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Allometric relationships for predicting the stem volume of Acer monspessulanum and evaluation of NDVI values to estimate some stand parameters using Sentinel-2 satellite image

Kaouther MECHERGUI — National Institute of Research in Rural Engineering, Waters and Forests, University of Carthage, Ariana, Tunisia

Wahbi JAOUADI — Silvo-Pastoral Institute of Tabarka, University of Jendouba, Tunisia

The objectives of this work are to evaluate allometric models for predicting stem volume and use NDVI index to estimate stand parameters of *Acer monspessulanum*, using Sentinel-2 images for the determination of NDVI index. Forty-nine (49) sample plots of 20 x 20 m were used as ground truth data and randomly split into two groups: 70% for fitting data and 30% for data validation. We determined 12 dendrometric characters and the spectral index NDVI for each tree. The heights of the trees varied between 2.2 and 10.8 m and the DBH (Diameter at Breast Height) varied between 0.15 and 1.2 m. The analyzed relationships were between: (i) individual stem volume and dendrometric parameters, (ii) individual tree NDVI and the dendrometric parameters and (iii) individual crown diameter and NDVI. The relationships were evaluated using ten allometric models. The regression study showed that the diameter and the height presented the robust relationship with tree volume in cubic and power models (R^2=0.997). Power and cubic equations were also confirmed as good predictors using NDVI. With these models, we can estimate dendrometric parameters and predict tree volume.

Keywords: Maple tree, NDVI, allometric model, dendrometric parameters, remote Sensing

INTRODUCTION

The Allometric model for determining tree volume is of great importance for silviculture and stand management (Malhi et al., 2006). The volume of forest stands is calculated by measuring tree diameters at different levels of tree height based on mathematical equations (Robinson and Wood, 1994). Subedi et al. (2011) showed that the prediction of tree diameters and volumes are based on regression models, which are very effective tools in forest management. These models estimate well the forest stand volumes and are needed for biomass and carbon stock quantification (Ketterings et al., 2001). In the regression models, tree diameter at 1.3 m is used as the only independent variable (Ong et al., 2004). Poungparn et al. (2002) used tree height to ensure high accuracy in allometric models and for the determination of forest tree productivity. A new variable D0,12 H (D0,1: diameter to the tenth of H) instead of D1,32H is proposed by Hagihara et al. (1993) and Khan et al. (2005) for improved quantification of stand production. Attiwill (1962) showed a robust relationship between the circumference of tree and the weight of the branch in Eucalyptus obliqua stand. Stem volume showed a significant correlation with basal area, and D2 is the most effective independent variable in both linear and quadratic regressions (Khan and Faruque, 2010).

Several authors showed that spectral indices including NDVI are effective and are relevant tools to study stand production (Carreiras et al., 2006; Hansen et al., 2002; Hirata et al., 2009; Song et al., 2010). Kumar et al. (2018) found that remote sensing tools are becoming a revolutionary analysis tools for assessing forest stand characteristics. Mirasi et al., (2019) showed that NDVI is the best index for estimating the production and yield. This index is widely used to study vegetation characteristics in low-density forests (Bendig et al., 2015; Ren et al., 2019). Godinho et al. (2017) and Pandit et al. (2019) concluded that NDVI is the most important variable to predict crown characteristics and estimate production of forests (Dube et al., 2016; Rasel et al., 2019; Sun et al., 2019; Deb et al., 2020; Turgut and Gunlu, 2020). The NDVI is widely used as a tool for the study of tree characteristics (Crist and Cicone, 1984) and this index is among the most relevant indices for the study of productivity of natural ecosystems (Silveira et al., 2019). In arid ecosystems, Rajabov et al., (2020) showed that NDVI is used to estimate stand productivity in these areas and it is considered as an effective and important index for determining the production of these lands. Collecting data to relate forest stand measurements to spectral data has facilitated analyses and minimized cost, effort, and expenses with remote sensing technology (Brown et al., 1989; Tomar et al., 2013; Rani et al., 2011; Maity et al., 2011). Based on satellite imagery, spectral indices of stand dendrometric measurements are detected by capture of the electromagnetic energy (dos Reis et al., 2018a). Brito et al. (2021) showed an important correlation between spectral indices including NDVI and dendrometric parameters of forest stands.

In this study, we analysed regression models without cutting and damaging trees. The objectives of this work are first to evaluate allometric models for predicting stem volume and then evaluate NDVI to estimate parameters of Acer monspessulanum stands in Serej National Park, Tunisia.

MATERIALS AND METHODS

Study area

Acer monspessulanum L. stand is located in Tunisia in Jbel Serej national park (Figure 1). This natural species is the only genus of maple in Tunisia. Jbel Serej national park is created since 2010 (Figure 1). The park area is 1720 hectares and is has been created for protection of maple trees. In the strategy of protecting forest ecosystems against degradation factors, Tunisia has created several national parks. Before the creation of the Jbel Serej national park, this ecosystem was exposed to several tree cuts and overexploitation of its natural resources. The Jbel Serej national park is created to protect A. monspessulanum (Mechergui et al., 2018).

Sampling, data collection and analysis

In Jbel Serej national park, forty two (42) sample plots of 20 m x 20 m were chosen randomly and used in fitting data. Seven (07) sample plots of 20 m x 20 m were chosen randomly and used in validation data. The plots of fitting data contain one hundred and twenty-two (122) A. monspessulanum trees. The plots of validation data contain thirty-seven (37) A. monspessulanum trees. Overall, the trees data were randomly split into two groups: 70% for fitting data and 30% for data validation. The field measurements were carried out in June 2017 and the acquisition date of the Sentinel-2 image is during the month of August 2017. We can ignore the influence of tree growth during this period because it is the summer period known by the slowing down or absence of growth. These plots are located in pure stands of Acer monspessulanum trees. The trees used for this work had a wide series of diameters and heights. We determined 12 dendrometric characters and the spectral index NDVI for each tree based on Sentinel-2 satellite image. The dendrometric parameters that were analyzed are: tree merchantable height (H), stem diameter at a height of merchantable height (H)/10 and stem DBH at D1.3. The basal area and the stem diameter at 1.0 m intervals thereafter up to the strong wood height (stem height at 07 cm diameter). We determined for each tree, the diameter at 1.3 m (D in cm), the height of the first branch from the ground (in m), the height of trees (H in m), the height of crown (in m), the diameter (D) at H (height)/10 (cm), the diameter (D) at H (height)/2 (in cm), the volume (V in cm3), the basal area at 1.3 m, the basal area at H (height)/10, the crown volume, the crown area and the crown diameter, morphological traits, and normalized the difference of vegetation index (NDVI). The diameter (cm) along the stem (1.0 m of interval) and the height (m) of trees are determined using Vertex hypsometer (Haglof, Sweden) and a Criterion RD1000 instrument. The successive parts of the wood of each tree from the base to the top are summed to determine the total volume of wood. The volume of each part of the tree is calculated by the following truncated cone formula (Van Coillie et al., 2016):

V = πh/12(d02+d0ds+ds2)

In which:

h = length of the part of wood (= 1 m); d0 = girth at the base of the part of wood, ds = girth end of the part of wood.

Multicollinearity Test

In a regression equation, there are important correlation between independent variables, namely multicollinearity, which can distort the estimate of the model or interfere with accurate assessment. The factor, namely VIF (variance inflation factor), was employed to exam for multicollinearity, and variables with significant collinearity (VIF ≥ 10) were progressively removed from the equation (Guo et al., 2016). Multicollinearity was identified by variance inflation factor (VIF). We considered that the results were not affected by collinearity between predictor variables when variance inflation factor (VIF) are lower than value of 10 in the best-fit regression model (Graham, 2003; Wang et al., 2020). In this study, the allometric relationships of the stem volume and many measures: D1.3, D1.32, D1.32H, D0.1, D2at H/10 and D2at H/10H, the basal area (BA= π (D/2)2), the crown diameter (Cd), the crown area (CA= π (Cd/2)2) and crown volume (CV= (π Cd2CH)/6) with CH= crown height (Yan et al., 2019), were calculated using models in table 1. Analysis of the 10 equations was carried out using SPSS software (SPSS 2004).

Model fitting and evaluation

Models are assessed by the statistical criteria according to their accuracy and precision. Bennett et al. (2013) and Cysneiros et al. (2020) showed that RMSE % (root mean square error, adj-R2 (values of adjusted coefficient of determination), R2 (coefficient of determination) are the statistical criteria used to select the best models. Hofiço et al. (2020) and Sharma and Parton (2007) reported that the lowest values of the RMSE and the highest of R2 and adj-R2 indicated better results for model adjustment. The coefficient of determination (R2) is determined using the following equation:

To examine the performance of the models, we used adjusted coefficient of determination (R2adj):

Image data and image analysis

In this study we used the Sentinel-2 satellite data of March 2017. This satellite imagery was used to determine NDVI values from the sampled maple trees. The software used for image geometric correction is Envi 5.1.

Normalized Difference Vegetation Index

Pettorelli et al. (2005) showed that NDVI is used to identify and quantify the vegetation. NDVI is determined using the equation: NDVI= (NIR-RED/NIR+RED) (Rouse et al., 1974).

RESULTS

Test for Multicollinearity

Four independent variables, the height of the first branch from the ground, the height of crown (in m), the diameter (D) at H (height)/2 and the basal area at H (height)/10, were not used and eliminated since the multicollinearity was determined based on the VIF test. For regression model, the remaining nine independent variables are designated.

Relationship between tree volume and dendrometric parameters of the species

Table 2 shows robust relationship between stem volume and DBH, DHB2, that DBH2 H, H, Dat H/10, D2at H/10, D2at H/10, H ,CV, CA, Cd and BA. R2 values vary between 0.981 and 0.998. The best model is the power equation for the description a relationship between: Stem v. DBH (cm), Stem v. DBH (m), Stem v. CV (m3) and Stem v. CA (m2). The best model is cubic equation for the description a relationship between: Stem v. DBH2 (cm2), Stem v. Dat H/10 (cm), Stem v. D2at H/10 (cm2) and Stem v. BA (m2). The best model is linear equation for the description a relationship between: Stem v. DBH2 H (cm2.m) and stem v. D2at H/10 H (cm2.m). The best model is growth equation for the description a relationship between: stem v. H (m) and stem v. H (cm) (Table 2). The cubic and power equations as well as the linear model are robust in fitting the dendrometric parameters DBH, DHB2, DBH2 H, Dat H/10, D2at H/10, D2at H/10 H, CV, CA, Cd and BA, with R2 value is between 0.993 and 0.998 (Table 2).

There are robust relationships between stem volume and H (R2 = 0.981), the growth model as well as the other equations for the variable H (m) and H (cm). The variable D2at H/10 showed solid relationship than when it is used as independent variable in cubic equation (value of R2 of D2atH/10 (R2 = 0.998) was greater than D at H/10 (R2 = 0.997)). We conclude that cubic model is close fit as compared to the quadratic equation. Both DBH2 H (R2 = 0.998) and D2atH/10 H (R2 = 0.998) were the most effective fitted in linear model and would be calculated by the height of tree. The other variable D2at H/10 showed robust relationship same as Dat H/10 used as an independent variable by cubic equation (value of R2 of D2at H/10 and Dat H/10 (R2 = 0.997 and 0.998). We found that cubic model was best fitted for DatH/10 (R2 = 0.997) than any other model regression and the degree of linearity can be improved based on D2at H/10 H in place of Dat H/10 value. The R2 of validation data range of 0.980-0.996 (Table 2).

Relationship between tree volume and the spectral index NDVI

Table 3 shows the relationship between tree volume and the spectral index NDVI. We noticed clearly in Table 3 that there are important relationships between NDVI and DBH, DHB2, DBH2 H, H, Dat H/10, D2at H/10, D2at H/10 H, CV, CA, Cd and BA. R2 value varies between 0.905 and 0.966. Table 3 showed that DBH had robust relationship with NDVI in relation to DBH2 using S-curve equation, when utilized as a independent variable. R2 value of DBH (R2 = 0.965) was greater as compared to DBH2 (R2 = 0.905). The cubic model had the best fit for DBH (m) (R2 = 0.970). Another variable (Dat H/10) showed robust relationship with NDVI than D2at H/10 (value of R2 of Dat H/10 (R2 = 0.963) is greater than the value of D2at H/10 (R2 = 0.934)). The best model is logarithmic equation for the description a relationship between NDVI. BA (m2), NDVI. Cd (m), NDVI. CV (m3), NDVI. CV (m3), NDVI. D2at H/10 H (cm2.m), NDVI. D2at H/10 (cm2), NDVI and DBH2 H (cm2.m). The best model is cubic equation for the description a relationship between: NDVI. DBH (m), NDVI. H (m), NDVI. H (cm) and NDVI. CA (m2). The best model is S-curve equation for the description a relationship between: NDVI. DBH (cm), NDVI. DBH2 (cm2) and NDVI. Dat H/10 (cm) (Table 3). The R2 of validation data range of 0.933-0.969 (Table 3).

The relationship of species: the crown diameter Vs the basal area and crown area Vs NDVI

Figure 2a and Table 4 show the relationship between crown diameter and basal area. This correlation is determined: it shows that basal area can be dependably estimated from crown diameter (Figure 2a).The correlation is important with an r2-value of almost 0.8-0.9 (linear model), indicating that basal area and NDVI can be distributed in the study area exclusively based on crown diameter. The basal area is calculated assuming a circular stem shape. We studied the relationship between crown area and NDVI (Figure 2b and Table 4). The correlation between the crown area and the NDVI shows that NDVI can be reliably estimated from the crown area (Figure 2b). An approach to expand the surface area of the crown is determined from the image analysis using a plot scale correlation between the crown area and the NDVI is carried out by Hansen et al. (2002) and Carreiras et al. (2006). The results of the analysis of correlation are shown in Table 4 and Figure 2b where we found important correlation between this two parameters. The correlation is important with an r2-value of nearly 0.8-0.9 (linear model), indicating that basal area and NDVI can be analysed in a reliable way in the whole site survey only on the basis of the diameter and surface of the crown. The R2 of validation data of crown diameter vs BA (m2) and crown area vs NDVI were in the range of 0.713-0.984 and 0.671 -0964, respectively (Table 4).

The relationship between height and crown area

Figure 2c and Table 5 showed the relationship between the height of the tree and the crown area. To analyze the relation between crown diameter and basal area, we also established equation models for the relation between tree height and crown area. The correlation between tree heights and crown area shows that tree height can be estimated from crown area (Figure 2c). For tree height, maple tree show important performance with r2-values of 0.98 and 0.96 respectively (logarithmic and cubi model). The correlation is good with an r2-value of almost 0.8 (linear model), demonstrating that tree height can be estimated based on the study site only across on crown area. The R2 of validation data range of 0.933-0.969 (Table 5).

DISCUSSION

The results showed stronger relationship between stem volume and DBH, DHB2 That DBH2 H, H, Dat H/10, D2at H/10, D2at H/10, H ,CV, CA, Cd and BA. The best model is power equation for the description of the relationship. For management practice, the linear and growth model s are used for evaluation tree volume. Kumar et al. (2018) confirmed that this allometric equation was highly significant with p-value < 0.01 and these authors showed strong correlation of volume tree and D2H. Van Coillie et al. (2016) found that the allometric models allowed to determine tree height and volume based on field-measured crown diameter with important levels. These authors showed increasing variance with increasing crown diameter. These results showed that the best model is cubic equation for the description a relationship between: NDVI. DBH (m), NDVI. H (m), NDVI. H (cm) and NDVI. CA (m2). Kumar et al. (2018) found that the regression equations of NDVI and dendrometric parameters showed an important relationship of D2H with NDVI using linear model (R2=0.904). The results show that NDVI can be used to estimate the crown area. An attempt is done at upscaling the crown area found from the image analysis using a plot scale correlation between the crown area and the NDVI as it was carried out by several authors (Hansen et al. 2002; Carreiras et al., 2006). Crown area and NDVI indicate that NDVI is the best index to estimate crown area. Our results are in opposition to the ones presented by Rasmussen et al. (2011) and are similar to the values presented by Kumar et al. (2018). Dos Reis et al. (2018a) showed that there is a strong correlation between spectral data and forest stand characteristics for Eucalyptus plantation sp. These authors concluded that NDVI is correlated significantly with basal area and tree volume. Brito et al. (2021) concluded that among the spectral index, the best correlation is recorded between NDVI and tree volume which is deduced from height and diameter (R-adj=0.92, p-value < 0.0001, RMSE= 0.03). Spectral indices including NDVI are effective tools for monitoring the growth of forest trees and for effective management of forest ecosystems (Brito et al., 2021). For the species P. taeda and P. caribaea var. hondurensis, Alvares et al. (2013) showed positive correlation between wood volume and spectral index NDVI. These authors found highly significant correlations between NDVI and forest productivity based on their dendrometric parameters, both at stand and at individual tree level. In Spain and in a pine forest, González-Alonso et al. (2006) found a linear regression (r2 = 0.79-0.82) between the spectral NDVI and volume of tree. Dos Reis et al. (2018b) showed that there is a strong correlation between NDVI and the dendrometric parameters: volume (r = 0.49) and basal area (r= 0.83). Finally, based on our study we consider remote sensing as a valuable technique to assess stand structure as similarly presented by Van Coillie et al. (2016)

for an Acacia tortilis stands. Desertification is fought by restoration of the original species, particularly by means of creation of the national park. Basal area is calculated from the diameter, which is directly related to the size of the crown which, in turn, explains the reflectance of the crown (dos Reis et al. 2018a). The relationship between spectral index and dendrometric measurements is explained by Ponzoni et al. (2012) who showed that the crown of trees and their physiological characteristics are responsible for a greater absorption of electromagnetic radiation (Ponzoni et al., 2012). Several authors confirmed that there is a good relationship between basal area and spectral indices including NDVI (Berra et al., 2012; Bolfe et al.,. 2012 ; Almeida et al., 2014). In that sense, Berra et al. (2012) and Pacheco et al. (2012) showed that spectral index have a great potential to explain the dendrometric measurements of the forest stand. Lu et al. (2004) studied the correlation between dendrometric measurements of forest trees and their spectral responses and concluded that there is a strong correlation between these measurements and spectral index, these results are similar with the results of our work and corroborate the results found by dos Reis et al. (2018a). Hall et al. (2006) and Thenkabail et al. (2003) found that spectral bands were effective in detecting the relationship between forest tree crown reflectance and dendrometric characteristics such as basal area and stem volume. Berra et al. (2012) who studied the correlation between dendrometric measurements of Eucalyptus sp. trees and vegetation index showed a positive correlation of 0.79 between NDVI and stem volume. The study of remote sensing index (NDVI), stem volume, based, and indirect attribute modeling finally assessing the structure of the maple in Tunisia. The established equations are found to adequately estimate stem volume. This work can easily be adapted to other types of images and to other ecosystems, providing stands management and decision makers with important data for management practices in forest stands.

CONCLUSION

We used ten models to study the morphological characteristics of trees for predicting their stem volume. For predicting volume of stands, cubic regression equation (R2=0.969) is shown as the best-fitting equation (p-value < 0.01) and found important relationship between stem volume and D2H. Spectral index NDVI and dendrometric parameters showed a strong relationship in cubic and power regression equation (R2 varies between 0.96 and 0.98). The approaches applied in this work proved the potential of using remote sensing index for tree production analysis, which can eventually be applied for biomass estimate. Determination of crown area using a relation between crown area and NDVI has succeeded, due to the strong correlation between the two parameters. Power and cubic regression model can be used to correctly predict tree volume of forest stand. The study presented can be extended to other satellite images and to different forest stand characteristics, thus giving forest managers and decision-making authorities some basic information for management applications.

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