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RESEARCH PAPER

Reduction of uncertainty in projection of growth and yield of Hyrcanian trees in Jabowa-4 model by applying artificial neural network (Case study: kheyroud forest- Nowshahr of Iran)

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Highlights

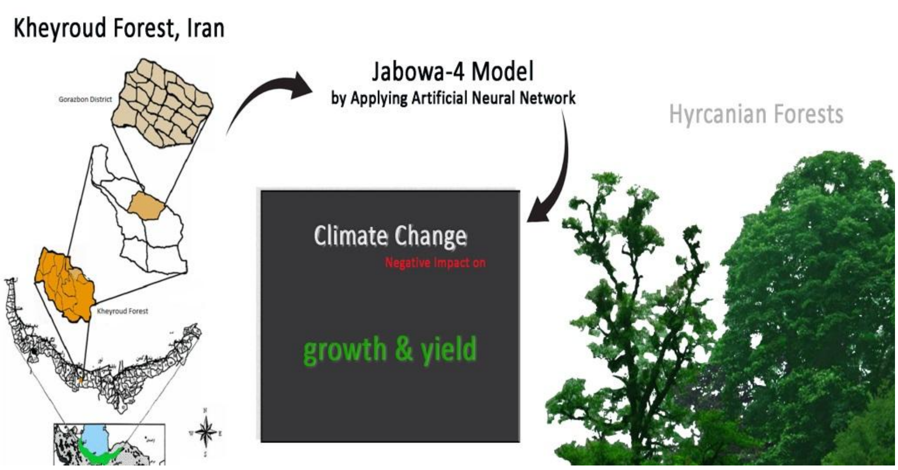
• The present study conducted due to the lack of efficient growth and yield models in important forests of northern Iran.

• The effect of environmental factors such as climate change, which until now were considered static, was examined.

• The use of gap models for the first time in these areas in order to depict the dynamics and succession of forest stands examined.

• The use of artificial networks to reduce growth and yield prediction uncertainty was investigated.

Graphical Abstract



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Abstract

Gap models have a long history in assessing the potential effects of climate change on forest structure and composition. In Hyrcanian forests, there is a lack of efficient models for predicting growth and yield. Therefore, to fill this gap in this study, we tried to use the Jabowa-4 model, which has the ability to predict forest dynamics by considering climatic factors. To apply the model in Hyrcanian forests, the main species selected and parameterized in different modes using experimental models. After the simulation process over 90 years, the values related to the observed and predicted BA, correlation coefficient and RMSE calculated and the species response to climate change evaluated. The results of this simulation show that climate change can have a negative impact on growth and yield by reducing rainfall and creating drought conditions in the studied forests. Due to these changes, the percentage of more resistant species such as Oak increases. On the other hand, the results of this study showed that Jabowa-4 is effective in providing forest performance predictions. However, it has a weak ability to explain the amount and height of trees in Hyrcanian forests.

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1. Introduction

Today, forestry faces several complex issues, such as assessing the effects of climate change and long-term sustainability. Solving such problems with empirical data is often difficult, requires long-term investment, or is impossible (Ashraf et al., 2015). Adaptive forest management planning requires forestry modeling tools that can be used in conditions of changing environment. Predicting future forest growth and yield in different climatic conditions by the models is a key element of sustainable forest management (Kimmins, 1990; Peng, 2000; Bayat et al., 2013). By planning forest management, forests can be adapted to environmental changes. Thus, growth and yield models, which are abstracts from reality, are widely used by scientists as research tools to test hypotheses, understand system behavior, and conceptualize the key relationships of a system (Mohren et al., 1994). These models should be able to use traditional forest inventory information as input to generate reliable predictions of forest growth and yield for practical forestry application scales (Vanclay, 1994). Models currently used as research tools in forest management can be classified into statistical (experimental) growth and yield models and process-based (physiological and Gap) models (Ashraf et al., 2015).

So far, statistical models of forest growth and yield have been used more than process base models, but they cannot take into account the effects of environmental change on tree growth. In other words, they are opposed to physiological models in which climatic and edaphic factors interact with the growth process of trees. Although an important principle in modeling is to show that models should be as simple as possible, they should be as complex as necessary. Based on the findings of a study by Pukkala et al., individual tree models can be the most appropriate approach for modeling the dynamics of uneven sized stands (Pukkala et al., 2009). In the meantime, we can refer to the gap models, which is a special type of forest ecosystem models that can consider climatic and environmental impacts based on ecological principles (Ashraf et al., 2015). Jabowa-4 as a Gap model is primarily a population dynamics model that is a valuable tool for studying tree growth, species composition and fixed structure dynamics in different climatic conditions (Botkin, 1993). JABOWA-4 is heavily dependent on ecological theories and interpretations of species dynamics in relation to competition conditions and the environment (Botkin, 1993). In other words, it can predict long-term forest succession and incorporate environmental theories into long-term scale simulations by considering a variety of Natural turbulence factors. These computer models might provide predictions about how forest stands respond to different climatic scenarios. Thus, they allow land managers to predict future forest yields, consider management options, and consider silvicultural alternatives before investing time and money into actual implementation (Vanclay, 1994). Forests are usually home to diverse populations that increase biodiversity and resilience of forest ecosystems.

Forest stand where its age classes are not recognizable called heterogeneous (Raymond et al., 2009). The Hyrcanian Forest, with a large proportion of deciduous commercial species such as Oriental beech (*Fagus orientalis* Lipsky) and hornbeam (*Carpinus betulus* L.) is a heterogeneous natural forest located at an altitude of 110-1000 m above sea level. Forest stands are often spatially heterogeneous and vary widely in tree size that tightly managed for timber production and mostly managed under uneven-aged schemes. The products of these forests are an important part of Iran's economy, so tools are needed to accurately describe and predict the various characteristics of the eastern beech and hornbeam stands dynamic and their impacts on the relevant forest traits. The objectives of the present study are to evaluate the use of the JABOWA-4 model in depicting the dynamics and determining how the heterogeneous Hyrcanian forest stands respond to different climatic scenarios, which can be integrate into forest management strategies.

2. Materials and Methods

2.1. Study area

This study conducted in the educational and research forest of Kheyroud, where belongs to the University of Tehran and is located on the northern slopes of the Alborz Mountains. This area is located 7 km east of Nowshahr city (Gilan province -Iran) and in the range of 36°34′–36°37′N, 51°32 E and an altitude of 0 to 2200 meters above sea level (Fig. 1). This wide range of heights is the foundation of various plant communities. Kheyorud forest has 27 sections; three of them protected and the rest of them are productive. Current research has carried out in the third part of the Kheyroud forest, called Gorazbon, which covers about 2308,557 hectares of land (Forest management project of Gorazbon Section, 2009). The average annual rainfall in Gorazben is 1532.35. In addition, the average temperature in the cold months of the year is about 6.15 °C and in the warm months up to 13.9 °C.

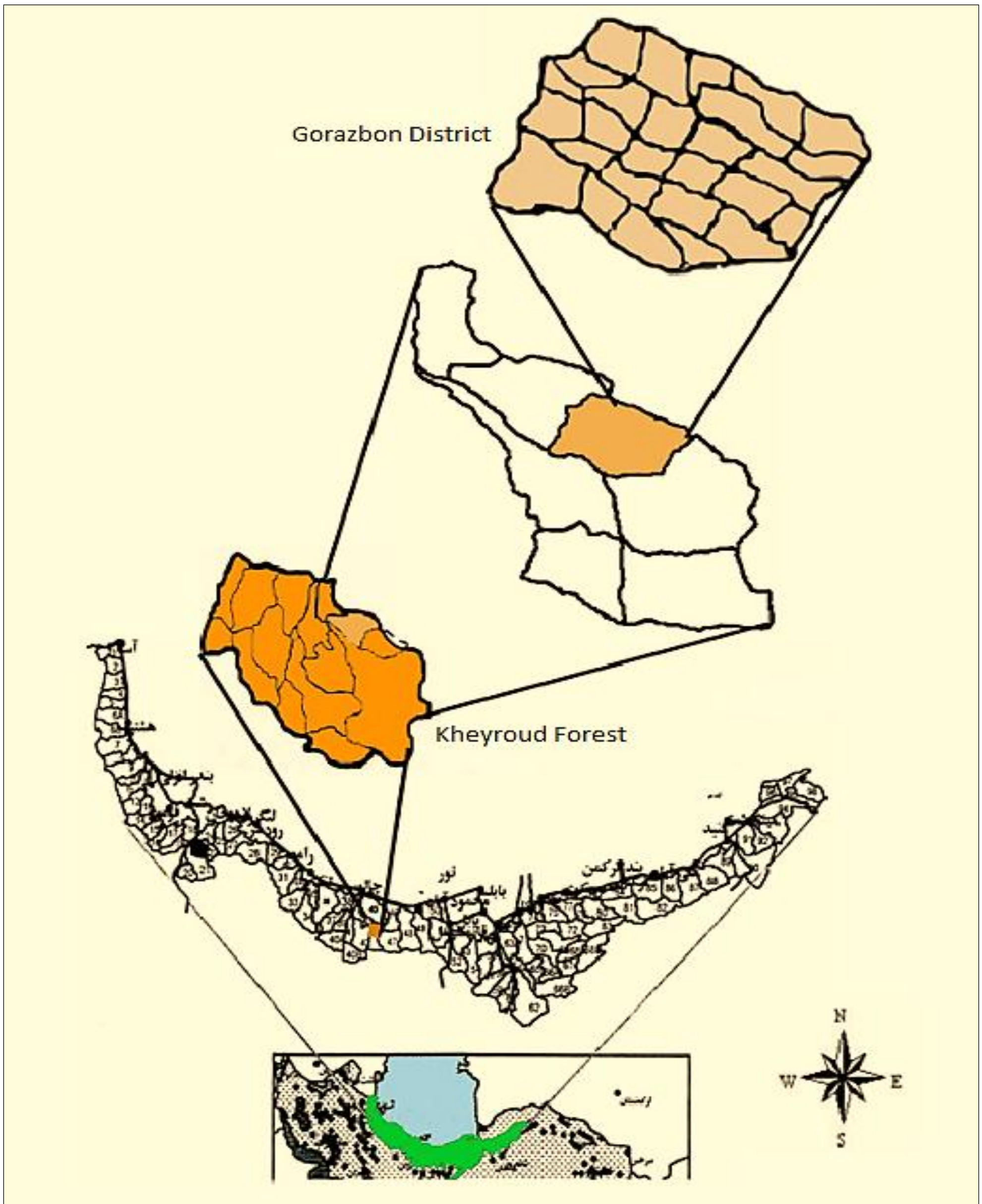


Fig. 1. The map of Kheyroud Forest, Iran.

2.2. Data collection

Permanent sample plots that are the best source of data for growth and yield modeling used in this study. In 2003 with the help of a 150 × 200 m rectangular inventory network, with a random start, 258 permanent sample plots that placed in mentioned forest, measured. These circular sample plots with an area of 10 R systematically disturbed throughout the Gorazbon district. Based on the general slope of the unevenness in Gorazbon, the main direction of the rectangular network is north south and then implemented on a 1:10000 topographic map. After determining the center of each sample plot, in the direction of its maximum slope, the grid placed horizontally. It should be noted that after determination the main slope of the sample plot, with the help of the slope correction table, the appropriate radius calculated.

The first measurements of PSPs done in 2003 with follow-ups in 2010 and 2016. The Diameter at breast height with range of 10cm (7.5-12.5) was the minimum diameter required for the inventory.Therefore, the diameter of all trees (5279 tree) thicker than the desired threshold(by Caliper), as well as the height of the tree closest to the center of the sample plot and the height of the largest tree in the sample plot measured. The growth rate of the diameter obtained from the difference between two consecutive measurements. In the PSP selection process, priority was given to PSPs consisting of target commercial tree species. Due to the small area and the lack of climatic diversity in the region, only one permanent sample plot selected and all of the analyzes performed based on this data.

The JABOWA-4 model requires an average monthly temperature and precipitation of at least 30 years to simulate future forest conditions (Botkin, 1993; Ashraf et al., 2015). Historical weather records used to prepare this model, consisting of monthly data on average temperature and total precipitation (from 1988 to 2017) were prepared from Nowshahr meteorological station. In addition, projected climatic information for future climate conditions under three climate change scenarios extracted from the CanESM2 global climate model. It is consist of large-scale data provided by the Canadian Center for Climate Modeling and Analysis (CCCMA) and the fifth assessment of IPCC.

2.3. Using of jabowa-4

Forests are created because of the interference of the following three processes: regeneration, growth and removal. In the process of growth, individual trees reach the DBH threshold (7 cm) and as they grow in height and width, they increase their volume and reach successive DBH classes. Growth values include volume, volumetric increment, and ingrowth values that are measured. First, the JABOWA-4 model calibrated based on the studied forest site conditions (Botkin, 1993). Simulations for current climate and climate change scenarios (RCP 2.6- RCP 4.5- RCP 8.5) were performed using JABOWA-4 for current and future (end of century) site conditions for the selected PSP (end of century). The model runs eight times to reduce the number of random events. The growth of a single tree under optimal conditions defined by using the fundamental growth equation (1).

$$\delta(D2H) = R \times LA\left(1 - \frac{DH}{D_{\max(i)}H_{\max(i)}}\right) \times f(environment) \tag{1}$$

D = diameter at breast height, H = height of tree, R = a constant, LA = leaf area of tree, Dmax (i) = maximum known diameter for trees of species (i), Hmax (i) = maximum known height for trees of species (i), F is a function of the effects of climate, shading, soil moisture, and fertility on tree growth.

In this equation, dividing DH by Dmax (i) Hmax (i) sets as an upper limit to the size that a tree can reach. The important thermal characteristic of the environment for trees, is the product of temperatures above zero-growth level (here, set at 10 °C), and the duration of those temperatures, this is known as growing degree-days. Where actual local weather records are not available, can estimate degree-days for each month from January and July average temperatures (Equation 2) (Botkin, 1993).

$$\mathrm{DEGD} = \frac{365}{2\pi}\left(\mathrm{T_{july}} - \mathrm{T_{jan}}\right) - \frac{365}{\pi}\left[50 - \frac{\mathrm{T_{july}}+\mathrm{T_{jan}}}{2}\right] + \frac{365}{\pi}\left\{\frac{\left[50-\left(\mathrm{T_{july}}+\mathrm{T_{jan}}\right)/2\right]^2}{\left(\mathrm{T_{july}}-\mathrm{T_{jan}}\right)}\right\} \tag{2}$$

2.4. Model evaluation

We can test the forest model to determine whether its projections are consistent with the competitive exclusion principles or not. Model evaluation is an important part of model preparation and some models reviewed at all stages of model design, installation and implementation. We must keep in mind that basal area and volume are among the most important variables in assessing forests as criteria for forest density (Botkin, 1993; Robinson and monserud, 2003; Ashraf et al., 2012). Because the focus of this study is to test the suitability of Jabowa-4 in producing reliable growth and predicting yield for uneven aged forests, these two variables selected. In order to compare the overall accuracy of the model for growth and yield, a paired t-test used between the observed and predicted variables (Table 1). RMSE, on the other hand, is a measure of accuracy and precision. It is often helpful to express the r^2 and RMSE as a percentage of the mean. Models with high r^2 and low RMSE are usually preferred.

2.5. Artificial neural network in predicting ba increment

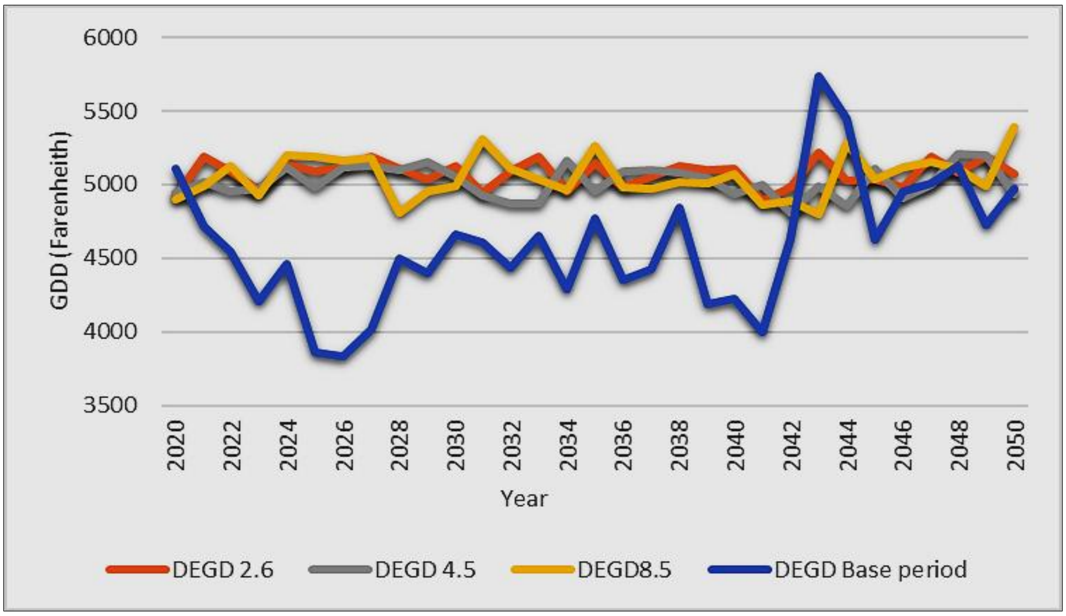
For this purpose, Feedforward Neural networks with single and double hidden layers (1-30 neurons) designed and trained for the studied Parameter. The data set divided into training and a validation subset. The backpropagation (BP) algorithm used for network training (Park et al., 1996). The outputs compared with their target values, the differences calculated, and the values were back prorogated along the neural network for weight optimization and error reduction by the Levenberg-Marquardt (LM) algorithm. Sigmoid and linear transfer functions considered for the hidden layers and the output layer, respectively. Development of neural network performed using MATLAB software (Rumelhart et al., 1985).

2.6. Neural network input layer nodes

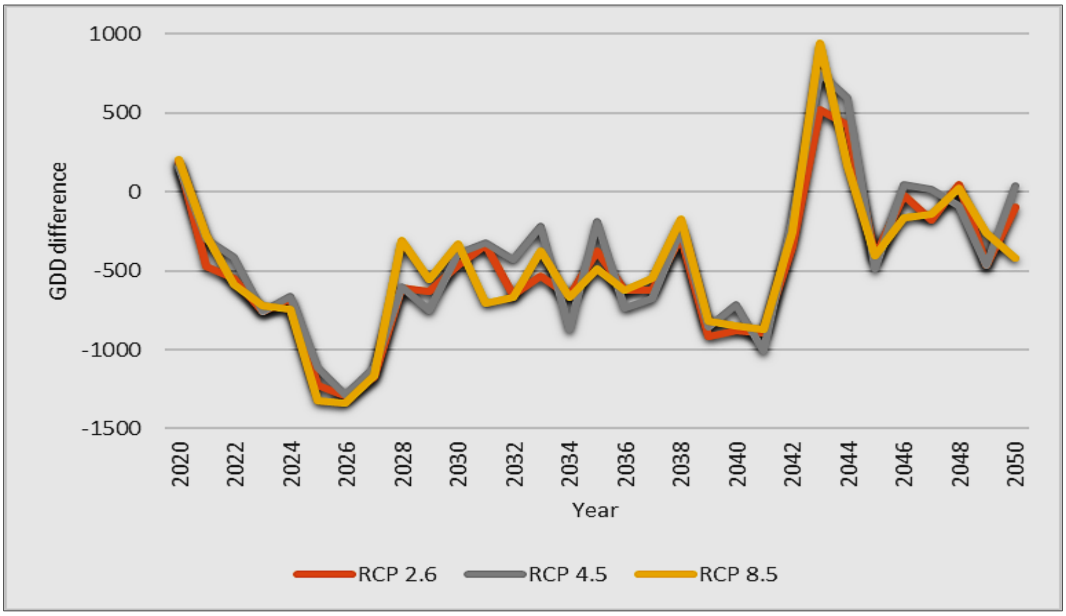
At the tree level, single trees in the model defined by species type and size. Habitat and growth conditions defined by biophysical variables such as radiation, growing degree-day, soil nutrient index and soil moisture (Pojar et al., 1987). The number of hidden layer nodes is a sensitive structural parameter of neural networks. Thus, a small number of nodes lead to under-fitting and the large number of nodes leads to over-fitting.

3. Results and Discussion

The results of predicted GDDs based on three-climate change scenarios (Rcp2.6, Rcp4.5 and Rcp8.5) compared to today's climate are depicted (Fig. 2). Climate change scenarios that simulate global development with particular emphasis on greenhouse gas emissions extracted from the CanESM2 global climate model. This model, developed by the Canadian Center for Climate Modeling and Analysis (CCCMA) in the Fifth IPCC Assessment (AR5), Provides Large-Scale Data. In addition, today's climate is based on a 30-year replication of historical weather data during the 90-year simulation period.



(a)



(b)

Fig. 2. Observed and Projected growing degree-days (GDDs) under three climate-change scenarios (RCP 2.6, RCP 4.5, RCP 8.5) from 2020 to 2100 (based on data collected at the Nowshahr meteorological station).

According to Fig. 2a, all three-climate change scenarios show approximately the same trend for GDD and the differences were not large, but after calculating the differences between them, the RCP 4.5 scenario showed a trend closer to today's climate path.

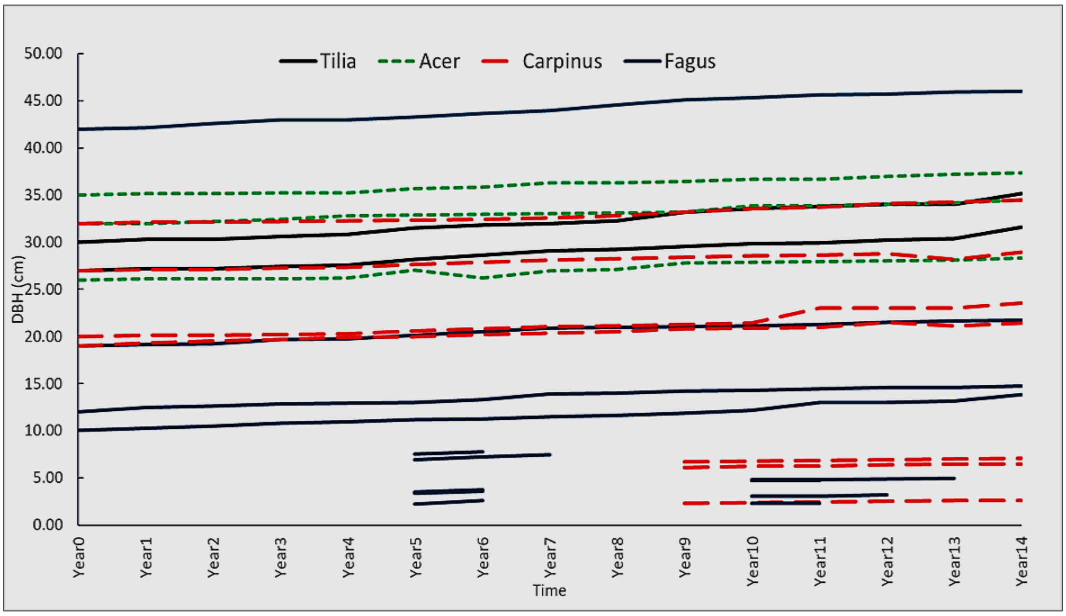


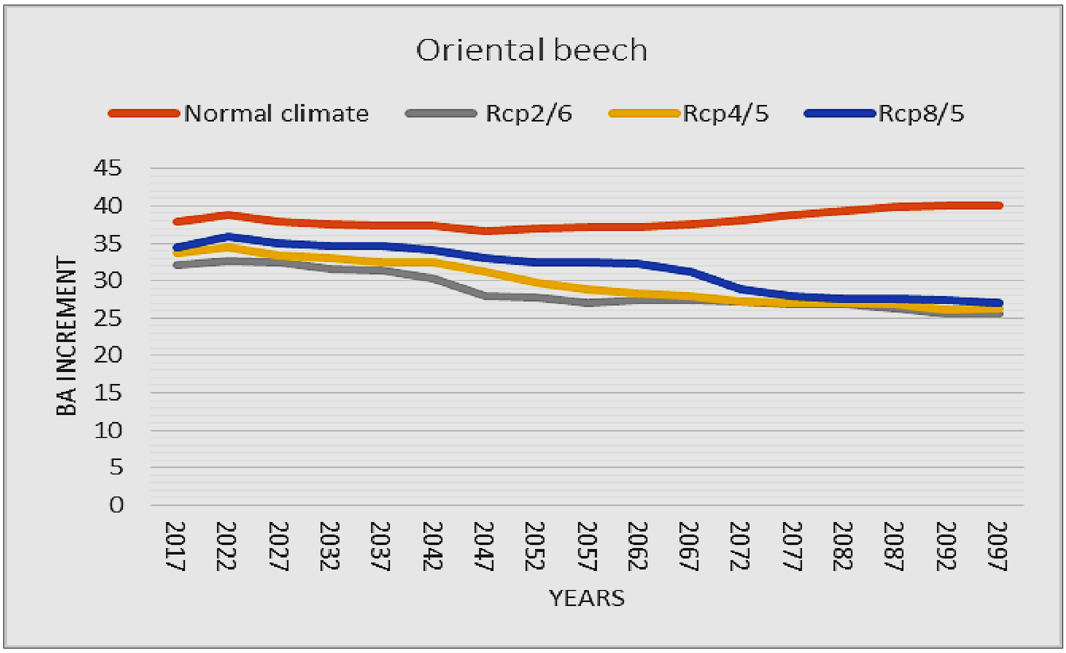
Fig. 3. Results for predicting diameter dynamics (cm) for trees in selected plot using JABOWA-4 at 14 years with real data available to determine model accuracy. Each line indicates the life span of the tree and the end of it determines the time of death. Regeneration established in the plot from the 5th year.

To compare the Basal area of trees in real and predicted conditions based on the first 14 years of simulation, paired t-test performed, the results of which are shown in Table 1. The RMSE and r^2 coefficients calculated to be 1.734 and 0.98, respectively. In addition, the T test shows that there is no significant difference in the values of the two variables (Fig. 3). However, after comparing the actual and predicted values for the volume, the differences were significant and identified Jabowa-4 as an inappropriate model for predicting the dynamics of this variable in the studied forest stand.

Table 1. The result of paired-sample t-test for Projected vs. Observed values in selected plot

	Std. Error Mean	Std. Deviation	t	df	Sig (2-tailed)
Basal area	0.4431	1.5875	-1.787	12	0.085
Volume	0.5714	0.206	-1.663	12	0.122

Moreover, Projection of BA yield for the most important tree species in area for present-day climatic conditions and three climate-change scenarios presented in Fig. 4.



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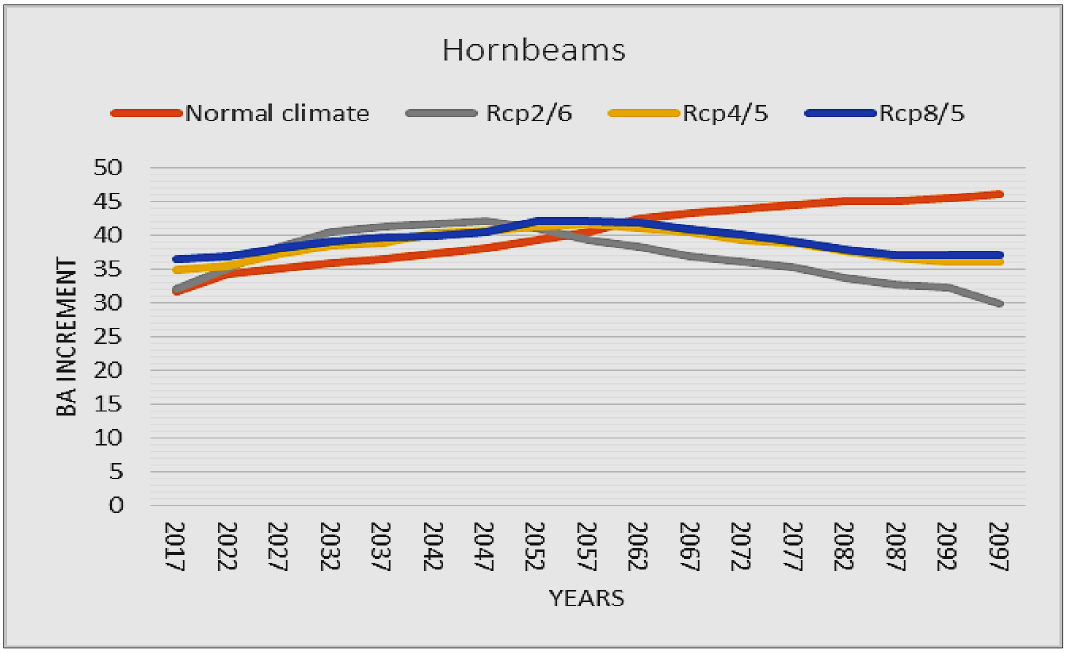

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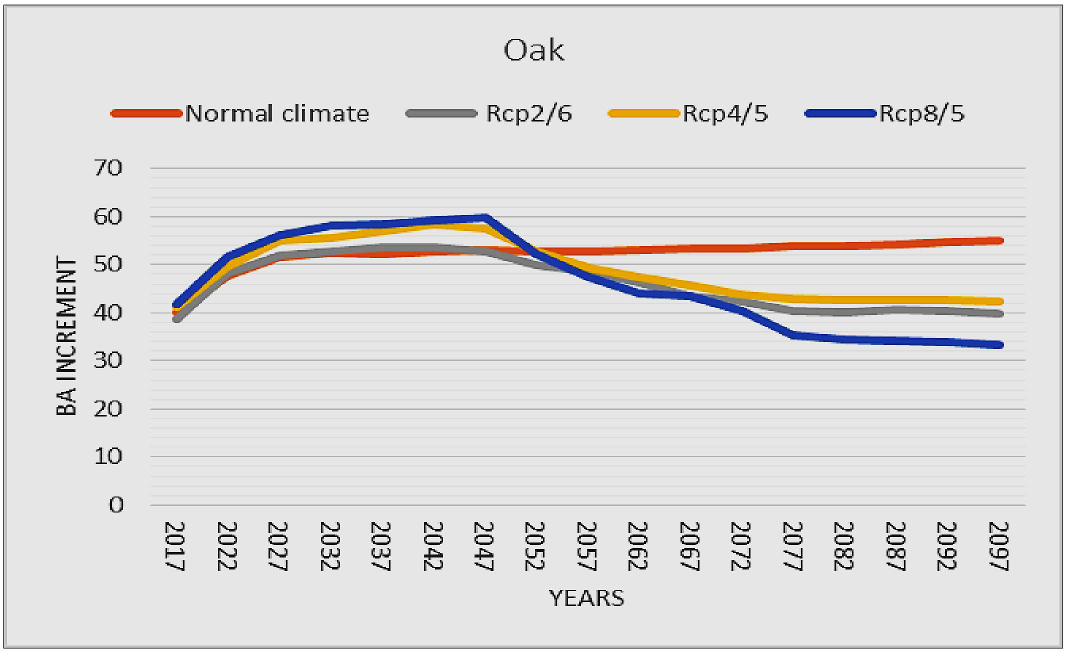
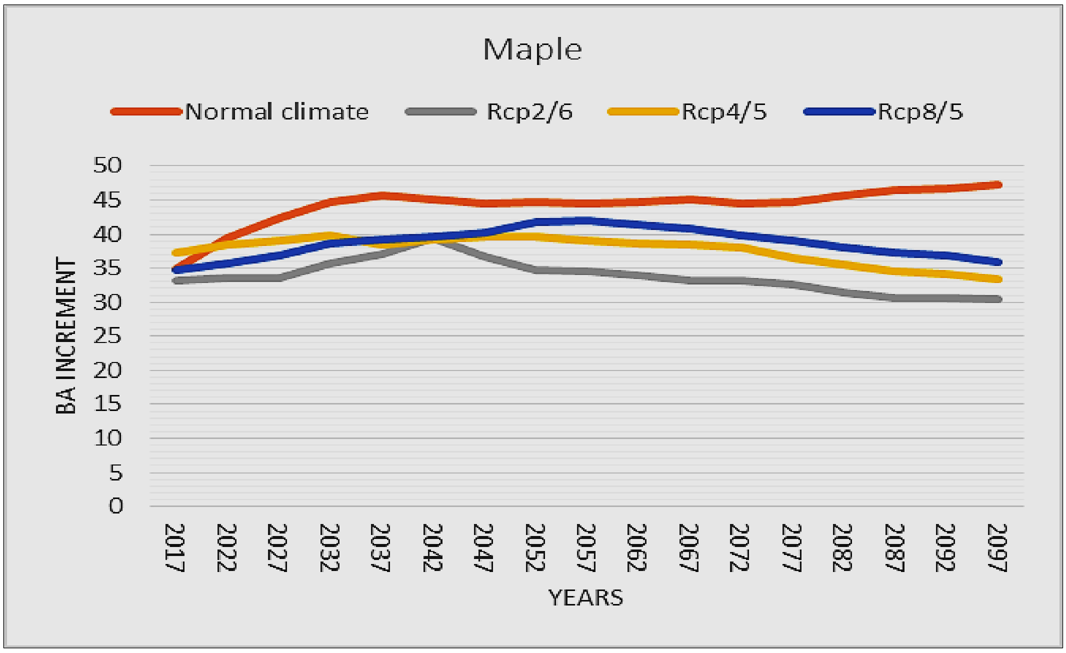


(c)



(d)

Fig. 4. Projection of 90 years of basal area (BA) yield for Present-day climate and three climate-change scenarios.

The results of BA prediction related to climate change scenarios showed that the growth of BA for beech and maple species, regardless of the type of scenario, showed a significant decrease, especially in the period of 2070 to 2100. In contrast, hornbeam and oak species showed a slight increase in BA in the first half of the simulation, and a downward trend in the second half. Showed that for hornbeam and oak, there were more differences in the RCP 2.6 and RCP 8.5 scenarios. In this study, the increase in BA of beech compared to other species was about 31%, which is greater in the RCP 2.6 scenario. The growth of oak BA initially increased, after a while its direction changed and decreased 17% by the end of the century. The trend for BA increment of hornbeam was increasing but about 20% lower than the real situation. In addition, a 25% reduction shown for maple.

In this study Feed forward, neural networks with 1 to 30 nodes in hidden layers designed and trained for the desired parameter. The values of r^2 ranged about 0.98 and RMSE from 0.5 to 0.825, which indicates the appropriate accuracy of trained neural networks. Finally, the lowest RMSE value calculated for neural networks with 16 nodes in two layers (0.504) and the largest with 10 hidden nodes (0.825). In Fig. 5, the output of training, validation and test subsets looks reasonable on the fitting line for all four outputs. As can be seen, according to the designed model, the correlation coefficient for making regression diagrams (R-value) is more than 0.99, which indicates the appropriate network reaction and its high accuracy in simulation. In other words, high correlation coefficient indicate a very close dependence of observational and estimate values.

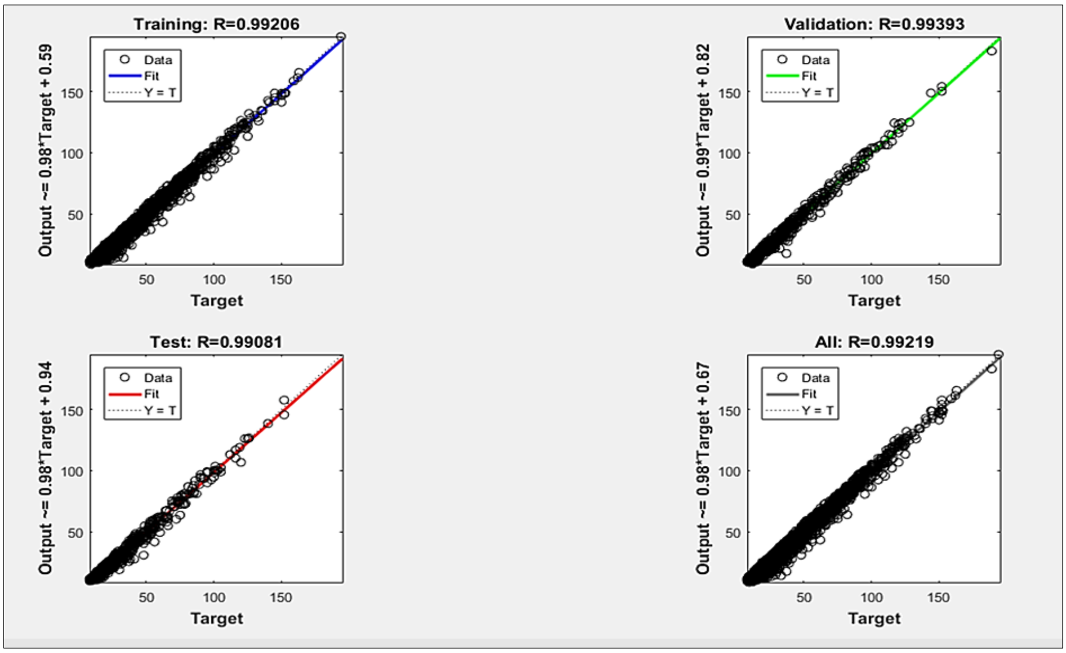


Fig. 5. Output of neural network training, validation and test using 16 nodes in hidden layers.

Due to the complexity of forest ecosystems, it is difficult to synthesize information about its dynamics and understand the concepts and hypotheses related to the growth of these areas. Contrary to popular belief, computers to date have little activity in simulating forest growth. As previously discussed, the purpose of this study is to evaluate the feasibility of Jabowa-4 to predict BA increment over a period. As mentioned in the materials and methods, in this study, since various climates are not observed in the study area, we evaluate only one permanent sample plot by JABOWA-4. The model successfully reproduced competition, succession and changes in species composition, as a function of time and climate. As mentioned earlier, GDD is a temperature range that sets the lowest temperature (here 50 degrees Fahrenheit) for trees to grow. The difference between GDD for Normal climate (based on past ~30 years trend) and three climate change scenarios (2020 -2050) compared in Fig. 2. The values for all climate scenarios were close to each other and ranged from 4795-5394. After comparing the minimum and maximum values for cumulative GDDs, the prediction of RCP 4.5 scenarios shows the closest trend to the present climate and is likely to occur in the present century.

In order to evaluate the capability of the model in reconstructing competition between trees (Fig. 3), a sample plot examined. In this sample, the thickest tree available was a beech tree with a diameter of 42 cm. In the simulation process, this sample depicted as a small sample of the forest. Regeneration entered to the PSP from the fifth year of simulation but has often eliminated due to the impact of competition. In JABOWA-4 software, as mentioned earlier, direct competition between individuals is limited to competition for light. (Taller, broad-leaved trees shade on shorter, smaller trees). This simple curve shows that the model successfully produces the quantitative and qualitative dynamics of local competition among trees in a heterogeneous mixed deciduous forest and larger trees dominate over smaller trees in terms of growth rate. Species strategy can also be explained by the probability of species-specific survival and the difference between adding new seedlings in relation to light at the forest floor level.

After comparing the observed and predicted values of BA in the selected period with real data, the parameters r^2 and RMSE calculated to be 0.98 and 1.734 respectively, which shows a good correlation in predicting the increase in BA for the JABOWA-4 model. It should be noted that what this software predicts is applicable only in the study area. Ashraf et al., produced linear regression between observed and predicted values and evaluation of r^2, RMSE and ME showed good performance for JABOWA-3 in growth and yield prediction (Ashraf et al., 2015). In another study in Australia, r^2 in diameter and height predictions calculated to be 0.97 and 0.59, respectively, indicating the high performance of JABOWA in diameter predictions (Ngugi and Botkin, 2011). Similarly, in Trasobares et al., study, the amount of absolute and relative RMSE for projection of diameter increment was 0.68 and 50.8% (Trasobares et al., 2016). The statistics of the present study were consistent with the growth and yield studies mentioned using the same data type. Other studies, such as Lee and Giulding, found significant differences between exist and projected diameters (Lee and Goulding, 2002).

It has also been observed in Gel and Bella, and Ringvall and Kruys, that the need to modify existing models has been raised (Gál and Bella, 1995; Ringvall and Kruys, 2005). The regression of modelled on observed is not expected to be consistent with unity for stochastic models such as JABOWA (Boote et al., 2010). To confirm the predictions of the JABOWA-4 model, records of actual tree growth in well-defined forests and environmental conditions are required, but no such data are available (Botkin, 1993). In fact, measurement errors in field data usually affect the statistical analysis based on this data. Inaccuracies in tree measurements of one year can lead to greater inaccuracies in subsequent years (Trasobares et al., 2016). Therefore, careful examination proposed for interpretation of statistical tests (Boote et al., 2010). The mentioned results of these studies are in a good agreement with the results of the present study regarding the prediction of BA increase.

In the BA time series of the four selected species in the region, beech growth has decreased by 31%, which is more than other species. High air temperature and low humidity have a detrimental effect on trees, especially those with smooth bark such as Beech trees. This problem is sun burning and can be cause of insects and fungi attacks. Therefore, because of unfavorable growth condition in lower altitude, BA increment for Beech trees will be limited. In Chaumont study, a decrease in the level of beech sites area has been reported due to rising air temperature (Chaumont, 2014). It has also been reported that the height of the sites in Rcp 2.6 and Rcp 8.5 scenarios increases from 1378 meters to 1679 and 1943, respectively. The beech species will lose many of its favorite sites in the area due to rising temperatures. Iverson and Pracad, predict that Fagus grandifolia's favorite sites in the United States will decline due to climate change (Iverson and Pracad, 2002).

In Europe, a decrease in favorite places of Fagus grandifolia has also been predicted based on climate change (Kramer et al., 2010). In Monserud, reported that in Hyrcanian forest, in order to sensitivity of beech trees to climate change, in the optimistic scenario (RCP 2.6), in 2070 about 72.97 percent of favorite sites will be damaged (Monserud, 2003). It can be concluded that in beech trees the effect of temperature is more than humidity (Fang and lechowicz, 2006). Also in Matsui et al., in the study of the effect of climate change from the distribution of Fagus Crenata in Japan, concluded that the temperature and the decrease in rainfall are the result of a decrease in favorite sites of this species (Matsui et al., 2009). All results are consistent with the current study. Oak initially showed an increase in growth and then a 17% decrease in climate change by the end of the 21st century. Oak species have a higher resistance to light and height compared to beech species and show better performance against climate change. However, after sharp reduction in precipitation in all of scenarios, because of environmental limits, increment of Oak also decreased.

Hornbeam needs more heat than beech, so its growth process is increasing, but it should be noted that this increase is 20% less than the potential growth of this species. Maple also showed a negative relationship with climate change and its growth reduced by 25%. This is because maple is slightly sensitive to rising temperatures. All of these results correspond to the history of the region. Engler et al., after studying mountain ecosystems concluded that species decline ranges are common in mountain ecosystems, in mountainous areas there is often a little space for species to move to higher altitudes (Engler et al., 2011). Hyrcanian forests are a type of these ecosystems, so a change in the distribution range of the species will definitely occur. In a similar investigation by Botkin et al., in withe mountain forest plots, by applying Jabowa-3 the projection were least accurate for balsam fir, more accurate for sugar maple, yellow birch, pin cherry, spruce and withe birch, also the results suggested that parameters for balsam fir are incorrect or the least accurate and they have to be corrected (Botkin et al., 1972). In Ashraf et al., investigation, after applying jabowa-3, most of the assessed species respond positively to climate change and their BA yield increased by rising temperatures associated with climate (Ashraf et al., 2015). Also after comparison of different climate change scenarios, A1B showed the most similar trend to current condition result of 30 years of cycling weather parameters. In general, these results, which show the performance of growth and yield simulators, are similar to the present study.

On the other hand, in applying neural network in this study, a large number of neural networks with random initial weights evaluated and trained to avoid local minimization (Park et al., 1996). In other words, all the performances and structures of the model measured in the test, in which the best neural networks for modeling BA growth consisted of 16 nodes in two hidden layers. The RMSE and r^2 values indicate good performance of the model compared to other traditional designed methods in which climatic conditions are considered static. Based on the finding, it can be concluded that the use of neural network model is useful to increase the accuracy of growth and yield predictions.

The findings of this study in relation to the JABOWA-4 model predict that the optimal habitats and consequently the distribution of beech species in the Hyrcanian forests will be strongly affected by climate change. Beech accounts for about 17.6% of the total forest area in the north of the country and includes 30% of the standing volume and 23.6% of the number of Hyrcanian forest trees. As a result, the effects of climate change on this species can greatly affect Hyrcanian forests. With regard to these cases, management and conservation decisions about these species should taking into account the effects of climate change and adaptation to these changes in Hyrcanian forests. Hyrcanian forests provide a wide range of services to the environment and local communities and are vital in soil conservation and water treatment. Climate change will have a major impact on the desirability of beech habitats, and in general, as the most important element, under the most optimistic climate change scenario, RCP2.6 will have the most preferred habitats in the Hyrcanian forests. These changes can pose a great risk to the functions and services of these forests. Finally, it is suggested that in forest management, decisions and methods of forestry compatible with climate change be used and beech conservation plans be prepared in accordance with the effects of climate change For example, use new methods for forest management that aim to preserve species diversity and their resilience to environmental stresses. Research also should be conducted to investigate the effects of climate change on other tree species in these forests.

4. Conclusion

Recently many studies conducted to reduce uncertainties in forest growth and yield predictions. One of these methods is the integration of information from process-based and experimental models. In this study, a modeling method to improve the constraint Current growth and yield models were introduced using information from process models which can simulate the BA of single trees at intervals of 5 years. This model represents a new modeling approach to integrate the effects of climate change on forest growth and yield models, as well as the benefits of using artificial intelligence in modeling forest growth and yield assessed.

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