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Estimating and mapping forest biomass using regression models and Spot-6 images (case study: Hyrcanian forests of north of Iran)

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Abstract Hyrcanian forests of North of Iran are of great importance in terms of various economic and environmental aspects. In this study, Spot-6 satellite images and regression models were applied to estimate above-ground biomass in these forests. This research was carried out in six compartments in three climatic (semi-arid to humid) types and two altitude classes. In the first step, ground sampling methods at the compartment level were used to estimate aboveground biomass (Mg/ha). Then, by reviewing the results of other studies, the most appropriate vegetation indices were selected. In this study, three indices of NDVI, RVI, and TVI were calculated. We investigated the relationship between the vegetation indices and aboveground biomass measured at sample-plot level. Based on the results, the relationship between aboveground biomass values and vegetation indices was a linear regression with the highest level of significance for NDVI in all compartments. Since at the compartment level the correlation coefficient between NDVI and aboveground biomass was the highest, NDVI was used for mapping aboveground biomass. According to the results of this study, biomass values were highly different in various climatic and altitudinal classes with the highest biomass value observed in humid climate and high-altitude class.

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Introduction

Nowadays, among the most important global concerns is the increasing trend in atmospheric carbon dioxide, global warming, and its potential for global climate change. As the largest surfaces covering the non-glacial lands of the earth, forest ecosystems absorb large amounts of atmospheric carbon dioxide via photosynthesis (Lorenz and Lal 2010) and by storing 86% of carbon dioxide in terrestrial lands and 73% of soil carbon (Sedjo 1993) forest ecosystems are considered to be the most important carbon sink or sponge in

nature, which play a key role in global carbon cycle (Vashum and Jayakumar 2012), mitigating to global warming and adaptation with global climate change (Günlü et al. 2014. So, the process of deforestation and forest degradation in recent decades could result in emission of carbon into the atmosphere (Lu et al. 2014). In order to avoid this process, it is necessary to estimate the quantities of carbon content in the forests. Above-ground biomass (AGB) serves as the basic component in studies of estimation of carbon stocks of forests and their changes (Gómez et al. 2014), which mainly includes trees as the most important element of forest ecosystems and the largest living biomass reserves in the forests (Lorenz and Lal 2010).

Three main approaches for estimating forest biomass include field measurements, remote sensing and geographic information system (Lu 2006). Although it serves as the most common and the most accurate technique for estimating biomass, field data seems to be costly, time-consuming, destructive, and impractical at large scale (Devagiri et al. 2013; Du et al. 2014; Deb et al. 2017). Modern RS-based and GIS tools provide a powerful tool for quick, realistic, practical, and relatively low-cost assessment and monitoring of AGB and carbon storage and solving the challenges for estimating AGB in the field (Zhu et al. 2015; Kross et al. 2015; Hirata et al. 2014; Devagiri et al. 2013; Yadav and Nandy 2015). Remote sensing data do not directly estimate the biomass values, biomass but is calculated using a strong statistical relationship between the spectral responses taken from the sensor, which mainly comprise various vegetation indices (VIs), and the AGB information obtained from ground plots (Clerici et al. 2016; Kumar et al. 2016; Lee et al. 2017). Generally defined as mathematical transformations of surface reflection from sensors by applying of red and infrared spectral bands (Yan et al. 2013), VIs are among the most important and the most commonly applied processing techniques for forest structural attributes (Kalbi et al. 2014). In recent years, many studies have been carried out using remote sensing and various satellites, as well as using different VIs for calculating, predicting, and monitoring AGB. Each of these systems has its own advantages and constraints to produce valid and acceptable estimates at various scales. Clerici et al. (2016) applied Pleiades-1A and GeoEye-1 satellites for estimating the AGB and carbon in Colombian forests (Andes mountainous area) using linear models and VIs and achieved satisfactory results. In order to modeling

the volume and AGB, Dimitrov and Roumenina (2013) evaluated the data obtained from the spectral bands and indices derived from Spot-5 satellite with field data based on a regression model in Bulgarian pine forests. Günlü et al. (2014) assessed the relationship between ABG and spectral bands with VIs from Landsat TM satellite, using multiple regression models in Anatolian Mountains of Crimea, and concluded that VIs could better estimate AGB compared to individual bands. Dube and Mutanga (2016) by studying three Eucalyptus and Pine plantations in South Africa concluded that integrating the data extracted from eight bands of WorldWiew-2 satellite with indices from environment variables could lead to better and more reliable results for estimating AGB values. Kumar et al. (2016) reported better results for combination of spectral indices of Landsat-8 satellite data and ALOS-2 radar for estimating biomass compared to applying these indices individually.

Iran is considered as LFCC (low forest cover countries) (Vahedi et al. 2016). As the remnant of Tertiary, Hyrcanian forests in North of Iran are extended throughout the south of Caspian Sea and are now increasingly under the risk of degradation, fragmentation, and conversion into other forms of land uses (Mohammadi and Shataee 2010). Therefore, it seems necessity to study these forests in terms of ecology. This study aims to present a model for estimating AGB in Hyrcanian forests of North of Iran using SPOT-6 satellite data.

Materials and methods

Study area

Hyrcanian forests are located in a narrow strip in the south of Caspian Sea extending from east to west on the northern slopes of Alborz Mountains (Mohammadi and Shataee 2010), ranging from sea level to a maximum altitude of 2800 m (a.s.l.) in terms of altitude. North of Iran is characterized by semi-Mediterranean and temperate and humid climate. Mean annual temperature is 15–18 °C, with annual rainfall varying from 2000 mm in the western parts to 600 mm in the eastern regions. Hyrcanian forests are classified as deciduous, broad-leaved, uneven-aged forests with a canopy cover ranging from 40 to 90%, and pure and mixed stands (Marvi-Mohajer 2005). In this study, three forest areas in the western (Asalem) (1 and 2), central (Sardabrud) (3 and

4), and eastern (Kordkuy) (5 and 6) parts of Hyrcanian forests characterized by virgin forests or forest stands with the lowest level of man-made disturbance were selected as the study area (Fig. 1). The climatic and topographic data for the studied compartments were extracted and collected from Building a Multiple-Use Forest Management Framework to Conserve Biodiversity in the Caspian Hyrcanian Forest Landscape (BMUFMFCBCHFL 2016). Based on the data obtained from BMUFMFCBCHFL, compartments in this study are characterized by semi-arid to humid climate types (according to de Martonne aridity index), temperature ranging from 12.5 to 20 °C and altitude varying from 600 to 1650 m (Table 2).

Field data and estimating AGB

In order to making a homogeneous conditions in the study areas and for comparability reason after

creating land form unit maps in compartments, the altitude classes of 600–800 and 1500–1800 m with a mean slope of 15 to 45% at northern slope aspects (N, NE, NW) was mapped on a 1:25000 topography map and defined in GIS environment. In the next step, square-shape plots (30 × 30 m) were sampled randomly in summer of 2016 and coordinates of each plot was recorded using GPS device (Zhu et al. 2015). In each plot, tree height, diameter at breast height (DBH), diameter of tree crown in two directions perpendicular to each other, log length (tree height from ground to a point at which the crown starts), and foliage percentage were measured for all trees (Vahedi et al. 2016; Haghdoost et al. 2013). Allometric equations proposed by Ponce-Hernandez et al. (2004) were applied for calculating tree AGB. To do this, we divided tree were into two parts of stem and crown for calculating tree biomass according to tree morphology (Vahedi et al. 2016; Haghdoost
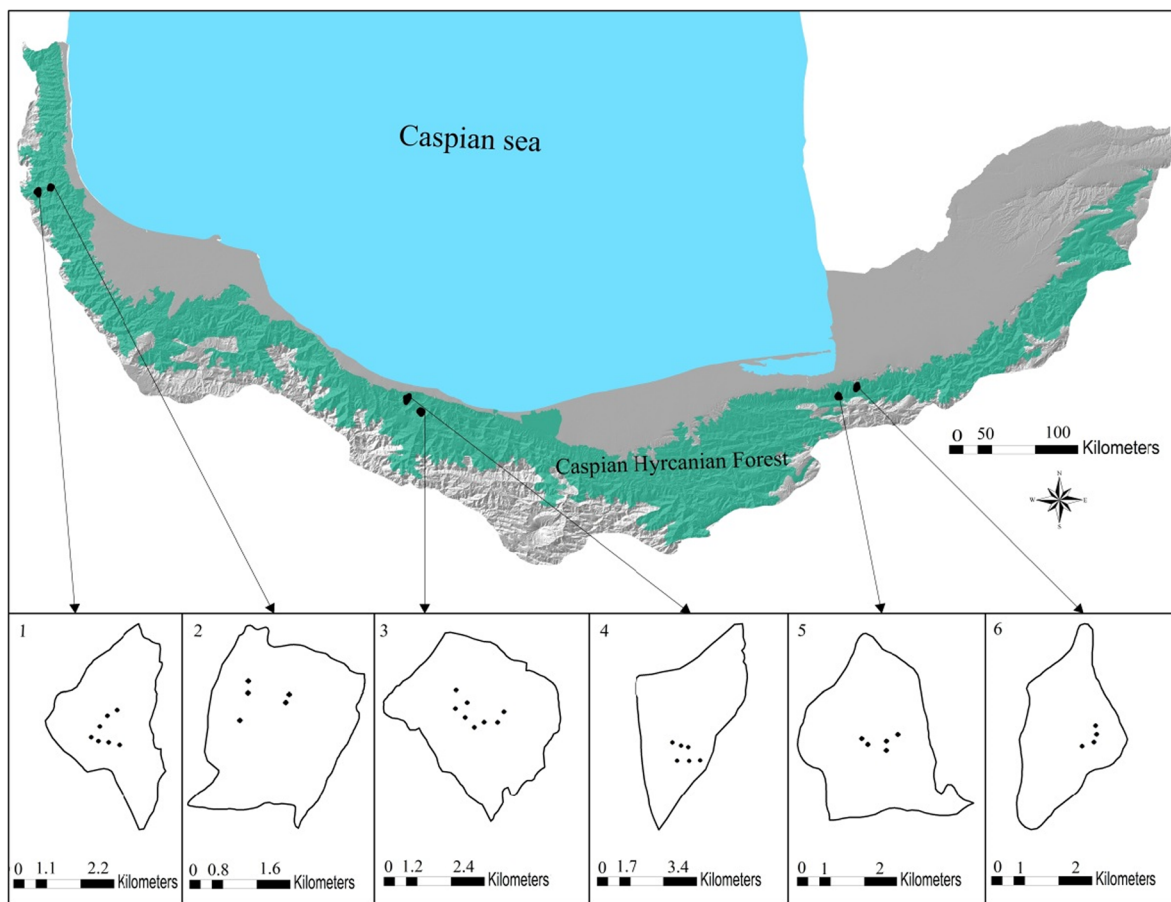

Fig. 1 Geographical location of the studied compartments in Hyrcanian forests of North of Iran

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et al. 2013). Equations for calculating biomass are presented in Table 1.

Equations 1 and 2 were used for calculating basal area (BA) and stem volume (Vs) for each tree. Based on the architecture of each species, form factor in Hyrcanian forests is considered as 0.5 on average (Namiranian 2010). Equation 3 was applied to calculate the crown volume (Vc) for broadleaf species. Correction factor is related to proportion of foliage in crown volume. One can obtain an acceptable approximation of canopy structure by standing beneath the crown or canopy, beside the trunk, and taking a careful visual appreciation in order to estimate the actual volume of crown occupied by the foliage. In the next step, Eq. 5 is used to calculate the total biomass (stem and crown) of the tree per kg. Wood density (WDk) in this study was obtained by taking wood samples (2 cm^3) from tree and the ratio of dry mass of each sample (gr) by placing it in an oven at 105 °C to a fresh volume of the same sample.

Finally, the obtained values of AGB in sampling plots were summarized and converted to Mg/ha a per hectare unit (Table 2) (Günlü et al. 2014; Haghdoost et al. 2013).

Remote sensing data and processing

The estimation of biomass based on remote sensing technology is a widespread procedure with many steps (Aricak et al. 2015). After ground data collection, the next step in this research is the provision of satellite images. In this study, Spot-6 satellite images with the resolution of 6 m were used (Table 3). Selected images

corresponded to the inventory in terms of timing with suitable resolution.

Pre-processing of satellite images

Geometric correction of the images was performed using a digital ground model of the region derived from a topographic map of 1:25,000 with a precision of 10 m (Kalbi et al. 2014; Noorian et al. 2016) and a number of ground control points based on the Image to Map method in ENVI 5.1 software (Zhu et al. 2015). Accuracy of geometric correction was evaluated using road vector layer and ground control points recorded in GPS (Fallah et al. 2014). Images with a mean geometric error of less than 0.5 pixels were corrected. Due to the lack of clouds in the images, we did not perform atmospheric corrections.

Processing of satellite images

The most important processing on the images is band ratio to create VIs. VIs are mathematical transformations, which are defined based on the different bands of the sensors and are used to evaluate the biophysiological characteristics of plants in multispectral satellite observations (Wang et al. 2016; Kalbi et al. 2013; Lee et al. 2017). To determine the relationship between the values of AGB collected from ground data as a dependent variable and various extracted indices based on spectral ratios of images as independent variables are calculated by regression models (Günlü et al. 2014; Yadav and Nandy 2015). These indices were

Table 1 Equations presented for calculating AGB

Equation ID	Equation	Reference	Parameters
1	$BA = \left(\frac{\pi}{4}\right) \times DBH^2$	Vahedi et al. 2016; Haghdoost et al. (2013)	Basal area
2	$V_s = BA \times h \times F_{fa}$	Vahedi et al. 2016; Haghdoost et al. 2013	Stem volume
3	$V_C = [\pi \times Dd^2/12] \times CF$	Vahedi et al. 2016; Haghdoost et al. 2013; Ponce-Hernandez et al. 2004)	Crown volume
4	$WD_k = \frac{M_{wk}}{V_{wk}}$	Henry et al. (2010)	wood density
5	$Biomass = 1000 \times WD \times (V_c + V_s)$	(Ponce-Hernandez et al. 2004)	Total tree biomass

average diameter Dd $\pi = 3.141592$**,** *tree form factor* F_{fa}, *diameter at breast height* DBH, *tree height* h: $Dd = (L + W)/2$ *of crown, fresh volume* V_{wk}, *dry mass* M_{wk}, *correction factor* CF, *crown width* W, *crown length* L

Table 2 Compartment number, number of sample plots, average altitude, mean temperature, climate type, and calculated values for biomass

Compartment ID	Number of sample plots	Average altitude (m)	Annual precipitation (mm)	Mean temperature (°C)	Climate type	Aboveground biomass (Mg/ha)
1	28	1500	1500	12.5–15	Humid	1173.41
2	20	725	1300	15–20	Humid	994.77
3	32	1530	1000	12.5–15	Semi-humid to Humid	666.49
4	24	600	800	15–20	Semi-humid to humid	389.92
5	20	1650	600	12.5–15	Semi-arid to semi-humid	370.75
6	16	750	500	15–20	Semi-arid to semi-humid	367.80

selected based on previous studies (Wang et al. 2013; Yan et al. 2013; Clerici et al. 2016). All pixels within each plot were selected and a mean value of VIs per plot was obtained by averaging for the three indices (Clerici et al. 2016). Spectral ratio of VIs was calculated (Table 4). Figures 2, 3, and 4 show maps for values of VIs calculated in the studied areas.

Results

Regression analysis of the relationship between biomass and VIs

Using field data and data obtained from the mean values of VIs at the sample plots, regression relationships between biomass and VIs were estimated. To develop the best regression model, R^2, R, RMSE, and P values were computed (Zhou et al. 2013). The results showed that the best regression relationship between the studied variables was a linear relationship and these

Table 3 Properties of satellite images used in this study

Compartment ID	Sensor	Date (day/month/year)	Multispectral imagery resolution
1	SPOT-6	13/08/2016	6 m
2	SPOT-6	13/08/2016	6 m
3	SPOT-6	20/08/2016	6 m
4	SPOT-6	20/08/2016	6 m
5	SPOT-6	15/08/2016	6 m
6	SPOT-6	15/08/2016	6 m

relationships had the highest R^2 and the highest level of significance compared to other relationships. The highest level of significance, as well as the highest R^2 value was related to NDVI, followed by RVI with the lowest value for TVI. The relationship between NDVI and TVI with AGB was a positive relationship so that the values of AGB increases with increasing the value of these indices. This trend is inverse for RVI, so that the value of AGB decreases with increasing value of this index. Therefore, the relationship between RVI and AGB values is negative. For the relationship between NDVI and the values of AGB in all studied compartments was significant at confidence level of 0.01, indicating a strong positive relationship between NDVI and AGB values as AGB values increased by increasing NDVI. Based on the results, R^2 coefficient for NDVI varies from 0.56 to 0.62 in different compartments, so it can be stated that 0.56 to 0.62 of changes in AGB are dependent on NDVI. In case of all other VIs, the results showed that in some compartments, there was a significant relationship between changes in AGB and these indices at confidence level of 0.05%. In case of all these indices, R^2 was less than 0.50. Therefore, changes in AGB were much less dependent on changes in RVI and TVI indices.

Comparison of regression relationships based on climate and altitude

As cited in research methodology, this study was carried out in three different climates and two altitude classes of middle altitude and high altitude. Based on the results, the highest level of significance in case of NDVI and AGB was observed for the regression relationships

Table 4 Selected indices for derived from studies on ABG estimation based on remote sensing data

Vegetation index	Equation	Reference
Normalized difference vegetation index (NDVI)	$(NIR - RED)/(NIR + RED)$	(Rouse et al. 1974)
Ratio vegetation index (RVI)	RED/NIR	(Pearson and Miller 1972)
Transformed vegetation index (TVI)	$\frac{(NDVI+0.5)}{|NDVI+0.5|}\sqrt{|NDVI+0.5|}$	(Perry and Lautenschlager 1984)

calculated in semi-arid to semi-humid climatic region in middle altitude class (6) and the lowest value was found for humid climate and high-altitude (1) class. In case of RVI, the highest R^2 coefficient of AGB was found in semi-arid to semi-humid climatic region and high-altitude (5), and the lowest was related to humid climate in the middle-altitude class (2). Also, the highest and lowest R^2 coefficients between TVI and AGB was
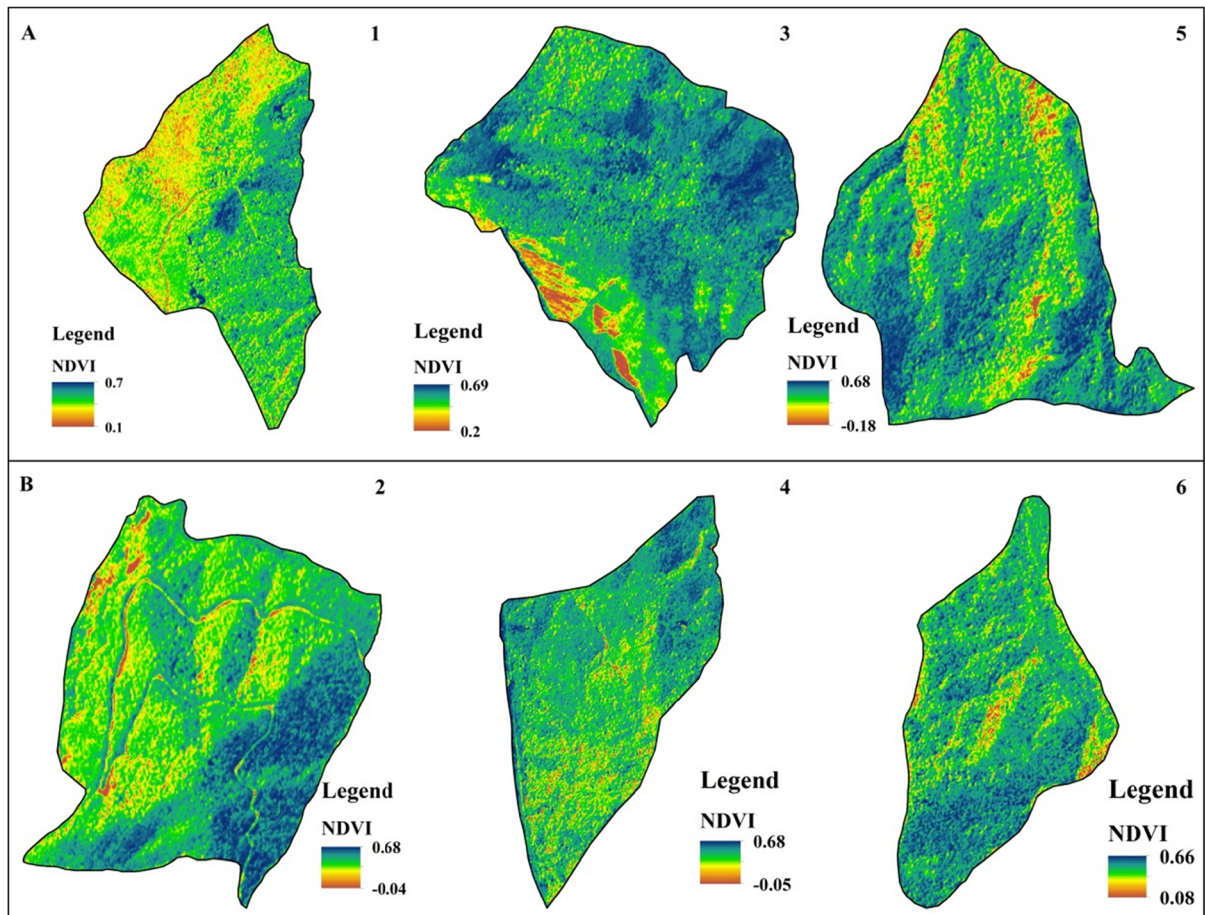
Fig. 2 NDVI for the studied compartments (**a**: high-altitude; **b**: middle-altitude; 1 and 2: Asalem; 3 and 4: Sardabrud; 5 and 6: Kordkuy)
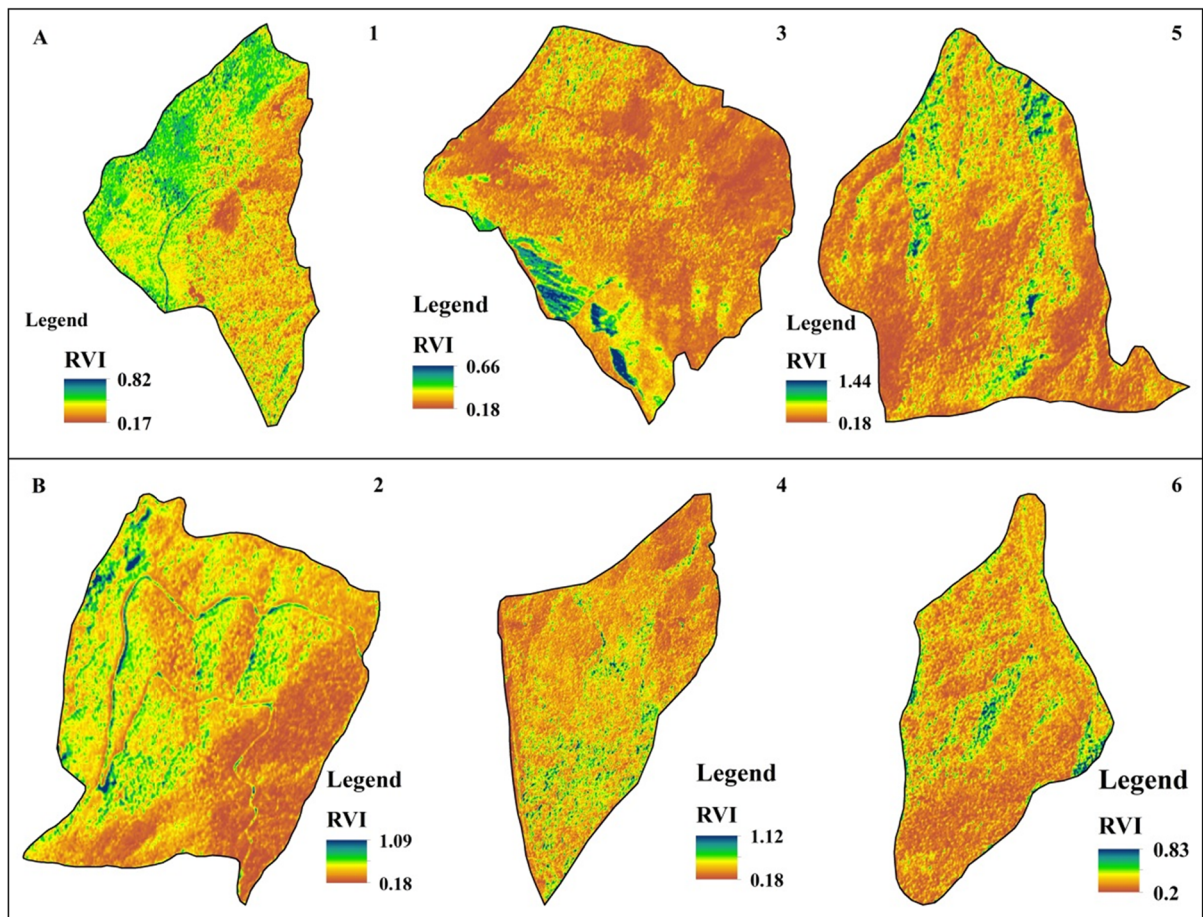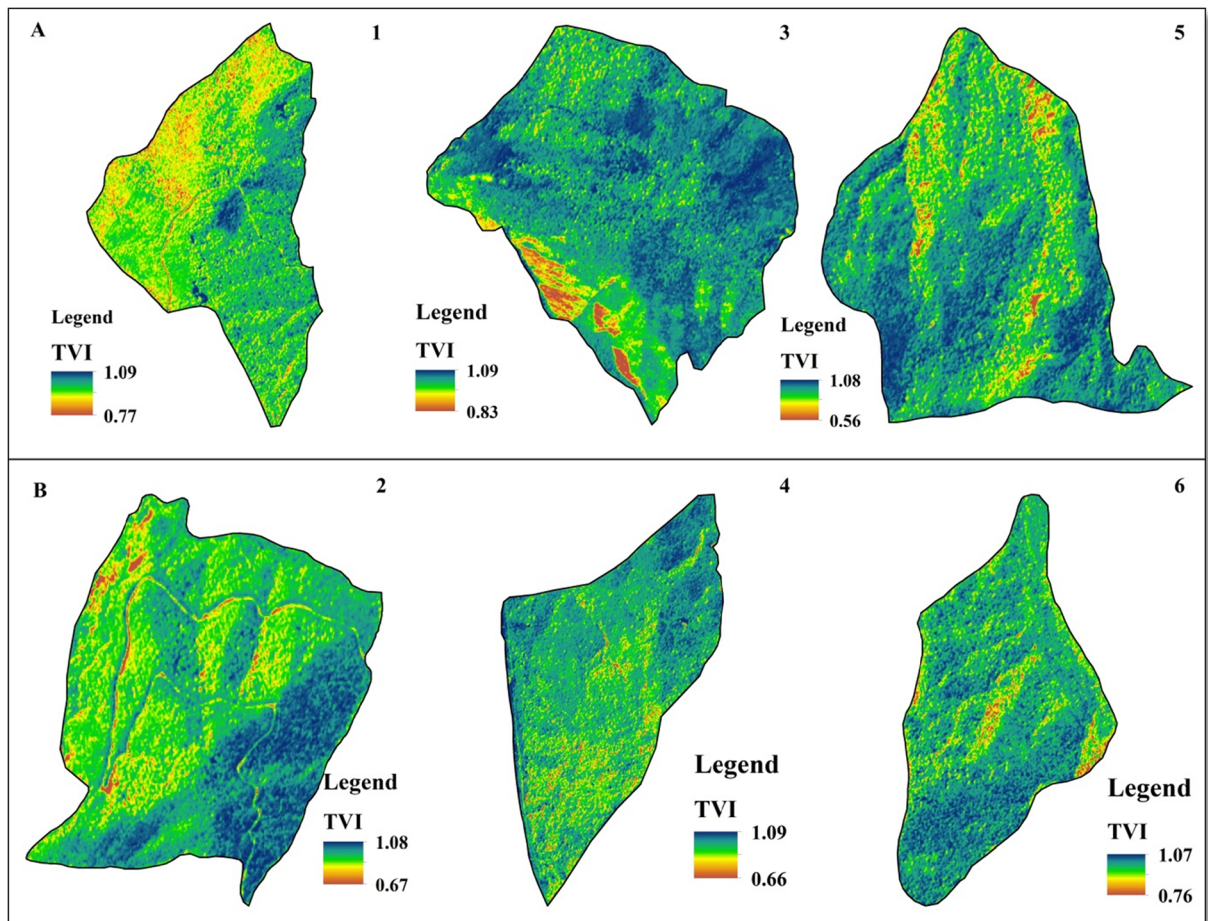
Fig. 3 RVI for the studied compartments (**a**: high-altitude; **b**: middle-altitude; 1 and 2: Asalem; 3 and 4: Sardabrud; 5 and 6: Kordkuy)

belonged to regression equations calculated in humid climate in middle-altitude (2), and humid climate class in high-altitude (1), respectively, (Table 5).

Choosing the most optimal regression model for estimating biomass

In order to estimate AGB at compartments, the most suitable indices for calculating and mapping of AGB were selected based on R^2 coefficient and significance level of the regression relationship. According to the results, NDVI is the most suitable index for estimating and mapping of AGB in all compartments because the results showed that the relationship between NDVI and AGB had the highest level of

significance compared to other indices. As stated earlier, this is a positive linear relationship which means that the values of AGB increases with increasing the value of this index (Fig. 5). After selecting the most suitable relationships between aboveground and VIs in each of the studied compartments, the AGB was mapped in terms of Mg/ha unit. Based on the results, the highest average AGB estimated in compartments were found in high-altitude and middle altitude of compartments 1 and 2 in Asalem region, followed by average AGB estimated in compartments 3 and 4 of Sardabrud region. The lowest average AGB estimated were observed in low altitude and high altitude of compartments 5 and 6 in Kordkuy region (Fig. 6).

Fig. 4 TVI for the studied compartments (**a**: high-altitude; **b**: middle-altitude; 1 and 2: Asalem; 3 and 4: Sardabrud; 5 and 6: Kordkuy)

After selecting the most optimal regression equations for mapping biomass, the NDVI is entered to the equation as an independent variable and the log AGB map is generated. Then, the estimated log AGB was converted into Mg/ha unit (Table 6 and Fig. 6).

Discussion and conclusions

In the first step of this study, biomass values at compartments were estimated using statistical methods. Based on the results, the highest biomass was found in the western part (Asalem) and in high altitude. As in many studies regarding the biomass value and growth rate of Hyrcanian forests in North of Iran, ecological and climatic parameters fluctuate highly from the east to the west in which rainfall increases considerably, while the length of dry season decreases (Marvi-Mohajer 2005; BMUFMFCBCHFL 2016). Therefore, forests in the western parts of Hyrcanian area are of a higher growth rate and biodiversity compared to the eastern parts (Vahedi et al. 2016; Mohammadi et al. 2017; Amirnejad et al. 2006), and the results of this study also indicates that AGB estimated from field inventory increases from east to west. In addition, in this study, biomass was estimated in two altitude classes of high altitude and middle altitude. Based on the results, the AGB estimated was higher in high altitude compared to middle-altitude classes.

Table 5 Regression equations, R^2, R, RMSE, and significance level of the variables at the studied compartments
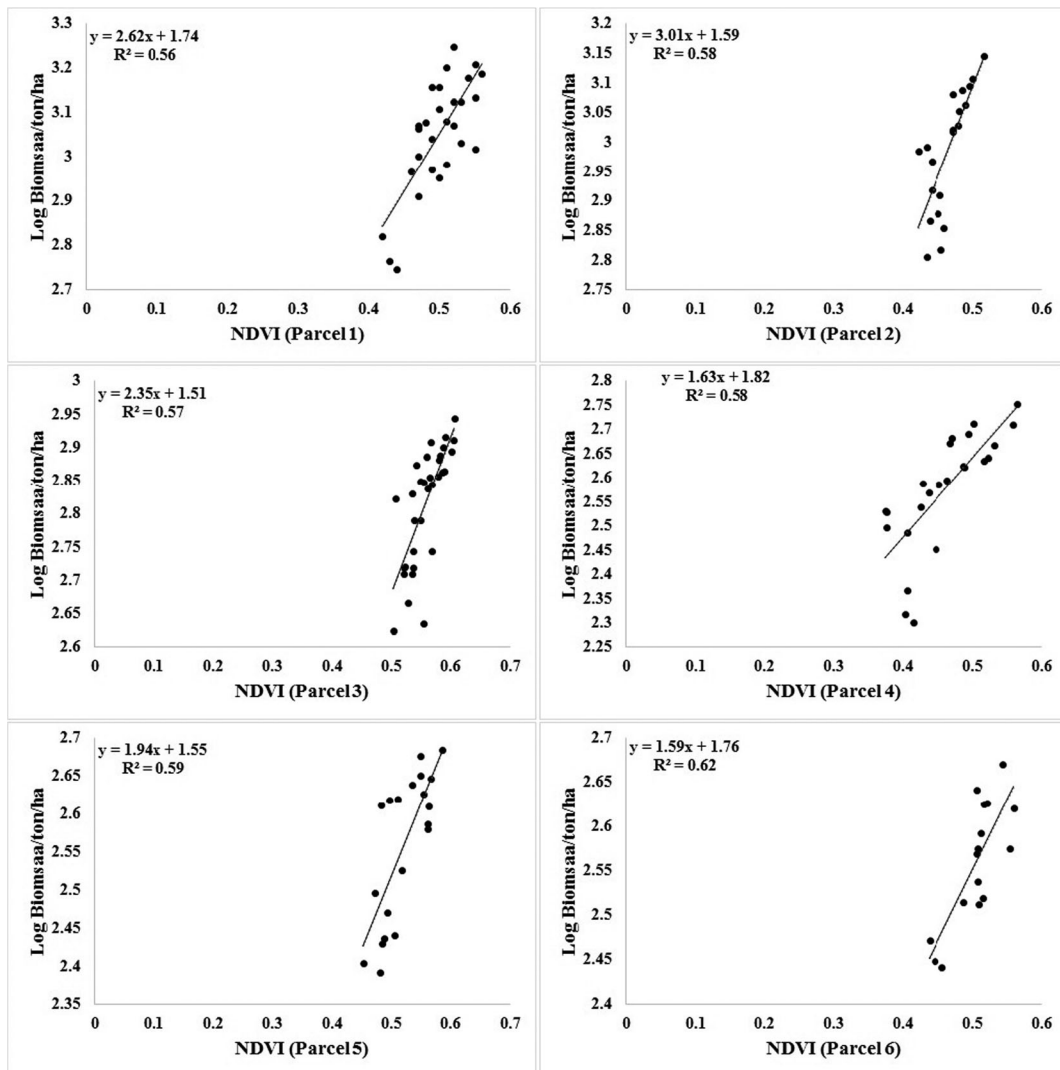
Compartment ID	Compartment name	Vegetation index	Regression model	R^2	R	p	RMSE
1	Asalem high-altitude land forest	NDVI	Log AGB = 2.62× + 1.74	0.56	0.75	0.000[**]	0.08
		TVI	Log AGB = 5.64× − 2.60	0.25	0.50	0.06	0.013
		RVI	Log AGB = −2.01× + 3.64	0.33	0.57	0.01[**]	0.012
2	Asalem middle-altitude land forest	NDVI	Log AGB = 3.01× + 1.58	0.58	0.76	0.000[**]	0.005
		TVI	Log AGB = 3.90× − 0.90	0.35	0.60	0.06	0.007
		RVI	Log AGB = −1.90× + 3.64	0.21	0.46	0.044[*]	0.009
3	Sardabrud high-altitude land forest	NDVI	Log AGB = 2.35× + 1.51	0.57	0.75	0.000[**]	0.003
		TVI	Log AGB = 3.00× − 0.23	0.28	0.52	0.02[*]	0.006
		RVI	Log AGB = −1.74× + 3.31	0.38	0.61	0.000[**]	0.005
4	Sardabrud middle-altitude land forest	NDVI	Log AGB = 1.63× + 1.82	0.58	0.76	0.000[**]	0.007
		TVI	Log AGB = 1.95× + 0.68	0.31	0.55	0.05[*]	0.011
		RVI	Log AGB = −2.22× + 3.42	0.35	0.60	0.02[*]	0.010
5	Kordkuy high-altitude land forest	NDVI	Log AGB = 1.94× + 1.55	0.59	0.77	0.000[**]	0.004
		TVI	Log AGB = 2.77× − 0.26	0.29	0.54	0.016[*]	0.007
		RVI	Log AGB = −2.37× + 3.27	0.40	0.63	0.003[*]	0.006
6	Kordkuy middle-altitude land forest	NDVI	Log AGB = 1.59× + 1.76	0.62	0.79	0.000[**]	0.002
		TVI	Log AGB = 2.84× − 0.27	0.34	0.58	0.017[*]	0.004
		RVI	Log AGB = −1.41× + 3.02	0.37	0.61	0.011[*]	0.003

Significance level $p* = 0.05$ $p** = 0.01$

The results showed that altitude had a significant effect on AGB so that it was found that AGB increases with increasing altitude, which can be attributed to changes in ecological conditions along altitude gradient, especially changes in temperature and precipitation and subsequently changes in the species and structure of Hyrcanian forests. In these forests, despite the decrease in temperature with increasing the altitude, rainfall increases with increasing altitudes according to observations and surveys carried out (Marvi-Mohajer 2005; BMUFMFCBCHFL 2016), and with improvement in conditions associated with the change in forests species, the average basal area per hectare increases and subsequently the biomass of trees increases. Based on the studies and forestry plans carried out in these areas, anthropogenic forest degradation rate as well as presence of livestock in middle-altitude range of these forests are higher compared to high-altitude range (BMUFMFCBCHFL 2016; Sefidi et al. 2011). While some studies have shown a contrasting trend for AGB with increasing altitude in tropical mountainous forests,

indicating that AGB decreases with increasing altitude (Girardin et al. 2010). There is a lack of information on biomass and carbon reserves along the altitude gradient in the temperate forests of the world (Gairola et al. 2011). In case of the areas studied in the present research, the limited access to mountainous forests, lack of comprehensive statistical data in the research areas, impact of different successional stages and the effects of other site factors involved as well as the process of degradation and disturbance in Hyrcanian forests of North of Iran, which, according to many studies, has been started from low-altitude regions so that one can find virgin forests in high-altitude areas (Sefidi et al. 2011), can be among the factors influencing on the results of the present study.

Estimation and mapping of AGB are performed in forest areas with different goals. The main reason for this is the identification of sensitive forest areas that are prone to conservation. Since many parameters of tree are measured in the study of AGB, field inventory seems to be inappropriate because of high costs and being

Fig. 5 The most optimal regression model between biomass and VIs at the studied compartments

time-consuming. Therefore, applying remote sensing techniques is a good alternative approach for studying vegetation (Zhu et al. 2015; Kross et al. 2015; Hirata et al. 2014). Regression models and relationships between AGB and VIs has been considered as the most common methods for studying biomass using remote sensing techniques (Wang et al. 2016; Clerici et al. 2016; Kumar et al. 2016; Wang et al. 2013; Yan et al. 2013).

Since the study area in all compartments had the appropriate cover percentage, the soil background effect was at its minimum level. Therefore, indices such as

NDVI, RVI, and TVI are considered to be suitable indices (Wang et al. 2016). According to the findings of the research in all compartments of the study area, among the selected indices in this study the NDVI showed the most suitable relationship with AGB for estimating AGB followed by RVI. This index, RVI, had a reverse relationship with the AGB. The results of study by Clerici et al. (2016) confirmed that the indices used in the present research are the most suitable indices for studying biomass in areas with a relatively good vegetation cover. In the study of Clerici et al. (2016), RVI showed the highest R^2 coefficient with
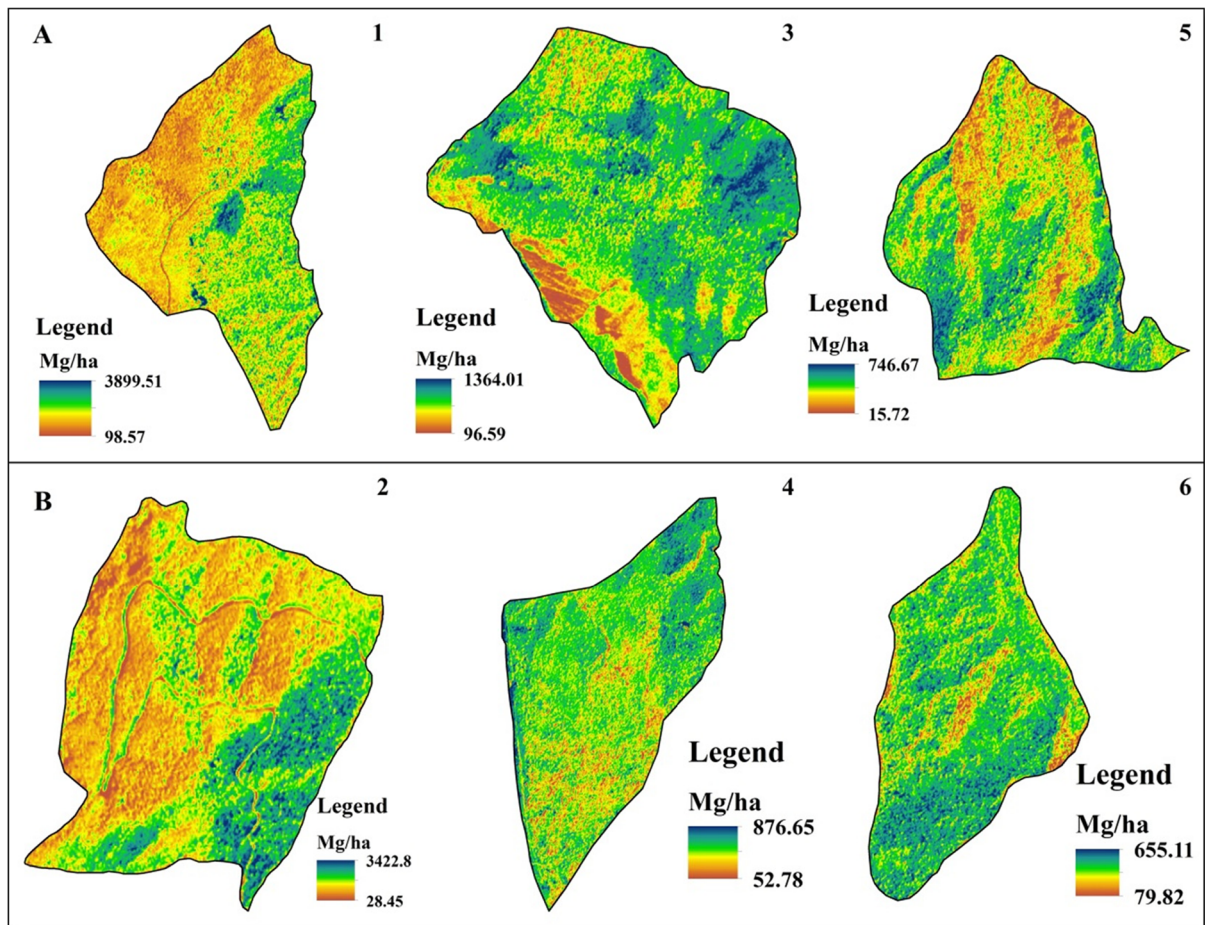
Fig. 6 Mapping of biomass in terms of Mg/ha for the studied compartments (**a**: high-altitude; **b**: middle-altitude; 1 and 2: Asalem; 3 and 4: Sardabrud; 5 and 6: Kordkuy)

AGB. The results presented by Kumar et al. (2016) showed that EVI, SAVI, and RVI indices showed a better relationship with AGB compared to NDVI. Günlü et al. (2014) also demonstrated that the VIs, especially the EVI could lead to better results for biomass modeling compared to Landsat individual bands and NDVI. The most important point regarding to choosing VIs is the use of suitable VIs for estimating biomass with respect to climatic conditions and land cover (Wang et al. 2016; Yavaşlı 2016).

Table 6 The most optimal regression model between AGB and NDVI—calculation of AGB in terms of Mg/ha unit

Compartment ID	Compartment name	Vegetation index	Regression model	AGB (Mg/ha)
1	Asalem high-altitude land forest	NDVI	$\text{Log AGB} = 2.62 \times + 1.74$	$10^{\text{Log AGB}}$
2	Asalem middle-altitude land forest	NDVI	$\text{Log AGB} = 3.01 \times + 1.58$	
3	Sardabrud high-altitude land forest	NDVI	$\text{Log AGB} = 2.35 \times + 1.51$	
4	Sardabrud middle-altitude land forest	NDVI	$\text{Log AGB} = 1.63 \times + 1.82$	
5	Kordkuy high-altitude land forest	NDVI	$\text{Log AGB} = 1.94 \times + 1.55$	
6	Kordkuy middle-altitude land forest	NDVI	$\text{Log AGB} = 1.59 \times + 1.76$	

Conclusion

In this research, considering the characteristics of the study area and comparing with other studies conducted in this regard, the most appropriate indices were obtained for estimating biomass based on regression equations. The results show that the satellite images used in this study provide satisfactory results regarding modeling of AGB in Hyrcanian forests and estimating biomass by applying remote sensing in order to obtain rapid and acceptable estimation of these forests using VIs can be a desirable and cost-effective method to manage and protect these valuable forests.

Compliance with ethical standards

Conflict of interest   The authors declare that they have no conflict of interest.

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