-date techniques on important topics such as forest fires, which have been difficult to predict, rather than traditional approaches. However, hybrid approaches can be used by adding different techniques to minimize the error rate with successful estimation results being obtained by using the artificial neural network technique. The study is considered to be very important because it demonstrated the abilities to eliminate or prevent major damages that may occur by using the predictive feature of artificial neural networks.

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