Chapter 16
Estimation of Aboveground Stand Carbon using Landsat 8 OLI Satellite Image: A Case Study from Turkey

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Abstract Accurate and consistent measurement of carbon stocks and flows in forest ecosystems has recently gained global importance. This study aims to estimate the aboveground stand carbon (AGSC) using Landsat 8 OLI satellite image in pure Crimean pine stands and to compare the results of various modeling techniques. In this context, a total of 108 sample plots were firstly taken in a case study forest area. The AGSC of each sample area was calculated using a species-specific carbon equation developed for the case study area. The band values, vegetation indices, and texture values for each sample plot were also obtained from Landsat 8 OLI satellite image. The relationships between the AGSC and the band values, vegetation indices, and texture values were investigated by multivariate linear regression (MLR), support vector machine (SVM) and artificial neural networks (ANN) models. The results demonstrated that the ANN models with Bayesian regularization are better than the MLR and SVM models to estimate the AGSCin pure Crimean pine stands. Also, the band values showed better predictive performance in explaining the variation in AGSCthan vegetation indices and texture values.

Keywords Aboveground stand carbon · Landsat 8 OLI satellite image · Multiple linear regression · Artificial neural network · Support vector machine

16.1 Introduction

Forest ecosystems provide a lot of goods and services such as timber production, water conservation, soil protection, oxygen production, aesthetics, and recreation. Forest ecosystems are also an important part of the carbon pool. Changes to the size and efficiency of this pool can act as a carbon dioxide storage or source of forest ecosystems (Milne and Brown 1997; Karjalainen et al. 1999; Nowak and Crane 2002; Keleş and Başkent 2006). Forest trees behave like a CO_2 pool by holding

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CO_2 during photosynthesis and storing it in biomass. Forest ecosystems accumulate carbon mainly in biomass and soils. These are divided into sub-components as carbon stored in aboveground biomass (AGB), underground biomass, litter, dead cover, soil organic and inorganic matter. These are also the basis for carbon budget calculations (Lim et al. 1999; Ney et al. 2002; Kaipainen et al. 2004; Lal 2005). The total amount of carbon stored in a forest ecosystem at any given time is estimated as the sum of the carbon contents stored in live biomass, forest soil and wood products. With the calculation of these components, carbon stocks and flows in a forest can be calculated. On the other hand, the carbon held by the forest ecosystems from the atmosphere is released into the atmosphere with the decomposition of wood products, litter and organic matter in the soil. Also, some interventions such as production in forests, degradation as a result of excessive cuts and exploitation in forests, forest fires, insect attacks, tree species diseases, and the conversion of forests to different land uses such as agriculture and settlements are important factors causing CO_2 emission from forest ecosystems to the atmosphere. As a result, these processes cause forest ecosystems to be carbon sources (Karjalainen et al. 1999; Brown 2002; Keleş and Başkent 2006).

Accurate and consistent measurement of these carbon stocks and flows in forest ecosystems has recently gained global importance. Remote sensing techniques that are easier, cheaper and require less labor are an important alternative way to estimate the amount of carbon stored in forest ecosystems. In this context, different spectral variables such as band values (Rahman et al. 2008; Kelsey and Neff 2014; Safari et al. 2017; Li et al. 2018), vegetation indices (Myeong et al. 2006; Rahman et al. 2008; Kelsey and Neff 2014; Safari et al. 2017; Li et al. 2018) and texture values (Kelsey and Neff 2014; Li et al. 2018) have been used to estimate forest stand carbon using Landsat satellite data used extensively in forest resources management. Many statistical models based on the MLR analysis for predicting the AGSC values from the remote sensing data have been developed in forest studies. However, these MLR models require some statistical assumptions, normally distributed residuals and homoscedastic trends in the AGSC predictions, and when these assumptions are violated, these AGSC predictions can be biased and erroneously obtained in forest applications. To overcome this problem in tree predictions, Artificial Intelligence (AI) Techniques has been increasingly and successfully used as an alternative method in forest literature. Numerous prediction models based on AI, especially ANN, have been developed for modeling various individual tree and stand attributes such as tree volume (Diamantopoulou 2005a, b; Diamantopoulou et al. 2005; Özçelik et al. 2008; Görgens et al. 2009; Diamantopoulou and Milios 2010; Özçelik et al. 2010; Soares et al. 2011; Miguel et al. 2016; Sanquetta et al. 2017), tree taper (Diamantopoulou et al. 2005; Leite et al. 2011; Nunes and Görgens 2016), total tree height (Brandao 2007; Ranson et al. 2007; Diamantopoulou and Özçelik 2012; Özçelik et al. 2013; Ercanlı et al. 2015), tree mortality (Hasenauer et al. 2001), survival model (Guan and Gertner 1991), regeneration establishment and height growth (Hasenauer and Kinderman 2002), bark volume (Diamantopoulou 2005a, b), leaf area index (Ercanlı et al. 2018), diameter distributions (Ercanlı and Bolat 2017), biomass prediction

(Özçelik et al. 2017), basal area and volume increment growth model (Ashraf et al. 2013), the stand carbon (Ercanlı et al. 2016).

Besides many ANN studies, the other AI technique such as SVM stand out as another prominent AI technique. SVM may attractive potential usability to predict the stand carbon from the remote sensing data in forest inventory. The AI technique with SVM may be mainly regarded as a nonparametric technique with kernel functions, which have been proposed by Vladimir Vapnik and his co-workers in 1992 (Vapnik 1995). In the 1960s, the preliminary applications of SVM were introduced based on the nonlinear generalization of the Generalized Portrait algorithm (Vapnik and Lerner 1963; Vapnik and Chervonenkis 1964). As being artificial intelligence technique, the learning algorithm based on the SVM relies on simple ideas that originated in statistical learning theory (Vapnik 1995), thus the SVM may be utilized for both regression and classification tasks (Wang et al. 2005). In forest applications, SVM can be distinguished as a regression method, preserving completely the key structures that characterize the training algorithm. The other attractive feature of the SVM is the actual particular class training algorithm including kernel functions which considered a nonparametric technique. According to the knowledge of the forest biometric studies, no studies have been achieved to compare the SVM models and ANN models to predict the AGSC, especially based on the remote sensing data, and so the evaluation of the these AI techniques including SVM and ANN in predicting AGSC have been uncertain and needs to be clarified.

In this study, it is aimed to evaluate the capability of the usability of these AI techniques such as SVM and ANN models in predicting empirical relationships between the AGSC and the remote sensing data as a leading and innovative application.

16.2 Materials and Methods

16.2.1 Study Area

Yenice Forest Management Unit has been selected as the case study area since there is enough data about this forest area. It is located within the borders of Ankara Regional Directorate of Forestry, Ilgaz Forest Management Department in the north Turkey (Fig. 16.1). The average annual precipitation is 474 mm, and the average annual temperature is approximately 5 °C. Main tree species in the study area are Scotch pine (*Pinussylvestris* L.), Crimean pine [*Pinusnigra* Arnold. subsp. *pallasiana* (Lamb.) Holmboe], and fir (*Abiesbornmülleriana* Matttf.). The total forest area in the study area is 7144 ha and approximately 1700 ha of this area are composed of pure Crimean pine stands as the main object of the study.

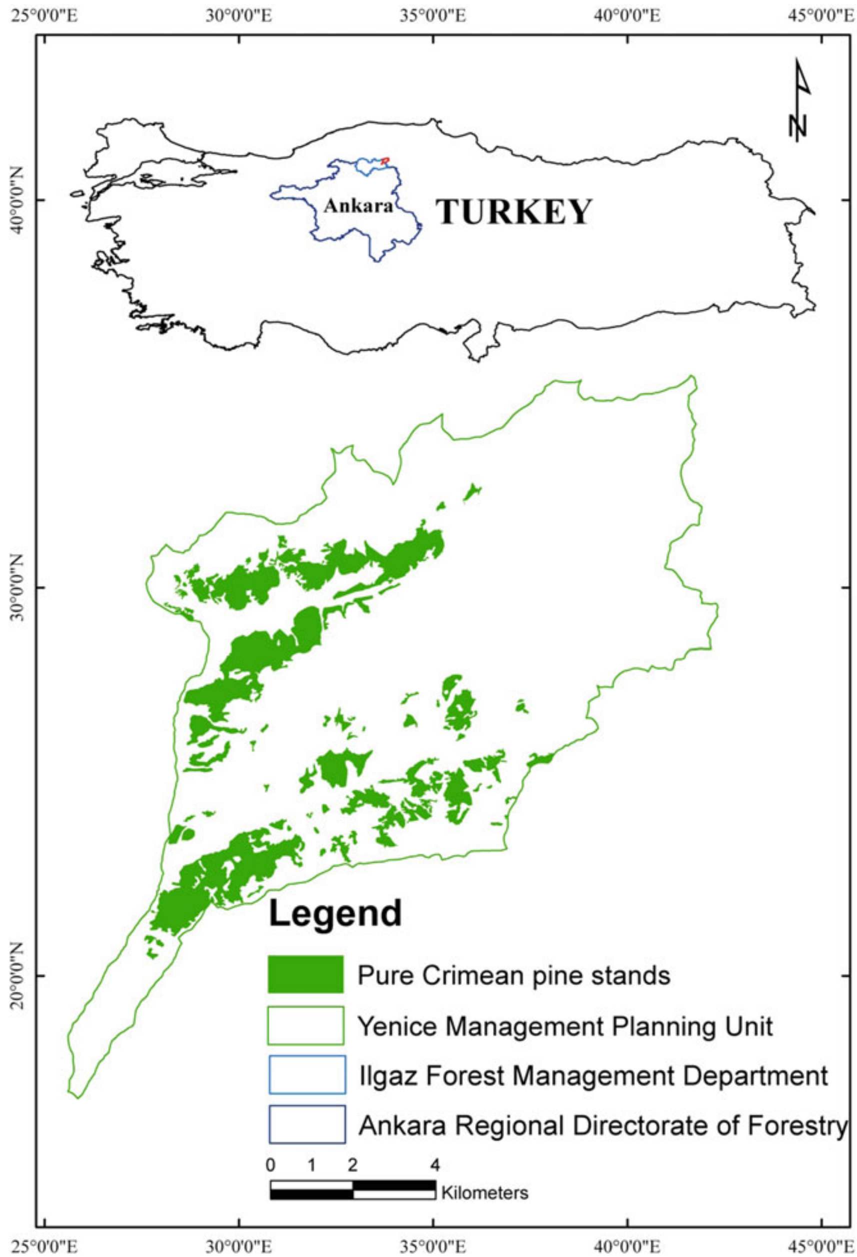

Fig. 16.1 Map of the study site and interaction area

16.2.2 Calculation of Aboveground Stand Carbon

A total of 108 sample areas were taken in this study. The size of the sample plots varies between 400 and 800 m^2 depending on stand crown closure. In each sample area, the diameter of all the trees with diameter 8 cm and over was measured at breast height level. The amount of AGSC by each tree in each sample area was calculated using the local equation for the Crimean pine forest stands developed by Sakıcı et al. (2018). Using this Eq. 16.1, the amount of AGSC by each tree in the sample plot was first calculated. Then, by collecting the amounts of AGSC by the trees in the sample plot, the AGSC amount was calculated for the sample plot. Finally, the AGSC amounts calculated for each sample area were converted to hectare using the conversion factor to the hectare.

$$C_{AG} = 0.054 \cdot (dbh)^{2.362} \tag{16.1}$$

where C_{AG}: Aboveground stand carbon (ton) and dbh is the tree diameter measured at breast height (cm).

16.2.3 Remote Sensing Data

A total of 108 sample areas based on site index, crown closure, and development stage and Landsat 8 OLI satellite image dated 14 August 2014 were used as materials. Six bands (band 2, band 3, band 4, band 5, band 6 and band 7) with a spatial resolution of 30 m were used in this study. Landsat 8 OLI satellite image was applied to some processing before being analyzed. These processing steps are listed below. The six bands used in the study were combined into a single satellite image and a single satellite image cut according to the outer boundary of the study area. Necessary atmospheric and geometric corrections were performed on the satellite image. 108 sample points were overlaid with satellite images and band brightness values were obtained for six bands and each sample plot. However, using the band brightness values obtained for each sample plot, some vegetation indices values in Table 16.1 are calculated. Also, the texture values were calculated for six bands and each sample plot using eight texture features (mean, correlation, homogeneity, dissimilarity, second moment, variance, entropy and contrast) and four different window sizes (3 × 3, 5 × 5, 7 × 7 and 9 × 9).

16.2.4 Multivariate Linear Regression

To model the empirical relationships between the AGSC values and, band brightness values, vegetation indices, and texture values obtained from Landsat 8 OLI satellite

Table 16.1 The vegetation indices used in this study

Vegetation indices	Description	Formula	References
NDVI	Normalized difference vegetation index	(Band4-Band5)/(Band4 + Band5)	Rouse et al. (1974)
SAVI	Soil adjusted vegetation index	(Band5-Band4) * (1 + L)/(Band5 + Band4 + L)	Huete (1988)
DVI	Difference vegetation index	Band5-Band4	Clevers (1988)
SR	Simple ratio	Band5/Band4	Jordan (1969)
TVI	Transformed vegetation index	Band5-Band4/Band5 + Band4 + 0.5	Deering et al. (1975)
ND64	Normalized difference	Band6-Band4/Band6 + Band4	Lu et al. (2005)
ND65	Normalized difference	Band6-Band5/Bnad6 + Band5	Lu et al. (2005)
ND67	Normalized difference	Band6-Band7/Band6 + Band7	Lu et al. (2005)
ND42	Normalized difference	Band4-Band2/Band4 + Band2	Lu et al. (2005)
ND74	Normalized difference	Band7-Band4/Band7 + Band4	Sivanpillai et al. (2006)
ARVI	Atmospherically resistant vegetation index	(Band5-2 * Band4-Band2)/(Band5 + 2 * Band4-Band2)	Kaufman and Tanré (1992)

L = 0.5

image, the MLR were used in this study. The Ordinary Least Squares technique was utilized to acquire the parameters and other statistics of the MLR model. To select predictive satellite data including the band brightness values, vegetation indices and texture values, the stepwise variable selection regression technique was used to obtain the AGSC predictions significantly ($p < 0.05$).

16.2.5 Artificial Neural Network Models

The ANN models based on the Feed Forward Backprop training algorithms were used to predict the AGSC from the satellite data in this study. This training algorithm has commonly been used to predict tree and forest attributes in forest literature. While estimating single tree and stand features with ANN, previous studies have frequently used a network training function, also called as *trainlm*, based on Levenberg-Marquardt optimization. Also, the Bayesian regularization including a network training function, called as *trainbr*, reduces a combination of squared errors and weights, and then regulates the correct combination of these values to improve predictions from the network. In this study, these network training function including *trainlm* and *trainbr* were used and compared to determine which training function gives the best predictive results.

In this ANN model, input variables were best predictive stand parameters, in which these independent variables were selected by the stepwise variable selection technique in regression analysis, and the target variable was the AGSC value obtained from the ground measurements. These ANN models include three layers such as the input layer, hidden layer, and output layer and these activation functions linking with these layers are another important network parameter in its structure. In our preliminary analyses, the activation function alternative based on the log-sig function between the input layer and hidden layer and tan-sig function between the hidden layer and output layer gave better predictions than those by other activation functions, thus this activation function alternative was selected to train the ANN models in this study. Further significant restriction of the network structure is the number of neurons in the hidden layer. Thus, some alternatives for the number of neurons that ranged from 1 to 100; 1, 2, 3, …, 20, 30, 50, 70, 90, and 100 number of neurons were compared to select the best predictive neuron alternative in this study. Besides these values of parameters in ANN structure, the value of 200 for epochs, the value of 1×10^{-10} for performance goal, the value of 0.0001 for the learning rate and the value of 1×10^{-10} for minimum performance gradient gave the best predictive results to train these ANN models in the preliminary of this study and so these parameters were used to obtain the AGSC predictions.

A total of 200 ($100 \times 2 = 200$ alternatives) network alternatives including 100 number neurons and 2 network training function alternatives (*trainlm* and *trainbr*) based on the Multilayer Feed Forward Backprop training algorithms, were trained and used to obtain the AGSC predictions. These network trainings for 200 network alternatives for ANN models were carried out using newff syntax for the feed-forward back propagation network codded in MATLAB software (MATLAB 2014).

16.2.6 Support Vector Machine Models

Another alternative artificial intelligence model is the SVM technique, which is currently attracting attention and importance subject being an artificial intelligence technique. This SVM technique can be used to carry out general regression to predict forest and tree attributes and classification to obtain similar and dissimilar forest units and fractures. The concept of SVM has been proposed by Vladimir Vapnik and his co-workers for classification purposes, then the regression application of the SVM hasbeen developed based on the same principle with the SVM for classification.

It trains SVM models, the significant way of adding non-linearities in SVM is by the use of kernel functions, which this function defined by the input data into a high-dimensional feature space to improve the predictive ability of this network. Especially, Radial-based function (RBF) kernel can offer successful modeling results in nonlinear data. In applications involving regression estimation, including continuous number to predict, "eps-regression" type of the SVM can be trained to perform a regression task. In this SVM models, input variables were best predictive stand parameters as with ANN models, and target variable was the AGSC values. In this study, the SVM model was applied based on "eps-regression" type of the SVM and the RBF Kernel of the e1071 R package (R Development Core Team 2018).

16.2.7 Comparison Criteria

In this study, several comparison criterion values were used to compare and evaluate the predictions of AGSC that were obtained by the MLR, ANN and SVM models. These fitting criteria are (2) Sum of Squared Errors (SSE), (3) the root mean squared error (RMSE), (4) % root mean squared error (RMSE%), (5) the fit index (FI), (6) Akaike's information criterion (AIC) and (7) Bayesian information criterion (BIC). These criteria are calculated as follows:

$$SSE = \sum_{i=1}^{n}\left(SC_i - \widehat{SC}_i\right)^2 \tag{16.2}$$

$$RMSE = \sqrt{\sum_{i=1}^{n}\left(SC_i - \widehat{SC}_i\right)^2/(n-k)} \tag{16.3}$$

$$RMSE\% = \left(\left[\sqrt{\sum_{i=1}^{n}\left(SC_i - \widehat{SC}_i\right)^2/(n-k)}\right]/\overline{SC}_i\right)\cdot 100 \tag{16.4}$$

$$FI = \frac{\sum_{i=1}^{n}\left(SC_i - \widehat{SC}_i\right)}{\sum_{i=1}^{n}\left(SC_i - \overline{SC}_i\right)} \tag{16.5}$$

$$AIC = \ln(RMSE) + 2k \tag{16.6}$$

$$BIC = \ln(RMSE) + \ln(k) \tag{16.7}$$

where, SC_i is the measured AGSC value in the sample plot (observed values), $\overline{SC}_i$ is the average of observed AGSC values, $\widehat{SC}_i$ is the predicted AGSC value obtained by the MLR, ANN and SVM models, k is the number of inputs or independent variable in the prediction methods, ln is the natural logarithm with the base of the mathematical constant *e*. From these fitting criterion values, it is desired that the FI, which is between 0 and 1, should be as close to 1 as possible. Smaller values of other criterion values indicate that better predictive AGSC is obtained.

The flowchart of the method used in this study is given in Fig. 16.2.

16.3 Results and Discussion

The goodness-of-fit statistics of SSE, FI, RMSE, RMSE%, AIC and BIC for various prediction techniques and Landsat 8 OLI satellite data are given in Table 16.2. Seeing this Table 16.2, the ANN model with trainbr and # 85 neurons gave the best predictive fitting results including SSE value of 34,180.132, RMSE value of 17.957, the RMSE% value of 17.352, AIC value of 315.902, BIC value of 386.762, FI value of 0.887 for the band brightness values. For the vegetation indices, the ANN with trainbr and # 89 neurons resulted in the best predictive fitting statistics with SSE value of 48,670.930, RMSE value of 21.428, the RMSE% value of 21.461, AIC value of 334.987, BIC value of 405.847, FI value of 0.839. For the texture values, the ANN with trainbr and # 92 neurons presented the best predictive fitting results with SSE value of 54,862.021, RMSE value of 22.750, the RMSE% value of 21.644, AIC value of 341.453, BIC value of 412.313, FI value of 0.819. Considering completely these prediction techniques, the prediction model based on the ANN with trainbr and # 85neurons and the band brightness values showed better predictive performance in explaining the variation in AGSC than those by various prediction techniques and, vegetation indices and texture values.

In Table 16.3, the means of error and fitting values for SSE, FI, RMSE, RMSE%, AIC and BIC for various prediction techniques and, band brightness, vegetation indices and texture values were presented. From these mean values, the band brightness values and a network training function with the Bayesian regularization, trainbr, resulted in the best predictive AGSC compared the those for the vegetation indices and texture values, and prediction techniques. These results suggested that the band brightness values and the prediction technique based on the ANN with the Bayesian regularization outperformed by presenting better predictive results for the SSE, FI, RMSE, RMSE%, AIC and BIC than the vegetation indices and texture values, and prediction techniques.

The relationships between observed (x-axis) and predicted AGSC (y-axis) by (a) the ANN with trainbr and # 85 neurons and the band values, (b) ANN with trainlm and # 41 neurons and the band values, (c) SVM, (d) MLR were shown in Fig. 16.3. This graph presented the evidence of the best predictive ANN with trainbr and # 85 neurons and the band brightness values, which tend to more angle of 45 degrees with axes than those for other prediction methods and, vegetation indices and texture values.

Figure 16.4 presented the plot of residuals against the predicted AGSC obtained from by (a) the ANN with trainbr and # 85 neurons and the band brightness values, (b) ANN with trainlm and # 41 neurons and the band brightness values, (c) SVM,

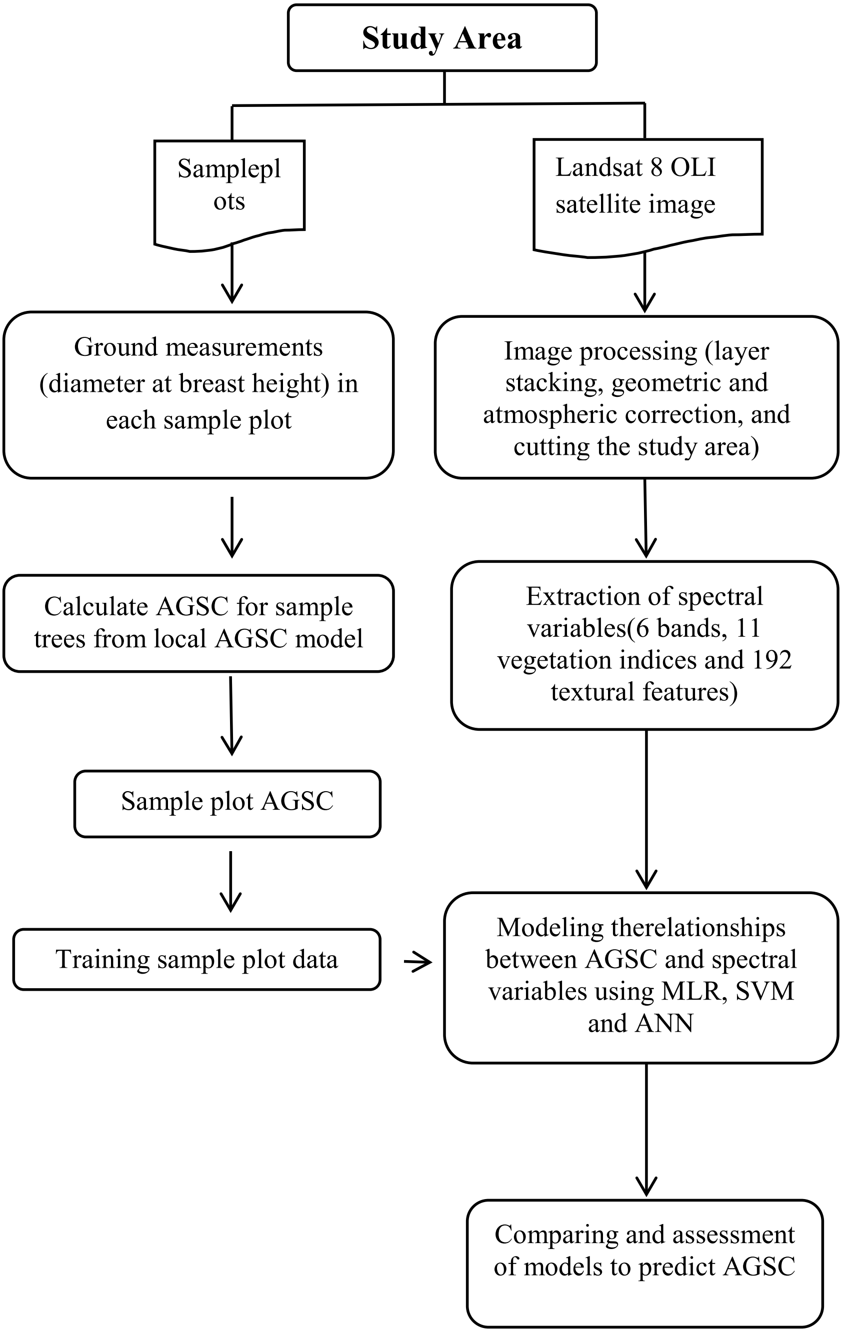

Fig. 16.2 The flowchart of the path followed in the study

Table 16.2 The goodness-of-fit statistics of SSE, FI, RMSE, RMSE%, AIC and BIC for various prediction techniques and satellite data

Satellite data	Technique	SSE	RMSE	RMSE%	AIC	BIC	FI
Band	MLR	79,203.562	27.335	26.414	361.282	432.142	0.738
	ANN with trainlm and # 41 neurons	55,333.613	22.848	22.078	341.916	412.776	0.817
	ANN with trainbr and # 85 neurons	34,180.132	17.957	17.352	315.902	386.762	0.887
	SVM	75,491.309	26.687	25.787	358.690	429.550	0.751
Vegetation indices	MLR	90,968.310	29.295	29.340	368.761	439.621	0.699
	ANN with trainlm and # 62 neurons	53,317.556	22.428	22.462	339.911	410.771	0.824
	ANN with trainbr and # 89 neurons	48,670.930	21.428	21.461	334.987	405.847	0.839
	SVM	83,208.216	28.018	28.061	363.946	434.806	0.725
Texture	MLR	161,319.467	39.011	39.072	399.696	470.556	0.467
	ANN with trainlm and # 86 neurons	86,497.352	28.566	27.177	366.039	436.899	0.714
	ANN with trainbr and # 92 neurons	54,862.021	22.750	21.644	341.453	412.313	0.819
	SVM	114,894.416	32.923	31.322	381.370	452.230	0.620

Table 16.3 The means of error and fitting values for SSE, FI, RMSE, RMSE%, AIC and BIC for various prediction techniques and satellite data

		SSE	RMSE	RMSE%	AIC	BIC	FI
Satellite data	Band values	61,052.154	23.707	22.908	344.447	415.307	0.798
	Vegetation indices	69,041.253	25.292	25.331	351.901	422.761	0.772
	Textures	104,393.314	30.813	29.804	372.140	442.999	0.655
The prediction techniques	MLR	110,497.113	31.880	31.609	376.580	447.440	0.635
	ANN with trainlm	65,049.507	24.614	23.906	349.289	420.149	0.785
	ANN with trainbr	45,904.361	20.712	20.152	330.781	401.641	0.848
	SVM	91,197.980	29.209	28.390	368.002	438.862	0.699

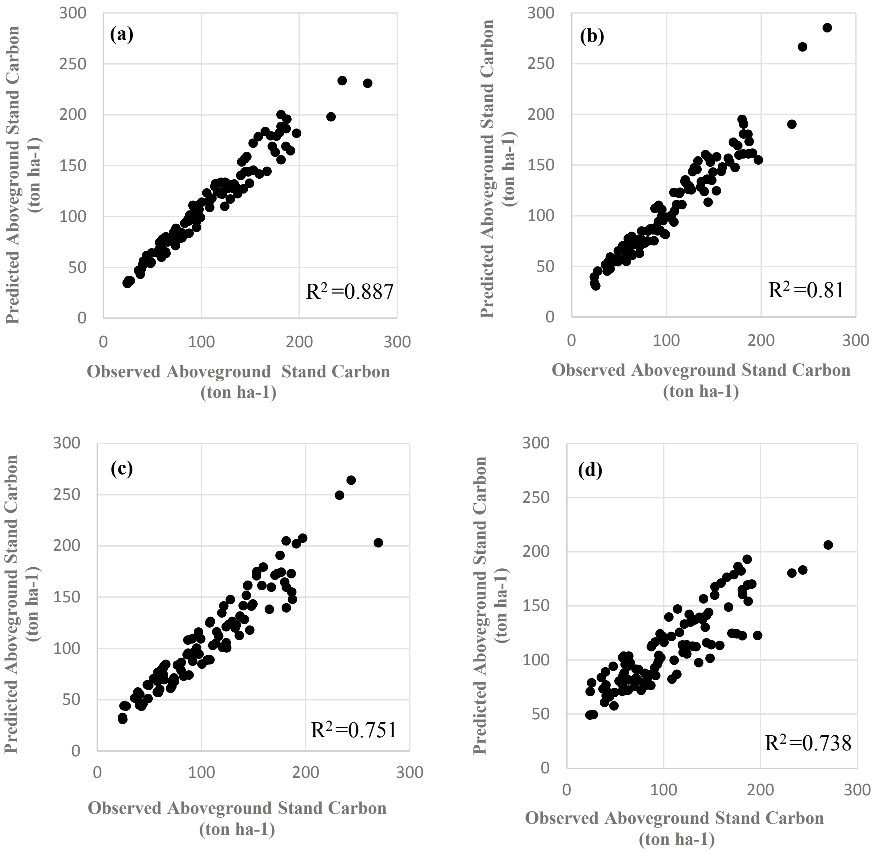

Fig. 16.3 The relationships between observed (x-axis) and predicted AGSC (y-axis) by **a** the ANN with trainbr and # 85 neurons and the band brightness values, **b** ANN with trainlm and # 41 neurons and the band brightness values, **c** SVM, **d** MLR

(d) MLR. This best predictive ANN with trainbr and # 85 neurons and the band brightness values resulted in significant improvement in these residuals with a lower range compared by other alternatives. These residual results in Fig. 16.2 indicate that predictive estimates of AGSC values have been achieved by this best predictive ANN with trainbr and # 85 neurons and the band brightness value.

The MLR, SVM and ANN models were applied for estimating the relationships between AGSC and the band brightness, vegetation indices and texture values obtained from a Landsat 8 OLI satellite image in this study. When the literature is analyzed, it is seen that there are many studies performed using different modeling techniques with different data obtained from different satellite images. The results obtained in this study were compared with other studies on this subject. Foody et al. (2003) estimated forest biomass using vegetation indices obtained from Landsat TM

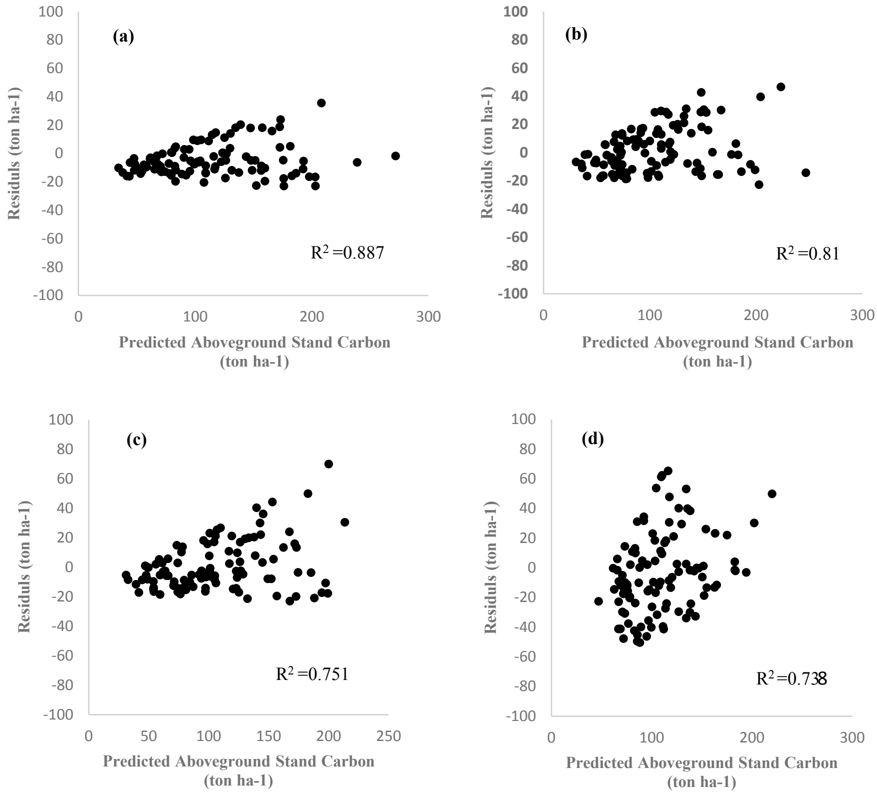

Fig. 16.4 The plot of residuals against the predicted AGSC obtained from by **a** the ANN with trainbr and # 85 neurons and the band brightness values, **b** ANN with trainlm and # 41 neurons and the band brightness values, **c** SVM, **d** MLR

satellite image. They predicted the relationships between forest biomass and vegetation indices by using MLR and ANN models. Their results showed that predictions derived from a neural network-based approach were strongly and significantly correlated with the forest biomass estimate derived from ground measurements in comparison to MLR model ($R^2 < 0.32$).In a study developed by Lu et al. (2005), it was tried to predict AGB with band, vegetation indices and texture values obtained from Landsat TM satellite image using MLR model. The results of the study showed that band values give better results in predicting AGB in simple forest stand structure. This is in line with the findings in our results. Conversely, it was seen that the texture characteristics gave better results in predicting AGB compared to the bands in complicated forest stand structure. In a study conducted by Min et al. (2009) the relationships between band and vegetation indices values obtained from Landsat TM satellite images in three different forest types (softwood forest, hardwood forest and mixed forest) and AGB were tried to be determined by MLR analysis. In the results obtained, the model produced with vegetation indices was found to be more successful Xu et al. (2011). Used linear regression, partial least-squares regression and ANN models to estimate AGSC based on the combined use of Landsat ETM+ data and field measurements. As in our study, their results showed that the ANN model ($R^2 = 0.912$) provided better results than the MLR model ($R^2 = 0.247$) in estimating AGSC Günlü et al. (2014). Developed MLR models to estimate the AGB using optical band brightness values and vegetation indices derived from Landsat TM data in pure Crimean pine stands. Contrary to our results, their results indicated that vegetation indices better estimation of AGB as compared to optical bands. Similar results were obtained by Günlü et al. (2016) in the same study area, the relationships between band brightness values and vegetation indices obtained from Landsat 8 OLI satellite image and the AGSC values were investigated by MLR. In the results obtained, it has been seen that vegetation indices give better results than band brightness values. The difference between this study (2016) and the present study is the method differences used in determining the AGSC of the sample areas. While the AGSC amounts of the sample areas were calculated using the coefficients developed by Tolunay (2014) in this study, in the current study, the AGSC amounts of the sample areas were calculated with the carbon equations developed by Sakıcı et al. (2018). However, in a study conducted by Turgut and Günlü (2020), different results were obtained. In their study, the relationships between the band brightness, vegetation indices and texture values obtained from the Landsat 8 OLI satellite image and the AGB values calculated from ground measurements were estimated by MLR method in pure Crimean pine stands. Contrary to our study, the model obtained with texture values gave better results in estimating the AGB. In this study, the success of the model obtained with texture values was higher from our study, whereas the success level of the model obtained with band and vegetation indices was lower than our study. In another study conducted by Günlü and Ercanlı (2020), the relationships between texture values obtained from Alos Palsar data and AGSC in pure beech stands were tried to be estimated by MLR and ANN modeling techniques. As in our study, in their study results demonstrated that the ANN was better than MLR models to estimate AGSC values Baloloy et al. (2018). Modeled that the relationships between band and vegetation indices values obtained from two different satellite images (Rapideyeand Sentınel-2) andAGB were estimated by MLR and Multivariate Adaptive Regression Spline (MARS) method. When the results obtained were examined, it was seen that MARS method gave better results than MLR method. However, models with vegetation indices (except for Rapideye satellite data) gave more successful results. The R^2 values between vegetation indices generated from Rapideye and Sentinel-2 satellite data and the AGB were found the 0.82 and 0.89, respectively. However, the R^2 values between band values and AGB were found the 0.92 and 0.62, respectively. Thapa et al. (2015) predicted the relationships between texture values obtained from Alos Palsar image and AGSC amounts by MLR method, the R^2 value was found to be 0.84. In this study, a certain amount of predictive ability in predicting AGSC can be obtained by with artificial intelligence models. Safari et al. (2017) estimated AGSC in coppice oak forests using Landsat 8 image and four machine learning algorithms. Their results showed that the AGSC estimation of SVM, boosted regression trees, random forest and multivariate adaptive regression splines algorithms (MARS) had

R^2 values of 0.64, 0.57, 0.64 and 0.58, respectively. They also found that the simple band ratios more accurate AGSC estimates in comparison to the use of Landsat 8 OLI satellite image derived raw bands and vegetation indices. In a study conducted by Dong et al. (2020) predicted the relationships between band, vegetation indices and texture values obtained from World View-2 image and AGB were estimated by using ANN and SVM methods. In the model with band values, the ANN method ($R^2 = 0.238$) gave better results than SVM ($R^2 = 0.046$) method. Similarly, the ANN ($R^2 = 0.248$) model with the band and vegetation values together gave better results than the SVM ($R^2 = 0.052$) method. On the other hand, the SVM ($R^2 = 0.970$) model with texture values better results than the ANN($R^2 = 0.831$) method. In addition to these predictive findings, another important finding is that, despite the intensive use of the *trainlm* training function based on Levenberg-Marquardt optimization in previous studies, better predictive results are found with the network training function based on the Bayes approach, *trainbr*, which may be an alternative to this *trainlm* training function. The network training function based on the Bayes approach, which can be used as an alternative to the standard training function based on Levenberg-Marquardt optimization, provides a slower training at an acceptable scale, but offers better predictive results than those by this standard training function. The reason for such a result may be fact that this network training function based on the Bayes approach can improve the ANN generalization, which the weights and biases of the network from this network training function are assumed to be random variables with specified distributions. Comparison of similar training functions was made by Kamble et al. (2015) and the best predictive results were obtained with the training function based on the Bayes approach.

16.4 Conclusion

The relationships between band brightness values, vegetation indices and texture values obtained from Landsat 8 OLI satellite image and AGSC values obtained by ground measurements were evaluated by using MLR, SVM and ANN (trainlm and trainbr) methods in pure Crimean pine stands. The ANN method outperformed than the SVM and MLC methods for AGSC prediction. Also, the best predictive accuracy was obtained for the ANN with trainbr model used band brightness values and followed it by ANN trainlm method with band brightness values. Using different modeling techniques such as deep learning, mixed effect modeling and MARS, and different satellite images such as passive, active and fused data (combined the active and passive satellite data) can improve the model achievement criteria in similar and different forest ecosystems.

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