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PREDICTING LANDSCAPE STRUCTURAL METRICS USING ASTER SATELLITE DATA

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Abstract. The aim of this study was to predict landscape structural metrics using the features extracted from the ASTER multispectral satellite imagery with 15 m spatial resolution. The landscape structural metrics were calculated on the basis of forest map polygons generated from 1:15000 scaled aerial photos by photo-interpretation technique. The landscape metrics and corresponding image features that are texture parameters and segmentation polygons were determined for four different landscape extents. A stepwise multiple linear regression analysis was carried out to identify the most significant image-derived predictors of landscape metrics for each extent. The regression models established for the landscape metrics including the Number of Patches (NUMP), Edge Density (ED), Shannon's Diversity Index (SDI) and Patch Richness (PR) performed moderately with adjusted R^2 values of 0.50 and 0.53 ($P<0.01$), indicating that 50–53% of the total variation in these landscape metrics can be explained by image-derived features. By contrast, the regression analyses showed that there were weak relationships between the image features and Interspersion Juxtaposition Index (IJI), and Shannon's Evenness Index (SEI) (adj. R^2 is varied from 0.12 to 0.30, $P<0.01$). According to the results of model evaluation, the Entropy measures based on Grey Level Co-occurrence Matrix (GLCM) calculated from the infrared and red bands of ASTER were found as the most correlated parameters with the landscape metrics. Besides, the window size (extent) of 81–144 ha (between 900× 900 and 1200×1200 m) might be recommended in estimating the landscape metrics using the ASTER or similar satellite imagery. It can be concluded that the 15 m resolution satellite data used for estimating landscape spatial structure cannot replace aerial photos or very high resolution satellite imagery for local-level inventories. However, it might have potential for predicting landscape heterogeneity for large-scale inventories.

Keywords: landscape ecology, landscape diversity, remote sensing, texture, image segmentation, landscape metrics, forest structure, biodiversity.

1. Introduction

An important challenge for forest managers is how to maintain biological diversity and to integrate it into existing forest management plan (Baskent *et al.* 2008; Ozkan, Mert 2011). It is widely agreed in the literature that biological diversity is best addressed at the landscape level when managing forests (Baskent, Jordan 1995, 1996; Schindler *et al.* 2008). One straightforward way to maintain biological diversity that is recommended by many ecologists is to maintain landscape diversity as a structurally diverse landscape provides foraging, breeding, and hiding habitat for numerous species (Harris, Smith 1978; Smith 2000; Fortin, Melles 2009). Therefore, the spatial structure of forest landscape should be controlled and enhanced by proper management systems that mimic natural spatial patterns (Baskent 1997, 1999; Kucas 2010).

The spatial structure of forest landscape describes the composition and configuration of landscape patches. It changes over time by both management activities including regeneration, reforestation, rehabilitation and disturbances such as fire, insect attack, windstorm and urbanization, etc. Monitoring the changes in landscape structure by definite time intervals and taking necessary silvicultural precautions is vital for sustainable management of forest ecosystems. Existing digital forest maps provide a good source of information to characterize spatial structure. Based on these maps, landscape spatial structure can be quantified by using landscape structural metrics (McGarigal *et al.* 2002). Using Geographical Information System (GIS) maps, landscape spatial structure can be mapped using either a static (geographic stratification) or a dynamic approach (moving window). In the static approach, the reference units are pre-defined and then landscape metrics are calculated for each reference unit. On the contrary, in the dynamic approach, the metrics are calculated using a window moving across the landscape. In this approach, a structural index value is assigned to the centre of each window and then the index values are transferred to an output raster image. In the next step, the index value of each cell of the output image is determined by means of the surrounding index values. Bilinear interpolation algorithm can be used to calculate index value for each image cell (Eiden *et al.* 2000). Therefore, a landscape structure map can be obtained using these approaches, which is the basis for future monitoring tasks. Such diversity maps will attract wildlife managers' attention and may help forest managers to integrate biodiversity into existing management plans.

Although GIS-ready forest maps are a convenient resource for mapping and monitoring landscape structure (Bauza 2007), they are often out of date for extensive areas. Wide-area satellite remote sensing appears to be a useful alternative to forest maps. Remotely sensed data has been widely used in biodiversity studies including prediction of species richness (Rocchini *et al.* 2009; Rocchini 2009), canopy heterogeneity (Hyde *et al.* 2006; Goetz *et al.* 2007), tree size diversity (Ozdemir *et al.* 2008; Ozdemir, Karnieli 2011), and characterization of forest spatial structure (Egbert *et al.* 2002; Kadiogullari, Baskent 2008). Digital satellite data may be used to estimate landscape metrics in case there is a relation between image features and real landscape metrics. If a strong relation exists, the structural diversity can be mapped inexpensively using satellite data. Accordingly, the potential of satellite data should be investigated in order to predict and map landscape pattern characteristics.

Spatial scale is one of the most important issues in landscape ecology. Different organisms have differential response to environmental gradients at different scales. Spatial scale could be both 'grain' (spatial resolution of the image or the mapping unit) and 'extent' (window size and/or extent of the study area) (Gustafson 1998). When landscape extent increases, more patch types can exist, resulting in higher landscape diversity (Turner *et al.* 1989; Peters, Goslee 2000). For that reason, the landscape extent should be taken into consideration in estimating landscape structural metrics by employing remotely sensed data.

The main objective of this study was, therefore, to explore the relations between landscape metrics calculated on the basis of forest stand polygons and the features extracted from ASTER imagery with 15 m resolution. In addition, the study aimed to determine the best landscape extent to predict landscape diversity using ASTER data.

2. Materials and methods

In this study, firstly, landscape pattern metrics were calculated for different landscape extents based on manually delineated stand polygons from aerial photos. Secondly, landscape metrics were calculated for the same extents using the polygons automatically generalized from the ASTER imagery by multi-resolution segmentation method. Thirdly, texture image features were derived from the landscape extents. Lastly, the relationships between landscape metrics and image derived features were determined using the stepwise multiple linear regression analysis.

2.1. Data preparation

2.1.1. The GIS-ready data

The five digital forest maps of the Isparta Forest Regional Directorate prepared for the purpose of forest management in 2006 and 2007 were obtained. Forest stand delineation was performed based primarily on aerial photo (1/15000 scaled) interpretation in these maps. It was decided that the forest stand maps prepared for timber management purpose were too detailed to analyze spatial landscape structure due to the similar habitat characteristics of several stand classes. Therefore, such stand classes were combined in the GIS database. Moreover, there were many adjacent polygons that belong to the same stand class in these maps because a forest stand can normally be divided into sub-compartments within a main compartment in the mapping system used in Turkey. The adjacent polygons with the same attribute (patch class) were merged to one polygon. Also, the roads or firebreaks defined as lines on the map were converted into a strip with a width of 10 m and then, they were attributed as forest openings in the database. The last modification was made for the clear-felled areas practiced after the map preparation date and before the image acquisition date. These areas were easily defined and delineated from the ASTER imagery due to their remarkable spectral response.

2.1.2. The image data

The image features were derived from the three bands with 15 m spatial resolution of ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) satellite data with an image acquisition date of 5 May 2007. The spectral ranges of the three bands were 0.52–0.60 μm (green), 0.63–0.69 μm (red) and 0.76–0.86 μm (near infrared). The image was clipped based on the boundaries of the study area. For a precise match, the clipped image was geo-referenced by means of well-defined image features such as the intersections of streams and roads on both the forest map and the image. The nearest neighbor re-sampling method was used to preserve the original pixel values. The root mean squared error was 10 m, which is less than one pixel (15 m).

2.2. Calculation of response landscape structural metrics

The landscape metrics were calculated on the basis of square-shaped windows using the forest map polygons. For this purpose, study area has been divided into square units with the size of 225 ha (1500 by 1500 m) and then, 50 sample units were randomly selected for evaluation (Fig. 1). Taking the top-left corner of square-shaped units as a reference point, the three extents were also formed, which are 1200×1200 m (144 ha), 900×900 m (81 ha) and 600×600 m (36 ha) (Fig. 2). Thus, we employed four landscape extents (sizes) to test which one is best to model landscape pattern metrics using the features extracted from ASTER data.

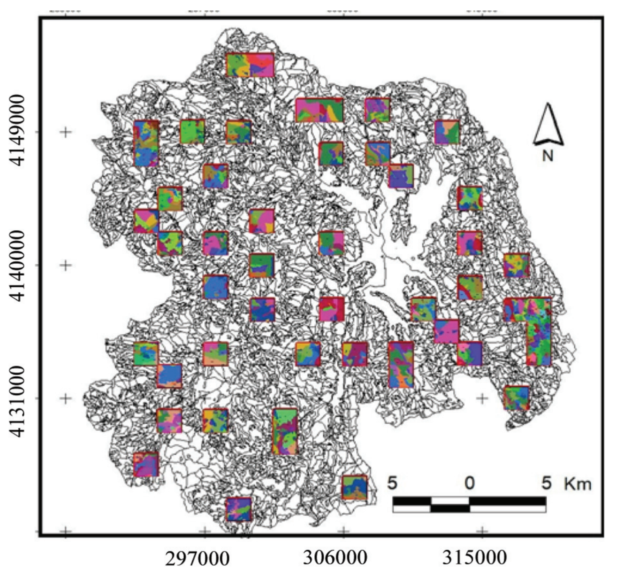

Fig. 1. Randomly selected 50 sample units (extent is 1500× 1500 m) on the forest map

The 36 ha area was determined as the minimum landscape extent because the areas smaller than this were not sufficient for calculating some landscape metrics (e.g. IJI and SEI). The 225 ha area was determined as the maximum landscape extent because the variation in the landscape metrics among sample units was decreased when the landscape extent was larger than 225 ha, which may reduce the correlation between landscape metrics and remotely sensed variables.

For each of the four landscape extents, landscape patch polygons were intersected by the 50 square-shaped units. In the next step, each square-shaped unit was done independent by assigning them a region number. Then, the units in vector format were converted into a raster image. Lastly, the landscape metrics were calculated for each sample unit independently using the ArcView 3.1. Patch Analyst extension software.

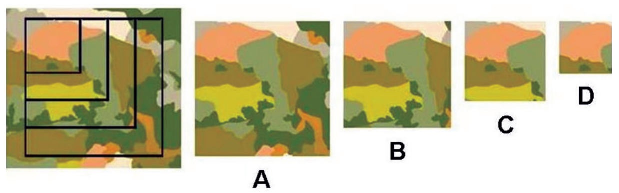

Fig. 2. The four extents used to compute landscape metrics based on the forest stand polygons (A: 225 ha (1500×1500 m), B: 144 ha (1200×1200 m), C: 81 ha (900×900 m), D: 36 ha (600×600 m))

Many landscape metrics have been developed to quantify spatial landscape characteristics. This study focused on the three groups of statistics provided by the Patch Analyst, which are; i) patch size and density, ii) edge metrics, iii) diversity and interspersion metrics. The six landscape metrics were selected from these categories, including Number of Patches (NUMP), Edge density (ED), Interspersion Juxtaposition Index (IJI), Shannon's Diversity Index (SDI), Shannon's Evenness Index (SEI) and Patch richness (PR). The formulas and their units of the landscape metrics were given below (McGarigal *et al.* 2002):

$$NUMP = N\ ; \tag{1}$$

$$ED = \frac{E}{A}(10000)\ ; \tag{2}$$

$$IJI = \frac{-\sum_{i=1}^{m}\sum_{k=i+1}^{m}\left[\left(\frac{e_{ik}}{E}\right).\ln\left(\frac{e_{ik}}{E}\right)\right]}{\ln(0.5[m(m-1)])}\ ; \tag{3}$$

$$SDI = -\sum_{i=1}^{m}(P_i \ln P_i)\ ; \tag{4}$$

$$SEI = \frac{-\sum_{i=1}^{m}(P_i \ln P_i)}{\ln m}\ ; \tag{5}$$

$$PR = m\ , \tag{6}$$

where, N is the total number of patches in the landscape, E is the total length of edge in the landscape, A is total landscape area (m^2), e_{ik} is the total length of edge in the landscape between patch classes i and k, m is the number of patch classes present in the landscape, P_i is the proportion of the area occupied by patch class i.

2.3. Extraction of remote sensing variables

2.3.1. Multi-resolution segmentation polygons

Image segmentation algorithms have been widely used in forestry applications such as in forest mapping (Kim *et al.* 2011; Chen *et al.* 2012; Vega, Durrieu 2011; Addink *et al.* 2012), in quantifying landscape heterogeneity (e.g. Morgan, Gergel 2010) and in exploring forest structural complexity (e.g. Lamonaca *et al.* 2008). The multiresolution segmentation algorithm provided by Definiens software is a sophisticated method grouping image pixels according to a rule set, including scale parameter and homogeneity criteria. The scale parameter is an abstract term which determines the maximum allowed heterogeneity of the resulting image objects. As the scale parameter is increased, the homogeneity of segments decreases and the standard deviation within the resulting image objects increases. The segmentation process is also guided by defining the homogeneity criteria according to the color shape, compactness and smoothness of the resulting pixel groups (Blaschke 2010). This operation generates ecologically meaningful image objects. The resulting objects should be visually assessed for correct feature delineation since there is no statistical method for evaluating the accuracy of the segmentation process (Baatz *et al.* 2001). Therefore, several experiments were undertaken toward high-quality segmentation by modifying the scale parameters and homogeneity criteria to capture real landscape features. The resulting image objects were compared to the manually-delineated polygons of the forest maps. As a result of the visual evaluation process, the best segmentation was obtained using the scale parameter of 25 and homogeneity combination of “0.8 color – 0.2 shape” and “0.5 compactness – 0.5 smoothness”.

The segmented image object polygons, and their mean brightness values, were exported as a vector file. The segment-based landscape metrics was calculated with regard to the four extents using this vector file (Fig. 3). It should be noted that, the mean brightness values of image segments were used in the evaluation instead of patch classes in the forest map. Consequently, six landscape metrics as explanatory variables were Segment-Based Number of Patches (SB-NUMP), Segment-Based Edge Density (SB-ED), Segment-Based Interspersion Juxtaposition Index (SB-IJI), Segment-Based Shannon’s Diversity Index (SB-SDI), Segment-Based Shannon’s Evenness Index (SB-SEI) and Segment-Based Patch richness (SB-PR). These explanatory variables were called the “A group” variables.

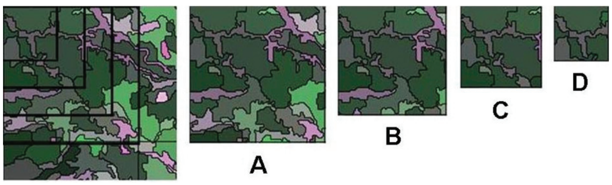

Fig. 3. The four extents used to compute the landscape metrics based on the multi-resolution segmentation polygons of the ASTER data (A: 225 ha (1500×1500 m), B: 144 ha (1200×1200 m), C: 81 ha (900×900 m), D: 36 ha (600×600 m))

2.3.2. Image texture parameters

Texture based classification of satellite imagery is a new opportunity and challenge for improving classification accuracy (e.g. Ota *et al.* 2011; Chang *et al.* 2011). The texture features also have potential for monitoring insect infestation (e.g. Dye *et al.* 2008) and evaluating parameters related to biodiversity (e.g. St-Louis *et al.* 2006; Ozdemir *et al.* 2008).

Texture features were extracted from the simple chessboard segmentation approach in order to assess the same windows used in the calculation of the landscape metrics. This method simply splits an image into square image objects. According to a given object size, the image objects are generated starting from the top-left corner pixel of an image in this approach provided by Definiens (Baatz *et al.* 2001). In this case, when using the entire image, we were not able to segment the fixed areas (1500×1500 m = 100×100 pixels; 1200×1200 m = 80×80 pixels; 900×900 m = 60×60 pixels and 600×600 m = 40×40 pixels) generated for calculating the response landscape metrics. In order to solve this computational limitation, the image was broken up into subsets according to the top-left corners of the 50 sample windows as a reference point in order to run the texture analyses. Consequently, 50 independent windows with an area of 1800×1800 m (bigger than the largest landscape extent, 1500×1500 m) were segmented by chessboard segmentation approach (Fig. 4). As a result, we generated same extents used in calculating the landscape metrics and the texture parameters were, therefore, precisely matched to the landscape metrics determined for the four landscape extents in the forest map.

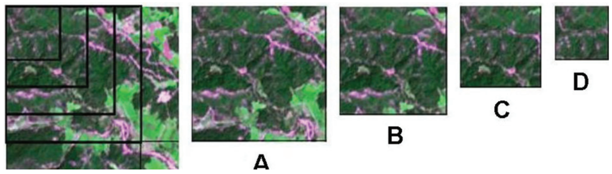

Fig. 4. The four extents at which the texture parameters of the ASTER data were calculated (A: 225 ha (1500×1500 m), B: 144 ha (1200×1200 m), C: 81 ha (900×900 m), D: 36 ha (600×600 m))

The texture parameters of the objects were calculated based on the grey level co-occurrence matrix (GLCM) (Harralick *et al.* 1973) which is a tabulation of how often different combinations of pixel grey levels occur in a given direction in an image object. Several statistical measures can be derived from the GLCM. These are grouped into three main categories; i) contrast, ii) orderliness and iii) descriptive statistics. Hall-Beyer (2007) recommended using one texture parameter from each category in an examination. Therefore, three texture measures not well correlated with one another, including GLCM Homogeneity (GHO) from the contrast category, GLCM Entropy (GEN) from the orderliness category and GLCM Standard Deviation (GSD) from the descriptive statistics category were examined in this study. Three GLCM parameters were calculated for each of the 50 plots based on the three ASTER bands separately. Consequently, nine texture variables (GHOB1, GHOB2, GHOB3, GENB1, GENB2, GENB3, GSDB1, GSDB2, and GSDB3) were generated for the statistical evaluation. These texture-based explanatory variables were called the “B group” variables. The formulas and their units are given below (Hall-Beyer 2007):

$$GLCM-Homogeneity=\sum_{i,j=0}^{N-1}\frac{P_{i,j}}{1+\left(i-j\right)^{2}}; \quad (7)$$

$$GLCM-Entropy=\sum_{i,j=0}^{N-1}P_{i,j}(-\ln P_{i,j}) \quad (8)$$

$$GLCM-S.Deviation=\sqrt{\sum_{i,j=0}^{N-1}P_{i,j}(i,j-\mu_{i,j})}, \quad (9)$$

where, i is the row number, j is the column number, V_{ij} is the value in the cell i,j of the matrix, P_{ij} is the normalized value in the cell $i,j,$ N is the number of rows or columns, $\mu_{i,j}$ is GLCM mean.

2.4. Statistical analyses

A stepwise multiple linear regression analysis was carried out to identify the most significant image-derived predictors of landscape metrics for each extent. This method determines the variables that make the most contribution to regression model. The adjusted coefficient of determination (adj.R^2) was used in assessing the goodness of fit of models. In a multiple linear regression model, adjusted R^2 measures the proportion of the variation in the dependent variable accounted for by the explanatory variables. Contrary to R^2, adjusted R square makes allowance for the degrees of freedom associated with the sums of the squares. In spite of the residual sum of squares decreases or remains the same as new explanatory variables are added, the residual variance does not. Therefore, adjusted R^2 is generally considered to be a more accurate goodness-of-fit measure than R^2. The residuals (differences between observed and predicted values) from the model were analyzed by Residual Standard Deviation (S_{res}). It is assumed in multiple regression that the residuals (experimental errors) are distributed normally (Moore and McCabe 1993). Kolmogov-Simirnov Z (K-S) test was used in order to inspect the distribution of the residual values. If $P>0.05$, the residuals of a regression model were accepted as having a normal distribution. SPSS package program (13.0) was used for the statistical analyses.

3. Results and discussion

The multiple linear regression models predicting landscape metrics gave different results depending on both landscape extent and the kind of metric. All of the regression models were statistically significant at an alpha level of 0.05. According to K-S test the residuals of the models were distributed normally. In examining the highest R^2_{adj} and lowest S_{res} values, there was no important difference between A and B group variables in terms of explained variance and standard error of estimate. However, Shannon Index, a widely preferred metric, was better modeled using image texture features. Furthermore, since deciding the optimal parameters (e.g. scale parameter) for multi-resolution segmentation is somewhat subjective, the texture parameters based on grey level co-occurrence matrix may be preferred to model the landscape metrics.

The findings showed that all landscape metrics examined here were associated with the image parameters except IJI and SEI at least for one landscape extent. The models providing best fit were obtained using the sizes of 900×900 m and 1200×1200 m. More than 50% of variance in the Number of Patches, the Edge density, the Shannon's Diversity Index and the Patch richness was explained by the regression models. In contrast, although some models predicting the Interspersion Juxtaposition Index and the Shannon's Evenness Index were statistically significant ($p<0.01$, adj. R^2 is 0.12 for the IJI; $p<0.01$, adj. R^2 is 0.30 for SEI), they might be insufficient for making an estimation of these metrics. The extent of 144 ha (1200×1200 m) seems as an effective size for modeling the landscape metrics including the NUMP, SDI, ED and PR by the features of ASTER bands.

The equations of the best regression models in terms of the explained variance and the residual standard deviation are summarized for the A and B group of variables, in the Table 1. All regression models predicting the landscape metrics except the NUMP contained one independent variable, might indicate the existence of high correlation between some independent variables of the A group. The R^2_{adj} and S_{res} values showed that the response NUMP, ED and PR were correlated with the image segment-based landscape metrics. The response ED, SDI and PR were modeled as a function of the SB-ED, SB-SDI and SB-ED respectively that are calculated by same index formulas from the segmented ASTER imagery. Therefore, it can be concluded that automated multi-resolution segmentation yields the patch classes and patch boundaries (edge lengths) that are close to the forest map polygons. Moreover, the multi-resolution segmentation approach may also give a great opportunity to predict the Contrast-Weighted Edge Density (CWED) index more accurately than ED. The CWED taking into consideration edge contrast as well as edge length quantifies edge from the perspective of its functional significance. Edge contrast is defined by structural (e.g. basal area, tree volume and crown size density)

Table 1. The best fitted regression models

Land. Metric	Landscape Extents (m^2)	Equation	The Group of Independent variables	Adj. R^2	S_{res}	*p*
NUMP	1200×1200	= –32.073 + 1.152 SB-PR + 0.446 SB-IJI	A	0.53	4.04	<0.01
	1200×1200	= –42.894 + 10.542 GENB3 – 32.084 GHOB2	B	0.51	4.13	<0.01
ED	1200×1200	= 29.348 + 0.607 SB-ED	A	0.52	14.02	<0.01
	900×900	= –165.546 + 23.09 GENB2 + 21.895 GENB3	B	0.43	19.31	<0.01
IJI	900×900	= 37.449 + 11.211 SB-SDI	A	0.12	8.81	<0.01
SDI	900×900	= –0.463 + 0.895 SB-SDI	A	0.44	0.31	<0.01
	1200×1200	= – 4.747 + 0.55 GENB3 + 0.508 GENB2 - 0.044 GSDB2	B	0.52	0.26	<0.01
SEI	900×900	= 0.12 + 0.273 SB-SDI	A	0.30	0.13	<0.01
	1500×1500	= –0.114+ 0.09 GENB2	B	0.25	0.08	<0.01
PR	1200×1200	= –0.784 + 0.641 SB-PR	A	0.50	2.57	<0.01
	1200×1200	= –40.135 + 5.332 GENB3 + 2.449 GENB2	B	0.52	2.52	<0.01

and floristic characteristics between adjacent patches composing that edge. Consequently, in addition to edge length (or edge density predicted well in this study), we expected that the edge contrast can be quantified by brightness or texture features of image segments. In conclusion, the response CWED might be more accurately estimated by the satellite-based CWED than the ED.

The NUMP, ED, SDI and PR can be predicted employing the models as a function of the texture parameters of ASTER bands. The GLCM-Entropy calculated from the near infrared band (GENB3) was the most correlated variable as it entered into these multiple models except SEI as a variable. GLCM-Entropy calculated from the red band (GENB2) was also a good predictor, which was included into the regression models except the model of NUMP. Only one model predicting the NUMP contained the GLCM-Homogeneity derived from the red band (GHOB2) as an explanatory variable. Similarly, the GLCM-Standard Deviation extracted from the red band (GSDB2) was present only in the model estimating SDI.

The results demonstrate that the Entropy measure, the level of spatial disorder of grey levels in GLCM, is superior to the other texture measures (the Homogeneity and Standard Deviation) in estimating the landscape metrics. Based on the findings of this study, it is reasonably to conclude that if a landscape (within the limits studied here) has more patch types, edge or number of patch, the GLCM-Entropy value of that landscape is increasing, which shows the elements of GLCM are equally distributed. Another result of this study is that the near-infrared and red bands yielded the strongest explanatory variables of the landscape metrics except IJI. The superiority of these bands over the green band may be due to their capability to distinguish vegetation communities (Lillesand, Kiefer 1994). Similarly, Levin *et al.* (2007) found that the normalized difference vegetation index (NDVI) calculated using infrared and red bands is a good predictor for species richness. Furthermore, NDVI is correlated with Vegetation Fractional Coverage (Gu *et al.* 2009). Also, Rocchini (2007) and Rocchini *et al.* (2007) reported that near infrared band is better than visible bands for estimating species richness. The lack of contribution of the green band may be the result of the small openings within a stand. Gaps smaller than 1 ha, which are typical in the study area, are ignored in the forest stands delineation in Turkey. Therefore, the green band produces unsuitable texture values for predicting landscape metrics because it is more sensitive to these small openings than the red and infrared bands. However, this characteristic of the green band may sometimes provide an advantage depending on the topic under consideration. For example, Ozdemir *et al.* (2008) reported that tree size diversity at the sampling plot level was correlated with GLCM Homogeneity of the green band of ASTER image with 15 m resolution.

The image-based explanatory variables investigated in this study were able to explain considerable amount of variance (50–53%) in particular landscape metrics. However the unexplained variance is due to unknown causes. The main reason may be due to the heterogeneous stands. Most stands except plantations and naturally generated stands cannot be completely delineated as homogeneous area in terms of species or diameter class because of the complex structure of Mediterranean forests. For that reason, the landscape metrics calculated based on the stand boundaries are prone to error. A heterogeneous stand delineated as one polygon can incorporate small tree groups that might be recognized as several polygons in carrying out the multi-resolution segmentation algorithm to ASTER imagery. Furthermore, while an area composed of the heterogeneous stands seems structurally simple in the forest map, its corresponding ASTER image is highly textured. Consequently, sample windows having several heterogeneous stands yield the landscape metric values that are less correlated with the image derived features. In order to reduce this effect, more detailed forest maps are needed for assessment instead of the timber management map. These maps can be obtained by improving traditional forest maps using higher resolution satellite images (e.g. Ikonos, Quickbird). Therefore, we expect that the landscape metrics calculated based on an edited stand map might be predicted more accurately by the image parameters of ASTER.

The landscape metrics alone, which were calculated based on forest patchiness (spatial structure), may not be sufficient for quantifying forest structural diversity. In this sense, a new index that will take into account both the forest patchiness and the vertical structure (e.g. tree size diversity) should be developed. Thus, the fit of satellite-based model might be improved if the structural diversity could be defined using such a combined index. Hence, a future study integrating horizontal and vertical structure is needed to understand more clearly the potential of satellite data for modeling forest structural diversity. Any future study should also focus on satellite imageries with different spatial resolutions.

4. Conclusions

1. It can be concluded that it is possible to use the ASTER data to estimate spatial structure of forest landscapes with a reasonable accuracy at large scales. However, the ASTER spectral bands with 15 m resolution cannot replace aerial photos or very high resolution satellite imagery to predict landscape diversity in decision-making regarding forest management at local level.

2. The texture measures calculated from the red (0.63–0.69 μm) and near infrared (0.76–0.86 μm) bands of ASTER imagery (B group variables in this study) have a great potential for characterizing landscape spatial structure. Our results suggest that image texture may be a cost-effective way of mapping the landscape heterogeneity in the Mediterranean forest landscapes.

3. The other conclusion that can be drawn from this study is that the landscape extents between approximately 81 and 144 ha may be convenient to compute the texture features in order to predict the landscape diversity in the Mediterranean forest ecosystems.

4. The multi-resolution segmentation was also a promising tool for delineating land cover polygons that were employed as the base in calculating the landscape metrics (A group variables). Furthermore, the object-based approach might address some problems with the use of categorical data. For example, forest stand maps might not show the real forest vegetation polygons since many small landscape elements are potentially merged as one stand. In contrast, landscape patches can be accurately delineated using appropriate satellite data and the multi-resolution segmentation algorithm.

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KRAŠTOVAIZDŽIO STRUKTŪRINIŲ METRIKŲ NUSTATYMAS REMIANTIS *ASTER* PALYDOVINIAIS DUOMENIMIS

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S a n t r a u k a

Tyrimo tikslas buvo prognozuoti kraštovaizdžio struktūrines metrikas, gaunamas iš *Aster* daugiaspektrių 15 m rezoliucijos palydovinių vaizdų. Atsako kraštovaizdžio struktūrinės metrikos, taikant fotonuotraukų interpretavimo techniką, buvo apskaičiuojamos remiantis miškų žemėlapių, gautų iš 1:15 000 mastelio aerofotonuotraukų, poligonais. Nustatytos keturių skirtingų kraštovaizdžio lygių metrikų ir atitinkamos vaizdų savybės (reljefo parametrai ir poligonų padalijimas). Palaipsnė sudėtinė tiesinė regresinė analizė buvo atliekama identifikuojant reikšmingiausią kiekvieno kraštovaizdžio lygmens atvaizdą. Pagal modelio įvertinimo rezultatus, entropijos matavimo duomenys, pagrįsti Grey *lygio tų pačių bendrų įvykių matrica*, apskaičiuota remiantis infraraudonųjų spindulių ir *ASTER* raudonosiomis horizontaliomis juostomis, buvo labiausiai su kraštovaizdžio metrikomis koreliuojantys parametrai. Be to, vertinant kraštovaizdžio metrikas pagal *ASTER* ar panašius palydovinius duomenis, gali būti rekomenduojama 81–144 ha (tarp 900 ir 900×1200×1200 m) lango dydis (dydis). Galima daryti išvadą, kad 15 m rezoliucijos palydoviniai duomenys, naudojami vertinant kraštovaizdžio erdvinę struktūrą, lokaliajam lygiui inventorizuoti negali pakeisti aerofotonuotraukų ar labai didelės skiriamosios gebos palydovinių vaizdų.

Reikšminiai žodžiai: kraštovaizdžio ekologija, kraštovaizdžio įvairovė, stebėjimas iš palydovų, tekstūra, vaizdų suskirstymas, kraštovaizdžio metrika, miško struktūra, bioįvairovė.

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