Forest Stand Density Mapping Using Landsat ETM$^+$ Data, Loveh's Forest, North of Iran

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Abstract:
Estimation of tree density in a large area using remotely sensed data has considerable significance for sustainable management and utility of natural resources. This paper explores relationship between forest stand density and Landsat ETM+ reflectance values. Multivariate regression techniques were used to predict tree density. The regression model with ETM4 and ETM5 as independent variables were better predictor of tree density (adjusted R^2=73.4%; RMSE=170.13 n/ha) than other combinations of ETM$^+$ bands and vegetation indices. Results showed that adding slope to tree density improved the results (adjusted R^2=79%; RMSE=168.69 n/ha). Results obtained from this study demonstrate the relationship between forest stand density and ETM+ reflectance values and the utility of certain transformed bands and ancillary data. Forest managers could use ETM+ data for gaining insights about tree density and this information would be also useful for generating maps required for developing forest management plans and identify locations within stands that might require treatments and plan other management activities.

1. Introduction

Forests are widely distributed on earth and are important for human survival (Lu et al., 2004). Sustainable management and utilization of forest resources require accurate information about forest extension and spatial distribution of stand parameters, such as volume or biomass and tree density. Furthermore, because forests undergo change it becomes imperative that inventory data be updated periodically (Dodge and Bryant, 1976; Sivanpillai et al., 2006). Traditionally, inventory information has been collected trough field surveys, aerial photo interpretation, or a combination of these techniques (Avery and Burkhart, 1994 and Sivanpillai et al., 2006). Field survey methods are often difficult, cost and time-consuming to conduct in a large area. Acquiring and interpreting aerial photos can also be expensive and labor intensive, in addition to requiring trained personnel with knowledge of local forest management practices (Avery and Berlin, 1992; Lillesand et al., 2000). Remote sensing may be the only feasible way to acquire forest stand parameter information at a reasonable cost, with acceptable accuracy, and feasible effort due to its advantages including repeated data collection, multispectral and multitemporal images, synoptic view, fast digital processing of large quantities of data, and compatibility with geographic information systems (GIS). Remotely sensed satellite data could provide some of the required information for updating stand inventories (Danson and Curran, 1993 and Wulder et al., 2004) in the northern forests of Iran. The relationship between spectral reflectance and important stand characteristics in different geographic setting is not well documented (Lu et al., 2004; Sivanpillai et al., 2006). Consequently, the utility of satellite data must be tested for different species at different geographic locations and under different management strategies. This paper describes a study of the relationship between Landsat ETM+ data and forest stand density in the Loveh's forest, north of Iran. Studies conducted elsewhere have demonstrated relationships between forest stand characteristics such as stand density, volume, age, canopy closure and leaf area index (LAI) with satellite reflectance values (Ahern et al., 1991; Steininger, 2000; Wulder et al., 2004 and Sivanpillai et al., 2006). Sivanpillai et al. (2006) analyzed the relationship between Landsat ETM+ reflectance values and commercially managed loblolly pine (*Pinus teada L.*) stand characteristics in east Texas. Landsat data were able to predict stand age and tree density with R^2=78% and R^2=60%, respectively. Nilson et al. (2001)

analyzed changes caused by thinning in boreal forests and concluded that there was an increase in a red reflectance value and a decrease in the near-infrared reflectance value in the thinned stands. Lu et al. (2004) examined the relationship between forest stand parameters and Landsat TM spectral responses in the Brazilian Amazon Basin and concluded that single band TM5 and linear transformed indices such as PC1 (first component of principal component analysis), KT1 (brightness of the tasseled cap transform), and albedo are most strongly correlated with forest stand parameters. However, in spite of these studies, satellite data are not routinely used for stand inventories in commercial forestry (Smith et al., 2003). Several studies have mapped density in boreal, temperate, and tropical environments using remote sensing data. Considerable efforts have been directed at using remote sensing to estimate forest stand density of cover, age, crown closure, and height (Franklin, 2001). The objective of this study was to investigate the relationship between reflectance values recorded by Landsat ETM+ sensor and stand characteristics, using multivariate regression analyses. If satellite reflectance values can be related to stand characteristics then resource managers could gain valuable insight. This information would enable the managers that to monitor changes place within the stands due to management practices and natural factors such as pest infestation and stress. In addition, forest managers can use this information to select and prioritize stands for detailed field survey. A key step towards using remotely sensed images for this purpose is investigating the relationship between spectral information and forest structural properties that are indicative of forest condition. The spectral response of forest stands determined by the structure of a canopy cover (Danson, 1993), which controls the amount the under story vegetation, leaf litter and soil in somewhere that are visible to the sensor (Franklin, 1986). Features that shape the structure of canopy such as density, age, mean tree height, and basal area (Ingram et al., 2005) indirectly determine the spectral response in satellite imagery. Many of the features, such as tree density are also indicators of forest condition. Forest stand density of large stems has shown to be higher in protected areas and old growth forests and tend to decrease with increasing levels of disturbance (Bhuyan et al., 2002 and Ingram et al., 2005).

2. Methods

2.1. Study area

The study area comprise 7800 hectares and located in the east north of Iran, Golestan province, extending from 37˚14´to 37˚24´N latitudes and 55˚33´to 55˚47´E longitude (Fig. 1). Elevation ranges between 400 to 1900 m above mean sea level and soil types of the area are Eutric cambisols, Calcaric cambisols, and Fluvic cambisols (Zarrinkafsh, 2002). The main tree species are *Quercus castaneafolia, Carpinus betulus, Acer cappadocicum, Cerasus avium, Tilia begonifolia, diospyros lotus,* and *Parrotia Persica*.

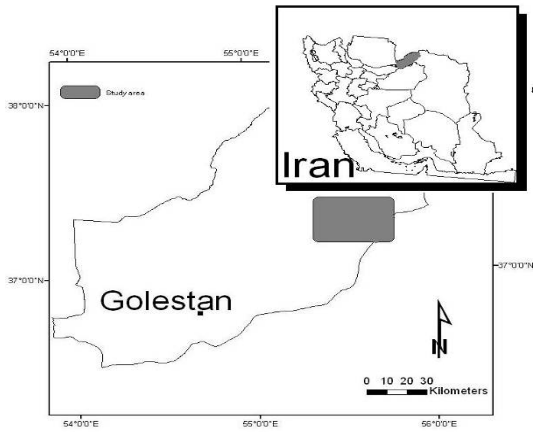

Fig.1: Location of study area in the Golestan Province, Iran

2.2. Field data

A systematic cluster-sampling network was applied to collect field data. The 11 clusters contained 99 plots (each cluster included 3×3 systematic plots) so that distances between clusters and plots were 1000 and 200 meters, respectively. The plots were square with an area of 60 × 60 (0.36 ha) meters area (corresponding to 2 × 2 pixels in ETM+ data). In each plots, information about tree density and geographic coordinates center plot were recorded

2.3. Landsat ETM$^+$ data

Landsat ETM$^+$ satellite data (WRS-2: path 162 and Row 34) was acquired for August 7, 2002, orthorectified, and georeferenced to a UTM zone 40 projection based on the WGS84 datum. Geometric rectification, radiometric and atmospheric correction of remotely sensed data is often required for many applications (Lu et al., 2002). In this study, cost method has been used for atmospheric normalization in the visible and near-infrared band (Mahiny and Turner, 2007).

2.4. Transformed bands and vegetation indices

After geometric rectification and atmospheric calibration, various that are vegetation indices were generated for the study area. These vegetation indices including, simple ratios (TM4/3, TM5/3, TM5/4 and TM5/7), Normalized ratios (NDVI, ND53, ND54, ND57, ND32, ND73, NDMI and NDWI), complex vegetation indices (ARVI, ASVI, GEMI and NR) and linear transformation of multiple bands (DVI, VIS123, MID57, Albedo, and PCA) (Lu et al., 2004; Sivanpillai et al., 2006; Gao, 1996; Clevers, 1988 and Rouse et al., 1972). In addition, pansharp method has employed for remote sensing data fusion. The tasseled cap transformation was applied to generate the brightness, greenness and wetness index values for each pixel. Tasseled cap components were generated a linear combination of the six non-thermal ETM+ bands. The method is widely used in vegetation mapping and monitoring applications (Lillesand et al., 2000; Jensen, 2004).

2.5. Spectral signature extraction of the plots

in order to analysis spectral responses of trees in sample plots, average digital number of pixels within a 2 × 2 pixels window, similar to plot size, were extracted from all Landsat ETM+ bands and vegetation indices.

2.6. Statistical analyses

The correlation analysis was applied between all independent variables (original bands, vegetation indices and fusion bands) and a correlation matrix was created in order to select the best band set for modeling. The Pearson's correlation coefficient was used to select the best bands. Where the Pearson's, correlation coefficients (R) was greater than 0.9, bands were based on selected computation easiness and strong correlation with tree density. Therefore, between 38 independent variables (original bands, vegetation indices and fusion bands), five independent variables including ETM4, ETM5, greenness; DVI and NR were selected to model tree density.
The best subset regression analyses were used to analyze the relationship between tree density (as dependent variables) and five independent variables. The best subset regression analysis identifies the best fitting regression model that can be constructed with the predictor variables. By default, all possible subsets of the predictors are evaluated; beginning with all models containing one predictor, and then all models containing two predictors, and so on. Models are evaluated based on R^2; adjusted R^2, Mallow's Cp- statistic, and MSE (Mesdahgi, 2004).

2.7. Estimating and mapping of tree density

Tree density as a function of Landsat ETM+ spectral response were modeled using multivariate regression. Linear regression models were generated for tree density using calibration of sample data and associated mean Landsat ETM+ band values. The models with the highest adjusted R^2 and lowest root mean square error for stand volume and tree density were chosen as the best function to model the stand structure. The model form, regression coefficients for tree density was then applied to the Landsat ETM+ image (Fig.4). Eighty five percent of the plots were used in the modeling and the rest 15% were used to evaluate the outputs of the models. The results were checked by comparing the estimated values with the actual values based on the field inventory. The reliability of the estimates was measured by RMSE and bias (Eqs. 1 and 3)

(Makela and Pekkarinen, 2004). The relative RMSE (RMSEr) and relative bias (Biasr) were calculated as a proportion of the mean estimated value (Eqs. 2 and 4).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (\hat{y}_i - y_i)^2}{n}} \quad (1) \qquad RMSE_r = \frac{RMSE}{\bar{\hat{y}}_i} \quad (2) \qquad Bias = \frac{\sum_{i=1}^{n} (\hat{y}_i - y_i)}{n} \quad (3) \qquad Bias_r = \frac{Bias}{\hat{y}} \quad (4)$$

$\hat{y}_i$ is the estimate; $\bar{y}$ the mean of the estimates; the observed value of y; n the number of observations.

3. Results

3.1. Descriptive statistics of tree density

Tree density ranged from 227.1 to 1136.11 (n/ha), which represented a full range of stand structures in the study area (Table 1.). Tree density mostly ranged from 300 to 800 (n/ha), respectively. The mean tree density was 514.4 (standard deviation (s) =227.1) (Fig 2).

Table1. Descriptive statistics of the model and validation samples for stand volume and tree density

	Tree density (n/ha)	
	model	validation
N	75	15
Mean	514.4	571.1
S.D.	227.1	268.85
Range	952.78	816.67
Minimum	183.33	286.11
Maximum	1136.11	1102.78

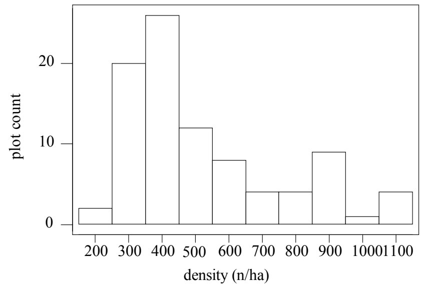

Fig. 2. Distribution of tree density in the study area depicted by tree density histogram for field plots

3.2. Estimating tree density using satellite data

The regression model with ETM4 and ETM5 (Table 2) as independent variables could better predicted tree density (adjusted R^2=73.4%; RMSE=170.13 n/ha) compared with other combinations of ETM^+ bands and vegetation indices. Consistent with previously reported studies (Sivanpillai et al., 2006), spectral reflectance of ETM4 and ETM5 bands increased with tree density.

Table 2: Multivariate regression results for estimating tree density by Landsat bands and slope

Dependent variable	*Independent variables*	*Coefficient*	*Constant*	R^2*(adj)*	*RMSE(n/ha)*	*Bias(n/ha)*
Log_{10} tree density (n/ha)	ETM4	0.0182	1.66	73.4%	170.13	61.475
	ETM5	-0.0154				

All regression significant at 95% level (p=0.05).

3.3. The relationship between reflectance value and stand structure

Results showed in Table2 expresses that ETM4, greenness, DVI and NR resulted in the highest correlations for tree density *R*-value of 0.807 (p<0.001), 0.826 (p<0.001), 0.819 (p<0.001) and 0.786 (p<0.001), respectively (Table3). Consistent with previously reported studies (Sivanpillai et al., 2006), reflectance in ETM4 and ETM5 increased with tree density that younger stands density covered with trees had higher ETM4 and ETM5 values, whereas older stands containing taller trees with lower density had lower values (Sivanpillai et al., 2006). In older stands there are more gaps in the canopy due to tree mortality and thinning, resulting in multiple scattering and absorption (Danson and Curran, 1993). The physical properties of the forest structure such as height, basal area and biomass can be predicted using visible and middle-infrared bands. The models presented in Tables 2 were used to generate tree density maps (Figs.4). Depict that the forest stands range mostly from 300 to 800 (n/ha) for tree density (Figs.2). Tree density were best estimated for stands with 300 to 800 (n/ha) tree density (Figs.2).

Table3: Correlation coefficients observed between tree density of the plots and the image spectral response. *Statistically significant at p = 0.01.

	Tree density	
	R	*p-value*
ETM+4	0.807*	0.000
ETM+5	0.511*	0.000
Greenness	0.826*	0.000
DVI	0.819*	0.000
NR	0.786*	0.000

These same attributes were overestimated at the low end for the tree density 300 (n/ha) and underestimated at the high end for tree density greater than 800 (n/ha) (Fig 3).

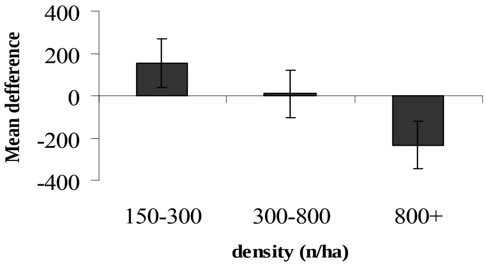

Fig.3. Distribution of prediction differences using ETM+ data for tree density estimation based on the validation samples. The vertical bars show the mean difference computed as predicted subtracted from actual values for three classes. The error bars represent the standard errors.

3.4. Tree density mapping

The improvement and regenerating units were easily identified by the darker green tones, which represented the higher density maps. The region with lower (light green) density estimates represents mature forest (Figs. 4).

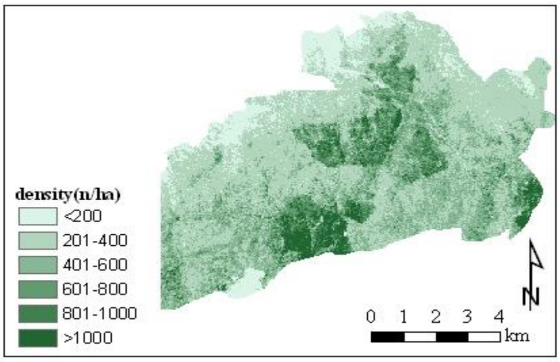

Fig. 4: density (n/ha) map generated from ETM4 and ETM5 (The region with higher (dark green) density estimates represents improvement unit).

4. Discussion and Conclusion

In this study, the relationship between reflectance data recorded in the Landsat ETM+ bands and Loveh's forest stands tree density were analyzed through multivariate regression analyses techniques. Statistically significant relationships were found between stand characteristics and corresponding reflectance values recorded by the ETM+ sensor. A linear combination of ETM4 and ETM5 explained more variance in tree density than other combination of original bands and vegetation indices. The model for tree density resulted in adjusted R^2=73.4%; RMSE=170.13n/ha. Tree density values compared favorably to RMSE and R^2 values by Sivanpillai et al., (2006) (RMSE=312.5n/ha, R^2=60.4%). For young and dense stands, there were fewer gaps in the canopy; therefore, infrared reflectance was very high. However, in mature stands with lower density, there were more gaps in the canopy resulting in canopy shadows. In this situation, infrared radiation would penetrate deeper into the forest and internal scattering and absorption might take place, reducing total outgoing radiance (Danson and

Curran, 1993). These results are similar to those obtained in other studies (e.g., Nilson et al., 2001), but the R^2 values obtained for managed stands were higher than those obtained for natural forests were. These results demonstrated that the reflectance values recorded by ETM+ sensors are related to stand characteristics, and could be used by resource managers to gain insights about variations within managed stands. This information could be used to support the design of harvesting strategies, update existing stand maps, identifying locations within stands that might require treatments and planning other management activities. However, the models generated in this study are limited to this geographic area. Nevertheless, this methodology could be adapted to other geographic regions. A combination of continuous variable modeling of stand structure from the Landsat ETM+ image and ancillary data was applied to tree density estimation and mapping. Larger area application requires transferring the model coefficients to adjacent scenes. Thus, while the model form used in this study appears reasonable, confirmation of model coefficients would entail refitting the model with a larger sample of plots representing a geographically larger area for a full range of deciduous, coniferous, and mixed wood species. Based on the results of this study, we conclude that ETM+ data are useful to estimate density and to gain insights of structural characteristics about Loveh's forest stands.

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