# Modeling Stand Volume using Landsat TM data for Fir stands (*Abies bornmuelleriana* Matth.) Located in Buyukduz Planning Unit, TURKEY

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**Abstract**

Remotely sensed data in the form of satellite images have been used for decades to estimate forest parameters in support of forest management planning (Leyk et al., 2002). Since satellite data can be repeatedly acquired with reliable data quality, methods about modeling some stand attributes with data-originated satellite images is appropriate for obtaining information on land cover on forest areas (Wulderand and Seemann, 2003). Based on 97 sample plots, it is aiming to model relationships between stand volume and band values based on Landsat TM data for fir stands (*Abies bornmuelleriana* Matth.) located in Buyukduz Planning Unit, TURKEY. Multiple linear regression models were used to predict stand volumes with band values, including TM 1 - TM 5 and TM 7, originated from Landsat TM satellite image. The regression models, including different independent variables alternatives and band values, were compared with some information criteria, e.g. the adjusted coefficient of determination ($R^2$), with Reduced Akaike's Information Criterion (*AIC*), Sawa's Bayesian Information Criteria (*BIC*), Schwarz Bayesian Criteria (*SBC*), the root mean square error (*RMSE*) and Mallow's Cp, which criteria are measures of goodness of fit for regression models. These statistical analyses were performed by PROC REG and PROC RSQUARE procedures of the SAS/ETS V9 software (SAS Institute Inc, 2004). The best results for predictive performance were obtained by multiple linear regression model including TM 2 and TM 4 as independent variables. This model, statistically significant at 95% level with model parameters, explained 54.09% of the observed stand volume variability with 634.29 of *AIC*, 637.02 of *BIC*, 640.36 of *SBC*, 28.69 of *RMSE* and -0.315 of *Cp*. The results showed that the Landsat TM data are beneficial to estimate forest stand volume. Thus, forest managers could use remote sensing data, e.g. Landsat TM data, for predicting stand volume and for generating maps necessary for developing forest management plans.

**Keywords:** Landsat TM satellite image, Multiple regression analysis, Stand volume, *Abies*

## Introduction

The estimations of forest stand parameters such as stand volume, basal area, tree density, dominant height and stand diameter are important for forest management planning, and required for effective and successive resource management. Furthermore, estimating changes in forest stand parameters through time is a keystone knowledge for many forest requests, such as decision-making (Zimble et al., 2003), forest planning and management (Sironen et al., 2001).

Sustainable management and utilization of forest resources need accurate information about forest extension and spatial distribution of stand parameters such as volume and tree density. In addition, as forests undertake change it becomes imperative that inventory data be reorganized periodically (Dodge and Bryant, 1976; Sivanpillai et al., 2006). Traditionally, these forest stand parameters such as stand volume, basal area and tree density data have been collected through national forest inventories, inspections, terrestrial surveys of sample plots and by extrapolating from prior inventories.

Forest national inventories can be carried out at various levels and scales from regional to national or for a small area unit (Chapman et al., 2006). In recent times, remote sensing data have been used to predict forest stand parameters for supporting forest management planning (Leyk et al., 2002). Since remote sensing data can be repeatedly attained with reliable data quality, this method is suitable for obtaining information for land cover on forest areas (Wulder and Seemann, 2003). Since the per-unit area cost is much cheaper, capacity of satellite remote sensing for large-area coverage is another advantage (Malingreau et al., 1992).

Forest resource observing with Landsat satellite images and other moderate resolution satellite image is an important module for a wide range of forest applications. The attractiveness of Landsat satellite images data can be qualified to several basic characteristics of the Landsat program, including low imagery costs and free data distribution facility widespread use of a spatial resolution enough to characterize typical forest cover dynamics related to forest management (Cohen and Goward, 2004).

The objective of this paper is to investigate and model the relationships between reflectance values recorded by Landsat TM satellite image and stand volume obtained from sample plots, using multiple linear regression analysis for fir stands (*Abies bornmuelleriana* Matth.) located in Buyukduz Planning Unit, TURKEY.

**Material and Methods**

**Study Area**

The study area is Buyukduz planning unit located in Karabuk city in the northwestern part of Turkey (45°51'08''-46°82'88'' E, 45°68'23''3-45°76'46''0 N, UTM ED 50 datum Zone 36N) (Figure 1).

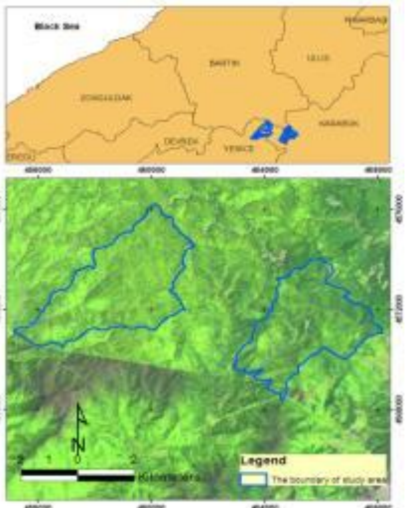

Figure 1. The geographical location of the study area

The study area covers 3020.0 ha. The elevation ranges from 800 to 1,736 m with an average of 1,270 m. The study area has an average slope of 45%. The mean annual temperature is 12.0 °C and the mean rainfall is 650 mm (Anonymous, 2010). The study area is covered with fir (*Abies bornmuelleriana* Matth.), Scots pine (*Pinus sylvestris* L.), anatolian black pine (*Pinus nigra Arn. ssp. pallasiana* (Lamb.) Holmboe), oriental beech (*Fagus orientalis*) and Çoruh oak (*Quercus petraea ssp. iberica* (Steven ex Bieb.) Krassilin).

**Material**

The data used in this paper are forest cover type map at 1/25.000 scale for year 2010, 97 sample plots obtained from data base of forest management planning and Landsat TM satellite image acquired on September 3, 2010. In these ground measurements, the forest inventory plots were distributed by 300x300 m grids. The size of sample plots ranged from 400 $m^2$ to 800 $m^2$ depending on stand crown closures. In each sample plots, diameter at breast height (dbh) was measured to the nearest 0.1 cm with calipers for every living tree with dbh>8.0 cm. The classical inventory calculations were performed from each sample plot and the tree volume was calculated using local tree volume formulas, single or two-entry volume equations (Forest Plans, Forest agency of Turkey, 2000).

**Methods**

Data processing, interpreting and analysis were performed using Erdas Imagine 9.1™ version (Erdas, 2002). The Landsat TM data was acquired for September 3, 2010, ortho-rectified, and geo-referenced using 1/25.000 scale Topographical Maps with UTM projection (ED 50 DATUM, Zone 36) using first order nearest neighbor rules. A total of 20 ground points were used to register the TM image subset a rectification error less than 1 pixel image. Solar zenith angle and atmosphere influence spectral value of satellite image. Thus, radiometric correction must be done to convert digital number to reflectance value. In the process of radiometric correction, the digital number of Landsat TM must be converted to radiance value, and then to reflectance. The information for the coming radiometric correction (solar zenith angle, acquisition date and so on) can be obtained from Landsat TM ancillary data.

**Statistical Analysis**

The reflectance value of pixels within a 1x1 pixel window (similar to the plot size) was extracted from all Landsat TM bands. To examine and model the relationships between Landsat TM satellite image based on the spectral reflectance values, TM 1-5 and 7, and stand volume values, the multiple linear regression analysis was used in this study. In this study, the following linear relationship was assumed:

$$V = \beta_0 + \beta_1 \cdot X_1 + \beta_2 \cdot X_2 + .... + \beta_n \cdot X_n + \varepsilon \quad (1)$$

where V is the stand parameter, stand volume, , $X_1$ …… $X_n$ are variable vectors corresponding to remote sensing data, e.g. the spectral reflectance factors, TM 1-5 and 7, $\beta_1 \ldots\ldots \beta_n$ represent model coefficients and $\varepsilon$ is the additive error term (Corona et al., 1998; Fontes et al., 2003). The estimate of each parameter for variables of these regression models should be statistically significant at 95% probability level. The null hypothesis $H_0 = \beta_0 = \beta_1 = \ldots\ldots\ldots \beta_n = 0$, was tested and parameters that were not significantly different from zero were rejected (Fontes et al., 2003). The regression models, including different independent variables alternatives and band values, were compared with some information criteria, e.g. the adjusted coefficient of determination ($R^2$), the Reduced Akaike's Information Criterion (*AIC*), Sawa's Bayesian Information Criteria (*BIC*), Schwarz Bayesian Criteria (*SBC*), the root mean square error (*RMSE*) and Mallow's Cp, which criteria are measures of goodness of fit for regression models. Beal (2007) defined and coded these criteria for selecting best subset of independent variables to model stand volume in SAS statistical program.

The adjusted coefficient of determination $R^2$ is the percentage of the variability of the dependent variable that is explained by the variation of the independent variables after accounting for the intercept and number of independent variables (Beal, 2007). Therefore, the adjusted $R^2$ value ranges from 0 to 1 and is a function of the sum of squares error and total, number of observations n, number of independent variables. The equation for the adjusted $R^2$ is shown as follow:

$$R^2_{adj} = 1 - \frac{(n-1) \cdot SSE}{(n-k) \cdot SST} \quad (2)$$

Akaike (1973) introduced the concept of information criteria as a tool for optimal model selection (Beal, 2007). Other authors using AIC for model selection include Akaike (1987) and Bozdogan (1987, 2000). Akaike's Information Criteria (AIC) is a function of the number of observations n, the SSE, the number of independent variables and looks as follows:

$$AIC = n \cdot \ln\left(\frac{SSE}{n}\right) + 2k \quad (3)$$

The first term in Eqn. is a measure of the model lack of fit while the second term (2k) is a penalty term for additional parameters in the model. Therefore, as the number of independent variables k included in the model increases, the lack of fit term decreases while the penalty term increases (Beal, 2007).

Sawa (1978) developed a model selection criterion that was derived from a Bayesian modification of the AIC criterion (Beal, 2007). Bayesian Information Criteria (BIC) is a function of the number of observations n, the SSE, the pure error variance fitting the full model ($s^2$), and the number of independent variables $k \leq p + 1$ where k includes the intercept. It looks as follows:

$$BIC = n \cdot \ln\left(\frac{SSE}{n}\right) + \frac{2(k+2) \cdot n \cdot \sigma^2}{SSE} - \frac{2 \cdot n^2 \cdot \sigma^4}{SSE^2} \quad (4)$$

The penalty term for BIC is more complex than the AIC penalty term and is a function of n, the SSE and $s^2$ in addition to k.

Schwarz (1978) developed a model selection criterion that was derived from a Bayesian modification of the AIC criterion (Beal, 2007). Schwarz Bayesian Criteria (SBC) is a function of the number of observations n, the SSE, and the number of independent variables $k \leq p + 1$ where k includes the intercept. It is as follows:

$$SBC = n \cdot \ln\left(\frac{SSE}{n}\right) + k \cdot \ln(n)$$
(5)

The penalty term for SBC is similar to AIC in Equation but uses a multiplier of ln n for k instead of a constant 2 by incorporating the sample size n.

The RMSE is a function of the sum of squared errors (SSE), number of observations n, and the number of independent variables k = p + 1 where k includes the intercept. It looks as follows:

$$RMSE = \sqrt{\frac{SSE}{n-k}} \quad (6)$$

The RMSE is calculated for all possible subset models. Using this technique, the model with the smallest RMSE is declared the best linear model. This approach does include the number of parameters in the model. Additional parameters will decrease the numerator since the SSE decreases as additional variables are included in the model and the denominator decreases as k increases.

Mallows' Cp (Mallows, 1973) is another model diagnostic that is a function of the SSE, the full model pure error estimate $s^2$, number of observations n, and the number of independent variables $k \leq p + 1$ where k includes the intercept (Beal, 2007). Mallows' Cp is as follows:

$$Cp = \frac{SSE}{\sigma^2} + 2k - n \quad (7)$$

Mallows' Cp is calculated for all possible subset models (Beal, 2007). Using this technique, the model with the smallest Cp is declared the best linear model. As the number of independent variables k increases, an increased penalty term (2k) is offset with a decreased SSE (Beal, 2007).

In these criteria, the more adjusted coefficient of determination ($R^2$) means better predictive performance for model, and the less other criteria eventuated in the superior model prediction results. All these statistical analyses were performed by PROC REG and PROC RSQUARE procedures of the SAS/ETS V9 software (SAS Institute Inc, 2004).

## Results

Table 1 presents the information criteria, including the adjusted coefficient of determination ($R^2$), with Reduced Akaike's Information Criterion (*AIC*), Sawa's Bayesian Information Criteria (*BIC*), Schwarz Bayesian Criteria (*SBC*), the root mean square error (*RMSE*) and Mallow's Cp, for all possible independent variables, the spectral reflectance factors, TM 1-5 and 7, to model stand volume. The best results for predictive performance were obtained by multiple linear regression model including TM 2 and TM 4 as independent variables. In these selected regression models for stand volume, the F statistics and coefficients were significant at a probability level of 95 percent (Fvalue=33.40, $p<0.05$). The standard error, t values and the predicted values of model's parameters were presented for the selected best regression sub-group models including TM 2 and TM 4 independent variables in Table 2. This model statistically significant at 95% levels with model parameters explained 54.09 % of the observed stand volume variability with 634.29 of *AIC*, 637.02 of *BIC*, 640.36 of *SBC*, 28.69 of *RMSE* and -0.315 of *Cp*.

To further evaluate the quality of the model fit and the parameter estimates, we used the standardized predicted (fitted) values versus standardized observed stand volume values given in Fig. 1. The model values indicate that there are no observable patterns in Fig. 1, and thus there are no serious violations of the assumption of constant variance, such as homoscedasticity.

Table 1. The information criteria for all possible independent variables, the spectral reflectance factors, TM 1-5 and 7, to model stand volume

| Model Group | $R^2$adj. | Cp | AIC | BIC | RMSE | SBC | Independent Variables | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.1808 | 38.3275 | 665.7609 | 665.9519 | 374.9391 | 669.8116 | TM2 | | | | | |
| 1 | 0.1157 | 45.5014 | 670.0407 | 669.9758 | 389.5436 | 674.0914 | TM3 | | | | | |
| 1 | 0.0461 | 53.1842 | 674.2881 | 673.9804 | 404.6002 | 678.3388 | TM1 | | | | | |
| 1 | 0.024 | 55.6217 | 675.571 | 675.1922 | 409.2612 | 679.6217 | TM4 | | | | | |
| 1 | 0.0047 | 58.7769 | 677.1892 | 676.7223 | 415.2172 | 681.2399 | TM5 | | | | | |
| 1 | 0.0184 | 60.2958 | 677.9518 | 677.4439 | 418.0542 | 682.0026 | TM7 | | | | | |
| **2** | **0.5409** | **-0.315** | **634.2876** | **637.0179** | **280.6871** | **640.3636** | **TM2** | **TM4** | | | | |
| 2 | 0.4345 | 11.204 | 645.9641 | 647.4395 | 311.5298 | 652.0402 | TM2 | TM5 | | | | |
| 2 | 0.4115 | 13.6866 | 648.1907 | 649.4374 | 317.7852 | 654.2668 | TM2 | TM7 | | | | |
| 2 | 0.3118 | 24.4745 | 656.9538 | 657.3423 | 343.6477 | 663.0298 | TM3 | TM4 | | | | |
| 2 | 0.2437 | 31.85 | 662.2419 | 662.1475 | 360.2624 | 668.318 | TM3 | TM5 | | | | |
| 2 | 0.2061 | 35.9144 | 664.9559 | 664.6243 | 369.0988 | 671.0319 | TM3 | TM7 | | | | |
| 2 | 0.1796 | 38.7875 | 666.798 | 666.3095 | 375.2197 | 672.874 | TM1 | TM4 | | | | |
| 2 | 0.1769 | 39.0731 | 666.9778 | 666.4742 | 375.8226 | 673.0538 | TM1 | TM2 | | | | |
| 2 | 0.1664 | 40.2135 | 667.6902 | 667.127 | 378.2208 | 673.7663 | TM2 | TM3 | | | | |
| 2 | 0.1239 | 44.8172 | 670.4774 | 669.6859 | 387.7513 | 676.5535 | TM4 | TM7 | | | | |
| 2 | 0.1215 | 45.0692 | 670.6261 | 669.8226 | 388.2663 | 676.7022 | TM1 | TM5 | | | | |
| 2 | 0.1011 | 47.2834 | 671.9154 | 671.009 | 392.7615 | 677.9914 | TM1 | TM3 | | | | |
| 2 | 0.0761 | 49.9815 | 673.4474 | 672.421 | 398.1709 | 679.5234 | TM1 | TM7 | | | | |
| 2 | 0.0676 | 50.9004 | 673.9597 | 672.8937 | 399.9965 | 680.0358 | TM5 | TM7 | | | | |
| 2 | 0.0348 | 54.4582 | 675.9003 | 674.6865 | 406.9874 | 681.9763 | TM4 | TM5 | | | | |
| 3 | 0.5353 | 1.3467 | 635.905 | 638.9472 | 282.4068 | 644.0064 | TM2 | TM3 | TM4 | | | |
| 3 | 0.5344 | 1.4408 | 636.0117 | 639.0378 | 282.6759 | 644.1131 | TM1 | TM2 | TM4 | | | |
| 3 | 0.5331 | 1.5791 | 636.168 | 639.1706 | 283.0709 | 644.2695 | TM2 | TM4 | TM7 | | | |
| 3 | 0.5322 | 1.6745 | 636.2758 | 639.262 | 283.3432 | 644.3772 | TM2 | TM4 | TM5 | | | |
| 3 | 0.4275 | 12.7878 | 647.582 | 648.9395 | 313.4398 | 655.6834 | TM2 | TM5 | TM7 | | | |
| 3 | 0.4245 | 13.101 | 647.8698 | 649.1879 | 314.2462 | 655.9712 | TM1 | TM2 | TM5 | | | |
| 3 | 0.4245 | 13.1074 | 647.8756 | 649.193 | 314.2627 | 655.977 | TM2 | TM3 | TM5 | | | |
| 3 | 0.4003 | 15.6801 | 650.185 | 651.1911 | 320.81 | 658.2865 | TM1 | TM2 | TM7 | | | |
| 3 | 0.4002 | 15.6862 | 650.1904 | 651.1957 | 320.8252 | 658.2918 | TM2 | TM3 | TM7 | | | |
| 3 | 0.3066 | 25.6273 | 658.3131 | 658.2831 | 344.9573 | 666.4145 | TM3 | TM4 | TM7 | | | |
| 3 | 0.3012 | 26.1939 | 658.7424 | 658.6604 | 346.2822 | 666.8438 | TM3 | TM4 | TM5 | | | |
| 3 | 0.3009 | 26.2322 | 658.7712 | 658.6857 | 346.3714 | 666.8726 | TM1 | TM3 | TM4 | | | |
| 3 | 0.2327 | 33.4763 | 663.9857 | 663.2886 | 362.8787 | 672.0871 | TM3 | TM5 | TM7 | | | |
| 3 | 0.231 | 33.652 | 664.1063 | 663.3956 | 363.2699 | 672.2077 | TM1 | TM3 | TM5 | | | |
| 3 | 0.195 | 37.4739 | 666.668 | 665.6716 | 371.6745 | 674.7694 | TM1 | TM4 | TM7 | | | |
| 3 | 0.1928 | 37.708 | 666.8211 | 665.8079 | 372.183 | 674.9225 | TM1 | TM3 | TM7 | | | |
| 3 | 0.1697 | 40.161 | 668.4014 | 667.2168 | 377.4715 | 676.5028 | TM1 | TM4 | TM5 | | | |
| 3 | 0.1613 | 41.0559 | 668.967 | 667.722 | 379.3825 | 677.0684 | TM1 | TM2 | TM3 | | | |
| 3 | 0.1293 | 44.4551 | 671.0646 | 669.5993 | 386.555 | 679.1661 | TM1 | TM5 | TM7 | | | |
| 3 | 0.1215 | 45.2759 | 671.5596 | 670.0432 | 388.2671 | 679.661 | TM4 | TM5 | TM7 | | | |
| 4 | 0.5269 | 3.2694 | 637.8171 | 641.1459 | 284.9384 | 647.9439 | TM1 | TM2 | TM3 | TM4 | | |
| 4 | 0.5267 | 3.2874 | 637.837 | 641.1625 | 284.9906 | 647.9644 | TM2 | TM3 | TM4 | TM7 | | |
| 4 | 0.5264 | 3.3201 | 637.8748 | 641.1925 | 285.0852 | 648.0016 | TM2 | TM4 | TM5 | TM7 | | |
| 4 | 0.5263 | 3.3257 | 637.8811 | 641.1976 | 285.1013 | 648.0079 | TM2 | TM3 | TM4 | TM5 | | |
| 4 | 0.5257 | 3.3873 | 637.951 | 641.2541 | 285.2793 | 648.0778 | TM1 | TM2 | TM4 | TM7 | | |
| 4 | 0.5255 | 3.4135 | 637.9807 | 641.2781 | 285.3548 | 648.1074 | TM1 | TM2 | TM4 | TM5 | | |
| 4 | 0.4168 | 14.7367 | 649.5349 | 650.7428 | 316.3648 | 659.6616 | TM2 | TM3 | TM5 | TM7 | | |
| 4 | 0.4167 | 14.7391 | 649.5371 | 650.7447 | 316.3711 | 659.6639 | TM1 | TM2 | TM5 | TM7 | | |
| 4 | 0.4136 | 15.0626 | 649.8345 | 650.9917 | 317.2124 | 659.9613 | TM1 | TM2 | TM3 | TM5 | | |
| 4 | 0.3885 | 17.6799 | 652.1849 | 652.9498 | 323.9394 | 662.3116 | TM1 | TM2 | TM3 | TM7 | | |
| 4 | 0.294 | 27.5197 | 660.2312 | 659.7346 | 348.0682 | 670.3579 | TM1 | TM3 | TM4 | TM7 | | |
| 4 | 0.2934 | 27.5813 | 660.2781 | 659.7745 | 348.214 | 670.4048 | TM3 | TM4 | TM5 | TM7 | | |
| 4 | 0.2893 | 28.0052 | 660.5998 | 660.0484 | 349.2157 | 670.7265 | TM1 | TM3 | TM4 | TM5 | | |
| 4 | 0.2188 | 35.348 | 665.8974 | 664.5872 | 366.1305 | 676.0242 | TM1 | TM3 | TM5 | TM7 | | |
| 4 | 0.1848 | 38.8944 | 668.287 | 666.6518 | 374.0261 | 678.4138 | TM1 | TM4 | TM5 | TM7 | | |
| 5 | 0.5195 | 5.0557 | 639.5737 | 643.2324 | 287.149 | 651.7259 | TM2 | TM3 | TM4 | TM5 | TM7 | |
| 5 | 0.5187 | 5.1433 | 639.6736 | 643.309 | 287.4052 | 651.8257 | TM1 | TM2 | TM4 | TM5 | TM7 | |
| 5 | 0.5178 | 5.2282 | 639.7703 | 643.3832 | 287.6535 | 651.9224 | TM1 | TM2 | TM3 | TM4 | TM7 | |
| 5 | 0.5177 | 5.2387 | 639.7823 | 643.3924 | 287.6843 | 651.9344 | TM1 | TM2 | TM3 | TM4 | TM5 | |
| 5 | 0.4053 | 16.7165 | 651.5162 | 652.572 | 319.4596 | 663.6684 | TM1 | TM2 | TM3 | TM5 | TM7 | |
| 5 | 0.2803 | 29.4779 | 662.1993 | 661.2318 | 351.4318 | 674.3515 | TM1 | TM3 | TM4 | TM5 | TM7 | |
| 6 | 0.5103 | 7.0000 | 641.5101 | 645.4693 | 289.8996 | 655.6876 | TM1 | TM2 | TM3 | TM4 | TM5 | TM7 |

Table 2. Parameters of the 'Best fit' regression models of stand volumes based on the spectral reflectance values, TM 2 and TM 4

| Model Group | Model description | | Coefficients of Independent Variables | S.E. of Variables | t statistics | $Pr > \|t\|$ |
|---|---|---|---|---|---|---|
| | Dependent Variables | Independent Variables | | | | |
| **2** | Stand Volume | Constant | 5020.8902 | 624.8097 | 8.04 | 0.0001 |
| | | TM 2 | -294.3667 | 37.4444 | -7.86 | 0.0001 |
| | | TM 4 | 28.3923 | 4.3121 | 6.58 | 0.0001 |

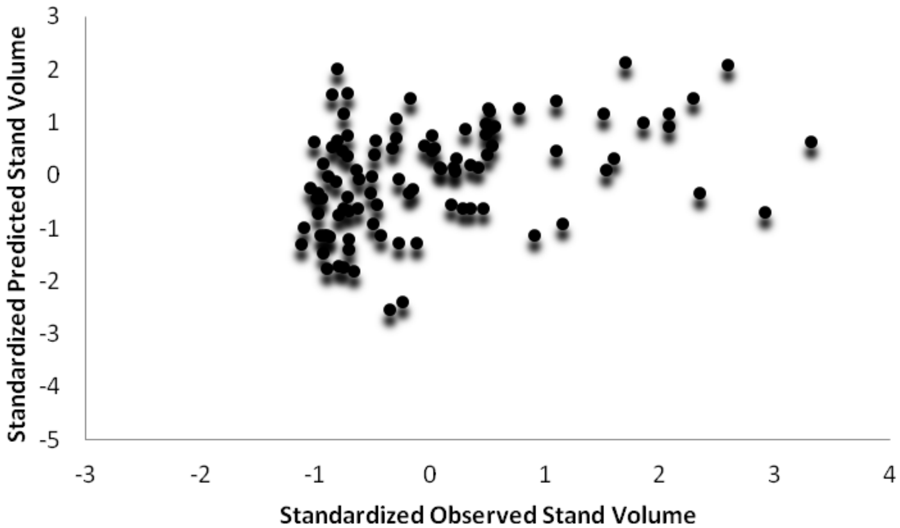


Fig. 1. The standardized predicted stand volume values versus standardized observed values

**Discussion**

In this paper, we evaluated the relationships between stand volume and reflectance values obtained from Landsat TM satellite image. Results obtained from this study show the significant relationship between stand volume and Landsat TM reflectance values and the utility of transformed bands in modeling stand volume. A linear combination of TM 2 and TM 4 described more variance in stand volume than other combinations of TM bands. The important relationship at the 95% possibility level, normality of the residuals, $R^2$=0.5409 and RMSE of 280.6871 $m^3$ $ha^{-1}$. $R^2$ values obtained from this study were higher than the ones obtained through direct estimation to forecast stand volume ($R^2$=0.43, Mohammadi et al., 2010; $R^2$=0.3, Hall et al., 2006; $R^2$= 0.3, Trotter et al., 1997). Makela et al. (2004) predicted forest stand volume using Landsat TM imagery and stand-level field-inventory data. They predicted total stand volume using Landsat TM images with an estimated RMSE of about 48%. Huiyan et al. (2006) have studied the possibility of estimation of forest volume by integrating Landsat TM imagery and forest inventory data. They estimated RMSE of about 44.2%. Mallinis et al. (2003) found that multiple regression analysis with TM 2-5; TM 2, TM 3 and TM 5; TM 1-5 and TM 7 as independent variables could better and low predict ($R^2$=0.183), ($R^2$=0.172) and ($R^2$=0.117), respectively for stand volume.

**Conclusion**

Forest stand parameters can be defined by many stand parameters such as stand volume, basal area, age, tree density and height. However, these data gathering are time- and labor-consuming by conventional forest inventory. Remote sensing is alternatively a better method for obtaining vision of forest characteristics. Results obtained from this study showed that the TM data are beneficial to estimate stand volume and could be used by source directors to advantage visions about variations within managed stands.

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