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Forest Type Mapping Using Incorporation of Spatial Models and ETM+ Data

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Abstract: Results of former researches have shown that spectrally based analysis alone could not satisfy forest type classification in mountainous mixed forests. Forest type based on composed different parameters such as topography elements like aspect, elevation and slop. These elements that are affected on occurrences of forest type can be stated as spatial distribution models. Using ancillary data integrated with spectral data could help to separate forest type. In order to find the abilities of using topographic spatial predictive models to improve forest type classification, an investigation was carried out to classify forest type using ETM+ data in a part of northern forests of Iran. The Tasseled Cap, Ratioing transformations and Principal Component Analysis were applied to the spectral bands. The best spectral and predictive data sets for classifying forest type using maximum likelihood classification were chosen using the Bhattacharya seperability index. Primary analysis between forest type and topographic parameters showed that elevation and aspect are most correlated with the occurrences of type. Probability occurrence rates of forest type were extracted in the aspect; elevation, integrated aspect and elevation as well as homogeneous units structured on elevation and aspect classes. Based on occurrence rates of forest type, spatial predictive distribution models were generated for each type individually. Classification of the best spectral data sets was accomplished by maximum likelihood classifier and using these spatial predictive models. Results were assessed using a sample ground truth of forest type. This study showed that spatial predictive models could considerably improve the results compared with spectral data alone from 49 to 60%. Among spatial models used, the spatial predictive models constructed based on the homogeneous units could improve results in comparison to other models. Applying other parameters related to forest type like soil maps would generate accurate spatial predictive models and may improve the results.

Key words: Forest type mapping, spatial models, topographic factors, improvement, prior probability

INTRODUCTION

Forests of Iran with an area about 12.4 million hectare comprise 7.4% of the country's area. These forests have various geographic conditions, producing different forests of various tree and shrub species and production capacity in different edapho-climatic conditions (FAO, 2002). Among five large vegetation regions in throughout Iran, the most important vegetation region according to density, canopy cover and diversity, is the Hyrcanian (Caspian) region that covers an area of 1,925,125 ha, extending throughout the south coast of the Caspian Sea in the northern part of the country. The Hyrcanian vegetation zone is a green belt stretching over the northern slopes of the Alborz mountain ranges (Sagebtalebi *et al.*, 2003). It has a high production capacity due to humid temperate climate and suitable soil. Hyrcanian forests extend for 800 km in length. These natural mixed-hardwood forests have rich diversity based on tree species. Species such as beech (*Fagus orientalis*), hornbeam (*Carpinus betelus*), alder (*Alnus glutinosa*), oak (*Quercus castaneafolia*), maple (*Acer velotonia*), ironwood (*Parotia persica*) are the main species in these forests (Sageb-Talebi *et al.*, 2003).

Conservation and protection of these forests are a major duty for the government of Iran. Mapping forest variables such as types and stands is fundamental for forest management. Forest type mapping through field study is time-consuming and cost-intensive. Satellite data and its potential are new tools to manage

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and mapping of the forest-covered area. Forest extent mapping has been reported feasible with good certainty using satellite data in the northern mountainous forests of Iran (Darvishsefat and Shataee, 1997; Rafeian, 2003). The next step for forest managers was a feasibility study to apply satellite data to classify northern forest types.

Previous results have shown that the discrimination of forest types that are composed only of one species, as pure types is very successful by using satellite data (Walsh, 1980; Mayer and Fox, 1981). When a forest type is composed of two or many species such as in the study area, separating the type may be more difficult (Shataee *et al*., 2004) because, the classes of interest are often poorly separable in the feature space provided by remotely sensed data. Also, spectral signatures used in supervised classifications may overlap considerably, making effective discrimination unachievable based on spectral reflectance characteristics alone. Making an attempt on the improvement of the classification results has been the main objective for those interested in forest type mapping using satellite data. Many attempts have been made to use different techniques such as rule-based classification (Bolstad and Lillesand, 1992) incorporated domain knowledge in the way of slope, aspect and spectral data (Hutchinson, 1982) and using ancillary data. Information from ancillary data sources has been widely shown to aid discrimination of classes that are difficult to classify using remote sensing data (Apisit and Sherestha, 2000; Hopkins *et al*., 1988; Hutchinson, 1982; Strahler, 1980). In these cases, ancillary data sources and expert knowledge related to spatial distribution of types can provide useful information to help distinguish between inseparable classes.

Using ancillary data related to forest types as site variables and environmental factors can be incorporated to spectral data to improve forest type classification (Brockhaus *et al*., 1992; Franklin, 2001; Hopkins *et al*., 1988). Determination and delineation of site elements and environmental factors which have effective roles in the spatial distribution of forest types or groups of homogeneous species is the first step to incorporate this non-spectral data with spectral data. This study presents results using different spatial distribution models, generated with topographic parameters to improve classification results. A primary objective of this study was to investigate how these spatial models, in combination with spectral data, improve forest type classification.

Spatial distribution models: The distribution of forest types can be affected by a number of characteristics such as soil, microclimates, as well as specific terrain-related features such as elevation, slope and aspect. These characteristics can be considered as indicators of tree type composition and distribution. Hence, the variables may be incorporated into predictive models to estimate likelihood of the occurrence. These models can help make accurate decision that a pixel belongs to a class by algorithms based on accurate location and distribution range of forest types. One means of incorporating ancillary data is using prior probabilities of class membership.

Spatial distribution models can be instructed based on environmental parameters that have high correlation with occurrence of forest types. Recognition of specific places for each type, which is referred to as ecological factors of species is very difficult in the mountainous forests. In complex forest sites like the present study area, forest types commonly are related to many variables. These variables expose specific ecological conditions for each type, called homogenous units. Homogenous units are where specific ecological or topographical condition causes to grow particular species or specie is dominated on other species to comprise a homogenous vegetation cover, forest type or stand. Homogenous unit is a place where a unique forest stand or type is related on specific condition. It means that some ecological elements such as topographic parameters effect on the spatial distribution of forest type. They can be delineated by dominant species on canopy cover or most frequented compare to other species. For example, the pure Fagus type that *Fagus orientalis* is dominant specie or frequented above 90% is seen only at altitudes greater than 700 m above sea level and generally founds at northern aspect. With a simple assumption, homogenous units can be generated based on environmental variables such as topographic factors (elevation, aspect and slope) that have important restrictive roles on species growth.

Determination of occurrence rate of each type in one homogenous unit based on some variables and construction of this spatial model to incorporate remotely sensing data may improve classification results versus using each variable individually. For this reason, finding a relation between spatial occurrence of types and environmental variables in the northern mixed hardwood forest of Iran was the first objective of this study. Of course, based on some ecological and edaphic conditions, species can be individually exposed in some places, but collection of the same species as groups and dominant species may occur in specific places. Consequently, grouping of these species as homogeneous units called forest stand can be reached by these rules.

If these rules could be expressed and constructed as spatial models, they would help accurate assignment to a class of pixels of a homogenous unit. Delineation of natural requirements of species may lead to specify their spatial distribution. However, these requirements may be different when a type is determined with dominant species and non-dominant species. Thus, specification and determination of type characters against species characters can better help to construct types spatial models. Discrimination of these rules commonly leads to production of expert knowledge about types (Franklin, 2001). This knowledge can be extracted in different ways and from different sources such as aerial photos, existing maps and expert knowledge. In addition, they can be obtained from forest inventories through field work and sample plots.

MATERIALS AND METHODS

Study area: The study area is located in the educational and experimental forest of Tehran University in the north of Iran between 51°33'12"E and 51°39'56" E longitude and 36°32'08" N and 36°36'45 5" N latitude. This forest has been subdivided into seven districts. However, the study has only been performed in three districts (Patom, Namkhaneh and Gorazbon, respectively) with about 3000 hectares area (Fig. 1). Altitude ranges from 50 to 1350 m. Regarding different aspects and altitude zones, a variety of forest types have established.

Data: In order to investigate ETM+data potential for forest types mapping, a small window of the 164-35 Scene from 2 August 2000 was selected. Except for the thermal band, all multi-spectral and panchromatic data were used for this study. In addition, some ancillary data extracted from DEM such as aspect and elevation maps were resized to the spatial resolution of satellite data. These data were imported as thematic layers in the classification process.

Ground truth: The accuracy assessment of classification results and comparison of classification methods requires a ground truth map. Since a forest type map has not been available in the study area, a sample ground truth of forest types was designed and generated. The square sample plots were distributed systematically throughout a 3000 ha study area. The minimum typical area to recognize a forest stand or type is one hectare (Shataee and Mohajer, 2002). On the other hand, the minimal area for selecting samples on the remote sensing data is about 3×3 pixels (i.e., 8100 m^2 for ETM data) (Curran, 1985). Therefore, the size of each plot was designed 10000 m^2 (1 ha). The diameter of trees with the DBHs (diameter at the breast height) greater than 12.5 cm were measured in each plot and the kind of species were noted for all trees. 193 plots were measured in the non-protection section of the study area.

In highly dense and mixed hardwood forests like the study area, the forest has multiple layers with large diameter trees (thick) dominating the canopy (Shataee and Mohajer, 2001). Selection of about 100 thick trees for determination of forest types in each plot refers

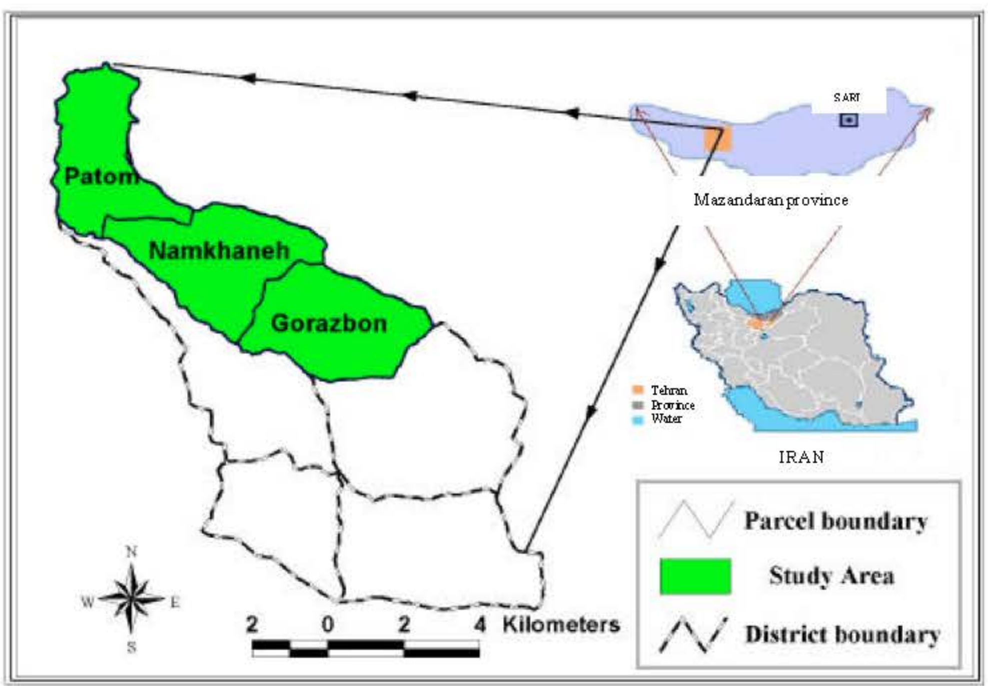

Fig. 1: Location of the study area at the research forest of Tehran University in the north of Iran

due to theirs canopy compose forest canopy cover and theirs reflectance are registered by sensors. The digital number of remote sensing data is based on the reflectance of forest crown. Therefore, based on experience, by computing 100 thick trees and the percentage of species frequency, the kind of forest type in each plot was determined. In addition to plantation area, six forest types were recognized by dominant species frequency of 100 thick trees (Table 1). A vector g round truth map was generated from square sample plots using GIS software. The map was then rasterized using a spatial resolution similar to the panchromatic ETM data (Fig. 2).

Pre-processing and processing of images: The first step before the image analysis is the pre-processing of images for classification. Because, the ETM+bands have been received as orbit-oriented images and not registered to given references, they were geo-referenced in two steps in PCI software. First, the panchromatic band was geo-referenced by ground control points extracted from digital 1:25000 maps and ortho-rectified using DEM. The final RMSe was about 0.65 pixel (19.5 m) with second order polynomial transformation and nearest neighbor resampling method. The multi-spectral images have then been rectified with the pan image using image to image matching technique by image control points, the same

Table 1: Determination of forest types through computing frequency percent of 100 thick trees

Forest types	Frequency percent of species
Pure fagus	>90% *Fagus orientalis*
Mixed fagus	50-90% *Fagus orientalis*
Pure carpinus	>90% *Carpinus betelus*
Mixed carpinus	50-90% *Carpinus betelus*
Mixed alnus	>90% *Alnus glutinosa*
Mixed hardwood	Other species, under 50%

transformation equation and resampling method. The total RMSe was found to be about 0.54 pixel (16.2 m). All images corresponding to ground truth map were resized to 10 m resolution.

Before the classification of images, some suitable image processing analyses were applied to the ETM+ main bands: Ratioing, tasseled cap transformation and Principal Component Analysis (PCA). Ratioing is mathematical or logical operation on the certain spectral bands to generate artificial bands. The Ratio transformations are often used in image processing to reduce radiometric effects of slope, illumination angle or seasonal variability (Ivits and Koch, 2002). The first three components of Principal Component Analysis contain more information contrary to each band individually. The brightness, wetness and greenness axes of the tasseled cap calculation can be useful in the topographic variations as well as to differentiate between closed forest canopy conditions (Cohen and Spies, 1992).

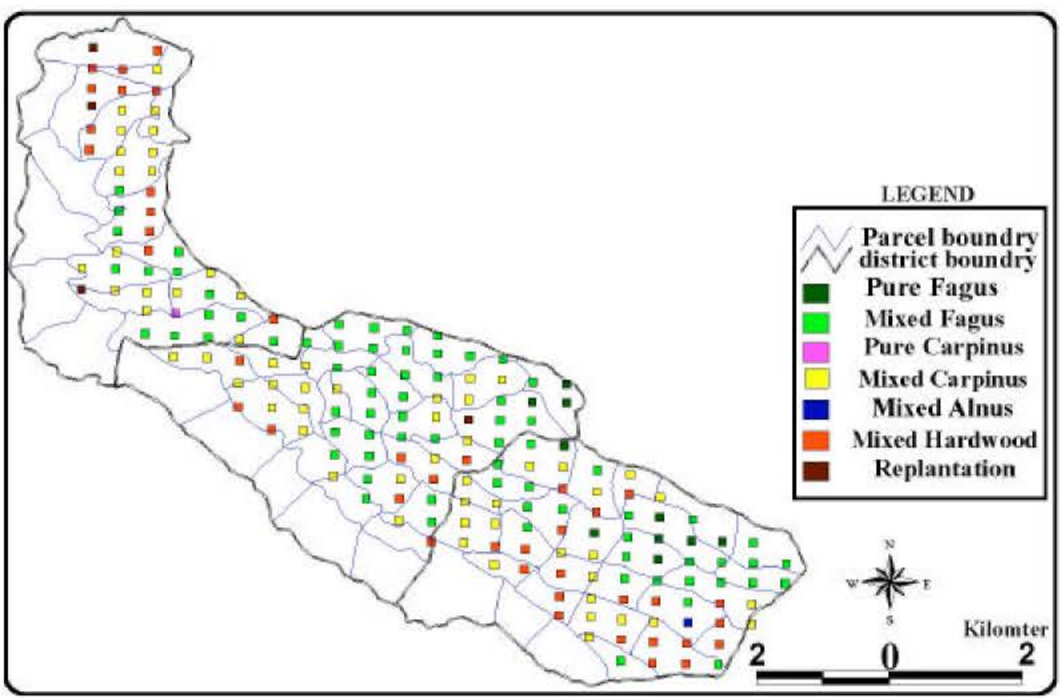

Fig. 2: Sample ground truth map of forest types in the study area

These processing were applied to the main bands to create new artificial bands. Using seperability analysis the best channel set was selected and specified to be useful for some artificial bands. These new images were used in combination with ETM+ images in the classification processes.

RESULTS

Specification of the best channel set and classification with spectral data: In order to compare using spectral data and integration of spectral and ancillary data for classification of forest types, classification of ETM+ bands and some artificial bands was accomplished. In supervised classification, some pixels known from fieldwork were selected as training area for each type. The feasibility of being separable and a good extraction of forest types were tested using the Bhattacharya seperability index. Finally, the best bands set were selected based on spectral properties of the training areas by the Bhattacharya seperability index (Table 2).

Following many studies, where the maximum likelihood classifier was reported as a suitable classifier (Hopkins *et al*., 1988; Williams, 1992; Darvishsefat, 1994; Shataee *et al*., 2004), this classifier was applied to separate forest types.

Determination of parameters related to forest types to construct spatial predictive models: As mentioned before, the maximum likelihood classifier has the capability to use prior probabilities of class occurrences as values and as spatial imagery models. It means that as an alternative, prior values may be specified according to spatial characteristics associated with defined classes. To construct spatial models, it should be first specified which environmental and ecological parameters have the greatest effect on the spatial distribution of forest types and consequently can be used as spatial predictive models. This information can be extracted in different ways such as information of obtained sample plots inventories. In this study, this information was collected through ground plots. On the other hand, some forest researchers have found that topographic parameters have strong correlation with forest types in medium scale in the northern forests of Iran (Asadollahi, 1987). With respect to these reasons, a digital elevation model (DEM) was generated using the 1:25000 digital topographic map. From DEM were extracted the elevation map with 100 m intervals, slope and aspect maps with defined classes. These maps were compared with the ground truth map to specify correlation between these parameters and forest types. The primary results showed that elevation has more effect on the distribution of forest types than other topographic parameters i.e., aspect and slope. Table 3 shows the range of occurrences of forest types in the each of topographic parameter.

The results showed that the slope parameter is not a useful parameter for differentiating forest types. Also, since ranges of each forest type overlapped with respect to the topographic variables, these topographic variables were studied individually and in combination. Results of these analyses are summarized in the following sections:

Classification with spatial predictive model based on elevation: According to Table 3, the elevation parameter is more effective on the spatial distribution of forest types. Based on this primary result, a spatial predictive model was created using information of occurrence rates of forest types in each 100 m elevation class. These prior probabilities were computed as:

$$P\ (f/h) = N\ (fi/h)/\Sigma N\ (fi/h) \qquad (1)$$

Which:

P (f/h) = Probability of type of A in the elevation classes

N (fi/h) = Number of pixels of type A in the elevation classes

Σ N (fi/h) = Total number of pixels of type A in the elevation classes

For this reason, the digital elevation model was classified in 100 m classes. Consequently, for each forest type a spatial predictive model (six models) was created as layer (image) (Fig. 3). These images had values, which showed prior probabilities rates for each forest type in the elevation classes. Classification of forest types was accomplished using integration of the best band set and spatial predictive imagery models.

Classification with spatial predictive model based on aspect: In natural forests, distribution of forest types is additionally correlated with aspect (Asadollahi, 1987). In this study, the aspect-based prior probabilities of each forest type were calculated and the improvement of classification by using spatial distribution models was investigated. An aspect class's map was extracted from the DEM to create the aspect distribution model. The occurrence rates of forest types in the each aspect classes were computed the same as elevation (Table 4).

Based on these prior probabilities, for each forest type a spatial predictive model (six models) was created as layer (image). Classification of forest types was accomplished using integration of the best band set and spatial predictive imagery models.

Table 2: The ETM+, artificial bands and best bands set selected by seperability index

ETM+ Bands	Artificial Bands	Best bands
1, 2, 3, 4, 5,7 and Pan	PC1, PC2, PC3, Brightness, Greenness, wetness, Ratio (NIR-G), Ratio (NIR/G), Ratio (NIR/R+G), Ratio (NIR-MIR/NIR+MIR), Ratio (NIR -R/NIR +R)	PCA1, PCA3, Brightness, Greenness, Ratio(4/2), Ratio(4/3+2), ETM4

Table 3: Distribution of forest types in the topographic parameters

Forest types	Elevation (m)	Aspect	Slope
Pure Fagus	1100-1350	All aspect	0-40%
Mixed Fagus	400-1300	All aspect	0-40%
Pure Carpinus	700-800	Southern	0-40%
Mixed Carpinus	400-1350	All aspect	0-60%
Mixed Alnus	1100-1300	West southern	7-40%
Mixed	0-1300	All aspect	0-100%

Table 4: Occurrence rates (Total 1.0) of forest type in the aspect classes

Total	Pure Fagus	Mixed Fagus	Pure Carpinus	Mixed Carpinus	Mixed Alnus	Mixed	Replantation	Forest types/ Aspect Classes
1	0.04	0.53	0.00	0.13	0.00	0.24	0.06	North
1	0.14	0.61	0.00	0.11	0.00	0.12	0.02	Northeast
1	0.00	0.46	0.00	0.15	0.00	0.32	0.07	East
1	0.07	0.08	0.02	0.47	0.00	0.32	0.04	Southeast
1	0.06	0.23	0.02	0.43	0.01	0.25	0.00	South
1	0.02	0.36	0.00	0.38	0.01	0.22	0.01	Southwest
1	0.03	0.46	0.00	0.26	0.00	0.23	0.02	West
1	0.09	0.47	0.00	0.29	0.00	0.13	0.02	Northwest

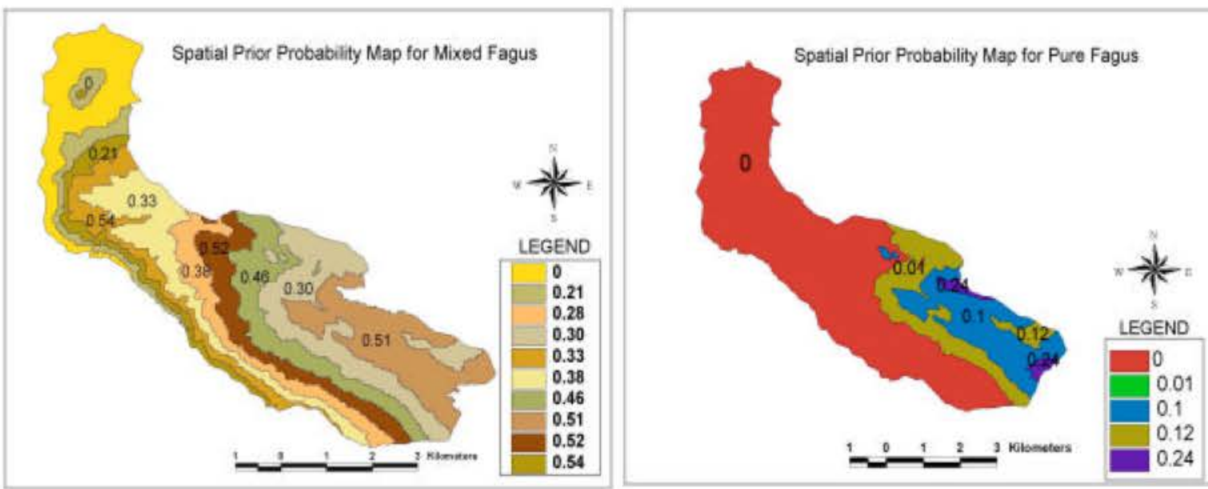

Fig. 3: Elevation spatial models as prior probability images for pure (a) and mixed (b) Fagus types

Classification with spatial predictive model based on integration of elevation and aspect: As expressed before, distribution of forest types is not related to only one parameter. Therefore, for integrating ancillary data with spectral data, it seems that using a multi-parameter spatial model may improve the classification results better when it is integrated with spectral data. By this assumption, a spatial distribution model was constructed by incorporating aspect and elevation parameters. This multi-parameter spatial model was built as follow:

- Addition of aspect and elevation occurrence images that subdivided two created aspect-elevation occurrences images.
- An elevation likelihood image was built on condition that where each forest type is occurring will be '1' and other places will be '0'.
- Spatial distribution model was obtained by multiplication of the last step images.

An aspect-elevation spatial model was created for each forest type separately (six models). Classification of forest types was accomplished using integration of the best band set and these spatial predictive imagery models.

Classification with spatial predictive model based on homogenous units: Homogenous units are places having equal conditions regarding the variables such as aspect,

Table 5: Accuracy assessment results obtained from spectral data only and spatial models

Methods/Accuracy	Spectral data	Spectral data aspect and spatial model	Spectral data and elevation spatial model	Spectral data and elevation-aspect spatial model	Spectral data and homogenous units model
Overall accuracy (%)	49.680	56.28	57.65	58.34	60.87
Kappa coefficient	0.275	0.34	0.35	0.37	0.41

elevation or slope. In mountainous regions, some different aspects can be found in each elevation class. Regarding the impact of aspect on the distribution of forest types, the occurrences rates of forest types can also be different in a given elevation class. Thus, the homogenous units can be considered for different aspect and elevation conditions. For these reasons, comparing elevation and aspect class maps created the homogenous units. Corresponding to previous ways, the occurrence rates of forest types were extracted and homogenous spatial models were built for each type (six models). Classification was accomplished using the integration of the best band set and homogenous unit spatial predictive imagery.

ACCURACY ASSESSMENT AND COMPARISON OF CLASSIFICATION APPROACHES

In order to obtain the results of integrating different spatial models with spectral data, the accuracy assessment of the results was done with the sample ground truth map (Table 5).

DISCUSSION

This study showed that the maximum likelihood classifier has high capabilities to integrate ancillary data as prior probability and spatial models. The study confirms the results by (Hopkins, 1992; Darvishsefat, 1994; Apisit and Sheresta, 2000) that spectral data alone are insufficient for the classification of forest type in mountainous areas. Specifically, classification based on solely on spectral data resulted in the relatively low values for overall accuracy (49.68%) and kappa coefficient (0.275).

When integrating ancillary data it should be first investigated which parameters are effective on the spatial distribution forest types and second how they should be incorporated into the spectral data. This study confirmed that using topographic data related to classes could improve the results, which agrees with other studies (Janssen *et al*., 1990). The primary results showed that the elevation parameter has more impact on the forest types distribution than other topographic parameters i.e., aspect and slope. Results showed that the slope is not a parameter that can differentiate forest types.

Ancillary data could be imported as prior probability imagery into the classification processes. Compared with spectral data, these spatial predictive models could improve the classification results; in this study, ancillary data improved overall accuracy by 6.5-11% and kappa by 0.065-0.135.

Using spatial predictive model created by aspect in combination with spectral data could improve the overall accuracy by 8%. This is a significant increment in accuracy compared with only spectral data. This increment refers to accurate addressing of some types by aspect and increment of occurrence probability.

Construction of a spatial predictive model based on elevation parameter and integration of this model with spectral data, specified that increment of overall accuracy improved more (about 1% more than aspect). This result exposed that elevation has almost more impact on the distribution of forest types compared with aspect. The silviculture knowledge (Asadollahi, 1987) confirms the role of elevation parameters on the spatial distribution of certain species like beech and refers to the equal impact on the formation of forest types or grouping establishment of species that comprise a forest type.

Incorporated spatial predictive model based on aspect and elevation could not improve classification results considerably. Although a little increment (about 0.02) was found in the overall kappa compared with using aspect and elevation spatial models that constructed as earlier, but this improvement is not attractive.

Creating homogenous units based on aspect, elevation and using this spatial predictive model with spectral data showed that the classification result could be significantly improved by 11% in overall accuracy and 0.14 in overall kappa.

This study showed that if spatial models accurately are specified addressing of forest type occurrence and/or be determinate the distribution of forest types with strong related parameters, are capable to improve the classification results when integrated with spectral data.

Although, the overall accuracy of both spectral data and integration of spectral with spatial data results were generally low and insufficient to illustrate applicability, the results emphasized the considerable improvement. They may be inadequate for uses requiring high precision, but they probably give the best available picture of forest type in the region. These results encourage us to investigate other techniques and methods that may improve classification results so that it would be feasible to apply them for forest management.

Other factors related to species distribution, such as soil and climate, may be of future use in the classification process or geographical knowledge to integrate them with spectral data. Other techniques such as rule-based classification or expert system should be investigated to improve the results so that an executive forest type mapping method would be obtained using satellite data without extra time and cost consumption.

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