Deep Learning Estimation of the Industrial Wood Production Level with Respect to the Natural Harm Factors

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Research Article

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Abstract

Protection and sustainability of forest assets are possible with planned production of the forest products. Among these products, industrial wood is the most important raw material for various sectors. Thus, the estimation of the industrial wood production level is important to use this product optimally, without disturbing the balance of forest assets. This article aims to estimate the industrial wood production level based on four natural harm factors, which are forest fires, outbreaks of insects, outbreaks of diseases, and severe weather events. The estimation model was built by using a deep learning method, which is an artificial neural network model based on the multilayer perceptron architecture. The study shows that the most harmful factor decreasing the industrial wood production level is outbreaks of diseases. The second effective factor, however, appears to be severe weather events. The third and the fourth factors were determined to be outbreaks of insects and burned forest areas, respectively.

1. Introduction

Forests are important natural resources. In addition, forest products are indispensable for many needs. Wood is the main product of forestry and it is used for many purposes. Wood that is used in production of industrial products, except wood used as fuel, is called industrial wood. The annual level of wood production in the world is around 3.4 billion m³, 53% of which is firewood and 47% is industrial wood. United Nations (UN) reports that, while approximately 90% of the firewood is produced and consumed by the developing countries, 79% of industrial wood is produced by the developed countries (UN, 2011). Industrial wood is the most important raw material of the sectors such as construction, furniture, or kitchen sectors. Thus, increases or decreases in industrial wood production directly affect these sectors. Therefore, estimating industrial wood production level gains importance to protect forests as well as sectors depending on wood industry.

In the literature, when the studies concerning the estimation of industrial wood or timber production level are examined, it is seen that the number of these studies is very limited. Among these studies, by using a growth simulator, Söderberg (1988) described a method of constructing functions that are based on long-term forecasting of timber productions. Stage and Renner (1988) made a comparison of the production-forecasting techniques using long-term stand records. MacLean (1990) reviewed the impacts of pests and fire on stand growth and timber production and reported that damaging agents reduced the tree growth, killed the trees, and destroyed their commercial values. Murray and von Gadow (1993) developed a flexible production model for regional timber forecasting depending on age-class based timber resource projection. Vanclay (1996) reviewed the tools, the techniques, and the information sources for estimating timber productions. Pukkala et al. (2003) developed and demonstrated a new method to make forecasts on the future timber supply. Churakov et al. (2011) studied the influence of heartwood rot on industrial wood production in aspen stands. Yildirim (2012) investigated the industrial wood production and consumption in Turkey and concluded that the industrial wood production would decrease in future, as the demand would increase. Atik and Yilmaz (2014) performed a study to determine the factors affecting the industrial wood production in Turkey using various conventional statistical analyses. They examined 26 variables and they found that the most important factors affecting the industrial wood production are fertility, aspect of land, skidding method, stand structure, skidding distance, growing stock, transportation, and harmful abiotic factors. They also reported that insect harm was among the most dangerous forest threats after human intervention. In another study, Atik and Aslan (2015) repeated the study of Atik and Yilmaz (2014) by building an artificial neural network model to show that artificial neural network models can efficiently be used for industrial wood production level estimation. In another study, Buongiorno (2015) suggests a model to predict timber prices and production.

Forests are affected by biotic or abiotic harm factors. Thus, the objective of our study is to estimate the industrial wood production level based on various biotic or abiotic harm factors, which are forest fires, outbreaks of insects, outbreaks of diseases, and severe weather events, using a deep learning method, which is based on the multilayer perceptron algorithm.

2. Materials And Methods

2.1. Artificial neural networks

Artificial neural networks are models that imitate the working mechanism of the nerve cells in the human brain, in a mathematical structure. The basic structure of artificial neural networks is made up of artificial nerve cells, called neurons. To form an artificial neural network, neurons need to work together. Neurons are also given names such as nodes, units, or processing elements. In an artificial neural network, the structure formed by neurons coming together in the same line is called a layer. Layers are also basic parts of artificial neural networks. There are three types of layers in an artificial neural network, which are the input layer, the intermediate (hidden) layer, and the output layer. The layers are also in contact with each other.

Neurons in the input layer are responsible for reception the input data transmitted to the model. However, they do not proceed with the input data. Instead, they only transmit the input data to the hidden layers. The hidden layers are responsible for building the model. Finally, the output layers are obliged to transmit the output values, obtained in the model, to the required environments. While an artificial neural network has only one input and one output layer, the number of hidden layers may be more than one. Any neuron in the hidden layer proceeds with the information it receives from the input layer and transmits it to the neurons in the next layer. However, in some types of artificial neural networks called feedback networks, this transmission is in the form of transmitting to the previous layer or to the input layer. The first step in the working mechanism of a neuron is the reception of the inputs and weights from the outer world or from the other neurons. These inputs and weights may be provided by sample data or by the outputs of other neurons. After the reception of inputs and weights, the neuron expresses this information as an additive model called the net function. The output of the neuron is formed by a function called the activation function whose input is the net function. The general expression of a net function is given in Eq. (1).

$$a = \sum w_i x_i$$

1

where x_i denotes the input values and w_i denotes the corresponding weights. There are many different types of activation functions. For example, sigmoid function is a popularly used activation function whose structure is given by Eq. (2).

$$F(a) = \frac{1}{1 - e^a}$$

2

where a is the value resulted from the net function in Eq. (1). The result produced by the activation function is the output of the neuron. Although neurons may have input values more than one, they have just one output value. Figure 1 briefly displays the working mechanism of a neuron.

An artificial neural network needs to be trained to produce accurate and consistent results. The training process is to make the network gain the ability of producing the correct outputs by calculating the necessary coefficients with the help of the input values in the sample data set.

Artificial neural network models have some advantages over the classical models. One of this advantaged is that they store the information over the entire network and a few pieces of information loss do not prevent the model from working. Additionally, they can produce outputs without getting affected by errors or corruptions in the data drastically. Moreover, the model can be trained with the help of other examples and previous studies, as the network is also capable of learning from similar networks. Artificial neural networks can work together to complement each other. Thus, they can perform multiple tasks at the same time. Another advantage of the artificial neural networks is that they can solve complex and nonlinear problems more successfully than the conventional approaches. They also do not require any assumptions or prerequisites in terms of data and model structure. Artificial neural networks are also able to learn from data and make decisions. Unlike the other classical models requiring fixed variance, they are still able to model the data when the assumption of fixed variance does not hold.

However, there are also some disadvantages of the artificial neural networks such as their performances are heavily dependent on the hardware level of the computer used. Additionally, there are not definite rules to follow to build a model except for a few thumbnail rules. Thus, building an appropriate model may depend on personal experiences and trials. As causality is not considered when building a model, they may produce unexpected results. Moreover, there is a necessity of converting all the input values into numerical data, which can be difficult sometimes for some kinds of variables. During the learning phase, it is not possible to observe how artificial neural networks operate. Thus, it is not possible to explain the reason behind the output values. Finally, it cannot be guaranteed that the estimated artificial neural network is the optimum one.

2.2. Multilayer perceptron model

A multilayer perceptron model can be defined as an artificial neural network, which is based on the perceptron model. The perceptron model is simply a single layer artificial neural network. Perceptron itself can also be defined as a type of neuron, where the net function includes the sum of weighted data and a bias value. During the introduction period of artificial neural networks, it was seen that the perceptron model was insufficient in solving nonlinear problems. Thus, Rumelhart et al. (1986) proposed the multilayer perceptron model by adding a new layer of neurons called the hidden layer, which exists between the input layer and the output layer, to the perceptron model. Artificial neural networks having more than two layers are also called deep neural networks. Thus, the multilayers perceptron models are also deep neural network or deep learning models. An example of the multilayer perceptron architecture is demonstrated in Fig. 2.

Multilayer perceptron model is a supervised learning model. The model is trained by a sample input and output data set so that the network learns to produce outputs that are close to the real output values existing in the data set. The difference between the observed data and the estimated data is called error (ϵ). During the training process, the model adjusts the parameters, or the weights and biases, to reduce the error, so that to produce the most accurate outputs. The most important property of the multilayer perceptron model is the backpropagation process, which means recursively adjusting the weights to minimize the difference between the observed and estimated values. During the backpropagation process, the total loss is propagated back into the network to calculate the amount of loss for which each neuron is responsible. Meanwhile, the weights are re-adjusted to minimize the loss and the process continues until the amount of error is stabilized. The error can be measured in various ways such as the mean absolute error (MAE), the root mean squared error (RMSE), the relative absolute error (RAE), and the root relative squared error (RRSE). MAE can be defined as the mean of the absolute values of the error terms. Calculation of MAE is given as follows.

$$MAE = \frac{1}{n} \sum_{i=1}^n |\epsilon_i|$$

3

where n is the data size and ϵ_i are the error terms. RMSE is the square root of the mean value of the squared error terms, which can be calculated as follows.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n \epsilon_i^2}$$

4

RAE and RRSE can be calculated using the formulas provided in Eq. (5) and Eq. (6), respectively

$$RAE = \frac{\sum_{i=1}^n |\hat{x} - x|}{\sum_{i=1}^n \left| \frac{\bar{x} - x}{\bar{x}} \right|}$$

5

$$RRSE = \sqrt{\frac{\sum_{i=1}^n (\hat{x} - x)^2}{\sum_{i=1}^n \left(\frac{\bar{x} - x}{\bar{x}} \right)^2}}$$

6

where x is the observed data, $\hat{x}$ is the estimated data and $\bar{x}$ is the mean value of x .

The correlation coefficient (ρ) indicates the direction and the degree of the linear relation between the actual data instances and the estimated instances produced by the constructed model. Calculation of the correlation coefficient is as follows.

$$\rho = \frac{\sum_{i=1}^n [x - E(x)][(\hat{x} - E(\hat{x}))]}{\sqrt{\sum_{i=1}^n [x - E(x)]^2} \sqrt{\sum_{i=1}^n [(\hat{x} - E(\hat{x}))^2]}}$$

7

where x is the observed data and $\hat{x}$ is the estimated data given by the model. $E(x)$ and $E(\hat{x})$ are the expected values of x and $\hat{x}$, respectively. The correlation coefficient ρ is a value between -1 and 1. A ρ value close to 1 indicates a strong positive linear relationship between the observed and estimated data instances while a ρ value close to -1 is an evidence of a strong negative linear relationship. If the ρ is 0, there is no relationship between x and $\hat{x}$.

When building artificial neural networks, there are not definite rules to decide about the number of layers, and the number of neurons existing in each layer. These values are highly dependent on personal experiences and trials. However, during the model selection phase, the models with higher correlation coefficients and lower error measures are preferred.

2.3. Study area

Turkey is among the industrial wood producer countries in the world. In Turkey, the owner and the manager of the state forests is General Directorate of Forestry (GDF). Ministry of Development (MOD) reports that the annual wooden raw material consumption in Turkey is approximately 25.9 million m³. Moreover, 15.5 million m³ (60%) of wood is produced from the state forests by GDF, while 4.8 million m³ (19%) of the production belongs to the private forestry companies. It is declared that 15% (4 million m³) of the wood production comes from illegal harvesting from the state forests, while 6% (1.6 million m³) is obtained by importing (MOD, 2014). Figure 3 presents the yearly levels of the industrial wood production in Turkey between 2000 and 2020.

When Fig. 3 is examined, it is seen that the levels of the industrial wood production display a decreasing trend from 2000 to 2003. However, except for the slight decreases in 2009, 2013, and 2017, it is possible to say that the industrial wood production levels tend to increase every year.

Figure 4 presents the production densities and the regions, where industrial wood is produced in Turkey as of 2020 (GDF, 2020).

It can be seen in Fig. 4 that the production of industrial wood is denser in the western and the mid-western parts of Turkey. It is also evident that the regions with the most intensive production levels are the seaside areas in general. Figure 5 presents the levels of the industrial wood produced in the forestry regions in Turkey as of 2020.

Figure 5 suggests that the most intensive production of industrial wood is observed in Kastamonu region, which significantly differs from the other forestry regions. The first four regions Kastamonu, Bolu, Zonguldak, and Amasya having the highest production levels are all in the Black Sea region that forms the northern part of Turkey. Bursa and İzmir, which have the second highest production levels, exist in the western part of Turkey. The third highest production levels, however, are observed in the regions Muğla, Adana, and Antalya, which are in the Mediterranean region forming the southern part of Turkey.

Figure 6 presents the kinds and the percentages of the industrial wood products that are produced from coniferous and non-coniferous wood in Turkey.

Figure 6 indicates that, log is the most popular product that is produced from coniferous wood (42%). The second and third most popular products produced by using coniferous wood are fiber-chip wood (32%) and pulpwood (17%) respectively. When non-coniferous wood is used, however, the most popular product appears to be fiber-chip wood (56%). The second and the third popular products produced by using non-coniferous wood are log (29%) and pulpwood (8%), respectively.

2.4. Data and variables

The data were collected from various resources. In the study, two reports of FAO were used to derive the data belonging to the variables (Koc et al., 2014; Özel et al., 2020). Additionally, a forestry sector report provided by The Union of Chambers and Commodity Exchanges of Turkey (UCCET) was also referred

(UCCET, 2011). Additionally, two reports of GDF were also used (GDF, 2012; GDF, 2020). Moreover, a report about Turkish forestry published by Foresters' Association of Turkey (FOT) and the forestry statistics published by Ministry of Agriculture and Forestry (MAF) were referred to collect the data used in the study (FOT, 2019; MAF, 2019).

The data involve one dependent variable, which is the industrial wood production level, and four dependent variables, which are burned forest area, outbreaks of insects, outbreaks of diseases and severe weather events. The data belong to the years from 2000 to 2017, consisting of 18 instances. The variables, their units of measurement and descriptions are provided in Table 1.

Table 1
The variables employed in the study

Variables	Descriptions
Industrial wood production	The yearly level of industrial wood production (m ³)
Burned forest area	The yearly amount of burned forest areas in forest fires (1000 ha)
Outbreaks of insects	The yearly amount of harmed forest areas due to outbreaks of insects (1000 ha)
Outbreaks of diseases	The yearly amount of harmed forest areas due to outbreaks of various diseases (1000 ha)
Severe weather events	The yearly amount of harmed forest areas due to severe weather events (1000 ha)

Figure 7 presents the yearly amounts of harmed forest areas with respect to burned forest area, outbreaks of insects, outbreaks of diseases and severe weather events factors.

3. Results And Discussions

Using the collected data, an artificial neural network model based on the multilayer perceptron architecture was developed to estimate the yearly industrial wood production level in Turkey. The flowchart provided in Fig. 8 demonstrates the model development phases of the study.

Weka (2021) software was used to build the artificial neural network model. During the model validation stage, the data were split into two parts as 75% for training and 25% for testing. After trying various parameter combinations, the artificial neural network model with two hidden layers, each containing four and two neurons, respectively gave the best assessment scores. An iteration period of 500 epochs was applied to estimate the model. Figure 9 demonstrates the layers and the neurons of the constructed artificial neural network model, based on the multilayer perceptron architecture.

Table 2 displays the actual and the estimated instances with the corresponding errors calculated for the testing data.

Table 2
The actual instances, the estimated instances, and the errors for the testing data

Instant number	Actual industrial wood production (m ³)	Estimated industrial wood production (m ³)	Error
1	4,913,900	5,995,542.74	1,081,642.74
2	9,299,000	5,607,923.498	-3,691,076.502
3	12,569,000	11,391,383.563	-1,177,616.437
4	16,637,598	15,885,947.216	-751,650.784

As 25% of the 18 instances were allocated for the training set, the training set involves four cases. When the results provided in Table 2 are examined, it is seen that the actual data used for testing and the corresponding estimated values are satisfactorily close to each other. The assessment scores for the constructed artificial neural network model are presented in Table 3.

Table 3
Model assessment scores

Score	Metrics
92%	Correlation coefficient
1,675,496.6157	Mean absolute error (MAE)
2,046,078.9412	Root mean squared error (RMSE)
44.6987%	Relative absolute error (RAE)
47.4323%	Root relative squared error (RRSE)

When the model assessment scores in Table 3 are examined, it is seen that the correlation coefficient, calculated for the actual values and the estimated values, appears to be 92%. This coefficient value is quite close to 1. In this case, it is possible to conclude that the degree of linearity between the actual and the estimated instances is quite high. This means that the estimated instances are quite close to the actual instances, which implies that the estimation

performance of the constructed artificial neural network model is quite satisfactory. Figure 10 presents the comparison of the actual and the estimated instances for the testing data.

It can be seen in Fig. 10 that the actual and the estimated values are satisfactorily close to each other. Thus, the constructed artificial neural network successfully estimates the industrial wood production level.

To measure the contribution of the variables in the model a feature selection study was performed. The variables and their ranked attributes that are based on the correlation coefficients are presented in Table 4.

Table 4
The attributes of the nodes

Inputs	Ranked attributes
Outbreaks of diseases (ha)	0.861
Severe weather events (ha)	0.449
Outbreaks of insects (ha)	0.289
Burned forest areas (ha)	0.255

When the weights provided in Table 4 are examined, it is seen that the industrial wood production level is decreased mostly by the outbreaks of diseases in forests. The second effective factor decreasing the industrial wood production level is the amount of forest areas affected by severe weather events. The third effective harmful factor, however, is the level of outbreaks of insects occurring in forest areas. Finally, the least effective harm factor decreasing the industrial wood production level appears to be the amount burned forest areas in forest fires.

When a comparison is made between the findings of our study and the other findings, such as the ones provided by Atik and Yilmaz (2014), it appears that they only consider the abiotic harm factors among the other harm factors. In our study, however, as well as two abiotic factors (forest fires and severe weather events), two biotic factors (outbreaks of diseases and outbreaks of insects) are also taken into consideration. Moreover, they report that harmful abiotic factors are among the most important factors affecting the industrial wood production level. In our study, however, the most important factor reducing the industrial wood production level appeared to be a biotic factor, which is the outbreak of diseases. Atik and Yilmaz (2014) also state that insect harm is the most dangerous forest threat after human intervention. On the contrary, our study suggests that there are more harmful factors than insect harm affecting the industrial wood production level, such as outbreaks of diseases and severe weather events.

4. Conclusions

Industrial wood is an important part of forestry products, as industrial wood is used in many areas such as construction, furniture, and kitchen sectors. Moreover, industrial wood is also a source of income for many countries as an export item. Therefore, it is important to estimate the industrial wood production level to use the forest resources in a balanced way. In our study, the estimation of the yearly industrial wood production level was made through an artificial neural network based on a deep learning model (multilayer perceptron). Four kinds of forest harm factors, which are burned forest area, outbreaks of insects, outbreaks of diseases, and severe weather events, were taken into consideration. The estimated artificial neural network model shows that deep learning models can be used in industrial wood production level estimation very efficiently, as they have no restrictions like linearity or fixed variance, which are required by some conventional estimation models. The deep learning model developed in this study has quite satisfactory performance metrics such as a high correlation coefficient of 92% and a low relative absolute error score of 44.6987%. As a continuation of this study, a comparison study can be performed between the results provided by artificial neural networks and conventional estimation models, which may be constructed for the same or different harm factors.

Declarations

Compliance with Ethical Standards

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Ethical Approval: This article does not contain any studies with human participants or animals performed by the author.

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Consent to Participate: The sole author of the manuscript consents to participate.

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Figures

Figure 1

Basic structure of a neuron

Figure 2

Example of multilayer perceptron architecture

Figure 3

Yearly levels of the industrial wood production (m³) in Turkey

Figure 4

Industrial wood production regions and production densities (m³) in Turkey as of 2020

Figure 5

Levels of the industrial wood production (m³) in the forestry regions of Turkey as of 2020

Figure 6

The kinds and the percentages of the industrial wood products produced from coniferous and non-coniferous wood

Figure 7

Yearly amounts of harmed forest areas (1000 ha) due to the harm factors

Figure 8

Flowchart of the artificial neural network model development

Figure 9

The constructed model for the industrial wood production level estimation

Figure 10

Comparison of the actual and the estimated instances for the testing data